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Artificial Intelligence-Powered Finance

Algorithms, Analytics, and Automation for the Next Financial Revolution

Subramanya Bharathvamsi Koneti

Artificial Intelligence-Powered Finance: Algorithms, Analytics, and Automation for the Next Financial Revolution

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Preface

This book offers a deep and insightful examination of how Artificial Intelligence is revolutionizing the modern financial ecosystem. From the rise of algorithmic trading and autonomous investment platforms to cutting-edge fraud detection and credit risk modeling, the book illustrates the profound impact of AI on traditional and digital finance. Readers will gain a practical and technical understanding of how machine learning, natural language processing, reinforcement learning, and generative models are driving innovation in banking, insurance, wealth management, and regulatory compliance. Through real-world use cases, code examples, and architectural blueprints, the book bridges the gap between theory and execution, empowering readers to implement AI strategies in real financial environments. As finance enters a new era defined by speed, precision, and data-driven intelligence, this guide serves as an essential roadmap for professionals and students navigating the AI-powered financial revolution.

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Chapter 1: Artificial Intelligence in Financial Systems: Digital Transformation, and Machine Learning Applications

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1. History of Artificial Intelligence in Finance

The use of artificial intelligence (AI) in finance began in 1988, and its functionality steadily expanded through the 1990s. The earliest applications were a straightforward translation of the traditional function of the financial analyst to one performed by a computer. It was not until roughly 1997 that there was systematic and continuous expansion in the functional use of AI in finance. The first explorations of fuzzy logic to apply generalizations were expanded to examine linguistic variables through fuzzy classification of qualitative information: executive composition, structure, and strategies of financial groups. AI techniques were also used to investigate the connection between the bond market and the stock market, support for the investor in maintaining a structured portfolio, bank performance prediction, credit assessment models, and U.S. stock price prediction.

Between 1997 and 2014, the emergence of new data sources and the so-called big data revolution brought the possibility of building, sampling from, and analyzing much larger datasets, and therefore of moving beyond correlation to prediction and forecasting. The digital colossus Google was founded in 1988, but it took roughly 10 years more to become the leading company in search engine result, followed by the emergence and development of social networks such as Facebook (2004) or Twitter (2006). Humongous amounts of information and data are shared by people on the Internet, for example, on those social networks. This information contains data about many different kinds of entities, such as people, places, products, events, and so on. New datasets related to the news, internet search behaviours, and social media activity have become accessible thanks to the information generated in the digital era and available online, which potentially may contain early signals about the economy and financial markets.

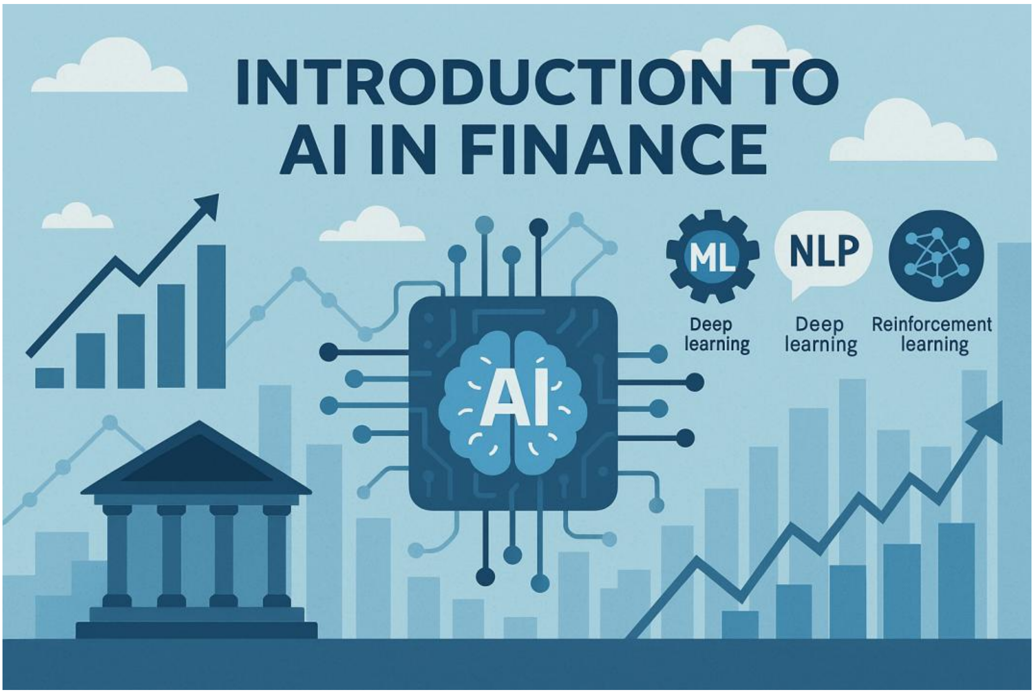

Fig 1. Introduction to AI in Finance

2. Trends in AI within the Financial Sector

Automation has long been a trend in finance, including the introduction of algorithmic trading as far back as the 1970s with the arrival of the first computers. The current automation wave differs from earlier developments because it leverages the availability of huge amounts of data, automated interactions, and fast computers. The convergence of these factors enables Data-driven Automated Decision Making and introduces new possibilities for automating financial decisions. These separate trends are discussed in the following paragraphs.

The digital shift in financial products and services, especially recent developments in digital and open banking, is creating a whole new ecosystem with higher interaction levels between financial entities and individuals [1]. This increased interaction is enabling a fast convergence of big data and finance onto data-driven decision making in the financial domain. Financial products are becoming more complex and difficult to address. Data-driven decision making is a challenge because the products and services of incumbent financial institutions are often based on structured data and artificial intelligence (AI) techniques [1-3]. Customer interactions generate large amounts of unstructured data that cannot be ignored anymore in decision-making processes.

3. The Digital Shift in Financial Services

When Artificial Intelligence is applied to the financial sector, the result is Finance Artificial Intelligence, or FinAI. The growing volume, variety, and veracity of data and the exponential growth in computational power make it possible to conduct advanced and frequent risk simulations [2,4]. As a result, engagements between private banks and clients become richer. Transaction monitoring systems become reactive instead of merely compliant, and investment strategies can be automatically adapted based on emerging events.

The new digitalization of financial institutions threatens the traditional client-facing industry and stimulates the search for new revenue models. It allows banks to operate in different client-facing business models [5-8]. The new client interaction channels in the digital realm permit a client onboarding process and relationship management without physical contact. The use of digital channels is intrinsically linked to the ability to better classify the client; i.e., according to consumption patterns and banking product features. The increased availability of data and the use of digital channels enable a better understanding of each client profile and its specific needs, resulting in a more tailored offering.

4. Overview of AI Technologies

AI can automate repetitive tasks with greater ease and efficiency than humans, allowing institutions to allocate their resources more effectively. The ability of AI to process and analyze large datasets far surpasses human capabilities, leading to improved decision-making and results. AI models use historical data to train themselves and generate accurate predictions [6,9]. Since AI utilizes human-generated data, its decisions are susceptible to human biases. Furthermore, addressing emergency situations that fall outside historical patterns presents an ongoing challenge.

Artificial Intelligence refers to systems that exhibit intelligent behaviour by analyzing their environment and taking actions, with some degree of autonomy, to achieve specific goals [10]. Narrow AI systems focus on particular tasks, often employing techniques like machine learning or expert systems. Machine learning enables systems to automatically learn without explicit programming, with deep learning utilizing artificial neural networks and unlabeled data to understand intricate relationships. Data analytics examines datasets to uncover hidden patterns, while knowledge-based systems rely on structured rule sets or algorithms developed by domain experts. Several AI techniques play roles in finance, including expert systems, neural networks, Bayesian networks, support vector machines, case-based reasoning, fuzzy logic, evolutionary algorithms, hybrid intelligent systems, and natural language processing.

4.1. Machine Learning (ML)

Artificial intelligence (AI) commonly refers to the capability of a computer program or machine to tackle tasks that are traditionally solved via human intelligence. AI is mainly divided into two major subdomains called narrow AI (or weak AI) and general AI (also strong AI) [10-12]. Narrow AI is designed to perform well for a narrow task, for example, playing chess, driving a car, or tailoring ads. The ambition of general AI is to solve a wide variety of tasks. General AI is still in its infancy but most scientists are convinced that it will be developed at some point in the future. Closely related to both narrow and general AI is machine learning (ML). It often refers to explicit computers that learn from experience. In the narrow variant, it is about developing an algorithm on the basis of training data that is later validated on the test data. This is similar to the human learning process, where generally learning behaviour is validated by a final exam. For example, one can develop an algorithm to predict future stock prices based on past prices and a training and test data split.

4.2. Natural Language Processing (NLP)

Natural Language Processing (NLP) leverages computational and statistical techniques to formulate and present formal representations of textual or speech input. These formal representations' structure reasons about the content in a consonant manner. NLP enables the exploitation of unstructured material, including earnings call transcripts, news, and social media, within financial machine learning models [7,13-16]. Specific NLP methods used in financial applications encompass text classification, information extraction, sentiment-analysis, and topic-modelling techniques.

Processed concepts allow statements, quotes, or articles to be linked to a particular company, date, or other attributes. Two primary types of data used in NLP financial machine learning models can be distinguished. The first type measures the impact of market events or public opinion on the price of a company. Examples include earnings call transcripts, news articles, and social-media posts. The second type consists of data examining the inner operations of a company, such as earnings press releases and analyst reports.

4.3. Deep Learning

Models designed for pattern recognition tasks involving agents operating concurrently in a dynamic and uncertain environment require the estimation of the agents' value functions or policies for decision-making purposes [2,17-19]. Deep learning architectures such as the transformer are useful for approximating policies in multi-agent reinforcement-learning-based decision-making. Long Short-Term Memory (LSTM) neural networks can extract low-dimensional features while encoding the environment's temporal evolution. Multi-Head Attention (MHA) mechanisms allow concurrent attention to various aspects of other agents, capturing relational features across entities in the environment. Multi-agent reinforcement-learning setups must also consider the effects of dynamically changing agent population size on the agents' policies.

When performing complex probabilistic inference tasks such as predicting the future price distribution of fiat currencies, leveraging a Synthesized datasets-based Model Architecture Search (SMAS) framework can be effective [3,20-23]. An SMAS framework generates a diverse set of candidate data-generating processes (DGPs), trained machine learning base-models, and automatically identifies the best-performing model for a specific number of steps ahead, mode, and prediction region type. Historical fiat currency datasets that reflect the data characteristics of specific DGPs can then be used to train the identified best models for different prediction tasks.

4.4. Reinforcement Learning

Following the completion of the supervised learning phase, the successful allocation configurations undergo a reinforcement learning phase that exploits the objective function coefficients for configurations pre-selected by the previous phase [9,24-26].

Agent closures are assigned to all clients and centers/cards. At each iteration, one agent closure is updated—comprising agents associated with one of the centers/cards—and the new closure is then tested with all the pre-selected configurations. The closure that yields the highest accumulated penalty score is retained and then used in the next iteration. Algorithm 2 details the closure initialization technique.

5. Impact of AI on Financial Decision Making

Artificial intelligence (AI) has broad applications across many financial services and functions, including credit scoring decision-making, algorithmic trading, and financial advisory [27-29]. The technologies behind AI include natural language processing, machine learning, and deep learning, albeit the selection of a particular AI application for solving a business problem depends on the objective and input data. In the credit control domain, for instance, a customer who is unlikely to default on payment can be offered credit in order to enhance the revenue and profitability of the business. Applying AI for business decision-making involving financial credit control is of paramount importance, as an erroneous decision can result in credit loss—one of the biggest reasons for business failure for British enterprises during 2018–19.

Financial services rely heavily on financial decision-making applications of AI, which process sound data and enable enhanced economic benefits. By means of AI applications, it is possible to extract the essential features of a financial decision-making problem, forecast the impact of decisions, and generate alternative solutions to support the final decision. Further, the impact of AI on financial decision-making can be assessed by examining companies that measure the performance and risk variables of financial transactions. Evaluation of an organisation’s financial performance helps predict its operating risk and credit risk, and provides a benchmark to assess whether prediction models based on company particulars and financial value drivers can generate the same outcome. The purpose of financial decision-making is to maximise profits and value, or, at the very least, to optimise the state of financial affairs despite uncertainties. Financial judgements, both prospective and retrospective, are an assessment of the anticipated or realised consequences of an action or a decision, with the aim of leading to planned objectives and outcomes.

6. Challenges and Limitations of AI in Finance

The use of AI in finance is associated with various risks that practitioners, users, and consumers of such technologies have to take into consideration. For instance, decisions and market predictions based on third-party data sets or on AI systems, cannot always be fully explained, even by the data scientists who have designed the system. This poses a significant challenge for regulators and market authorities in their efforts to supervise financial markets [30-32]. The speed at which AI may operate can also generate serious risks. Deep learning techniques, such as Generative Adversarial Networks (GANs), can be used to generate vast quantities of synthetic content. This ability to create artificial patterns and data that appear real may be exploited for manipulative purposes.

It is worth pointing out that deep learning algorithms are typically context specific, perform well only on certain classes of problems, and require extensive data for training. Additionally, the problem of overfitting arises when a model learns noise rather than signal in the input data. The AI research community has been actively pursuing solutions to these limitations. For example, Gaussian process is a probabilistic model that can provide uncertainty measurements on predictions, while Bayesian optimization automates algorithm configuration to reduce manual effort. Meta-learning aims to adapt a learned model or design new learning algorithms to quickly solve new tasks from limited data.

7. Regulatory Considerations for AI in Finance

Implementing AI for banking and finance faces significant regulatory restrictions [9,33-35]. Many areas within finance are highly regulated, particularly those directly affecting consumers, such as loans, mortgages, banking, and insurance. Other specialized areas—hedge funds, trading, financial advice, and portfolio management—have fewer direct regulatory constraints. Financial regulations also address areas like money laundering, fraud detection, and transaction monitoring to ensure the system's integrity.

The main objective of financial services regulation is to protect consumers. Historically, this has prevented promising technologies like chatGPT from entering banking and insurance products, or placed restrictions on the pipelines and approaches used. However, this perspective is gradually shifting. Regulators are recognizing the potential of AI to increase competition, efficiency, and consumer safety. They are also leveraging AI techniques to support their own objectives—automating compliance checking, screening transactions, and monitoring the industry. RegTech, the sub-sector focused on developing such technologies, is growing rapidly.

8. Future Prospects of AI in Financial Services

The ever-increasing universality of artificial intelligence permits financial services organizations to leverage AI innovation in all aspects of their functioning. Within payments and transactional services, AI underpins account verification and financial inclusion initiatives by validating records and documents submitted for Know Your Customer (KYC) checks, reducing the time spent by agents on the verification process, and minimizing exposure to financing risks and fraud [36-38]. AI enables financial institutions to explore new customer acquisition models by investigating potential hidden segments otherwise inaccessible because of the high cost of agent-driven servicing.

Financial services companies utilize AI for sentiment analysis of unstructured data at scale. Such applications include monitoring geopolitical conditions, currency sentiments, news reports, speech sentiment analysis of government bodies, opinions hunting in analyst calls, earnings conference calls, or news feeds, and microeconomic variables. This helps identify important signals within noisy data and categorize information for further investment decisions. The potential future growth of AI in finance appears limitless, as innovation continues to refine current applications and unleash new possibilities.

9. Case Studies of AI Implementation in Finance

Several companies have successfully applied AI in the financial industry. For example, Wells Fargo uses AI in its mobile banking service to offer voice recognition capabilities. JPMorgan Chase uses a program called COiN, which relies on machine learning to analyze legal documents and extract important data for its attorneys and loan officers. GPT-3 can be used for portfolio management, financial forecasting, customer service, fraud detection, and automated report generation. Its text generation capabilities can assist in creating custom investment research, communicating with clients, and managing risk.

Numerous studies have demonstrated that artificial intelligence has considerable potential applications in the financial industry. A major advantage that banks have is the ability to obtain data from the interactions they have with customers, which are in the form of natural language. However, the use of natural language in interactions costs a lot, as it requires a worker's time to manage the interactions. Natural language generation systems are able to bridge this gap between data and natural language, reducing costs and allowing banks to exploit customer experience, natural language processing, and automatic reply to customers of banking services.

10. Ethical Implications of AI in Finance

Application of AI in financial industry is associated with moral consequences, such as discrimination, unethical use of private data, privacy violations, and security risks [3,39-41]. Advanced technologies often bring both positive and negative impact, so at the application stage, appropriate regulation and ethical guidelines must be established. At present, some countries and institutions have taken lead in the aspect, such as the G20, which emphasized responsible evaluation of AI-based product features and impact enforcements. The goal of the G20 Principle is to "make AI-based products more traceable, transparent, and responsible" to protect rights of all parties. The Institute of Electrical and Electronics Engineers has issued IEEE P7003 standards to promote the formation of AI ethics framework in a multinational and multiform way. The European Commission published a White Paper on Artificial Intelligence with the stated purpose of "supporting the industry and society to make the most out of AI and addressing the risks associated with certain uses of this new technology".

Specific to the financial industry, the main direction is to prevent psychological manipulation, information abuse, and privacy leaks during application of AI technologies [36,42-44]. For example, excessive dependence on personalized recommendation technologies might deepen users' psychological inertia, forming discussion barriers and social bubbles. Targeted marketing might cause excessive psychological manipulation and intrusions into daily life. Lastly, improper use and leaks of personal asset counterparties' privacy information related to credit cross-selling, risk control, and early warning might lead to redundant marketing and privacy information-handling issues.

11. AI and Risk Management in Finance

Artificial intelligence (AI) applications in the evaluation of credit lending are also effective in assessing eligibility for a mortgage loan. In contrast to the practices of some financial institutions, which consider various factors such as bank balances, debts, even the applicant's social aspirations to assess creditworthiness, artificial neural networks examine only those factors that relate visas-à-vis risk [40,45-48]. The intent of such processes is to minimize the probability of default and to optimize the lending process.

Where a bank receives various repayment applications prior to its maturity, it must then analyze the risks associated with an early repayment request. Artificial neural networks (ANNs) are trained with a data set of customers, where the recorded output indicates whether a customer opted for early repayment in the past. The ANN is then used for the identification of a specific probability of risk associated with an individual customer's expected modus operandi. The prediction of risk associated with each customer is critical in devising subsequent policy strategies, closing of accounts and charging of penalties for customers associated with high risk.

12. Data Privacy and Security in AI Applications

Data privacy and security are fundamental considerations in the design, training, and deployment of AI models. The primary rule stipulates that sensitive information must never appear in training data; any sampled content containing such data must be excised before inclusion in model training sets. Model developers and ownership may not be fully cognizant of the individual training examples utilized by the model, heightening the risk of privacy breaches. Therefore, models like OpenAI's language framework undergo filtering to exclude explicit personal information. Nonetheless, the potential for users to elicit sensitive training details from models persists, as exemplified in earlier-stage models such as GPT-2.

Financial organisations have extensive historical record repositories, and predictive models could, in theory, be trained using patient data. Institutions might wish to restrict patient groups from accessing the Internet or prevent web scraping by public-facing websites. Given the sensitivity of such workflows and datasets, ensuring security is paramount. AI models are inherently vulnerable to hacking, exfiltration, or adversarial attacks. New technologies like differential privacy, federated learning, homomorphic encryption, and secure multi-party computation are gaining traction to counter these threats. Conversely, model behaviour might expose insights about the model itself or data, posing disclosure risks for insurers. Techniques such as model masking and model watermarking can be employed to thwart these risks.

13. AI-Driven Customer Service in Financial Institutions

Financial institutions such as banks, insurance companies and asset management companies have long relied on specialized customer advisers to provide a personal, competent and tailored service to their clients. However, this service is usually only available during office hours and entails significant costs for the institutions, which need an appropriate number of qualified and specialized employees for the large number of potential customer requests. With the 24/7 availability and the automation of low-effort-user inquiries, chatbots have already taken over support functions in many institutions and were able to reduce costs and introduce new customer access channels.

With the increased availability of models for natural language processing, the quality of chatbots has risen significantly in recent years and now also allows for further tasks in the customer relationship. However, these capabilities have so far been applied only to a very limited extent in the financial context due to the delicate nature of the information accessed. Within the present work, the area of responsibility for customer advisors is therefore divided into support roles for increased cross-selling, support roles for reducing customer churn and a information duties and regulatory framework. Further areas of interest include the organization and implementation of customer service as well as the role of sustainability in customer service.

14. AI in Investment Banking

A revolutionary transformation driven by AI, robotics, and automation is unfolding within the investment banking sector. Technological innovations are set to redefine daily banking operations, reshaping the roles of human bankers and their relationship with clients. The advent of "robo-banks," specializing in areas such as corporate banking and investment secondary markets, is anticipated. In the retail segment, fully automatic, online branchless, and cardless banks are becoming increasingly prevalent.

In the credit card business, AI systems excel at fraud detection, property cardholders, spot unusual credit activity in corporate or retail banking portfolios, and automate early detection of bankruptcy or non-payment. The preparations for Initial Public Offerings necessitate compiling hundreds of pages of financial data and analysis in a cohesive presentation; today, AI-driven software effectively performs the majority of these tasks, significantly reducing human labour. Additionally, during mergers, AI software can construct hundreds of modeled scenarios to determine the value of a proposed new company combined with the current clients and offered services of two particular merging parties. In the field of insurance, AI systems detect fraud and reduce the approval time for various types of insurance; they also assist in the capital investments needed to support paying for claims. Furthermore, stock portfolio management combines both AI and human decision-making, while stock price prediction requires AI's assistance in analyzing vast amounts of financial data to prevent losses or determine the causes of abrupt financial drops or rises in financial markets.

15. AI in Retail Banking

Many areas of application of AI in the banking sector relate to retail banking. These include banking advice, communication, warning systems, account management, security, marketing, fraud detection, and borrower default probabilities. Lending is a bank's most important business: Private households without sufficient equity can more easily borrow for consumer purposes – e.g., buying a car. Even for real estate investments, a large portion of the financing is provided by the bank. Due to the high loan volume, the bank naturally also establishes a certain risk provision, the so-called risk provision for risk-classified loans. For installment loans, the average borrower default rate is approximately 2%.

In the lending process, a balance must always be struck between profitability and credit risk without compromising customer satisfaction. Potential customers with a low default risk should receive a credit decision as quickly and automatically as possible, as otherwise customer satisfaction suffers. However, if a customer's application has a default rate that would result in a loss for the bank, it is not profitable to extend the loan. The trick is to determine the optimal loan amount for the customer as quickly as possible, using as much automation as possible.

16. AI in Wealth Management

Artificial intelligence (AI) heavily influences wealth management by conducting sophisticated analyses of large data volumes, surpassing human capabilities and introducing challenges in validation, regulation, and cybersecurity. A Milken Institute report identifies AI's impact on financial services in automation, recommendation generation, the transformation of human advisors' roles, and the creation of new services. Despite the industry's conservative reputation—attributable to its fiduciary obligations and role in mitigating company-specific risks—the successful implementation of AI-based investment models has yet to become fully established. Nevertheless, the focus remains on harnessing AI's potential for wealth enhancement in both asset management and financial advisory.

AI can consider investor and portfolio characteristics comprehensively when generating investment recommendations. Portfolios can be constructed in line with the client's investment profile, ensuring that the client's appetite for risk remains decisive. The automation of basic interaction processes facilitates close integration with virtual assistants that already permeate everyday life. The advisory foundation is supplemented by real assets linked to the company, such as strategic minerals like copper or lithium. Additionally, the management of the private clients of companies that benefit from the goods produced can also be addressed.

17. AI in Fraud Detection and Prevention

Numerous financial institutions have integrated artificial intelligence into their fraud detection systems. AI excels in fraud detection systems, with more organizations adding AI to these platforms each year to make them more sophisticated and better suited to identify even the slightest hints of potential fraud. Additionally, AI helps reduce false positives, a common challenge in fraud detection.

AI's ability to analyze extensive transaction datasets in milliseconds makes it near impossible to fool. Machine learning models learn from actual fraud patterns, enabling them to identify unique behaviors or transactions of particular individuals or groups that may indicate fraud. These models swiftly detect any deviation from normal transaction behavior and alert the relevant institutions. This approach extends to industry-standard methods such as biometrics and pattern and geolocation analysis. By developing advanced AI-driven solutions, financial institutions can detect fraud early or even before it takes place. Traditional rule-based engines analyze planned transactions, whereas AI models are trained to analyze past transactions in real-time, identifying patterns and nuances that may indicate fraudulent behavior.

18. AI in Credit Scoring

Credit scoring aims to estimate a borrower's default probability, i.e., the likelihood that the borrower misses loan payments. Since lending decisions are financial investments, committing money now in return for anticipated future payments—lenders are interested in assigning a score to each application that reflects its risk level. The borrower pool might be segmented into numerous groups; default rates then offer a natural way of defining the risk level associated with each group. For example, with 1,000 applications and a 10 percent default rate, there could be 100 defaulters and 900 protected borrowers. Credit scores might be defined in groups of 20 applications, then a good risk ranking ensures that the group with the worst assigned score encompasses 20 defaulters, the second "best" group contains 15 defaulters, and so forth.

A lending decision is a financial investment that involves committing money now in return for future payments. From this viewpoint, one might consider credit scoring primarily as a method for assigning a risk level to each application. The basic lending principle is that borrowers with increased risk must pay higher interest rates, thereby compensating the lender for the greater risk assumed. Combining credit scoring with this pricing principle makes it possible to run a profitable lending business that is also fair to borrowers. A scoring model can be used not only to rank applications by profitability but also to select only those with high scorable probability, consequently reducing risk. Economic authorities regard credit scoring as an automatic way of controlling the quality of loans.

19. AI in Algorithmic Trading

Trading in financial markets is an extremely popular application of AI. True enough—algorithmic trading is reported to account for over 70% of the trading volume in the most liquid financial markets around the world (EURUSD in the forex market, EURUSD and SP500 stock indexes futures) [49]. It is also one of the best candidates for active management of investment money.

So what is algorithmic trading, exactly? Algorithmic trading—or algo-trading—consists of executing a set of trading instructions automatically through a computer program.

20. Collaboration between AI and Human Analysts

Artificial intelligence (AI) plays an ever-increasing role in financial markets valuation. AI systems have no emotion and can process volumes of information far beyond the capacity of a human analyst. Yet, there is much data in human history that AI is not trained on and may not be able to generalize from, which makes human analysts essential to the process of asset valuation. New asset classes are also being introduced that AI systems were not built to recognize or classify cryptocurrencies, for example.

An AI system can quickly process the bullet points of an earnings release and determine the financial health of a company based on its net income, liabilities, assets, and debt levels. However, if a stakeholder changes their pattern of consumption—just like a human being might change their pattern of consumption—the AI system might miss the stadium-filling crowds that appear when a basketball team makes it to the final four. In other words, AI systems are powerful tools, but human analysts must always remain involved in the decision-making process.

21. Conclusion

In finance, artificial intelligence (AI) is applied to systems that mimic cognitive functions that humans associate with other human minds, such as learning and problem-solving. AI in the finance sector utilizes specialized computer systems or software to perform operations that normally require human intelligence, such as identifying trends, learning from new data, interpreting complex data, and making decisions or recommendations. However, successes in one area do not predict successes in any other area.

Computer vision is used for automated insurance claim processing, by identifying damage and classifying images. Systems specializing in tactile feedback, like robots, automate warehouse insurance claim processing and document control. Computer networks are used to identify trends in financial markets and make predictions about future market behaviour. Patient records are rapidly sorted and classified; information extracted can be used to create labels that can predict how likely a patient is to require preventative measures. Automated trading systems attempt to make human trading decisions at speeds hundreds or thousands of times faster. Flight Delay Billing Systems detect and predict flight delays and compensation eligibility for airlines.

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Chapter 2: Algorithmic Trading and Quantitative Finance Strategies: High-Frequency Trading, Market Microstructure, and Risk Optimization Models

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1. Introduction to Algorithmic Trading

Computer programs execute trades at very high speeds by using a variety of advanced quantitative models and algorithms [1-2]. In recent years, algorithmic trading activity has experienced tremendous growth in the trading volume [2]. Major advantages include low-cost, low-risk and high-speed execution design. However, complex algorithmic trading systems face substantial glitches, malfunctions and unexpected market crashes, leading to huge losses to both financial institutions and investors.

Rapid advances in communication, networking and computer technology have had a significant impact on the transactional side of securities trading [2-4]. Today electronic trading platforms (such as BATS and ARCA) account for more than 50 percent of the total volume of securities traded in the U.S. Due to low execution cost and reduced adverse selection risk, institutional traders are more than ever interested in executing large volume trades as quickly as possible without causing much market impact, and they rely heavily on specialized algorithmic trading services offered by brokers or independent algorithmic trading providers. Many brokerage houses mainly focus on building robust trading infrastructure and execution services.

2. Fundamentals of Quantitative Strategies

The build-up of quantitative strategies starts with fundamentals. A statistical factor is a characteristic that exhibits significant, persistent differences in average returns in cross-sectional data [5-6]. A clear example is the size factor, which shows that smaller-sized stocks tend to yield higher risk-adjusted returns.

Factors become practically useful when combined into a portfolio, which is known as a predefined factor, driving portfolio returns in a consistent fashion across market cycles. For instance, value portfolios containing stocks that are attractively priced relative to their denominator, typically earnings or assets, tend to outperform growth portfolios with high growth in earnings or assets [7,8]. Factors thus capture risk-premia that are compensated by the broad market due to the existence of associated risk exposures.

Fundamental factors, on the other hand, map to a company's fundamental risk, which cannot be diversified away, and stems from economic intuition. For example, the value anomaly plays out both at the stock level and the bond market. Low credit rating companies with low debt-to-equity ratios, like value stocks, offer higher inflation protection but experience cyclical risk due to lower debt coverage ability.

3. High-Frequency Trading

High-frequency trading (HFT) is a subset of algorithmic trading characterized by securities being bought and sold across multiple markets with multiple competing order types, at the highest speeds available. HFT leverages powerful computers to transact a large number of orders in fractions of a second. It uses complex algorithms to analyze markets and execute orders based on market conditions. HFT strategies profit by exploiting price inefficiencies and by quoting bid and ask prices that provide liquidity to the markets. The growth of HFT is attributed to technological advancements, regulatory changes, and market structure evolution that lower the cost of algorithmic trading.

Market microstructure, execution strategies, and risk management play pivotal roles in high-frequency trading [9-12]. Market microstructure examines how specific trading mechanisms affect the price formation process, involving the study of order books, trades, and quotes in security markets. Execution strategies aim to devise optimal trading schedules and order types to enhance trading speed and quality. Managing risks—market, execution, counterparty, and model risks—is essential to mitigate losses arising from unexpected events linked to market movements, delays, or contractual failures in the real-time environment of HFT.

3.1. Overview of High-Frequency Trading

High-frequency trading (HFT) refers to a specialized area of algorithmic trading that pays particular attention to the development of sophisticated techniques and tools to optimise the execution of orders in a trade process. Literature lists a variety of re-bundling names for HFT, e.g. fast trading, ultra-fast trading or electronic lightning trading. The fundamental characteristic of HFT is its undoubted technological superiority (lock-in advantage) addressed for the implementation of its trading strategies that use powerful computerized trading engines to match the right execution price with order placement at a very high speed and in sizeable amounts. HFT operates on relatively lower profits per transaction but the high volume of these minimised-profit transactions cumulatively results in a significant profit. The advantage of executing orders much faster than other market makers simultaneously raises the chances of being exposed to the risks of other market makers not acting fast enough. One of the most important aspects of the race for the automation of all the available information is its effect on the structure of the market itself, moving from the classical Central Limit Book (CLB) towards the Current Limit Order Book (CLB) structure. The literature insists the necessity of using the artificial-intelligence-support techniques for managing heterogeneous trading strategies developed in this race, in particular through machine and deep-learning algorithms to take advantage of the information embedded in the market microstructure.

3.2. Market Microstructure

The market microstructure, a term coined by economists Albert S. Kyle and Maureen O'Hara in the 1980s, encompasses the mechanisms and rules that govern how exchanges operate, including order book behavior, type of transactions, order types, price formation, transaction costs, and information that can be extracted from price and volume series. It captures the regulatory and operational framework under which trading takes place in a predefined environment that sets the trading rules. Among its main components is the interplay among assets and actors. Asset features could be liquidity, volatility, price, correlation with other assets, or type of instruments. An actor is a prompt in the market; usually a group of investors with similar beliefs or characteristics regarding type of products, investment horizon, or objectives. Traders and investors can specialize in looking for bursts of high volatility or in particular stocks. It is in the microstructure where the environment is set and where the market-makers develop their strategies.

Understanding market microstructure also provides detail on the function of the central authority, called the exchange; its set of rules and requirements; and how the mechanisms for matching orders play an important role in the choice of the trading strategy [7,13-15]. Information about the execution price, transaction costs, and regulation of the exchange has a direct effect on the construction of the trading algorithm. Because price discovery takes place through the order-matching system, a mismanaged algorithm could tip the balance on one side of the order book, upsetting supply and demand. Hence, a good model must understand the interaction of orders in the book.

3.3. Execution Strategies

Execution strategies dictate the manner in which a trade order is carried out [16]. Pursuing orders on lit order books too aggressively can potentially move prices against one’s interest and, hence, may be costly.

Such strategies aim to place such large orders on lit order books with precision and control so that they are executed quickly without exposing too much of a large dataset. Smart order routers that understand the microstructure of multiple lit markets could potentially be used to seek liquidity efficiently in those venues. At peace with price-moving events, however, crossing-venue-level and cross-asset correlation that could potentially provide the best opportunity for doing so quickly and relatively cheaply. Cross-asset smart order execution encompasses information, correlation, market impact, and Smart order types that leverage intra-day cross-venue relationship complexity.

3.4. Risk Management in High-Frequency Trading

Risk management techniques are crucial for mitigating the inherent risks of high-frequency trading and assist in reducing exposure not only for trading desks managing high-frequency strategies but also for market makers operating in financial markets. Market makers tend to hedge their market risk exposure at the end of the day, whereas market takers hedge their risk exposure at the end of each trade [9,16-18]. In this context, it is essential to highlight the difference between market-taking and market-making activities. Execution risk—as experienced by a market taker—is mainly related to the partial or non-filling of his orders and in an adverse context. On the other hand, market-making strategies rely on the placement of liquidity–intensive orders into the first limit of the order book and are exposed to inventory risk, as these assets need to be held for a short period of time.\n\nExecution risk can be addressed through the usual metrics previously presented in the section on execution strategies, but a further analysis has to be made in the context of market-making risk management. From this point of view, risk metrics can be classified in three categories: inventory risk measures, adverse selection risk measures, and loss and profit measures. Inventory risk measurements focus on the exposure of the market maker to underlying assets given, for example, a deviation of prices; they are intended to reduce price risk—associated with an adverse movement of the price of assets—that market makers are exposed to during the period in which they are in possession of an inventory imbalance [2,19-20]. One of the most important approaches of this kind is associated with the calculation of value at risk (VaR). Adverse selection risk, on the other hand, can be viewed as a risk metric related to the estimation of order-related information, in particular of the first level of information embedded in the order book. Contrary to inventory risk, it denotes a measure of execution risk associated with a given prospect of filling a limit order. Finally, loss and profit measures focus on the realized profit and loss (P&L) on transactions executed up to the present instant T on the holding of security positions. The P&L measures represent standard measures that can be calculated during the trading session to monitor the primary results of an implemented market-making strategy.

4. Artificial Intelligence in Trading

Experience from other industries shows that the rise of AI platforms drives new productivity gains even while reshaping jobs. The number of AI trades is growing as well as those executed by a hybrid of algorithmic and electronic methods. Algorithmic trading, also by exploitative AI, has led to increased job disruption in the trading sphere though AI does offers new support roles such as better use of material assets and facilities for cost reduction, supported by cooperation between human workers and AI systems in a variety of industries [9,21-23]. A study from the Bank of Canada results that the automation of trading and investing has led to heavy job losses; one of the better sectors for humans has been public relation.

New developments in automated trading also related to advances in decision theory, and the recently introduced discipline of algorithmic mechanism design, are leading to arguments for implementation of AI techniques in trading, trading rules and mechanisms. New research is building on the topic to improve general AI trading capabilities for the application of trading-rule discovery, decision support, game-theoretic models, simulation methods, portfolio optimization, pattern recognition, and other related topics.

Research is taking advantage of emerging methods for analyzing and modeling human decision-making and decision behavior, such as Prospect Theory. A considerable amount of research in the use of AI techniques is currently devoted to investment analysis, especially in the areas of portfolio management and securities valuation.

4.1. Introduction to AI in Finance

A maze of intricate relationships, a method of constant scrutiny, a state of permanent strategic analysis — these, for the philosopher Daniel Bernoulli, were the principal aspects of gambling (Betting on the Future) Algorithmic trading appeared to correspond closely to such an understanding, as it took the idea of placing bets with probabilities and combined it with the possibility afforded by computers to place overwhelmingly many bets every second, based on a continuous audit of the variations in the different elements that determine a global market's state. The algorithms are also designed to take into account all sorts of exogenous elements such as news and sentiment.

Today, many investment banks and hedge funds are involved in algorithmic trading, and at least half of all stock transactions on the New York Stock Exchange (NYSE) are generated through algorithms. Automated execution and strategy algorithms are the fastest-growing trading segment [24-26]. They generally work on the basis of historical information to forecast short- or medium-term price movements. More specifically, automated execution aims to optimize the execution of orders to minimize costs. There are various types of strategies — such as momentum, price arbitrage, statistical arbitrage, and order book prediction — that can take a long, short, directional, or market neutral position. The strategies can be centered on price movements, volatility, or order book signals.

4.2. Machine Learning Techniques

Inducing a function approximation from the available data to predict the prices of the financial instrument at specified points of the future is one way of developing an optimal strategy.

The trading strategy is a function that takes the current position and past prices and signals as input and outputs the decisions. The decisions regarding a particular transaction can be any of the following: the timing of the transaction, the instrument, the transaction type, the type of order, and the price and number of shares remaining in the order. In the above framework, credit risk, liquidity risk, market impact, execution risk, and transaction costs are all consequences of the function approximation; that is, the function approximator tries to maximize the total return.

4.3. Deep Learning Applications

The field of deep learning represents a rapidly growing branch of machine learning where the profound interconnectedness of eyes, ears, tongue, and skin in a human brain has inspired the design of neural networks for pattern recognition [8,27-30]. After the advent of convolutional neural networks (LeNet-5) in 1998 for optical character recognition, it took just over a decade, thanks to graphics processing units (GPUs), release of massive labelled datasets such as ImageNet, and deeper interconnected network design, for them to revolutionize the field of Computer Vision. There are several areas where deep learning, which makes fewer assumptions on the domain, becomes invaluable, such as identifying hidden features for a prediction task or learning a complicated nonlinear mapping in the data.

Recurrent layers, such as the long short-term memory (LSTM), have been used for modelling time and sequence. LSTMs have been previously proposed for financial prediction, aiming to predict shorter-term market fluctuations. In essence, instead of manually defining the nonlinearity in the state transition as done in hidden Markov or Kalman filters, LSTMs learn this transition from the data in a nonlinear manner. Convolutional neural networks have also been used for predicting exchange rate fluctuations, transforming the signal to a wavelet-transformed image first, before relying on a resnet for predictions.

5. Reinforcement Learning for Portfolio Optimization

Portfolio optimization entails allocating capital in numerous assets to maximize returns for a given risk level. The problem is formulated with allocation vector w, asset return vector r_t, and discount factor γ. The Markowitz model aims to maximize expected portfolio return minus γ times its variance over T periods, with portfolio return $X_t = w \cdot r_t$. Applying reinforcement learning (RL) supports sequential decision-making in dynamic, uncertain environments. Portfolio management models an RL agent maximizing cumulative rewards, equating allocations to actions and factor-based and style-adjusted returns to the state space for strategic adaptation.

Q-learning is well-suited for data-driven, model-free learning in financial applications and natural-state-space problems. Policy-based methods, favored in certain deep RL contexts, are criticized for low sample efficiency and local optima convergence. Estimating a value function alone simplifies action selection and enhances interpretability. Deep Q-learning expresses the optimal action-value function $Q*$ as a neural network $Q_\theta(s, a)$, trained via a mean-squared error loss function that updates parameters along the gradient of temporal-difference errors. Portfolio allocation aligns with an MDP, where portfolio allocation A_t, factor-based return F_t, and portfolio return Q_t at time t correspond to state s_t, action a_t, and reward r_t, respectively.

5.1. Basics of Reinforcement Learning

Consider an agent interacting with an environment. The agent perceives the state of the environment, on which basis it selects an action [9,31-33]. The environment responds with a reward and a transition into a new state, which are observed by the agent. The goal is for the agent to select a sequence of actions so as to maximize the accumulated discounted reward.

Central to formalizing this setup is the Markov decision process (MDP). An MDP is a tuple ⟨S,A,P,T⟩, where S is a set of states, A is a set of actions, P is a transition probability distribution, and T is a reward function. S and A can be either discrete or continuous. The transition probability distribution $p(s'|s,a)$ gives the probability of the environment transitioning into state s' after the agent takes action a in state s. $T(s,a)$ is the reward provided by the environment after the agent takes action a in state s. In the model-free case, the Markov decision process is unknown and must be learned through interaction with the environment.

5.2. Portfolio Management Framework

Portfolio management constitutes the heart of most trading systems. It maintains the overall record of positions and generates signals upon opening or closing a trade. Additionally, it performs various inventory and risk controls. In the context of a long–short equity trading strategy, the formal objective is to deliver alpha, achieve a low correlation to the underlying market index, and attenuate market risk [34-36]. Typically, the method starts from the belief that with a given quant ranking, forming a sector-neutral portfolio is a crucial and effective way to reduce beta. These portfolios are generally industry-neutral, exemplified by the Fama–French 12 industry classification.

In practice, creating a sector-neutral long–short portfolio involves summoning the base model portfolio to achieve sector neutrality. Such portfolios are designed to be market-neutral, beta-neutral, and sector-neutral, as well as low-risk. A specific example—a market-neutral algorithmic long–short portfolio selecting the top- and bottom-ranked stocks with the highest and lowest scores—is instructive. For positions currently in the money (i.e., profit), the relative profit exceeding a preset threshold triggers a percent-based reduction or liquidation. Similarly, existing losing positions with yields below a preset negative threshold are also partially or entirely closed.

5.3. Case Studies

The case studies examine the design and implementation of automated execution systems, portfolio management of multiple strategies in various asset classes, integrated analysis of risk and return characteristics of related securities or portfolios, as well as statistical arbitrage for related securities [3,37-39]. These examples highlight recent developments and offer a template for readers wishing to develop their own systems.

The first case study exemplifies an automated execution system designed to minimize market impact in a single security or work order. Proper execution of large orders is of vital concern in investment management since commissions may easily exceed both management fees and trading profits. Later case studies focus on portfolio management and risk control of multiple strategies in various asset classes, illustrating important areas within the evolving field of quantitative trading.

5.4. Implementation in Python

Implementation in Python

In order to test the elaborated strategies, a back-testing environment was created in Python Programming Language, allowing the simultaneous evaluation of different trading. This section details the developed platform.

5.4.1. Market Data

For back-testing, historical market data was obtained from Binance, containing 1-minute candlesticks from 2017 to 2022, as well as daily candlesticks from inception to 2022. At the same time, the historical chart data interface in text format provided by Bitstamp was also used. Because Bitcoin had not been traded for several years in the proposed exchanges, value extrapolation was necessary [36,40-42]. For that purpose, the price for the first missing timestamp was calculated by multiplying the last price of the last known timestamp by the coefficient of variations between the daily close prices of the BTC-USD pair and the synthetically generated BTC-XXX pairs if dealing with external quotes or between the last known symbol and the ones being calculated if dealing with the quote currency. Five different quotecurrencies were selected, grouped in index QUOTE: QUOTE = {USD, USDT, ETH, LTC, XRP}. Equation (5.26) illustrates the computation of the missing prices, whose parameters are detailed in Equation (5.27) and Equation (5.28) as follows:

p_{t, bt, sym_2} = p_{t+1, bt, sym_2} imes Q

where

Q = rac{ rac{1}{n} imes extstyle extstyle extstyle extstyle extstyle extstyle extstyle extstyle extstyle extstyle sum_{i=0}^{n} C_{t-i, BTC, USD}}{ rac{1}{n} imes extstyle extstyle extstyle extstyle extstyle sum_{i=0}^{n} C_{t-i, sym_1, sym_2}} \

6. Algorithmic Trading Strategies

Most high-volume equity trading is done by algo trading agents, either on a proprietary basis for firm inventory or on a client basis for the execution of large institutional orders that are too large for "natural" counterparties. Strategies and programs designed to achieve specific goals are then used to trade equity portfolio allocations with minimal market impact. Algorithmic trading strategies have both passive and aggressive components. The passive component consists of hunter algorithms, which try to identify large orders and take the other side of them. The aggressive component comprises order slicing of large parent orders into smaller child orders and execution of these orders according to a well-specified schedule.

The hunter or predator algorithms include Trend Following or Momentum Bots, Sentiment Scanners, Arbitrage or Spread Trading, News-Based Trading, and Pair or Basket Trading. The hunter algorithms trade actively, anticipating price movements.

On the other hand, order-slicing trader algorithms such as VWAP (volume-weighted average price) Trading, TWAP (time-weighted average price) Trading, and Implementation Shortfall Strategies follow a predetermined schedule while trying to minimize signaling risk and market impact.

6.1. Mean Reversion Strategies

Mean-reversion strategies represent one of the classical approaches to trading that exploit the theory that asset prices have a tendency to revert to an average price level over time. The simplest form of mean reversion is pairs trading, which involves creating a portfolio with two historically correlated assets and looking for divergence between them [40,43-44]. If the price of one asset increases substantially while the price of the other stagnates or decreases, one would buy the cheaper asset and short the more expensive asset to capitalize on expected price convergence.

To determine the actual portfolio allocation when engaging in a pairs trade, one can consider using the mean-variance approach pursued in the Markowitz framework, or delve deeper into stochastic optimal control. Another enhancement to pairs trading is to optimize over all available stock combinations, which allows the identification of the relative relative price levels. Instead of a simple look at the spread between two assets, it is better to normalize by the standard deviation of the spread. Empirical evidence suggests that such a “Kelly” criterion helps in identifying the most profitable pairs defined that way.

In situations when there is a cluster of price-sensitive stocks, a market-neutral portfolio can be constructed by running a regression of all stock returns on an index, and then constructing the portfolio as the remaining vector of residuals, given expected beta by company, when stock price levels diverge from their historical averages.

6.2. Momentum Strategies

Momentum styles, also known as relative strength (RS), often combine several types of momentum. Absolute prices rising steadily over an extended period generate two distinct kinds of momentum. A trend-following approach to relative strength identifies assets in rising trends, even when those assets have underperformed other assets with more jerky or unstable price action. The so-called 52-week high (52WH) version of RS targets assets that have performed well relative to their peers, even if the absolute path of prices has been generally sideways or downward-biased. These RS effects can be found not only in equities but also in most asset classes.

Although absolute performance across asset classes tends to be much less correlated than across countries within one asset class, the 52WH effect is similar for years and is dashed in September 2008. More exotic versions of momentum involve myriad attempts to combine RTS with market returns being led to extremes, on the premise that market leadership is particularly strong during market expansions. Another approach involves an attempt to identify assets with unusual positive or negative momentum that lie just outside traditional look-back periods. A final class of strategies incorporates excess margin or leverage in the analysis, concentrating on assets with superior momentum when margins are rapidly expanding, and on assets with very poor momentum when leverage and margin balances are plunging. Considered broadly, momentum strategies are well supported by academic evidence and can be profitably applied within or across asset classes, in combination with Valuation or RTS.

6.3. Arbitrage Opportunities

An arbitrage opportunity is a particular kind of trade that involves no risk, no initial investment, and yet offers a positive cash flow [3,45-48]. Such trades do not persist in efficient markets for long because many market participants pursue them aggressively, bringing prices back to equilibrium [5,19,49-51]. The notion of arbitrage-free markets is central to numerous finance models, including the iconic Black–Scholes model of European options pricing.

However, markets are often neither efficient nor free of arbitrage processes. As a result, genuine arbitrage possibilities still arise. Automated trading provides a suitable means to detect and exploit such opportunities rapidly. For a classic example, consider a European call option with strike price K, maturity T, underlying share price S_t, and the current price of the option C_t. Arbitrage arises if the following inequalities are violated:

1. C_t

2. C_t > S_t

The first inequality states that buying the option alone cannot satisfy any investment goal better than the zero-coupon bond; otherwise, an arbitrage trade is to buy the option and sell the bond short. Also, buying the option should not be more expensive than buying a share of the underlying; otherwise, an arbitrage opportunity is to short the option and buy the underlying. The algorithmic trader can monitor the market and detect any violation of these relationships to capitalize on the resulting arbitrage opportunity.

11. Conclusion

The essays collected in this volume present a comprehensive overview of many of the most famous algorithmic trading strategies. Much of quantitative finance focuses on modeling the behavior of individual market participants; these essays, by contrast, emphasize the behavior of the market itself. Beyond stocks, bonds, and other traditional securities, more and more exchanges are adding new trading venues for alternative assets including bitcoin futures, U.S. dollar futures, interest rate swaps, and longer term currency contracts. Nevertheless, the structure of the underlying continuous double auction remains consistent, suggesting that the principles of algorithmic trading will play a large role in the evolution of new markets and new assets.

Further advances in microstructure research will limit the continued development of algorithmic strategies in practice, but new concepts and new ideas will remain in the academic literature. Invariably, there will be winners and losers, although price discovery will be optimized as a result. Books that make important teaching points—whether it is the classic Market Microstructure Theory (Madhavan, 2000), the influential High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems (Barclay and Hendershott, 2008), or the more recent Empirical Market Microstructure (Menkveld, 2016)—will have continuing appeal.

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Chapter 3: Credit Scoring and Risk Assessment in AI-Driven Financial Systems: Predictive Analytics, Probability of Default Modelling, and Risk Management Frameworks

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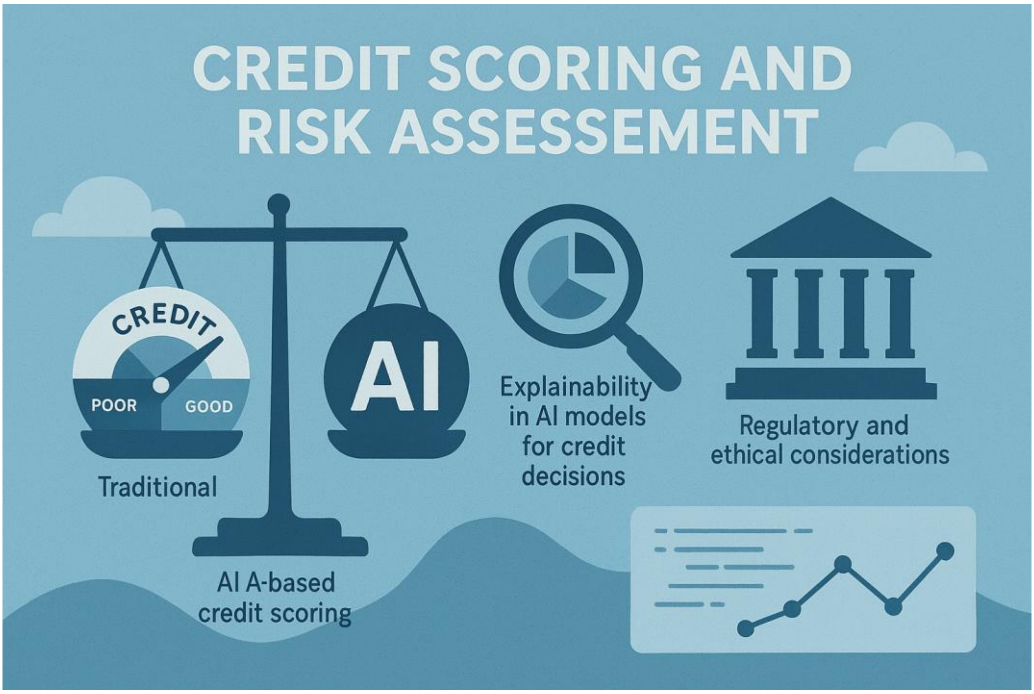
1. Introduction to Credit Scoring

Credit scoring is a statistical analysis performed by lenders and financial institutions to access a person's creditworthiness [1]. It is a regular feature in the banking system, and a system developed by Sucharita Karmakar and the National Informatic Centre (NIC) is used to credit score in India. The credit score in India is given by CIBIL, an institution authorized and regulated by the Reserve Bank in India responsible for credit. This data is available to banks/lenders to access the person's creditworthiness to determine whether the authority will be given to borrow money. The analysis of credit risk begins with a borrower's loan application form, application query, then the related loaning information and loan structure [1-2].

Credit risk scoring is the process to assess the credit risk associated with a particular account or counterparty. It incorporates the responses obtained from the scored sources/strategies present [3-5]. Risk is the exposure to a contagion that may affect the lender financially, leading to the borrower's failure to make loan repayments as agreed, and the lender has to re-finance the amount. Default does not always result in a financial loss for the lender but can create an opportunity cost by blocking the funds and affecting the cash flow. The risk of default has a major impact on the lender's attitude. Risk-based pricing determines the interest rate based on the borrower's risk level. Further assessment of future credit risk requires information about macroeconomic factors or the business cycle.



2. Traditional Credit Scoring

Credit scoring is the process of taking Standard Industry Classifications (SICs) and Financial Statement Ratios, and reducing them to a numerical number indicating a company's creditworthiness. The earliest known attempt of such scoring was undertaken by Dillon, Read & Co. in 1941. By 1958 there were already 1200 companies scoring credit. The first credit scores designed to be applicable to consumers were developed by Fair, Isaac, and Co. and published in 1956. The score received most popular attention is the FICO score. Key metrics include Payment History, Current Level of Indebtedness, and Length of Credit History.

Traditional approaches to credit scoring are frequently used to set a benchmark for performance against other methods [6-8]. They fall short when it is important to continuously learn and predict changes, since this normally involves retraining at large intervals and does not account for any interpretative information that may be available.

2.1. History of Traditional Credit Scoring

The origins of credit scoring date back to the 1950s through the work of Bill Fair and Earl Isaac, founders of FICO. Credit scoring is now an essential part of credit risk assessment and for making credit decisions. Traditional credit scoring models provide lenders with statistics about the likelihood of default to enable them to take an informed risk when lending their money [9]. These models allow lenders to compare the creditworthiness of different prospective borrowers, determine the most appropriate price for the credit risk and assess the potential for future business with their customers. Credit scoring relies on a rich data history to develop a model that will identify and discriminate good customers from bad. A customer's credit score sums up information in their credit report associated with whether they repay their loans or not [7,9-10]. Credit scores provide a measure of credit risk. The FICO Score is a loan risk score developed by FICO using a large number of data points.

Each data point describes one aspect of the customer's credit behaviour. Experience in the US has shown that certain parts of a customer's credit report contain valuable information on the customer's propensity to repay a loan on time. The credit score combines the value of these attributes into a single figure that summarises a lender's model estimate of the risk of lending to this customer. A credit score is a number derived from a statistical model that is developed from historical data on customers who display either good or bad credit behaviour. During model development, the customer attributes with the strongest relationship to subsequent default are selected as explanatory variables.

2.2. Key Metrics in Traditional Scoring

FICO scores remain the most widely known and used traditional method for determining a credit score. They are calculated using the information supplied in the credit report. Although there are several different FICO score variants, they all use the following information: Payment history, Amounts owed, Length of credit history, New credit, Types of credit used—usually abbreviated as RATINGS. Payment history has the most impact on the score, with 35 percent weight, while length of credit history is the least important with only a 15 percent weight.

FICO scores range between 300 and 850. The higher the score, the better the credit is determined to be. According to Experian, scores between 720 and 850 are generally considered excellent, representing a low risk for lenders, 690 to 719 is good, 630 to 689 is fair, 300 to 629 is poor, and 300 to 579 is considered bad. Average U.S. FICO scores in the past fifteen years have constantly hovered in the 690 to 710 range. Recent data indicates the average FICO score in the United States is slightly above 704.

2.3. Limitations of Traditional Models

Traditional credit scoring methods have remained largely unchanged in the last 50 years and have thus missed the opportunity of many new technologies for assessing credit risk and granting credit. The FICO scores, for example, have been used since 1989 and have evolved over time; however, the models continue to be based on a handful of key factors. Three main limitations hinder the use of traditional methods. First, standard banking models do not work well in many countries, and banks usually partner with multilateral organizations for credit scoring and providing credit to people that cannot be scored with the internal models of the bank. Second, the scoring process is very expensive. Third, the current scores do not offer a very user-friendly experience. App users do not get detailed information regarding the credit decisions made for their requests; instead, they only know that their score is high, medium, or low.

The combination of these factors suggests that current credit scoring methods do not meet the level of granularity that people expect from a modern score. That is why the use of AI–ML models is more relevant in the field of credit scoring today. Several studies have explored the application of AI techniques such as support vector machines (SVM), K-nearest neighbor (KNN), random forests (RF), and artificial neural networks (ANNs). These methods have demonstrated improvement in credit scoring performance compared with traditional credit-scoring models in terms of predictive power, costs, and convenience. However, the complexity of AI–ML models causes difficulty in comprehending the rationale behind credit decisions and provides insufficient interpretability for practicing credit scorers. Large-scale financial applications of AI indeed require not only strong prediction ability, but also a good explanation and interpretation ability of these models.

3. AI-based Credit Scoring

Over recent years, artificial intelligence (AI) has demonstrated high potential for application in credit scoring and credit risk assessment [1,11-14]. While traditional credit risk assessment involves the analysis of a borrower's creditworthiness by the lender, credit scoring applies a statistical or current data-based model to predict the probability of a borrower defaulting. This

SCARFS research theme addresses the challenge of evolving credit scoring and risk assessment through the use of AI techniques, utilizing both internal and external data.

The digitalization of different industries, individuals, companies, and governments has driven the AI-age with its AI-driven industry and society. Although it is widely accepted that AI shapes finance, a specific focus on credit scoring and credit risk assessment reveals that AI adoption in these areas is still in its initial phases. Considerable potential lies in the use of AI techniques for credit scoring and risk assessment, particularly when applied to a combination of internal and external data resources.

3.1. Overview of AI Techniques

Several artificial intelligence (AI) techniques are used in credit scoring, including multilayer perceptrons (MLPs), radial basis function neural networks, support vector machines, and self-organizing maps (SOMs). MLPs are one of the simplest and earliest neural models and have been extensively employed for credit scoring [13,15-17]. Radial basis function networks have also demonstrated satisfactory performance.

Support vector machines are another widely employed classification method, particularly effective when combined with genetic algorithms for parameter optimization. Additionally, the self-organizing map is a useful tool for behavior scoring. In credit scoring, it can serve multiple purposes: segmenting portfolios according to customers' financial and portfolio characteristics, detecting outliers, and inferring inherent classes in clients' profiles. These grouping and discriminative characteristics are invaluable for behavior scoring because customers with similar behaviors are expected to have similar profiles.

3.2. Benefits of AI in Credit Scoring

The adoption of automated processes has been transformational across many different fields and industries, with the finance sector serving as no exception. The development of new intelligent systems, alongside emerging technologies, has granted valuable assistance in maintaining effective crisis management, both on a national and global level [18-20]. The identification of problematic sectors operating at a loss or, conversely, flourishing within the economy, has undeniably proven useful in the endeavor to minimize bankruptcy.

Moreover, the implementation of AI has greatly benefited the traditional credit-evaluation process [19,21-22]. Although the fundamental objective of maintaining balance between profitability and risk assessment remains unchanged, the utilization of automated risk management solutions has enabled the simultaneous evaluation of multiple variables pertinent to a customer's financial status. This approach has markedly enhanced the prediction of possible defaults [11,23-25]. The much quicker evaluation made possible by automation results in a significant reduction of human error; in addition, improved management of new clients enhances customer experience. In-depth analysis that incorporates demographic data into customers' credit profiles facilitates product customization, providing more personalized credit services.

3.3. Challenges in AI-based Scoring

Despite its advantages and widespread usage, the scoring model also presents some limitations [26-28]. Such models inherit existing social bias, and this is particularly conspicuous when scoring is used to make decisions on sensitive groups of people (for bank loans, insurance and other decisions). People that belong to a group that is underprivileged in society often get lower credit scores and worse financial services from the banks [29-32]. The explainability of these models is also an issue, since the decision-making involves many parameters and complicated calculation. Some research focuses on the interpretation of black-box machine learning scoring models. It is not easy to have an easily interpretable and explainable model with high prediction accuracy at the same time.

With the development of AI and influence of social media, the scope of platform-scoring appears to be expanding [31,33-35]. The Facebook platform-scoring model, Libra Score, describes the contribution of a user to the Facebook system and business. By entering Facebook, users can choose whether to give permission to the Libra Score for accessing data. If permission is granted, each user will obtain a Libra Score, which is similar to the credit score from the traditional financial system. It can be used to assess his or her service level in the social network [36-38]. By making an overall evaluation of a user's strength and assigning a corresponding score, the corporation can make corresponding decisions on the user, such as whether to add the user as a new friend and whether to blacklist the user if he or she has committed a crime. In fact, Facebook has attempted to apply the idea of credit scoring to a broader range of behaviors through the application of artificial intelligence [1,39-41]. AI is capable of using the data collected from every aspect of customers to judge whether an individual is creditworthy, thus impacting the decisions of customers. This approach incorporates new elements into the traditional credit-scoring system and will be further expanded in the future.

4. Comparative Analysis: Traditional vs AI-based Credit Scoring

Traditional scoring techniques are designed by experts and empirical knowledge. Companies use credit information, such as credit records, account information, and previous repayment histories, as the basis for credit ratings; some use demographic information, such as age, gender, marital status, education, or occupation. Numerous scoring systems use the Local Stability Property, which is the assumption that creditworthiness does not change drastically in a short period of time [42-44]. Traditional scoring techniques are mainly based on either regression or scoring. The development of scoring models can be categorized into two groups—the discriminant model by methods developed by Edson and Page and the branch and bound algorithm by Whitney, and the regression model by methods based on the work of Altman and Ohlson. The discriminant model is optimal in the sense that it maximizes the non-overlapping area of Score A and Score B, assigning α to all cases above a threshold (selectivity) and β to all cases below the threshold (usefulness) as either "good" or "bad."

AI-based scoring techniques, such as probabilistic neural networks, backpropagation neural networks, generalized regression neural networks, RL (a fuzzy backpropagation neural network), and machine learning-based scoring techniques, are compared [45-46]. AI-based techniques require only a few variables for scorecard design and demonstrate greater accuracy, a more robust selflearning capability. Further, they are capable of handling non-linear relationships between variables and between dependent and independent variables. Clustering techniques, such as k-means and self-organizing feature maps (SOFM), are useful when neither the exact number nor the labels of the groups can be predetermined.

4.1. Performance Metrics Comparison

The NCCS and KFANN in multi-layer perceptron (MLP) architecture were integrated with the Backpropagation algorithm, designed to predict neural network forecast accuracy more precisely. The comparison involved fourteen criteria, such as sensitivity and specificity, over-training, detect-ratio, falsealarm rate, Type I and Type II errors, and the Area Under the Curve (AUC). The analysis encompassed Receiver Operating Characteristic (ROC) curves, convergence rate, and Bayesian Information Criterion (BIC) score. Results indicated the two criteria outperformed other existing performance metrics of the MLP network.

In recent decades, computational intelligence techniques have solved challenging banking and finance problems with enhanced performance. Consequently, a reliable performance measure is necessary to predict the potentiality of a chosen computational intelligence algorithm. A review of existing literature reveals no performance measure for the Credit Rating algorithm, prompting the proposal of a Novel Credit Scoring Criterion (NCCS). Meanwhile, a hybrid model combining a Fuzzy Neural Network with the principle of Kapur entropy (KFANN) calculated credit-rating-categorical vector entropy for classification. Both methods outshone existing performance measures of the MLP Credit Rating algorithm.

4.2. Cost Effectiveness

Businesses, regardless of whether they belong to the banking sector or not, always pursue profitability [18,47-50]. This leads them to consider the principle of cost effectiveness, which involves determining whether the credit provided is fruitful and inflicting the minimal possible costs on the company. Companies cannot, of course, issue loans merely to increase their income. Similarly, they must stay away from overestimating the default risk in order to prevent a drop in the profits they would earn from interest rates. The costs associated with default risk and the cost of collecting relevant information should be balanced.

Each decision entails specific costs. The costs created by issuing credit are generally categorized as credit risk cost, evaluation cost, follow-up cost and performance cost. The credit risk cost is the amount that occurs if the granted credit suffers from any default. The risk cost, which accounts for the part of the cost that remains unpaid in the event of a default, can be calculated as follows:

Risk Cost = Default Rate × Unpaid Percentage × Credit Amount

4.3. User Experience and Accessibility

The app offers a simple and intuitive interface for performing credit scoring and risk assessment. Users select an individual person or a company and enter the main information regarding a client. For example, the Residential status of that client or Representative Rating is needed to execute credit risk scoring and assessment.

The user interface follows a clean design. Clients review output results and explore the data that they loaded. A screenshot illustrates the final Credit Risk Score for an applicant. The user interface does not presently offer English as an option, yet English has been selected to present these screenshots. The Microsoft AppSource Marketplace delivers the App in the user's language.

5. Explainability in AI Models for Credit Decisions

Understanding the impact of individual variations within a system is paramount; thus, it is desirable to build beyond-the-average or non-local explanations that address groups of similar variations. Adaptive methods for model-dependent counterfactual explanations deliberately shape the diversity of proposed groups, increasing coverage and reducing overlap. The viability of such approaches is demonstrated using real data from applications involving credit and credit-card fraud detection.

Adaptability is key to simultaneously satisfying the antagonistic properties of coverage and non-overlapping groups. Coverage ensures that the smallest group contains at least a predefined number of variations, coupled with the closest proximity of its centroid to the query. Contrary to the common requirement that the set of groups should be totally non-overlapping, a maximum tolerable overlap is established as an input. A custom optimization model determines the optimal complexity of groups. The usefulness of the proposed procedure is supported by experiments with the recent Credit Fraud Detection Data and Credit Card Application Data.

5.1. Importance of Explainability

The growing regulatory concerns surrounding a possible lack of transparency and explainability of machine learning methods have resulted in a focus on evaluating systematic and statistically significant credit risks as revealed through the corresponding data. Explainable machine learning models allow the creation of reliable credit ratings early on in the credit underwriting process. At the same time, including relevant explanatory variables in the model allows for a more comprehensive assessment of the credit decisions. New rules with regard to explainability of credit decisions have been put in place in the U.S., Europe, and several other countries. In an increasingly automated world, explanation capability would be very important in the judging of various processes for identifying risks.

In the financial industry, explainability has become a major factor in the selection of credit scoring models. Regulators want to understand the reasons for deferring or accepting a credit application, as well as combinations of variables leading to a superior or inferior credit rating. An insightful model with transparency in its decisions would send a signal to the millions of borrowers and lenders about the risk behind the transactions. Explainable AI is an important policy priority. Advanced AI techniques will be needed to secure the future of lenders, and the industry must simultaneously focus on these algorithms being explicable.

5.2. Techniques for Enhancing Explainability

The growing use of AI and ML in credit scoring has triggered a demand for and interest in XAI techniques. Various methods aim to enhance the transparency of AI-based credit scoring and risk management. The outputs of interpretable models are directly explainable; for example, coefficients of lean logistic regression models, rules of decision trees, or feature importance scores of ensemble models. However, even these methods may not be sufficiently simple for practical explanations. For instance, the features used in credit-scoring models, especially those based on comprehensive bank-customer information, are often meaningless to customers and challenging to interpret.

Several approaches address the federal regulatory requirements for explicit explanation of actions based on credit-score results. Many commercial services, such as CredoLab, EuroScore, Experian, FICO, Finexkap, CoreLogic, Neustar, RapidScan, and Score More, provide SMEs and lenders with not only credit-score metrics but also comprehensive risk-assessment reports. These include risk-assessment information that helps institutions understand the factors contributing to a high risk of default. Consequently, techniques for clarifying the contribution of features and rendering credit scoring more interpretable have been proposed and extensively studied. The schemes extend the traditional linear-regression coefficients approach to modern AI-based credit-scoring models by explaining the computation process and its results.

5.3. Case Studies on Explainable AI in Credit

Using XAI techniques involves accounting for additional resources. More interpretability can require additional storage for model parameters, more computation power and latency during inference, or larger training datasets. For example, a post-hoc XAI model such as Kernel SHAP might require an explanation each time a sample is predicted, thereby increasing latency. When dealing with Deep Models, usually more training data is needed to perform better since they are generally prone to overfitting. When deploying XAI techniques, even if the computational or memory overhead is low, there could be legal or ethical ramifications of providing fraudulent explanations. Providing explanations without these considerations could backfire and result in loss of credibility for an entity.

An early work on interpretability in credit scoring employed the General Arching System (GAS) to generate binary or real-valued features from nominal features from the German dataset that could be used as input to a Logistic Regression Model (LRM). It was noted that this approach yielded higher accuracy than when ordinal features were used with LRM. A more recent study proposed using a Decision Stump Forest (DSF) algorithm that generates decision stumps that can be combined to yield a powerful ensemble. The rationale for using a decision stump was its simplicity of representation, and decision stumps were augmented by adding a probability distribution shape between the attribute and the outcome, which could be visualized to explain the model's output. A case study on explainable AI in credit scoring explored the tradeoff between performance and explainability by moving from tree models to deep neural networks.

6. Regulatory Considerations in Credit Scoring

Exploring the regulatory aspects of credit scoring wagers further consideration. Various countries regulate the use of credit scores in providing consumer credit, with some even banning their use entirely. The controversial aspect of credit scores—and perhaps the most difficult to quantify—is how much they protect uninformed consumers from long-term, binding contracts that will thoroughly damage their credit rating.

Regulatory frameworks are constantly evolving to address perceived issues of discrimination in credit scoring models and creditworthiness decisions. In the United States, Consumer Financial Protection Bureau (CFPB) regulations prohibit credit-scoring products that correlate with credit approval decisions if they lead to unintentional discrimination on the basis of age, religion, sex, race, or ethnicity. Because consumers are sensitive to privacy and security issues, especially the possibility of identity theft, most countries have enacted laws that govern the handling of their personal information. Institutions that maintain consumer reporting agencies, credit bureaus, or credit-scoring agencies must comply with these laws.

6.1. Current Regulations Governing Credit Scoring

Credit scoring is governed by a wide range of regulations at the national and international levels. As of June 2024, one of the key frameworks for the regulation of credit scoring is the Basel regulatory framework, formulated by the Basel Committee on Banking Supervision and operationalized by the Basel Accords. For credit-taking corporations in the banking industry, the original Basel I Accord in 1988 focused on credit risk and proposed a capital riskweighting scheme designed to improve the ability of banks to absorb potential losses arising from credit risk. The national regulatory authorities for banks generally require the minimum amount of regulatory capital to be held by each bank for credit exposure. Subsequently, the Basel II Accord in 2004 addressed regulatory treatment of operational risk and outlined comprehensive risk management requirements. Under Basel II, the regulations provide a broad definition of credit risk, encompassing risks arising from on- and off-balance-sheet, direct and indirect exposures of banks due to their role as credit providers, arrangers, and counterparties in various transactions. The regulations establish capital requirements designed to promote the maintenance of a level of capital commensurate with the levels of credit risk assumed by banking organizations.

From the perspectives of bank creditors and consumers as potential debtors, the use of credit scoring models assists banks in controlling credit risk and extending credit to potential debtors with different backgrounds and characteristics. Credit scoring models for retail banking or consumer lending under the Basel regulations must be capable of differentiating the borrower’s creditworthiness. In addition to minimum capital requirements, Basel II aims to promote enhanced risk management practices by encouraging banks to examine capital allocation in greater detail, economic capital in comparison to regulatory capital, and internal ranking systems capable of differentiating customers based on differences in credit risk.

6.2. Impact of Regulations on AI Adoption

Both the financial sector and financial regulators recognize the application of innovative technologies such as artificial intelligence (AI) as important sources of system-wide efficiency and resilience gains. The AduAifin regulation of the European Banking Authority (EBA), for example, specifies that AI can help identify fraud when concluding business transactions. Regulators are thus encouraging the application of AI techniques and supporting the creation of knowledge management systems that leverage the expertise of financial institutions' risk experts. At the same time, the EBA regulatory framework underscores that AI models must be interpretable. Interpretability helps to mitigate model risk during the model's lifecycle and serves as a key pillar for the validation process required by business units, risk control functions, and internal and external audit functions.

According to EBA InFocus 09/2022, 97% of financial institutions believe that AI in credit underwriting represents a business advantage, and 90% consider AI in credit underwriting as a means to improve the customer experience. While the potential of AI is widely recognized, only 13% already use it extensively on a production level, with 28% at an experimental stage. Among the inefficiencies encountered, the inability to explain AI models is listed as the first reason. Consequently, there is a demand for a knowledge expert system that extracts intrinsic knowledge from AI models and assists risk experts and auditors in navigating decisions inferred by these techniques.

6.3. Future Directions in Regulation

Regulators need to consider the overall effectiveness of a credit scoring model. For example, one might find that a model built with demographics and that appends a CRO intelligence score performs better than one using only a credit bureau score. In the event the CRO intelligence definition of crime changes, this might affect the model's discriminatory impact and overall performance. It may be suggested that a model should not use the same data from two different time periods—or the model should undergo regular validation and be refreshed when it begins to lose predictive power.

The way in which the CRO intelligence information is used should also be reconsidered. One possibility is that separate models could be developed for different groups, thereby optimizing the score for each and increasing the overall accuracy. Instead of appending the CRO intelligence data as a new column to the existing credit bureaux, a separate over-arching system of risk assessment might be developed. This dedicated system could take credit bureau information and CRO intelligence into account, along with other relevant input data such as crime-type data, crime location data, and offender's income and asset data. The options are almost unlimited.

7. Ethical Considerations in AI-based Credit Scoring

The development and application of credit scoring models are complex undertakings, encompassing ethical concerns that warrant careful consideration. Ethical evaluations must address both the methodologies and practices of credit scoring as well as the fairness of the forecasts generated. Owing to their use of extensive datasets, advanced AI techniques, and potentially unexplained forecasting mechanisms, these models face heightened levels of scrutiny.

Credit scoring is a multidimensional activity embedding both social and business dimensions. It introduces an inherent responsibility to promote beneficial social and financial services for society while concurrently safeguarding data privacy and reducing discrimination risks. Sensitive factors such as the borrower's age, gender, disability, and race introduce further complexity. These attributes must be handled with care to avoid discrimination concerns. AI design and use standards, developed by authoritative bodies like the European Parliament, underscore the significance of building trustworthy and reliable AI systems. They advocate for transparency, auditability, human oversight, and clearly defined accountability, thereby laying the foundation for ethical AI credit scoring.

7.1. Bias and Fairness in AI Models

Credit providers are obliged to show that their credit decisions are not biased against certain groups or individuals. Demonstrating that credit decisions are made without bias can be difficult since the distribution of bad credit risks in society is often non-uniform.

Accordingly, statistical models used for credit assessment should incorporate elements of fairness that remove discrimination to the largest extent possible. Fairness in AI models is a well-studied notion with many desirable mathematical definitions including statistical parity, predictive parity, and equal opportunity, as well as others. Different notions of fairness can be incompatible with each other under some conditions. In the credit underwriting scenario, indirect discrimination is usually of greatest interest; it occurs when a protected attribute, such as race, is not used explicitly in the classification, but other attributes, such as zip codes, are correlated to it. Numerous methods can eliminate such discrimination before, during, or after the training of a machine-learning model. Applied to credit scoring, fairness constraints can reduce indirect discrimination of the minority class of credit applicants, while typically sacrificing some accuracy of automatic credit decisions.

7.2. Transparency and Accountability

Transparency and accountability in the credit-scoring process entail systematically disclosing the information, models, and weightings used. Since inverse and proxy correlations are employed to achieve more meaningful score-to-risk mappings, consumers and regulators alike are able to better understand the model, make informed application decisions, and reproduce its output. Model originators, on the other hand, can more efficiently validate and defend their models.

The Launch Credit Cards model offers an example of a transparent credit-scoring system. Approved applicants receive a score and an internal grade ranging from 0 to 10. These internal grades form the performance rank for each solution, enabling a clear mapping to target rates of default, loss, or approval. Maintaining the full information set and scorecard for each applicant ensures ease of periodic validation against the actual credit performance of the population along the risk continuum. Internal validation metrics confirm the stability and predictive power of the approved-customer model, with similar or better results compared to application-model validation.

7.3. Consumer Privacy and Data Protection

Credit scoring activities require the protection of individual privacy rights. Credit information has historically been protected under banking secrecy, reflected in regulations. Consumer credit reporting is governed by the Fair Credit Reporting Act, newer state legislation, and the European Directive on Data Protection. In addition, the evaluation of creditworthiness cannot entail discrimination concerning religion, race, sex, marital, or veteran status.

Many countries have adopted a consumer-oriented approach to data protection and privacy. The national credit bureaus certainly support such legislation. Unfortunately, broad data-protection legislation can also severely inhibit the legitimate flow of credit data. Similarly, the use of public records can greatly enhance the range of credit scores that can be produced, but there is considerable opposition to their use on privacy grounds. Damaging consumer privacy necessarily remains a central issue and an ever-present threat.

8. Future Trends in Credit Scoring

New developments in credit scoring will be led by the financial technology sector. The growing usage of big data, telecommunications, expenditures, and repayment patterns have led to increased attention by large financial institutions to alternative credit scoring methods, such as psychometric credit scoring. The shifting economic landscape in the United States, with growth rates below historical averages, has forced many lenders to use alternative credit scoring; those borrowers that perform well on a Federal Reserve Bank of Chicago model used by alternative lenders are profitable to credit unions, while in the past, a majority of people with credit scores below 780 were a risk for these institutions. The Continuous Approval and Monitoring Enhancing Responsible Lending Act of 2022 appeared in the US House of Representatives in March 2022; the Act would require the Consumer Financial Protection Bureau to publish guidelines on the use of alternative data in credit scoring.

The future of credit scoring lies in predictive analytics, an area of growing importance in financial services and marketing. Experian's DEC Market Advisor is a supply-and-demand database that predicts demand for over 4,200 product categories, at up to the zip+4 level. A Google Patent Application for a Consumer Analytics System for credit worthiness assessment of an individual or entity uses a breadth of data beyond traditional financial and legal data sources, to include behavioral patterns, consumer habits, and commercial trends in the same geographic area. This system generates a prediction of consumer behavior and a degree of creditworthiness for the subject consumer, with levels of granularity sufficient to make incremental lending decisions. A Fintech patent application describes a system that classifies the risk category of a potential borrower based on an assessment of their social media profiles, with classifications ranging from A1, for the lowest risk group, to E2, for the highest risk.

8.1. Emerging Technologies

Although credit scores are thoroughly analyzed and well understood, the industry continues to struggle with several challenges. The US is considering banning the use of credit scores when determining insurance rates, and the European Union is demanding simpler, more understandable credit scoring methods with fewer variables. Additionally, many companies are expressing a need to find additional data sources beyond traditional credit scores to gain an extra advantage over their competitors. Moreover, several large companies simply want more oversight and transparent modeling to aid their compliance needs in an ever-changing regulatory environment.

The answer to each company's needs could be new sources of data, such as social media data, and new methods of analysis, including fuzzy logic, genetic algorithms, support vector machines (SVM), artificial neural networks (ANNs) and their multilayer multilocal perceptrons, rough sets and decision trees, in addition to traditional logistic regression. These emerging technologies are examined more closely in the following sections.

8.2. Integration of Behavioral Data

Additional data, statistically linked with a person’s future economic behavior, can improve the predictive power of credit-scoring systems. Included in this category are behavioral characteristics, such as payment histories on utility bills and rental payments, life milestones and events, such as getting a job or graduating from college, changes in wealth or income, the use of financial assets, savings behavior, and repurposing of credit cards.

Research supporting the use of behavioral scoring showed that payment histories of nondebts (utility bills, phone bills, and rental payments) are predictive of credit performance. Researchers found that car ownership, house or apartment ownership or renting, marital status, and having more than two dependents were predictive as well. Even the educational background of the applicant can be used in behavioral scoring. A number of researchers found that behavioral scoring systems, when added to other credit data, help lenders to better determine the likelihood of default on a credit or other loan product. The use of these variables can improve the prediction of applicant risk and thereby help decrease charge-offs and bankruptcies for both the financial institution and the consumer.

8.3. Global Perspectives on Credit Scoring

Emerging economies, where formal credit scoring models may be lacking, suffer from substantial credit misallocation. The advantages of credit scoring models for individuals with high scores include increased loan access and lower credit costs. Conversely, the disadvantages for individuals with low scores include reduced approval rates and higher borrowing costs. The global expansion of credit systems varies significantly within Asia. Economies commonly associated with formal credit scoring models, such as South Korea and Taiwan, base scoring on traditional credit or lending information. In contrast, Myanmar neither establishes nor adopts such models. Similarly, credit scoring based on firm-specific information is absent in several Asian economies.

More than 90% of Asian countries lack a credit scoring system. However, certain Southeast Asian countries have developed credit scoring models to assess creditworthiness, primarily focusing on individuals and small and medium-sized enterprises. Among these are Indonesia, Malaysia, the Philippines, Singapore, and Thailand; all employ either credit or loan information, yet none utilize firm-specific data. Informations of this nature, which help lenders-appraisers analyze the likelihood that a firm may default on its obligations, are crucial for reallocation of financial resources. In addition to these countries, Hong Kong, South Korea, and Taiwan also possess such models, with all three employing either credit or loan information.

9. Conclusion

Although economic theory exhorts banks and other financial institutions to use credit risk models, they often rely on credit scoring only for consumer lending decisions. Credit Scoring Techniques provide current research on statistically based consumer credit-risk models. Problems with these models are demonstrated with a loan portfolio allocation example, and methods for alleviating this are examined. New credit scoring models based on the AHP technique and Genetic programming method are introduced and verified by real consumer credit data with incomplete or no prior knowledge about the credit entries. Credit Risk Assessment explores the impact of different market-rating belief systems when assessing a corporate bond credit risk premium, emphasizing that the assessment depends significantly on the market-rating system selected and its credit rating history, especially in times of financial distress.

Financial institutions and suppliers of financial services consider the protection of their business as always a top aim. Monitoring economic and financial business cycles, the identification of early warning signals and the detection of upcoming and rising crises are the core of credit processing. Alternative statistical methods help to develop models that identify financial distress and/or bankruptcy and to increase the detection power of existing models; they also examine whether the type of model influences the forecast power.

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Chapter 4: Fraud Detection and Prevention through Artificial Intelligence: Anomaly Detection, Behavioral Biometrics, and Cybersecurity in Banking and Payments

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1. Introduction to Fraud Detection

Fraud detection involves the identification and prevention of illegal activities, particularly financial crime. When banks detect fraud using artificial intelligence, they can minimize it, with the potential to eradicate it altogether [1-3]. A strong anti-money laundering system can monitor suspicious transactions by comparing clients' profiles and transaction patterns in real time.

Anomaly detection is a process that identifies unusual patterns that do not conform to expected behaviour, known as outliers, exceptions, or anomalies [2]. In the context of financial security, such patterns may indicate fraud or money laundering. Systems for financial crime detection are usually classification-oriented, with labels distinguishing between normal and fraud-trafficking classes or different types of fraud. Anti-money laundering scenarios involve regulations designed to control money laundering.

2. The Role of AI in Anomaly Detection

Artificial Intelligence (AI) has become an important fact-finding tool in the fight against fraudulent financial transactions [2,4,5]. Mitigating these irregularities is key to safeguarding global financial institutions and maintaining customer state-of-mind. Anomaly detection is the identification of data points that deviate from anticipated or standard patterns [6-8]. Traditional methods include association rule mining, statistical approaches, and clustering techniques. Deep neural network models that have recently displayed outstanding performance in diverse domains are beginning to be applied in financial anomaly detection. In particular, GAN-based models have demonstrated significant progress.

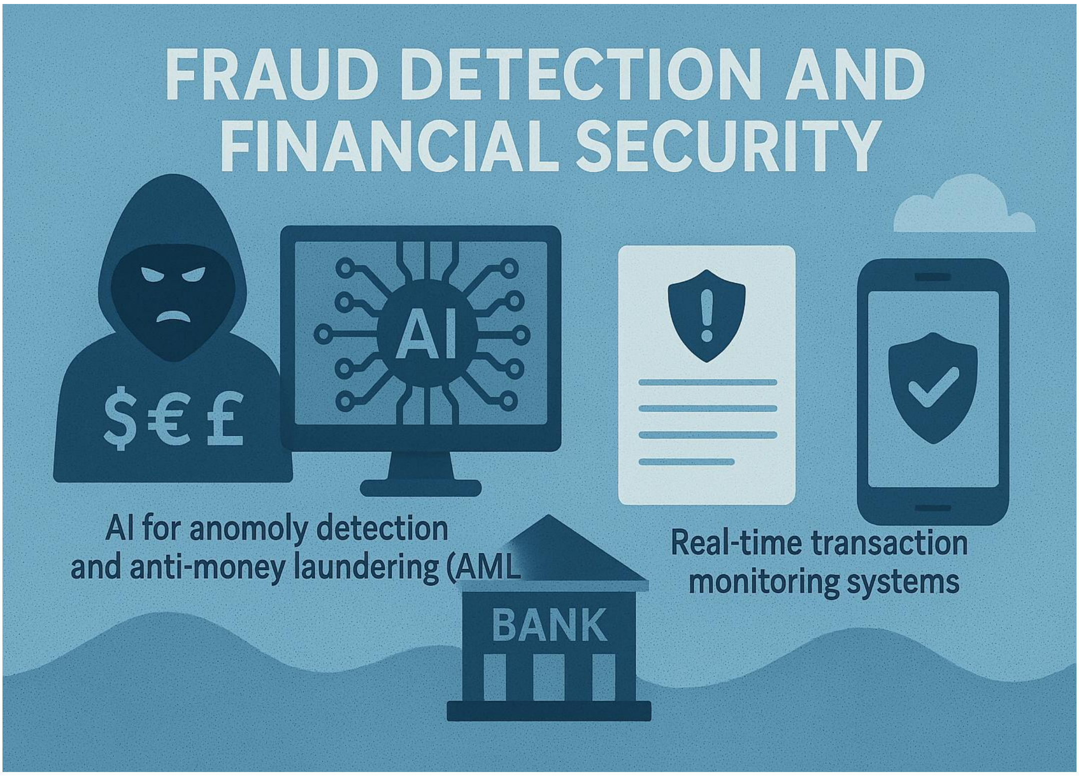

Fig 1: Fraud Detection and Financial Security

Generative Adversarial Networks (GANs) employ two competing neural networks to solve problems. Data is mapped to a multivariate Gaussian distribution by an encoder. The latent vector is then processed by a generator to generate data. Two discriminators are concurrently trained: one distinguishes between real training data and generated data, and another distinguishes between latent vectors from the encoder and the prior distribution. The final anomaly score is calculated as a convex combination of error values from both the data space and the latent space [9,10]. Testing on the KDDCUP99 dataset reveals that this GAN-based model achieves state-of-the-art performance, underscoring its potential for financial anomaly detection and its capability to learn complex data distributions for enhanced detection.

2.1. Machine Learning Techniques

Machine learning is a branch of artificial intelligence built on the idea that a computer program should be capable of self-learning. Since Janiesch published their work, more learning algorithms have been explored in connection with fraud detection [11-13]. For example, a framework has been established for experimental investigations of automated machine learning techniques, more specifically for credit card fraud detection. Also, an auto machine learning (AutoML) system is used to conduct a comprehensive assessment of classification performance in fraud detection. Besides AutoML, stacking models, where logistic regression is typically employed, are also used for credit card fraud detection. Amongst the learning algorithms, tree-based models, such as random forest and gradient boosting, are frequently applied.

The performance of machine-learning methods depends strongly on the transaction features used for detection. Duman and Ozcelik utilized principal component analysis (PCA) to identify features of point-of-sale (POS) fraud, demonstrating that dimensionality reduction through PCA can lead to enhanced classifier performance [2,14-17]. Feature engineering based on clustering customer behavior has shown better outcomes for logistic regression and artificial neural networks, whereas direct application of raw attributes from electronic funds transfer has yielded superior results with tree-based models. Other studies have implemented feature reduction techniques or ensemble methods on credit card data, extending the use of deep learning methods to behaviors in electronic commerce. The best-performing model incorporates a stacked autoencoder neural network that first reduces the dimensions of transaction features for subsequent detection of suspicious transactions by adaptive gradient-boosting.

2.2. Deep Learning Approaches

"Deep learning refers to artificial neural networks that are deeper and wider than ordinary single-hidden-layer networks."

Deep learning focuses on learning feature hierarchies with features from higher levels of the hierarchy formed by composing lower-level features [9,18-21]. In fraudulent activity detection, convolutional neural networks can be used for feature extraction, whilst a recurrent neural network focuses on classification. The fraud detection system is trained on real data in order to recognise instances of fraud. The usage of multiple deep-learning algorithms is one among the solutions proposed for the detection of fraudulent activities using features from the federal fraud list in conjunction with real-world transaction datasets.

The Gaussian mixture model is the only deep-learning algorithm used for fraud detection, while comparison with the motifs-based detection technique measures the effectiveness of each approach. The proposed method is evaluated on an authentic real-world financial dataset [22,23]. Furthermore, cash-flow data are analysed to identify customers with money facilities such as loans and overdrafts. Customers with a high risk of default are identified using the K-means clustering technique and a locally connected layer, LSTM, which is used to capture the temporal characteristics of customers. A technique that combines deep learning with an artificial intelligence system has also been proposed for detecting fraudulent activities. In these examples, the deep-learning model is trained on fake news generated by the deep neural network, so as to accurately classify the real and fake contents.

3. Anti-Money Laundering (AML) Strategies

Anti-money laundering (AML) describes the policies used by governments to regulate, investigate, and prevent financial crimes like money laundering. The FATF (Financial Action Task Force) publishes money laundering methodologies that classify products or services as high or low risk for money laundering attacks and details specific strategies for each product or service [24-26]. ML techniques have become a crucial process in the modern era where users have the flexibility to transfer, purchase, or exchange money across countries. The emergence of cryptocurrencies has attracted users by offering decentralized currency without security procedures for authorization, leading criminals to exploit cryptocurrencies for money laundering and crimes like drug trafficking, terrorism funding, and bank fraud.

Criminals use three classic processes—placing, layering, and integrating—to facilitate money laundering and clean money. The first step involves introducing illegal profits into the financial system through methods such as purchasing luxury assets, investing in legitimate businesses, transmitting funds abroad, or transferring money to other companies or countries [27,28]. The second step entails processing these dirty funds through various channeling activities within the financial systems to reduce tax burden, disguise the source and ultimate beneficial owner, and avoid discovery by authorities. The final step integrates the laundered money back into the economy and ensures the process remains undetected [19,29-31]. On the other hand, terrorism financing relates to the collection and provision of funds for terrorist acts. Funding sources for terrorist activities can include intelligence agencies and individuals, with money also raised through activities in legitimate business sectors.

3.1. Regulatory Frameworks

The regulatory frameworks that underpin the financial services and banking sectors seek to ensure that companies operate within strict guidelines and offer protection to consumers [32,33]. Such frameworks are often characterised by specific requirements, such as the conduct of firms, anti-money laundering, know your customer and credit checking, and the inbuilt safeguarding of security and privacy. There are street-level regulators who oversee individual transactions, such as the Financial Conduct Authority, which seeks to ensure compliance with benchmarks and standards. In addition, the Prudential Regulation Authority aims to promote the safety and soundness of individual financial institutions. These organisations also work closely with other bodies, both nationally and internationally, to maintain the integrity of the sector and consumer protection.

Despite the many benefits these requirements provide by supporting sound operations and consumer confidence, they may also be used to exploit less digitally experienced and vulnerable customers. In particular, where controls are undertaken by a live agent, the process incurs additional operating costs, which are ultimately passed on to customers. Current fraud detection and prevention systems are highly reliant on the fact that fraudulent behaviour is more unusual than genuine behaviour. This means that fraudulent transactions can generally be filtered out using data from genuine transactions, involving a process of anomaly detection. However, advances in AI and ML technologies raise concerns that these models could be progressively circumvented by increasingly realistic generated attack vectors, which will force the development of more sensitive, and consequently more costly and exclusionary, controls.

3.2. Risk Assessment Models

A credit risk assessment model produces a credit score. A credit score is a number that summarizes credit risk in one variable and represents the likelihood of the investigated party violating one or more contracts with the evaluator [34-36]. A predictive score is based on information about the client, past clients having a similar profile, and the likelihood for this group to miss or not fulfill financial charges, future payments, and contractual obligations.

One of the first quantitative models used for credit assessment was proposed by Altman in 1968 and was called a Z-score. Z–score is a method for assessing the financial strength of a company by measuring five key business ratios using data found on its balance sheet and income statement [37-40]. It can also be used for predicting whether a company is likely to go bankrupt or not. Z–score is based on a linear discriminant model. An adequately named model that generates, for any firm, a score indicating the financially good and bad, the financially excellent and distressed, and also the probability of these two conditions. The analysis is based on financial ratios using the control area as a parameter.

4. Real-Time Transaction Monitoring Systems

When a customer uses a credit card for a transaction, fraud detection involves analyzing the individual transaction as well as the customer's entire credit card history. According to survey data, the majority of newly authorized transactions have no connections yet [41-43]. When a credit card customer initiates an account, there is no way to judge the validity of the transaction, making the detection of fraud against newly opened accounts nearly impossible. By representing the relationships between new transactions and historical transactions, detection capabilities are enhanced, especially when transactions are based on links.

Credit card transaction networks have been developed for fraud detection. Their monitoring can be performed in various ways [28,44-47]. Once a new transaction begins, a new link-based feature is extracted and added to a feature vector in the data warehouse. A classification model then evaluates this feature vector in real time. Credit card transaction network monitoring is practical, and a series of realistic guideline rules assists future implementation. Currently, the majority of credit card transactions undergo monitoring. For new transactions, monitoring utilizes either of two feature sets: the resultant-feature set or the link-based appliance-feature set. Throughout these monitoring phases, a classification model evaluates the generated feature vector.

4.1. System Architecture

The architecture describes the components of the system and their interaction. It comprises three modules: integrated merchant and transaction information, data warehouse and data mining engine, and the graphical user interface [48,49]. The first module is responsible for integrating the merchant information data set and the transaction information data set to create the training data set that secures the data warehouse. Labeling a data set generates fraud-store data that serves as a comprehensive fraud data set. The transactions are linked with StoreID-invoice pairs, allowing for the tracking of the store where each transaction occurred. The data warehouse and data mining engine module implement storing the training data set in the warehouse and perform data analysis and mining tasks on the stored data. This module produces a fraud detection model that predicts whether transactions in the test data set are normal or fraudulent. The graphical user interface module displays the predicted results of fraudulent transactions and the merchants that have committed fraud.

The training data set, private data, and prediction model are created by the data mining algorithm engine. This engine integrates all data mining functions and can combine different algorithms and functions to perform comprehensive operations. Labeling creates the training data set and involves manually labeling the store information and transaction data to identify whether the data is normal or fraudulent. The labeling function generates fraud-store data, which is then stored in the private merchant database. Transactions linked with store invoice numbers are labeled, resulting in transactions matched to the training data set. The private function connects the transaction data with the training data set to produce a labeled training data set. The prediction function runs the Weka fraud-detection algorithm on the labeled data and exports the results to the database, marking testing data as either normal or fraudulent.

4.2. Data Processing Techniques

Considering the ability of criminals to use, among others, very powerful cloud algorithms derived from collective knowledge, it can be concluded that in the fight against fraud, cutting-edge IT solutions not only support legitimate cardholders and financial companies, but also open Pandora's box. The size of the crime is enormous. Companies such as Amazon and Walmart lose about two billion dollars each annually due to external fraud—internal fraud is numerous but less notorious. The European Parliament estimates the levels of dishonesty, fraud, and violations of best practices in agriculture contribute to annual loss of approximately EUR1.5 billion. These figures justify numerous efforts of all stakeholders. Data analysis, machine learning, and artificial intelligence are methods that not only put criminals behind bars but also save budgets and prevent fraud.

Fraud detection starts with collecting and processing large amounts of information about cardholders that are available on the Internet and in social networks. These data are processed in real time and some algorithms already provide operational outputs. SecurActive checks a selected sample of clients through 35 parameters (basic client attributes): type of contract and contract details, permanent address, residential addresses, type of housing, information about co-residents, domestic/foreign phone numbers, information about the time of use of services by other companies, relation to a company founding, information about the client's occupation and relations with the employment center, career center, education center, information about the client's age and family situation, regularity and place of spending, history of financial transfers, friends/contacts groups, friends of friends groups, and the contents of information available on Facebook and Google search engines. Data concerning the client are gathered for a large number of customers and then grouped into three groups: "normal," "fraud," and "internal fraud." Data are divided according to their character: macro-data and micro-data. Macro-data, which are related to the client, check more than 30 attributes of more than 115,000 clients. Information generated is then used in a simple logistic regression model, providing the variable PMML_Value, which may be called the probability of honesty. PMML_Value is a real number between zero and one, and it indicates the probability that the examined client is honest. If the value is close to zero, the client is probably not honest. The macro-data analysis is highly automated; data preparation and model building require a lot of human work but are conducted every six months. The system optimizes the results, giving priority to accuracy or higher prediction for honesty.

5. Case Studies from Banks

Subsection "" in "Fraud Detection and Financial Security" presents three real-life scenarios that highlight the vulnerability of banks to fraud schemes based on direct contact and the role of voters. Chapter 2 proposed a classification of fraud scenarios with actors and tasks. In each scenario, the payments department might receive a payment modification, a procedure for large-volume payments that generates an alert, the accounting department might verify that a transaction has been carried out by a bank or a third party, or a complaints department might investigate a claim from a client that a transaction has been carried out by a third party. The concerted actions of an open group for performing an intrusion followed by a vote to decide on the requirement and deployment of a botnet, enabling the attack, are susceptible to change. Fraudsters change their roles for tasks and different departments when preparing an intrusion and conceiving a new attack. If employees of a particular department require an intrusion, a botnet must be deployed. These commands are passed to the botnet developer and the botnet is created and placed in the appropriate country, as previously described.

The third scenario, classified as "Intrusion,» illustrates the Probability and Statistic Management Utility (Prosy: for the detailed description of the scenarios see "Research Method" of the main work and Supplementary Material). Prosy is a utility designed for banks, specifically targeting the areas involved in the payment process, such as the payment regulation department, anti-fraud, financial management, accounting, etc. Prosy manages payment statistics and probabilities, evaluating the probability of statistical coincidences. After testing the utility with the money transfers made in a particular Spanish bank during 2007, the results revealed three groups of fraudulent payments crafted to simulate legitimate business-oriented use. These groups represent three different fraud scenarios of increasing complexity, sophistication, and volume.

5.1. Successful Implementations

Fraud detection techniques in various fields demonstrate how detected anomalies and suspected fraud are carefully examined to confirm fraudulent behavior. In a typical e-commerce setting, a transaction is flagged as suspicious when the fraud detection model indicates a high probability of fraud. This transaction is then reviewed by a security analyst, who gathers additional information about the buyer, the shipping address, and compares the details with past transactions. Users may also be contacted to verify transaction details and ensure the use of genuine credit cards. These manual verification processes consume considerable time and resources and are susceptible to errors.

A successful enterprise fraud detection framework incorporates various layers of checks around an enterprise's fraud-related assets, with and without business context. Asset monitoring and transaction monitoring provide broad coverage of asset misuse, ensuring the security of enterprise assets. Comprehensive behavior analysis of assets, users, and transactions predicts potential fraudulent activities and highlights them for further analysis, enabling proactive detection. Continuously evolving rules, experimental analytics, and machine learning techniques covering the entire fraud realm prepare the enterprise to rapidly detect new and changing fraud patterns. Contextual and business parameters offer relevant insights that facilitate decision-making and act as early alerts before a bank or customer suffers financial loss.

5.2. Challenges Faced

The three primary challenges to achieving real-time fraud detection and screening in the payments industry are outlined below:

Latency

Payments processors must complete thousands of real-time decision requests per second. Even if each decision requires only five milliseconds, however, the sheer volume of requests means the cumulative amount of time consumed is many hours each day. The industry is also developing new ways to offer additional layers of decisioning to the payments processor and payment stakeholders. Scrutiny becomes even more critical with the development of open banking initiatives and third-party account access for spending money. Previous batch decisions involving deep machine learning analysis often take hours or days to complete. Algorithms designed for throughput suffer from a breakdown in quality, while algorithms designed to provide excellent results suffer from a breakdown in latency—in essence, determining merely the “result of a result” rather than producing a useful outcome.

Machine Learning

Machine learning algorithms prevail in the fraud space, and the industry is beginning to exploit the advantages of deep learning. These algorithms frequently rely on data that best describes the entity to be classified, such as a product or service. Many online retailers, for example, have predictive target variables that consider a customer to be “high risk” because of an existing relationship with another entity at the same financial institution. The challenge with payments fraud is the difficulty in predicting an inherently negative result: the detection of fraudulent behavior requires that an account be compromised, either through identity theft or card theft. Machine learning algorithms therefore face the hardest challenge of all in the entire payments ecosystem. These difficulties are addressed through a variety of techniques beyond the scope of this discussion.

Explainability

Model explainability requires a descriptive reason code for every decision, a critical factor in both approving legitimate transactions and rejecting fraudulent ones. Screening declined transactions also complies with financial privacy laws by reassuring the consumer that the outcome was linguistically sound and fair. Although requirements may vary by state or country, they have yet to be formally codified.

6. Case Studies from Fintechs

Every new advancement in web or app technology brings in more utilities, benefits, and exposed threats to users. Telecom, Social Media, Banks, and Payment Fintechs are the prime targets of such cybercrime. The recent rise in voice-prompt based banking apps also underwent a recent threat exposure due to this phishing attack, the Text-to-Speech (TTS) based phishing attack [239]. India is the second largest country in terms of internet users in the world. Most of the digital money transaction within India is performed either through Unified Payments Interface (UPI) or through mobile banking apps. Improper understanding about the malicious and benign call behaviour of any mobile app may lead to cash losses for the user.

This study focuses on the analysis of the call behaviour of some of the reputed fintechs in India. Interactive Voice Response Banking, popularly known as IVRB (Interactive Voice Response Banking), is one of the widely used technologies nowadays based on the IVR (Interactive Voice Response) technology. IVRB plays a key role in increasing the customer experience of a bank by providing the facility to check the balance and recent transactions, generating virtual credit and debit card, and enabling card hotlisting. All information is provided over calls in a text-to-speech voice of a bot. APIs are used by the apps for verifying the accounts and performing other functionalities. But this call behaviour of the apps can be misused for phishing attacks—namely, Text-to-Speech (TTS) based Phishing Attack. The TTS based phishing attack resides in the fact that the respondents of the fake apps are bots. Such callers can be exploited for phishing calls, by controlling the textual content to be spoken during the call. Study proposes and demonstrates such a call behaviour analysis for Text-to-Speech (TTS) based phishing attack exposure for some of the famous financial-based apps in India.

6.1. Innovative Solutions

Significant advances in science have facilitated innovation, making a society less vulnerable to economic and social disruptions. As a result, every industry is safeguarding its internal data and preventing misappropriation of confidential information. Information and communication technology has played an important role in the digital world. Since the early 1990s, fraud detection over phone and internet notifications has increased data security and reduced crime. Financial institutions safeguard exchange-related details of customers and partners. Credit and debit card transacting also require effective data protection to preserve all types of digital information.

Innovative solutions for data security make a society less vulnerable to economic siege, with every industry safeguarding its internal information. Handling substantial amounts of money seeks better recognition of customer experience and more transaction safety to prevent data breaches arising from erroneous use. Be it credit card transactions or accessing mobile and internet banking, support of information technology reduces crime and guarantees safety. When money is in transit and involves a number of players, data protection is a primary concern. Fraud detection considers an important part of advanced transactions that require greater security coverage.

6.2. Comparative Analysis

Before an online transaction is processed, it is first processed by the tree-based model and the killer mean model to predict whether the transaction is fraudulent or not. It is also processed by the BPs and RNNs. If it is a normal transaction, it is handled by the normal transaction module and the transaction is completed normally. If it is a fraudulent transaction, the killer profile is predicted by the killer profile prediction module. Then, according to the prediction result, the specific response module performs corresponding measures.

Online transactions are generated at a time point during the day, and the timing relationship between transactions also carries important information. Heartbeat pattern requests are generated in the same way during the day. As a result, they are taken into account during training when the model uses only the transaction amount of online transactions during the past 30 days and also uses the request count of HTTPS Plus Ball during the same period of time. In the training of the killer profile prediction model, the buyer-seller relationship between the killer profile and the transaction is considered. Male and female killer profiles tend to target buyers of the opposite sex (such as male phone numbers buying female leather bags), while group killer profiles tend to target sellers. The +/-1 relationship of the buyer-seller helps the model make better predictions.

7. Impact of Fraud on Financial Security

One of the important aspects in the context of fraud is financial security. "The question of financial security refers to the management of the safety of the disclosed information and the money of the customers and the users that utilizes the financial services through various electronic mode. It also revolves around those policies that are formulated and executed either by the government or by the concerned institutions to provide protection to the individuals, so that they do not suffer any loss or loss of confidential information due to any type of fraudulent activity or criminal activity of the defaulters." The question about the financial security of the millions of users, whose accounts and data might have been exposed during any of the hack and fraud cases or exposed by the people who are legitimate users could be on the minds of the customers, while using any of the products and facilities that is being facilitated by the financial institutions. Financial Security considers the processes, techniques and tools identifying and preventing misuse of potential vulnerabilities in business processes.

Risk Management focuses on the identification, measurement and control of operational and/or market risks: Losses arising from the inadequate or failed internal processes, people and systems or from external events, including legal risk (but excluding strategic and reputational risk), and Market risk relates to losses arising from movements in securities prices, interest rates, foreign exchange rates and commodity prices. Any policy on managing financial frauds has to take into account these risks also.

7.1. Economic Implications

The costs of insurance fraud are ultimately borne by the insured in the form of higher premiums. Federation of European Motorcyclists Associations (FEMA) estimates that French insurance companies increase the price of car insurance by 20 percent per year in order to offset the economic losses incurred due to fraud. Not only do these incidents hurt the companies' bottom line, but they also damage their reputations. Increasing accountability and transparency within financial institutions requires increasing the internal control capabilities of their respective accounting information systems (AISS). Governmental agencies aimed at reigning in financial abuses have created and implemented accounting information systems which are routinely subjected to both internal and external audits. Although the role of the internal auditor in fraud detection is increasingly being recognized, auditors may be hindered by a lack of understanding of this ever-evolving crime. Ultimately, many cases of fraudulent reporting can be linked back to lifestyle choices made by management.

Indeed, numerous frauds have been committed because of the lavish lifestyle maintained by company officials. Both auditors and investigators are required to pinpoint lifestyle changes of managers that are inconsistent with their known sources of income. Since the AISS assists in tracking the financial information of the organization, understanding the association between AISS and fraudulent financial reporting is of significant value. The application of a scoring system can detect financial fraud and create awareness among investors.

7.2. Consumer Trust Issues

Trust in financial systems and institutions is the cornerstone that enables financial transactions to take place smoothly and efficiently. Its role is especially critical in the face of growing financial insecurity affecting individuals, households, and businesses alike. When consumers design and develop systems to make financial transactions more secure and convenient, they also need to consider how best to restore trust and confidence in the institutions serving their needs. As noted by FCAC[1], "fundamental to the health of the financial services system are relations of trust between financial institutions and their clients. Confidence in financial institutions helps to maintain a stable financial services system." When consumers lose faith in the system, their financial health suffers, increasing financial insecurity.

A recent survey found significant concern about financial fraud and its impacts. Around four in ten Canadians expressed major or moderate concern about becoming a victim of fraud (42%) or having their identity stolen (40%). Slightly fewer were concerned about their family members becoming victims. Overall, one in four Canadians (26%) reported that they had experienced financial fraud or been the target of a potential financial fraud. Financial fraud was the concern most likely to affect Canadians' overall sense of confidence in using financial products and services—41% of those concerned about fraud indicated it affected their confidence at least to some degree. Furthermore, two in five Canadians who have experienced financial fraud or have been targeted by potential fraud indicated that their confidence in using financial products and services had been impacted as a result.

8. Future Trends in Fraud Detection

Fraud detection is crucial in protecting companies, their customers, and their reputation. Fraud risk management involves understanding the financial services industry's overall risk appetite, followed by robust control systems design. For these activities to be effective, organizations need to establish a sound ethical culture that conveys to customers and employees the importance of ethical behavior. Failure to do so could result in significant reputational and regulatory damage.

Financial crime risk management becomes even more critical as organizations embrace Artificial Intelligence and Machine Learning to utilize data for making business decisions. As AI becomes a strategic vehicle for change and growth, it is vital to balance the benefits of its implementation with the risks, especially those related to fraud. Proactively managing fraud risks helps individuals, communities, companies, and society as a whole to guard against unnecessary losses. Key areas include synthetic identities, romance scams, brand abuse, account takeover, and insider threats. Effective fraud risk prevention underpins consumer confidence in banking relationships, which are economic catalysts throughout the world.

8.1. Emerging Technologies

SolarWinds business statistics indicate about 300 000 customers worldwide. The company revealed the news on 13.12.2020. The company said in a statement that it immediately began containing the solarwinds hack in response to the attack. The security failure affected the products of an affiliate, SolarWinds Serv-U File Transfer Protocol (FTP) server. The hack was a widespread breach over several months that targeted U.S. government contractors and agencies. It was the latest high-profile attack attributed to suspected Russian state hackers.

The U.S. Treasury Department disclosed on 13.12.2020 that it had detected and mitigated a cyberattack just days earlier in late November. The agency also said it believed that the SolarWinds attack was partly responsible. Previously, it was alleged that a company that made software used by more than a third of the Fortune 500 was the source of the breach.

8.2. Regulatory Changes

The current regulatory landscape for cryptocurrencies is unclear, inconsistent, and incomplete. Subsequently, a substantial amount of money has been lost or stolen in crypto-related financial frauds in recent years, ranging from Ponzi schemes and scam initial coin offerings (ICOs) to privacy crypto coin mixers. Quieter crimes centered on layering and tax evasion, for example, have also increased significantly. Moving forward, regulatory changes could be the tipping point for cryptocurrency crime.

The field of cryptocurrency is perennially at risk of theft, scam, and fraud. Regulatory changes are expected to impact this landscape in three key areas: ICOs, money laundering, and taxation. Although crime detection in these domains has been widely studied using large-scale datasets, best practices, and lessons learned, these three areas represent pertinent research challenges in the coming years. Effective regulation is key to reducing fraud and increasing market place resiliency. Intelligent detection of crimes such as Ponzi schemes and layering support responsible regulators in securing the financial system and its investors.

Conclusion

Fraud detection remains a felony cat-and-mouse game, where defenders continuously fine-tune detection techniques while offenders adjust their modus operandi to remain undetected. Consequently, the success of fraud detection systems hinges on the quality of the underlying training dataset, the chosen detection technique, and the selected suspicious activity indicators. Indeed, the most effective method for an institution depends on its unique situation.

Data mining techniques are employed to analyze previously identified fraud cases and predict the likelihood of clients committing fraud. An effective fraud detection system should identify both non-suspicious and suspicious transactions. Rule-based fraud detection systems incorporate rules derived from discovered patterns; however, in practice, many organizations, including banks, still detect fraud through a manual review process. Fraud detection systems utilize various indicators, decisions, and action points; when a suspicious transaction emerges, appropriate decisions and alerts are generated. Detecting fraudulent transactions requires an understanding of various business behaviors, such as transaction history analysis and trend ranking, in addition to specific suspicious indicators. Credit card issuers constantly strive to reduce inherent risks in their operations.

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Chapter 5: Artificial intelligence Applications in Retail and Investment Banking: Personalization, Robo-Advisory and Behavioral Analytics

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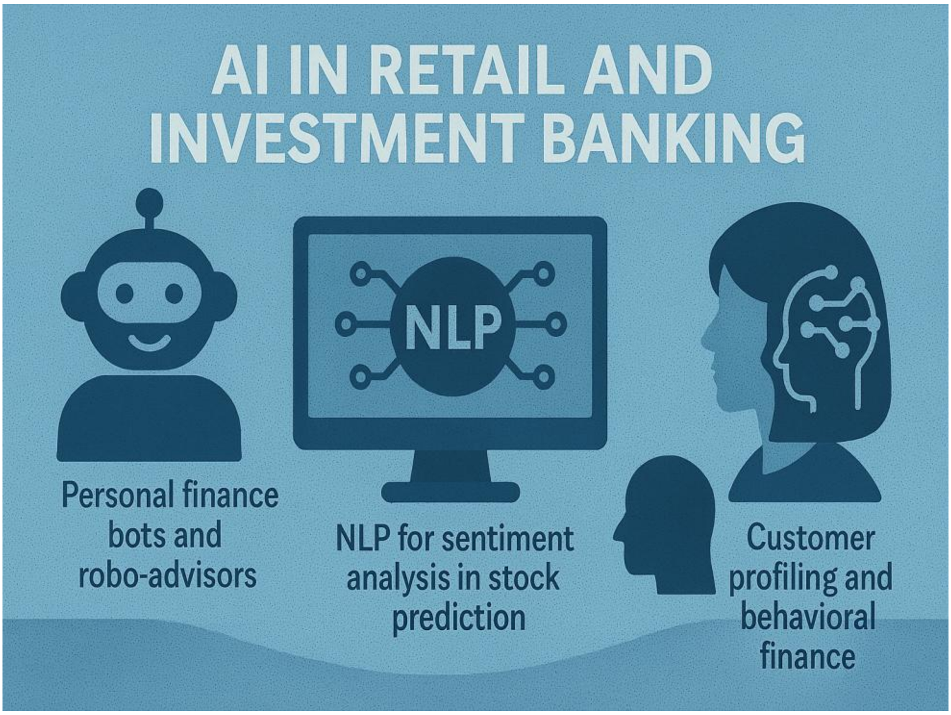
1. Introduction to AI in Banking and Retail

Artificial intelligence (AI) focuses on creating machines capable of mimicking human intelligence [1]. AI aims to automate routine tasks and perform activities that typically require human knowledge, understanding, and interaction, such as learning, planning, problem-solving, and decision-making [1,2]. As machines learn, they can improve accuracy, comprehend natural language, and predict earning potentials, leading to human-machine interaction. AI technologies—including chatbots, voice assistants, automated alerts, smart machines, process automation, and data classification algorithms—are being used in retail to enhance customer service and satisfaction.

Smart products are transforming the retail environment by enabling information optimization for timely product services. Application programming intermediaries customize products and services by gathering end-user information [3-5]. In the banking sector, applications include loan management, market risk assessment, fraudulent transaction identification, automated communication through voice and chatbots, credit risk evaluation, money laundering detection, and stock market prediction. The virtual assistant EVA, launched by HDFC Bank in 2017, processes around 60,000 customer queries daily via voice and text chat, replying within seconds. AIims to prevent fraudulent banking transactions through video and image recognition, face detection, and security camera analysis.



2. Personal Finance Bots and Robo-Advisors

Cordell describes personal finance bots as AI technologies that assist consumers in managing day-to-day cash flow, including financial services such as savings plans, credit, and investment advice. The development of conversational bots has evolved from relatively simple rules-based systems to complex NLP-based chatbots that can operate across multiple languages and contexts [6,7]. These advanced chatbots are capable of understanding natural language and engaging in interactive dialogue with investment-banking customers. In investment banking, AI advisers—known as robo-advisors—have become increasingly prevalent in the last decade. Well-known examples include Betterment (US), Nutmeg (UK), Moneyfarm (Italy), and Scalable Capital (Germany). Robo-advisors provide clients with a diversified portfolio based on modern portfolio theory. Their selection process is highly data driven; factors such as age, income, and investment experience contribute to the calculation of a client's risk profile, which is then mapped against exchange-traded funds as investment targets.

Various approaches have been proposed to forecast the financial market based on different types of financial data, including historical prices and volumes of equities, fundamental data such as profits and debts, and macro-economic indices such as the Consumer Price Index, following the principles of behavioral economics [2,8-10]. Additionally, sentiment extracted from text data is known as financial news, which is recognized as a key factor influencing traders' behaviors and stock movements. A specific group of investment-bank clients who make relatively frequent and small transactions—typically for speculation rather than long-term strategies—predominantly utilize conversational investment-banking bots. A substantial proportion of these customers are relatively young and possess an intermediate level of financial knowledge; hence, these AI advisers also encourage and assist in long-term investment. Examples include companies such as Cleo AI, Plum, Chip, Mitsuku, and Erica by Bank of America.

2.1. Overview of Personal Finance Bots

Personal finance management is a complex and effort-demanding task that has become increasingly important for individuals in recent years. Recognizing the significance of personal finance management, manufacturers are continually expanding their portfolio of personal finance bots. These bots attempt to provide information about the user's finances and recommend suitable measures. However, successful implementation requires contextual understanding of the user's financial situation and an active role in its management. In particular, small and medium-sized banks currently lack adequate investment support for their retail customers.

Consequently, users receive information too late or in inconsistent quality, and must actively seek information or advice when making investment decisions. This situation underlines the necessity for advanced personal finance bots capable of proactive engagement and providing timely, high-quality advice tailored to users' unique financial contexts.

2.2. Functionality of Robo-Advisors

Robo-advisors are automated, digital platforms that provide financial advice or portfolio management services without the use of human financial planners [1,11-12]. Their underlying goal is to provide algorithm-driven financial planning services with minimal human supervision, leveraging client data—including financial goals, and risk tolerance—to offer advice and/or automatically invest client assets.

Corporate finance firms and investment entities seek to increase revenue while minimizing operational costs and mitigating risks. Implementing robo-advisors addresses these primary requirements by reducing labor expenses, decreasing the scope for human errors, and providing customers with cost-effective personal wealth management solutions [13-15]. From the investor’s perspective, advantages include affordability, round-the-clock account access, ongoing access to professional financial advice, and automated portfolio rebalancing and diversification.

2.3. Comparative Analysis: Traditional vs. Robo-Advisors

Robo-Advisor systems are an emerging technology in investment decision making [16]. The systems automate wealth management using several different online tools and financial planning algorithms to generate optimized asset allocation strategies [16,17]. Robo-Advisors employ a layered architecture of services to interface with external stakeholders and also to communicate with back-end internal services. Customer profiling and investment risk tolerance classification services aid human advisors in day-to-day operations by rating investor risk profile based on the client's financial situation. Robo-Advisors maintain the client's goal with respect to inputs, including his net worth, desired monthly income, monthly savings, retirement age, existing loans, existing investments, number of dependents, and other factors.

Traditional wealth management platforms are highly personal and managed by human financial advisors [12,18-20]. The traditional and Robo-Advisor systems are contrasted based on several aspects. Traditional wealth management platforms allow for deep personalization by financial advisors, but their reach and scale are limited [21-23]. On the other hand, digital Robo-Advisors can scale much more quickly but lack the very personal human touch. The cost structure is uneven, with traditional advisors being significantly more expensive per asset under management and Robo-Advisors being relatively inexpensive and competitive. Robo-Advisors have distinct advantages.

2.4. User Adoption and Trust in Robo-Advisors

The algorithmic basis of robo-advisors may not naturally inspire investor trust or confidence [24,25]. Techniques have been developed to improve the interface used by robo-advisors with the aim of better meeting client needs. Canham and Wilska indentified seven barriers that prevent investors segmenting their portfolios. These include a lack of knowledge, interest and ability to organise money, and a lack of time and understanding of portfolios. Solutions, such as educational information and automated portfolio analysis, can be offered by AI-based financial advisers to reduce the impact of these barriers.

The development of appropriate recommendations depends heavily on understanding the client and the requirements of the task itself. An appropriate balance needs to be found between engaging the customer and threatening their sense of control. While the targeting of individual customers is expected to increase sales, it can also lead to customers turning against the company and a loss of trust if the levels of control are not handled carefully. Providing explanation, and particularly counterfactual explanations detailing what would be needed for an alternative outcome, has been shown to increase the sense of control experienced by customers and to reduce the perception of threat.

3. Natural Language Processing for Sentiment Analysis

The AI techniques examined in this article are Natural Language Processing (NLP) and its application to Sentiment Analysis [26-28]. Other considerations include the sub-types of Sentiment Analysis and its real-life applications within retail and investment banking.

Sentiment Analysis is the process of detecting, extracting, quantifying, and studying subjective behaviour in various daily pronouncements. These range from a sentence to a speech delivered by a government official, from a tweet to a newspaper's editorials, from a financial report to an earning call, and from a booking made by a single guest in a hotel to a thousand guests of the same hotel. Sentiment Analysis is most widely used in social media, retail, and investment banking. There are different AI technologies, such as Computer Vision, Internet of Things, and Soft Computing, but is the focus of this article on Sentiment Analysis.

3.1. Introduction to NLP in Finance

NLP in banking centres on human generated "language" resources, including text, transcripts and speech samples. The objective is to find, extract or generate content-based intelligence with invaluable applications in call centre support, market intelligence, financial news services and more [29-31]. Key to the generation of this market intelligence is the identification and understanding of the sentiment or implied judgment being expressed. Despite the appeal of these popular applications, sentiment detection is not "front-of-mind" or a coherent strategy for AI services in retail banking [3,32,33]. However, its seductive application of polling public opinion makes it highly suitable for external use.

Indeed, it is one of the most talked-about aspects of NLP – and a major economic driver for companies in the space. Yet for Banking Corporation, a consensus view of corporate clients.black is grey, it is perhaps most differentiated use.

Public opinion already provides governance on the transparency and ethics of holding assets that contribute pollution, overheating and overproduction. Although advanced clients.opinion already influence reputations, governance, asset allocation and portfolio management, it is equally disruptive to consider clients.black as opinion-makers, marketers and advertising agencies in real-time retail buzz channels. Listening to financial and retail chatter in public domains can directly affect strategy and tactical operational responsiveness. In such responsive strategies, the transformation centres on the ability to listen rather than to speak, through conventional speech-synthesis systems. As robots take centre stage, responsive operations move from proactive and predictive mechanisms to those that respond to public opinion and external stimulation in real-time. Hence the growth of interactive share pricing and dynamic pricing in retail markets.negotiation with clients.black for less profit that flows to. The U.S. Department of Commerce ranks financial market cost transaction costs as the highest industry sector. Dynamic pricing and those conversational, language-centric AI applications that involve.opinion challenge traditional pricing controls internal.

3.2. Sentiment Analysis Techniques

Sentiment analysis detects emotions, whether positive, negative, or neutral, to gain insights into how customers feel about various aspects of the retail industry [4,34-36]. It is performed on unstructured, semi-structured, or structured text analytics. The emergence of different sources such as Amazon product reviews or Trustpilot enables retailers to benchmark against both Amazon and their own stores, helping management teams identify opportunities and reduce risk. The sharing of customer reviews—whether they are satisfied, dissatisfied, or northeastern—accesses the collection of billion pieces of market data [37-40]. Retailers can analyze the volume of traffic to store websites that have the highest correlation to sales, analyzing the sentiments of visitors related to future performance. Positive feelings indicate a likely increase in sales, whereas negative sentiments suggest declining revenues.

Sentiment analysis capabilities can be used to support analytical endeavors in investment banking and retail sectors. Amazon product reviews and Trustpilot help the retail industry benchmark its products and services against Amazon and its own stores. The underlying process starts with the use of text analytics on customers' positive or negative comments, posted on the retailers' website through third-party services such as Brandwatch and Meltwater. The Retail Analytics Tool combines natural language processing (NLP) and regression to predict a site's sentiment on retail sales, thereby providing early information on retail revenue level changes.

3.3. Application in Stock Prediction

Investing in securities represents a considerable source of profit, yet uncertainties regarding future trends in the stock market make it an inherently risky endeavor [4,41,42]. The stock market, characterized by a vast number of traders and significant financial transactions, plays a critical role in a country's economic development. It facilitates the mobilization of funds from one sector to another, thereby contributing to overall economic growth [43-45]. The combination of these factors, coupled with the exponential growth of information in the data era, has generated substantial interest.

The AI revolution has permeated virtually every industry and sector, with retail banking emerging as a prominent player in this evolution. AI is extensively utilised to automate portfolios, forecast stock prices, and predict corporate bankruptcy. The banking and finance sector is rich in transactional data such as credit card records and personal loan information. Access to such diverse data enables models to learn the characteristics of each individual, thereby effectively predicting future trends and guiding decision-making.

3.4. Case Studies: Successful Implementations

Case Studies: Successful Implementations

Artificial intelligence (AI) is making deep inroads in virtually all sectors of the economy. AI systems use statistical methods to enable machines to improve with experience. A subset of imprutive machines —those that can interpret unstructured data such as images or natural language— is termed machine learning (ML). Deep learning (DL) is a subset of ML where artificial neural networks learn at successive layers of complexity. These three terms— AI, ML and DL — are often used interchangeably.

Some of the sectors where AI is having wide-scale deployment, the value delivered and key use-cases are shown in table plotted from the McKinsey report. Retail is the sector where AI is delivering significant value, chiefly through improving marketing and sales. For example, Deepart.ai uses the artificial neural networks that underlie DL for image recognition to turn ordinary pictures into visual art. In investment banking, AI is used to improve the customer experience by helping banks know their customers better and provide personalised products; better risk management; and cost reduction via intelligent process automation. Waymo's self-driving cars rely heavily on AI-generated solutions.

4. Customer Profiling in Retail Banking

Customer profiling is the process of gathering information about customer groups and generating descriptive information about them in various segments of the business [9,46-48]. A comprehensively created customer profile helps in stable business growth and generation of profits and revenues for business companies.

Retail banking is among the most competitive spaces the world has ever experienced; therefore, it has become imperative for the retail banking sector to develop a better picture of its clientele. Up-to-the-minute customer profiling is critical for determining where modern buyers are located. Retail banking companies can maintain their customer base and boost their profit-making potential by analyzing the markets and evaluating the products more adequately.

4.1. Importance of Customer Profiling

Owing to the peculiar and asymmetric situations of customer-related services, a real–time system that accurately and promptly responds to customer needs must be proposed and realized. A knowledge base is proposed for customers of retail banking services with individual behavioral profiles and their relationship with banks in the domain of project investment banking [49-50]. Based on the assigned profiles, the system automatically acknowledges the risk level of each portfolio or transaction and discloses the current state and possible future results of customer transactions or portfolios. The purpose of the development of the proposed OLAP–OLTP system is to collect data and support decision-making for different customer-related service needs. The system automatically sets a warning level and takes countermeasures to provide its customers with additional and prompt revenues and uses profiling knowledge for modelling customer behavior.

Acting as artificial intelligence, the system is designed to provide suitable characteristics for customers according to the services, markets, or targets of different banks. A project investment banking knowledge base analysis system is, thus, proposed on the basis of a real–time OLAP–OLTP decision-making model. It automatically diagnoses the risk level of portfolio loans or treasury and bond writing and discloses the current and possible future conditions. As the first stage, banking traffic analysis is investigated in which knowledge bases, in terms of customer profiling and different situational functions, are proposed and described. The overall feature of the system is knowledge-based decision-making.

4.2. Data Collection Methods

In the realm of AI applications in retail and investment banking, data constitutes the cornerstone for all endeavors. Within the sphere of artificial intelligence, data assumes a pivotal role, often likened to the oil for several AI applications. An adage underscores its significance by asserting: "garbage in, garbage out." Essentially, AI models rely on data for training and subsequent learning; consequently, models scrutinizing erroneous data are unlikely to deliver commendable outcomes.

Four principal approaches—web scraping, web crawlers, application programming interfaces (APIs), and crowdsourcing—serve the data collection activities underpinning scripts. Web scraping involves direct, often manual, retrieval of data from the World Wide Web (WWW). In contrast, a web crawler automates this task,Pioneer the web's aisles, tirelessly searching for new and updated content. When a user submits a request to a web server, web crawlers journey to the Internet Archive, retrieving stored copies of websites and delivering them to the recipient. The Internet Archive harnesses these collected copies to fabricate a comprehensive, infinitesimal map encompassing the entirety of the cyberspace.

4.3. Behavioral Finance Insights

Integrating behavioral finance concepts can critically enhance investment behavior modelling. Taking the Lens of Prospect Theory introduces features such as loss aversion, overweighting of small probabilities, and mental accounting bias in recognition of the human perception of utility and loss. Introducing these features in Utility Theory through Decision Balance proposes the development of a decision ratio that quantitatively describes the ongoing investment behavior by factoring in existing market conditions and quantifying the impact of classical prospect theory biases.

The implementation of the classical Prospect Theory four-fold pattern highlights how four investor profiles change their risk-taking behavior significantly as the market moves. The Decision Balance Ratio measure incorporates the impact of other biases like anchoring, mental accounting, greed and fear, and incorporates technical analysis heuristics during the investment. This quantitative behavioral model for investment decision making complements the traditional asset allocation models based on the Modern Portfolio Theory. It captures the ongoing behavior of the investor and thus allows the continuous recommendation of the appropriate desired portfolio. Combining these quantitative behavioral ratios with customer demographics, investment goals, risk-taking capability, and market movement characteristics enables the generation of an explicit personalized recommendation set for the investor.

4.4. Impact on Product Recommendations

Natural language technology enables instant customer service and scale product expertise at instore kiosks. Customers lodge complaints, seek solutions, and receive responses without needing a human customer service representative. In addition, the results regarding novelty, diversity and serendipity are provided in the literature in order to compare the performance between the proposed model and other well-known Product Search Ranking models.

These model extensions include a customer service agent, complaints processing, and resolution, and product information. The results show that the research model facilitates and satisfies customers during their shopping experience. The discussion also enumerates the benefits, challenges and positive impact of online shopping via chatbots with natural language processing technology.

5. Behavioral Finance and AI

Behavioral finance arose as a reaction to the theory of efficient markets, aiming to include psychological aspects in the analysis of investment decisions. As a result, current research on the efficient market hypothesis incorporates behavioral finance concepts in the description of asset prices. These concepts can also be considered in personal finance through the categorization of individuals into different behavioral levels: rational, emotional, and passionate. Each category requires an adapted investment strategy for the best investment choice.

The integration of artificial intelligence in retail and investment banking offers the opportunity to implement a behavioral analysis approach. Such an integration could enhance the design of investment strategies by incorporating behavioral finance insights. The following sections discuss specific applications of AI in retail and investment banking, including personal finance bots, robo-advisors, natural language processing for sentiment analysis, and customer profiling. These topics cover questions about the relationship between investing patterns and investor profiles, the impact of market sentiment on financial predictions, user adoption of investment tools, and the influence of customer profiles on product recommendation systems.

5.1. Understanding Behavioral Finance

Personal finance bots and robo-advisors engage customers by offering financial advice expressed in familiar terms, utilizing a conversational user interface. Their primary goal is to attract a broader customer base for banks, promoting diversified saving and investing habits. However, customers do not always adhere to good saving advice, introducing significant risks. Determining the level of confidence customers place in personal finance bots is crucial for successful adoption and retention. Furthermore, banks cannot rely solely on a set of rules driven by AI algorithms, as numerous unexpected situations emerge, necessitating behavioral analysis of customers in finance.

Behavioral finance constitutes an emerging field examining the effect of psychological, social, cognitive, and emotional factors on the economic decisions of individuals and institutions. It seeks to explain why individuals might make irrational financial decisions, such as succumbing to certain biases during risk-taking. These factors profoundly influence financial markets and decision-making processes. Social networks offer excellent tools for implementing these ideas; by analyzing behavioral aspects of customers in investment decisions, developing tools for portfolio risk matching becomes feasible, guiding users of personal finance bots and robo-advisors in investment decisions. Moreover, non-financial events significantly impact financial markets. With more than 50% of news being negative, Natural Language Processing techniques come into play, analyzing the mood of news articles related to stocks. The underlying assumption is that when a market is more positive, the stock price tends to increase. Following this, several products recommend certain stocks to customers in retail banking. Investment in stock markets is generally considered a long-term decision, with some people maintaining a share for 10-15 years. Yet, a good prediction assists in market timing, indicating whether to invest or sell.

5.2. Integration of AI in Behavioral Analysis

NLP applied to behavioral science has also been studied. By way of example, Zweig demonstrates the use of sentiment analysis to describe the emotions and sentiment expressed by the characters in books, with the results shown as a time series. In the field of business, Yu used sentiment analysis to help companies better understand their customers, thus improving customer service interaction processes. In recent years, studies have demonstrated that AI language models allow banks to associate information from different dimensions and uncover some insights between the interests, emotions, beliefs, and attitudes of people. Customer profiles are used throughout the financial domain to help institutions understand and organise their client base so as to increase services sales, customer retention, profitability, debt collection, segmentation, and direct marketing. It is noteworthy that the Internet and the Web have transformed the way of collecting information.

AI integration in retail and investment banking represents a foundational research topic. Personal finance bots are typically bots and robo-advisors with a strong focus on personal finance. Robo-advisor systems are nowadays largely exploited by banks and financial companies and can offer investment services online without human interaction. Studies have investigated the reasons that push people not to use the services offered by banks, while others have analysed how the trust that a person has towards the advisor can influence the investment made by the person. The integration of AI in retail banking calls for an assessment of how banks are using information, because it could enable financial institutions to detect anomalies or risks in investment choices or attitudes—signals that cannot be identified solely by human advisory services. Customers can also interact with their money in a more personalized way thanks to specific bots and systems.

5.3. Implications for Investment Strategies

Analysis of alpha generation based on sentiment reveals that, as expected, the alpha of all user groups declines substantially when sentiment is considered; nevertheless, the sentiment-based model still offers evidence of outperformance, suggesting that sentiment plays a role. It is clear that while the surrounding prediction issues are not yet resolved, there is value in predicting directional variances and incorporating client behavior updates as new information arises. This application of sentiment has implications for the construction of behavioral finance models and indicates that blending the behavioral school of thought with Bayesian techniques may enhance model accuracy.

The next step involves predicting the sentiment of a customer, which is crucial because, in addition to the macro sentiment effect, the retail banking customer center is an aggregation mechanism of customer sentiment and investment profile. This grassroots view complements the top-down perspective of market sentiment presented earlier. Customer profiling is an integral part of retail banking's product and service design. Data collected must encompass multiple dimensions, such as demographics and personal information, coupled with historical data or records of previous purchases. Through the construction of statistical models, banks analyze consumer patterns, gauge purchase potential, forecast market trends, and compile a pool of customers for targeted marketing product selection. In addition to classical financial indicators, behavioral finance insights are incorporated to enhance the comprehensive understanding of the customer base.

6. Challenges and Limitations of AI in Finance

Protected customer data is essential for the banking industry. Loss of customer data may result in a loss of trust and damage to the bank’s reputation, resulting in the loss of customers. Routers must be configured to avoid unintentional exposure of customer data. Connections to different networks, often referred to as VLANs (for example, sending printer data on one VLAN, accounting data on another, and Internet requests on a third), must be designed to restrict access to customer data from other networks. Access to the communications network must be actively monitored to detect, log, and report activities that access data for which the initiator has improper authorization.

Routers and firewalls must pass data at an acceptable rate for the performance level of the overall network. If a router cannot process data at an adequate rate, it will create a bottleneck that results in low network performance; if a firewall restricts packets to minimize security risks, it will also create a bottleneck. Routers and firewalls implemented in hardware, rather than software, can usually pass data without compromising performance.

6.1. Ethical Considerations

Artificial intelligence (AI) is a disruptive technology that has shown promising results in several fields, including retail and investment banking. However, AI faces its own challenges: ethical decisions cannot be taken by an AI model alone; therefore, it is the duty of the human being to establish parameters to minimize the collateral damage that an error may cause. Ethical and moral considerations need the experience that only a truly human force can provide. Nevertheless, AI can certainly assist the human decision-making process. AI in retail and investment banking is a disruptive innovation that has led the financial services sector to undergo a transformation on all fronts, including the moral and ethical one. An example of AI assistance in ethical decision making is that it has significantly assisted in the development of an automated Ethical Risk Management model.

Retail banking is perceived as a low-return business. The major banking services, such as loans, forex trading, mergers and acquisitions, and wealth/pension management, are provided under investment banking. The major AI initiatives are in retail and investment banking, insurance, capital markets, compliance, and risk management (Table 6.1). The attempts to identify the banking functions that are most suitable for the implementation of AI have been subjected to a detailed examination with the help of a Decision Support Model driven by the Analytical Hierarchy Process algorithm. The methodology examines the three dimensions of language, vision, and speech and analyzes various applications of AI that are capable of reshaping the future of banking from the customers' perspective. In addition, the applications of chatbots and Robo-advisers and the notions of RPA (robotic process automation) and smart ATMs are among the recent trends that are expected to revolutionize the banking and financial services domain.

6.2. Data Privacy Concerns

Before AI models take any decisions, there is the requirement of training these models through substantial data. Training models require a comprehensive dataset, which can encompass any data type such as text, video, audio, or image. Random data cannot be used since the results would not be meaningful. The data should be labeled to allow the machine to derive corresponding answers. For instance, in a dataset filled with car images, if some images are unlabeled, the machine will lack the necessary context. While models are trained intensively to achieve relevance, practical constraints restrict the training dataset to a few million examples. Although the extent of data required depends on the specific domain and application, models generally need to be trained on data that is sufficiently large to enable them to generate responses that bear similarity with those of humans.

One major concern is data privacy; a large amount of data is gathered from users and injected into different models. Companies they have not already agreed to share data with will also be exposed to their data. Uploading photos to get images back or using ChatGPT for code or travel planning results in the creation of a personalized profile, the details of which can reveal the user's thoughts. Complete reliance on these applications for suggestions undermines users' own decision-making capabilities.

6.3. Regulatory Challenges

Regulatory requirements are more restrictive in banking in comparison to retail. Therefore, investments needed to build AI capabilities also vary. Financial regulations revolve round protecting investor interests and involve lengthy processes to train and validate models before they go live. In the U.S., the SEC regulates model use in the financial sector; in Europe, regulations are uniformly required across all EU member states as per the GDPR. Data privacy emerges as a critical concern for clients, designers, and regulators. Furthermore, different MI fintech companies catering to the banking sector are affected differently by regulations. Services such as portfolio allocation and analytics have less regulatory oversight compared to those involved in account aggregation or advisory services. Another regulatory term to consider is the unbundling of services. Unlike in retail, where AI players provide end-to-end services, AI in MI caters to specific service lines. Flexibility in the choice of service provider ensures the client does not lock themselves into one vendor for all their needs. This unbundling of services is also driven by regulators in an effort to avoid anti-competitive practices.

Conclusion

The study of AI applications in retail and investment banking systems has produced two main outputs: a deductive taxonomy of AI applied to generic banking systems and a set of taxonomies tailored to retail and investment banking systems. Both sets of taxonomies are proposed for use in further studies of AI applications in retail or investment banking systems, providing an exhaustive overview of the topic at both levels of detail proposed.

AI applications in retail and investment banking systems can be identified and classified according to the service that is offered to a banking customer. After the application of AI technologies, these broad categories can naturally be grouped into four clusters, which are present in most banking systems: Know Your Customer, Risk Management, Marketing and Operations.

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Chapter 6: Artificial Intelligence for Financial Forecasting and Economic Modeling: Time Series Analysis, Predictive Analytics, and Macroeconomic Simulation

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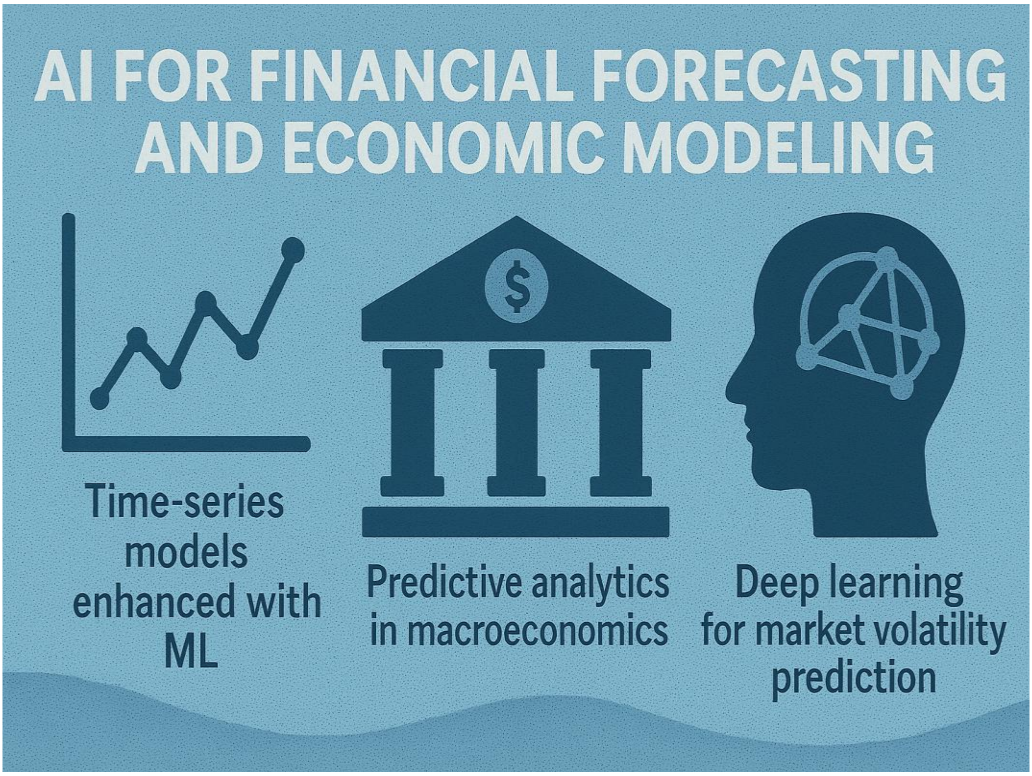
1. Introduction to Financial Forecasting

Financial forecasting is the prediction of the future state of a company's finances. Exposure to unanticipated outcomes such as political or economic changes can create risk in the forecasting process [1,2]. Formalizing the financial results restricts the ability of the business to respond to an ever-changing environment [2]. Methods such as planning, budgeting, and forecasting are considered important managerial activities within organizations. Forecasting is the process by which forecasts are packaged and made available to users. A solid financial forecast provides management, including the operating unit and corporate center, the information needed to make effective financial decisions about investment, debt, and stock repurchasing. With the growing usage of artificial intelligence (AI) it is imperative to recognize how AI can be used to improve the models used in the predictive process of financial forecasting.



Economics is the social science that studies production, distribution, and consumption of goods and services [3-5]. The behavior of an economy depends on the financial activity of its individual members and the country as a whole. The role of financial economics is to analyze the production and consumption of financial goods, to plan to control risk, and to forecast the prices of financial goods [2,6]. Economic modelling serves as a framework for insightful policymaking by allowing implications of shocks and policy changes to be analyzed in a systematic manner, thus offering informative insights into the proper functioning of the economy. In real-life situations, it is of great help in planning for the long-term economic development of a country. Planning plays an important role in all sectors and fields of life. One of the earliest but still useful applications of machine learning in the time-series arena is Financial Time-Series Forecasting, which is probably well understood by a lot of people.

2. Overview of Economic Modeling

Economic theories establish the framework of how economies operate. Economic modeling, in contrast, is the process by which economic data and economic theories are implemented by individuals or institutions for practical effect and forecasting economic values or performance variables [7-9]. These models are widely used for economic forecasting, especially in areas like monetary policy, taxation, debt management, and financial regulation.

The techniques employed in economic modeling are quite varied, and they are routinely applied to situations ranging from recession analysis to modelling the speculative effects of an interest rate change on the exchange rate. Broadly speaking, there are normative approaches, which prescribe what policy should be, and positive approaches, which seek to determine what effects a change in a given variable will actually produce.

3. Time-Series Models in Financial Forecasting

Financial forecasting employs predictive models to analyze financial markets and guide investment decisions, a process essential for risk management, budgeting, and trend analysis within accounting and economics [10]. A variety of time-series models, often combined with machine learning algorithms, have been developed to predict market volatility. Models commonly used in finance now produce inputs for existing time-series frameworks. Traditional time-series models—the autoregressive (AR) model, moving average (MA) model, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), along with extensions such as GARCH, EGARCH, and GJR-GARCH—are also applied for market volatility prediction. Nevertheless, machine learning forecasting methods are capable of producing superior forecasts, suggesting that ARIMA or GARCH models serve better as benchmarks.

An encompassing survey of machine learning methods for time-series forecasting reveals that these techniques fall into three categories: regression, classification, and clustering. Predictive analytics—the practice of extracting information from datasets to foresee future activity states—extends beyond time-series data. Incorporating predictive analytics into macroeconomic policies can significantly enhance forecasting quality. A case study from the United Kingdom exemplifies this improvement.

3.1. Traditional Time-Series Models

Financial and economic forecasting includes the creation of predictions concerning economic variables in the future. Forecasting is considered an important tool in the field of economics and finance: it serves as the basis for the decision-making process of businesses and governments [10,11]. Artificial intelligence has recently broadened its horizon in the financial and economic forecasting arena by assisting traditional time-series models in the prediction process. Time-series models in economics require the analysis of temporal datasets in order to extract meaningful insights and support the predictive process [12-14]. It is acknowledged that forecasting contributes towards generating alternative scenarios for the variables of an economy, as it provides useful information for the analysis of risks and policy planning.

Conventional time-series models seem to be unable to capture the possible nonlinear correlations that lie between past values of macroeconomic variables and unobserved future states, as they are based on assumptions of unbiasedness and efficiency. Therefore, machine-learning-regression methodologies are evaluated for forecasting a financial time-series domain. Specifically, the study addresses three important methodological questions regarding the use of (i) alternative methodological input–output frameworks; (ii) different feature-selection and data-normalization approaches; and (iii) the combination of machine-learning techniques in an ensemble-forecasting approach. The results confirm that the combination of feature-selection algorithms with specific input–output frameworks can lead to a significant increase in the efficiency of time-series prediction. Moreover, the application of an ensemble combination of machine-learning models outperforms the traditional autoregressive benchmarking model.

3.2. Limitations of Traditional Models

Time-series analysis is an integral part of financial and economic forecasting. It is common to observe daily data of financial index such as closing price. Time-series models are used to analyze the movement of economic or financial index in the past and forecast it for the future. An accurate forecast helps in leading the business in a right direction and avoid investment in business that forecast indicates as downturn [3,15-17]. A normal business decision would be to invest macroeconomic environment or for individual business organizations. The importance of macroeconomic environment prediction is highlighted in. Especially, when economy is rapidly changing, econometric models should incorporate advanced techniques for reliable prediction. The traditional method used for volatility forecasting is statistical GARCH family model. Because nowadays millions of predictive data for macroeconomics are taken into consideration, the use of statistical models for such datasets is questionable. So, it is necessary to study the predictive analysis of time-series datasets with the help of modern data analysis tools such as Machine Learning, Artificial Intelligence and Deep Learning.

3.3. Enhancements through Machine Learning

Many of the recent studies that introduced machine learning techniques into econometrics and financial forecasting focused on methods of classification, regression, and clustering applied to time-series analysis [18-20]. Examples include support vector machines, non-parametric Bayesian models, and ensemble learning methods. Artificial neural networks, deep neural networks, convolutional neural networks, long short term memory networks, and recurrent neural networks have been applied in time-series forecasting of stock prices, derivative prices, bond prices, foreign exchange rates, and volatilities.

In macroeconomics, predictive analytics have become essential to policymakers and analysts, but implementation has often been weak or inconsistent due to the absence of clearly defined objectives. A study explored forecasting the Brazilian risk premium and concluded that the consistent use of predictive analytics can enhance macroeconomic analysis and policy formulation.

4. Machine Learning Techniques in Time-Series Analysis

An important area for time series forecasting is financial analysis. Within a firm's business environment, profits gained through financial forecasting help organizations achieve better levels in development and thus competitive ability. There are numerous time-series forecasting methods [21-23]. Eo used Artificial Neural Networks and a Genetic Algorithm to forecast an exchange rate with stock market indicators and interest rate differentials as a part of Time Series Forecasting. Elija developed a method for forecasting based on neural networks and used it to predict the Indian stock market [9,24,25]. Sak and Ilhan proposed a new Financial Forecasting System to predict the direction of movement in the Bovespa index, the Brazilian Stock Index, using a combination of equipment based on Machine Learning and artificial intelligence. Stan implemented and backtested Machine Learning-based algorithmic stock trading strategies for the Quantopian trading platform. Wang proposed a clustering and classification framework for time series. Dastile, et al outlined the basic concepts of Financial forecasting, some methods and techniques for Financial forecasting.

The term Economic Forecasting refers to the process of making statements about the future values of economic indicators and variables such as interest rates, gross domestic product, tax rates, or unemployment, based on information taken from past and present data. Lee used a classification algorithm to classify financial data with a group of leading economic indicators. Forecasting is an integral part of planning, control, management and policy formulation of a firm and other organizations such as business units, government, and industrial enterprises. The essence of forecasting lies in the accumulation of available information and analysis of the inherent trends in these data series. Forecasting attempts to estimate the future values of a time series on the basis of its historical demand data.

4.1. Regression Techniques

Modeling the relationships between economic variables is one of the most fundamental aspects of economics and finance [26-28]. Among the various techniques available, linear or polynomial regression models constitute one of the simplest and most popular methods in these fields. The standard formulation involves determining a function $f(x)$ that minimizes the squared differences between predicted values and actual outcomes, expressed as $\sum (y_i - \beta_0 - \beta_t t x_{it})^2$. The well-known closed-form formulas can be generalized to include polynomial terms, thereby capturing non-linear relationships.

Regression analysis can be utilized to infer relationships between economic variables, and it can also serve as a method for forecasting. Some of the earliest empirical evidence in favor of the efficient market hypothesis consisted of demonstrating that variables known to be efficient-market predictors of stock prices also successfully predicted returns in historical data. Simple regression can often be misleading; two variables not linearly correlated may exhibit a non-linear relationship, such as an inverted "U" shape. Given that these forecasting techniques are most suitable for variables related to financial asset prices, and that the ratio of a variable's price to one of its components is generally a rough measure of profitability, the x and y variables discussed earlier are appropriate candidates for regression analysis.

4.2. Classification Techniques

Classification techniques, which assign objects to predefined categories or classes, represent a prominent part of artificial intelligence (AI) methods adopted in financial applications. Based on Bayes' theorem, these methods estimate the probability of a given instance belonging to a certain class, considering prior probabilities and the probability of that instance occurring within that class.

Applications of Bayesian techniques differ according to the specific context. Whether the goal is to determine bitryps, classes, or types, Bayesian classifiers in both cases function in a similar manner, despite being part of different AI subfields. A significant aspect in the implementation of Bayesian methods lies in how probabilities are estimated — a process that can profoundly influence the accuracy and reliability of the resulting classifications.

4.3. Clustering Techniques

Cluster analysis is an unsupervised machine learning technique whose primary goal is finding structures or groups in data to provide insight into a particular problem [6,29-31]. This can be valuable in many financial areas, such as the stock market or insurance. In inner class classification, the core idea is to maximize the similarity of objects inside a group by using nearness or similarity measures and minimizing the similarity of objects across different groups.

Financial unsupervised machine learning can support various applications, especially those that do not rely on any pre-defined classes or outcomes. For example, cluster analysis has been used in several studies investigating the European financial crisis, credit card loss forecasting, and the insurance market. To illustrate the potential of cluster analysis, the following studies utilize it in financial market environments.

5. Predictive Analytics in Macroeconomics

Timely recognition of upcoming financial crises is a critical policy imperative. Data-driven, predictive models are now capable of anticipating crises several years into the future [32,33]. While machine learning methods have achieved notable success in consular fraud detection and the identification of money laundering activities, such approaches are scarcely applied in formal predictive macroeconomic analyses [34-36]. The long time horizons and highly imbalanced class distributions characteristic of crisis prediction complicate the application of predictive analytics in economics.

Predictive analytics in macroeconomics support policies designed to enhance welfare by improving decisions related to forecasting, planning, and budgeting. They empower policymakers and business leaders to make investments that optimize outcomes. Driving these developments is the exponential growth of stored data and advancements in artificial intelligence [16,37-40]. The accumulation of information across economics, finance, natural resources, and other fields continues at a rapid pace, reinforcing the interdependencies among sectors and economies. The availability of these data has enabled the scientific community to produce accurate and robust predictions through artificial intelligence.

5.1. Importance of Predictive Analytics

In the realms of financial market analysis and macroeconomics, forecasting models play a crucial role. They are used to predict the direction of the economy and the financial markets, thereby directing economic and monetary policy [41-43]. Despite their importance, highly nonlinear and unstable relationships between variables often cause poor forecasting performance, especially in the short term. Economic data thus pose an interesting challenge to predictive analytics.

A series of case studies illustrates the predictive performance of several underlying methods. The predictive performances of individual machine learning methods, as well as an ensemble method, are assessed across a range of economic data series. Depending on the sampling frequency of the data and forecast horizon, the tree-based methods generally outperform linear models. The results also show the benefit of using an ensemble method for prediction.

5.2. Applications in Economic Policy

Financial forecasting involves estimating the future value of a company's stock or market, rooted in analyzing past prices and trading volumes, as well as fundamental economic factors [44,45]. Forecasting provides investing insights and helps measure risks and reduce uncertainty in financial decisions. Economic modeling employs mathematical equations to describe past and predict future economic activities and relationships. Accurate predictions of economic variables are essential for formulating and implementing appropriate economic policies and for managing the national economy and public finance. The introduction of predictive analytics can reduce uncertainty in economic forecasting, supporting macroeconomic analysis and policy formulation both in developed and emerging economies.

Large historical financial datasets have engendered interest in machine-learning methods for stock price prediction. Machine learning is developing classification and regression algorithms, including support vector machines, regression analysis, Bayesian analysis, and clustering techniques. In the context of time-series data, these algorithms can be used for classification, regression, and clustering [22,30,46-48]. Deep learning, a subset of machine learning, applies artificial neural networks to solve unsupervised, supervised, and semi-supervised tasks, modeling data with complex architectures and achieving notable success. A concise survey of relevant case studies highlights the growing role of predictive analytics in macroeconomic policy.

5.3. Case Studies in Predictive Analytics

Predictive analytics—the application of forecasting techniques to business, opinion, and financial data—is a primary beneficiary of recent advances in machine learning. Macroeconomics, however, has yet to reap these rewards despite the potential predictive power embedded in large, disaggregated datasets. One study investigates whether predictive analytics can improve forecasts of inflation and output growth at a two-year horizon, presenting three case studies: forecasting German inflation using features extracted from the balance sheets of the Bundesbank's main counterparties; evaluating the predictive power for inflation in the low countries relative to the Euro area; and forecasting growth in the G7 countries using world-level features extracted from the IMF's World Economic Outlook database.

6. Deep Learning for Market Volatility Prediction

The financial market is an extremely volatile and highly dynamic system. Working as a predictive tool, an expert's intuition coupled with a deep understanding of any respective financial market is extremely helpful to predict the volatility and market trend otherwise conceivable with a higher degree of certainty [49-50]. Machine learning has been increasingly used for financial forecasting applications as it is expert-independent and process large amounts of data and its corresponding presumption. Deep Learning, a branch of machine learning, uses multiple layers to progressively extract higher-level features from the raw input. For financial volatility prediction, this implies using multiple levels to extract higher-level temporal abstractions. An Artificial Neural Network has been used to predict financial volatility. Deep Learning models such as Doc2Vec are used to gauge the sentiment from the financial news articles which is then used as an input to LSTM along with technical indicators for the final prediction of the Volatility index.

Market sentiment plays a significant role in any investment-related decision-making and the knowledge of the market trend has a ripple effect on all other sectors in the economy. The market sentiment can be gauged from the news reports, headlines or social media posts. A Deep-Learning-based method detects and analyses the market trend in the light of the COVID-19 pandemic using linguistic data and technical indicators. Market sentiment analysis is performed using theories such as the Keynesian beauty contest, the lead-lag effect and descriptive and predictive capability of news articles. Market volatility forecasts are generated using a Support Vector Machine model. On the other hand, other research predicts the sentiment present in these news reports from the news headlines itself using the Natural Language Toolkit. The sentiments are used to judge whether the market volatility increased or decreased for that day. Market volatility prediction also is performed with news headline sentiment information through a stacked LSTM network.

6.1. Introduction to Deep Learning

Deep learning enables multiple layer (hence "deep")-structures of well-connected artificial neurons. This topology facilitates a computational structure capable of learning and approximating increasingly complex hierarchical structures and behaviors. Through the volume of data, the representation of features themselves can be learned, facilitating an end-to-end solution, thereby directly addressing the feature extraction problem that exists in classical machine learning approaches.

Deep learning refers to the ability of neural networks to evolve through various transformations into highly nonlinear complex models, optimized to approach target outputs as accurately as possible during training by adjusting parameters. The optimization depends on the loss function associated with the task performed by the network. Backpropagation is used to propagate the loss gradient throughout the network. The first multilayer perceptrons (MLPs) were trained in the early 1980s with only a few layers, due to computational restrictions and the vanishing gradient problem. Over the years, developments in initialization techniques and activation functions allowed increasing the number of layers to up to 1000, setting the base for very deep networks known as deep learning.

6.2. Architectures for Volatility Prediction

Volatility, or price fluctuation, is an essential component in the asset valuation process. Volatility is one of the inputs in the famous Black Scholes model. Managing risk by predicting future volatility trends enables the creation of appropriate hedge positions. Accurately predicting the volatility of stocks is crucial for financial risk assessment. Financial analysts frequently use GARCH-type models to predict volatility. Because of its ability to capture time-varying volatility in financial time series, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model has become widely adopted for estimating asset return volatility. The Markov Regime Switching GARCH (MRS-GARCH) model extends this capability by allowing different parameters for distinct volatility regimes, thereby capturing volatility clustering and regime shifts in financial markets.

Researchers are employing various deep learning models such as the Long Short-Term Memory (LSTM) network and the Gated Recurrent Unit (GRU) network to predict volatility in financial markets. They leverage the ability of gated recurrent-based models to derive hidden representations of historical volatility from data. Models based on Gated Recurrent Units (GRUs) capture temporal dependencies in historical volatility, enhancing volatility forecasting. Recent studies involve a comparative analysis of Bidirectional LSTM (BiLSTM) and BiGRU models, examining their architectures to determine which performs better in predicting volatility.

6.3. Evaluation of Deep Learning Models

Evaluation metrics are of paramount importance due to the nonlinear and complex nature of financial time series forecasting. Model performance assessment requires error metrics that are scale-independent, symmetric, and highly sensitive to large errors. In regression problems, error classification typically revolves around residual errors on the output variable of the model. The metrics examined include Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Normalized Residual Quantile (NRQM), Normalized Residual Average (NRA), as well as simple residual analysis.

For classification problems, the Receiver Operating Characteristic (ROC) curve has been extensively used to represent the sensitivity of a classification method. Added to the ROC curve analysis, the Area Under the Curve (AUC) metric provides an overall summary of model capability in terms of sensitivity and specificity. RMSE is employed to compute errors between the predicted values and actual values of the Dow Jones index.

7. Comparative Analysis of Forecasting Methods

Forecasting is a popular analytic technique in many industries. Advanced analytics techniques—machine learning, deep learning, and artificial intelligence—are being explored for forecasting models. Data used for forecasting aren't limited to just the history of the variable being modeled. Machine learning models help recognize connections between prices of various commodities. Hence, they are expected to forecast the price of one commodity using the prices of other commodities. Forecasting refers to predicting future events, trends, and values through historical data and analysis. The method and data used depend on the purpose.

Univariate forecasting models use a single dependent variable to model the series and predict future trends. These methods mainly study the historical behavior of the variable being forecasted. Using the analysis of the series, a model is constructed to describe the series. Using this model, the variable is forecasted for future dates. The classical forecasting models such as Moving Average, Weighted Moving Average, Autoregressive, Infinite Impulse Respond filter, and Autoregressive–Moving Average use univariate approaches. It is possible to forecast the series more efficiently when the price of a commodity is correlated through time or price movement with that of another commodity. Forecasting models for such a commodity group, which are believed to be correlated and affect each other's price movement, use multivariate analysis. The autoregressive—moving average—multivariate model (ARMA—VAR) is a popular multivariate method for forecasting time series data.

7.1. Statistical Methods vs. Machine Learning

Both Statistical Methods and Machine Learning (ML) use historical and current data for prediction purposes. Traditionally, statisticians have focused on inference, employing historical data to identify optimal models for describing real-world data generating processes. In contrast, typical ML models are evaluated primarily based on predictive accuracy. Model improvement through cross-validation, for example, aims to reduce prediction error rather than enhance process understanding. Consequently, ML models often resemble "black boxes," with less emphasis on comprehending their parameters.

There is considerable overlap between the techniques applied in both disciplines, including k-nearest neighbor methods, regression analysis, support vector machines, and neural networks. Unlike traditional prediction, which forecasts future data generated by the same process that produced training data, some ML applications predict future states of the real world. For instance, using historical images to predict the visual appearance of a landscape in 30 years or analyzing mammograms to forecast the development of breast cancer—scenarios that diverge from traditional statistical prediction models. Although

Alex Krizhevsky's landmark work in computer vision advanced these methods, they remain underexplored in economics and finance.

7.2. Strengths and Weaknesses

While AI use in financial forecasting and economic modeling represents a natural component of the new AI economics, careful inspection warns of limitations ahead, including conceptual difficulties and psychological limitations. Practitioners must perform a detailed cost/benefit review before choosing suitable AI methods or AI Approaches with Awareness of Method Strengths and Weaknesses.

Researchers and practitioners must understand AI methods and economic specifics in detail. Each AI method has knowledge strengths and relative weaknesses arising from foundational differences in the operating mathematics. Each economic domain demands a particular mix of knowledge. Anticipating AI economics outcomes can thus proceed by matching known method strength against the economic domain's bootstrapping knowledge needs and human beings' psychological blind spots. AI's economic successes or failures largely derive from the convergence of these three dimensions.

8. Challenges in Financial Forecasting

The implementation of financial-forecasting methods presents multiple challenges. One of the main problems relates to the quality of financial data fed into the models. Unreliable data inputs can result in unreliable forecasting outcomes. The second challenge involves striking a balance between underfitting and overfitting; underfit models generally produce low forecasting accuracy, while an overfit structure for a training model could cause poor forecasting results on test data. The third challenge is associated with the interpretability of models. A non-straightforward nature of a particular forecasting model can complicate the interpretation of prediction results generated by that forecasting method. Therefore, the practical applications of forecasting methods can be hindered by these aspects.

Financial forecasting is concerned with predicting the market’s future development using historical data. Its significance is tied to the market's potential—if predictable, it offers considerable benefits. Financial forecasting methods utilize historical data for training. Traditionally, these methods are classified under macroeconomics, an area that deals with the prediction of the economy’s future. Predictive analytics in macroeconomics is currently the area of interest, as it aims to foresee changes in the world economy. The applications of predictive analytics are crucial in the decision-making process of public and private entities, providing guidance on the direction of major economic parameters and the likely long-term effects of currency fluctuations.

8.1. Data Quality and Availability

The quality and availability of data are crucial for building financial forecasting models. Factors affecting data quality include accurate data collection and recording, the level of aggregation (high-frequency versus low-frequency), the number of missing values, and the number of outliers. Any inaccuracy in these factors can hinder the proper development of a forecasting model by obscuring the hidden information in the data. For instance, financial markets operate continuously, generating high-frequency data, whereas some macroeconomic variables are reported quarterly or annually, resulting in low-frequency data. Testing the role of economic variables as leading indicators for financial forecasting can be problematic if these inaccurate factors are not addressed properly.

The availability of diverse data is equally important because it determines the coverage period for model training and generates information on the financial horizon's shape. Diverse and high-quality data help point out model predictability, which may vary over time and the business cycle. Accordingly, model performance can be explained as being time-varying: a model that performs better within the in-sample period may provide less accuracy beyond the training period.

8.2. Model Overfitting and Generalization

Financial forecasting is concerned with building models capable of predicting various types of financial data for a specific company or country. Models may vary broadly in both size and objective, ranging from microeconomic models that address a particular share price or foreign exchange rate to macroeconomic models aimed at forecasting economies of countries or the entire world. Evaluating the accuracy and performance of such models is essential to choose the most appropriate one for the task. Such predictive analytics are vital within macroeconomic policy, with a wide variety of case study examples.Application of deep learning to market volatility prediction has also been explored.Deep learning is considered a more complex form of machine learning, combining layers of artificial neural networks to perform classification and prediction tasks.Deep learning models are considered part of machine learning, as they are a subset of its major applications. Time-series models are a popular approach for predicting stock prices. While these models generally require less computational power, they demand careful preprocessing of data before model application. Techniques such as regression, classification, and clustering are widely applied in monetary and stock markets to support various activities. Each technique serves a different purpose: regression predicts future prices or trends; classification categorizes data based on similarities; and clustering groups similar data sets or clusters to support investment decisions.

Although traditional models such as linear and logistic regression have been successful in forecast applications, they can suffer from overfitting, limiting their generalization ability. Overfitting occurs when a model fits the training data too closely, capturing noise instead of the underlying pattern, which leads to poor performance on unseen data. This poses challenges for time-series datasets, as models tailored to historical patterns on training data may fail to generalize effectively but instead rely on temporal patterns present only in the training set. With the advent of more powerful computational devices and the rise of big data, machine learning models have been developed to enhance predictive accuracy and overcome the overfitting issues inherent in conventional regression models.

8.3. Interpretability of Models

Interpretability of forecasting models carries varying significance. For financial analysts, interpretability is a prerequisite for using a model's predictions; it allows them to ensure that forecasts are based on credible relationships, judge their validity and accuracy, and explain them to others. However, for systematic traders, the final trading algorithm maintains interpretability, and forecast tests focus on its bias versus the market; explanatory forecasts are therefore less critical. Agents in other domains may likewise assess the soundness of models in different ways and may not require clear interpretations. Nevertheless, every forecast, regardless of the agent's end use, demands a certain extent of validity.

A well-trained single time-series model typically forms a concise yet highly parameterized approximation of the underlying process, often utilizing a particular set of economic variables. Forecasts beyond this model's capability are difficult, if not impossible, to provide. Conversely, multivariate models receive input variables determining the price at a given time and the set of variables used for the forecast, enabling them to encompass much more than the single series model. Formal methods exist to enhance the interpretability of multivariate models. Ultimately, understanding the validity of forecasts remains fundamental for all forecasting scenarios.

Conclusion

The metaverse is a driver of the economy. It contributes to creating demand for existing jobs and professions, but it also creates opportunities for many new professions. It opens the door to forming new ecosystems and launching new businesses. However, it also entails the risk of technological unemployment and related social disorders. The implementation of the metaverse reflects a very complex phenomenon, including technological, economic, legal, and educational perspectives.

Currently, the level of metaverse implementation is very narrow. Its complete implementation will take at least 10 years. Its establishment will first be undertaken by the commercial sector with the opening of booths and stores, investing in advertising and promotion, and providing the possibility of e-commerce. Universities and schools should benefit from the possibility of virtual presentations, lectures, and lessons, and government institutions with virtual services. With the development of metaverse technology, other communities will also be able to tap into its benefits.

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Chapter 7: Fintech Innovation and Artificial Intelligence Startups: Ecosystem Dynamics, Adoption Pathways and Regulatory Challenges

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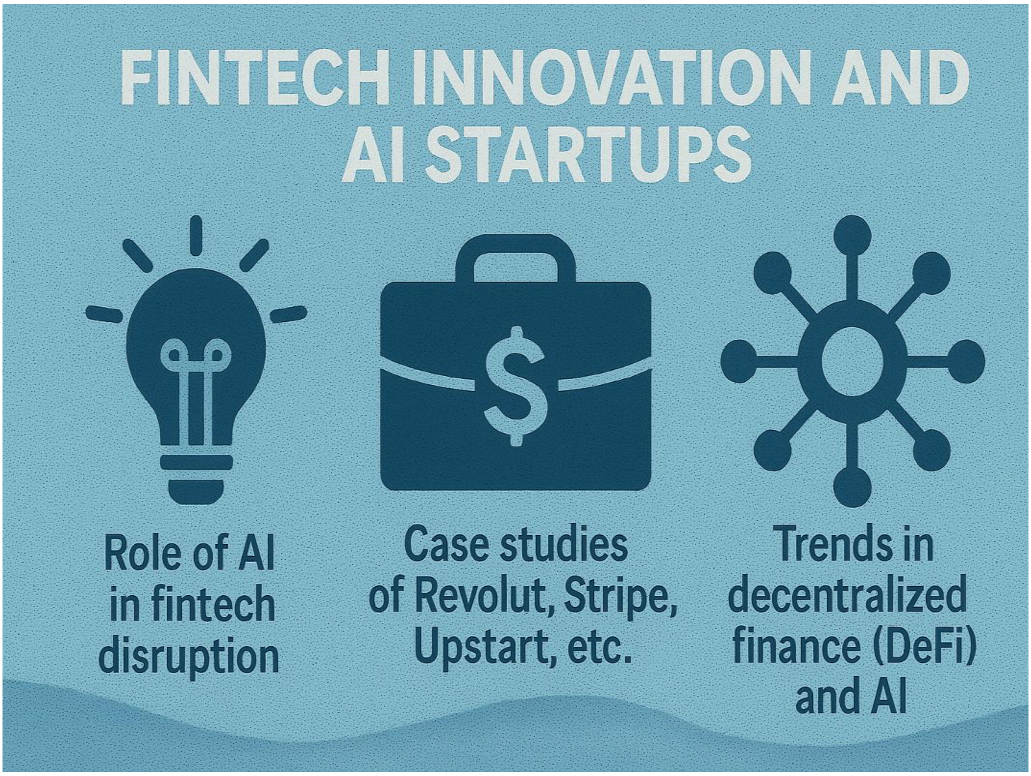
1. Introduction to Fintech Innovation

Unlike the more traditional banking industry, nowadays, the field of financial services is ripe for innovation due to the rise of frontier technologies and the increased availability and accessibility to technology driven start-ups [1]. Thus, innovation is revolutionizing the financial service industry and the traditionally held boundaries of the banking system are being broken by the advent of banking applied through technological innovation in associate fields such as e-commerce, social media, Big Data, mobile technology, Cloud Computing, Artificial Intelligence and Blockchain [1-2]. As a result, the influence of new players within the financial services industry such as technology and fintech companies is continuously rising, proposing innovative customer-oriented products that appeal to the public. Consequently, the customers tend to migrate towards these alternatives because of the better value proposition, service design and delivery of financial services.

The developments in Artificial Intelligence (AI) have spurred companies to find new application areas. The banking and financial services industry is one such example where there has been a growing attempt to leverage AI [3-5]. There is a growing presence of AI startups targeting the banking and financial industry often supported by venture capital funds and investments by large technology firms [6-8]. As in any other industry, this rise has led to a negative response by incumbents that try to introduce regulatory hurdles in order to eliminate emergence of such startups.



2. The Role of AI in Fintech Disruption

In recent years, Fintech innovators across a broad spectrum of sectors have employed Artificial Intelligence to disrupt traditional business models. Alongside Robotic Process Automation (RPA), AI is among the earliest wave of cognitive technologies being embraced. While Banking-as-a-Service (BaaS) provides developers with Application Programming Interfaces (APIs) to streamline the writing of transaction documentation, AI tools help interpret these documents, filtering information and creating data sets to support process automation in the cloud.

Beyond backend process automation, AI is also used for customer support functions, such as chatbots and robo-advices, which interpret and respond to customer queries and reach out proactively [9]. BaaS facilitates operational automation, yet the interpretation of external conditions still requires human involvement. To assemble these puzzle pieces effectively, bridging the divide between banking and technology is essential, giving rise to innovation centers and startup incubators. Google's Assistant platform, for example, collaborates with the Hong Kong Monetary Authority to furnish local banking information.

2.1. Overview of AI Technologies

Despite potentially being among the least explored areas, advanced AI technologies in Fintech startups seem compelling, supported by numerous news portals like Secfi, Greenhouse, Turing, Raistone, and Salary Finance. Indeed, Fintech has become one of the main application areas of Artificial Intelligence, impacting all its business lines [7,9-10]. Both consumers and organizations utilize AI-based products and services in news, content, security, IT operations, marketing, affecting every industry and domain. The expected benefits of AI include automation, reducing repetition and human error, contributing to improved productivity, time savings, and enhanced control and governance.

The interest in automating financial activities through AI dates back to its early days. The first topic on advanced stocks application of AI, particularly Genetic Algorithms and related techniques, emerged in the 1990s. After two decades of significant development in the financial services sector, the debate continues on the current replacement and job extinction effects. Researchers strive to discern whether these actually reduce the number of jobs related to specified advanced technology or transform a hierarchical upgrading change due to the high value generated in finance.

2.2. Impact of AI on Financial Services

Artificial Intelligence (AI) radically transforms the financial services industry by reconfiguring the value chain. Investment, operations, service delivery, and risk management account for substantial expense and risk exposures. Historically, technological breakthroughs in finance and investment prompted the emergence of dominant established financial institutions that leveraged technology to offer superior services to retail and institutional clients [1,11-14]. However, AI algorithms are rapidly altering the specialized knowledge and execution skills these dominant institutions amassed, providing new tools and capabilities to entrepreneurs and the founders of nascent FinTech startups.

Today's financial domain cognoscenti recognize that AI is a disruptive force capable of enabling new and major players to overtake formerly dominant incumbents [13,15-17]. In AI's wake, entirely new AI-first FinTech players can enter the financial arena to compete in specific business lines across the financial value chain. These players are already booming in residential and commercial mortgage lending, consumer and commercial credit underwriting, retail personal wealth management, investment banking, cross-selling and selling financial products and services, human resources management, and corporate administration. They are also emerging in risk management, fraud detection, and financial crime prevention. AI's entry into financial services promises to foster an unprecedented democratization and inclusion, reshaping the legacy and often exclusionary financial ecosystem.

2.3. Challenges in AI Implementation

The debate surrounding the implementation of AI in FinTech highlights that all innovations face some threat, with AI being a rapidly changing technology. Incremental innovations, which take new ideas to new markets or involve adapting an organization's products or services, pose minimal threat to the market and incumbents [18-20]. In contrast, disruptive innovations, which create new markets and values, have a significant impact on existing products, services, and industries [19,21-22]. The Digital Revolution is an example of disruptive innovation, compelling companies to reconfigure business models and shift to services rather than products.

AI adoption in FinTech presents challenges. The constant evolution of AI implies that FinTech companies using it as a core technology must be willing to fine-tune their core services and solutions continuously. Fine-tuning can be a necessary part of any innovation, but companies must gauge whether their AI innovation is incremental (requiring only small changes) or disruptive (necessitating a complete transformation). Given AI's inherent disruption, especially in the financial services industry, FinTechs face ongoing change rather than maintenance phases.

3. Case Studies of Leading Fintech Companies

Scaleflex offers cloud-based solutions tailored for an AI startup, facilitating efficient online image display, compression, optimization, and delivery. These capabilities enable minimization of bandwidth consumption, storage, and CDN cost, alongside minimizing design team-size and time-to-market.

Wise employed Evervault's developer-friendly platform to build an encryption system that integrates seamlessly with its product development, allowing engineers to focus on client experience rather than data privacy.

Google Cloud's services support the innovation capabilities of Wise, a digital money transfer company registered in the UK and operating in more than 70 countries. The company uses BigQuery, Bigtable, and Biglake, and employs

AutoML and other Vertex AI tools to help deliver money 7 times faster and 5 times cheaper.

3.1. Case Study: Revolut

Establishing operations in the United Kingdom in 2015, Revolut serves as a compelling example of innovation through augmented intelligence in the Fintech sector by translating its services through artificial intelligence. The London-based startup offers a banking app designed for today's generation, providing real-time spending notifications, instant overseas card payments, and 24/7 in-app instant card freezing. The primary objective is to render global finances global and fair for everyone, which is why customer needs remain paramount. It supports payments in more than 120 currencies and 29 fiat currencies, allows for cryptocurrencies and commodities trading, credit cards, virtual wallets, and integrates with third-party services such as air tickets, hotels, donations, and investments.

Revolut was part of an augmented intelligence ecosystem that blended customer support operations with actual artificial intelligence, resulting in unique synergies. Its back-end technology moved beyond handling simple queries; managers were interested in how it could empower employees undertaking the more complex inquiries that humans excel at. By using back-end technology powered by AI to augment tasks, time spent by human employees was effectively freed for engagements demanding creativity and empathy—qualities confined to the human brain. It thus succeeded in shifting focus from costs and efficiency towards more strategic aspects of customer support such as loyalty and satisfaction.

3.2. Case Study: Stripe

The fintech environment is influenced by the specificity of each market. The conditions that favoured the rapid rise of the US fintech companies are not applicable to many EU countries. The fintech ecosystems evolved differently, the US market has been relatively more open to new players and traditional banks have been less dominant than in Europe. Hence, the innovative activity of fin-tech startups has been more focused on the B2B segment in the US and the US players have more advantages in the banc-as-a-service segment. Their main target is helping banks to reach more customers, while in Europe fintechs are competing with banks.

Stripe offers payment processing services and APIs for ecommerce and mobile applications. It was founded in 2010 by two Irish brothers and for five years did not ask for external funding. It has been an extreme success story. In March

2018, Stripe was valued at USD 20 billion by investors after a new funding round that raised USD 245 million. Stripe also uses artificial intelligence techniques, detecting frauds by combining kartu and machine learning models.

3.3. Case Study: Upstart

Founded in 2012 by ex-Google executives aiming to revolutionize the outdated US loan industry, Upstart now seeks to expand this innovation across all developed economies. The company offers a platform that connects borrowers with a diverse array of financial institutions in a unique manner. It claims to have processed over $15 billion in loans on behalf of 30 partner banks. Its artificial intelligence-driven platform is said to benefit not only the banks—improving efficiency, reducing losses, and increasing profitability—but also the customers, through faster loan approvals and more credit access.

Upstart enhances its processes using AI and automation, focusing on four components: credit decision-making, fraud detection, operational workflows, and capital allocation. Eighty percent of monthly loan decisions involve Operational AI, which employs predictive analytics and supervised machine learning to enhance decision quality for partners and borrowers. AI-based operational workflow automation reduces manual involvement in tasks such as document review and loan underwriting. Furthermore, automation enables Upstart to dynamically allocate capital from its marketplace partners, assessing periods of high demand or supply shortages to draw capital from sources that most prefer holding it at any given time.

3.4. Comparative Analysis of Case Studies

AI technology is a main determinant of fintech business models and startup success because of its ability to interact with the environment. The insight that AI technology may be the main determinant of startup success in the fintech sector goes beyond the technological capabilities it provides. The reason is that AI techno-logies with the necessary inputs, brought into action with the help of fintech infrastructure and fintech operations data, apply fintech functions to address the pain points of customers." additional insight on how the fintech business models layer can also be compared with real-case companies in the industry, based on their shared and distinct characteristics, is provided further below.

Comparative analysis of case studies in the different fintech segments sheds light on how TMT dimensions are reflected in the business models of real AI startups. Business models consist of the fintech functions provided to the users, and an understanding of these functions is useful to grasp the underlying characteristics of the companies under analysis. Table 3.3 presents features of the selected case studies in each segment based on their service provision in relation to the same underlying characteristic.

4. Trends in Decentralized Finance (DeFi)

In recent years Decentralized Finance (DeFi) has emerged as one of the fastest growing trends in Financial Services. DeFi leverages blockchains—cryptocurrency's underlying technology—to take the idea of decentralization beyond currency and beyond payments [11,23-25]. The goal is to create complete decentralized financial products and services. While still in its infancy, DeFi aims to recreate traditional financial products in a decentralized architecture, outside of companies' and governments' control. It is still in the early stage of its development and therefore has considerable risks attached, including operational risks, economic and systemic risks, volatility risks, fraud and malpractice risks, as well as financial crime risks. However, it has the potential to lead the way toward a more decentralized financial infrastructure for the world.

Babylon Finance is a blockchain protocol built on the top of Avalanche that connects a group of decentralized applications into a unified ecosystem for lending and borrowing that any Avalanche user can participate in. Babylon enables users to lend and borrow assets, earn interest, and mint stablecoins in a trustless and non-custodial manner, with superior capital efficiency and best-in-class oracle security protocols [26-28]. Built on the Avalanche C-Chain—in contrast to Ethereum's current and serious gas fee amounts—Transaction fees on Babylon Finance remain nominal, neither compromising user savings, nor DeFiStable passion for his work and the results25percent of the innovation showcased.

4.1. Introduction to DeFi

The evolution of financial technology has empowered individuals in past decades, enabling quicker and more efficient tasks. Technology created innovative features such as debit cards, phone banking, SMS banking, and Internet banking, making it more secure and user-friendly [29-32]. DeFi has taken these advantages to the next level, enabling customers to be their own bank without dealing with intermediaries. It has introduced the ethical aspect of finance and removed the jar of money lenders. Customers can now directly lend to an individual borrower and make a profit.

Decentralized Finance (DeFi) is a blockchain-powered form of finance that does not rely on central financial intermediaries such as brokerages, exchanges, or banks to offer traditional financial instruments [31,33-35]. Instead, it utilizes smart contracts on blockchains, the most common being Ethereum. DeFi platforms allow people to lend or borrow funds from others, speculate on price movements on a range of assets using derivatives, trade cryptocurrencies, insure against risks, and earn interest in savings-like accounts. Decentralized applications can be accessed by any internet-enabled device [36-38]. Regardless of education, status, income, gender, or geography, anyone from any location can transfer, invest, or borrow money.

4.2. AI's Role in DeFi Innovations

DeFi projects are moving toward new stages by operating as starter kits or starter packs. DeFi starter kits provide the necessary infrastructure for new projects to launch their specific dApps. The FundStarter kit, for example, contains tools for creating and fundraising with NFTs and bonding curves. Alchemy is another supporting provider that offers APIs for nearly every blockchain, allowing new projects to connect to it without operating with nodes. New liquidity pools are also emerging, specialized in Crypto Covalent Bonds or options.

Both centralized and decentralized finance have paved the way for AI applications powered by smart contracts [1,39-41]. These applications encounter challenges in data fetching; synchronous calls to external sources are either dangerous or inefficient. Derivatives, insurance, oracles, and weather reporting dApps have implemented Application-Specific Virtual Machines (ASVMs) that run off-chain in an isolated environment, with their state published on-chain periodically. The confluence of AI and DeFi leads to new proposals such as Roge AI.

4.3. Risks and Opportunities in DeFi

While the DeFi ecosystem has witnessed spectacular growth, evident in the Stars of DeFi, it must also contend with the concept of StarFish DeFi. The latter name can be attributed to SmartContract.com, a DeFi start-up that raised US$3.7 million in its early rounds, coinsparency.com, and Coinvest, a decentralised investment for both accredited and unaccredited investors. Nevertheless, in a 2020 Whitepaper entitled Risks and Opportunities in DeFi, “StarFish DeFi” denotes the risks connected with DeFi.

The overview of the favourable economics of DeFi is as compelling today as it must have been for Users investing in Ether or other utility cryptos in 2017 and

2018. However, just as those markets matured, so do the same forces work to regulate and stabilise the economics of DeFi. Legal requirements will soon be placed on such outing services, making them unacceptable or non-viable for them to remain permanently decentralised [42-44]. Equally, the need for such exchanges to offer a seamless User experience will entail risks for Users that will previously have been allayed by the technical nature of DeFi/DEXs.

4.4. Future Outlook for DeFi and AI

Fintech and artificial intelligence stand among the fastest-growing industries of the present day. Artificial intelligence, in particular, is often cited as the next technology of the future; it is making a rapid transition from science fiction to business applications. Due to the promising nature of these industries, venture capital (VC) firms have invested heavily in both sectors despite the economic recession. In the last decade, VC investment in fintech companies addressing banking problems has increased by a staggering 500%, while investment in AI companies has risen by 6,422% [45-46]. The Viewpoint section highlights the correlation between venture capital investments in fintech and AI startups.

The rapid growth of blockchain technology has led to the development of decentralized finance (DeFi), which aims to democratize the financial system by eliminating control from any single authority. Through the use of smart contracts, DeFi builds services based on distributed trust and automatic enforcement of conditions encoded in computer code. Smart contracts are self-executing pieces of code with contractual conditions encoded and distributed on the blockchain. They enable business capabilities such as automated payment of asset interests, lending based on verifiable on-chain collateral, and cross-border automatic execution of business processes. The future outlook for the DeFi ecosystem appears promising.

5. Regulatory Considerations in Fintech and AI

The rapidly growing segments of AI and FinTech are of particular interest to both pre-IPO investors and public market investors. These industries demonstrate promise in innovative finance technologies and provide business models with significant opportunities for scaling [18,47-49]. The spotlight on a sector can usher in the emergence of many startup enterprises and attract substantial investment from private capital sources looking to develop new business models. Private investors generally view start-ups in their early stages as high-risk ventures with potentially high returns on investment. Hence, startups in these sectors receive considerable attention during their private investment rounds.

Governments are naturally drawn to these technologies as well, aiming to capitalize on the benefits afforded by innovation in the financial services sector. This interest has spurred initiatives such as "Fintech for Access to Finance" and "Fintech for the Common Good". Whether slash how to regulate FinTech and AI remains a hotly debated topic, especially when it comes to the anticipated effect on emerging business models like Platform Banking. The movement of capital into a sector increases scrutiny, as recent experience in platform companies demonstrates. Apprehensions about overvaluation, post-market negative adjustment, or risky speculative behavior — whether founded or unfounded — often lead to expectations that regulators should intervene to deflate interest in such activity.

5.1. Current Regulatory Landscape

Aggressive competition exists among the emerging digital banking startups that promise automatic credit decisions, fast credit disbursements, and, often, less expensive credit [50-51]. Fifty-one countries have adopted digital banking regulations, including Brazil, the United Kingdom, and, in Southeast Asia, Singapore and Hong Kong. The Singaporean Regulation Digital Banks Initiative targets digital banks and sets the regulatory landscape for digital banking licenses in the country. Five of Etsy's largest competitors have also been convicted of fraud.

Nations and governments with fintech initiatives include India's Unified Payments Interface and Aadhar, China's UnionPay QR, Swish in Sweden, SOCGEN and BPCE in France, and Revolut in the United Kingdom. In 2017, the People's Bank of China initiated Project Aurora, selecting institution participants to help with doing proof-of-concept work using various technologies. The Federal Open Market Committee (FOMC), the Fed's top monetary policymaking body, meets every six weeks to assess the economy and adopt appropriate policy measures. Although the digital banking trend is surging, some countries, such as the United States, have yet to establish regulations.

The digital banking domain is rapidly changing, with almost every day or two witnessing the entrance of another financial lender, competitor, or credit institution. Aggressive competition exists among the emerging digital banking startups that promise automatic credit decisions, fast credit disbursements, and, often, less expensive credit. Digital banking licenses offer a great opportunity for banks to target unbanked customers, which are nonexistent among incumbent banks. The creation of new banking licenses is of crucial importance, as the funds lending space is currently dominated by a few big banks that account for a significant market share.

5.2. Impact of Regulation on Innovation

Fintech Startups Confronting a Regulatory Whirlpool

Regulation is important — for users, for safety, for trust, for the needs of the market. FinTech startups face a regulatory whirlwind owing to the highly regulated nature of the financial services industry. They therefore need to accumulate compliance capital in order to be licensed, as well as to be able to attract capital from investors. What Turing award winner Leslie Valiant calls "probably approximately correct learning" (PAC learning), entails being approximately right not only for our sample but also for all of future, as an inductive bias. Compliance capital, it might be thought, is the regulatory analogue of inductive bias convected through the seas of Public Capital Hypertrophy.

Pacific Computer, the Next Big Thing, and the Line Between Specialist and Generalist

The following items were overheard in an elevator: • Bruce lacks a web site. • He's the only one left in the department who missed the era of Pacific Computer and Prosperity Software, and he can still feel the heat. • Now they call it Public Capital Hypertrophy, and somebody in Australia just read George Gilder and says it will create the Next Big Thing: investing in ideas rather than in profits and sales.

The specialist has no clients; meanwhile, the generalist cannot carry out operations because of a Public Capital Hyperinflation Event." This dilemma had begun to disintegrate the rule that individuals within an organization should be specialized in the last five years. "The Consequences of Specialization" argues that if demand is predictable, it is better to produce a specialist who can perform an operation better than others. However, if demand becomes unpredictable and volatile, the demand for a specialist becomes thin, and the economic life of a specialist then becomes shorter. In addition, if the market is very sensitive to the news, it may be better to create a generalist who can be involved in many operations instead of specializing in one operation.

5.3. Future Regulatory Trends

As regulators become more familiar with AI and more details of the technology become widespread, the general trend is toward additional regulatory considerations. In the US, the New York Office of the Attorney General solicited public comments and hosted a roundtable discussion on the topic of artificial intelligence and automated decision systems. The meeting included representatives from a broad range of fields and addressed the dangers of emerging technology as well as the benefits. One suggested that given the large set of questions raised by emerging technology, the appropriate response might be “a moratorium or, better still, some kind of new New Deal.”

In August 2022, New York City enacted a law prohibiting the use of automated employment decision tools unless the tool has been assessed for bias and the results of the analysis have been made public. Regulators in several states have brought enforcement actions against alleged unlawful uses of facial recognition in real estate transactions.

Conclusion

The emergence of Generative AI startups has accounted for 11.5% of all new venture capital-backed ventures in the first five months of 2023, amounting to $6.3 billion in funding. Venture capitalists have committed $18.2 billion to 1,900 Generative AI startups since the fourth quarter of 2021. In the last 12 months, the number of deals in US Generative AI startups has grown by 442%, and funding has increased by 827%. The Asian startup ecosystem has recorded a 480% increase in deals and a 338% growth in funding. Globally, deal counts have surged by 45%, while funding totals have decreased by 24%.

Despite the widespread trial of AI, only about 3% of organizations realize actual business outcomes from their projects and investments. The critical element for winning with AI is business readiness. Adopting AI is not a mere product of budget size or having a Chief AI Officer role; rather, it reflects the attitude of businesses towards data and AI, recognizing them as catalysts for achieving strategic objectives. Such companies cultivate a culture that embraces artificial intelligence and data, and they employ business and data storytellers—skilled in understanding and communicating the challenges faced by their organizations—to ensure AI solutions are both valuable and impactful.

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Chapter 8: Regulation, Ethics and Fairness in Artificial Intelligence for Finance: Governance, Explainability and Compliance

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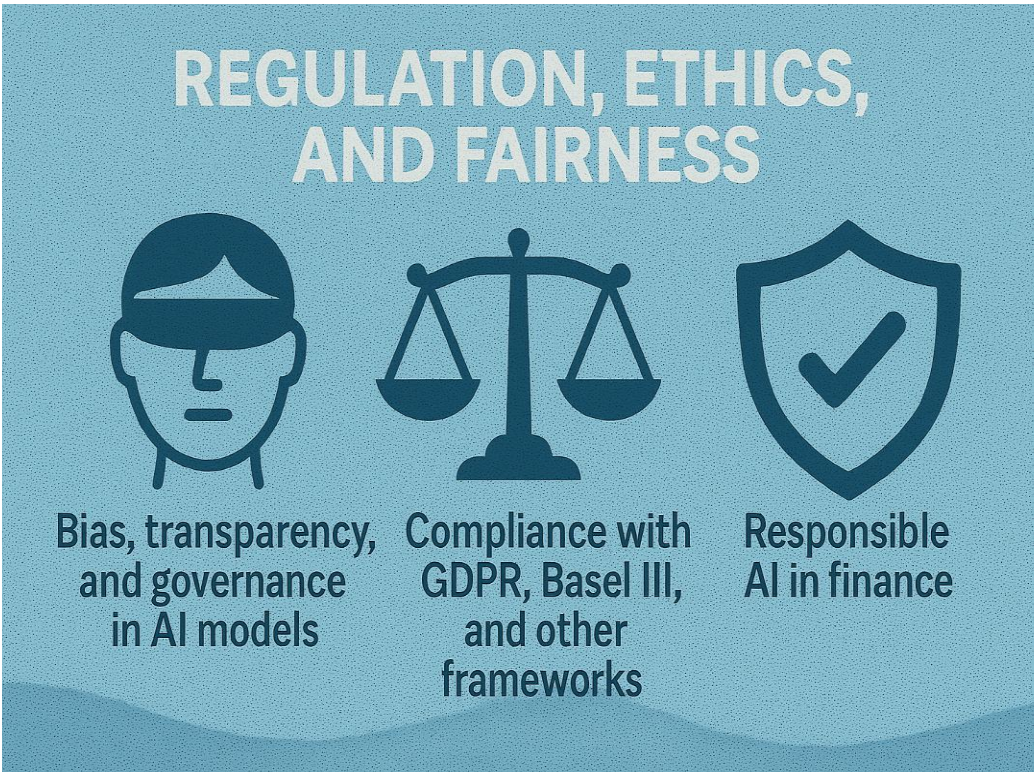
1. Introduction

Government bodies around the world are beginning to intervene in the use of artificial intelligence (AI) technology with the goal of protecting public safety, or directing its use in a way that benefits a wider group of people [1-2]. The European Commission has proposed the Artificial Intelligence Act that would set new standards for the marketing, usage, and operation of AI technology. There are also growing concerns that AI models can make decisions that lead to outcomes that are unfair or discriminatory [2]. Machine learning practitioners uncover that discrimination at every stage of the AI model-building process is a serious problem, including in the choice of problem, dataset, model, and people in the loop. Driven by such concerns, several jurisdictions have started requiring declarations of conformity for AI-enabled systems.

Conformity declarations assess whether AI models meet a set of high-level conditions that are expected of them. They can be developed in a number of areas such as algorithmic bias (discrimination/fairness), transparency, explainability, privacy, and/or robustness against adversarial attacks. Unfortunately, the path to conformity declarations is fraught with challenges at each stage, all of which are faced by the EU Artificial Intelligence Act and the goal that all AI models must be free from discrimination [2-4]. These challenges must be addressed for the Act to be effective in mandating the development of safer, fairer, and socially responsible AI models.



2. Understanding Bias in AI Models

Bias in artificial intelligence refers to mitigating biases that influence AI decision-making, particularly those perceived as unfair [5-6]. Biasing factors include data collection, feature selection, and algorithmic design choices. Developing an understanding of bias and methods to reduce, prevent, and monitor bias are crucial steps toward rendering AI decisions more ethical. Transparency in AI serves as an important element for assessing fairness. A lack of transparency hinders the explanation of bias, discrimination, or unfair output from models and is therefore a critical aspect of AI governance. Building stakeholder trust in AI-based decision-making systems necessitates establishing transparency.

Regulation of AI models can be viewed as a broader governance framework of the technology that guides companies to safeguard information, ensure compliance (for example, with GDPR and Basel III), and adhere to ethical standards—such as those explored in the context of responsible AI in finance.

Deeper insights into these topics are provided in dedicated discussions on Transparency (section 3), Regulatory aspects (section 5), and Ethics and regulation of AI models (sections 8 and 9).

2.1. Types of Bias

Bias in AI models appears in many forms and may have a significant impact on model decisions. Reducing bias in AI models is important from the perspective of regulation, ethics, and fairness. Several classifications of bias have been proposed [7,8]. Four broad types are identified here. Historical bias occurs when current procedures are affected by past experiences. For example, if individuals dislike a particular colour or shade of colour and reject all product packaging having that colour, the procedure to develop future products or design packaging for new products should not be influenced by these preferences. Sampling bias occurs when a subset of the population is represented in a disproportionately large or small way. For example, a survey on people's access to aviation frequency often ends up collecting responses only from people who have a good access. While these multiple types of bias may seem different or unrelated to each other, they are all inter-related through an overarching categoorization.

A global grouping of model bias identifies three main components: bias originating from the decision environment; bias in data; and bias in model design and operation [9-12]. Decision environment bias includes inherent characteristics that distinguish events and the operating context. Historical bias and representation bias represent models of the world that perpetuate the world that is being modeled. Undesired effects of training data in a model are captured through the category of data bias. This includes sampling and measurement bias that are inherent in data and affect the selection of training data. Label bias depicts the situation when labels representing the target variable help identify a population with some desired characteristics, but may contain disparate representation of the population. Evaluation bias is associated with the tasks and procedures used to evaluate the trained models. Data leakage arises when some information created outside the training data is used inappropriately for the design or training of a model [7,13-15]. In the model design and operation category, bias encompasses modeling procedures, rating implementation, and interaction with the environment. Modeling procedures include prejudice bias, where preconceptions held before modeling influence the constructed model, and algorithmic bias, where the algorithm itself introduces systematic errors.

2.2. Impact of Bias on Decision-Making

Machine learning models, trained on historical data, may inadvertently absorb and propagate social, historical, or latent biases present in society and the training data [16]. Bias refers to the difference between the expected value of the algorithm's estimate and the true value, indicating systematic errors harmful to overall model accuracy. Discrimination occurs when positive or negative prejudice is directed at an individual or group of people. Algorithms that classify people as belonging to disadvantaged groups may replicate these prejudices, resulting in unfair outcomes and reducing trust in machine learning.

Bias in machine learning arises from machine bias—reflecting prejudice held by the algorithm itself—and training bias, which contributes to machine bias and appears in the training data [9,16-18]. Machine bias emerges due to limited respect for fairness during model design, while training bias results from incomplete, unbalanced, underrepresentative, or polluted training data. These biases can compromise model accuracy and generalization. Recognizing the ethical implications, financial institutions are urged to integrate responsible AI principles into their business strategy and processes, as underscored by recent developments in the Basel Committee on Banking Supervision guidelines.

2.3. Mitigation Strategies

Bias affects the decision-making and predictions of AI models and, ultimately, the world they try to portray [2,19-20]. Detecting and reducing bias in AI systems is crucial for their safe operation, to avoid unfairness and discriminatory outcomes. A wide range of debiasing techniques have been implemented at different stages of the AI pipeline. Existing bias mitigation methods concern both the pre-processing of input data and the modification of the classification model during its learn-ing process. Although one type of bias is often merely a product of another, the directional training of mitigating methods in these two categories is applied only in the opposite direction of the respective bias type. For example, input data-based bias rarely tries to counter label bias, and vice versa. Nevertheless, models are grounded in data vocabulary, so that even label bias can be reduced at the input data level.

An important perspective on the different stages of debiasing and on the nature of biases is provided by associated tutorials. An overview table of pre-processing and in-processing mitigation methods is provided in Autore et al., and a general classification in pre-processing, in-processing, and post-processing approaches is given in Mehrabi Human bias can already be structured during the labeling process. For example, a study by Sheng demonstrated that annotators label texts differently depending on specific contexts. Generative models can also assist in human annotation, for example, by providing paraphrase suggestions to reduce dataset bias as shown by Grunschwager. Furthermore, Han introduced methods based on F2Rank to identify the most significant bias features in text data, facilitating bias-aware sampling and more balanced training data. Bokhari and Bader Alaya contribute strategies to mitigate bias in distributed AI models through specialized preprocessing and training techniques.

3. Transparency in AI Systems

Transparency facilitates auditing and examination of decisions, fostering awareness of mistakes or biases and safeguarding against harmful outcomes. It serves as a battery of tests that shields individuals from arbitrary decisions or discrimination [9,21-23]. A transparent AI model renders the criteria, methodology, and functioning of the decision process accessible and comprehensible. Deep learning models generally do not support this level of explanation. Crucial questions arise: Which public decisions should be explained using AI? What information needs disclosure? Which stakeholders should have access? When should explanations be provided to either individuals directly impacted or just society at large?

Supporters of transparency identify two principal reasons. First, a clear, open, and interpretable AI system enables pinpointing and rectifying mistakes or biases. Second, it permits evaluation of fairness, ethical considerations, and respect for human dignity. Legal experts assert that countries where officials rely on AI for public decisions typically require justification for such decisions and hence explanation of the AI involved. Consequently, these countries have enacted or proposed AI regulations mandating explainability. In the European Union, for instance, the General Data Protection Regulation introduces the right to "meaningful information about the logic involved," while the Artificial Intelligence Act empowers the Commission to require explanations for market authorization of specific AI applications. France’s AI strategy similarly calls for explanations of administrative decisions supported by AI when requested by the interested parties. The current trend favors substantial governmental involvement in explaining public decisions supported by AI.

3.1. Importance of Transparency

Many fields have now been impacted by the progress of artificial intelligence (AI) and an enforced major investment in dedicated technologies. The automation of numerous business operations has resulted in major time savings. AI adoption has influenced many areas of our lives, ranging from security to marketing, and even many engineering activities [24-26]. Almost all organizations around the world heavily collect data and use AI for a variety of purposes, such as COVID-related area monitoring [8,27-30]. Nonetheless, AI models have also been associated with a variety of issues related to security, ethics, and privacy issues. Regulatory authorities, governments, and lawmakers worldwide have recently emphasized the need for AI transparency for European Union residents as a result of the ethical and discriminatory biases associated with AI. Transparency is critical to understanding the decisions made by AI models. Some deep learning models have achieved the best results but lack transparency. Although regulations provide some relief, they are ineffective, and identification of unethical behaviour or unfairness and black-box behaviour in AI models remains a challenge.

The presence of unethical behaviour in AI raises concerns about privacy and security. Fairness is concerned with discriminatory bias in AI, which is a difficult task for automakers to address [9,31-33]. In the past, multiple algorithms were proposed to identify and remove discriminatory bias in data and models. Transparency suggests that AI decisions should be interpretable and explainable. Unlike traditional AI models, the decisions made by black-box models should be easy to understand. Major efforts have been made in recent times to automate these three parameters of AI. However, numerous aspects remain to be explored; for instance, although four models have been proposed in the literature, a collaborative approach among these parameters is yet to be explored. Algorithms that can find unfairness in secure decisions and clearly explain the cause of secrecy can help build more transparent AI models.

3.2. Mechanisms for Enhancing Transparency

Transparency plays a central role in AI governance, ethics, and law. Its importance is well understood from related concerns, including explainability, interpretability, fairness, openness, and verifiability [34-36]. With AI systems widely deployed, there is a growing demand for more transparent models, processes, and decisions, particularly for models and decisions that significantly impact human interests, rather than for trivial applications like game-playing ChatGPT. In tandem with enhanced transparency, AI regulators and enforcement bodies must develop the necessary capabilities and mechanisms to build organizations that are compliant and operate in a responsible and trustworthy manner.

There are three broad mechanisms for increasing transparency and enhancing understanding of AI models: external Transparency by Design (TbD), in which regulators set the appropriate regulator’s transparency and openness standards and requirements; internal TbD, in which stakeholders implement organizational and procedural measures for compliance; and model explainability, which opens the black box of the AI algorithms. Stakeholders preparing for AI governance in these areas benefit from understanding the specific regulatory transparency requirements, as prescribed by an ‘‘external TbD’’ paradigm, and from the measures that can be taken to satisfy such requirements under an ‘‘internal TbD’’ approach. For instance, external TbD requirements could shape standards for access to the content of AI communication and log data at various stages, formats, and levels of detail. In response, internal TbD would define the steps that underlying organizations must take, including tools, systems, and processes, to monitor, transform, load, and maintain the exposure and sharing of model information.

3.3. Case Studies on Transparent AI

The emergence of large and opaque artificial intelligence (AI) models—such as deep learning, large language models, and generative models—has sparked a debate on whether regulation is necessary [3,37-39]. Such regulation would address opacity, unchecked predictors, group harms, and the adverse effects of models trained on sensitive or biased data. While legal regulation is still some way off, implicit regulation by the market or ethics committees is likely in the near term [36,40-42]. These calls for regulation add to ongoing discussions concerning algorithmic fairness. Transparency in how decisions are made is often cited as a mechanism to achieve fairness, but paradoxically, opacity is also seen as advantageous.

Recent cases illustrate this tension. In 2019, the Chicago Police Department was sued because their predictive tool disproportionately targeted African American communities, yet the tool was too opaque to determine whether it had a protected group as a feature [40,43-44]. Consequently, the case focused on the selection of training data rather than the algorithm itself. This contrasts with Uber's approach of open-sourcing its autonomous vehicle algorithm, allowing post-legalization justice to evaluate the safety of an autonomous accident similar to that involving Uber. In the latter scenario, transparency permits the algorithm to be questioned, whereas in the former, bias cannot be rectified or evaluated without sufficient information.

4. Governance of AI Models

Frameworks for regulating AI models do exist, such as the European Union's AI Act, which provides guidelines on classification and monitoring. Current research typically focuses on detecting malicious use of models or acquiring sensitive information leaked by models [3,45-48]. In contrast, proposals aimed at proactively addressing ethical issues in AI models are still under development.

As organizations become more aware of the risks related to Artificial Intelligence Models, there is a growing demand for tools and services that systematically report on model risks and provide clear governance of the creation and usage of these models [5,19,48]. Many consider the implementation of a model governance process essential for the safe use of Artificial Intelligence Models in critical areas such as financial services and human resources.

4.1. Frameworks for AI Governance

Providing guidelines or controls on the development and application of AI systems may be considered as a dimension of the social awareness, responsibility, or regulation of AI. From a combined technological and societal perspective, government and institutional regulation or controls of AI involve guidelines, best practices, obligations, or prohibitions on the use of AI methods. In the EU White Paper on AI, regulation is discussed in the context of the European approach for AI, aiming to support the finalisation of a framework that promotes AI uptake while addressing risks of specific uses of AI and positioning Europe as a worldwide hub of excellence and trust in AI. Fair AI resources address the AI governance framework, spotlighting the behaviour of the organisations creating and releasing AI models. Key issues are related to intellectual property of models and the bias in support of ethical concerns. The focus is now on regulatory controls for foundation models that require massive resources in terms of data and compute to mitigate irresponsible corporate or government use.

Providing guidelines or controls on the outputs of AI systems is yet another dimension of the social awareness, responsibility, or regulation of AI. Regulating AI in this manner also supports responsible AI development and deployment in the era of foundation models. The policy—a license or terms of use—attached to an AI model demands an explanation of why a user is or is not allowed to ask the model a question, request further content, or use an API for business operations that can ultimately influence people, governments, and institutions.

4.2. Role of Stakeholders in Governance

The governance and regulation of AI require the involvement of experts from multiple disciplines, including mathematicians, computer scientists, economists, lawyers, and ethicists. Technical details surrounding the training and implementation of AI systems should be comprehensible to legal professionals, and the viewpoints and concerns of economists and politicians should be incorporated into AI model development. The technical community ought to consider the potential social impact of AI models during their inception and recognize distinctive cultural values when deploying AI systems across different countries. Achieving a regulatory framework that benefits all stakeholders calls for a comprehensive public debate addressing the risks of AI systems—such as misuse, bias, and fairness infringement—and potential prevention strategies. Closing the feedback loop can facilitate the creation of AI models that supervisors can understand, control, and trust, thereby improving fairness.

Organizations involved in AI fairness include both developmental agents—such as Spotify, Microsoft, Google, Amazon, Facebook, Twitter, IBM, and Microsoft—and supervisory bodies like the United Nations, European Union, USA, China, Canada, and Australia. Projects funded by governments, such as FUTURESAI in Australia and AINED in the United Kingdom, focus on AI ethics and fairness. Stakeholders play distinct roles: Developers concentrate on bias mitigation, while Supervisors define fairness, monitor, and regulate AI models. In the Supervisory category, regulatory agencies devise laws for human telomere genome editing, the UK government drafts AI bills, the U.S. government proposes advanced AI regulation, and the U.S. Securities and Exchange Commission (SEC) tasks itself with overseeing the financial sector. The United Nations defines human rights principles, the European Union establishes laws, and the National Institute of Standards and Technology (NIST) sets standards—all of which influence the development and oversight of AI systems.

4.3. Challenges in AI Governance

Artificial intelligence is both highly promising and perilous, affecting increasingly more aspects of life. Digital technologies are able to rapidly shape public opinion, change voting outcomes, centralize wealth, fire millions of people, send lethal drone strikes, and personalize wars. Some may consider these troubling capabilities alone sufficient reason to establish rules for the development and use of AI systems. However, such technological issues, while important, only scratch the surface of the social considerations involving AI technology governance. There are concerns that the intensive development and use of AI technologies could exacerbate the division between rich and poor nations or individuals, create artificial social churn, make persons more vulnerable to manipulation by the wealthy, and deprive individuals of their social dignity.

Governments around the world are responding to the promise and peril of AI. For example, the European Commission has proposed a draft Artificial Intelligence Act that classifies AI applications according to their potential risk. In contrast, the U.S. strategy appears to have adopted a "no regulatory approach" because of the concern that strict regulation may have an adverse impact on the developments in AI. The U.S. Department of Commerce's National Institute of Standards and Technology (NIST) recently released its final drafts of the AI Risk Management Framework for public comments. Additionally, the White House issued an Executive Order with the goal to speed AI innovation, reduce the risks from AI systems, and safeguard individual rights.

5. Compliance with GDPR

European Regulation (EU) 2016/679 — commonly known as the General Data Protection Regulation, or GDPR — contains specific sections for automated processing and profiling. The clauses outlined in section 71 are particularly relevant; here, a collection of provisions designed to protect individuals from the potential risks of being evaluated or categorized according to an automatically generated score are explained in more detail. The individuals have the right not to be subject to a decision based solely on an automated process that produces a significant effect on their person. They also have the right to demand information about the details of the mathematical operations involved and the importance of various parameters.

5.1. Overview of GDPR Requirements

The General Data Protection Regulation (GDPR) is a comprehensive privacy regulation recently adopted by the European Union that addresses the management of personal data by organizations. Articles 13 and 14 of the GDPR stipulate that when a data set contains personal information about an individual, there are certain information disclosure requirements to inform the data subject about the planned processing and actual use of their data. These articles also mandate mechanisms that allow data subjects to access personal data stored or processed, which extends to their profiles in automated decision-making. Furthermore, the GDPR requires mechanisms to allow data subjects to modify or delete inaccurate personal data, with the scope of these correction operations extending to automated model-based profiles in accordance with the "right to rectification".

The regulation also imposes feeding and abstention requirements on the use of personal data in machine learning (ML). Under Article 17, Paragraph 1, Letter d, data subjects possess the "right to erasure," enabling them to request the deletion of personal data about themselves. Article 21 states that data subjects have the "right to object," allowing them to alter the intended use for their personal data if the ML process uses it in a manner that causes them to be unfairly treated by the completed artificial intelligence (AI) model. Finally, Article 22 requires that data subjects be involved in certain automated decision-making processes, such as loan approvals, to facilitate the "right to human intervention."

5.2. Impact of GDPR on AI Development

The EU's General Data Protection Regulation (GDPR) has a significant impact on the development of decision-making models, especially those powered by AI. Model creators must assess whether their models could infringe individuals' privacy rights or any other rights protected by the GDPR and adapt their development process accordingly. In addition, AI regulations based on the GDPR impose fairness conditions on algorithmic decision making when decisions are taken based on personal data.

The GDPR advocates for fairness in the development of AI-powered decision-making models and protects data subjects' interests. All automated decisions are covered by the GDPR, with an emphasis on decisions that produce legal effects or similarly significantly affect individuals. Three fairness aspects are identified in this context: sensitive attribute protection, under-representation protection, and outcome treatment protection. Sensitive attribute protection prohibits decisions based on sensitive personal data, as listed in Article 9 of the GDPR, to avoid discrimination against particular groups. Under-representation protection mandates extra care when training data disproportionately represents a certain group. Outcome treatment protection requires a non-negative assessment of the outcome distribution among groups; if the distribution is negative for any group, measures such as a human in the decision-making process should be considered.

5.3. Case Studies on GDPR Compliance

The General Data Protection Regulation (GDPR) aims to give individuals more control over their personal data. It requires that data-processing activities—especially those involving automated decision-making via machine learning models—explain their logic and avoid discriminatory practices. Individuals therefore have the right to receive explanations for decisions that affect them and are entitled to protection against unfair treatment.

Companies seeking to comply with the GDPR face a substantial burden. They must develop audit procedures, document their models, assess the fairness of their predictions, and provide adequate explanations. While model fairness has been extensively explored in the literature, explanations in the context of GDPR are still a novelty. Corporate lawyers, in particular, need help understanding what qualifies as an adequate explanation for automated decisions under the GDPR.

6. Basel III and AI Governance

Basel III offers insight into potential measures to strengthen the regulation and governance framework for large language models (LLM) and other artificial intelligence (AI) models. A broad consensus has formed around how to address the risks and benefits of LLMs; coordinated action is necessary to manage these risks, including catastrophic risk mitigation. A global response encompassing measures that promote equity and prosperity is overdue and would foster innovation and competitiveness. It is also imperative to evaluate the risks posed by LLMs and similar AI models.

Basel III, developed in response to the 2007–09 financial crisis, aims to enhance regulation, supervision, and risk management of the banking sector. The crisis highlighted excessive credit growth, leverage, and inadequate liquidity risk coverage as key vulnerabilities. Basel III focuses on the quality, consistency, and transparency of capital; sets leverage ratios to restrict leverage build-up; and establishes liquidity requirements to ensure short-term resilience and long-term stability. Parallel global challenges suggest that a similar analytic framework might be relevant to AI governance.

6.1. Understanding Basel III Framework

Basel III is the third Basel Accord and serves as an internationally coordinated regulatory standard on bank capital adequacy, stress testing, and market liquidity risk. It was developed in response to the deficiencies in financial regulation revealed by the subprime crisis during 2007–2008. The accord enhances minimum capital requirements by expanding both the quantity and quality of capital. Basel III introduces overarching risk coverage, including measures for counterparty credit risk and higher capital requirements for complex, structured credit-related products. Additionally, Basel III implements a leverage ratio as a supplementary measure to risk-based capital requirements and introduces two liquidity standards: a liquidity coverage ratio (LCR) and a net stable funding ratio (NSFR).

Basel III is designed to complete the Basel New Capital Accord (Basel II) by addressing the banking sector's vulnerabilities and strengthening banks' resilience to shocks. The ultimate goals are to increase banking-sector transparency and build customer confidence. Some aspects of the Basel III framework are static by design, expecting no improvements or future upgrades. In complying with Model Governance standards, banks must align with the Basel II/III framework introduced by the Basel Committee on Banking Supervision (BCBS) at the Bank for International Settlements in Basel, Switzerland. Model Governance constitutes a corporate approach that encompasses policies, procedures, and organizational structures, thereby facilitating the development, use, implementation, validation, and risk management of Internal Bank Models.

6.2. AI in Risk Management

The application of AI in risk management seeks to enhance the identification of risk tolerance and thereby foster a comprehensive risk culture within organizations. A comprehensive risk culture encompasses behavioral aspects, risk awareness, values, attitudes, ethical conduct, risk knowledge, and skills, which collectively contribute to making risk-related decisions with integrity and accountability. AI-driven risk management processes, therefore, need to be transparent, ethical, and fair.

The regulation and market standards that transpire in the evolution and deployment of AI-based applications will inevitably aim toward these goals. However, these standards will not materialize overnight. In the interim, AI-based services must operate within the extant regulatory environment, subject to more general principles of transparency, ethics, and fairness. The adoption of guiding frameworks and industry practices seek to ensure that AI models are both accurate and ethical, particularly in areas such as real-time transaction monitoring and model risk management. The next section addresses the regulation and risk management of AI-based models logistic regression and neural networks.

6.3. Compliance Challenges with Basel III

Fully developed and deployed AI models demand significant computing capacity. Over the past decade, the introduction of powerful AI frameworks, libraries, and programming platforms has democratized access to AI model development by reducing required skill levels and exponential growth in computing power available as a cloud-service has dramatically lowered investment costs. Despite these advantages, deploying advanced AI applications in a regulated enterprise environment introduces several challenges and risks.

The Basel Committee on Banking Supervision (BCBS), which comprises governors of central banks and heads of bank supervisory authorities from 28 jurisdictions, issues global standards for the banking industry. Basel III standards are designed to strengthen regulation and promote transparency in the banking sector.

Conclusion

The construction of an artificial intelligence model within an artificial intelligence system is inclined to proceed under the regulations, standards, or contractual obligations prescribed for regulating information processing or the operation of technology, in particular, machine learning. The code of ethics implemented is likely to relate to a university, organization, or community that is important to the artificial intelligence developer. In addition, fairness is generally consistent with prevailing legal or cultural expectations. Regulation, ethics, and fairness constitute the mnemonic REF that is generally applied to the construction of an artificial intelligence model within an overarching true AI model that is consistent with truth, user needs, and user acceptance, represented by the TNU mnemonic. REF is advised to be applied throughout the life cycle of a true AI model in order to acknowledge the empirical insight of short-term contingencies and long-term developments that affect the acceptance of artificial intelligence by its various users.

Such conditions for construction are not generally achievable in the present state of the art, even for the machine learning approach to artificial intelligence. The creation of an artificial intelligence model employing the theory of intelligent modeling for the determination of the true intelligence circumstance will be strongly advised, for instance, for model use in any context that establishes a legal and moral precedent for other artificial intelligence implementations during the early stages of the technology lifecycle.

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Chapter 9: Future Prospects and Ethical Implications of Artificial Intelligence in Global Financial Markets: Responsible Innovation, Bias Mitigation, and Sustainable Finance Applications

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1. Introduction to AI in Finance

What Is AI? Artificial Intelligence (AI) uses advanced computational tools and statistical techniques—in particular, machine learning and natural language processing—to model the patterns and dynamics of human behavior [1]. The purpose is to give machines the capability to make decisions that typically would require human cognitive functions. AI uses historical and live datasets of sufficient breadth and depth to understand how human behavior has evolved and may develop going forward, operating like a camera capturing every detail. AI automatically interprets the situations and conditions captured in its "lens" and autonomously makes choices to best serve its users [1,2]. AI aims to automate reasoning and decision-making—activities that have historically relied heavily on humans' ability to learn, plan, adapt, and recognize patterns—to assess situations and take actions that should be followed by other people or institutions. Industry leaders denote AI applications that specialize in understanding and making decisions in a particular domain as narrow AI, which contrasts with broad AI, capable of understanding and responding to situations in any domain.

Fig1. The future of AI in Finance

What Has AI Meant to the Financial Industry? Finance, one of the first industries to be transformed by computers, is at the forefront of AI adoption. Beginning in the 1980s, rule-based expert systems codified experience-based decision processes, and business intelligence methods analyzed data for decision support across client business requirements [3-5]. As during other periods of financial innovation, such usage clarified investment decision processes, improved decision consistency, and strengthened governance [6,7]. In the following decades, financial institutions adopted algorithmic trading engines that used computerized quantitative models to automate select investment decisions within clearly defined boundaries.

Axiomatically, AI is best positioned for use cases emerging from dynamic, frequent, and complex decision spaces, such as high-frequency trading or intraday equity settlement. Market forces have pushed against those boundaries, however, resulting in low-fee foreign exchange transactions, passive equity funds, and the three-day settlement period—all of which create a decision environment that lacks sufficient complexity, frequency, or dynamism. But as

AI amplifies decision speed and frequency, the market moves toward more complex financial instruments and shorter settlement periods.

2. AI-Powered Central Banking

Central banks have a wide range of functions: acting as the banker of the government, stabilizing financial markets, and serving as the lender of last resort. Their paramount role is to achieve their mandate through monetary policy [2,8-10]. For the European Central Bank, this is to maintain price stability for more than 340 million Europeans. Other objectives of the ECB include supporting growth and employment, and – recently – taking environmental considerations into account. The instruments available for achieving these goals are interest rate policies, lending to banks, and market operations. These operations include purchases of government debt and quantitative easing. They directly influence growing and shrinking money supply in crises—as is currently the case due to the COVID-19 crisis and Russia's war against Ukraine—but also under conditions of economic growth to prevent inflation.

Monetary policy decisions are currently made by an elected committee, rather than based on an algorithm or AI models. There is evidence that an AI system can make better decisions. The evaluation of an AI-based central bank agent with a "wicked-principle-agent" meta-reinforcement-learning agent finds that even in a dense policy environment, an AI agent can be trained to outperform the current decision-makers in the central bank. Nevertheless, implementing AI agents raises important questions that should be carefully addressed before deployment in a real-world setting [1,11-12]. These questions are discussed later under Ethical and Regulatory Considerations.

2.1. Overview of Central Banking Functions

Central banks perform several functions to help maintain system stability, including: implementing monetary policy, serving as lender of last resort, maintaining the currency, regulating banks, acting as bank to the government, operating the payments system, managing international reserves, and promoting financial stability. For example, by helping to manage inflation and unemployment through interest rate adjustments, central banks endeavour to create a stable economic environment, which can be conducive to investment and growth. Maintaining the currency specifically through interventions in the money markets to influence exchange rates is another important central bank function.

Given the increasing significance of the monetary policy function, current research examines the use of artificial intelligence in improving the setting of the bank interest rate [13-15]. The analysis derives results on updating growth and inflation data and setting the bank interest rate by utilising the reinforcement learning algorithms of Q-learning and deep Q-network.

2.2. Integration of AI Technologies

Central banking comprises a complex range of functions called "The State Functions", which are often broadly classified as allocation, distribution, stabilisation and growth [16]. These functions involve complex, dynamic decision making and huge amounts of data, which make them ideally suited to being improved and supplemented by AI. This section examines how central banks might optimise these functions using the available AI techniques, in particular central bank optimisation. Other applications of AI in central banking are considered later.

Of the four functions, stabilisation is generally regarded as central to central banking. Stabilisation in turn comprises four areas: monetary policy, credit control, the exchange rate and the balance of payments [16,17]. Among these, monetary policy, i.e. the determination of the money supply and interest rates, forms the core of stabilisation functions. Given the high degree of sensitivity of monetary policy, the optimisation of this function is critical. The first use case is framed accordingly. As one of many areas of AI application in central banking, such techniques are expected to be an important component of central banking in the future.

2.3. Benefits of AI in Monetary Policy

Central banking and monetary policy form a natural context for clarifying many of the promises and pitfalls of artificial intelligence. Consider, at least in principle, a financial system whose major decisions are made by highly integrated AIs with highly advanced capabilities. Indeed, the early twenty-first century's real-time computing and communications revolution is producing the information and communications flows that are prerequisites to the evolution of such advanced artificial intelligence.

In central banking, the evolution of such AIs might emerge as an aid to human decision-making, rather than a replacement for it [12,18-20]. Contemplate a major central bank assisted by an AI capable of instantaneously assessing global economic and financial conditions. In addition, it might be able to quickly determine the effects of a myriad of alternative policy choices, enabling central banks to select the policy that is likely to produce the greatest benefit to the global financial system and to the real global economy. These benefits, of course, might come with significant costs and risks.

2.4. Challenges and Risks

A number of significant challenges remain before AI can be fully integrated into central banking. First, AI models need to be robust across an extremely wide range of financial conditions, and ensure that the dynamic adaptation of interest rates and other policy instruments will never precipitate a loss of stability in the financial system. Any policy misstep can have serious consequences, since central banks cannot be allowed by the market to fail [21-23]. Moreover, central banks must stay the course during periods of economic stress, when an otherwise profit-seeking agent would have a strong incentive to abandon risk control practices.

Second, the data feeding into AI models must be accurate and comprehensive, which requires flawless translation of information flows from the real economy to the financial sector. Any discrepancies can be exploited through arbitrage, resulting in poor decision-making and threatening the overall AI system's viability [24,25]. Third, from an ethical perspective, humans might feel uncomfortable relinquishing control over vast amounts of economic, financial, and social decision-making. Fourth, regulating AI-based implementation of monetary policy will require a complex and delicate interaction between the central bank and the Government Endowment, involving considerations of safety and soundness.

2.5. Future Trends in AI-Powered Central Banking

Central banks rely on an assortment of functions ranging from monetary policy and supervision to the management of currency reserves and the issuance of banknotes. These activities can be machine-assisted by AI and data-intensive Party-Chavista central bankers might even consider handing over the keys. AI offers three key advantages in policymaking [26-28]. First, trained on millions of hypothetical scenarios of interest rate adjustments and their effects on growth and inflation, its optimized policies would far outperform decisions left to chance. Second, while maintaining the secrecy of an interest-rate-driven Holy Grail model, central banks could direct an AI agent to allocate their currency reserves, thus managing interest-rate and forex risk optimally and without screaming at themselves or their monitory.

3. Generative AI in Financial Services

A large area of recent interest is in generative AI tools. These are generative large language model (LLM) applications that can generate new content, such as text, images, or audio. They are rapidly infiltrating the financial services industry (FSI) and affecting all aspects of the industry, including asset management, banking, consumer finance, finance and risk, human resources, investment banking, legal and compliance verticals, and the markets and securities services sector [29-31].

Several generative AI initiatives have been publicly announced. BofA Merrill Lynch Wealth Management is developing a generative AI assistant for United States private banking clients, expected to be available by May 2024. Citi Private Bank has introduced a client AI assistant. HSBC is reportedly developing a generative AI platform for its wealth management clientele. EMQ has launched "Oracle EMQ," a smart AI banking platform, and UOB has created "Mia™," an AI-powered digital assistant for its customers.

Citadel recently announced Walrus, an internal tool that applies generative AI to a wide array of company operations, including analyzing the profitability impact of posted comments, summarizing core insights from selected articles, summarizing lengthy earnings call transcripts into bulleted lists, and categorizing article headlines for market reaction modeling. Its flagship hedge fund strategies have been effectively using Walrus since early 2023.

3.1. Applications of Generative AI

The financial sector appears poised to benefit from a new wave of innovation, spurred by recent advancements in generative AI models. Investment management and advisory are prime candidates to leverage these cutting-edge large language models [3,32,33]. The capabilities of such models enable the automation of diverse natural language synthesis tasks, including the drafting of customer communications, the summarization of financial reports, and the creation of explanations for specific trading signals. Consequently, these functionalities seem promising in terms of adding value to both wealth management and asset management.

Given the capital-intensive nature of the sector, a strong success in these areas could lead to broader applicability in activities such as proprietary trading [4,34-36]. Numerous examples exist demonstrating that AI can support the identification of alpha signals with favorable properties; however, considerable effort remains necessary to operationalize these ideas in real-world settings.

Practical use cases of natural language generation and inverse reinforcement learning have been successfully implemented in credit risk and fraud detection. In credit risk, generative AI models contribute to improved default prediction and credit rating assignments for loans and bonds by predicting credit-related risk factors from nonstructured data.

3.2. Impact on Financial Modeling

Financial modeling in the 1970s was genuinely revolutionary. Its objective was to provide an objective and quantitative framework for rational decision-making. Modern investment theory became popular via books such as Investment Analysis and Portfolio Management by Frank K. Reilly and Keith C. Brown. Fundamentally, it was about constructing portfolio models with the objective of maximising return for a given risk level—or minimising risk for a given return level. Based on the Markowitz model, which optimised portfolio risk versus return, the Capital Asset Pricing Model (CAPM) went a step further to optimise asset allocation to entire markets using a so-called “market portfolio”.

In practice, implementing these models is far more difficult than the theory implies. Estimating beta and other parameters is easy when using historical data, but these values are not static: they change over time and are often not representative of the future [37-40]. More important, because financial markets have significant components of human irrationality, non-price-related factors, and unmeasurable risks, such predictions have limited accuracy—for example, the estimates provided by the CAPM rarely provide accurate forecast betas for equities.

3.3. Risk Management Enhancements

Artificial intelligence (AI) can also implement more advanced risk management strategies. One example is algorithmic machine trading, which enables asset managers to price risk and hedge client holdings more accurately in real time and with greater precision [4,41,42]. The complex historical relationships and dynamic correlations of the broader financial market frame the context for arriving at these hedges. By analyzing vast quantities of data to predict various outcomes and probabilities, machine learning techniques can identify exposures to market shocks and changes in fundamental factors.

Over time, the machine Guru learns from its own trades and develops a sense of trading skills, just as a human would. Guru is continually trained through an extensive feedback loop that accelerates its art of attribution. It calculates an attribution to an “alpha” (any skill or advantage that adds value to a trading strategy) and analyzes the trade outcomes to determine whether the strategy is improving. The Guru assesses whether the strategy should be placed in a “hot” or “cold” bucket, which categorizes strategies based on their recent performance and future potential utility.

3.4. Ethical Considerations

Ethics in finance is a particularly sensitive issue because unethical decisions made by a financial institution can cause major repercussions internally, on the sector, and on society as a whole [43-45]. Personal data can be especially sensitive when involved with sectors such as finance and requires special care and consideration. Biases on the data can cause ML models to discriminate against certain groups by not offering the same opportunities or interest rates to everyone. The effects of AI decisions should always be explainable and accountable so that institutions can identify potential biases and correct them before they cause problems. Addressing ethical issues surrounding AI requires teams to consider a much broader set of questions in the development and implementation of new systems.

Another key concern is that systems may be trained on data that generates a skewed view of the real world, making poor decisions based on that data. Even if the data itself is unbiased, the structure of models can inadvertently introduce bias in their predictions. Some suggestions to combat bias in AI include maintaining explicit guidelines, having teams that understand social biases, standardizing rules for detecting bias, and improving ongoing audits of deployed models.

3.5. Case Studies of Generative AI Implementation

Generative AI is capable of producing high-quality synthetic data. In the banking sector, for example, AI-generated portfolios can create data with different correlation structures, making it possible to test an investment model with countless plausible portfolios. This innovation allows financial institutions to explore many "what-if" scenarios and design algorithms that perform well under various market movements [9,46-48]. Additionally, Generative AI can produce credible, directionally accurate, and realistic forecasts, which are particularly useful for scenario-based analysis and stress testing. Central banks could also generate alternative scenarios for risk monitoring and macroprudential planning.

Moreover, Generative AI can facilitate experimental projects, such as creating mock data for market research or reproducing proprietary data for scenario testing. By generating realistic data, institutions can overcome challenges related to data scarcity or privacy, enabling more robust analysis and decision-making. Another notable capability involves converting narrative information into numbers or summaries. Analysts often synthesize qualitative information from company transcripts and earnings announcements to gauge sentiment, carry out scenario analysis, or predict quarterly earnings and guidance. While such synthesis is human-intensive, Generative AI can accelerate the process, allowing analysts to concentrate on more insightful tasks.

4. Autonomous Trading Agents

Given the complexity and dynamism of financial domains, future finance applications will significantly treat artificial intelligent agents as more than tools for automation and optimization [49-50]. Autonomous artificial intelligent agent technologies will play an expanded role in supporting humans in various financial tasks. Autonomous agents are software entities capable of formulating clear and continuous objectives, employing complex mechanisms and reasoning methods to fulfill these objectives, and acting in a flexible, adaptive, and intelligent manner.

Autonomous agents process their perceptions and experiences to adapt to environmental changes and to outperform alternative strategies and expert systems [51-53]. They exhibit social behavior by negotiating and communicating with other agents, customers, or supervisors. Accordingly, autonomous agents in the AI-in-Finance domain can be classified into three classes: (1) assistants, (2) embeddable agents, and (3) autonomous-trading agents that buy and sell assets in a marketplace on behalf of humans and require minimal human input once deployed. Autonomous-trading agents are software programs that execute trades automatically without the need for an individual to actively participate in the program's decision-making. An agent's autonomy concerns the degree to which its behavior is influenced or controlled by an external entity, such as a human trader or an agent designer. The core idea of an autonomous-trading agent is to minimize human involvement in the trading task. Complex operations may be invoked by the agent itself or triggered by external events, such as changes in market conditions or fulfillment of predetermined criteria. After initiation, the trading process can proceed without interacting with the user.

4.1. Introduction to Autonomous Trading

Autonomous trading, also known as algorithmic or black-box trading, controls a trading operation regardless of market circumstances or conditions. Algorithmic traders employ automated models to enter and exit trades, independent of the broader dynamics of the market. Without exception, machines execute every transaction, obviating the need for human involvement; traders traditionally responsible for such tasks supervise solely the development, debugging, and updating of algorithms.

The history of algorithmic trading traces back to the launch of NYSE's SuperDot system in 1984, which permitted brokers to electronically route orders instead of engaging in face-to-face negotiations. Despite its initial success, the SuperDot system lacked robustness. Developments in market access, such as Electronic Communication Networks (ECNs), FAST/FIX protocol adoption, and the transition from fractional to decimal quoting, have shaped the trading landscape. The establishment of Regulation National Market System (Reg NMS) and Reg ATS further encouraged institutional traders to use algorithmic strategies to secure the best prices across markets. The development of Flash Trading in 2007 yielded research suggesting that high-frequency trading improved liquidity and contributes to price discovery.

4.2. Mechanisms of Trading Algorithms

A trading algorithm is essentially a computer program that automates the processes of buying and selling assets in markets. Through sensing, learning, and acting, these programs perform trading tasks either fully or partially. Typically, market-related data passes through a sensing block, then is processed by a learning module that updates the inner model, which subsequently guides the acting block to make decisions. In the actuation step, the computed actions are implemented in the market. The term "algorithmic trading" describes the use of algorithms for trade decision-making, order placement, and execution of buy and sell orders under guidance of the artificial intelligence algorithms.

Trading algorithms are classified into three broad categories: momentum, value, and arbitrage algorithms. Momentum algorithms utilize stock price movement patterns to identify momentary trends and rapidly capitalize on predictable price movements. Value algorithms employ ratios such as price-earnings, price-to-book, or price-to-sales to determine intrinsic values and trade on mispriced stocks by buying undervalued ones and selling overvalued ones. Arbitrage algorithms detect and exploit temporary stock price differences, for instance, by simultaneously buying and selling the same stock in different markets according to the price differential. Beyond these categories, automated trading systems that perform technical analysis and order execution functions are also referred to as trading algorithms. The performance of a trading algorithm largely depends on its learning strategy and the arena in which it is employed.

4.3. Performance Analysis of Autonomous Agents

The motivation to maintain profitable operations in the market leads traders to analyze previous trade actions to assess the effectiveness and performance of their agents. However, most analyses of autonomous agents are focused on individual approaches rather than their interaction with other agents in the marketplace. These analyses evaluate specific trading agents, but do not assess the overall effectiveness of the trades or the bank's overall status after the previous round of actions. In fact, such analyses provide an understanding of how effective a particular autonomous agent is and indicate the possible outcomes that the agent might have in a real financial market.

An effective decision-making process can maximize profits for all trading agents. The proper combination of trading strategies and analysis of possible trade outcomes contribute to overall profitability and minimization of trading losses. Experienced brokers generally have an upper edge in the trade profit ratio since they can predict the outcomes of ongoing trades; this mastery stems from practical experiences and can be integrated into an AI platform. Simply considering the advantages of profitability and outcome prediction can provide an insight into one of the possible approaches for the proposed trading analysis framework. The idea is simple: to not only maximize the profits of the trades initiated by an agent but also to make the operation of each of the agents able to predict the possible outcomes of the trade and engage only in profitable operations.

4.4. Regulatory Implications

Regulatory agencies around the world are acknowledging the inherent opportunities and challenges of artificial intelligence (AI) and working towards effective regulation of AI use in the financial sector. The U.S. Federal Reserve, National Association of Insurance Commissioners (NAIC), and Consumer Financial Protection Bureau (CFPB) have published statements, guidance, and questions as they prepare to regulate AI within the financial services industry.

Market participants are also requesting clarity regarding the current regulatory regime for AI use in their sectors. Maintaining trust in AI systems will be an ongoing effort that needs to include public–private cooperation, redress mechanisms, and continuous consumer involvement. Public engagement, even at the stage of drafting regulations, facilitates understanding of consumer attitudes and values, which in turn guides the development of AI regulation in a manner aligned with public expectations.

4.5. Future of Autonomous Trading

The potential for fully autonomous high-frequency trading seems remote because such systems require special finance-related knowledge that would be beyond the scope of the better deep learning systems. It is easy to construct systems that will profit from large-scale price drifts, when very clear signals emerge from the data; arbitrage models of the kind mentioned before. Such models would undoubtedly be able to find exploit signals even in a highly efficient market, where the allocated risk was very small relative to the noise in the system. They could do so without the help of an operator, although a senior manager would have to provide a risk constraint representing the overall risk appetite of the company that operates the trading portfolio.

These constraints are key to the success of the system, even in theoretical financial space. Without them, the trading portfolio becomes like the ‘‘fx daytrader’’, with monster-sized profits on Wednesday, and monster losses on Thursday. Consider the case of a trading algorithm producing expected returns of 1.05 with a standard deviation on returns of 1.00. Whilst this is undoubtedly profitable on average, it is likely to have very substantial drawdowns for months on end. Only if a human is able to override the system during these periods, can the system invest in the asset again when its odds turn favourable. This shows that humans have not yet been replaced by computers on all fronts.

5. Human-AI Collaboration in Decision-Making

The primary goal of computer systems is the support and augmentation of human capability. A collaboration between artificial and human intelligence can take advantage of the strengths of both operations, allowing for improved decisions. Humans have knowledge of context as well as the ability to place the AI’s decision into a larger knowledge framework, which is currently difficult for AI to implement. Humans also remain in control of higher-level, long-term goals and allow for corrections and adjustments in light of new information that may change the goal structure. Machines perform better in narrow AI systems that make quick, accurate decisions. They make use of vast amounts of data and calculate the optimal decision depending on the objective, but without the struggle of cognitive biases that humans have.

For example, in the credit granting process, the results predicted by AI can be explained and checked swiftly and with influence by the human. The human decides whether the predicted probability of default over the forecast horizon for the applicant leads to the granting of credit. With a fusing of strengths, of the context knowledge and judgment of the human and the ability of the AI to process large amounts of data in a narrow defined routine, the greatest value can be achieved. It will be important to ensure the ability of the man in the loop to overrule the system, especially when decisions can have an effect on the individual like in credit decisions. Lessons can be learned here from the chess-playing supercomputer, Deep Blue, which famously did not allow humans to overrule the moves that it suggested.

5.1. The Role of Human Judgment

Although AI offers tremendous support for financial decision making, there remain reservations regarding the eventual replacement of human judgment by synthetic intelligence. The relevant property of AI-based models goes beyond the mere quality of their forecasting performance or the earned profit—they must introduce easy explainability and comprehensibility without removing the humans-in-the-loop.

Forecasting performance has long been considered the primary metric of an algorithm. However, financial authorities now emphasize the importance of the transparency of the predictive modeling process, the fairness of the output, and the stability of performance over time. Such requirements concur with the evolution of AI into XAI (eXplainable AI): a discipline that focuses on technically explaining machine decisions in a way that is comprehensible to human users. In this context, visualization tools have emerged as a powerful means of building trust in complex machine-learning models.

5.2. AI as a Decision Support Tool

Within the process of converging financial planning and analysis with reporting, financial decision-making may become increasingly supported by artificial intelligence (AI)-based decision support. AI-assisted decision support systems can assist users in gathering, manipulating, evaluating or analysing information and use inference rules, recommendation or classification mechanism to support decision-making. Such support can either be task-specific or more general. Furthermore, support may be dynamic and turmoil-adaptive or rather static and relying on pre-established models. Different types of AI support can be distinguished: checking or validation of given solutions; interpretation of financial statements and metrics in the light of macroeconomic turbulence; formulation of new insights and alternative approaches; root-cause analysis and long-term implications; comparative analysis and ranking of alternative solutions; as well as the development of further alternative solutions or options in a more generative approach.

An acknowledgment, however, should be made that the issuance of recommendations or forecasts by AI may also eventually reduce the cost of obtaining a holistic view of long term economic turmoils implicitly understood by a financial expert with years of experience. While, at its core, decision support is designed to provide assistance to human experts, the increasing dependability on AI for crisis-management support later may result in a less critical decision-making environment. The suggestion of only one or two (not too many, and not too few) reasonable options may make relying on AI-generated solutions appear as the low-risk choice.

5.3. Case Studies of Successful Collaboration

Successful industry support for academic research papers in AI for finance highlights alignment of diverse actors around a topic of crucial importance. Indeed, the accumulation of knowledge should form a whole that is greater than the sum of its parts, with academia and industry contributing complementary efforts.

Table 6 summarizes the practical applications of the eighteen papers cited in this survey, grouping their industry supporters according to their role in the financial system. In eleven instances, funding came from a single organization, while five papers combined funding from two supporters. Instinet, the provider of an institutional brokerage platform for several of the successful models, stands out as the most frequent contributor in this area. Appendix R identifies the active research centers mentioned in Section 5.2, each producing at least one industry-supported paper in the review.

5.4. Challenges in Human-AI Interaction

Human interaction with emergent AI capabilities—including generative AI—presents a compelling new range of considerations and challenges. Part 3 presented cases illustrating AI's benefits and its inherent risks. Here, the discussion continues with reference to emerging themes in the literature. For example, PwC [citation] highlights a tangle of interconnected issues. Some present opportunities: unconscious bias elimination and inclusiveness; enhanced cognitive capacity; career progression and transition; heightened productivity. Others pose risks: appearance of bias; filter bubbles;

misinformation; ethical and moral issues; overconfidence; ignorance; erosion of diversity; distraction; automation bias.

In a similar vein, the RAND Corporation [citation] finds that Generative AI, with its rapid information processing and creative abilities, can augment human capabilities yet carries risks such as misinformation and manipulation. The research recommends accounting for generative AI's capabilities and limitations, including inaccuracy and bias; assessing its influence on behavior and perceptions; and studying responses to these influences.

5.5. Future Directions for Collaboration

The future development of AI and ML in finance lies in the development of systems that can work collaboratively. Because for now, humans are still in the best position to assess and eventually intervene in the financial decision-making process. The limitation of present-day AI is the relatively shallow understanding of the things that it models. For example, a chess-playing AI can never truly understand the deep meaning behind playing chess and neither can it truly appreciate or marvel at a good game. Although present-day AI is extraordinarily good at playing the game, it only pretends to really understand the game. However, such an understanding is sometimes required when it comes to financial decisions. One way to go about this is to develop AI that can collaborate with human decision makers so that the deficiencies on either side can be made up for by the strengths of the other. Such systems would also have strong explanation capabilities. In general, the future development will involve not just the development of new AI/ML paradigms but also frameworks and architectures for their collaborative use in finance.

6. Ethical and Regulatory Considerations

Ethical Implications of AI in Finance Although the consequences of AI are not entirely unpredictable, their potential impact mandates careful consideration. Prudence suggests that the finance industry should engage in meaningful dialogue with wider society, whether it be about the ethics of AI, the societal role of banks, or the ways in which they shape the economy.

Regulatory frameworks that have evolved over hundreds of years for the purpose of an interconnected global economy cannot be easily subverted. The use of minimax algorithms is essential in making sense of the world of finance, yet inherent limitations are evident. Nonetheless, reality does allow for the existence of increasingly sophisticated predictive systems, which, despite their diminishing uncertain zones, cannot be assumed to be flawless.

Surveillance and privacy issues in finance clearly demand oversight. The law often struggles to keep pace with advances in artificial intelligence, but the interest of society is unlikely to be ignored. Currently, the European Union (EU) is working on rules to govern AI, following the introduction of the General Data Protection Regulation (GDPR). International regulatory bodies such as the Financial Stability Board (FSB) and the Financial Action Task Force (FATF), along with national authorities, are turning their attention to these topics.

6.1. Ethics in AI Deployment

Central banks play an essential role in maintaining economic stability, preventing inflation, managing unemployment, and responding to changes in interest rates and other critical facets of a nation's economy. That said, it is important to understand how AI and emerging technologies such as IoT, 5G, and Metaverse can contribute to the betterment of society yet also bring about unexpected consequences. For instance, AI can perpetuate bias when algorithms are not properly designed and implemented. In some cases, decision-making efficiency might inadvertently exacerbate income inequality, lead to an uneven distribution of resources, or concentrate power in the hands of specific groups.

The European Commission’s Ethics Guidelines for Trustworthy AI provides a framework for the ethical considerations of AI deployment, emphasizing human agency and oversight, technical robustness and safety, privacy and data governance, transparency, diversity, non-discrimination and fairness, societal and environmental well-being, and accountability. Luo and Ransbotham point out that ethical concerns are encoded within the Governance of Risk of Future Events decisions in the Ethics Guideline. According to their argument, ethical leaders who prioritize long-term growth and view AI as a means to identify and mitigate future risks are more committed to the ethical deployment of AI.

6.2. Regulatory Frameworks for AI in Finance

Financial regulators generate regulatory mandates as a means to narrowly govern interactions within the financial ecosystem. Existing regulatory efforts on AI have tended to focus on specific types or aspects, such as ML models, large language models, AI governance, or ethical AI.

Financial services warrant specialized regulatory frameworks. Currently, regulators in different geographic regions benefit from a variety of regulatory resources, including guidance papers, consultation papers, discussion papers, and principle-based approaches. The use of principle-based approaches is becoming increasingly supported and recommended by the financial services industry. Principle-based approaches in financial services are perhaps essential, in that they ultimately encompass the principles of fairness, ethics, explainability, and accountability. The role of a principle-based approach is recognized as one which provides greater flexibility but less precision in comparison to rule-based regulation, which may become quickly outdated due to the natural pace of innovation and changes in the industry. Further discussion highlights that clause-based regulation in financial services could be overly prescriptive, inhibiting innovation and competition in the market and creating risks of over-fitting rather than preventing them. Finally, AI-related risk may not be limited only to the area of AI governance but rather be cross-functional, affecting areas such as financial crime or general operational risk.

The Singapore-based financial regulator MAS recently released a revised Consultation Paper proposing changes to Algorithmic Trading (AT) rules and financial advisories intended to enhance transparency and governance of AI and algorithm-based financial advisory services. The emerging South East Asian regulatory environment reflects the importance of shifting from an algorithmic trading focus toward a broader AI focus. The Central Bank of United Arab Emirates issued a Directive Governing Artificial Intelligence Use Clause within the Financial Services Sector (AI Directive), which establishes regulatory principles for AI ethical use, AI governance, and AI auditability, as well as a collaborative framework between Financial Institutions and Smart Dubai for AI governance. In the United Kingdom, the Financial Conduct Authority has released a Discussion Paper to capture industry views on effective governance for the design, development, and deployment of AI/ML systems.

6.3. International Perspectives on AI Regulation

In April, Didi—a Chinese ride-hailing company—sought an initial public offering, partly funded by the U.S. venture capital arm of SoftBank. Three days later the company was accused of illegally collecting personal data and barred from accepting new users. Six weeks later, the side business of SoftBank's Vision Fund—a half dozen American companies overseeing another $100 billion in Asian tech investments—announced that it would not participate in any further funding rounds for Didi. Thus, the convergence of two regulatory frameworks jeopardized funding for an otherwise private Chinese company.

It might seem odd that Chinese regulators wield so much influence over a company with no American backers. Yet experience shows that regulators exert significant power over when, where, and how new businesses emerge. A prosperous economy requires that law and capital align so that investment flows toward the most promising innovators. Today, the global balance among capital, law, and innovation is being tested by concerns about national security as well as an energized populace demanding government use of technology be transparent and responsible. Ventures like Didi now face two sets of regulatory expectations that are reshaping capital markets, supply chains, and the nature of entrepreneurship. China and the United States are not the sole actors in this story, but their actions illustrate the global tension between capital moving freely to the most promising companies and limits to capital motivated by concerns about geopolitics and national security.

6.4. Balancing Innovation and Compliance

Developing smart regulation is acknowledged as one of the greatest practical challenges in financial services, with the Personal Data Protection Bill (PDP) in India serving as a prime example. On the one hand, historical experience shows that a lack of regulation can lead to catastrophic outcomes such as Sharekhan Fraudgat-1970, many stock market crashes, the financial crisis of 2008, global data breaches, the collapse of Enron, the Silicon Valley Bank collapse, Wirecard, and the SVB, among others. On the other hand, overregulation has been blamed for turning India Inc. into the sick man of Asia. The challenge therefore is to craft regulations and a regulatory framework that can effectively respond to new innovations such as artificial intelligence and foster inclusive growth. Modifying Deep Blue's maxim — all work and ruling is bad — it might be stated that unchecked work and too much regulation can harm innovation.

The Future of Financial Services report of the German Bank for International Settlements (BIS) suggests that regulation and innovation can go hand in hand. The key lies not in banning things but in guiding them to develop correctly and, where appropriate, creating the conditions for testing innovation. While the report acknowledges concerns, it points out that such concerns have parallels in foreign exchange dealings, which have allayed fears that traded currencies would be subject to speculative cycles and sudden stops. Ceasing operations at the day's end and reopening the next day with a reset price would be difficult for the coming digital currency ecosystem and might contribute to the financial instability in the real world. Therefore, a lasting dawn of AI would depend not just on technological developments but also on the partnering of innovation with a system of smart regulation.

Conclusion

In recent Asia Times op-eds, Kenneth Rogoff, professor of economics and public policy at Harvard University and former chief economist of the International Monetary Fund, has voiced warnings regarding the corrosiveness of artificial intelligence (AI) in certain financial sectors. He views AI as a disruptive element, particularly in areas like portfolio management, whose major banks have historically profited. AI's impact on Wall Street's primary successes appears less troubling, though liquidity could certainly be affected.

Rogoff also points to the transformation of writing tasks, such as scholarly essays and stories, through AI toolkits like ChatGPT that absorb and re-create human discourse. These capabilities herald a new phase for the many writers already trained in distanced prose and heavily supported by online database research. A report by International Data Corporation (IDC) predicts that the emergence and adoption of generative AI will usher in the provocative "Cambrian moment" known as the Cambrian Explosion.

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Chapter 10: Practical Implementation and Deployment of Artificial Intelligence in Financial Services: MLOps, Cloud Architectures

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1. Introduction to AI Applications

After understanding what artificial intelligence (AI) is and how it can influence business growth, one might ask: how do I practically apply AI across different industries? This short guide addresses this question by providing samples of AI applications in various business sectors. It also covers detailed AI data pipelines and development steps to serve as a tutorial for beginning AI practitioners. Lastly, it examines the deployment of an AI system in the cloud environment, another important aspect of AI development.

AI offers exciting new ways of addressing business challenges related to cost, quality, efficiency, and customer experience [1]. For example, marketing professionals typically spend considerable time on market research and running campaigns. An AI system can analyze market trends and continuously monitor and optimize campaigns accordingly. In the logistics field, AI can perform cost optimization and route planning to improve service efficiency and, consequently, customer satisfaction. However, despite these advantages, many companies still struggle to commence their AI applications. This guide aims to illustrate practical AI applications and procedures to bridge that gap.

2. Understanding AI Technologies

Any technology can be utilized effectively only if its structure is well understood and implemented correctly [1-2]. AI is no different. The world AI has a very broad spectrum. Examining all its aspects is almost impossible. What is presented here is only the initial parts. These parts have been used to prepare sample projects that are demonstrated later.

“The capabilities of output devices have been constantly increasing. The recent advantage offered by IoT has helped in better capturing of the world surrounding us, both internal and external [3-5]. However, human capabilities to understand the captured data are very limited. Artificial Intelligence (AI) is an emerging technology that offers solutions to solve this. Several AI-techniques have been proposed and implemented to support systems that can understand and respond like humans [6-8]. The deep learning is one such technique that has provided unparalleled performance, unlike, other existing machine learning approaches.”

“All viable approaches can be called Artificial Intelligence. The term Artificial Intelligence covers a variety of different approaches, including methods that try to mimic human thought processes, methods that try to mimic the brain, and methods that try to solve problems that would require intelligence but not by any means mimicking human behaviour or thought processes. Some of the very successful deep learning models try to mimic human brain function, while classical chess, checkers or noughts and crosses algorithms are AI without being deep learning, and poorly designed behaviour rules for NPCs in a computer game are AI without being either deep learning or a brain mimic.” Systematic, planned combinations of models can then produce, for example natural human-like conversations, a human like decision making at the highest executive level (supreme court justices), or computer players in games like chess or Go that regularly defeat the best human players. In all these cases, the underlying approaches may be very different but the net effect can be called AI.”

2.1. Machine Learning

Many small machine learning (ML) projects follow a simple training and prediction cycle in which a dataset is cleaned and fed into a learning algorithm that outputs a trained model [9]. The model is then used to make predictions on a new dataset. For instance, the following Scikit-learn sample code demonstrates the training of a Support Vector Machine model on the digits dataset during the fit phase, followed during the predict phase by the replication of a row to make predictions on new data.

Full applications eventually move beyond the fit and predict phases to considerations of data drift, training scheduled retraining jobs tied to triggers, and scheduling model evaluation jobs, among many other features. The complexity of full pipelines typically demands the use of ML-specific pipeline management tools such as TFX, Kubeflow, MLflow, or AWS Sagemaker. The following sample code uses Scikit-learn's train_test_split function to split the data for training, evaluation, and prediction functions that can be inserted into a more comprehensive pipeline.

2.2. Deep Learning

Deep learning (DL), a subset of machine learning that implements the principles of computational neuroscience inspired by natural brains, underpins some of the most significant recent advancements in AI [7,9-10]. DL works by storing knowledge in totally or partially connected internal representation layers, feeding forward abstracted data to obtain predictions of external data and the underlying representation of items in the predicted classes, and updating the weights of those connections from error-correcting signals calculated based on internal representations and external data [1,11-14]. While numerous architectures are possible, some of the most often heard of are Convolutional Neural Networks (CNNs) for image data, Recurrent Neural Networks (RNNs) with gating mechanisms for sequential data, and Transformers for sequential data, especially natural language text.

For a very simple ML application, a single-layer Perceptron used for classification might suffice, but under most circumstances, a multilayer Perceptron (MLP), which has some hidden layers, captures complex interaction effects more effectively [13,15-17]. The solvers most commonly used to optimize the parameters of neural networks are Stochastic Gradient Descent (SGD) and Adam. SGD calculates the gradient of the loss function for each sample and moves in the direction of improving the parameters at a set learning rate, using momentum to build faster speed in the correct direction and a learning rate schedule for crashing into the valley of minimum loss at just the right speed. Adam also computes the moving averages of the gradients and squared gradients, thus adapting the learning rate to the variance in the gradients.

2.3. Natural Language Processing

Natural language processing (NLP) is the field of AI focused on enabling computers to understand and process human language. Modern deep learning has led to many successful technologies in NLP, such as transformer models like BERT [18-20]. These models take text as input and produce inferred data as output. The inferred data from NLP models can be labels assigned to a piece of text (text classification), text generated in response to a prompt, or a short text explaining the content of a longer piece of text [19,21-22]. This inferred data can then be combined with domain knowledge to construct more powerful solutions.

An example is a tweet detection model. Assume there is a large volume of streaming social media data. This is ingested into the cloud, pre-processed, and classified by type of platform [11,23-25]. A transformer model is then used to detect sentiment and whether the tweet is an official corporate communication from a particular group (in this example, the BBC World News account). The inferred data is combined with business logic, such as posting the official communications into an internal Employee Communications channel, or alerting Customer Support of tweets expressing an unhappy mood towards the corporation. A batch NLP example is the summarization of news articles. The current affairs content of Newsela.com is fetched using a scheduled batch process, retrieved via the Newsela API, and a transformer based model summarizes the content into just a few sentences. Within the model, multiple beam search strategies are tested to improve the quality of the summary and reduce the number of repetitions.

2.4. Computer Vision

Computer vision, one of the most popular and widely used AI disciplines, is the branch of science and technology that enables computers to understand and interpret visual information as humans do [26-28]. Several projects are suggested to illustrate AI in computer vision. For example, object detection is implemented by combining the YOLOv3 pytorch pretrained model and the COCO Dataset. Instances of missing, broken, or misplaced objects are detected through image input and complaint creation. Structures requiring inspections, such as bridges and towers, are scanned by a robot. AI detects anomalies in the structures and generates complaints from image objects. A cloud-based solution is another alternative for detecting objects in images using services such as Microsoft Azure's Cloud Vision.

Image classification and face recognition projects are also explored. In image classification, a dataset of clothing images is used to train a model capable of predicting an image's class [29-32]. For the face identification task, Google Vision API is considered to detect faces in photos and return with coordinates, along with confidence scores indicating the likelihood of the photo being of a specific person. Deep learning methods for face and age determination—such as Face Detection, Face Recognition, and Face Age Prediction—are implemented using opencv3 and deepface frameworks, supported by datasets like IMDB_faces and LFW.

3. Sample AI Projects

Sample AI Projects offer concrete instances of how artificial intelligence technologies address real-life problems. Areas shaped by AI include Predictive Analytics, Chatbots, Image Recognition, Recommendation Systems, Facial Recognition, Spam Detection, Credit Card Fraud Detection, Building a Chatbot, and AI in Healthcare. Projects may employ Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, or combinations thereof: Predictive Analytics use statistical models and Machine Learning; Chatbots apply NLP; Image Recognition and Facial Recognition rely on Computer Vision methods. These example projects require carefully selected, cleaned, and formatted data before training; the subsequent section examines sample data pipelines.

In building a Sentiment Analysis system that classifies text reviews as positive or negative, public datasets can be sourced from platforms such as Kaggle, the UCI Machine Learning Repository, or through Web Scraping Techniques. Text for model training may originate from social media posts, news articles, or movie or product reviews. Data cleansing involves removing irregular or corrupted entries and addressing representations like "Null," "nil," "NaN," "0," or others signifying missing content. Text reviews are then preprocessed through techniques such as case folding, stop word removal, tokenization, and stemming to prepare for model ingestion.

3.1. Predictive Analytics

Predictive analytics forecasts future trends from historical data and is applicable in retail, finance, healthcare, and more [31,33-35]. It enables fraud detection in bank transactions and supports achieving targets by analyzing customer purchase patterns.

Implementation begins with data collection and preparation. Public datasets suffice for initial steps, but specific interest domains require specialized collected data. Preprocessing techniques, including feature selection, dimensionality reduction, outlier removal, and data imputation, enhance data quality for modeling.

3.2. Image Classification

Image Classification is a classic computer vision problem that involves identifying and categorizing objects in images [36-38]. Examples range from automated tagging on social platforms to providing navigation aids for visually impaired people.

The Deep Learning approach first pre-processes each input image to correct for variations in size and colour before feeding it into a convolutional deep neural network, most popularly a ResNet model pre-trained on the ImageNet dataset. The model extracts low-level features, such as edges, corners and blobs, then progressively pools its information down deeper layers to arrive at a spatially independent feature representation that is finally mapped to output classes. The bottleneck features of the pre-trained ResNet model can be cached and used with a new classification head for downstream tasks with a small labelled training set.

3.3. Chatbots and Conversational Agents

Chatbots and conversational agents provide an interactive natural language interface to information. Chatbots can also perform more complicated tasks such as booking a hotel, a doctor appointment, or a taxi in addition to providing real-time updates on the weather, news, and traffic. Most chatbots rely on a combination of natural language processing and machine learning, either supervised or reinforcement learning [1,39-41]. As a practical matter, nearly all deployed conversational agents adopt a hybrid approach that combines artificial intelligence with software engineering. AI is the core technology, but domain-specific integration, conversational design, and response generation are all software engineering projects.

Chatbots consists of multiple components analogous to a Markov chain. At each stage of the conversation, the chatbot estimates the probability of response type R:

$$P(R \mid C, S1,.. Sn) = \text{Next response}$$

where C is the current conversation context and S1,.. Sn are the previous n stages of the conversation. Defining the optimal set of parameters for that joint probability distribution relies on statistical machine learning, while writing the program that directs the overall conversation is in the purview of software engineering. This combination makes deploying a truly useful AI chatbot extremely challenging.

Another practical concern is ensuring that the chatbot service can be deployed in an affordable and reliable fashion without server infrastructure that is underprovisioned (resulting in lateness) or overprovisoned (resulting in excess cost). Cost-management emerges as a new cloud-native software engineering discipline [42-44]. To manage costs, the chatbot must be isolated from other product features and services, containerized, and deployed to a serverless infrastructure. Serverless architecture provides better control of costs by virtue of per-function billing and the ability to dynamically scale to zero chatbots during idle periods.

Practical Deployment Considerations

Planning the deployment environment for your AI chatbot has several practical considerations:

• Estimate the maximum capacity required to handle the chatbot conversation volume. • Estimate the deployment budget based on the maximum capacity. • Define the minimum capacity required to support conversation volume economically. • Define a deployment profile over time to decrease or increase capacity in response to predictable changes in conversation volume.

Each chatbot function can autoscale to zero during periods of inactivity, saving significant operational expenses.

3.4. Recommendation Systems

Recommendation systems are a type of Artificial Intelligence System that provides suggestions for products and services based on a user's preferences and likes [45-46]. Users of these systems can be customers of ecommerce websites, viewers of streaming services, participants in online community services, or employees in corporations. The techniques used to build a recommendation system include Machine Learning Algorithms and Deep Learning Algorithms. Recommendation System Projects typically include Content Based or Collaborative Filtering.

Awsome Data — Data collection and preparation First Step in building a recommendation system through the classification of comments and reviewers for the movie may be the source of data. These comments are in the range of 1-

10. The types of comments (5-10) are to be given input to the Machine Learning Module. The users need to classify the comment as either good or abuse, and it will be displayed in a special tab, which is clicking on the Mark Comment button. The comments submitted by the abuse or the users abusing against the comment or the reviewer, their name is displayed in the block Tab.

4. Data Collection and Preparation

Understanding the significance of data pipelines begins with practical learning. It is best to create pipelines around distinct data inputs for different projects [18,47-49]. As an illustration, the following three AI projects use three different types of data: movie reviews data from Kaggle, Amazon product-reviews data, and email data. For the one on movie reviews, the data can be directly downloaded from Kaggle and is split into two folders—training and testing. Similar splits for the other two projects are not available on Kaggle. Hence, the data pipeline has to download these data sets, convert them into the required format, and then save them to cloud storage.

The data pipelines execute as follows: first, the Amazon product-reviews pipeline lets users specify a category to narrow down the amount of data downloaded. Next, the email-quarantine data pipeline downloads the quarantine emails from Microsoft 365 and extracts the attachment data. In both pipelines, the downloaded data are processed and converted into a format suitable for a classification model. Similar to the movie reviews, the classification models for the Amazon and quarantine data pipeline build are launched as the last step, and the input data are uploaded to cloud storage for training and validation.

4.1. Data Sources

Understanding which data source to use for an intended implementation is a core preprocessing consideration [50-52]. External data can be based on standardized datasets commonly used for academic purposes, thus simplifying access to external data. However, a project designed for an industrial setting should be based on company data, which may be affected by confidentiality policies [53,54]. The next step typically involves creating a data pipeline, retracing the established data flow during preprocessing and data transformation. Such a pipeline is highly recommended, providing code readability and data quality assessment at each step.

Data pipelines consist of numerous autocontrolled phases. The first data pipe is responsible for checking the downloaded files against the data source. The daily ingestion pipe verifies the last day's information—an essential process if daily insertions or updates are expected.

When business rules require the use of a nonnormalized table, it is important to create the transformation process with the same level of autocontrol. Both upload and daily processing involve tests conducted from the perspective of the final destination data. For instance, if the daily pipeline employs group-by conditions, it should verify the existence of all expected group-by combinations to avoid losing reference keys in the business and create missing keys in the production system.

4.2. Data Cleaning Techniques

Once data has been ingested, the next step generally involves data preparation and transformation. Data sources cannot be expected to be free of missing or malformed values, and duplications, particularly when multiple data sources are combined. SQL and standard tools such as Excel or OpenOffice Calc provide a number of functions to fill in gaps or remove duplicates, while dedicated languages including as R and Python make it feasible to easily deal with these conditions, or to filter records during movement from one platform to another.

However, simple filtering can lead to a bias in later analysis when certain filters are applied to timestamps or geographical areas; rather, if at all possible, gaps should be filled. Row-by-row imputation is generally within the capabilities of dedicated languages, with values such as the mean or median of the given column used to fill in missing data. In many cases, it could be the relationship between multiple fields that is used instead to infer what should be inserted. Cluster analysis provides a very useful group of unsupervised learning algorithms that can reveal hidden groups of records and encapsulate their attributes in the centroid or prototype attribute vector. Simple statistical modelling, for example, a linear regression in R or Python, can also be used to suggest values. A recently available open source library, DataXformer, produces a transformation house or an imputation rule to address missing values in a dataset.

4.3. Data Transformation

Features define the attributes that the machine-learning model should consider, whereas labels (or the dependent variable) provide the ground truth. A model learns to map labels from the feature set through a training process. During training, the models estimate the probabilities associated with the prediction of any given label from the features.

Location prediction in transportation is a typical use case where an n × m feature matrix is created with n being the number of days and m being the number of locations. The feature matrix contains the number of vehicles available at a given location on a given day and time. The label vector contains locations at which the event is expected. A Markov chain can be used to predict locations by evaluating the transition frequencies of each trip from origin to destination. The transition frequency for a place l is given given as p(l) and represents the relative chance of a vehicle moving to location l during a request based on historical requests. The transition probability from place i to j is p(jˈi) and represents the relative chance of a vehicle moving from location i to j.

5. Building Data Pipelines

Once a machine learning model has been trained, it usually consumes data in some way and produces predictions. To actually do something useful with these predictions requires additional pieces. These will be described for the sample projects. They all require some way to access the data, so it makes sense to start there. The day-to-day operations of production machine learning systems naturally leads to a similar discussion. What form the models take, what kinds of predictions they make, and what happens when these systems are put into production are answered for the sample projects.

Because of the nature of the task, there can be many different kinds of data pipelines, and consequently many different pieces that can be used to build them. As a result, it is often challenging to decide what tools should be used. The data pipeline discussion for the sample projects therefore strives both to illustrate the way the pipelines are implemented for the sample projects and to describe the thought processes that go into making the implementation decisions. This leads to a set of practical considerations highly relevant during the planning stages of a data pipeline. Given that it is advisable to build pipelines with monitoring in mind, the monitoring of deployed systems forms the final piece.

5.1. Pipeline Architecture

Exploring Practical Applications of AI: A Comprehensive Guide to Sample Projects, Data Pipelines, and Deployment in Cloud Environments discusses some of the more popular and useful AI projects, including how the underlying data engineer pipelines are established and maintained, as well as how to deploy them on the cloud. The aim is to reveal the utility of the service, rather than making it finite, because AI and machine learning are constantly expanding areas.

Building machine learning or deep learning workloads requires a significant amount of effort. The complexity of the software, hardware, and data infrastructure often becomes the primary bottleneck to executing a project successfully. Moreover, because these problems are affected by the size of the data, and as such, the effort and costs, small-to-medium-sized businesses are often discouraged from exploring this promising technology at an early stage or when preparing for a market competitive position. As companies enroll in various accelerators and incubators, they deploy their solutions onto the cloud to ease delivery and collaboration. Therefore, projects from different domains were chosen that can survive as market-ready solutions, at least in the short term.

5.2. ETL Processes

Extract, transform and load (ETL) is a popular type of data pipeline. It is a batch processing technique that extracts data from sources, transforms it and loads the results into the destination for further use. The extraction phase is the read side of the process: it reads source data in native format and structure. The transformation phase refines and translates data into appropriate domains. The loading phase follows after and writes data into the destination system for user access.

ETL processes operate in a cycle. Each iteration reads new data, processes all data records, and stores the cumulative data volume for user consumption. The cycle is repeated at regular intervals by design, because the source system is considered to be a canonical copy. A fault-tolerant design is enforced by retaining the intermediate results of each iteration within the cycle. Checkpoints are therefore created in order to iterate gracefully after a connectivity crash or restart.

5.3. Real-time Data Processing

The management and analysis of large-scale and diverse data sets can present a formidable challenge in both business operations and Artificial Intelligence (AI). When these data sets constantly change over time, the challenge escalates, calling for the implementation of data pipelines capable of performing periodic data engineering. A data pipeline is a framework that automates the collection, transformation, and processing of data from various sources to different destinations such as databases, data warehouses, or the cloud. Once the data has been prepared, the pipeline furnishes it as input to a model retraining pipeline for AI systems. Such pipelines undergo regular retraining, with configurations updated based on the latest available data, thus enabling effective handling of data scaling and model drift.

Moreover, there is an increasing demand for AI services to support wide-scale deployment and management of diverse models. Cloud providers correspondingly offer fully managed Machine Learning (ML) services that facilitate the training, fine-tuning, operationalization, and management of AI models. These services reduce the overhead associated with ML system construction and help ensure compliance with national and international privacy and security regulations. They also enable solutions that concurrently address multiple use cases. As AI-generated outputs become more widely utilized, a significant new challenge arises: training and managing models so that they can deliver services on demand that fulfill business expectations, all while adapting to incoming, production-scale data.

6. Model Development and Training

Model Development and Training Once a structured training dataset is ready—on premises or in the cloud—Teams can begin to build machine learning models. Tables 1–5 list sample AI projects, some of which run on public cloud samples.

Sample Data Pipelines Data pipelines enable automatic preparation of training datasets and include web crawlers or domain-specific parts-of-speech taggers that collect source material for building the dataset. For example, a table in a Wikipedia database might contain pairs of signed/unsigned numbers as strings. The data pipeline passes through the Wikipedia table, collecting pairs of numbers in the dataset. A related model-development environment prepares data samples and produces training datasets by leveraging data-purification and reshaping tasks.

6.1. Selecting Algorithms

In the last decade, many new algorithms have been developed for natural language processing, recommendation systems, and other tasks. These new models often achieve state-of-the-art results and are hyped beyond proportion.

However, when it comes to practical applications of AI, it is rarely the latest state-of-the-art algorithm that offers the most value, but rather the simplest algorithm that is sufficient for tackling a particular business problem. Deep learning may in fact not be the best methodology for tasks that require explanations or confidence intervals. Medical diagnosis with AI should not rely on black-box methods whose inner workings cannot be understood.

Machine-learning algorithms vary by community and application domain. Most algorithms under consideration belong to the supervised learning category, with a few important exceptions, such as stochastic topic models in natural language processing, that belong to unsupervised learning. Here are a number of algorithms that have been applied in successful AI projects.

6.2. Training Models

Training models—building the machine learning model that implements signature detection—is the real goal of the project, but proceeding at a brisk pace is productive. Budding data scientists can always return to the detection project with the benefits of additional capabilities and experience gained elsewhere.

The process needs to start with the output of detection: a set of data samples, each one tagged with its corresponding label. The project that follows—Modeling1—combines and transforms the detection output to create labeled datasets used to train the signature classification model.

Modeling completes the first steps in the lifecycle, Initiate, Assess, and Model. A tutorial guides readers through the project on Microsoft Learn. A condensed summary follows here.

Pragmatism drives implementation details. Project files encapsulate the lifecycle approach in a ModelBuild pipeline running in the cloud, with training jobs executing in Amazon Web Services (AWS). The demonstration employs a lightweight Elastic Compute Cloud (EC2) instance optimized for CPU resources and balance between compute, memory, and networking. The cloud compute, memory, and networking options remain highly customizable, eventually incorporating Amazon SageMaker Hyperparameter Tuning for automatic optimization of CPU, memory, network, and storage settings.

6.3. Hyperparameter Tuning

The term “Hyperparameter tuning” refers to the process of searching for the set of hyperparameters of the machine-learning model that yields the best performance. Hyperparameter tuning should ideally be performed in the same cloud environment where the serving model is deployed and served. There are two types of workflows for hyperparameter tuning:

One workflow is to trigger the tuning process as part of the deployment, either through a cloud management system or an orchestration tool such as Airflow; the other workflow is to conduct interactive tuning using a Jupyter notebook in order to improve the hyperparameters identified through the first workflow. Experiment tracking can be performed with an interactive workflow, or it can be integrated into the training job of the deployment pipeline for better reproducibility. An interactive hyperparameter-tuning workflow looks like this:

1. The data data.csv is extracted from the data source and prepared for Modeling. 2. A new Jupyter notebook is created using the Best Practices Pipeline Template project template. 3. Hptuning.ipynb is selected as the Jupyter notebook name. 4. Hyperparameter tuning is specified.

7. Model Evaluation and Testing

The definitive guide to planning, building and deploying AI projects: Discover sample projects, design sample data pipelines, and examine how to deploy AI models in cloud environments. This section provides essential information for readers aiming to explore practical applications of AI from inception to completion.

Sample AI projects illustrate AI use cases in a broad range of industries, from banking and finance to gaming and online gambling. For each business domain, jobs to be done or use cases are examined. Sample data pipelines show how data engineers prepare data sources for AI model training and deployment. Sample production pipelines illustrate how production software engineers deploy, monitor, govern and troubleshoot AI running in production.

7.1. Evaluation Metrics

Evaluation Metrics Machine learning evaluation metrics serve the purpose of assessing models and making suitable choices. Although they share many similarities with statistical analysis, they remain simpler than complex, multifaceted business metrics. The selection of specific metrics is more of an art than a science; different choices lead to different conclusions. For example, in text classification, one can evaluate sentence-level precision or recall, word-level perplexity, word error rate, or semantic consistency alignment. Regardless of the model type (supervised, unsupervised, regression, or classification), applying appropriate evaluation metrics to training and testing results is necessary. During Stage 2 of the Sample Project Lifecycle, comparing various metrics helps determine the best approach. Machine learning evaluation metrics fall into three categories: classification, regression, and clustering. Classification Metrics Formal model testing requires the use of a dedicated test set, separate from the original training data; otherwise, final results might be misleading. Classification involves choosing the correct class label for each instance, as in spam-filtering email, part-of-speech tagging for text classification, or recognizing images of cats versus dogs. Important considerations include which classes are most important and how to handle incorrect classifications. Several evaluation measures exist: • Accuracy measures the percentage of examples accurately classified; however, it can be misleading with imbalanced classes. • Precision measures the proportion of correctly classified examples for a particular class. • Recall also considers how well all examples for a specific class were classified.Evaluation Metrics Machine learning evaluation metrics are useful for model assessment and selection. While related to statistical analyses, they are less complex than multifaceted business metrics. Choosing appropriate metrics requires careful judgment, as different selections can yield varying conclusions. For instance, in text classification, evaluation can focus on sentence-level precision or recall, word-level perplexity, word error rate, or semantic consistency alignment. Regardless of model type (supervised, unsupervised, regression, or classification), suitable metrics must be applied to training and testing results. During Stage 2 of the Sample Project Lifecycle, comparing multiple metrics informs the choice of final model. Machine-learning evaluation metrics are organized into three categories: classification, regression, and clustering. Classification Metrics Formal testing necessitates a dedicated test set, separate from training data, to ensure meaningful outcomes. Classification entails assigning the correct class label to each instance, as in spam filtering, part-of-speech tagging, or distinguishing cat and dog images. Key considerations include identifying critical classes and evaluating the impact of misclassifications. Multiple evaluation measures exist. Accuracy represents the percentage of accurately classified examples, but it may be misleading with imbalanced class distributions. Precision reflects the proportion of correctly classified examples within each predicted class. Recall assesses the completeness of correctly identified examples for each actual class.

7.2. Cross-Validation Techniques

When developing a deep learning model, such as one for the applied project in this book, it is always best practice to partition the labeled dataset into training, validation, and independent test sets. The rationale for splitting the data is to continually estimate model performance during training and perform repeated experiments to optimize model hyperparameters without overfitting the model on test data. This reality often generates debate among data scientists, with some arguing that the performance gained from cross-validation compared to having a separate test set is valuable enough to forego an independent test set. However, given the ever-decreasing costs of both data generation and computation, this debate is less relevant.

In k-fold cross-validation, a labeled dataset is split into k folds, or mutually exclusive and collectively exhaustive subsets. The model is then trained and tested k times, taking the output of the test fold, either the loss or performance metric, and averaging all test folds into an overall performance for the model. To optimize hyperparameters, this training and testing procedure is repeated for each hyperparameter combination. After identifying the combination with the best test results, the hyperparameters are fixed, and the model is retrained and re-tested on the training and test set using the same partitions that were used in the cross-validation process.

Conclusion

A detailed list of serverless applications hosted on [Link] is valuable for anyone interested in the serverless and event-driven application ecosystem. The collection is organised by Cloud providers, Applications, Utilities, Open Source Projects, and UI. Another useful resource is a serverless applications list designed to maintain a collection that inspires, highlights, supports, and promotes Serverless and Event-Driven Architecture.

The term "serverless" does not mean there are no servers; rather, developers do not have to manage any server resources. All resources are managed by the cloud provider cloud. Many companies dispense with server management for their services. Instead, their backend consists of functions hosted on cloud platforms. The provider manages servers, containers, and scaling, allowing developers to focus on business logic. Examples include API Gateway with Lambda from AWS, Cloud Functions from Google Cloud, and Azure API Management with Functions from Azure. For a practical implementation, the complete code of a 'Machine Learning Model Web Service' example demonstrates data pipeline automation, model deployment, and monitoring in the cloud.

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