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Advancements in Credit Score Analytics using Deep Learning and Predictive Modeling Techniques

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Abstract

The credit score is an important factor for the institutions while making decisions related to loan granting. Due to high dimensional data structure and constantly changing relationships within the different features, traditional statistical methods are less effective to understand the credit scoring problem. The advent of data mining and machine learning techniques allows easier implementation to discover latent but relevant features in the large and complex datasets inhospitable to traditional statistical techniques and also enable efficient handling of deeper analysis. Among many machine learning techniques, Artificial Neural Networks have been the most promising and with rapid advancements in the building blocks of these networks, many techniques like Convolutional Neural Networks or Deep Reinforcement Learning are being tested with popular use cases in multiple domains. In this chapter, we will perform comparative research on the popular supervised learning algorithms for the credit scoring domain. We also experiment with the deep learning technique called the Contrastive Divergence ANN, Energy Based Neural Network which is trained with approximate Inference methods. We argue that the Energy based model for supervised learning is more relevant to the problem statement, therefore, applied more complicated and dedicated architecture than the other models i.e. Multilayer Perceptron, Hybrid Neuro-Fuzzy model, and also Fuzzy Expert System and discuss their performance versus the complexity of each model. Finally, we briefly touch upon the credit policy decisions that were made based on the models' commercial applications, then elaborate on the conclusion of the research findings. We also suggest probable new domains of research related to the combination of energy-based learning and other popular self-supervised learning methods.

Keywords: *Credit Scoring, High-Dimensional Data, Traditional Statistical Methods, Data Mining, Machine Learning, Artificial Neural Networks, Convolutional Neural Networks, Deep Reinforcement Learning, Supervised Learning, Comparative Analysis, Contrastive Divergence, Energy-Based Neural Network, Approximate Inference, Multilayer Perceptron, Hybrid Neuro-Fuzzy Model, Fuzzy Expert System, Model Complexity, Credit Policy Decisions, Self-Supervised Learning, Model Performance.*

I. INTRODUCTION

Credit scoring is an integral part of consumer lending and financial management. However, traditional risk scoring models such as discriminatory analysis, logistic regression, tree-based methods, and neural networks suffer from fundamentally different structure and have limitations such as risk segmentation, sensitivity to outliers, phase transition, mixed categorical and continuous features, and model linearity. Accumulating evidence from the application of node-based methodologies using deep learning technology shows considerable improvement through automated feature engineering and superior predictability commensurating highly unbalanced and asymmetric cost of detection errors. Modern credit scoring is in the process of converging towards predictive modeling techniques to leverage big data.

The purpose of this paper is to explore artificial intelligence as a new paradigm within which traditional credit scoring concept is expanded and modelling methods are revisited to increase predictive power. Specifically, we outline the technology and methodology of deep learning and incorporate its implementation, improvements, and the direction of future research in predictive analytics in risk assessment. Finally, we furnish examples of deep learning applications and model comparisons across different domains such as customer credit rating, bankruptcy prediction, loan default forecasting, fraud detection, and others. Major themes include big data and the four Vs of volume, velocity, variety, and veracity; technology tools such as ensemble methods, predictive structure, estimation, calibration, and application of payoffs, performance metrics of accuracy curves, model scoring and ranking; methods such as neural networks, steepest descent or stochastic gradient, and applications in credit scoring such as estimating risk scores, tradeoffs generated by ranking, and calibrating model outputs to the true probabilities of default. We conclude with a discussion on conclusions and implications for research.

➢ *Purpose and Scope of the Study*

The purpose of this study is to address the question of whether advances in credit scoring analytics would improve the ability of financial institutions to detect the risk of default by delinquent consumers on unsecured loans and the predictive accuracy of insufficiently large sample sizes of some developed explanatory variables on default variables in the process of building credit scores. In general, as a by-product, this initiative will also evaluate the effectiveness of improving data depth and breadth, using new predictive modeling techniques, in addition to algorithmic approaches to enhancing the intrinsic predictive power of existing variables. Unsecured lenders rely heavily on credit scores and profile lending strategies on them. Their high cost of fund markets, colorful history of losses, and tenuous capital positions make credit management paramount in the risk-return decision-making apparatus.

Our research focuses on not-so-novel applications of deep learning techniques in credit scoring and analyses comparative advantages and trade-offs with the existing predictive modeling tools such as logistic regression and its extensions. A second area we delve into are methodological concerns associated with previously-uncommon and outdated techniques regularly dying hard: data pre-processing, measurement of predictive accuracy of the resulting scores, variable selection, and penalties for false negatives. We also entertain some questions typically untrammeled in the literature on scores – dollar estimates of predicted risk or its probability, risk of income fluctuations and growth, econometric artifacts such as temporal or geographical data problems - that have important implications for lenders and regulators but have received little attention. Using two large U.S. bank consumer credit data files as primary research datasets, we will compare and contrast various credit score models.

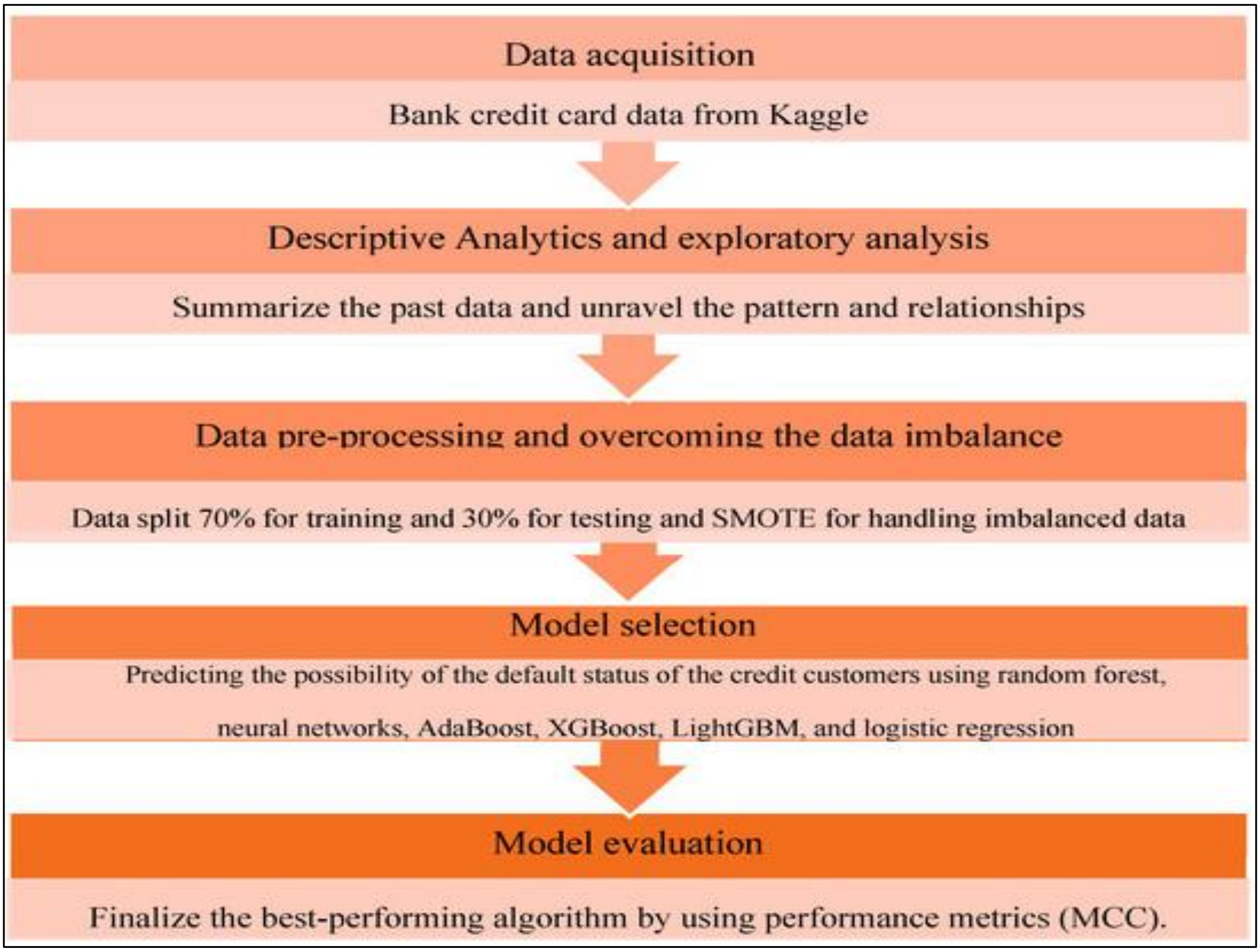

Fig 1 Credit Risk Prediction using Machine Learning and Deep Learning

II. BACKGROUND ON CREDIT SCORING

In a world where the number of financial transactions is on the rise, lenders face increasing risk with every decision to lend money or issue credit. Therefore, the assessment of credit risk is of great importance in the financial services sector. While lenders have employed various methods to justify their decisions, the general consensus in the finance community is to analyze the borrower's credit history. Around half a century ago, the use of quantitative algorithms became the dominant practice for assessing applicant risk. The initial models used logistic regression, a standard method for modeling a binary outcome, and were based on early research into cohort studies, using the existing data of thousands of borrowers to establish, and later refine, a "scorecard" for assessing the risk of applicants. With the advent of easily accessible software, the credit scorecard quickly became a "black box" that even novice modeling practitioners could use, and model validation metrics were established and adopted by the credit risk community.

While advances in computing and data management allowed for the improvement of the traditional scorecards, financial technologists are embracing more flexible machine learning approaches to build systems that assess risk. These new models augment the power of the modern scorecard with additional data sources to identify thin-file applicants who would be risk-blanketed by the traditional models, and therefore denied a credit opportunity. However, few alternative methods have been adopted broadly across industry. The sophistication of industry practices and regulations has enabled only slight improvements to the traditional scorecard methodology over the decades, with the dominant scorecard methodology listed in the guidelines of all of the supervisory banking regulators.

➢ *History of Credit Scoring*

The history and science of credit scoring is notably linked with a multitude of mathematicians, designers, business owners, and banks, originating in the ancient Chinese, who relied on prestige stamps or tokens to grant credit. The ability to borrow against an organization was extremely useful for merchants as a means of avoiding increased risks of carrying large amounts of coin; therefore, many of the tokens issued by banks became tools of greater mercantilism. The birth of banking occurred around 2000 B.C. in Sumeria in the form of temples and palaces that served as places to store grain and silver, along with the activity of making loans. While the token banking model served the needs of village economies in ancient China and the Middle Eastern areas as locations for trade and commerce, the European economy needed more flexible money. Based on reputations established over the years, his or her relatives and community elders would vouch for the moral character of the lender or borrower.

In England, King Henry II established a court system to settle disputes over money and property for both lenders and borrowers, but the speed of the process did not lend itself to intimate account management. Credit scoring emerged in its modern form as a branch of mathematical statistics with the development of the logistic function, often called the sigmoid function, which maps input to a value between zero and one. By that, this function is defined by a simple equation that allows the values to flow together. Whenever the original value is large and positive the result is close to one, and when it is very large in the negative, the result is close to zero, and when it is close to zero the function returns about one-half; that is, the important point around which the curve flows. All enterprises needed to share information about their customers in a common way.

Equation 1 Deep Neural Network for Credit Scoring

$$\hat{y} = \sigma\left(W^{(L)} \cdots \phi\left(W^{(2)}\phi\left(W^{(1)}X + b^{(1)}\right) + b^{(2)}\right) + b^{(L)}\right)$$

where
- $\hat{y}$: Predicted credit score or risk level
- X: Input feature vector (e.g., spending, debt, history)
- $W^{(l)}, b^{(l)}$: Weights and biases for layer l
- ϕ: Nonlinear activation (e.g., ReLU)
- σ: Output activation (e.g., sigmoid for risk, softmax for classification)

➢ *Traditional Credit Scoring Models*

Credit scoring models, used globally in developed and developing economies alike, portray the probability of defaults based on the answer to the question, “What is the chance that this customer will not repay the debt?” The scoring systems have time stamps, meaning that there is a period of repayment in which the credit models are trained to learn the potential predictors of defaulting. After the training time, the models are implemented, and the lenders must decide whether to lend or not. When a business lends, a contract is created between the bank and the customer that provides a set of rules to avoid future losses for both sides. Certain scoring systems are able to update themselves and learn over time, by introducing newer data into the model and analyzing the responses. Although manageable, these models require specific knowledge, a learning process, constant surveillance, and associated costs. According to the model results, if the borrower repays the loan in due time, banks may offer better conditions in new lending transactions.

Credit scoring models have evolved over time, attempting to better explain the relationship between the variables and the clientele’s response. These models have developed from expert judgment, scoring cards, logistic regression, data mining, through support vector machines, to the most recent advances using artificial neural networks and deep learning algorithms. Each of these advances has enriched the market tools, providing enhanced results along with their challenge of interpretation. Despite the advantages and indications that the most advanced models can overfit the sample and have high prediction error rates, traditional methods hold relevance by offering answers to business questions, providing stability, and making the results available and interpretable.

III. DEEP LEARNING TECHNIQUES IN CREDIT SCORING

Deep Learning provides the mechanisms that allow machines to build representations based on the non-linear transformation of the data. Deep Learning is based on artificial neural networks, which are inspired by the human cortex: a 3mm-thick tissue formed by some 15 billion neurons. By mimicking the organization of the cortex, a Deep Network is composed of several successive layers of simple units. The artificial neurons of these layers consist of basic processing functions akin to the semi-linear transformation properties of conventional threshold-regulated artificial neurons. The mechanisms of deep learning are characterized by the restriction of the types of transformations allowed in each layer to semi-linear transformations, as well as by the way the parameters of the transformations are found, using a multi-layer unsupervised learning technique called hierarchical feature learning. Furthermore, deep neural network architectures and algorithms are more efficient when dealing with large amounts of data. This is certainly the case in credit scoring: the CX industry is leveraging predictive modeling and offering insights based upon its mining on numerous terabytes.

A Convolutional Neural Network (CNN) consists of a series of Conv ReLU and Pool operations, followed by a further multi-layer perceptron. The major heuristic of the CNN is that, rather than performing a locally-connected layer operation and a non-linear activation in a single stage, one should have multiple such layers in a row, taken together with their super-positioned function. Indeed, a locally-connected layer followed by a pooling operation will tend to increase the covariance related to shifts, thereby reducing the number of feature maps necessary to characterize a pattern, and also the number of connections in the MLP stage that follows. Furthermore, because of the pooling step, a Boltzmann machine trained with this architecture is less constrained than a purely feedforward architecture storing greedy BM weights.

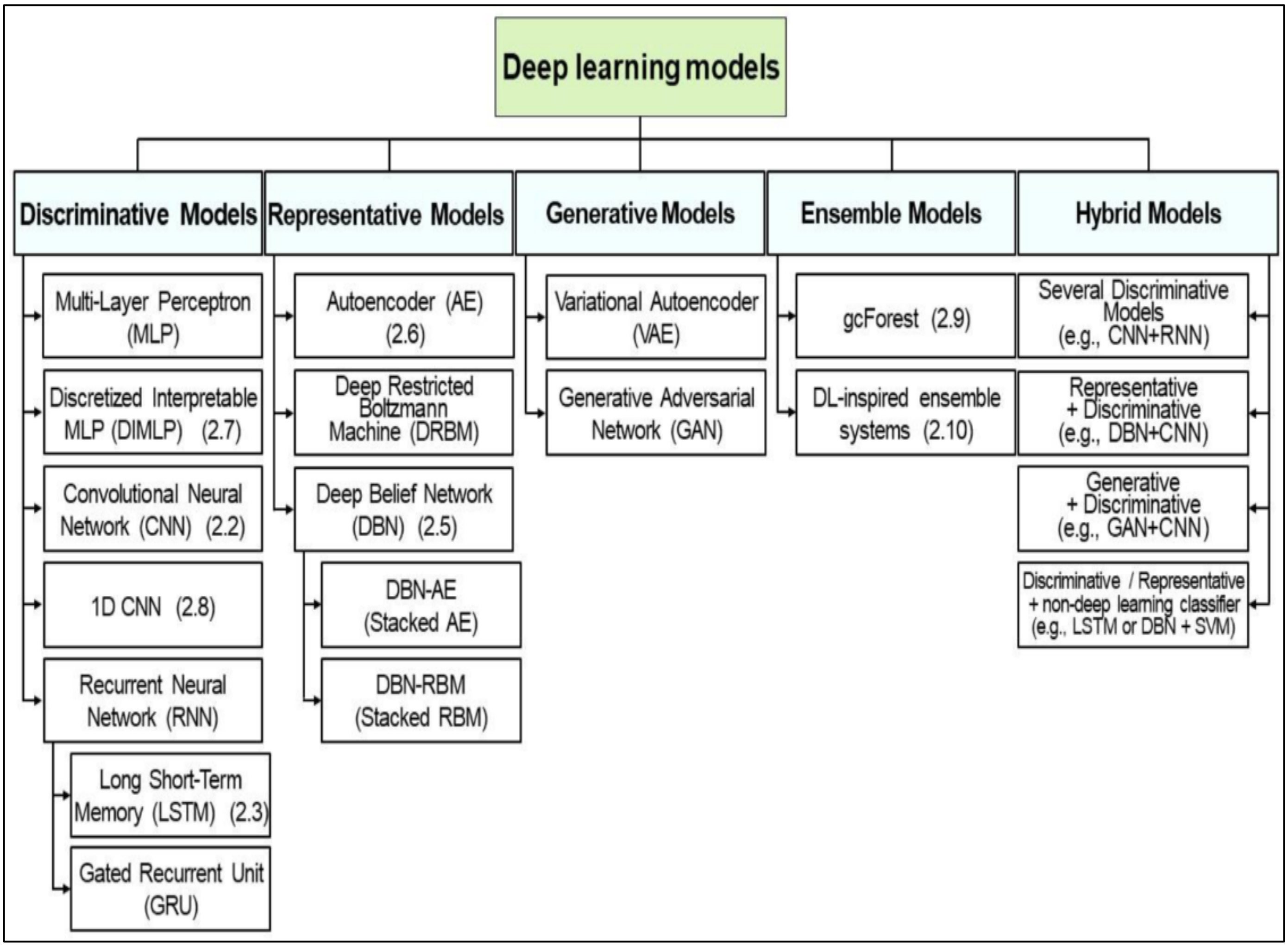

Fig 2 Deep Learning for Credit Scoring

➢ *Overview of Deep Learning*

Deep Learning is a class of machine learning algorithms that model high-level abstraction in data using deep directed and undirected graphical models. Its training is based on the use of layered structures with most of the parameters learned in stages, which is a key feature that allows representation of complex functions, using relatively little data. Represented as computational graphs, deep graphical models include Boltzmann Machines, Deep Belief Networks, Stack-Denoising Autoencoders, Deep Boltzmann Machines, Deep Mannich, Hierarchical RNNs, Stack Denoising RNNs, Deep Gaussian Processes, and

Deep Neural Networks. Deep Learning is a Universal Approximation and is suitable for many machine learning tasks. For many applications, it has been shown that increasing the number of layers improves classification performance (but not always). Despite their strong empirical performance and theoretical properties, research on deep graphical models is still in its infancy and is far from being considered solved.

While the standard neural networks can approximate a very wide class of functions with a given number of parameters, they need to set the number of hidden layers equal to just between the input and output layers, plus some additional hidden nodes in those layers. What makes the proposed deep architectures special is that they need a lot fewer hidden nodes to model a given function than do regular neural networks. When applying Learning, the number of hidden layers needs to be relatively large in practice; therefore, the computational cost of training a deep architecture is much higher than that of training a shallow one, until some recent large–scale algorithms become available.

- *Neural Networks Applications*

Several years before the boom of deep learning within the artificial intelligence community, the first successful implementations of NNs in business applications were pioneered in the area of credit scoring. Who would have thought that an early inventor of credit scorecards would incorporate NNs into the next generation of statistical score development? Prior industry pioneers had introduced logistic regression modeling to credit risk management, and they enjoyed great success. However, these same practitioners were also the first proponents of reconsidering the use of NNs, which by then had enjoyed some success in classifying data for application in marketing. NNs were actually recommended by a computing pioneer and a credit-scoring leader who first proposed the use of backpropagation NNs to do predictive modeling for credit risk management.

After that, a very small number of ingenious but brave modelers started to adapt NNs for predictive scoring along with their scores being deployed. Venture into this uncharted territory had begun to manifest some success. The first neural networks package developed for predictive modeling either employed any form of predictive modeling or was considered one of the earliest packages specialized for any form of predictive modeling! Since that embryonic phase, a slow but steady parade of papers began appearing. In a few of those early papers, NNs were shown to outperform logistic regression on some limited data sets. Some credit practitioners dismissed NNs with claims that with proper hyperparameter settings, logistic regression would outperform NNs. Although not originally intended to be specialized, some of the ANN packages written for pattern recognition had also been used in predictive modeling, but only by the bravest souls.

With the excitement regarding their success for replication within the artificial intelligence community, the interest in NNs had surged again. Enabled by the ready availability of much larger databases along with the increased computational capability provided by special-purpose hardware, their astonishing success demonstrated that large NNs capable of solving problems never previously successfully solved by NNs had very quickly gained widespread acceptance.

- *Recurrent Neural Networks (RNNs)*

Recurrent Neural Networks (RNNs) Recurrent neural networks (RNNs) represent the logical next step in complex data analysis after traditional feeds-forward neural networks (FNN's). In a standard FNN, an input vector of fixed temporal length flows through the input layer, is submitted to a weighted summation, reaches a non-linear transformation and generates a value in the output layer. The input will flow through the same weighing and non-linear transformation for instance and the same will occur with all the future instants in the temporal sequence. In fact, in a FNN, at a given instant, the data will flow through dedicated weights to generate the output but not it will cover a specific temporal window. The task of dealing with a data set from which we would like to train a prediction model or algorithm is that they have different temporal lengths even when the input vectors of a time window have the same number of variables. In this case, RNNs come into play. RNN extends the FNN notion by proposing to work on the input layer's node application function which allows retrieving compressed information from past temporality. This feature allows the model to "remember" timeless data that have influenced the prediction related to the last event. Novel RNN architectures also use more sophisticated attention mechanisms compressing in the weighting a sort of expert knowledge which could come from external events, controlling hidden events that have a great influence on the objective output which we would like to improve. The task dealing with input sequences of variable temporal length is not new in the engineering field and it has been covered with a box called Hidden Markov Model (HMM). RNN was invented to create another algorithm capable of predicting a temporality with discrete and binary values since this is the feature of the default HMM applied. The extraordinary feature of RNN is that it is a system treated in a unique architecture, allowing treating in a unified way computation and both regression problems of time series, probability evaluation, classification and recognition of generics temporal patterns.

- *Convolutional Neural Networks (CNNs)*

Convolutional neural networks (CNNs), also known as ConvNets, represent a specialized kind of neural network used particularly for image processing, recommender systems, image classification, medical image analysis, natural language processing, and financial time series. CNNs can be employed in the classification of data that has a grid-like topology, including, for image data (2-D grids of pixels), convolutional layers use 2-D convolution kernels that scan through the image dimension to produce 2-D activation maps expose the higher-level features of the images. The kernel visualizes most of the features.

The convolutional operation convolves an image with a kernel that detects a feature of the image. The kernel weights remain constant, but the neural network automatically updates them to detect different features in the image. During the forward pass, the kernel is moved over several positions in the image. At each position, it computes an inner product, recording the result in the corresponding position in the resulting feature map. In general, the number of channels in an input image is different from the number of channels for a feature map. In this case, two options are available. Expand the number of channels in the input by mixing several images adjacent for a short duration into one image; or apply the image in a loop, having each channel selectively process part of the data. Once the feature maps are calculated using the kernel, the result is passed to the next layer, which computes the feature maps using another kernel. In the deeper layers, the kernels are generally larger in size than in the previous layers. The final layer produces the fine-grained representation of the input image, based on which the corresponding label node of the classifier corresponding to the predicted label for the input image is activated, while the label nodes of the remaining classes will be inactive.

IV. PREDICTIVE MODELING TECHNIQUES

Predictive modeling serves as a distinctive form of data mining that employs statistical algorithms to anticipate outcomes. In credit scores predictive modeling context, predictive modeling describes any statistical tactic or method employed to gauge the potential reduced propensity to default of a single consumer and how that estimation evolves or changes over time. The models assisting in prediction are further applied in agencies to scrutinize future trends vis-à-vis portfolio quality and loss estimates. Herein, various predictive techniques have been employed to estimate consumer's credit propensity and validate their credit scoring models. In the contemporary scenario, credit scoring relies on border analysis or modeling methods to assess default risk research. As digital data spurred massive catalog of features and continual product roll out has made it hard to ascertain and spot most predictive pattern pipeline susceptible to ensure client onboarding and portfolio strategy with use of borderline assessments or predicted score based on functions.

In banking, a regression model is a definite predictive means used to enumerate probable future cost by coercing the estimated or predicted functional form on a set of input and output data. Similar to physics and engineering, regression elucidates the question why event x happened before event y. Similar to input and output mechanization of some real world engineering problem, banks have modeled it queries to ascertain potential dwelling propinquity. The banking data is estimated through a conditional choice probability or a probit estimation without considering recursive treatment. A logistic regression model outputs a number between 0 and 1 for each observation which indicates the probability of a classification rule. An interpretation of such score can be associated with any scam when the output is higher than a bank defined threshold. Thus defined loan scores can further fund wholesalers as well as bonded syndication.

- *Regression Models*

Predicting the Risk through Regression Models has been one of the earliest methods to estimate the Probability of Default. Traditional regression techniques for predictive models that follow a functional relationship. Classically, Linear Regression employs an Ordinary Least Squares objective function to minimize the model error on training data. The prediction error is expressed as the squared difference of model prediction (a linear function of variables) and observed outcome (the dependent variable, which could be a measure of financial risk). P is modeled as a linear relation in the range from 0 to 1 (hence the constrained linear target function). For Multiclass Logistic Regression, a descriptive Log-Loss function is optimized to minimize the likelihood of committing a classification error in predicting the class label. Out of the several classification techniques, logistic regression has been widely used for credit risk assessment. Lately, Logit models have also been used by financial analysts to predict defaults in Small and Medium Businesses.

Logistic regression is easy to implement and computationally efficient, however "Logarithm used in logit" cannot function for datasets with zero variance predictor variables. Logistic regression makes Gaussian assumptions about the dataset: predictor variables are independent of each other. Further, it can model only linear relationships. While linear projections and transformations of the logistic function are simple and fast, Logistic Regression is inevitably limited to linear approximations. In summary, Logistic models can be effective and widely used, but they can not handle nonlinear separation of prediction classes efficiently. Naive methods such as kernel mappings have poor performance with multi-dimensional data, and are generally inadequate.

- *Decision Trees and Random Forests*

Decision trees are non-parametric supervised learning methods used for classification and regression analysis. They represent dependencies between a dependent variable (target) and one or more independent variables (predictors) under an "if-then" rule structure. If the target variable is categorical, the tree performs classification, assigning points to one of the available classes. If the target variable is continuous, then the tree performs regression, predicting the value of the target variable. Classification trees are mostly used to predict default events, while regression trees are used to predict borrower scores.

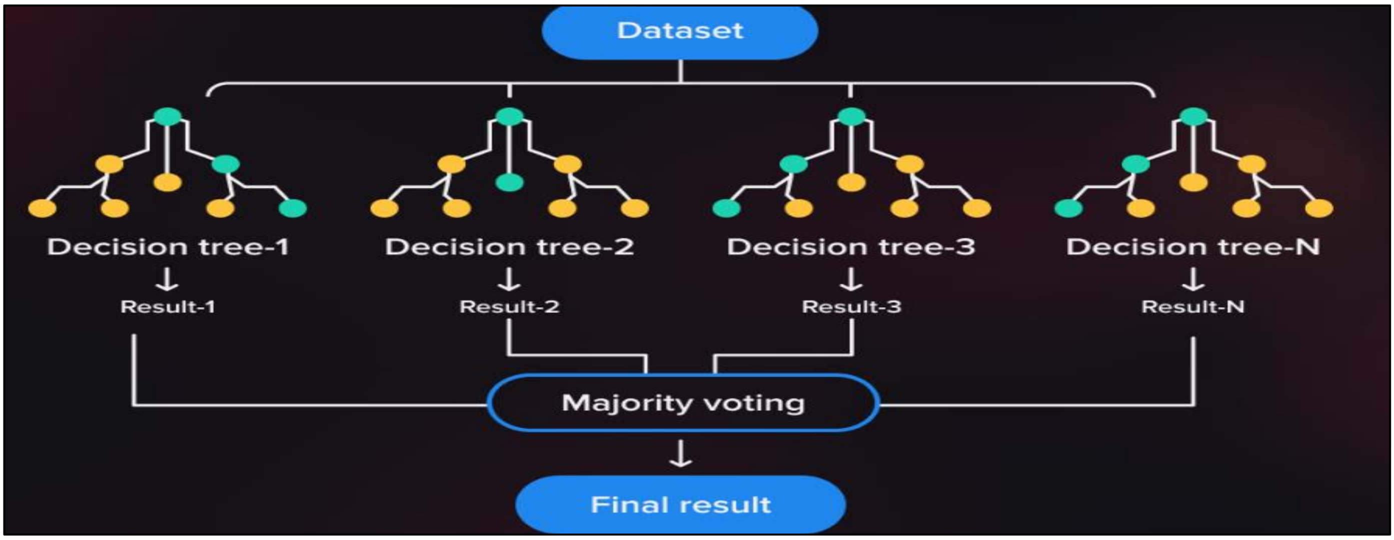

Fig 3 Decision Trees to Ensemble Methods

In predictive modeling, decision trees have the advantages of being intuitive in nature and easy to interpret. They allow nonlinear dependencies, are capable of handling categorical variables, efficient at computing internal decisions, and insensitive to transformations of the input variables. Experiments have shown that decision trees perform well in the area of credit scoring. There are many available algorithms for decision trees. The most recognized are ID3 and its extensions C4.5 and C5.0, CART, and CHAID. CHAID is designed for categorical variables only, while ID3, C4.5, C5.0, and CART can be run on numerical variables and can also produce classification trees and regression trees. The main difference between these algorithms is the splitting criteria based on information gain, gain ratio, Gini impurity index, and adjusted significance of deviation from independence.

Random forests are developed in an ensemble learning context for decision trees with classification function. They combine the predictions of multiple trees by constructing several decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression). They are trained using a modification of Bagging, which is an ensemble technique that decreases variance by averaging different versions of the prediction function.

- *Support Vector Machines (SVM)*

Support vector machines (SVM) are supervised learning models that analyze data for regression analysis and classification. They perform nonlinear classification and regression application by fitting the data into higher-dimensional space. In default mode, an SVM constructs a hyperplane in a high-dimensional space that separates data into classes. For example, assume two sets of representative samples taken from two unknown distributions, y1 = {-1, -1, -1, -1,...} points belong to the positive domain D+ and y2 = {1, 1, 1, 1,..} are from the negative domain D- (D+∩D- = 0). SVM employs hypothesized function f from the space of functions and draws lines between two classes. Here, y and x are the corresponding categorical and feature variables. The SVM function is constructed from a given training set (x1, y1), (x2, y2), (x3, y3),...,(xN, yN) and represented as a linear combination of simple functions defined by the support vectors xj for model selection. The training of SVM is searching for the optimal function selecting coefficients.

A typical approach for two-class classification addresses the direct optimization of SVM. Nonlinear patterns can be classified using kernel functions with operations in some high-dimensional space. The most popular kernel functions for SVM classification are Gaussian, polynomial, and sigmoid which construct separating hyperplanes on random dependencies. The kernel functions give an inner product in feature space which allows a simple representation of SVM without the need to map the inputs explicitly to some feature space.

SVM is appropriate when we have more dimensions than samples since it is compressive. Moreover, SVM gives sparse solutions, i.e., the weights are non-zero for only a small fraction of the training set. The SVM finds the best way of separating the data classes with the largest possible distance between the separating hyperplane and the nearest point in either class. Since there exist many separating hyperplanes, the SVM attaches importance to limiting the risk of error while maximizing the margin width to achieve the best generalization performance on unseen data.

V. DATA SOURCES FOR CREDIT SCORING

Credit scoring relies on a variety of data sources to assess the creditworthiness of both prospective and existing consumers. The most widely employed source are the credit bureaus; operating as a repository of behavioral credit history data including consumer demographic information, credit inquiries, consumer accounts, and collections; as well as account classifications such as open (active), open (inactive), closed, or derogatory (accounts reported late), which is further used for calculating the credit score. Recent years have seen a growing interest in the utilization of alternative data sources for credit scoring including financial transactions data, social media data, and psychometric data which may be used for as operationally useful sources by creditors for predicting the creditworthiness mainly of thin-file, no-file, and unscored segments of consumers who lack sufficient credit histories. In this section, we first discuss credit bureau data, then alternative data sources, and lastly, the impact of big data.

A consumer credit score is based largely on information contained in the credit report provided by the major credit bureaus. The credit report contains a summary of the consumer's history in utilizing and paying off credit. The particular factors related to credit history which are most important for credit scoring are length of credit history, number of recent inquiries, amount of unpaid debts, and types of credit. Predictive models which use credit bureau data significantly drive the consumer credit score. The predictive power of credit bureau data, as compared to alternative data sources, is supported by numerous studies. Credit bureau data score is routinely used in practice by the legacy consumer credit industry.

- *Credit Bureau Data*

Regression analysis requires a significant number of observations both for the model building and for model testing. Therefore the outputs of credit scoring models applied to credit bureau data are usually then applied to a much larger universe outside of the credit bureau patterns used to develop the models.

An individual's credit bureau report contains information on his or her credit payment history, the types of credit he or she has utilized, counts or balances of credit present on the report, credit inquiries, and, for some bureaus, additional public records information, such as a bankruptcy or other legal claim. Credit data residuals may also be available through credit bureaus. Not all of this information, however, is available at a level of granularity sufficient for advanced analytic techniques. In particular, much of it can be found only in aggregated or flagged form. Nevertheless, this information, when available, facilitates the effective use of both supervised and unsupervised statistical modeling methods.

Data, their combination, and data differences taken at different intervals are often used in advanced analytics to detect aberrant shifts in credit usage and notches in pre-existing normal distributions of credit life cycle behavior. Moreover, these differences can be weighted by functions of credit history done in the credit cycle interval period. Information on attributes that have caused shifts in previously normal credit behaviors for individuals may be useful in forecasting shifts in credit behaviors at the aggregate level. For example, an upward trend in the number of individuals exhibiting prepayment delay behavior may be indicative of an emerging trend at the aggregate level involving heightened levels of prepayment delays.

- *Alternative Data Sources*

The traditional data sources for credit scoring such as credit bureau data are becoming less frequent, and in recent years new data sources are becoming more common to enhance the current modeling performance or to replace traditional data sources. The alternative data market is expanding and there are new segments of consumers who are more frequently scoring either by both the traditional score and by a model with an alternative data attribute, or scoring only with an alternative data model. A consumer's alternative data score behavior can vary widely from that implied by the score, which puts these consumers into very low credit score bands where credit and underwriting restrictions are in practice much more restrictive. On the other hand, consumers who score in the middle of the alternative data scoring range may have scores above 700 or may not have an established score at all, yet are unconstrained in the types of credit they use, their credit utilization, and their responsibility in paying bills when they are due. Both identified segments represent business opportunities for lenders who are willing to take on added risk. In short, the alternative data world represents a large area for fissures and contradictions in risk scoring as we move toward allowing for a diversity of data attributes and methods.

They are used frequently and in specific areas of our lives: educational software that tracks online learning, social media interactions, location tracking, mobile phone use, and utility companies and the types of payments consumers make for those services. Utilizing and incorporating these well-known, readily available data sources into more precise predictive modeling, for more targeted and advanced solutions, will enhance and improve in meaningful ways the financial service market and its objectives. The opportunity to access, analyze and apply these unique data sources could regrow lender credit portfolios that had focused only on prime consumers, now too optimized for stability and less for generating revenue.

Equation 2 Predictive Modeling via Sequence Learning (LSTM/GRU)

$$h_t = f\left(x_t, h_{t-1}; \theta\right)$$

where

- h_t: Hidden state at time t
- x_t: Time-series credit behavior input
- f: Recurrent function (LSTM or GRU unit)
- θ: Model parameters learned from historical trends

- *Impact of Big Data*

During the last decade, we have witnessed the emergence of new data sources including transaction-based data from bank accounts, extensive data in social media, and different types of psychometric data obtained through alternative techniques such as text mining and mobile-phone data. In addition to the availability of new data sources, machine learning and other algorithm-based methods have emerged as powerful extensions of traditional regression-based approaches. With these advancements in predictive modeling and artificial intelligence technologies, many areas of knowledge have been deeply affected and, consequently, the credit risk industry has seen the rise of several big-data predictive modeling firms offering their expertise to provide loss mitigation services through optimally customized predictive models to different companies in varied sectors, namely, telecoms, retail, financial services.

The field of credit scoring has seen great strides in recent years and the sound predictions of the performance of the accounts who will eventually default continues to be an open challenge for researchers, practitioners, and companies. For decades the major players in the field of credit scoring, mainly retail banks and rating agencies, have extensively explored traditional statistical techniques, mainly regression models, to build their predictive models, but have in recent years expanded their toolsets to include some of the emerging machine learning techniques that properly deal with areas where traditional statistical methods tend to produce biased results such as small data and Big Data. The increasing availability of new sources of data has helped to further advance credit scoring and has opened up several challenging new questions such as how to combine new and traditional data sources, and how to integrate them into comprehensive modeling frameworks. Nevertheless, these technologies have manifested themselves not just by boosting credit scoring efforts in financial institutions but also by impacting other lending related areas in different industries and fields such as recovery.

VI. INTEGRATION OF DEEP LEARNING AND PREDICTIVE MODELING

Deep learning has redefined the bounds of model complexity. It takes on its own the burden of navigating the mind-boggling dimensionality of a feature space that can dwarf the pennies of the designer. The cost of this increased flexibility is an increased data hunger and the appetites are great — pun intended! Deep learning needs network size not to mention depth — a minimum of three levels — to learn appropriately. Data needs to be abundant, accessible, representative, and static over time. The combination of deep learning with classical predictive modelling thereby has much to recommend. Choosing a sweet spot solution is not easy because it involves considerable compromise; both types of models have their pros and cons. A hybrid version — borrow the best and leave the rest — combines the advantages while ameliorating some of the weaknesses of the two techniques.

Feature engineering is the tactile, intuitive domain of human experts, and identifying promising variables has been the secret sauce of the data scientist's recipe for success. Predictive modelling does a relatively good job until deep learning comes into the picture! The configuration/parameter fine tuning is comparatively easy, because what parameters do we need to fine-tune? The choices are few but crucially important: network size and activation functions. Feedback at the back end of the neural network provides the mechanism for an elegant solution that is difficult to reject theoretically: more complex problems need more complex solutions; whittling our favourite Curse of Dimensionality!

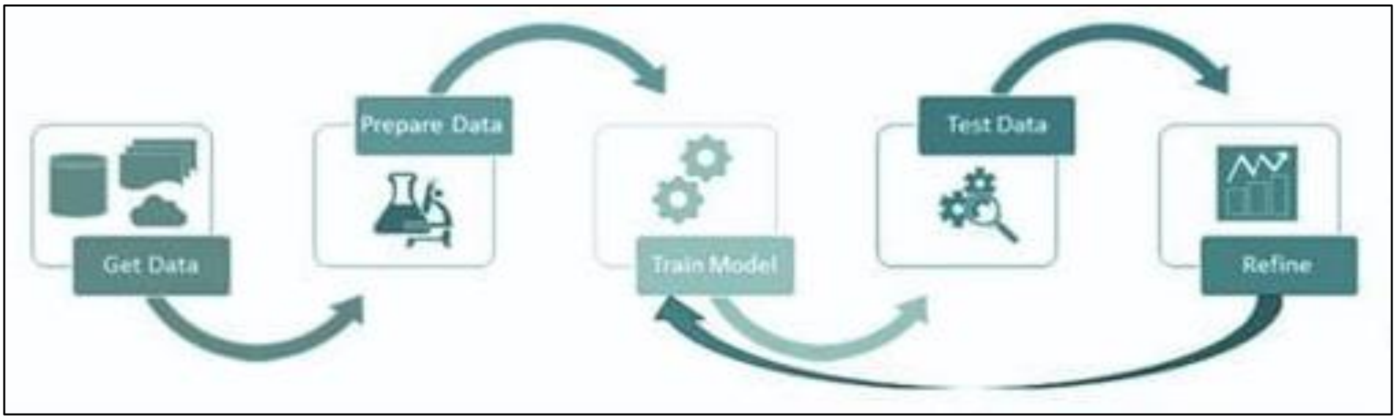

Fig 4 Predictive Modelling with Deep Learning

- *Hybrid Models*

Despite the strong performance of deep learning-based credit scoring models, their black-box nature raises concerns about the transparency and explainability of predicted scores. A credit score is a statistical measure of a specific consumer's creditworthiness based on the consumer's past and current credit history. These pioneering studies attempt to enhance the DNN and LSTM model and propose the attention model as a hybrid structure in conjunction with traditional machine learning algorithms. In particular, a hybrid framework converts customer transaction records into transaction images by selecting the first 60 transactions as image-output sequences and encodes them using the convolutional neural network, followed by feature fusion processing to classify default and non-default classes.

To improve the recognition accuracy of consumer default prediction, a hybrid model merges a GBDT based autoencoder and a LSTM network in order to couple the interpretability of GBDT and the temporal dependencies of LSTM. A novel interpretable Hybrid Neural Network Architecture is proposed, which adaptively incorporates the knowledge of a gradient boosting decision tree model into two types of neural networks, namely LSTM and feedforward neural networks. A general credit scoring framework is proposed that incorporates credit scoring and explainable machine learning based on a general GAN. In short, these above models, to varying degrees, incorporate other model-specific structures or modules into their deep generative models to make them practical and interpretable.

➢ *Feature Engineering Techniques*

Traditionally, credit scoring methods focus mainly on selecting the right variables for a predictive model. The predictive variables used in credit scoring models are often related to risk characteristics and individual behavior. These include demographic characteristics, account usage behaviors, credit history miscues, delinquent account counts, short-term and long-term risk indicators, and how borrowers service their existing debt. Various machine learning methods have been applied to discover credit scores, such as decision trees, random forests, support vector machines, and boosted trees. These models have been shown to outperform logistic regression in scorecard performance. However, all these predictive variables must be constructed, selected, and validated by experts. This process can be time-consuming and tedious, and there is no guarantee that the most predictive variables are selected and validated.

Deep learning can help automate variable creation. It can automatically identify the most predictive variables for risk assessment without the need for feature engineering. Specifically, leveraging deep learning, we can build models that accommodate millions of risk characteristics. The variable drift issue is particularly important for fintech companies, which face increasingly stiff competition from traditional banks offering lower fees and rates as they leverage better loss experience while sharing customers' costs on fewer products. Without continual monitoring, it is conceivable that the unique variable expertise can be taken over by a competitor, especially if the machine learning platforms of both companies are similar in other aspects. However, some specific types of data may still require human intervention for feature engineering. For example, interpretable features may be more essential in high-stakes areas like health care, where transparent decision-making models are necessary for building trust among consumers.

VII. CHALLENGES IN CREDIT SCORE ANALYTICS

Credit score analytics is relatively straightforward from a technical angle and has immense business capabilities. However, challenges unique to the area that are often not present in other predictive modeling scenarios deserve a mention. Some of these concerns – associated with credit score analytics and models – are legal implications, interpretability of models, fairness in prediction, and data privacy. We dedicate this section to discuss these problems and emphasize the need for modelers to be aware of such issues when involved with credit score analytics.

➢ *Data Privacy Concerns*

The area of consumer credit is associated with immense data privacy issues. A credit score modeler has access to very personal, confidential data about individuals that discontent, if leaked or misused, undermines the very integrity of society. Such issues are heightened with the advent of new technology that seems to necessitate constant surveillance by private companies or the laws enacted that permit law abstaining on the grounds of age, income, employment status, family size, status as a government employee, or homeownership, even in the situation of obvious prejudice in other aspects to an individual. Many models in the literature do not address ethical fairness of using variables like ethnicity or its proxies. Some studies are even suggestive of the stance that financial technology companies may have access to an individual's credit report without their consent. Lastly, consumer data is considered very sensitive, and the usage of data without credit reporting agency consent is against the Fair Credit Reporting Act.

➢ *Bias in Algorithms*

Credit scoring should not only help lenders minimize default rates; it should also be a fair system that does not discriminate against individuals belonging to a certain demographic group. There is no reason to expect that classification and regression task algorithms will necessarily be free of bias. All algorithms rely on historical data and biases. Hence, there is a large gathering of researchers and practitioners from several domains to advocate for algorithm information that accurately represents the underlying business context and supports specific use cases. Because many companies rely on algorithmic predictions, it is essential to address fairness so that these systems do not perpetuate inequality or mistreat society's most vulnerable members.

➢ *Interpretability of Models*

Even beyond problems of discrimination or bias in scoring models, there is a fundamental requirement for the prediction models to be interpretable. Then, purely by virtue of being black boxes, they may not become as widely adopted or trusted, and in the case of rejection, the organization implementing them must not seem to contain any liability for non adoption.

➢ *Data Privacy Concerns*

The key issue underlying work in this domain is data privacy. Credit bureaus have access to vast data that has not only information about the subject's finances but also associations with other individuals such as spouse, children, close family members, and financial institutions. Hence, these scores are used not only for new loans and mortgages but for a number of other purposes such as insurance links, employment, renting, and even immigration. It is a sensitive area that can be exploited by regulators and malicious hackers. The consequences of misuse of such data by technology-driven companies are well documented. The potential for privacy, security, and identity theft emerges whenever individuals report information pertaining to such potential events. The consequences may be severe as many of the businesses are long-term informed and current and future reporting of data needs to flow from automating and updating multiple data management processes to decreasing any losses from the misuse of private information.

Most credit score functions, models, and any related data are believed to be proprietary and can be assigned no more than a limited use. Therefore, much of the proprietary probability shown is based on internal and commercial experience with both the sample and scores are derived therefrom. So, if these companies do not share such models for the public to observe then the algorithms used to generate the scores will not be presented for public scrutiny to have the ability to manage, interpret, and act on risk for the potential client. In summary, privacy issues are a barrier to new data-driven techniques in these sensitive problems where past subway prediction cannot be safely assessed with current production data and actual score assessments.

- *Bias in Algorithms*

Recent advancements in credit scoring models using deep learning and predictive modeling techniques have borrowed innovative ideas from other scientific fields. The new modeling implementations become effective on the one hand, but on the other hand, they introduce concerns regarding bias-interpretation-justification of biased-predictions result, model governance, and explainability. In this section, we provide considerations about three key challenges, which have up to now not sufficiently analyzed from academia or industry while penalizing the advantages of these novel computational techniques. We strongly believe that the industry-run projects on credit score modeling applications need to take care of the problems discussed in the following subsections.

A model bias comes from the union of two different aspects, the statistical nature of the model, which gives an advantage to a specific underrepresented class, and the way the model is fit to the observed data that might be unbalanced over the same classes. Bias appears not only with respect to labels associated with observed data, but also the bias in a robust way outer model's predictive likelihood on the different classes. The problem of biased payouts is related to the fairness issue of credit score prediction and is investigated in various application scenarios, such as internal repayment of loan default prediction, loan approval prediction, loan/credit card limit prediction, and risk assessment with respect to sensitive cohorts, like gender or ethnicity.

The existence of hidden groups, such as gender and race, are in part buried in the patterns of behavior shown by the observed data for the model. These three hidden dimensions also play a central role, together with the tediousness of criteria, guidelines, and legal bindings introduced by the GDPR. No doubt, these considerations introduce a significant burden on the building and fine-tuning of sensitive credit score models.

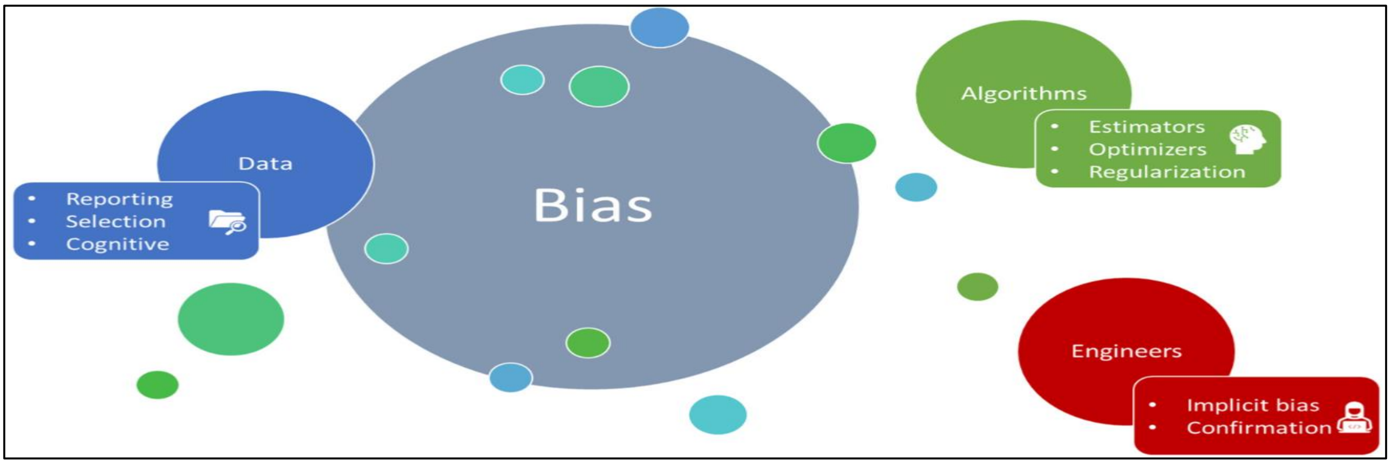

Fig 5 Bias in Machine Learning

- *Interpretability of Models*

Considering the possible impact of the credit score on people's lives, practitioners and credit scoring agencies will highly appreciate the explanations of the prediction. The advantage of tree models is that they are easy to interpret and are translated into a set of "if-then" rules. A carefully constructed decision tree can be considered as a model to better understand the data and the impact of different features. In addition, tree models can reduce dimensionality through feature selection. The same consideration, although at a lower scale, holds for linear models. In this respect, the advantage of deep neural networks and ensemble learners is that they achieve a higher score about the global performance but they are complex and it is hard to understand how they reached that solution. This poses a challenge in areas like credit scoring. There are several techniques developed to understand black-box methods. Among them we find local models, meaning that they only explain the prediction around the specific input data point by performing perturbations of the data around that value, looking for patterns and translating those patterns to the local model, which is easier to explain. Both techniques are used in practice and among the most popular. Local interpretable model-agnostic explanations is a technique for interpreting the predictions of any classifier. It explains how a classifier makes its prediction for an instance by measuring the changes in the classifier's predictions for instances in the neighborhood of that instance when those instances are perturbed. It has inspired numerous follow-up works on interpretability, both by creating alternatives and by generalizing the approach to a wide variety of settings.

VIII. CASE STUDIES

To illustrate the practical value of the proposed models and to outline a roadmap for implementation in practice, we present several case studies of applying deep learning and predictive modeling techniques to wide and long credit score data sets. They demonstrate the effectiveness of the proposed models and the importance of available data, its structure, and data quality. More importantly, the case studies show that predictive modeling developed in the credit score domain has much broader applications in other industries, such as insurance or health care, as they have similar challenges and end-user goals. For convenience, we divide the case studies into two sections, successful implementations and comparative analysis of models. In the following section, we present the model implementations that had the greatest success and interest and discuss the practical value of the results. We pay particular attention to the differences in modeling methodologies and final implementation to the longitudinal nature of the inputs used for implementations. Of particular interest to our audience is the version of the model that predicts the long-term credit score with the largest prediction horizon.

➢ *Successful Implementations*

Over the past years, many financial organizations have started exploring deep learning and predictive modeling. We provide the following summary of various successful implementations. A deep convolutional neural network (CNN)-based model was proposed and proved the significance of such a technique for financial problems. Our inferences from this work are as follows: 1. The proposed model can be used on all kinds of signal-based data. 2. Such a model is capable of recognizing only the desired signal and eliminating other undesired fluctuating signals such as noise. 3. The architecture of the proposed model can easily be modified according to the input signal data features. 4. So far, the model has been trained using supervised learning. However, its potential to be used as a semi-supervised or unsupervised system has not yet been explored. 5. Reinforcement learning can also be explored in the AI-based model design, which can provide further improvements.

Deep learning techniques were integrated with a reinforcement learning framework to develop a credit scoring model for predicting severity of default judgments. It was demonstrated that the model outperforms classical credit scoring techniques in terms of profits and risk adjustment metrics when evaluated on a real-world credit default dataset. The method is data-driven, and flexible, and could work well with both structured and unstructured data. A credit risk scoring model for microfinance was designed based on information from messages exchanged by loan applicants. Deep and standard learning methods were applied onto this model and better classification results were reported for the deep learning model specially implemented using recurrent neural networks.

➢ *Comparative Analysis of Models*

In today's digital era, every person utilizes credit in some form or another. When an individual applies for a loan or a credit card, the credit rating provided by credit rating organizations becomes a key component in determining the terms of the loan. Credit scores that are too low can cause people to be refused credit. The evolution of the World Wide Web has also played a role in the weakening of the previously straightforward measures used by financial institutions to determine whether to lend money. The use of predictive data analytics tools, predictive modeling, and clustering tools using the insights for predictive analytics become important as the financial sector adopts predictive analysis methods. The primary premise is that predicting a consumer's credit risk evaluation, which leads to loan repayment, would be useful for both lenders and borrowers. The lender is then able to issue loans to borrowers with higher limitations at lower prices while also more successfully adapting to the risk of default. Defaulting borrowers can receive counseling to help them reset their credit risks and avoid repayment failures as early as possible. In this case study, we compare CreditX AI and CreditX Regression against common types of Kernel Extrapolation and neural network autoencoders.

A comparison of various types of models is shown below. The base model is model 0, which is an extended version of the use of Kernel Extrapolation on arbitrary features previously described. The base model is fed penultimate features from the autoencoder of the stacked-denoise model. The model is retrained every-time Z arrives from the Accountant function, but we also provide an additional column in our alpha tables where we save a small share of predictions done with an older model. The column enables us to see new non-beta penalties coming in, as well as the usefulness of the recursive feature selection added in later versions of the autoencoder. Model 1 is a Gaussian Kernel Extrapolation Model of one of the granularized features. Models 2 and 4 are two noisy linear models of special types of granularized features. Model 4 draws mainly from features also used by the autoencoder of the stacked-denoise model. Model 3 is a small stacked-denoise model retained with low confidence.

IX. FUTURE DIRECTIONS IN CREDIT SCORE ANALYTICS

As the use of deep learning techniques for improving credit score behavior predictions continues to proliferate to make credit scoring, which has arguably become a standard tool for assessing financial risk, more accurate and efficient, in the near to medium term future, we expect to see an ever-deepening incorporation of various emerging technologies in a wide array of industries, domains, and spheres of operations. These technologies could vastly improve credit score analytics by providing more meaningful, secure, and convenient tools for customers to provide relevant data toward enabling more accurate, efficient, and secure credit adjudication in real time as well as for deployers of credit score analytic systems for the continual, real-time monitoring of risks of credit default or delay and other non-credit related risk exposures, such as fraud detection; anomaly detection; money laundering; tax avoidance; and insurance claim defaults, for individual consumers or corporate entities with respect to different organizations such as banks, insurance companies, or governmental entities engaged in relevant businesses and operations.

More specifically, with the emergence and mixing of novel technological offerings such as the Internet of Things, cloud computing, decentralized blockchain ledgers, augmented and virtual reality, and quantum computing, which forge mutually benefitting collaboration with existing technologies such as mobile connectivity, artificial intelligence, and edge intelligence, we expect that this fusion of capabilities-enabled advanced solutions and applications could lead to wholly new methodologies and processes that could become immensely beneficial to consumers as well as the deployers of credit analytics systems, such as banks and other institutions. In the short to mid-term future, there will be a rapid adoption of highly advanced, more secure solutions such as decentralized ledger unmanned autonomous decision environment systems utilizing artificial intelligence, with decentralized hybrid consensus that could become challenging to be hacked or corrupted and that could allow the instant completion of total or partial loans and other financial transactions virtually without the need for any trusted third parties while allowing customers to retain control of their personal data.

➢ *Emerging Technologies*

The advancements in credit models have focused on the design choices for the supervised predictive model class of algorithms and concepts embedded within the methods. When designing better credit predictive modeling, especially into consumer behavior in predicting their fallback to delinquency, it stands to reason that improvements will come from better embodying such consumer characteristics. The recent capabilities with emerging technologies enable other possible selections along both of those influential directions. The design choices in technology support greater sophistication in accounting for a consumer's lending terms as well as their behavioral motivations, abilities and tendencies, payment technique consolation, flexibility, value to the borrower, and more. Along the method direction, the deployment of emerging technologies coupled with better design choices can help improve models much more than just exploring prediction quality improvements via methods.

Introducing behavioral economics, natural language processing, and psychological indicators into predictive analytics in general will enable greater sophistication in determining behavioral drivers and influences. This can be done due to better information gathering from implementing wearable devices, emotion recognition tech, predictive processing, phone behavioral apps, behavioral digital footprints via tracking cookies, etc. As this data availability and variety increases, the discipline of distinguishing consumer types along the personal risk spectrum using in-depth qualitative psychographic analysis will reignite enabling multiple metrics versus just one rating score. It is no longer enough to just be considered 'good' and 'bad' consumers. Understanding each consumer signature will be vital for proper model performance outputs and better consumer risk categorization and pricing models. Now, with consumers being able to alter their identities to some degree, the dynamic shift values in digital footprints, consumer interaction tech, consumer emotion status, and leveraging behavioral economics will also contribute to better predictive outcomes.

➢ *Regulatory Implications*

Policymakers must determine how emerging modeling techniques will be integrated into the existing body of credit reporting law. This raises the question: when is a score a credit "score" and when is it merely a "model" that predicts the likelihood of default? Any score predicts the likelihood of default. What makes a score a "credit score" for purposes of disclosure requirements? Although no such precise definition exists, a score that is used to evaluate a consumer for any of the adverse actions covered by the relevant laws must be a "credit score" and governed by those laws, so long as no exceptions or exemptions apply.

Creating a taxonomy of risk prediction models not precisely defined as credit scores (and thus not subject to those requirements) would solve only some of the difficulties inherent in the emergence of new modeling techniques. Should a wider class of models that only peripherally predict credit behavior also be subject to disclosure requirements? Companies are increasingly using predictive models that assess creditworthiness, though they don't make loan decisions. Should that act bring them under the umbrella of the relevant laws? These laws are designed to improve the accuracy of the data contained in consumer reports. There is no separate, explicit disclosure standard for models that do not use consumer report data. These models could have a substantial impact on credit decisions, such that they might warrant special treatment under the relevant laws.

Equation 3 Risk Classification Probability

$$P(\text{Risk}_k \mid X) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

where

- $P(\text{Risk}_k \mid X)$: Probability of being in risk class k
- z_k: Logit output for class k from the final neural layer
- K: Number of credit risk categories (e.g., low, medium, high)

X. CONCLUSION

This paper discussed innovations in credit score modeling, with a focus on deep learning for credit scoring. We provided an overview of the credit score model development lifecycle, encompassing the data aggregation, data samples, replacement, exploratory data analysis, predictive modeling, and deployment phases. The data aggregation phase for credit scoring is particularly previously unexplored because of its reliance on data from a variety of sources across disparate information domains ranging from the credit bureau, bank transaction, payments, and account origination industries. We then extended prior research on loss function selection by comparing baselines on several traditional loss functions on a binary credit scoring task across deep learning architectures from the vision domain implemented using an efficient cross-entropy selection. We also extend and explore new architectures for scoring models applied to credit scoring problems, as well as ensemble-mode architectures.

Our results suggest that deep learning is relegated to becoming an ensemble model on top of more traditional and interpretable models such as the LASSO or trees on credit scoring data. However, before this work can be considered fully conclusive for reserving deep learning into ensemble models, more research is warranted on better ensemble modeling techniques within the ensemble framework and how to integrate deep learning at the very beginning stages of the credit score development lifecycle better. Additionally, further experiments are needed to identify whether its performance can be leveraged fully to create interpretable scoring systems using novel model-agnostic techniques, especially if techniques could be programmatically generated similar to how traditional scoring systems are built when supervised learning is introduced at the very beginning phases. In conclusion, while the present study has found that deep learning models are not entirely superior for credit score modeling problems, it can be concluded that further advancements can push their accuracy beyond that of previous models, rendering them a candidate for standalone building blocks.

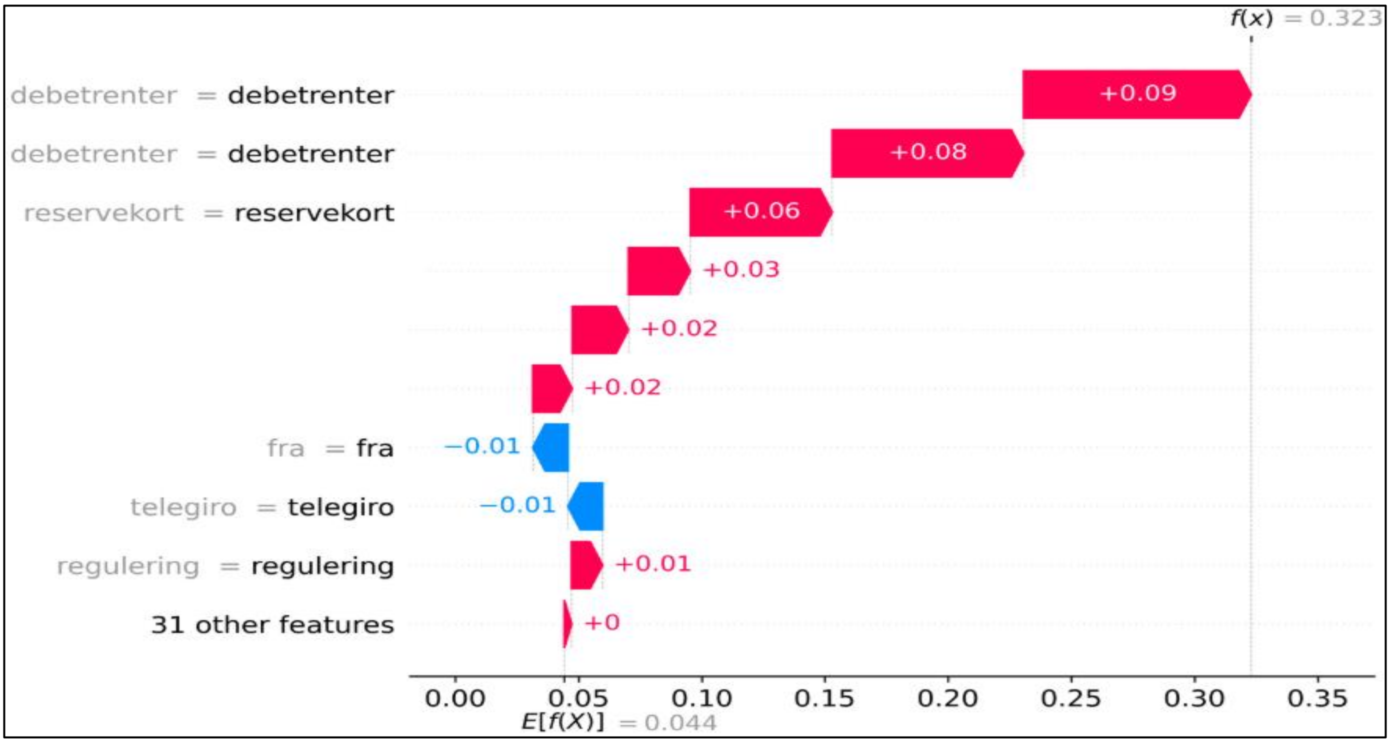

Fig 6 Deep Learning Models for Credit Scoring with SHAP

- *Final Thoughts and Implications for Credit Scoring Systems*

The objectives of this chapter were to answer the following research questions: which alternative data can be collected by banks and credit scoring companies to develop a strategy that works as effectively as traditional credit scoring strategies and to increase financial inclusion? How can that alternative data be exploited using machine learning and predictive modeling techniques to improve the level of accuracy of predictions, being fraud predictions and client's willingness to pay? Finally, can the use of alternative data and data analytics be used as digital responsibility tools for the financial service sector? In the first sections of the chapter, we describe the utility of the credit score, the need for innovation in this area, and we then present data sources used in the development of credit scores based on machine learning algorithms. We explored the main challenges and possible mitigation strategies. Our main contribution is to identify practical issues without technology understanding, in the quest for equitable innovative credit scoring applied to digital and financial inclusion.

We provide several practical implications from this process of systematization such as the need to innovate the product delivered by banks, the existing risk assessment methodologies and how to adapt and incorporate new variables and predictive methods into existing risk assessment products, as well as the alignment of strategies of innovative banks or that already use alternative solutions using alternative data for risk assessment, in relation to the accelerated change and how to design solutions that comply with inclusive practices, technical regulations, and data privacy laws. All these elements reinforce the need for credit scoring companies and/or banks to count on digital accountability that is an extension of corporate accountability.

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