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Chapter 10: Revolutionizing lending and credit operations using predictive and prescriptive artificial intelligence analytics models

10.1. Introduction

Lending and credit represent important components for the finance and banking sector, foster growth of various industries, and play a vital role in an economy. Predictable models help banks and credit providing organizations to identify different types of customers based on their profiles, behavior, needs, and repayment capabilities, thus reducing default risk and optimizing their lending and credit portfolios in terms of interest rate, credit limit, and tenure. However, traditional predictive analytics or decision modeling approach only explains or predicts "what might happen" in future and lacks the decision insight, thus unable to address the needs of financial institutions related to optimizing as well as improving their decision-making capabilities. Prescriptive analytics is a new emerging research area that goes beyond prediction to provide the decision insight by optimizing the objectives of lending and credit organizations using analytical models. However, within this broad definition of prescriptive analytics, the majority of the existing prescriptive analytics works perform the decision optimization and do not generate the prescriptive insight from the prediction (Addy et al., 2024; Addy et al., 2024).

These limitations led to our research to utilize predictive and prescriptive AI analytics models for credit risk management by lending financial institutions. This paper presents an overview of predictive and prescriptive AI models specific to lending and credit operations like credit bureau reporting, customer profiling, credit scoring, credit limit assignment and tenure optimization, and some of the major credit risk products surrounding default prediction, recovery prediction, loss given default prediction and prepayment prediction in the pillar area of analytics. The focus is on providing unique process flow, predictive and prescriptive insight, and framework of these lending and credit analytics models developed over a period of last 25 years.

In absence of lengthy evaluations by internal knowledge workers, Business by Business and Business by Consumer negotiations can be held fast and effectively to foster long-term relationships. The industry's perspective puts emphasis on the well-orchestrated Technology Enrichment Roadmap that is deliberately driving the Lending and Credit Transformation Cycle. Thereby, Lending and Credit Industry incumbents should want to transfer tried and tested predictive and prescriptive AI Model Assets on existing operations towards the futures, focusing beyond individual processes or capabilities on a portfolio of PAI models, which has to be created and harmonized over time (Purwar et al., 2024; Ramya et al., 2024).

Fig 10.1: Revolutionizing Lending and Credit Operations

10.1.1. Background and Significance

Over the last 20 years almost there has been no revolutionary innovation in the Lending and Credit industry. Most innovations, such as alternative data providers, use traditional banking models based on the FICO score, and borrow their strategies from other consumer-centric industries such as marketing and online distribution optimization. The Covid-19 pandemic has created destitute for millions of borrowers leaving financial solution providers to write off heavy millions in bankrupt loans, the ongoing war in

Europe further strains the economy and have people fear that their banking service such as revolving credit cards, loans or mortgages are in jeopardy because their banking service provider might go under. Leaders in the Lending and Credit industry are readily committing investments in Technology Enrichments which enable them to reinvent their businesses into digital-first financial institutions by investing in rebuilding and restructuring existing data ecosystems using digitized predictive and prescriptive AI analytics models and microservices where powered communication flows seamlessly.

In unlocking PAI Models for process enhancement, Lending and Credit Industry leaders are pioneering with consumer-centric strategies implemented through well-acquainted user experiences in their e-channels, giving their customers powers to evaluate, justify bids, approve and apply for best-fit loans completely independently by themselves in minuscule amounts of time.

10.2. Understanding Lending and Credit Operations

The overall goal of credit operations at a bank, financial institution, or lending organization is to provide funds to the client so they can implement their business or personal project and make profits with it. The lender collects a fee for these funds, which creates the bank's profits; therefore the lender should be careful to prevent default. Credit transactions are dependent on special technical aspects and are therefore very different from the transaction that borrowers can carry out without a lending institution's intervention. Different types of credit arrangements are possible, such as lease of durable equipment or machinery or support through a confirmed credit, delivery of the property or the amount covered by a credit item, establishment of sureties or guarantees, etc. Current credit policies proposed by international accounting standards are primarily focused on measuring risks of loss and their recognition. In the current market environment, the challenge is to establish a competitive lending policy and minimize the effects of negative risks from the statement of operations. Banks' lending portfolios are their main source of profit generation. Negative effects concerning credit operations will negatively affect the complete financial position of the lending institution. User interest groups expect banks to offer modern professional credit risk assessment models, methods, and information systems based on predictive and prescriptive analytics. Modern banks and lending institutions primarily act as suppliers of comprehensive credit solutions in order to secure competitive advantage. Such an approach demands implementing credit risk services based on predictive and prescriptive analytics models in risk management and decision theoretic foundations for taking credit risk in credit chains. Such services include integrated data warehouse for credit risk and complementary predictive and prescriptive models based on risk management, risk decision and credit chain management. Based on these building blocks, banks can create significantly better solutions for managing and implementing corporate credit that can cascade down to their clients.

10.2.1. Overview of Traditional Lending Models

The use of credit as well as lending is one of the earliest forms of trade between two parties. Credit is utilized when a buyer and seller do not enter into an exchange of value simultaneously. In this case, the buyer gets the goods from the seller on credit while agreeing to pay the cash price after some time in the future. Credit allows the buyer to defer payment until he/she has the necessary cash to pay for the goods. This, of course, is a major disadvantage for a seller because he/she cannot force the buyer to pay immediately after the exchange or transaction.

In early forms of lending, lenders charged interest and gave money to people who were in urgent need of it. When this amount plus interest was not paid back on time, lenders used various methods to collect. In today’s models, lenders approve a credit request by verifying the creditworthiness of the applicant. However, the lending and credit approval process did not stop at this point even after stringent terms were established. In fact, lenders made sure the creditworthy did not default on their payments and this monitoring took a long period of time to complete.

This simple model evolved for a long time until recent years when new elements changed the landscape of lending and credit approvals. First, the process was typically carried out internally by the lending institution itself. Some institutions had developed their internal models using scores designed for credit and lending decisions. However, most mainly relied on a small number of external credit scores. Organizations that developed these scores were called credit bureaus and credit decided lending by estimating probability of default, earmarking a percentage of applicants as too high risk – the above mentioned ‘bad credit’ category.

10.2.2. Challenges in Current Credit Operations

Recent innovations across lending markets have led to important changes in how loans and credit are approved and managed. Despite increased use of data in how credit is evaluated and offered, several near-term challenges remain. The most serious concerns relate to increasing service time and resource consumption, declining loan processing and service accuracy, sub-optimal loan proposals being offered, incompatibility of new lender origination technologies, high churn rates, difficulty in effectively utilizing advanced analytics and artificial intelligence, and disconnects between loan pricing and credit conduct. New lenders are investing in better customer experience by reducing friction points, streamlining access across lending origination platforms, and minimizing service time and resource consumption and they are re-discovering lost segments of small loans in niche, underserved markets.

A common complaint by borrowers is that other financial institutions have better access to data, better tools and techniques, or are more willing to take on more risk. Retail banks can quickly rewire technology stacks, create centralized teams, and automate decision making using AI, but often stay out of certain niche, underserved markets. Other institutions can provide all the back-end functionality, while finance companies, banks, or credit unions can keep the customer relationship and do the front-end work.

10.3. The Role of AI in Financial Services

Artificial intelligence (AI) has become an integral part of various industries while serving a wide range of applications in finance. Assessing and implementing the best use cases has become a priority for companies trying to adopt AI. Some of these applications include fraud detection and credit scoring, web personalization, algorithmic trading, robo-advisors, customer service, regulatory compliance, contract analysis, loan underwriting, insurance claims, and investment banking. Regardless of the many opportunities, the financial industry, similarly to other industries, has a problem with implementation. Developing an AI strategy is not enough; financials should be able to translate AI's potential into real business value. Financial institutions need to adopt a few key prerequisites: Strong capabilities in data engineering are essential and having data in the right format allows algorithms to ingest it more efficiently and outperform in model training. Disparate data sources need to be connected to aggregate historical data to help train and evaluate algorithms. Beyond data hygiene, intelligent automation of repeated machine learning pipeline operations can help firms operationalize machine learning at scale. Financial institutions also need a strong culture of collaboration where the business units responsible for implementing algorithms actively participate in ensuring the feasibility and value of different use cases. Close collaboration between data scientists and stakeholders from the business unit will reduce iteration cycles in model development.

Today, AI-based funding platforms enable borrowers to have easy access to loans, supporting automated loan origination whilst providing enhanced efficiency, decision-making accuracy, and risk prediction capabilities. AI-infused lending enables scoring to see which customers are trustworthy and credit-worthy, preventing default. Data is used to build predictive algorithms, providing lenders with better insight about risk levels. Banks applying AI technology in lending are expected to see a significant increase in income and an optimistically expected rise in profit before tax. AI-driven solutions provide decision aids and support advanced functions of specialized profiles in charge of the preliminary credit risk assessment and also of the credit risk management phase. Automated solutions are needed in this case to monitor large amounts of information continuously and report warnings in case of concerns.

10.3.1. AI Technologies in Finance

Various AI technologies provide an assortment of models that can be used to enhance quality, customer experience, and performance of various financial activities. AI enables enterprises to analyze massive amounts of data efficiently. Other benefits include data-driven support for decision-making, enhanced compliance, and improved ability to detect fraud and assess the risk of non-payment.

Fig : AI Technologies in Finance of Revolutionizing Lending

AI technologies in finance can largely be categorized into supervised learning, unsupervised learning, computer vision, natural language processing, and robotics. Predictive analytics models – the most widely used type – are used on massive historical data sets to predict the probability or size of loss, type of customer, and the required amount of reserve capital against predicted losses. Predictive models are also widely used for automating the processing of loan applications, obtaining additional information during application evaluation from customers and other sources, and risk assessment. Predictive models, using a variety of customer data during application processing and evaluation, identify false identification and suspected fraud cases for additional scrutiny.

Supervised learning has achieved great success in credit risk assessment, where hierarchical models based on logistic and probit and binary choice models are predominant. The supervised learning models developed using a variety of customer features are then used to evaluate loan requests. When feature selection is properly done, the prediction accuracy significantly improves, leading to higher repayment rates. However, these models usually do not yield sufficient explanation for the model-driven probability assessments.

10.3.2. Benefits of AI in Lending

Data scientists and data engineers are developing predictive and prescriptive analytics models to guide lending and lease professionals at the right time and the right level of intervention and adjust the exposure as per the level of risk. AI models are also used for automating the credit origination process and validating credit data. AI in lending can help detect riskier consumer deposit account behavior, make the right lending offer, identify the segment most likely to accept a lending offer, determine the right amount and terms, and price loans most effectively. These models may also be developed for improving credit underwriting of consumer loans, detecting consumer loan applications with potential errors or fraud, and developing collection strategies. AI models may also be developed for predicting default and loss rates, developing strategies for managing portfolios, stress testing, evaluating the right collateral value at default or recovery, avoiding risk concentration, monitoring for changing risk, and modeling climate-related risks. The lessons from the use cases suggest that predictive and prescriptive AI models can help enable better risk identification, pricing, and decision-making across the entire lending lifecycle, from engagement to portfolio management. Lenders can use these models to improve their ROE and ROA by gaining a deeper understanding of customer behaviors. Predictive and prescriptive models can address all key insights needed in lending. These models can help find the right offers for each segment and time, identify the best channels for the offers, discover the optimal underwriting strategy, test the right behavioral triggers, recommend the best collections strategy and time, and identify optimal recovery strategies and times.

10.4. Predictive Analytics in Lending

In recent years, it has become increasingly important for traditional lenders, alternative lenders and fintech lenders to determine what drives consumers' demand for credit and how they can significantly increase their lending pipelines. Predictive analytics has a large role to play in achieving this objective. Over the past decade, the US subprime residential mortgage market has seen increasing levels of competition among lenders trying to identify and capture market share. Yet, until recent years, none of the major participants had turned to implementing predictive models to improve their marketing and retention processes. Predictive analytics in lending is pervading the market and why shouldn't it be? The benefits for lenders of adopting models resonate strongly, reducing the costs of acquisition and increasing loan profitability while reducing risks of default, delinquency and charge-off losses.

Despite the increasing availability of alternative data sources, lenders today still rely primarily on credit bureau data containing the 3C data in their client acquisition and relationship management activities. Lenders have generally been buying the proprietary products of credit bureaus or using their general bureau scores. Special collections or segments of the population where socio-economic data might be more meaningful, such as young adults without any credit history, recent immigrants or post-bankruptcy customers are typically profiled, by bureaus employing algorithms that do not share variables or methods of data processing. In the past five years, lenders have begun using their own historical transaction files to build their own proprietary predictive models. These are often based on Fast-Modeling techniques and services suitable for relatively lower volume data and are developed at lower costs.

10.4.1. Definition and Importance

Predictive analytics is used to gauge the likelihood of future outcomes, based on past experiences and data. More specifically, it encompasses two technologies: predictive modeling and statistical algorithms. Although predicting the future has always held a unique allure, strong forces have made predicting the future increasingly essential for companies. Predictive analytics is steadily reshaping financial services – with a wide range of applications, it is one of several solutions that could reduce losses for the credit industry. For a growing number of applications in the financial service sector, predictive modeling and other forecasting techniques are gaining favor with bankers and business managers alike. In fact, predictive modeling of innumerable business developments and processes has become increasingly important for companies as they strive to achieve best-in-class performance while mitigating risk.

The importance of predictive and prescriptive analytics techniques are growing. Their mathematical techniques make it possible to spot hidden patterns in the data and at predicting key indicators of business success better than the crude methods still widely used. Consider a bank attempting to predict which customers will pay their loans on time this year. By analyzing past behavior, the bank can estimate which recent customers are likely to default. Using this knowledge in making lending decisions can greatly enhance profitability.

10.4.2. Data Sources for Predictive Analytics

One of the first steps in the predictive credit analytics project is to identify, collect, and describe relevant data to answer the perplexing credit questions and generate predictive models. For any given predictive credit model, the critical errors are usually not because of errors in the math of a credit model or not using the most sophisticated risk techniques but of two possible concerns. The first one is relevant data sources for the model. The second one is the relevant features identified from that data.

However, for many analytics projects, credit practitioners have traditionally had access to only a small set of data. Two important data sources are customer interaction data recorded from call tracking and interaction management systems and historical marketing response data collected in relational marketing databases. Predictive customer attribute models at the account, contact, or household levels analysis by risk considerations. For example, the development of predictive models for bank credit card solicitation highlights the use of customer response information to model future interaction with the credit institution. The availability of this historically rich behavioral data offers new promise for customer interaction and marketing response models. The customers who visit their branch most often pay the lowest transaction fees and are most likely to continue their relationship with the bank over time. On the negative side, low-activity customers who request information from their bank or telephone customers who interact infrequently when they request information are at risk.

10.5. Conclusion

Predictive and prescriptive artificial intelligence analytics techniques could potentially address some of the deep-rooted problems faced by the lending and credit industry. The key interest in predictive modeling for credit risk originates from both the lender's need to maximize profit while controlling risk and the borrower's right to receive fair treatment. At lenders, predictive models can be very useful in solving and optimizing problems at every stage of financial transaction, such as risk assessment for direct marketing, screening applicants for underwriting, providing customer action support and forecasting account conduct for portfolio management help in targeting the right customers at the right time with the right product. They can be regarded as a key to offering a service that is both competitively priced and yet profitable for the lender.

It is important to emphasize that while predictive modeling is an important aim it is also essential for lenders to appreciate the commercial advantages of using more advanced models. More often than not, without the proper commercial considerations new models are likely to be overfitted leading to increased lending losses. In addition to predictive techniques, lenders, especially large banks, could also consider prescriptive AI techniques to effectively optimize their business processes. For smaller banks this might be a possibility for the foreseeable future due to lack of data. In conclusion we have attempted in this chapter to provide an introduction to these two types of techniques and how they can be used to help empower lenders and borrowers in the complex lending and borrowing environment.

10.5.1. Emerging Trends

The future of AI-powered lending is being shaped by the ongoing evolution of consumer protection policy, new banking regulations, the introduction of new financial products and services, technologic advances, and competitive pressure. Major retail banks, who are the most mature and data rich lenders, are investing heavily in predictive analytics and prescriptive modeling. However, the majority of these investments by major retail banks involve technology and outsourced vendors, and these institutions lack a well-conceived strategic plan for doing it themselves. As a result, major retail banks have fallen behind Internet-only banks and certain credit card issuers in the development of more automated lending and credit decision processes. New retail challengers, having embraced a fully digital experience combined with same-day approval for all consumer loans as their market positioning, are attracting more customers with easy-to-use products. These consumers see no difference between the experience of lending and other forms of online shopping. Moreover, undertaking new products and services also requires lenders to structurally change their organizations and modify their mindsets. Historically, the organizational structure within larger retail banks has inhibited the sharing of ideas, talent, technology, processes, products, and customer data across the institution. With the rise of digital banks not hindered by such historical barriers, the challenge for retail banks will be whether they can also become more agile organizations, ready to exploit big data in its lending operations. Important new consumer protection regulations mandated the testing of algorithmic decision models for adverse impact on poor and minority communities, causing large banks to rely increasingly more on vendor-supplied models. Developments in generative AI, including natural language processing, hold out the promise for automating significantly the design of important submodels.

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