Deep Science Publishing
https://doi.org/10.70593/978-93-49910-41-6_5

Chapter 5: The anatomy of credit risk: Traditional models vs. intelligent systems

5.1. Introduction to Credit Risk

Credit risk management is a field that continues to require thorough research, owing to the fact that the inability of borrowers to service their obligations has led to the failure of numerous financial institutions. Traditional models, some of which were developed over half a century ago, have been used widely to evaluate counterparty defaults. However, as demonstrated in the latest financial crisis, these models have not been successful in capturing the main risk drivers that have been responsible for the adverse developments in the credit quality of borrowers. The purpose of this paper is to present the evolution of credit risk modeling from traditional models to intelligent systems. We aim to draw useful conclusions, which could add to the credit risk research and its application in contemporary risk management systems. In Section 2, we provide an overview of the most significant developments in the area of credit risk, which date from the 1930s, when the first bankruptcy models were developed and have contributed to the establishment of traditional statistical models. Next, we present the risk measurement framework required in contemporary risk management systems together with several methodologies of traditional statistics. In Section 4, we provide a thorough description of intelligent systems, including traditional methods of artificial intelligence such as expert systems, rule-based systems, and genetic algorithms, as well as methods belonging to the realms of data mining and machine learning, such as neural networks and support vector machines. In Section 5, we contrast traditional models with modern methods that are used for the purpose of forecasting company default events. We conclude with a few final thoughts and focus on areas that require further research aiming to assist scholars and practitioners in improving their risk management systems (Galindo & Tamayo, 2000; Baesens et al., 2003; Bellotti & Crook, 2009).

5.1.1. Overview of Credit Risk Dynamics

Despite a long tradition of academic research, the concept of credit risk is still far from precise. While this could be attributed to different modeling and valuation approaches prior to the intense data paradigm, such an argument seems to be at least partially true also in the present setting. While previous research that constructs credit risk measures was partially data-driven, the results stayed within the boundary of particular models based on particular credit risk characteristics. This paper takes an initial step in evaluating the significance of data-driven artificial intelligence methods in the credit risk sphere. Even though the present paper heavily relies on a case study approach, the first finding of the study is the similarities in the meta-modeling results achieved for the default probability based on very different variables and approaches (Hand & Henley, 1997; Thomas et al., 2002).

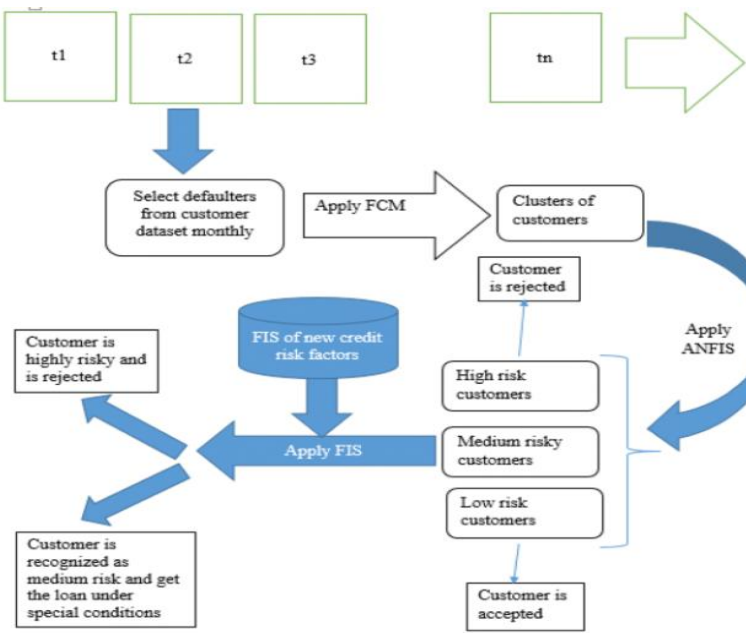

Fig 5 . 1 : A dynamic credit risk assessment model with data mining techniques

These include: (i) exogenous variables identified as significant most commonly and, although not significantly when taken alone, they have strong predictive power across different model configurations; (ii) the predominance of one-step-based valuation techniques whether acquired by historical stocktaking; (iii) the ascertained non-linear relationship with default distance; (iv) issues stemming from lack of linearity in transfer learning credit risk models; and (v) the presence of a non-random pattern in learning and rendering high-value predictions by the models. Due to the amount of minorities in the set, it can be assessed safely that there is no observable difference in the predictive performance of the models based on different exogenous variables or established for different companies or for different stock exchange selections.

5.2. Understanding Traditional Credit Risk Models

The practice of identifying good and bad risks, or in general terms the problem of sorting firms in a way that divides them into grades ranging from excellent to poor, is a very old exercise. However, most of the credit-scoring techniques used in contemporary finance for consumer, corporate, and sovereign lending have been developed in the last two decades. These techniques have been vastly improved by the development of scoring systems, which are empirical prediction rules that attempt to predict the likelihood of default. The basic challenge faced by those engaged in scoring loans is that historical data on bad loans represent a random sample of the set of conditions under which loans go bad, meaning that the lender typically has examples of only the combination of conditions that led to observed defaults. No data exists on the set of conditions where loans are in good standing, and certainly no data exists on future economic climates.

First, notice that these definitions all deal with loan default only, typically defined as an unanticipated event in which the borrower does not meet the obligations established in the loan contract. Second, notice that these definitions tie credit risk only to the borrower, ignoring the lender. Third, these definitions also typically ignore the effect that loan default may have on third parties. For example, if the bank suffers large enough losses and these become public, every depositor in the bank will make a run on it, even though the bank is perfectly solvent at that moment. Given the high costs of society's resolution of a banking crisis, credit risk measures that do not consider the effect that bank default has on society are not complete.

5.2.1. Historical Context

The launching of the new era in financial modeling is a result of two revolutions in the fields of economics and applied computer science: the revolution in the concept of information processing and the possibility of implementing it. As for high-speed computing, it began to spread in 1952. In the 1952 market letters, it was already addressed the possible application of high-speed computing to thematically analyzing groups of individual enterprises, remembering that some 2000 issuers of long-term equity and debt securities listed or reporting to state and federal agencies were disclosing a universe of knowledge about a test group for the various elements of long-term security valuation theory. The examination of this large and constantly replenishing body of data and of the characteristics of certain holders and prospective buyers furnished insights into the real purposes of the market, which market activity itself never could yield. It should be observed that an approach based on this specific concept of information initiated a highly influential alternative planning model.

In 1952, two important volumes appeared in the field of financial modeling: "The Stability of a Dynamic Economy" and a Master's Thesis for the University of Chicago "Portfolio Selection." The accompanying efforts in economics were directed at the dynamic role of resource allocation, and as regards the database, the tools of mathematical programming and quantitative models of economic planning. However, the possibly satisfactory employment of high-speed computing on a large-scale database directed at collecting and processing corporate financial data did not seem plausible until 1960, when rapidly spreading computer technology was waiting for able-footed management to grab. Although a pioneering role in discussing the role of computers in economics seems to have been played in 1951 by economists working at the University of Lyon within the same team that had previously developed linear programming, it was two years later that researchers at the same university, in conjunction with the French banking industry, were able to compute, starting from 1953, the national accounts of December 1952.

5.2.2. Key Components of Traditional Models

Under the Basel II capital accord, the banking regulatory authorities allow banks to use the internal ratings-based approach to quantify the capital requirements for credit risk exposure. Under this approach, banks use their internal models and data to measure most of the components of credit risk: the expected loss, the loss given default, and the exposure at default on a particular credit facility. For example, credit scoring models are used to predict the probability of default. Credit scoring models are the simplest models in the realm of quantification of credit risk. Under the risk rating approach, internal models are used to estimate the probability of default and, at a minimum, the probability of default for each loan category.

In the internal ratings-based approach, there are many methods used to break the portfolios of credit facilities into various categories - these are called the risk rating methodologies. Once the classes of expected probability of default are decided, banks have to assign the specific cutoff probability of default that will be used to discriminate between the classes. In the credit risk management of a specific lending entity, there is an additional rating migration component of the rating drift. Pooled data are often used in the external validation of credit risk models. A number of types of sensitivity analyses are used to determine the impact of model misspecifications. It was noticed that the impact of calibration errors could be greater than the 'true' sensitivity of the model.

5.2.3. Limitations of Traditional Approaches

Traditional models have limitations. They are based on stylized biases and assumptions that detract from their prediction and classification power. For example, the assumptions of normality and linearity might not hold in banking, where financial series are highly volatile. Especially in the case of nonperforming loans, both the presence of outliers and the leverage at work tend to strongly violate these prerequisites. In addition, there is a fixed geography in the relationship between financial and the NPL ratio at hand, and the residuals are heavy-tailed. Moreover, assumptions of full disclosure might also be ideal and unrealistic in the lending industry, where informational asymmetry and moral hazard problems provide an opportunity for the use of credit models that are more coherent with the expected behavior of the economies at hand. Features of NPL series that have been identified also include a patchy rate of occurrence or non-negligible conditional or unconditional forecasted probabilities of larger occurrences, e.g., on the right tail of the distribution related to financial losses.

Other limitations arise from traditional approaches relying on overly simplistic and inflexible linear relationships between financial and economic variables, exhibited without a clear theoretical basis for all possible underlying specific factors relating to loan default. These models thus tend to lose significant explanatory power because of their essentially 'black box' nature. From a different standpoint, another problem arises from the constant low level of NPLs in the system: in this environment, banks increase their speculative market positions, leading to higher NPLs. Consequently, these NPLs should be stripped from the default definition that is currently used. However, the capital requirement might also need to be increased. Other reasons related to the negative sign of the nonperforming loan series include moral and behavioral hazard and speculative bank behavior. In the transition period of an economy, both effects are likely to play a role, modulo the inflation bias and game theory-based conceptual thoughts at work in this domain. The resulting volatility of the probability of occurrence of nonperforming loans leads us to model the NPL ratio via local skewed uncertainty.

5.3. Emergence of Intelligent Systems in Credit Risk Assessment

The known arguments for the shift from traditional to intelligent systems are related to the need to include in the process information that is only presupposed at the simple data level. The traditional credit-scoring models use a few dimensions of attributes extracted from data available at the time of the modeling process. Although efforts are made to enrich such data with supplementary indicators taken from the closest environment of the monitoring entity, these additional sources of information have the same basicness and reliability issues already existing at the simple data level. Such supplementary indicators are correlated with those used in the traditional models, explaining the same or similar puzzles on the monitored entities with the same or similar types of models (various linear combinations of available characteristics, with or without accounting for their mutability). The emergence of intelligent systems gives the opportunity to use, with increased reliability, supplementary direct or related indicators, such as information that, even if not present at this moment in time, can become crucial for future entity functioning (reorganization, substantial delays in meeting obligations, clear evolution in the structure of the monitored entity, etc.).

Intelligent systems allow more than dynamic classification based on a large set of indicators of an entity or discovering peculiarities of the structures that most often generate some type of classifications. They can make decisions considering time as an active component of treatment and proving direct or indirect links between various indicators that precede or are related to the phenomenon under surveillance. Additional information between data points can be discovered from different sources, including visual representations generated from descriptors that are correlated with the individual decision. From a less technical perspective, the development of intelligent systems does more than allow the expression of the need for integration of different types of information, of different granularities, temporal completeness, or accuracy during various processes of decision support. In an era that seems to prioritize interdisciplinarity, when banking models borrow results and techniques from more distant fields and these products are upgraded, sometimes unexpectedly, as must-use tools, morphing from research facilitators into discoveries themselves, the additional features attached to intelligent systems can be perceived as a robust opportunity for inclusion and reliance on works and wider scientific communities.

5.3.1. Overview of Intelligent Systems

Intelligent systems is an emerging field that is already impacting most of the disciplines in science. Since these techniques have been applied at least a decade after traditional models, and they are more focused on financial statement analysis and not on the analysis of bank loans, the range of their application is limited to bankruptcy prediction. However, this procedure reveals fundamental weaknesses in the credit assessment model for investment project financing. Although the scope of intelligent systems methods will continue to grow, this work is restricted to induction for two major reasons. First, these methods address some of the fundamental weaknesses of discriminant closures. Second, it provides a comparative picture not only of the few studies based on bank loans but also among the possible combinations of those methods in this sense. The applications of intelligent systems can be classified into six types: financial decision-making, financial forecasting, financial planning, fraud detection, bankruptcy prediction, and investment management.

5.3.2. Machine Learning Techniques

The aim of this section is to offer a brief introduction to some of the machine-based methods now available. These tools offer certain advantages – insight, flexibility, ease of control – that are not present to such a high degree in traditional models. In addition to reviewing the leading models, the hope is to provide a background for the application of these new techniques that will assist in the future development of these systems. The techniques presented are some of the most popular ones and are considered the best in terms of cost-benefit analysis. This investigation suggests that traditional models will, beyond any doubt, remain at the heart of financial forecasting, especially in risk management applications. They are relatively compact and provide insight and a direct measure of risk. This contrasts with some complaints about the ease of ascribed risk measures associated with the application of neural networks.

A variety of criteria must be considered when selecting an empirical model. The forecasting accuracy of a model is a first step in the process. Another important consideration is the development of an index that has the possibility to customize the risk measure from one potential creditor to another. The criteria associated with the success of a model will depend heavily on the final use of the model. The choice of a model in credit scoring might therefore depend upon the commercial environment in which the model will be used. The choice of the model will have to pass beside restrictions of price, speed, ease of use, robustness, security, clear understanding of the model's internal logic, management interest, and senior management support. The importance of a measure of expected loss compared to the current level of risk to the potential lender or the overall bank loan portfolio will also contribute to the selection of a specific credit assessment model.

5.3.3. Artificial Intelligence in Finance

Despite progress in risk measurement through traditional models, the complexity of financial markets and the massive size and complexity of the data used to estimate financial models offer considerable challenges. The most plausible and genuine solutions for such difficulties with data growth have been long provided by intelligent systems. In line with the trend given to artificial intelligence in statistics and econometrics, primarily because both approaches seem to have the same targets. As a pioneering applied science, financial economics has access to large datasets. In general, the complex datasets provide investors with much potential profit; however, at the same time, they offer a considerable amount of noise. In addition, datasets are often incomplete. Forces of supply and demand greatly affect individual assets, and linked markets can be subject to the effects of market inefficiency and irreversible mistakes. It is worth mentioning that several years ago, prominent thinkers in economics addressed this issue and stressed the usefulness of combining data from other scientists in an effort to understand the modern economic environment.

Since 2016, most theoretical models in financial economics have suffered a neglect of implementing their arguments in the financial business. Some related nonsense exhibits expressive knowledge without providing satisfactory results to advances in solving any purely applied problem in financial economics. In line with a criticized commodity trend from 2018, the corporate researchers responsible for estimating effective models in economics have now become increasingly concerned with developing models for broader use, with the aid of extensive non-exclusive data. Furthermore, they have begun the initial design of two new access technologies for modeling algorithms, which involve all behavioral patterns associated with real models such as limited learning and adaptation to a multiplicity of contexts. The empowerment of a higher theory of intelligence imposes a rethinking of the concept of intelligence as the ability to guess the correct answer to the corresponding question. Additionally, a similar study was conducted based on an interactive framework. Summing up, the inadequacy of traditional financial models in response to various real-world challenges is highly remarked.

5.4. Comparative Analysis of Traditional Models and Intelligent Systems

In this section, we compare traditional credit-risk models to intelligent systems. Since intelligent systems are used in some financial institutions alongside more traditional models, we initiate our research to determine what value these new modeling systems add, if any. The task-inventory approach is used. The dimensions along which the reviewed credit-scoring models involved in the comparisons are identified from the knowledge blocks of a comprehensive knowledge framework.

The widespread normal distribution of credit losses discussed may also suggest the use of classic portfolio credit-risk models purportedly up to the task of calculating economic capital for the credit-risk section of a financial institution’s portfolio. These portfolio credit-risk models, unfortunately, are using exactly the same modeling concepts as the single-obligation models—exponential smoothing—applied to the time series of obligor behaviors. Why would a corporate planner or shareholder trust such economic analyses and use them as risk management and capital allocation methodologies in such wildly different directions if the models showed promising performance characteristics in terms of expected loss? It begs the question. Such a performance dichotomy signifies a lack in the mapping from modeling concepts and techniques to measures of economic risk unbedazzled by the models when coupled with illusion-based risk management frameworks for the client business models themselves.

5.4.1. Performance Metrics

The accuracy of a classifier is, in fact, a simplistic measure of the model's performance and does not necessarily demonstrate how good a job a model is doing in solving the business side of the problem. Models are built for the sake of the objectives they promise to achieve, which in the credit risk domain are to identify those who will fail to repay a loan as well as to evaluate those who are willing to repay the loan. Frequently, the performance of these models is assessed by means of the confusion matrix, which summarizes the results of a binary classification model in tabular form. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class. From the confusion matrix, several performance metrics are derived.

It is important to select an appropriate performance metric that will lead to increased accuracy and confidence in our model, or in other words, a metric that best reflects the business question close to the interest of the credit risk problem under consideration. For example, while the accuracy of a model is likely to be very high, the findings would not be useful if the misclassifications (both Type I and Type II errors) have high business costs associated with them. In the credit risk domain, it is commonplace to want to maximize the detection rate of low-quality loans, even at the cost of having a high number of misclassified good-quality loans. This harmful misclassification of the good clientele is caused to a great extent by a firm's inability to carry out an exhaustive credit screen. Key words, interpretable models, performance metrics, business goals, monitoring, and improvement are all essential parts of the model.

5.4.2. Accuracy and Predictive Power

One of the most essential attributes of the credit risk model is its accuracy. Accuracy is the closeness of the agreement between the result of a measurement or the value of a test and the true value of the measurement or the real value of the attribute tested. Accuracy is expressed as a number of units, each unit corresponding to the degree of specificity that is appropriate to the particular situation. One of the ways to measure the accuracy of predictive models is to use a confusion matrix, which is a common way to calculate widely used metrics such as accuracy, recall, precision, F-score, Matthews correlation coefficient, etc. Contrary to the number of researchers trying to avoid logit and probit models, the main advantage of these models is the existence of different binary classification evaluation metrics like lift and receiver operating characteristic. This avoids the problem in terms of comparability of competing models addressed by many researchers in the field, where different binary classification models produce results that cannot be compared. On the other hand, logit and probit models belong to non-linear functions, and intelligent systems can also be developed for this type of functions.

The main disadvantage of these models originates from the underlying normality assumption that does not suffice with the real properties. This concerns the obvious imperfections in terms of heteroscedasticity and collinearity that should be addressed with their appropriate tests and criteria. Since a credit risk model exists to measure credit risk, not to comply with the theoretical assumptions of logit and probit models, the latter can be treated as a sophisticated framework composed of many other functional form models that include parameters compatible with real-world properties. The current mainstream belief that intelligent systems in terms of neural networks, decision trees, and support vector machines are far superior is not justified since the choice of the appropriate model should take one major consideration in terms of the nihilism expressed that every metric could be achieved. Since all the components of the proposed credit risk model systems would behave differently across the business cycles, the final error of the model would be the main factor in the choice of the appropriate credit risk model.

5.4.3. Risk Mitigation Strategies

The mitigation of operational risk involves cutting down the likelihood of event occurrence and reducing the quantum of losses, either through insurance and diversification strategies or by carefully crafting the contract terms. Most likely, operational risk can be treated with a combination of internal control models. Business risk is a proprietary risk, and reducing it clearly requires switching out of competing businesses where risk-adjusted returns are inadequate. Although the banking model is mostly inherently diversified in its activities that it offers through management fees.

Fig 5 . 2 : Risk Mitigation Strategies

5.5. Case Studies: Implementation of Intelligent Systems

The purpose of this section is to illustrate how certain intelligent systems, such as case-based and neural network models, can be used in articulating credit risk management. Four case studies are presented. They illustrate the utilization of intelligent systems for improving financial decision-making in a data mining setting of the bank credit card market, enhancing customer profitability modeling by using intelligent systems techniques in the banking sector, and evaluating the effectiveness of credit scoring in banking by using artificial boosting credit scoring algorithms. The final case is a future study. It presents the application of genetic programming for one-day-ahead prediction of giant banking losses. The findings of this work provide managerial, methodological, and public policy implications.

Credit risk is considered a critical issue in banking and a growing area of research. Although the banking literature includes the application of several statistical models explaining credit risk, this is the first work presenting intelligent systems capable of further enhancing credit risk management in banking. This paper contributes to both the artificial intelligence and the banking literature. It is the first to illustrate the usage of case-based reasoning, boosting, and artificial neural network techniques in the domain of retail credit risk analysis. The plethora of work studies the application of traditional quantitative/statistical models. The use of a wide variety of credit risk quantification approaches is expected to vary across banks.

5.5.1. Banking Sector Case Study

In this case study, we tried to detect how the portfolio of a bank can be affected by different rating attributes and find a sensible model to rank different sets of attributes and some logical connections between the ratings. We use the ratings history of the whole portfolio to evaluate some of the turnover, migration, and stability trends. Despite the well-known drawbacks of such data – especially since it covers only this bank’s portfolio, reality is heavily dependent on the ratings of the rating agencies, on what is going on in the ratings market, and how much ratings are really adverse. They still provide a picture of what is going on with the active portfolio of this bank and in which ratings the bank’s analysts trust more. In the conclusion of this paper, two ideas could be extracted: First, that rating agencies are as inaccurate in their ratings as any other economic agent. The second statement is that, different from traditional models, intelligent systems are not biased on the so-called 'concordances' between the objective and subjective ratings and do not need to have equally good and bad classifications to provide data mining utility to banks.

5.5.2. Insurance Sector Case Study

MSE checks the performance of the hybrid credit rating module for the case of the insurance sector implementing option pricing models. The sample includes financial statements and market data of a dataset of 43 European firms from 2003 to 2011. MSE applies a quality credit rating test found by performing multiple regression analysis of yearly differences in financial statement data and dummies with different rating classes. As the null hypothesis, the correct tests confirm to be true, and for classification purposes, the credit rating scheme performed well. As sample design, only firms that have adopted the "traditional" limited liability debt structure are considered, so the call option price and the debt value do not require modifications. As a performance measure, MSE considered the WoE together with the traditional prediction criteria: accuracy, true and false positives and negatives, precision, recall, sensitivity, specificity, and the F1 score.

These findings advise a limitation to be imposed on the number of branches in the valuation tree and are robust to policyholder behavior and parameter settings. As a future extension, MSE plans to compare the performance of the model in explaining the sample's time series of the insurance firm's credit spreads with the existing models, addressing the present caveats to the regulations. During insurance market conditions like those of the sample period, the cost of borrowing should not be overly penalized when applying the proposed capital allocation scheme.

5.5.3. Peer-to-Peer Lending Case Study

In this section, we will present a study of the real-life situation of a particular peer-to-peer lending platform to showcase the different intelligent systems presented in this chapter. Namely, we will focus on a specific platform, casting it as a classification problem. For the study, we will consider a dataset of more than 150,000 records and around 30 predictors, some of them categorical and others numerical. We will focus on the predictors and the data setup given in the available data. Known predictors such as FICO range, subgrade, loan amount, term, interest rate, etc. will be used. Contrary to previous studies, the performance will be reported in terms not just of its accuracy, but also of the area and confusion matrices, through a picture. All datasets are given in a seemingly structured way, lending a potential interest to real datasets. It is apparently easy to collect the large amounts of information required to create these datasets.

5.6. Regulatory Considerations

In Basel II and in most credit ratings for regulatory purposes, the one-year estimate of PD is essentially the criterion used to determine how much regulatory capital the banks will have to hold against the loans. While regulators have made explicit their preference for banks validating and adapting their own internal risk models to the Basel II standards, and claim to be happy with a significant portion of total regulatory capital being based on "internally developed models," in practice it may turn out that only very few banks will join this select club since creating and implementing such models is very costly and lengthy, requiring a powerful IT infrastructure and an expertise that is in very short supply.

Regulators have also stressed that being accepted into this elite group rests on clear and theoretically coherent relationships between the risk drivers and their effects adequately tested on relevant out-of-sample data. It is very hard to see how the rating agencies will be able to offer a model that would satisfy the regulators' criteria and deliver estimates of probabilities of default consistent with the key criteria set by the rating agencies: meaning stability through time, stability across market sectors, stability relative to population dynamics, and that clearly differentiate the risk associated with different instruments. And it is hard to see that the regulators could trust such an opaque system.

5.6.1. Compliance Challenges

Cross-border business and regulations in conflict give your organization a greater reason to think ever harder about good corporate governance and risk management. After all, whereas your organization might want to go to China or any other country classified as a high-risk area, in the eyes of the regulator, you are presumed guilty until proven innocent. Your organization must carry a heavy burden to prove compliance with a complex web of financial services regulations. Additionally, as a CRO serving Basel II, you have even more reason to enhance credit risk practices so that your organization can demonstrate that its enterprise-wide approach to preventing money laundering makes full use of best practices and all available intelligent systems technologies. The benefits drop straight to your bottom line. You stave off business-threatening fines and bad press, and instead gain higher efficiency, decrease customer frustration, and improve the offering of legal, diversified, non-criminal services, which allows your organization to focus on its real business.

Information is the currency for defense and for proving that your organization can demonstrate compliance with complex financial services regulations when delivering new services over the Internet. Unfortunately, too many organizations today still employ application silos that generate fraudulent gains for those who do not wish to play by the rules. The numbers are compelling: "by 2005, 20 percent of enterprises will spend more on complying with information security than on information security itself." Companies can expect to spend anywhere from $2 per customer to $30 per customer with an e-business selling "threat" insurance. Yet an effective anti-fraud detection product—synergistic anti-money laundering and know your customer solutions—costs less; some projections say as little as 2 percent of the total value of the transaction initially. Up to 80 percent in some estimates of revenues, personnel anti-fraud spending can be reclaimed and reallocated once the project is completed.

5.6.2. Impact of Regulations on Model Selection

Regulatory capital requirements for credit risk leverage the power of a model to provide the means to differentiate risk, measure that risk, and devise measures to control and manage that risk from banks. In making that assessment, both traditional and intelligent credit risk models contain common elements that measure the same constructs, such as PD, LGD, and IRB. However, the regulation also defines those constructs, and it is reasonable to expect that the model/construct definition and measurements would fit hand in glove. Given the requirement for regular reporting and the audit of model outputs, these require model systems that are transparent, readily explainable, and congruent with the definition. Impact of Regulations on Model Selection From the point of view of a bank, the risk model choice should capture as effectively as possible all relevant dimensions of risk. That would allow the bank a better reflection of its true-to-risk business model and enable it to optimize its revenues, diversification possibilities, securitization, and so on. Clearly, other things being equal, model consistency would provide a decision aid. The simplest call for action is at the level of PD, which is for most banks the crux of the trade-off. Dual models are vendors' solutions to the model risk dilemma, but are they not passing much of the construct and model risk problems to the banks and regulators? On the other hand, would regulators not gain if bank models are more complex?

5.7. Future Trends in Credit Risk Assessment

The analysis of the methodology applied to predicting risk has shown a significant evolution, emphasizing the work that has been developed both under traditional models and intelligent systems. The escalating growth in the sophistication of the models for predicting bad credit has been combined with the increasing utilization of computational tools inherent to business intelligence systems and data mining. Despite the huge contribution of traditional models, there are remaining issues that lead to the development of more sophisticated systems by investors and analysts. Developed new and more effective mathematical programming algorithms, which, integrated into business intelligence environments, adjusted to credit risk prediction models, enable the building of novel hybrid systems that are more rigorous and technically reliable than the present models. In contrast to traditional credit risk prediction models, intelligent systems seek to merge rules previously learned from historical data with fuzzy logic concepts and a higher sensory capacity, similar to human ones, in order to evaluate the intricate interactions between determinants of debt default. Regarding new subjects of research, the future trends related to credit risk assessment can be essentially focused on three domains. First, frequency domain analysis techniques including fast optimization algorithms in line with developments in science and methods of processing data, toward the creation of novel real-time systems; second, 'turn-key' technology of proprietary origin adopted by investment banks, insurance companies, and other firms, providing systems that are easy to use for analysts and new methods to utilize proprietary code toward more effective financial analysis; third, the application of recent developments in computer science and mathematics in credit risk prediction models for the establishment of entirely new and valid scientific subfields characterized by the creation of novel financial theories using complex networks, fractals, and other advanced multidisciplinary studies.

5.7.1. Integration of Big Data

Many traditional methods used in finance were designed long before the present big data and computing era. The computing power is no longer a constraint, and the great advances, relatively low costs, and availability of all kinds of data allow for models to be developed together, thus exploiting the valuable information within. Data integration is a process by which heterogeneous data, independent of the methods used and the particular details of real-world entities involved and their representations, may be combined in meaningful, informative ways. It is not a new issue in Information Science and is obviously linked with the complexity of the models built. However, big data's speed, scale, capacity, variety, and complexity have made linking databases of data an even more important issue.

Data integration is what makes big data 'big.' This occurs in four major ways: firstly, the connection of previously unlinked data due to similarities between datasets. For example, data about the government bond market and nearby professional traders could be linked by properties of the firms or individuals in the area. Secondly, big data can pull together traces that we leave behind when engaging in specific activities. A combination of geolocation data from a smartphone and big data on spending habits sampled through credit card data is needed to provide a full picture of the regional economy during the crisis. Thirdly, big data can be combined with traditional policy analysis methods through the linkage with small-scale samples. Recent innovations in intelligent urban administration have combined the data of mathematical models and city-level results with on-the-ground observations and data. Finally, new kinds of big data can be created by combining existing layers of data. For example, codifying and harmonizing datasets of corporate bond ownership also requires effort and time to bring them together, and the end result is a new dataset with considerable breadth and accuracy. Data integration plays a major role in finance because, to undertake financial stability and supervision, policy analysts need to address policy questions that cannot be answered by individual datasets.

5.7.2. The Role of Blockchain Technology

Among its many potential applications, blockchain technology might offer the credit risk assessment process some considerable benefits. It could offer a real-time, immutable, and verifiable audit trail of all stages of underwriting a security or loan and then of its subsequent performance. It can also offer potential benefits with regard to fraudulent transactions, reporting, verification, and transparency. By replacing the ledger of financial transactions with a distributed ledger, the entire credit risk model can, in theory, be eliminated. This pre-empts the possibility of agency risk, where the agent in the underwriting transaction seeks to maximize minimal prong share while also efficiently hedging any portfolio risk they may hold. Despite all this, banking regulatory capital models remain the same. Blockchain technology also eliminates the need for a complex regulatory model of traditional fractional banking, where banks have relatively low reserve capital, are able to fund on the liability side of the balance sheet theoretically without full asset backing, and are also required to fund the capital requirements of entities that are generating a defined capital return.

The key role of the regulator becomes to adjust risk weightings and loan loss reserves to ensure the safety of the entire system. This operates on the core tenet of deposit insurance, which suggests that the provision of implied creditworthiness allows the largest financial institutions to enjoy interest cost premiums in their funding structure. With blockchain technology, less lending is no longer required or desirable, since any entity receiving funds must be fully financed by the lender through a tokenization process. Although the banking minimum capital requirements and the loan loss requirements aim for a banking system that is booked on the assumption of losses that will have loan loss needs in most cases and prevent moral hazards, they also create an uneven lending playing field with other capital market participants. Tradable tokens could, in theory, be used for many different product types. Commercial real estate, for example, could be tokenized with cash flows going directly to token holders. The main institutional players in this market remain intact, but some additional funding options are created in the securitization, crowdfunding, and mezzanine ranges by the arrival of a new funding source with a slightly different return profile.

5.7.3. Ethical Considerations in AI Models

In the future, we expect to see ethical regulation guidelines that the data should be subject to, which is used to train and later validate a model. In our view, this is necessary in order to avoid models and algorithms – especially when these may result in self-enforcing mechanisms – making decisions that are not optimal from the point of view of

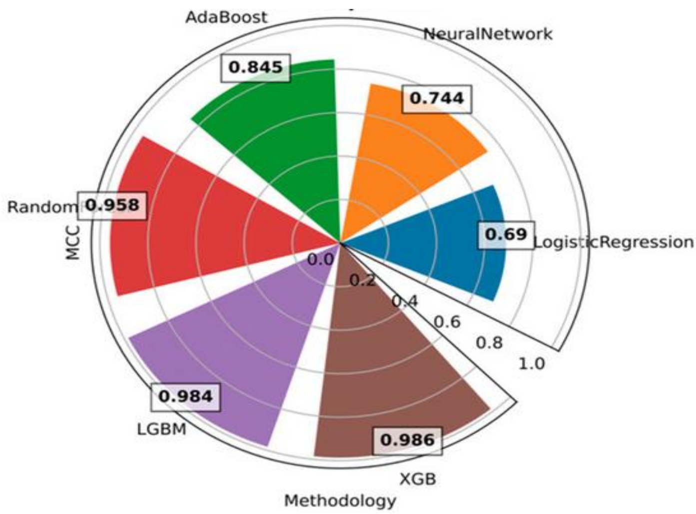

Fig 5 . 3 : Credit Risk Prediction Using Machine Learning and Deep Learning

society in welfare terms. In spite of the fact that ethical regulation is significantly important, in our view, introducing this will not be an easy task. We have, for many years, regulatory agencies responsible for banking, financial, and general product markets. There are governmental bodies responsible for regulating the internet, common carriers, utilities, insurers, and many other sectors in the economy. Yet these agencies, despite their best intentions, are unlikely to come up with the optimal set of regulatory rules that will incorporate ethical concerns.

5.8. Conclusion

Credit risk models have always been the most challenging part of banking. Traditional models - which look at some relative rankings, but do not have a proper calibration in terms of probability - tend to be amazing in their capability of turning everything quite subjective. From historic data with no defaults or GPAs available, to scenarios such as mere assumptions or even scenario-biased inputs, everything is interesting to them. Intelligence naturally seems to be the most dangerous opponent, combining non-linearity and self-adaptation. It is never easy to fight what one does not properly understand, making a need to study it. But, in opposition to some historical approaches, anesthesia is definitely not the best attitude to adopt. When one cooperates, ethics and curriculum vitae reflect - and the market speaks. Indeed, financial economic capital requirements are a natural and heuristic evident criterion of model efficiency. The benefits of new systems are equally interesting, as their power to influence supervisor-suggested floor ratios and the weight of credit derivatives in bank rating systems seems clear. Many new applications can also be mentioned: like the use of neural networks to process PD, LGD, and F tags in portfolio credit risk management systems. Other evident continuing trends are hybrid in their nature, combining multi-disciplinary panels with intelligent systems capable of supporting the model calibration process, basically by recommending weights from the particular and multiple inputs/plans/experiences available, as tends to be the case. Bankruptcy prediction systems are also concluded to be essential in banking. If, in marketing, the frontier of one's customer base needs to be confirmed every time some new technology is introduced, in banking the same occurs, given the importance of the role that lenders assume when funding them. Also given that, in the coming years, a revolution in terms of the payment speed limits and costs in e-banking services is already being expected, a new technological banking competition that goes beyond those that differentiate external communication and credit risk capabilities may be desirable. This can be suggested by means of models, which can be freely used and are basically nonspecific, or shown in rather good form by other models. With convergent, intensive or selective criteria for new references for other specific markets, regulators may encourage the introduction of those new standards.

5.8.1. Final Thoughts and Implications for the Future of Credit Risk Management

The primary objective of this chapter was to act as a bridge between the realms of traditional quantitative models of credit risk management and those that have been slow to adopt or even recognize the potential benefits offered by biologically inspired paradigms for learning and inductive inference. In our assessment, one overarching conclusion can be made regarding the comparative computational abilities of these approaches: at their current state of development, traditional models are superior since they are entrenched within a solid theory of probability fundamental when dealing with environments characterized by extreme levels of uncertainty and even chaos. The task is far from complete, however, and new developments in computational techniques will further narrow the computational chasm that separates simple neural networks from much more expressive techniques, let alone the more sophisticated classes of biologically inspired techniques discussed in this study.

Thus, building on the arguments advanced in support of our views, we will conclude this chapter by reemphasizing the central question raised earlier. Specifically, we have attempted to establish that the use of biologically inspired paradigms for learning and inductive principles, most notably neural networks, is well founded with respect to one area of interest within the financial services sector. Thus, we need to address a broader question: what distinguishes credit risk models using intelligent systems from other emerging methodologies in empirical finance and what might we learn about the future of finance when contemplating the role intelligent systems will play in shaping the future of financial organizations?

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