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Machine Learning for Credit Scoring: An AI-Powered Big Data Approach to Financial Inclusion

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Abstract: In the contemporary era, characterized by the rapid expansion of the internet, social media, and mobile communication, substantial amounts of new data, sometimes called 'big data', are being generated every day. Machine Learning (ML) which is one important technique of AI, has the ability to extract significant information from big data. The financial industry continues to invest in machine learning models to better utilize big data. The most exciting Iceberg of big data occurs in the 'pay-as-you-go' market such as peer-to-peer lending platforms, where most data is generated by borrowers. Low Credit Scoring (CS) has been a critical problem for many individuals and small-sized businesses in emerging markets under financial exclusion. Traditional financial institutions rely heavily on fixed and well-structured information, restricting many creditworthy applicants from financial products. Peer-to-peer lenders often lower the entry barrier by adopting models on new data sources in the short-term, considering process efficiency. However, a significant percentage of applicants with no records on the platforms would not be able to access credit. The home-grown online lenders who best incorporate big data and machine learning are well positioned to succeed.

In this work, a bootstrapping ensemble voting model was developed combining traditional credit scoring statistics with new data sources along with machine learning and ensemble techniques, which is proven to be capable of answering the inquiry well. Exploring more discriminative local data sources by clustering the online lending market and attention mechanisms could be future research agendas. Despite recent progress, credit scoring in peer-to-peer lending remains an open topic, and exploratory research is a rewarding direction. New localised lending patterns, data sources, and variables on credibility scoring for different platforms or markets deserve more attention, both in terms of theory and application. However, the problem still exists. An increasing amount of general and unstructured big data have the potential to yield actionable insights but requires extensible AI-powered platform solutions to efficiently aggregate, normalize, transform, and apply the data. In emerging markets, AI-powered credit scoring has traditionally been a luxury enjoyed only by wealthy groups and a specific number of well-known companies, limiting its extensive applications to the majority of people in need. Substantial investments and over-engineered solutions disallow small financial institutions to step in. In most cases, data themselves are not valid and informative, and lack transparency in terms of matching or separating. In addition, validation and explanation are very hard to obtain.

Keywords: Machine Learning for Credit Scoring, AI in Financial Inclusion, Big Data Credit Assessment, Alternative Credit Scoring Models, Predictive Analytics in Finance, Non-Traditional Data Sources, AI Credit Risk Modeling, Financial Behavior Analysis, Digital Lending Algorithms, Fair and Explainable AI in Credit, Credit Scoring for the Unbanked, Behavioral Credit Scoring, AI-Driven Risk Assessment, Open Banking Credit Models, Data-Driven Lending Solutions.

I. INTRODUCTION

In recent years, the development of information and communication technology, the Internet, and similar products has created the opportunity for individuals to expand their businesses faster and easier. However, individuals and small traders often cannot obtain loans to expand their businesses due to high poverty rates and the problems of evidence required to obtain loans such as track records, bonds, properties, and collateralized land ownership documents. This has created information asymmetry, adverse selection, and moral hazard. Banks and other lending institutions use these types of information for credit risk analysis, i.e., risk evaluation of borrowers defaulting on the loans they have taken. To address this problem, using machine learning classification algorithms on public alternative data of the customers acquired during the initial registration process can help with credit risk prediction. For the application of these machine learning techniques, credit risk data cleaning, preprocessing, and training data generation were performed. Using different machine-learning classification algorithms, the performance of models was assessed, which included Naïve Bayes, Decision Tree, Random Forest, Logistic Regression, Support Vector Machine, and Ensemble classification model. With the proposed approach, banks and financing institutions can perform credit risk analysis based on alternative public data

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for millions of customers. A proper credit risk prediction using machine learning algorithms can mitigate the information asymmetry problems in the financial industry, which can lead to large-scale business expansion and financial inclusion. In developing and emerging economies, credit scoring has traditionally been done by credit bureaus using a conventional approach collecting customer financial records such as loans, deposits, and transactions from financial institutions. However, credit bureaus require a formal credit track record as prior evidence of application. Currently, millions of people, especially in the developing and lower-income segment of society, lack the credit history track record. The result is a severe limitation in obtaining loans for expanding their businesses. Data sources such as public records are alternative and alternative data for the credit scoring or credit risk process. Proper credit risk prediction based on alternative data can create a large number of loan receivers (unbanked and underbanked) and open up opportunities for businesses to grow, create new jobs, and reduce poverty. The alternative public data attributes of customers applying for credit loans at a financial institution are investigated to help perform credit risk analysis for people with limited access to formal financial systems.

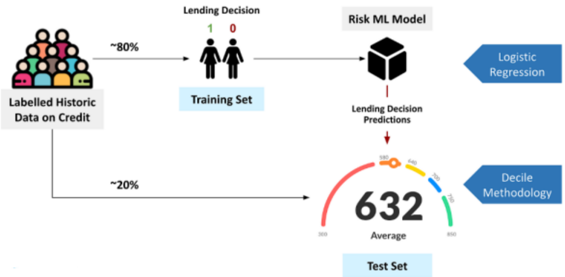

Fig 1: Credit scoring and machine learning.

1.1. Background and Significance

Almost everywhere around the world, having access to some form of financial services has become the norm. These services encompass all forms of support and assistance that individuals and enterprises seek as financial information; savings options; availability of credit, loans, and other forms of financing; as well as insurance. Consequently, these services are essential not just for the benefit of the individual but for the upholding robustness of any market economy. Since there is a strong correlation between the strength of the economy and access to financial services, it is no wonder that everywhere in the media, development agencies, and even many governments, financial inclusion has become a priority.

Contrary to the above narrative, there remains a significant part of the world's population that struggles to access financial services. In emerging markets, the hardest hit include underbanked individuals such as women, the youth, the poor, and those living in rural areas, as they find it difficult to access the traditional forms of collateral or means of identification that creditors or lenders require to avail their services. In essence, they are denied access to or rough access to mainstream financial services, and are thus subjected to low amounts and prohibitively high costs for any services they manage to obtain from microfinance lenders and loan sharks. These groups are denied access to the internet, accurate measures of their business performance or assets, formal employment, and in many instances even formal identification documents. As a result, lenders cannot determine the creditworthiness of these individuals and enterprises.

Nonetheless, various emerging methods are in turn being developed and applied to make credit assessments on these underbanked consumers, allowing them to access necessary funds and financial services. One such method that behoves great promise is the application of alternative data sources, such as company registers and public data, to assist lenders in determining credit risk in the absence of traditional data sources. These alternative data sources, when combined with the rise in computing power and internet speed over the last two decades, enable the extraction of alternate information.

II. UNDERSTANDING CREDIT SCORING

Prior to the development of credit scoring, lenders had to rely on traditional methods, mostly personal judgment and intuition—a time-consuming task where their biases were quite apparent. By reducing the subjectivity of this arduous and sometimes perilous task, credit scoring has become a valuable and trusted tool for lenders and consumers alike. Credit scoring is the process of aggregating all the available data about consumers' payment history, financial status, and transaction patterns, and condensing them into a uniquely generated score for each. A consumer's credit score provides lenders with a preliminary judgment on the likelihood of default.

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Credit scoring has become the primary method for evaluating borrowers' risks in general banking, consumer loans, mortgages, car loans, and credit cards in recent years. Most institutional lenders now subscribe to comprehensive credit reports to support their lending decisions, containing hundreds of statistical descriptors of consumer transactions. Using complicated statistical models, lenders could utilize this rich source of information to develop risk assessment systems. Unfortunately, due to the risk of discrimination and unfair treatment, a lot of the potential parameters of consumer behavior cannot be used when assembling credit scores.

The earliest approach to consumer credit scoring can be traced back to Fair Isaac which released its first credit scoring report in 1956. Its general approach to consumer credit scoring was then adopted widely in the industry. Its credit scores and credit scoring systems represent one of the earliest large-scale commercial applications of statistics. It has for long been the foundation on which decisions on the entire lending industry are based. Due to potential market dominance and unfair treatment, its scores and the secrets behind them have become a topic of widespread interest and litigation. Unsurprisingly, people have devised various methods to contest the scores. The lack of transparency in the calculation of these scores poses hurdles for lending credibility and further aggravates the already-misleading perception of risk by the borrowers.

2.1. History of Credit Scoring

Credit scoring is arguably one of the oldest use cases of analytics. The extremely high costs associated with lending money have led banks and other financial institutions to assess the creditworthiness of potential borrowers. According to several estimates, the credit scoring market size was around USD 400 billion in 2017, and it is expected to exceed USD 1 billion within the decade. Credit scoring is even more important for banks operating in developing markets where competition is limited and the borrower base is inertial. In these markets, banks' willingness to lend money is often governed by their reluctance to enter into new borrower relationships, thereby driving up information rents. New borrowers are typically issued small loans with an excessively high interest rate to partially mitigate lender uncertainty about borrower default risk. To maximize financial inclusion, banks need to widen their lender base and lower initial margins. Credit scoring is key to achieving this goal because it enables the quantification of potential borrowers' creditworthiness using alternative data sources such as mobile phone records. Despite banks' immense interest in small-scale, data-driven credit scoring applications, a surprisingly limited number of academic papers exist on the subject. The existing literature typically focuses on how to predict borrowers' creditworthiness with alternative, mobile phone-based datasets, while little attention is devoted to how such systems can be feasibly implemented in practice. To date, there are only a small number of papers that have offered open-access alternative datasets suitable for machine learning-based credit scoring.

The first commercial use of retail credit scoring can be traced back to 1956 when Fair Isaac was founded in the US. The company's first FICO score, which quantifies consumer payment behavior in terms of a score between 300 and 850, was introduced in 1981 as a premium product. Consequently, it took some time after the first mass-market credit scoring model was deployed for it to be used in qualitative risk analysis tasks such as credit decisioning. Nevertheless, this model proved extremely successful. The FICO score remains the key ingredient of many consumer credit scoring applications, and the analytic company has grown to a multi-billion dollar revenue firm. The first predictions of corporate creditworthiness using publicly available information emerged in the late sixties with Edward Altman's development of the z-score model for bankruptcy prediction.

Equ 1: Logistic Regression for Binary Credit Risk Classification.

$$P(y=1 \mid \mathbf{x}) = \frac{1}{1+e^{-(\mathbf{w}^\top \mathbf{x}+b)}}$$

- y: Outcome (1 = default, 0 = non-default)
- $\mathbf{x}$: Feature vector (e.g., income, payment history)
- $\mathbf{w}$: Weight vector
- b: Bias term

2.2. Traditional Credit Scoring Models

In such a context, many lending platforms are not equipped with the same decision support systems used by banks for evaluating the creditworthiness of borrowers. Banks have scores that take into account a multitude of data (wealth, capital, assets, education, etc.) in various proportions. Hence the emergence of the internet popularization and enhancement of online lending platforms leads to a need of scoring models that provide an evaluation for any internet user based on simple available data.

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Such evaluation should not be unfair because it concerns consumers significantly background. Their profiles follow unknown distributions, and the social network construction is vague and apprehensive. In addition, real-time analysis (within seconds) is strictly required to provide decisions after new requests are made. Failure on time means losing the opportunity of profit. Hence neural network models should bear the aforementioned advantages and provide a scoring evaluation for internet users.

A scoring model is a model, either statistical or artificial intelligence, that provides a score for users on a special object. The score is an assessment of the object by a subject in a determined scale. If a board collects data of the stocks in a country, it may evaluate the companies scored 51-85 as stable and 85-100 as safe, but obtain a uncertainty arrangement on companies scored less than 51. The same case also applies in evaluating risk probability for individual borrowers. In a Big-Data era, lending platforms have data tracked millions of users. Given a new indication, extracting missing structured information bound to the indication which is available in the seeking environment is extremely difficult. Open prediction for any new consumer/user requests and hence the potential smart loan investment opportunity are urgently needed.

In speech recognition, the matching pattern of a phoneme in a user's voice relative to a corpus of phonemes already recorded is sought. In stock forecasts, the past pattern of a stock price would provide insights of its future movement (trending up/down/constant). In language translation, the similarity (visual or sound or semantic meaning) of a word relative to a dictionary is employed to find its translation to other languages. In score modeling, the judgment on the propriety of loanting amounts to online consumers is made given their available data, the same scenario of which as input have been offered judgments before. Hence judgments of unknown users are constructed by searching similar inputs and their mapping outputs.

2.3. Limitations of Traditional Models

Banks and other financial institutions regularly conduct credit assessments to evaluate their clients' creditworthiness and evaluate potential credit risk. A series of data-driven judgments that evaluate an applicant's credit risk is known as credit scoring. Credit scoring has been a part of banking and financial engineering for over a century, but it has recently gained much attention due to breakthroughs in machine learning and the availability of large datasets. People from various fields, such as finance, sociology, economics, marketing, and social applications, conduct research on this increasingly relevant topic in both academic and non-academic realms. Banks utilize credit scoring as an indicator for financial strength and eligibility for credit. All scoring models aim to assign probabilities for predicting nonpayment risk in a quantitative way.

Limitations of traditional models could be divided into two categories. First, many traditional models, such as logistic regression and linear discriminant analysis, can estimate the probability of nonpayment, but their theoretical constructs are based on unrealistic assumptions. For example, logistic regression assumes that the logit of the event, such as a default, is a linear combination of the explanatory variables. Furthermore, many models produce an intermediate or transformed score based on scores estimated through the selected models. Therefore, the estimates may not be probabilities any more. Such issues lead to a trust deficit in the estimated scores. They pose serious threats to social media, diseases, and other applications with sensitive stakeholder interests, and they have also posed serious economic threats to the financial sector and credit scoring.

On the one hand, many machine learning algorithms have more relaxable structures than traditional methods and have little to no limitation in estimating the score. They can be classified into one of the following categories based on surrogate focus: Model-agnostic explanation methods: These methods do not require the model of interest to be transparent and can provide a model-agnostic mechanism and some general understanding of any given models. For example, LIME and SHAPE consider the observations locally around the target prediction and provide solutions with a trusted model. However, these methods do not take the surrogate model into consideration and cannot provide the rules viewed globally.

III. THE ROLE OF BIG DATA IN FINANCE

It is likely that the majority of economic agents have financial agents (institutions), enabling them to do business, obtain credit, and improve their standard of living. Limited access to credit and financial markets will lead to limited business expansion capabilities, low economic growth, and poverty for the poor. The same holds for other actors that do not have a degree of trustworthiness, such as the small and medium-enterprise groups. In general, it is difficult for individuals without a formal credit score to access credit. The global credit information market is limited to those who have high-quality information and an established credit history. This has unintentionally excluded a large portion of low-income earners in developing countries who are usually creditworthy but lack a formal credit score from credit and financial agents.

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Big data in finance will allow such economic agents to use machine learning algorithms for credit assessment, improving their chances of obtaining credit and confronting stigma from being unbankable. AI will have to provide economic agents with opportunities similar to those provided by credit scores. Once they have been provided with sufficient amounts of data for a learnable model, it will develop a level of inferences that estimates the agents probability of default. Therefore, it becomes vital for institutions like banks to invest more of their capital in AI and machine learning. The banking sector must identify investment opportunities that will assist small businesses, smallholder farmers, women, and low-income groups in obtaining formal credit. Such an investment can reduce exposure to risks for these economic agents, improve their capacity to flatter poverty, and increase their standard of living. Credit data will be collected from local businesses, mobile money transaction data, market data such as supply chain data, and social media information. This data will be cleaned, analyzed, and applied to machine learning models, producing a learnable model. The model will then be used to predict applications. Borrowers can either accept the result or reject it. Financial inclusion scores could range from 0 to 1. Scores closer to 1 suggest better access to credit and financial products.

Fig 2: Big Data in Finance.

3.1. Definition of Big Data

Big data has been used in different paradigms that collect diverse kinds of data into a data warehouse and apply mining algorithms to extract information and knowledge. However, in addition to the massive data storage and retrieval problem, big data presents a number of challenges. The rapid growth and evolution of the world's data is presenting challenges in dealing with its volume, variety, and velocity. The level of data and information management required to allow future applications to cope with the growing challenges of big data requires a comprehensive strategy, which is a system that is explicitly designed for try to analyze that "data tsunami." Big data is becoming a reality. What are the starting attributes of big data? Big data is defined as high-volume, high-velocity, high-variety, and high-veracity information assets that require new modes of processing to enable enhanced decision-making, insight discovery, and process optimization. The thesis delves into the high-volume, high-velocity and high-variety aspects of this definition. It explores important attributes of big data, such as volume, variety, velocity and veracity. It exemplifies big data challenges and presents a framework and active research areas in big data. At last, it highlights future research opportunities in various domains of interest.

Volume, the quantifiable size of the data, immediately comes to mind in thinking about big data. While data volume is relatively easy to measure, it is harder to contextualize. Different fields deal with different orders of magnitude in data volume. For example, a petabyte of rainfall data may count as big data for a weather agency, whereas a few terabytes of search query data may be routine for a search engine company. Given that volume is relative, it is not a sufficient measure of whether a data set can be classified as "big." The renowned analyst postulated that variety, velocity, and veracity are other equally important attributes for big data to attain a higher value. Variety is often overlooked in definitions of big data, but is of profound importance. For example, the perceptual gap between the availability of various types of data in CCTV footage and the ability to make sense of it is huge. Yet, a pipeline that allows people to convert input data into the expected output is still needed.

3.2. Sources of Big Data in Finance

Online lenders capitalize on the massive volumes of publicly available information on their loan applicants to enhance their consumer credit scoring models. A variety of natural data sources are analyzed: from publicly available information scraped from the web to one-off reports produced by specialized firms that aggregate information across different

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platforms and sell them to the lenders online. Textual, numerical, and categorical variables are extracted from these sources using machine learning techniques. Empirical results show that these extra features significantly enhance the prediction accuracy of the lenders' models. Online lending is considered a new financial technology-powered innovation in the retail credit industry, where an online platform directly connects lenders and borrowers without intermediaries that characterize traditional banks. This funding model is much more cost-efficient than those of traditional equity/patent/peer-to-peer marketplaces, which rely on credit scoring information gathered by score providers. The key innovation is an automatic scoring function that facilitates credit evaluation without the need for external mechanics. This scoring function is constructed based on certain predefined and frequently revised criteria that online lenders use as screening rules for prospective borrowers. Each criterion is designed to elicit a credit-relevant feature that reflects the borrowers' credit worthiness, such as their credit status and trustworthiness.

In recent years, with the rapid growth of the online lending market has come increased scrutiny from regulators, who just recently allowed banks to engage in the online lending business. These lenders in turn have noticed a dramatic performance drop of their scoring functions, further fueling the concern. Then, how online lenders can systematically recover from the deteriorating scoring performance is examined. Online lenders harvest massive amounts of publicly available information on their loan applicants to ameliorate their consumer credit scoring models, resulting in a better understanding of the employment status, social profile, and relational behavior of the borrowers. A two-stage information accumulation and model fitting procedure was applied, where the hypersensitive and adaptive boosting model trained only on the text features obtained on depreciated borrowers' online activities was relied on. The assumptions for consecutive ratio testing variable selection were relaxed to allow the simultaneous incorporation of the social profile and online behavior to prediction. Importantly, in view of the market pulse, seasonality, inspections, and large surge bids, care was also taken to avoid over-reaction by bounding the effect of price drops on feature selection.

3.3. Impact of Big Data on Financial Services

Financial services around the world have changed dramatically due to increased access to mobile devices, the possibility of information being stored in the cloud, and the availability of large amounts of data from various sources. The use of Big Data in favor of financial inclusion represents a paradigm change in financial services. New non-standard data sources are becoming the primary source of information used by financial institutions for credit risk assessment. Big Data refers to vast quantities of structured, unstructured, or semi-structured data, which are characterized by the 5Vs: Volume, Velocity, Variety, Veracity, and Value.

Machines have begun to overtake humans in data processing and decision-making thanks to the convergence of inexpensive cloud computing, easy access to vast amounts of data, and the development of machine learning algorithms. Thanks to wider access to mobile phones and smartphones, equality in the availability of data has favored financial inclusion. Banks and other financial institutions cannot readily access traditional information sources on the majority of the low-income population in emerging countries because it is difficult or too costly. Alternative data on mobile phone usage, social network relations, past transactions in other service domains, and repayment behavior can now be readily gathered and processed as big data. And automated analysis of these data through machine learning and AI algorithms can reveal the creditworthiness of potential borrowers.

However, the same data availability that benefits low-income borrowers also presents significant challenges for emerging market financial institutions. The business model for financial inclusion has changed from offering credit products to poorly informed retail clients to the data-driven, multi-product approach that underpins the platforms' business model. As a result, alternative data sources have proliferated, big data analytics has become common, and fraud risk has increased. Companies offering credit products are now seeking validation of their credit scoring algorithms and best practices to mitigate fraud threat, as well as the developing complex regulatory environment governing financial services.

IV. MACHINE LEARNING FUNDAMENTALS

Machine learning (ML) is an emerging technology with increased importance and application in the financial services domain. Transparent ML-based credit scoring models are constructed using loan applications with both accepted and rejected labels. Examining the explainability of credit scoring models is crucial as ML/AI technologies have become widely used in the financial services sector for a variety of decision-making tasks including pre-approval, credit underwriting, investments, fraud detection, and marketing. ML has been employed to address these issues with an emphasis on automated data-driven processes that can speed up decisions and decrease human error. In the context of credit scoring, ML can potentially enhance the traditional scoring process by automatically detecting complex non-linearities and interactions in data.

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Several methods for interpreting ML-based credit scoring models, including approximation models and feature importance measures, are being actively researched and developed for a wide range of industries. These methods are referred to as explainable AI (XAI) and are broken down into two classes: (i) model-agnostic post-hoc explanations, which are separate from the ML model and can apply to any input-output mapping; and (ii) model-specific methods, which generate explanation features directly from the model. Successful application of XAI methods enables non-experts to understand what data, data parts, or data points a model uses in its decisions, ensuring a better understanding and acceptance of ML/AI technologies.

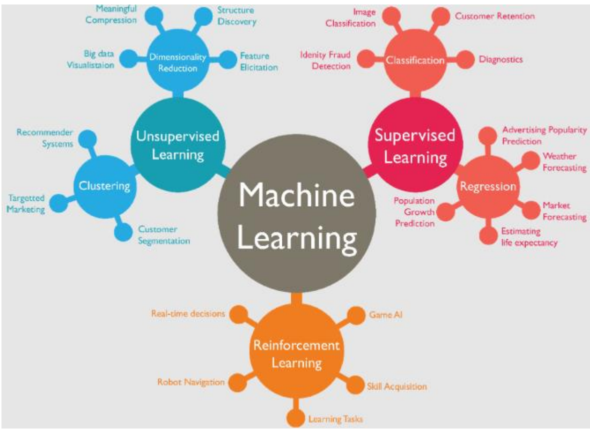

Fig 3: Machine Learning Fundamentals.

Compliance with regulations is a critical element for establishing a reliable technology. The General Data Protection Regulation (GDPR) enacted by Europe and an increased focus on ethical AI demanded by governments and industry led to the need for explanation of credit decisions made by ML models. On March 29, 2023, the European Parliament approved the regulation of AI, which will enforce stricter penalties for violations of privacy, data security, and system bias across industries, with the financial system as one of the initial targets. Interpretation is particularly important for credit scoring because credit scores essentially explain how information in a loan or financial product application has been processed to a score. High stakes regulation in the US also stresses the need for explainability. For example, the US Equal Housing Lender Rule prohibits banks from engaging in lending discrimination and requires companies to disclose information for model decisions.

4.1. Overview of Machine Learning

Modeling through Machine Learning (ML) has found its way around most parts of the industry. ML, a collection of statistical tools, keeps learning and improving prediction scores as it is exposed to more experiences. ML has contributed to many incredible applications used regularly today. Wireless networks and autonomous cars utilize ML methodologies to learn and make secure decisions to help citizens. Traditional rule-based architectures in financial systems have become heavily reliant on many internal and intermediary services. Complex financial systems cater to domestic and global issues using ML. Several applications for ML methodologies in finance include price trend prediction, credit risk assessment, market risk management, fraud detection, and money laundering. Problems like fraud detection, risk assessment, and algorithmic trading can be best tackled with ML based methodologies due to their higher versatility, knowledge generalizability, and prediction capabilities. The global financial crisis stimulated by the American key mortgage loan market collapse left millions of middle-class citizens homeless while the expensive finance world was shaken by a mere blunder. Model and data transparency have gained significance for better corporate governance in finance. ML methods have been substantially applied for anomaly detection and minimizing statistical variance in finance.

Business owners need credit prediction models to assess individuals borrowing requests against internal and external credit history credit scoring variables. Any individual showing a higher probability of default on his loan should be denied funding. Robust ML models avoid loan denial whilst allowing the bank and the client to learn which behaviors should be changed to avoid damaging credit scores. Scoring behavioral variables is achievable by lending companies purchasing anonymous customers’ transaction history raw data from e-commerce companies and processing it to fit expensive machine learning tools. Credit scoring model development continues considering that advanced techniques were explored for years in an industry where linear regression has remained state of the art even during emphatic increases of alternative methods’ successes in other sectors. Determining statistically valid behaviors from transaction history data is an unsolved problem in many industries. Fraud detection on credit cards depleted by millions per day at a bank has yet to find an effective solution. Lending companies online experience fraudulent attacks worth millions.

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4.2. Types of Machine Learning Algorithms

Machine Learning applies AI algorithms to find patterns within data while technically being a method for statistical inference. It has successfully impacted multiple areas, and now it is used for credit scoring. The credit scoring industry has been backed by traditional statistics since its inception. However, this traditional take is increasingly questioned in terms of robustness against big data applications. The scenario where commonly adopted machine learning techniques perform considerably better than traditional ones must be studied, as both techniques are still used concurrently by credit scoring institutions (CSIs). This leads to a re-investigation of what makes some algorithms better for credit scoring data than others, without consulting any proprietary information.

Machine-learning techniques are classified into general-purpose, specialized, and hybrid. General-purpose techniques are flexible tools that may be successfully applied in a variety of contexts. They require relatively little auxiliary knowledge about the problem under consideration. However, since they are generic, their performances need to be tuned through exploratory tuning stage. Among these techniques, the most simple one is the linear regression. Even though this very classical model commonly yields good performance in many applications, it has some well-documented limitations. In recent years, more complex techniques have gained popularity, mainly thanks to access to massive amounts of data and powerful computational resources. Whenever general-purpose techniques are used, CSIs should also present strategies, special arrangements, and usage patterns accordingly. A topical example of this approach are methods to pre-process data to reduce training-time. This way, either some general-purpose technique must be utilized, or particular credit scoring mechanisms must be ignored.

Applications of specialized techniques to credit scoring are scarce. This approach usually requires good knowledge about the problem at hand, both from the data perspective and its background properties. For credit scoring, the best-known methods include the Adaptive Boosting, random forests trees, and extreme gradient boosting trees. Hybrid techniques combine both general-purpose and specification. A hybrid technique is also a good example of this approach for credit scoring.

4.3. Evaluation Metrics for Machine Learning

Often referred to as performance measures, evaluation metrics derive quantitative assessment of the performance of a model, a method or an algorithm . These metrics are constructed around the definition of a successful prediction – ranging from passive approaches like statistical measures to active approaches where performance measures implicitly define the loss function. In contrast to the probability distributions of a scoring model (where differentiation is needed), in binary classification problems it is required to score a risk on a continuous value (usually between 0 and 1) such that all models produce this ranking in order to apply binary event rates (for example 30% risk division into 60% chance of rejection for the case being scored). The following key metrics are suggested for applicability in model selection, alongside the required visualisations: ROC-AUC and GINI.

By plotting the trade-off between the predictive power and the business cost of a forecast (like approval or negation costs), these plots enable the selection of a model according to risk versus reward. It is necessary to obtain visual output of the selected model's and its competitors' predictive power in order to provide decision support. This section describes a combination of widespread and domain-specific base metrics that generate intuitive interpretation and visual quality for decision makers. It discusses ROC-AUC, GINI, and KS metrics and visualisation followed by the NPS and Population charts for added quality checks. The major machine learning methods (both traditional and contemporary) are suggested to be evaluated on the aforementioned metrics which together provide an actionable and strongly informative description of a models' and an algorithm's predictive performance for decision makers and domain experts. A selection of business critical parameters (such as event rates) are suggested to be reported. The best performing machine learning methods and discussed new methods are employed to score the PSA case study of a loan approval system.

V. MACHINE LEARNING APPLICATIONS IN CREDIT SCORING

Credit scoring has become vital for evaluating borrowers' risks due to the proliferation of online financial services. Limited studies have explored P2P lending's influence on borrowers' investment decisions or reflected on machine-learning (ML) and Artificial Intelligence (AI) applications for structural and organizational design. Few studies have incorporated profit-scoring approaches into risk-prediction algorithms for P2P loans. The focus is on credit scoring, a classic application of AI/ML. The aim is twofold: to predict default trends and to provide feedback on loans.

First, the proposed Ph.D. project analyzes the learning patterns of four ML algorithms in predicting the probability of default, including Random Forests (RF), XGBoost, a feedforward neural network, and an LSTM model.

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To improve transparency and accountability, Explainable AI (XAI) methods will be employed to interpret the models' predictions. Besides the predictive performance, the feedback provided by the models is evaluated based on the general feedback quality and whether decision-makers actively incorporate the feedback.

The research proposes a framework for profit-optimization in P2P lending based on the context of the Gustme P2P loan marketplace. Building on a risk-prediction model, an active investment strategy for selecting loans is developed that maximizes return for a given risk level. Using rich data from Gustme, the algorithms are benchmarked against a classical transfer-with-expectation framework. Portfolio construction based on the Shannon's measure of entropy and a logistic-regression-based weight-adjusting approach is also explored as an alternative to dynamic strategies. Summary statistics, cumulative return distributions, and metrics of outperformance and risk-adjusted return quantify alternative strategy performance.

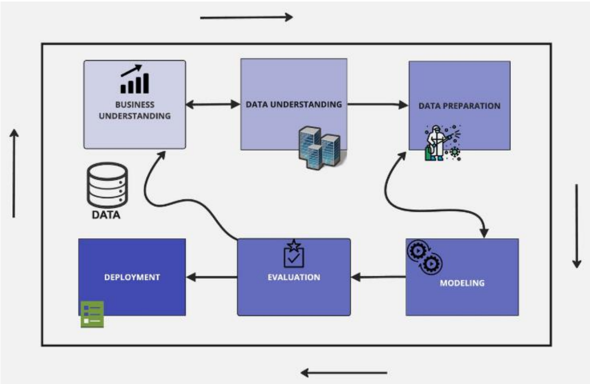

Fig 4: Machine Learning Applications in Credit Scoring.

5.1. Predictive Modeling Techniques

In this section, the prediction methods will be discussed. Two different scripting files were created for modeling techniques in R language. A number of techniques were used, specifically seven machine learning techniques. These methods were used to establish prediction models. Performances of these models were checked and interpreted using performance measures. This was done to see which method was the best technique to estimate the default behavior in credit card data over this period.

A classification model is a predictive model that assigns one of two or more classes to observations, from a set of features. The model learns the relationship between class labels, also known as outcomes or responses, with explanatory variables, or features and predictors. The model is then used to classify new and unseen observations. Classifiers are common in statistics and machine learning, solving several important problems in different domains. In this project, models are created that could predict whether customers default on payments using credit card data from the period of 2015 to 2019. The data will be split into 70% training and 30% test data. Predictions will be produced on the test data set using the modeling workflows. The performance of the predicted model will be measured smartly using all performance measures suggested in literature. The modeling approach will be defined and used on the trained model. The trained model will be interpreted regarding important predictions. Investigating the credit defaults and insights will also be another model to be built using R language for extra metrics that might be interesting to discover.

Logistic Regression is a statistical model that uses a logistic function to model a binary dependent variable. In this case, the model predicts the probability of an event occurring (credit default) based on one or more independent predictors. The predicted probability can then be classified as "yes" or "no" based on a threshold value. It has been heavily used in initial credit scoring studies.

Support Vector Machine (SVM) is also a linear model for classification. The most common one is the "MAXIMUM MARGIN" classifier. The support vector machine constructs a hyperplane to separate different classes in the feature space. The hyperplane is chosen to maximize the distance between the two closest points on either side of it. If a point is above a hyperplane, it is classified into one class. K-Nearest Neighbors (KNN) is a non-parametric classification model. Given a new data point, it looks for the k most similar points based on features and assigns a class based on majority voting. A Decision Tree is a supervised machine learning model with a binary tree structure. Starting from a single point, it splits data into two child nodes based on conditions using feature values.

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The process continues until a leaf node is reached. Credit scoring analysis performs well with decision trees, which allow automatic examination of key features for prediction as well as examination of overall performance. Visual representation allows easy understanding of the model and features.

5.2. Feature Engineering for Credit Scoring

Although it is a well-known fact that the predictive power of the statistical models used for credit scoring depends to a large extent on the quality of the features, there is little information on how to efficiently create them. In credit scoring, feature engineering is difficult, time-consuming and requires expert judgment due to the complexity of financial products. The objective of this work is to investigate the feasibility of an automated feature engineering process, by assessing the true predictive power of a variety of potential features that are readily available.

Credit scoring is the task of predicting the probability of a customer defaulting based on their characteristics and behavior. Feature engineering for credit scoring implies the (semi) automatic creation of features to improve the predictive power of statistical models. After a short review of the current state of the art in feature engineering and selection, this paper presents an extensive analysis of the performance of a variety of simple, well-known features on the default prediction task. The newly engineered features include customer characteristics, demographics, transaction data, credit card type, and something novel for credit scoring: use of features from the field of graph mining.

Given the rapidly increasing volume of transaction and social network data, banks are interested in incorporating this data into their credit scoring models to enhance financial inclusion. This outlines the large-scale extraction of features based on social network and transaction data. Based on these labellings, the extraction of link-based features, computation of PR and SPA exposure scores together with link-based exposure features is performed. Finally, the feature groups x_PV, x_LB, x_PR and x_SPA are extracted and the provided credit scoring data assembled. In total, this results in 303 features: 8 demographic features, 138 features from the social network, 74 transaction features and 83 credit card features.

Equ 2: Decision Tree Split Criterion (Gini Impurity).

$$G = 1 - \sum_{i=1}^{C} p_i^2$$

- C: Number of classes (e.g., good vs. bad credit)
- p_i: Proportion of samples in class i at a node

5.3. Case Studies of Successful Implementations

As a part of the project on the application of Artificial Intelligence for Financial Inclusion, several case studies of instigations in Credit Scoring and other related activities are documented. These latters are awaiting to be appended for dissemination through the site. The Credit Scoring system and applications in India is also described.

Home equity lines of credit (HELOCs) are often made against a line of credit where customers can refinance their loan in periodic increments. Default prediction from a bank's perspective is a short- lived binary event, as better credit history portals become available to assess the risk of default. The study predicts the default risk in this rapidly changing scenario by developing a portfolio of supervised learning algorithms on the portfolio data. The implementations were executed using a programming language, 25% of the data were held-out to assess the performance of the models and their predictions were communicated using a visualization tool. The explanation, implementation, and performance assessment of machine learning algorithms (logistic regression, random forest, gradient boosted trees, neural networks, and voting ensembles), and data manipulation functions, in addition to the predictive model development and deployment methods are provided. The sequential evaluation of suitability of algorithms along with domain knowledge inputs will provide an adequate solution open to current requirements of science transfer to end users.

Predicting Default Risk in the Home Equity Lines of Credit using Machine Learning.
Default risk prediction for loans has been a concern for the banking sector. Loans are often issued against an asset, thereby limiting losses arising from a default. Thus, a default of the loan is a choice and can impact a bank's liquidity position. For this purpose, default prediction is essential for banks and lending institutions, in order to take pre-emptive actions to minimize losses.

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VI. CHALLENGES IN IMPLEMENTING MACHINE LEARNING FOR CREDIT SCORING

Despite the advantages of ML in credit scoring, its implementation faces significant challenges. These issues encompass multidimensional aspects, including complexity, liability, transparency and explainability, data protection and privacy, fairness, discrimination, responsible utilization, and high costs. However, the present study exclusively emphasizes the foremost six concerns based on their potential impacts on credit scoring and evolution.

The incorporation of ML methods into credit scoring requires advanced Human Capital (HC) to grasp their data-driven AI and predictive nature. Nevertheless, the majority of banks in developing countries are relatively small financially, technologically, and knowledgeably, depending on either traditional methods for solvable problems or adopting already implemented and coded ML methods from other developed countries. As a result, they experience challenges hiring and maintaining those skilled ML specialists required for the successful implementation of ML in credit scoring.

The technical means of ML are advanced, proposing novel techniques frequently. Therefore, existing models in use quickly become outdated and need tuning or replacement by new and better performing ones. This perpetual change is not a concern in incapacitated adopted approaches, as they require little or no changes or replacements over long periods. Although the use of ML improves predictive accuracy with better performance than traditional CRAs, understanding the working of data-driven or black-box models is problematic. Even though outcome-based interpretability, such as deciding on predictions or impact assessment, can work, many banks and CRAs prefer event-based interpretability. In most traditional models, banks sometimes comply with the opposite direction of reasoning for credit following interpretation through business aspects, rules, and constraints. Therefore, an unsatisfactory basis of determining credit amounts or rules to capture the floor for continuously changing credit risk environments makes it difficult to understand.

Another concern is data protection and privacy, as well as the protection of sensitive banking data. ML models are trained on historical applicant data through parameters learned or tuned. It is challenging to disentangle sensitive information from this learned model. In contrast, traditional models only use rules based on business mechanisms transparent to all stakeholders.

6.1. Data Privacy and Security Issues

Modern society would be difficult to imagine without loans for individuals and companies, which are a source of finance for planned expenditures. For individuals, loans can be used for the purchase of cars, TV sets, furniture, or repair of apartments. For companies, loans are necessary for project financing, enlarging production or necessary purchases. Credit institutions, aside from banks, include microfinance, credit card questionnaires, factoring companies or alternative lending institutions. Each institution must assess the risk, thus deciding whether to approve the loan and under what conditions (the interest rate, repayment period). In the past, such decisions were made by a loan advisor, who, on the basis of an applicant's form, available data, credit history and subjective assessment, decided whether or not to grant the loan. The approval of loans increasingly migrated from a personal decision-making process to a mathematical model (scoring).

Scoring applications play an important role in modern society. Opportunity to take loans is primarily governed by rules defined by scoring models. Such models are commonly based on large data sets, and their actual implementation is complex enough. One approach to scoring can be modeled as a complex process, in which each score is defined by the output of the scoring models or directly by explanatory variables. There are dedicated scoring languages, which integrate with database engines and allow one to implement complex scoring sub-systems. With the development of new technologies, such as data mining, this scoring instrument sometimes becomes a black box, having parameters that are some optimized decision rules instead of simple variable values. Such an instrument using huge data sets is very powerful. However, it raises many important questions. How should these complex decisions be supervised? How are they created and maintained? What is the best way to contest the decisions? Can individuals understand them? What explains the decisions? Credit scoring is a very popular area of which decision-making systems are widely used. In recent years, it has been also investigated by researchers in the data mining, machine learning, and artificial intelligence domains, who try to implement the best scoring models by analyzing large data sets.

6.2. Bias and Fairness in Algorithms

Models based on data-driven machine learning approaches for credit risk are widely used in many financial institutions and have gained increased international attention. While the effectiveness of machine learning is demonstrated by analyzing its evolution through years, despite its efficiency and the great predictive accuracy it offers to creditors, there has been concern about the usage of automated decision-making processes that assess and rank individuals in terms of creditworthiness.

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The prospect of model scores being translated in do-not-lends where subprime or disadvantaged individuals are re-discouraged from bank credit is thought to put increased risk of a financial crisis, defaults and runaway. Starting from this idea, the present study analyzes bias detection and mitigation methods that support lenders in the pre-approval stages of credit application processing. It applies machine learning algorithms and scores on real-world data, produces models that are able to achieve a high predictive accuracy. Furthermore, bias detection and mitigation methods are applied in order to evaluate fairness metrics related to group and individual unfairness. By systematically comparing numerous recent bias mitigation approaches, it was found that there exist multiple opportunities in deploying and tuning fair methods to achieve better discrimination metrics. Conversely, it remains challenging to achieve fairness with better predictive accuracy, highlighting some trade-offs in enforcing fairness.

The usage of algorithmic scoring methods has been considerably growing in the finance industry to use historical records of clients and assess the risk of lending a certain amount of money. This paper investigates the emerging challenges of developing fair risk scoring models. With the increasing use of machine learning models in the scoring context, some developments were made in terms of implementation and compliance with regulators. However, reporting scores of loan applicants to regulation seems to be insufficient to ensure fairness of scoring. There are broader aspects in terms of fairness which are still completely ignored by risk management departments in banks. As there is awareness for these broader aspects, there is a growing demand for developing algorithms that do not only respond to regulatory requirements, but which also aim to improve fairness from an ethical perspective. The paper derives a series of challenges that characterize the problem of fair risk scoring from both a development and a business perspective. In addition, several suggestions are offered which serve as guidance for practitioners and researchers.

6.3. Regulatory Compliance Challenges

By implementing machine learning for credit scoring, several challenges can arise. The first group concerns the quality of the used data. While utilizing external datasets is not new to the finance world, the increasing availability of new data sources can provide opportunities and challenges. The need for data governance arises, which has implications for topics such as data quality, data ownership, and data bias. In particular, model bias is of interest in this study, as decentralized multi-party learning architectures are of interest. This is important because, despite attempts to mitigate biases before usage, data are often hard to remove from bias. Historical biases could flow into the reporting of the AI credit score. As a consequence, some regulatory initiatives concern auditing and certification of AI models by institutional private parties or initiatives of industry alliances.

Regulatory challenges concerning black-box algorithms also arise. Research on credit scoring processes by supervisory authorities is still scarce. However, there is a growing body of financial and legal experts who argue that transparency obligations do not obligate disclosure of the financial institution’s inner workings. Meanwhile, fairness of the scoring processes is a requirement of the GDPR and other initiatives. The black-box nature of neural networks could make it hard for financial institutions to show compliance with fairness requirements, both during incident reports and spot checks by supervisory authorities.

Additionally, responding to legislative challenges also involves further developments of AI foundations, such as uncertainties or evolving knowledge. AI’s applicability to credit scoring processes must be improved, as AI no longer needs to be deterministic in giving fixed predictions. Further, stakeholder preferences and types of fairness must be elicited and monitored, so that stakeholders can evaluate an AI credit score’s fairness. Besides, flexible responses involving improved ML could replace or diminish test scores that may allow to deliver human-understandable scores.

VII. FUTURE TRENDS IN CREDIT SCORING

The COVID-19 pandemic has hastened the development of fintech. Amid concerns that more loans may lead to more defaults, fintech platforms are under pressure to rethink their borrow-lending model. For loans to consumers with limited or no credit history, credit scoring acumen is crucial. On the other hand, we'll try to identify the sorts of factors that affect the financial exclusion of youth in Bangladesh regionally. The job seeking behaviour impacts the ability to get a loan. For the financial formation of any nation, youth is a potent engine. Fintech would facilitate microfinance. Recent changes in consumer lifestyle and habits present a significant chance for growth in the fintech lending sector. The BFSI sector will continue to see increased demand for online platforms as a result of the strong acceptance of digital-only banks, wallet-based payment solutions, and other financial apps like investment and insurance. Automation Technologies and Robotic Process Automation (RPA).

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Disparate data sets that reflect inequality in access to financial services provide the opposite perspective. For example, access to education and mobile phone ownership can lead to savings, while those without access to mobile services or basic education are likely to have zero bank accounts. This leads to the introduction of traditional credit scoring algorithms based on deeply entrenched constructs of financial history and the USA as a gold standard. In developing regions similar to Bangladesh, where the general public has only scant knowledge, digital trails are scarce, and paper trails are non-existent, accurate scoring is problematic. This poses a question regarding a process that suffices the requirements for screening potential customers in order to enable a lending product that serves the unbanked and underbanked across developing regions. The case for alternative, machine learning-based applications that are substratum agnostic to the problem therefore. The recommendation of enabling alternative, currently available data sources in financial institutions in addition to machine learning algorithms, is building a case around the dataset requirements of baseline machine learning algorithms and presenting a proof-of-concept of a scoring mechanism on otherwise unscorable individuals based on a client's simulation of historic submissions using only network data.

Feature engineering being one of the major contributors to the success of the task of credit scoring, guidance on the issue of current collaboration trends is provided as they are not consumable as such by these baseline scientific algorithms. Emerging areas for future works are also outlined, such as the potential application of language-based models to unstructured data sources. Recent findings in behavioral science regarding biases in credit scoring models and data required to construct a relevant substitute is also summarized. From an unexplored dimension, beyond its technological implications, the case is made for a theoretical examination of outcomes sourced from recently developed financial technology.

7.1. Emerging Technologies in Finance

In the last decade, technologies such as the Internet, mobile phones, advanced data storage, and payment systems have rapidly improved access to financial services. Concerns have been expressed about the downsides of digital finance, but much of the concern centers on new phenomena such as the potential for "data monopolies," data privacy abuse, and systemic risk, rather than technological innovations per se. If finance tech is well-designed, it can support the development of a safe, functional, and accessible financial system. The 1.5 billion adults who do not have access to formal finances are often in emerging economies, and primarily women and people living in poverty. Given that finance is a critical asset for development, this inequity is concerning. Foremost among technologies for improving access to finance in emerging economies is the ability now to analyze large amounts of data. This big-data capability is the backbone for recent innovation in digital finance. The behaviours of a person, whether individual or institutional, can be tracked if digital payment mechanisms and data analytics technologies are available. Such data, whether precise or indirect, represent actionable information for credit scoring, akin to a GPS location that does not capture identity but allows for contact. In parallel, the low marginal cost of creating a ledger, storing data, and using it for financial or financial-like contracts has made it viable to lend small amounts or take deposits of small cash amounts. Credit histories can thus now be formed for everyone. The availability and accessibility of voice, SMS, and the web in most emerging economies have made it feasible to send payments and conduct financial transactions on mobile devices. All these younger-than-5-year-but-mature technologies are presented as novel because they have not existed together at this scale and convergence. However, alternative financial services, e.g., information-heavy “social lending” practices, have been widespread in the informal economy. Risk assessment using social networks has a long history. Alternative data and technological advancement enable recent experimentation with more scalable, cheaper, and professionalized social lending practices. Alternative data and machine learning are favourable to credit assessment in that they add information and predictive power to better mitigate adverse selection. They are disadvantageous, because alternative data is less transparent and audit-able, and existing at a cheap scale enables click-bait crediting behaviour that leads to over-lending rather than inclusiveness.

7.2. The Role of AI in Financial Inclusion

More than 1.7 billion adults still do not have an account at a financial institution or through a mobile money provider. The largest share of unbanked adults lives in developing economies where 66% of adults are unbanked. In many emerging markets, entire segments of the population find themselves excluded from the traditional economy. Banks consider them too risky as borrowers as they do not fit any lending profile and cannot provide any collateral. They do not own any credit or loan repayments history nor do they have any form of identification paper for financial institutions to rely on in order to assess the likelihood of loan repayment. Most traditional lenders are adopting obsolete scoring and risk techniques, slowing the adoption of digital finance and the growth of the customer base in developed markets.

A motive to widen their customer base, lower funding costs, and accelerate profit margins is necessary for financial service companies, banks, and fintechs. They all have to rely on low-cost means to more efficiently and precisely score borrowers.

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Traditional criteria and prediction techniques are inferior on several grounds compared to machine learning and AI from traditional scorers and analytics. Companies, lenders, and banks allowing and using openly accessible alternative data and a rich array of advanced statistical techniques based on AI and machine learning are helping to produce a fast, low-cost, automated, scalable, and high-performance means to assess borrower risk. The latter initiative is propelling lenders into the digital credit era.

Alternative and innovative scouting, scoring, analytics, and financial inclusion services are offered by digital fintech companies. Innovative analysis and predictive credit scoring models applicable to Telco data, social networks, behavioral information, and e-commerce, among others. Several companies operate in this domain and become increasingly important in a rapidly moving worldwide industry with potential to divert market share from banks and take over the future of financial inclusion. The biggest players in this field, both in terms of customers and overall volume, are MyBucks and Lenddo. Both companies have developed a novel predictive scoring algorithm to include millions or even billions of unscored individuals and yet excluded populations from the traditional economy. Fintech companies concentrate on machine-learning-based scoring analytics capable of rapidly generating predictive scores from alternative data. They make use of open-source and proprietary machine-learning libraries to evaluate and model extensive datasets from which financial intelligence and business insight can be derived.

7.3. Predictions for the Future of Credit Scoring

Artificial intelligence and machine learning were solutions to capture the main but hidden patterns of previously seen data to answer future unknown cases. In line with this advanced and innovative approach, the need for faster and more accurate credit scoring mechanisms arose. Evaluating creditworthiness has a crucial importance for financial regulation and determining the eligibility to borrow. The traditional credit risk evaluating methodologies, especially credit scoring (CS), are time-consuming, based on lengthy processes, costly, unfair, and untrustworthy since they rely on surrounding guesses and past experiences. Several machine learning techniques outperform traditional statistical ones, which are already integrated into existing knowledge bases to discover rules based on a set of relevant features. In the CS literature, ML-based solutions are able to respond to highly complex patterns of new data compared to traditional CS approaches.

These techniques manage to capture the complexities involved in CS data and reveal patterns borne of historical behaviors to classify a sample as “good” or “bad” applying to unseen test data. As known, credit scoring is a well-known application of ML techniques, firstly pioneered by logistic regression. Several variants were proposed over time, among which the partially scored models are highly flexible, allowing for high-dimensional regression settings. A trade-off between interpretability of the model and exploitable credit data is obtained similar to other solvable graph models while still rendering a linear precision.

VIII. ETHICAL CONSIDERATIONS

Ensuring ethical use of AI in its decision-making processes has drawn wide attention as algorithmic decision making becomes more prevalent. The concern is that the automated decision-making processes by powerful algorithms result in unequal treatment of groups or individuals. In consequence, the decision-making policy exhibits statistical discrimination against certain subgroups as a result of historical injustice, resulting in the poor quality of the decision-making process. The topic of this proposed talk is Algorithmic fairness in financial credit scoring. Nowadays, the usage of machine learning tools in finance increases significantly. One of the main fields in finance is the development of credit scoring models both for companies and individuals. The growth of digitally collected data, as well as enhanced processing power, stimulate this trend. While the banking sector is almost fully regulated in terms of risk management, the usage of models for credit scoring is often confined to business sense. For this reason, a model can learn correlations from the data and discriminate certain subpopulations. Consequently, a default risk score calculated for particular clients might depend on their gender, nationality, etc.

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Fig 5: Ethical Considerations of AI for Credit Scoring.

While the topic of fairness in algorithmic scoring also becomes very popular, often the definition of fairness itself is not exactly formulated. The vagueness of the definition leads to a variety of measures and a lot of different sets of algorithmic methods that can guarantee fairness. In addition, it is necessary to check the output logs of the results to assure the measure's intersectionality property (i.e. faulty model will be fair if all subpopulations are treated in the same way). This talk presents a parsimonious definition of fairness from the social sciences, proposes a set of measures and generates a list of algorithmic methods able to guarantee fairness under this definition. A prototype checking model is developed and its usage is demonstrated. Also, the talk explains the usage context of a financial scorecard as well as the strict regulatory requirements in terms of model auditing that are often non-fulfillable for black-box algorithms. Therefore, in this case, simpler statistical models with a higher standard of explainability should be preferred over complex ones.

8.1. Ethics in AI and Machine Learning

Ethical questions pertaining to the algorithmic decision-making process have attracted the attention of researchers and the public. Discriminatory outcomes may arise notwithstanding similar input data when the model takes disparate decisions for logically equivalent individuals. Questions such as whether excluding age or income as features in a credit scoring model renders the final decision fair rest on philosophical values that determine the fundamental fairness principle that any decision with regard to individuals' loan applications depending on income, age, or any other feature is per se unfair. The idea that an algorithm may not tell everything about a person, but a comprehensive set of features with proxies may be used raises the possibility of wrongful reintroducing attributes that were excluded from the model. If this is unacceptable it follows that a financial institution may not exclude such attributes after any transformation from usage in the algorithmic process. However, it remains unclear whether this intuitively sound statement with respect to initial decisions is still true with respect to post hoc characteristics. Justification would then have to compete with the need to provide transparency, and opacity would pose considerable regulatory challenges, especially to lenders offering credit to the masses. Prior work on generally applicable testing criteria for the legitimacy of heuristics would need to be scaled up considerably. Specific questions that arise in the automated management of accounts and generalization of heuristics from banking to retail need to be scrutinized further.

Aspects such as the sustainability of algorithmic decision-making processes, accountability including non-compliance detection, and risks pertaining to machine learning as widely boundaryless heuristics need to be considered in more detail. Specific institutional factors and data-related aspects would also need to be more fully understood, especially given their concrete relevance for compliance with an ethics-by-design approach, including accountability. In reviewing and consolidating the relevant literature, twin notions to supporting ongoing work that are not mutually exclusive are presented: algorithmic self-awareness and explicit ethics. Current scientific understanding in these areas appears somewhat limited and perspectives on how to advance knowledge and understanding further are outlined.It is essential to address these difficulties to avoid unintended consequences of AI implementation in credit scoring systems. The traditional credit scoring systems in use today have been thoroughly and deeply studied by academics and regulatory institutions. With the rise of AI, there is a need to reassess the efficacy of existing regulation and whether it might be possible to address similar problems within the AI paradigm.

In addition to standardizing interpretation, ML-based systems should employ processes that would duplicate those employed in traditional systems to minimize the side effects of ML choices. It may be possible to build governance systems for ML-based credit scoring systems that are proportionate to those available for FICO scoring models, provided that adequate caution is taken.

Equ 3: Credit Score Calculation Using Weighted Linear Model.

$$\text{Credit Score} = \sum_{i=1}^{n} w_i \cdot f_i$$

- w_i: Weight of feature i
- f_i: Feature value (e.g., credit utilization, loan repayment behavior)
- n: Total number of features

8.2. Transparency and Accountability

A major requirement for credit scoring models is to provide a maximally accurate risk prediction. Additionally, regulators demand these models to be transparent and auditable. Thus, in credit scoring, very simple predictive models such as logistic regression or decision trees are still widely used. This paper presents a framework for making machine learning models transparent, auditable and explainable. Following this framework, an overview of techniques is presented and demonstrated how they can be applied in credit scoring. A real world case study shows that a comparable degree of interpretability can be achieved while machine learning techniques keep their ability to improve predictive power. The effectiveness of machine learning in evaluating the creditworthiness of loan applicants has been demonstrated for a long time. However, there is concern that automated decision-making processes may result in unequal treatment, leading to discriminatory outcomes. This paper evaluates the effectiveness of bias mitigation methods across fairness metrics, assessing their accuracy and potential profitability for financial institutions. Challenges in achieving fairness while maintaining accuracy and profitability are identified, highlighting both successful and unsuccessful mitigation methods.

8.3. The Impact of AI on Consumer Rights

With the rise of AI and ML in credit scoring systems, there is increasing stakeholder concern over their potential negative consequences, particularly regarding consumers' rights in the lending process. While traditional credit scoring systems are perceived as black boxes, the process by which these credit scoring decisions are made in traditional systems is straightforward. This can be easily accessed by policymakers and regulators, enabling them to pinpoint the flaws of traditional credit scoring systems. The costs of encouraging compliance can be spread across multiple parties in the traditional system, which is usually well established and dominated by some major providers.

In contrast, stakeholders face a specialist or programming layer with new credit scoring systems based on ML methods such as ANN, involved in creating deep learning and new credit scoring approaches. These new credit scoring systems have a complex algorithmic layer consisting of several programming pieces controlled by specialists. The costs of encouraging compliance with the legislation will be primarily absorbed by the community of specialists. Hence, it is likely that the action governed by such legislation will be altered to exploit loopholes. Furthermore, because of the complexity of these programming systems, it is unlikely that policymakers will acquire in-depth knowledge of them, potentially preventing them from understanding how these ML systems can affect consumers' rights.

IX. CONCLUSION

The adoption of machine learning for credit scoring has the potential to enhance the possibilities on the demand and the offer side of the credit market. It presents significant opportunities for protecting banks against financial ruins while increasing the profitability of loans and improving credit access for everyone. It remains a challenging enterprise, however. Government regulations should encourage its desirable uses while minimizing the risk of its undesirable ones. On the demand side, lower predictive performance of traditional models allows borrowers with poorer credit histories to gain access to loans, though also subjects them to higher interest rates. On the offer side, increased profitability is balanced against an increased financial ruin risk, an imbalance that could be mitigated by risk-reward mechanisms. Evidence is warranted that this balance is efficiently maintained. On the constraining side, model misuse and possibly destructive algorithmic discrimination remain risks that are difficult to minimize. Adjustments to existing regulations may be warranted, including multiplexing credit scoring, disclosing scoring-enhancing features, and getting rid of strict performance constraints. Existing regulations for estimating borrowability probabilities may remain valid for the scoring of loans, despite a pronounced difference between scoring functions and risk prediction functions. The monetary policy effects of these models and their lenses are very different, however, which may motivate adjustments in monetary policy regulations.

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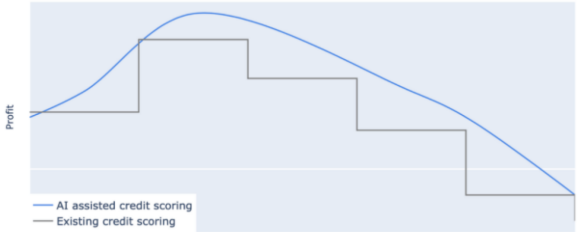

Fig 6: Machine Learning in Credit Scoring.

Inherent properties of machine learning allow for broader credit access and improved loan offer profitability through increased predictive performance and richer communication, respectively. Combination architectures granted opportunity for gain-the-lumps distributions, which may rebalance properties away from risky borrowers. Their maintenance brings forth costs, however, that must be considered down the line. Regulatory issues are targeted next.

Essentials of credit scoring using machine learning were introduced, including their beneficial and detrimental effects. Unresolved questions around these prospects remain, however. Ongoing research should grapple with their practicality. Possible research avenues include insights into the practical realities of credit scoring, further investigating lending efficiency and credit access, and exploring application opportunities across banking and finance.

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