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Chapter 6: Credit intelligence: Real-time credit monitoring, scoring, and management using artificial intelligence models

6.1 Introduction

The aggregation of data from a variety of sources opens up a wealth of actual-time insight into the health of a business in several sectors, such as manufacturing, retail, and telecommunications. Many credit bureaus already monitor effects of ongoing events on the creditworthiness of businesses instantly. These realities introduce the need for a trustworthy AI credit risk evaluation system that produces scoring results that are motivated technically. Such transparency and trust of the scoring agents are important for acceptance in the Board of the agency or to the top management of this agency. Gatherings of norms and standards for trustworthy AI systems also reinforce this necessity. Therefore, typical documents from the loan application or other financial reports are seen as insufficient. A combination of these documents with techniques that are capable of understanding the language of natural language processing (NLP) is a promising solution to be investigated (Chang et al., 2017; Hsihui et al., 2017; Bandi et al., 2023).

When analyzing a re-balance of credit scoring agencies in terms of scores that followed a newcomers' defaults of loans, retroactive shock impacts on score behaviors are carefully examined in further depth. With appropriate explanations based on the changed parameters, an essential feedback to the modeling agent is reported to be essential to avoid future similar issues. In terms of accounting systems changes, explanations designed for the credit score agency are similarly found useful. It is also desired that retail institutions whose services are impacted by such changes get intelligible explanations, so that their product offerings may be modified accordingly.

The number of credit scoring models in use, their corresponding formulae, and their authority within an organization all grew in the last decade of the twentieth century. Fundamentally since the turn of the twenty-first century, many societies in every part of the world began to experience a level of laxity in two markets, credit and housing, because consumer demand far exceeded the available supply. There was a general sense that the World was riding a boom characterized by a wealth effect, but for a few sharp analysts, the models under scrutiny were clearly outdated. The first hint of mispricing was offered by the collation of credit scores – models learnt a decade and more before and meant to benefit the inclusion of the financially marginalized in a more general economy. These models demonstrated clearly that a new class of Big Data was ready to be accepted for credit risk assessment. The idea that the more data the better was no longer universally credible (Munoko et al., 2020; Munoko et al., 2020).

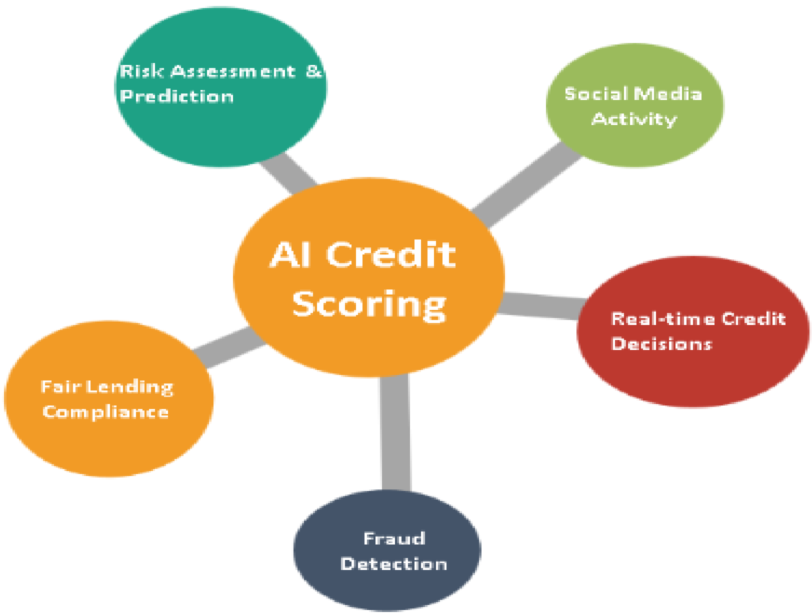

Fig 6.1: Artificial Intelligence Credit scoring

6.1.1. Background and Significance

Credit scoring, a statistical analysis method for assessing creditworthiness, is one of the oldest applications of analytics. The Fair Isaac Corporation, established in 1956, is an American corporation that provides analytic software and services to assist businesses in finding, acquiring, and retaining customers, as well as in credit solutions and fraud investigation. Fair Isaac was an early leader in developing credit scoring services for retail credit and is best known for its FICO score, a proprietary credit score developed in 1989 that uses data from commercial repositories. FICO scores can affect an individual's credit rating, automobile insurance costs, and employment prospects. Banks, credit unions, retailers, insurers, and utilities companies all use FICO scores. In fact, corporate credit scoring gained popularity in the late sixties with the development of the z-score model for bankruptcy prediction. One of the original z-score models is still in heavy use today, fifty years later, for its faultless predictive performance. Nevertheless, corporate credit scoring was mainly built on the back of statistical methods such as linear programming, discriminant analysis, or logit regression, all of which were novel forty years ago. Models were built using smoothly collected and likely punctual, but limited, accounting data, especially because corporate credit risk assessment was initially restricted to the corporate purchasing or supplier agreements. However, the use of credit scoring models by financial institutions began to proliferate in the nineties with the rise of a new regulation horizon within and outside the US. The Basel Accords imposed a risk-weighting approach for assessing Financial Risks at the level of credit portfolios.

6.2. Understanding Credit Intelligence

Historically, banks and other financial institutions utilized the Cost-to-Income Ratio to gauge a current account holder's eligibility for a credit card, loan, mortgage, insurance plan, etc. However, determining this ratio proved arduous and impractical due to the multitude of factors that constituted it. To mitigate fraud and defaults on loans given to the applicants or account holders, a subset of organizations has hired analysts, Forensic Auditors, Statisticians, and Risk Management and Liquidation professionals to assess a current account holder's reliability. Likely, fraudsters learned to conceal records related to their insufficiency or falsify existing records. The foreseen complexities rendered the traditional regime ineffective, requiring a solution that could yield a higher degree of detection. Consequently, a system that employs the constituents of the Cost-to-Income Ratio, their weights, and a model trained with historic mistakes cases, credit behavior, and changes in macroeconomics to generate a real-time scoring for a current account holder was developed.

In the context of a company's credit risk, the Credit Risk Assessment (CRA) line of business estimates the probability of default of companies, allowing for a rejection of the requests that are deemed too risky and the establishment of a loan plan for the accepted ones. Automated Credit Risk Scoring (CRS) models have been developed to assist credit risk experts in their task. However, it is known that the employed Machine Learning (ML) approaches are black boxes.

6.2.1. Definition and Importance

Credit risk and credit score can be regarded as the same things. The latter can be defined as a number that reflects the credit risk of a borrower, whereas credit risk can be defined as the risk of loss that arises from the failure of a borrower to make required payments. Credit risk is recognized as one of the biggest risk categories in the banking sector. A proper credit score enables the understanding of this risk. Credit score is often obtained from complicated by-learned models such as logistic regression or neural networks. Recent works show great interest in mixed models or ensemble models, which combine models of different types to obtain one final score based on individual scores from different models.

Some interpretability techniques that suit the understanding of individual or one type of models are also employed to mix models. Simplicity-based techniques such as LIME are not only popular but also relevant for mixed models. However, most of the existing techniques are post-hoc techniques that often prevent insights from credible expert risk analysts from being utilized in the model building stage. Feature importance, model simplicity, interaction, and data distribution are some of the most important properties for explaining a model. Good mix interpretation offers insights into both interpreting a model and using it in practice with experts. Understanding how to make a good mix interpretation brings interpretable boost to mixed models. Under this insight, a new family of interpretation techniques is developed by interpolating the objective functions of existing models to search for interpretable mixed models.

Seven years later, credit intelligence based on credit scoring is missing in practical applications. Credit scoring is a procurement service for allowing intelligent lending decision based on personal information. Using simple rules to score a potential loan is one of the common practices in small or personal loans. Credit scoring services are not new. However, there are still many unexplored areas in this field, especially on the research side. Constellation of basic modules are employed in the bank loan credit scoring based on commonly available data sources and are also considered as a reference framework to implement commercial credit scoring services.

6.2.2. Historical Context

Credit scoring, a widespread application of analytics, has become crucial for financial institutions globally. Traditional scoring models are based on historical credit data and the assumption that past behavior is a reliable predictor of future behavior. Computation of credit scores using these traditional models is typically a slow batch process, making it impossible for lenders to adapt credit policies in response to rapidly changing external or internal events. The recent success of AI models has raised hopes for overcoming these difficulties.

Part of the failure of traditional models to react to events in a timely way is due to the choice of the historical data upon which the models are based. Credit scoring using databases with dynamic information has been dismissed as impractical. A new approach is proposed: Credit Intelligence. The main idea is to monitor credit risks in a way analogous to monitoring stock market trades. As in the latter case, it is proposed that data describing consumer behavior towards service provisions, specifically mobile phone usage, can be exploited. Moreover, automated procedures for classifying risks and for scoring them based on machine learning methods are developed, creating the possibility of adjusting credit policy in real time or on a very short basis. A very low threshold is suggested for ensuring baseline performance of the credit scoring model.

The proposed framework is intended to complement but not replace complex traditional credit scoring models. Generalized credit monitoring capabilities capable of producing simple credit risk scores are envisaged as a new and worthy tool for lenders that do not possess historical credit data. The focus here is on its applications using mobile phone data.

6.3. The Role of AI in Credit Monitoring

Credit risk predictions from alternative data have limited testing on its generalization ability and soundness. This study presents an extensive set of recent datasets to facilitate the evaluation and analysis of credit prediction models. With the presented datasets, common credit prediction models are evaluated regarding their performance and vulnerability to test data carryover. Social network data and graph-based methods are shown to be leading solutions for credit risk prediction tasks. For the credit score estimation task, feeding a tailored longitudinal view of the financial activity is beneficial. The presented data sets reveal the credit risk assessment process and encourage more attention towards alternative data and edge case analysis. Credit risk scoring is vital for financial institutions, as it allows a better understanding of a customer's credit risk profile before granting loans. Recent developments in Machine Learning (ML) and other Artificial Intelligence (AI) setups are being applied to credit risk applications. Nonetheless, most AI applications are labelled as black-box models as they lack explainability concerning the output decision. Therefore, understanding the model logic is crucial for effective decision making. In this study, credit assessment is followed as a test case towards lightening the black-box behaviour of AI techniques. Indeed, credit assessments allow the global economy to grow and are fundamental products offered by financial institutions. Furthermore, automating the credit risk assessment process allows credit risk experts to reduce their workload, therefore spending less time conducting credit risk analysis and making room for other analyses or improving the decision making process. This study aims to benchmark different ML models predicting whether a company will experience financial problems with the focus of analysis on explainable AI techniques. In order to tackle the black-box problem, i.e., understanding the credit scoring decision made by one of the selected ML models, the eXplainable Artificial Techniques is addressed. The proposed approach provides an expert-aligned feature relevance score to quantify the convergence towards better human-aligned decision making. Credit risks refer to the risks that the borrower is unable to repay the principal in time in the loan. The financial institutions, which are the lenders, will suffer in the case of credit default, which means the loan failure to repay. The theory of credit risk describes the uncertainty in the borrower's ability to service their debt in terms of credit default. A credit default is the credit event that the borrower has entered into bankruptcy, delayed repayment for a long time, or failed to make loan repayments for many days. When a credit event happens, the lender financial institution has to calculate a series of economic losses according to the amount of loan defaulted. The valuation of credit risk is therefore of great importance and value. Credit risk analysis attempts to discover a mathematical model to evaluate the credit risk in the lending process, based on historical loan status data of a debitor.

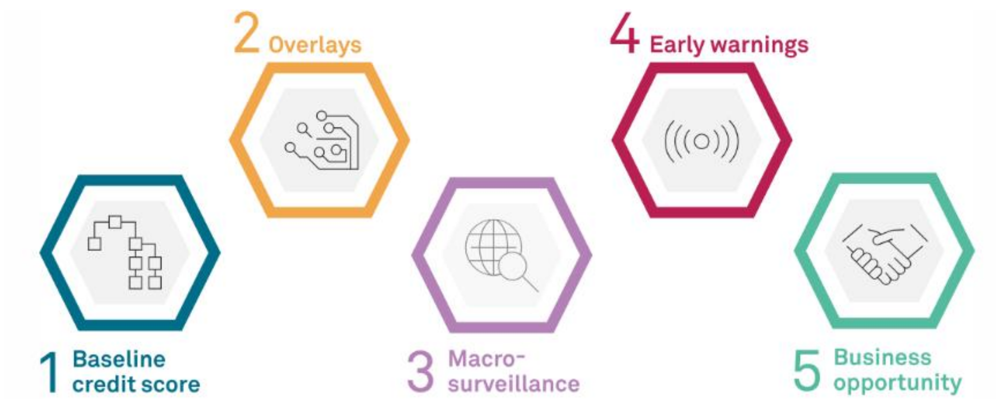

Fig 6.2: AI for Credit assessment and monitoring

6.3.1. Overview of AI Technologies

The Big Data revolution, fueled by the Internet and the explosion of social media, has become a significant contributor to companies' transformation journeys. Companies are flooded with masses of data generated daily by natural and human activities. These datasets, characterized by their sheer volume, variety, and velocity, have spurred the emergence of the term "Big Data." In the past decade, the injection of Big Data into various industries has led to unprecedented opportunities to drive innovations in product development, marketing strategies, and consumer engagement approaches, giving rise to disruptive changes to a company's value chain. A suite of new technological frameworks has been proposed to facilitate the processing and analysis of Big Data. Cloud Computing has been frequently adopted by companies around the globe to harvest the power of unified data storage and processing resources while minimizing maintenance costs and maximizing self-service convenience. Social Network Analyses have been developed to mine commercial value from consumer-generated posts disseminated on online social media. Machine Learning and Algorithmic Forecasting methods have been leveraged to predict customer behaviors and automate data-driven decision-making processes. While companies are benefiting from the Big Data revolution, the black-box nature of non-explainable AI has been limiting the applicability of AI in high-risk industries – such as Finance. AI's automatic decision-making abilities on high-stakes applications may unintentionally exacerbate algorithmic discrimination and systematically disadvantage certain groups. To tackle the Opacity challenge, a plethora of eXplainable AI techniques – which facilitate human understanding of the decision-making logic behind AI predictions and recommendations – have been studied. However, transferring existing XAI mechanisms from traditional machine learning methods to the interpretable designs is nontrivial. The goal of this section is twofold, starting with a brief overview of the various AI technologies that have been used in Credit Range Technologies, followed by a discussion of how these technologies can be enhanced by using novel designs, such as explainable and robust AI tools. In the past decades, a surge of algorithms from AI domain-dedicated disciplines has unlocked unprecedented capabilities to perform "intelligence tasks" with varied types of real-world data.

6.3.2. Data Sources for Credit Monitoring

Given the deluge of consumer data with profound ramifications on creditworthy assessments, the prolonged interactions between networks of customers, banks, and lenders can reasonably be seen to pose an identity risk that these organizations were oblivious to. For example, with advancements in technology and a switch to data-driven approaches for risk management, banks are relinquishing their positions as central actors in credit networks. Private investors, credit bureaus, and insurers circumvent the walls of banking secrecy by using proprietary black-boxed models whose ramifications on society remain unknown. Following the selling epidemic on revolving student loans at American banks, the veiling of the workings of and data on the mathematical tools used for consumer risk modeling is not new. Academia needs to embrace mathematical modeling as a well-informed responsibility.

New avenues for research encompassing the surveillance of consumer data are foreseen, which could fixate on analyzing changes throughout recent pandemics or a looming cashless society. New lines of mitigation, validation, compliance, and regulation, and a basis of assessment and potential accountability for the role of mathematics in data-predicted risks on consumers is foreseen. With the increasing possibilities entailed in university courses, hiring skilled students on high-level mathematics modeling may become vital. It is nevertheless enunciated that safeguarding privacy concerning mathematics-fed models is difficult, if not impossible.

6.4. Real-Time Credit Scoring

The estimated annual revenue for the global over-the-top (OTT) market grew significantly from 12 billion USD in 2014 to 314 billion USD in 2022. OTT is defined as the delivery of film and TV content via the Internet, without the involvement of a multiple-system operator (MSO) in the control or distribution of the content. In order to gain a greater share of the OTT content delivery market, OTT service providers need to make decisions regarding investment, acquisition, and promotion on services containing arbitrary content. Due to the abundance and geographical diversity of services and subscribers in the industry, OTT service providers are facing a significant challenge to accurately assess and adopt the right end users and content.

To evaluate OTT services and subscribers, four domains of general issues need to be considered: subscribers' state assessment, ranking and recommendation of services, content sequence analysis, and anomaly detection. Specifically, they include dimensionality reduction of service contents and subscribers' behaviors, high-dimensional pattern discovery and modeling, and real-time scoring of the dimensionality-reduced contents. In addition, the increasing size of streaming media services has made it a challenge to accurately assess and rank content in a reasonable amount of time. In order to keep anonymity, the names of companies and products are replaced by fictitious ones while the case is based on real research. Similar thoughts and work are expected to be applied and drawn with regard to other services.

It is believed that the proposed research ideas, architectures, and methodologies could sufficiently address the challenges in both the OTT and crowd-sensing service industries. In particular, with regard to the OTT services, they will go through the evaluation of the contents and the subscribers. Once an appropriate method for subscriber state assessment is established, the establishment of other evaluation methods is simplified since they all work on the same view of context knowledge computation. In addition, as deep learning models have been used for the service quality and subscriber behavior assessment on streaming media contents, the adaptation of existing models or encoders will be feasible for the evaluation of other types of services once the assessment procedure is established.

6.4.1. Mechanisms of Real-Time Scoring

Credit instability threatens the smooth running of the banking business, and dynamic supervision around credit scoring, assessment, and allocation is needed to prevent loan default. Major banks allocate extensive resources to regulatory compliance, credit monitoring, more detailed analyses, and reporting procedures, often resulting in impoverished data limitations on creditworthiness prediction, which neglects some of the default cases since the model lacks online data. Financial institutions can turn to public big data as an alternative to formal credit report data for information inference through model transfer. However, these data-driven methods are still held back by the cold-start problem, as users with limited credit records would not attract sufficient attention. Development of a novel online decision towards financial beyond the challenge makes use of online consumer-generated content and turns real-time supervision around and credit scoring as a secondary priority. The novel solutions based on text mining and transfer learning successfully break the deadlock by providing a personalized, comprehensive, and transparent credit insight. The in-depth analysis of designer rules sheds light on better feature engineering towards credit scoring. Extensive experiments validate the effectiveness of credit intelligence on a large-scale dataset.

With the rapid growth of the online financial market, credit assessment and scoring based on historical data, models or rules and documentation are lagging behind since the on-time generation, trade, and analysis of new data present unmatched challenges for the traditional credit methodologies and tools. Online public information, like user posts on social networks and transaction records on e-commerce or thematic websites, provide unprecedented opportunities for information inference in decision tasks like credit scoring, but are often held back by the application resistance risk brought by the biases when being misused. Public big data-driven credit scoring systems also face the cold-start problem. To resolve the core problem of real-time monitoring and credit scoring in a nature collaborative paradigm of trade-off transparency and data protection, Credit Intelligence deals with consumer-generated content that is unstructured data of diverse nature and heavy redundancy and takes advantage of community economy by extracting a flow of on-time user-focused demand calls. This enables an integrated inference of creditworthiness, even on users with limited historic credit records along with novel approaches of text mining and transfer learning that are advanced from nuts and bolts.

6.4.2. Comparative Analysis with Traditional Scoring

The credit score is often reduced to a single number, which does not fully express the rationale for it. Most traditional scoring models in use today behave in a way that doesn’t comply with such best practices for machine learning models. They are typically used as a black box: A client is scored, and the lender receives solely the value of the score.

In most cases, corporate lenders only use the score, leading to a situation where often judgment is not backed up with data-driven rationales. The introduction of a better and more interpretable score is then paramount to improve transparency in the credit industry, speed approvals, and offer better user experiences in general. In addition, banks, credit bureaus, and regulators all need to explain the criteria for producing a score to stakeholders. With the rise of Non-Banking Financial Institutions (NBFIs), the rapid turn-around of Artificial Intelligence (AI) approaches that are too smart, and the widespread adoption of proprietary models that are hard to extract from, this is increasingly becoming a challenge. The results of a comparative analysis between the benchmarking traditional model and recent AI/ML techniques are presented. First, it is shown that traditional models outperform deep ensemble techniques in terms of classification performance and in its role to discriminate and resist extreme values. More traditional models have better calibration, higher interpretability, and require a far lower number of parameters. The practical implications of providing only the score versus providing the model as well point to the direction that while scoring techniques could be used as a service given, the implementation of model-based systems cannot be decoupled from the lenders' decision-making. Traditional models outperform recent AI approaches in both classes of reasons supplied to explain the final recommendation.

6.5. AI Models for Credit Risk Assessment

The models presented in this section use credit activity history, i.e., past loan payments and account management behavior, as input features to monitor creditworthiness in real time. Models can have online and batch settings. In the online setup features such as event count or recent payment streak counts are updated immediately on a new observation while weights or a model are updated every few new observations or when new data are available in the batch manner. The underlying machine learning models can be parametric, such as logistic regression or support vector machines, recurrent architectures such as long-short term memory or non-parametric models such as k-nearest neighbors.

The earliest work on machine learning models in credit scoring is by Weiss et al. who use regression trees as classifiers on banks data. Ridge and lasso models are used to compute the probability of default among a population of firms based on balance sheet data. Boosting and bagging algorithms are used to improve the performance of credit risk models based on financial statement data. Random forests are used to obtain a better understanding of the impact of explanatory variables on credit risk through variable selection as well as prediction accuracy. Other machine learning models such as path and combination trees as well as k-nearest neighbor regression are used. Support Vector Machines (SVMs) ensembles account for a larger share of the credit scoring marketplace. Small, selected, simple and interpretable models are preferred in banking, for compliance reasons. Despite this regulatory burden, it can be expected to see an increasing use of more sophisticated machine learning-based models in credit scoring.

Several supervised learning techniques from different research domains, such as classification, regression, and time series, can be applied to credit scoring. From the latter mentioned groups, only regression techniques are applicable. The first two groups are accommodated with the system's design. Classification-based systems are also able to monitor a subject’s credit score on a day-to-day basis. Depending on the availability of data on the subject, it can be either extensive or sparse. Owing to the fact that, generally, not all if any attributes from the descriptive model are reliable on a daily basis, different modeling techniques are applied for the exhaustive and occasional data update scenarios.

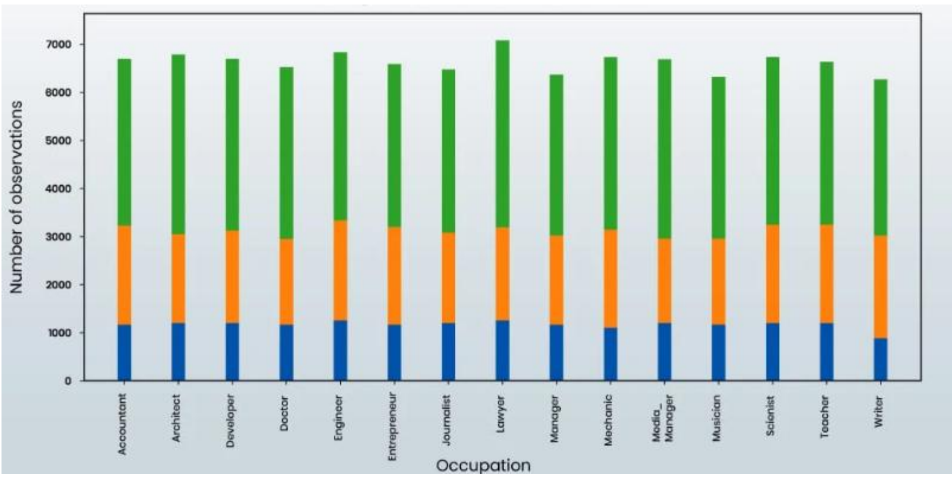

Fig : Credit Scoring Model

6.5.1. Supervised Learning Techniques

Many regression and classification tasks can be treated as credit scoring problems. One of the areas where machine learning techniques are used extensively is credit scoring, particularly for consumer loans and credit card services. Consumers are evaluated when they apply for a credit card, a loan, or a mortgage. Based on the evaluation scores, the consumer’s application is either approved or rejected. The classification models developed in this area are classified as credit scoring models. Main assessment criteria on these models being: Maximal predictive power (score accuracy) of their results, or maximum credit risk prediction. The final assessment score that represents the level of risk is usually a function of the credit scoring model. Some models output a faultless classification, for instance, a tree-structure-based credit scoring model in which the branches end in either a good or bad classification.

6.5.2. Unsupervised Learning Techniques

The unsupervised learning methodology can be used to find patterns in enormous amounts of data. Since credit decisioning has been around for centuries and loan data has been collected for almost as long, massive amounts of information have accumulated that hold insight into the circumstances that influence defaults and prepayments. When evaluating the decisions made when turning information into scorecards, machine learning for data representation, dimensionality reduction, and feature extraction could produce useful feature variables that would either tackle the scorecard evaluation of the most valuable proportions of the data or act as blocks in scorecards.

A definite area of opportunity in terms of data outside of the procedures defined is that while most lenders focus on customer data against which to score applications, post-contract data is an unused field of data that is readily available and would score exposure against appropriate data. There are often patterns indicative of an event before the outcome occurs and a consideration of post-contract behavior can augment a model to identify fraud at or soon after the time of application. There is often a certain period where adjustments will occur on a loan. For instance, with a number of interest only term loans, the behavior on the run-off date would become markedly different. Not allowing for this within a default model can lead to distorted outcomes. Consideration of a pool's performance can allow asset scores to be created prior to exposures being originated. Consideration of these factors could lead to a market advantage, which could result in a clear strategy to implement as the techniques used in evaluation are fairly clear-cut.

A scorecard data pool would allow for consistency in data preparation and modeling across the industry and potentially allow a new data source for industries that are either emerging or currently unbanked to commence development of the methodology for scoring. Thought would have to be given to the concerns surrounding data quality, classification, standardization, and privacy, and a consortium approach would likely be necessary to deal with standardizing practices potentially across industries. There are parties that have operated in this arena previously in other industries which could provide a foundation on which to build. Quality is paramount in ensuring equitable discrimination and would require robust processes to filter out outliers in rating factors prior to variable selection.

Meaning extraction from these models has often proven elusive with techniques typically not well understood nor industry standardized having to be leveraged. There are a number of parties who have invested significantly in making advancements in this field and who would be suitable partnerships for cross-industry validation in this area, especially as there would be a mutual benefit. Given that a number of corporations or start-ups have begun operating in this area and provided results, the time to investigate partnerships for the development of competitive advantage is now.

6.6. Data Privacy and Ethical Considerations

Currently, it is problematic for non-response analysis to use the maximum likelihood method to prevent extreme values from affecting the achievement of the population mean since 1) the extreme value is true and has high trust, excluding it from analysis would cause bias; 2) the extreme value score high for the credit score-testing indicator as result of obtaining exposure to extremely high risk loans, yielding incorrect merits of trustworthiness if included in analysis; 3) impossible to characterize acceptable range for extreme value since extreme situation differs vastly among users. Based on these limitations, potential users thereby legitimate credit intelligence so as to enhance decision efficiency, including a) inclusion of a well-defined set of user behaviors into the information collection process, balancing between ever-growing index library and user modeling accuracy; b) maximum likelihood estimate of parameters in propensity score model with a fixed/assumed behavior screening criterion; c) Active information subsampling and ranking to facilitate personalized real-time credit intelligence from copious signal information. Although there are to some extent government regulations or ethical standards ensuring against AI and big data cost-sharing equity and social responsibility. Credit intelligence modeled by AI could infringe on users' freedom of choice and cause gray microtargeting, similar to online recommendation video, ad, and post-purchase analysis. Fairness/legitimate methods or mechanisms thereby adjusting behaviors of credit intelligence modeling could be explored. Another structural or integrity analysis could be eliminating effects/usage distribution of the tagged legitimate/illegitimate credit intelligence with test datasets.

6.6.1. Regulatory Frameworks

The amount of digital data generated by the applicants has risen quickly in the last fifteen years, and financial institutions have shifted their approach to credit scoring models and the credit risk management system as a result. AI is becoming more popular for the creation of credit scoring models that reduce human interference in the modeling process and expedite model development and monitoring. Traditional Machine Learning (ML) models have been professionally grounded in an interpreter-dominated view of risk assessment. However, with the emergence of automated and self-learning models, concerns about an interpretation-dominated mentality are arising. Recently, regulatory entities have moved fast to catch up with this evolving world. The European Parliament and the Council of Europe have released the General Data Protection Regulation (GDPR) and the Machine Learning Act (MLOPS). In a similar vein, the European Union Banking Authority (EBA) has published the guidelines on ICT and security risk management. Natural language processing (NLP) and ML models have become available for credit scoring modeling in the last two years. The provision of these models raises the issue of whether they comply with the requirements of these regulations. The potential lack of compliance with consumer credit regulation is also another regulatory risk encountered in compliance-oriented assessments. The one million loan application records the recent event through an application programming interface. The goal is to develop interpretable credit scoring models that are compliant with the Machine Learning Act. Bridging the gap between regulatory requirements and modeling practice is a challenging goal due to the stringent requirements of explainability, fairness, and non-discrimination on model output, input features, and training datasets. Within a pipeline with diverse pre-processing, feature engineering, and model building modules, ML models with different levels of interpretability are developed. A comprehensive set of policy regulations is also established, where each regulation is linked to the refunded compliance strategies with a conformity check mechanism. The risk assessment task of financial credit scoring can be modeled as a binary classification problem, in which the goal is to predict whether a company will experience financial problems in a given time horizon. Together with a dataset containing company features and information of past bankruptcies, this model can help credit risk experts in the identification of relevant companies for credit risk inspections. XAI methods, aftershocks, and application silhouettes, have been developed to help experts gain deeper insights into the model predictions and representations. Output explanations are provided in the context of model-based and model-agnostic approaches, where tree-based, and black box, models are attempted to explain their predictions. As a case study, the explanation of a voting classifier featuring ensemble learning with local interpretable model agnostic explanations is provided. Besides, the effect of interexpert disagreement on explanation evaluation is highlighted in a pilot study.

6.6.2. Ethical Implications of AI in Credit

Artificial Intelligence (AI) has been heralded as a great potential solution to the challenges financial institutions face and can potentially offer solutions to issues from ML onboarding to customer complaint log processing. Although AI has great potential, it could just as easily be a potential threat to the financial system and global economy as it was with mass loan defaults leading up to the 2007 Crisis.

While methods including supervised and unsupervised learning and generic algorithms have been studied, their ethical implications have not been thoroughly discussed. The most pertinent ethical implications of AI systems in finance are biased decision making leading to systemic discrimination against marginalized groups, unintended exploitation of consumers via artificially intelligent trading bots, lack of accountability for financial decisions rendered by AI systems, and greater systemic fragility. In vulnerable communities, machine-learned algorithmic trading strategies could exploit avoidable volatility, keeping market prices stable for the wealthiest before gamifying the disorder for profit.

Critics generally argue that for the AI-based credit risk assessment to genuinely increase efficiency, it must be thoroughly examined for biases in the training data set. Prior to any deployment, scrutiny must be undertaken, engendering proper checks and balances across the process (not just on the model where blame could easily lie). Without proper attention, little-known and insidious biases could be exploited by any party with access to or means of directly altering the training data set. Otherwise, previously unexamined institutions might become perpetuated simply because they were the ones to benefit financially from credit-scoring transparency initially.

By intelligently contemplating lip service to fairness and glamour-shrouded adventures into the trumpeted dawn of explainable AI, the well-intended exasperations surrounding 21st-century credit risk assessment could render it dangerously inert. In the wake of the great market crash, with the wealthiest firms "gaming" the system and the other actors' vulnerability preserved, "responsible AI" may need to be decidedly defined or again face iterations of puffed promises to algorithmically render the world more fair. In legacy systems where human input is a necessity, tradeoffs could be made regarding comprehensively scanning the market for credit assessments from history.

Generative approaches to the task of credit assessment upon policy contract compliance satisfaction inevitably relegate control to the unscrutinized discretion of the machine. Understanding the valid mechanisms by which an AI implements process payoffs could obfuscate much of the resulting delineations with respect to knotted, difficult-on-its-face decision sets.

6.7. Conclusion

This chapter reviews the important applications of AI models in credit-related topics. Specifically, this chapter discussed recent works in regard to real-time credit monitoring, scoring, and management. The comparison is made between traditional methods versus accommodate AI model applications. Also, the needs for AI-based methods with all relevant operations, including credit data processing, credit default signal definition, model training and validation, model deployment and interpretations, and system implementations, are summarized.

As the market's demand for credit institutions for real-time credit-related tools continues to grow rapidly, accommodating AI models for credit operations will be a critical task in financial institutions. Moving forward, several challenges have to be addressed, the first would be data-to-Inference framework building, where it can involve traditional and non-traditional data exploitation, appropriate credit analysis and labelling choices, model setup definition, and ready-to-market environment building. Combined with properly designed workflows, the building of AI systems can reach timely and explainable outcomes. In addition, enhanced interpretability aspects have to be put in place to gain the trust of the internal users, where borrowers most affected by the predictive decisions should be reviewed.

Turning back the positive prospects of AI models application across credit operations, financial institutions should be informed with data-driven insights on their internal equity as credit analysis is basically a people-driven edge. One way to unfold non-transparent code embeddings could be to view estimations at an individual ‘customer level’ .

6.7.1. Emerging Technologies

Banking institutions typically perform a series of scans when processing a credit application. The application is assessed against predefined parameters and an investigation into the applicant profile is performed. Then, data is gathered from credit bureaus and alt-data sources respectively. Finally, this data is transformed for Automated Decision Making processes. On the other hand, during the credit scoring process, only some of the data gathered in the previous step is used to calculate a score and make a decision. Given the multitude of data sources and methods of processing this information for credit scoring, a cloud-based platform was developed for real-time credit monitoring, scoring and management by banks, financial institutions and alternative credit companies. The application streamlines the data sourcing, analysis and scoring processes for the user, but has functions that allow banks and credit institutions to manage their clients and loans. Start-up has created a cloud-based platform for credit monitoring and scoring by integrating and refining multiple data sources using knowledge on credit scoring and machine learning. It allows banks and credit institutions to manage their portfolios, loans and clients. During the design process of the platform, attention was paid to both financial inclusion and ethical use of data to provide fair credit opportunities. The software gathers data, analyses it and calculates a score and a recommendation. It can act as an interface for credit monitoring, management and scoring and as a tool for data sourcing, aggregation and enrichment for other systems. The input for the score can either be a person or organization profile, so the number of entities and formats that a bank has to handle can be minimized. By doing a single investigation of a potential client, the bank has access to credit scores for consumer loans, small loans to micro enterprises, and corporate loans. Negotiations can be carried out in person, via chat sessions, or directly on the platform GUI via numerous prepared documents, tables, and reports.

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