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Chapter 3: Deep Learning Techniques for Risk Modeling and Predictive Analytics

3.1. Introduction

From the perspective of an academic, risk modeling represents the solution of an ill-posed inference problem where some risk level must be predicted with accuracy for a large population on the basis of limited historical data, possibly obscured by the presence of noisy predictors. Risk is generally understood in a probabilistic framework, and therefore risk models are often required to predict probabilities of default or default losses on the basis of sample means or sample proportions. Furthermore, risk modeling typically refers to the construction of predictive models for financial, operational, or insurance risks.

Predictive analytics in these application areas can be formulated using either traditional statistical models (e.g., linear regression) or deep learning techniques that employ multilayer feedforward or recurrent neural networks. Feedforward architectures allow any nonlinear function to be approximated to an arbitrary degree of accuracy as long as the distribution of the input predictors is known. Recurrent architectures can additionally capture temporal dependencies of sequential data by representing the inputs as a univariate or multivariate time series. However, compared to traditional approaches, the development of risk models using multilayer neural networks remains challenging, requiring careful attention to the quality of the available data, the representativeness of the input features, the model training procedure, and the definition of risk-based evaluation metrics.

3.1.1. Overview of the Study and Its Importance

Risk modeling and predictive analytics have gained increasing attention from researchers and practitioner thanks to factual evidences collection, management, industrial application supported by computational mathematical models. The artificial intelligence especially big data technology and techniques applied has promoted tremendously the risk modeling and predictive analytics. The deep learning technology has rapidly developed driven by big data and GPU parallel computing technique. Though having some theoretical foundation, the risk modeling remain hardly explored and researched from deep learning perspective. This investigation collects available studies from data repository and literature involving classification, regression, time sequence prediction, generation and so on deep learning modelling methodologies, discusses the architectures, data, feature consideration, model validation and evaluation beside other contributions related to the modelling in risk areas. The collected studies reveal that the deep learning modelling in risk classification and predictive analytics such as credit risk mostly takes supervised feedforward neural network and recurrent neural network approach. Credit and market risk predictive models heavily considered network structure and training hyper-parameter optimization, while operational risk and fraud detection modelling widely investigated features and representation for model performance enhancement.

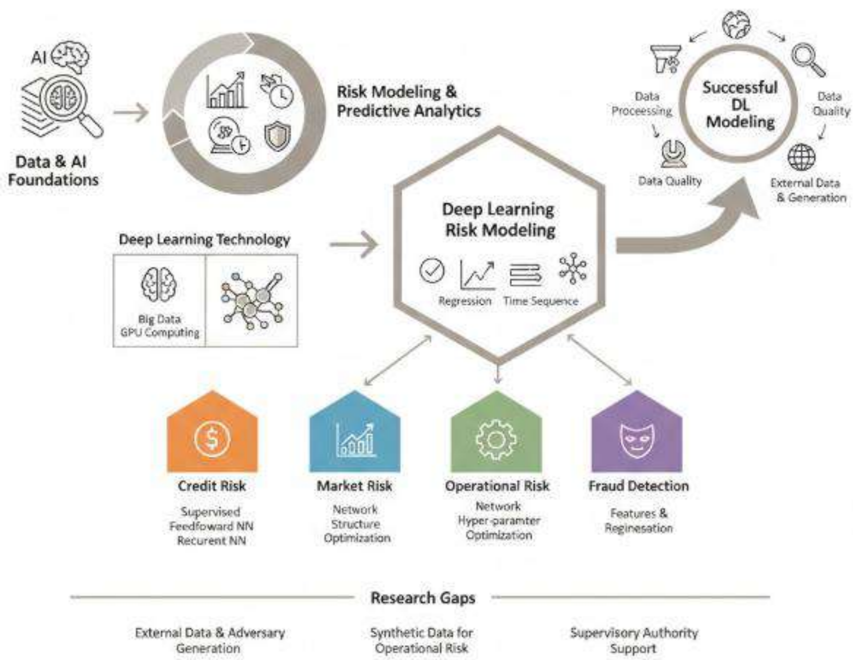

Fig 3.1: Deep Learning Paradigms in Financial Risk Modeling: A Systematic Review of Architectures, Data Synthetics, and Supervisory Gaps

The risk modeling study number and application areas substantially differ. External data consideration, adversary generation technology and operational risk synthetic data preparation lack research; although application support supervisory authority the area is rarely explored, needs more focus to guide and minimize future industry loss. Moreover, strong evidence shows that data preprocessing, quality control, feature engineering beside generation are very important for risk modeling. The success of the deep learning modeling and predictive analytics in risk classification and forecasting needs not only a good architecture of network structure and optimization of training hyper-parameters, but also effective data preprocessing and representation.

3.2. Foundations of Risk Modeling

1. Definitions and Scope

Risk is an inherent feature of any economic or financial environment. At a high level, risk modeling consists of assessing the economic value of specific exposures associated with uncertain future conditions and realizing the appropriate use of quantitative considerations and frameworks in establishing logical and coherent estimates of potential risk. Risk is characterized by uncertainty and ambiguity, and the modeling typically relies on a quantitative causation paradigm tailored to exploit the information revealed in the relevant data. Therefore, risk models can be associated with any set of techniques used to estimate and predict the level of risk, and the modeling for risk is usually defined relative to the phenomena under consideration within any domain of interest or application.

Although risk is an all-inclusive concept, defining risk more specifically in the context of modeling provides coherent and logical domain-specific results. The estimation of the risk of a particular financial transaction or a risk position within a portfolio determines the risk of loss for a particular exposure. Risk measures are traditionally obscured because a complete set of sensible measures has not been formally stated, and the modeling consequently has evolved along different lines characterized by estimation rather than the direct application of sensible measures. Careful consideration of the possibility of quantifying aspects of risk by an underlying structure based on coherent risk measures is showcased, providing insights that exposes why current attempts to measure or model a particular aspect of risk often fail to deliver a coherent description of risk within a particular domain.

2. Traditional versus Deep Learning Approaches

Despite the widespread use of complex econometric models, many effects of interest are omitted from the descriptions. With the application of machine-learning techniques, econometrician modeling has entered into a new stage where neural networks are used to model features that are hard to suppress. The problem of obtaining a useful approximation of an unknown relationship between certain inputs and its corresponding output can be addressed purely in a machine-learning sense using a fully connected network without tapping into any econometric rationale. However, the advantage of exploiting economic relationships has not diminished, especially when designing a neural network for accurately capturing a conditional distribution that can be very complex and difficult to learn. More sophisticated recurrent neural networks can help capture the temporal dependency and repetition hidden in the underlying relationship.

3.2.1. Definitions and Scope

Risk refers to the dependence of a factor, element or outcome on an uncertain event that can have a negative effect on the achievement of goals, including: loss of money; loss of property or means of subsistence; loss of saving; economic effects of pure speculation; distortion of social relations and values; risk for health and the environment; risk of error and mistake; and the probability of occurrence, the level of improbability and level of causation of unexpected, disastrous events. Risk modeling tries to describe and assess the risk of isolated and interconnected systems.

Shifting the perspective of data outside the traditional paradigm opens the door to new types of analysis, including risk modeling using deep learning techniques. Although risk modeling and credit scoring often use similar data, they focus on different phenomena and use distinct theoretical methodologies and conclusions. Risk modeling typically describes the possibility of default or any undesirable event, whereas credit scoring aims to predict the probability of repayment or recovery of a given credit. Risk modeling can be conducted in various aspects of everyday life. Credit risk, market risk, operational risk, fraud detection and risk intelligence are relevant application areas. Credit risk focuses on assessing the risk associated with an individual borrower or portfolio of borrowers. Market risk predicts movement in the value of securities and investments. Operational risk is related to loss resulting from inadequate or failed processes and systems.

3.2.2. Traditional versus Deep Learning Approaches

Risk modeling can be traditionally performed using statistical methods such as generalized linear models (GLM). However, the risk's association with certain dependent variables is often difficult to express using GLM. A vast range of algorithms could be used as alternatives to GLM, such as classification trees and support-vector machines (SVM), through the use of different types of architectures for the data. Nevertheless, the training of those algorithms is only performed once without any adaptations when data diversity increases during time, which leads to a decrease in performance.

Moreover, non-normalizing methods (classification trees and SVM) do not allow for probabilities to be interpreted nor for classes to be generated with confidence levels. If a bank has detected separate regions with different behaviors, it should treat each region in a different way and, if possible, use different architectures that learn the risk features in a specific way. Instead of building a different architecture for each region, it is viable to build a different ensemble that combines the best classifiers for each range. Deep learning architectures, such as multilayer perceptrons (MLP) and recurrent neural networks (RNN), offer new and elegant solutions for handling these problems. A feedforward neural network is an MLP with one direction and no direct connections back.

3.3. Deep Learning Architectures for Risk Modeling

Risk modeling and predictive analytics can leverage a number of advanced architectures from the realm of deep learning for modeling dependencies between the features in the set and the risk measure under evaluation. Risk variables are typically governed by various factors that may behave with different forms of dependencies, ranging from simple single-factor scenarios or multivariable scenarios without any temporal linking to temporal links, e.g., seasonal dependencies over time spanned data. Risk analysis across these key groupings can benefit from the application of an ensemble classification framework within a supervised learning scenario.

Feedforward neural networks can be readily employed for modeling static forms of risk variables. Each risk measure can be assigned to a dedicated feedforward neural network, capturing the unique feature-risk dependencies of that risk measure. An ensemble aggregation of these dedicated feedforward networks can potentially enhance the predictive accuracy of the framework if each individual network captures a distinct aspect of the feature-risk mapping as dictated by the samples during the training. Risk features derived from detection or predictive models that are expressed in a binary classification form can be classified within a feedforward neural architecture dedicated to the operational risk spanning a banking institution.

3.3.1. Feedforward Neural Networks

Feedforward Neural Networks (FNNs) are perhaps the simplest class of deep learning architectures. Given their structure, these architectures are better suited to problems in which the data set can be described with respect to the input variables at a particular moment or instance. In risk modeling terms, this translates into scenarios where predictions do not rely on any temporal dependence. For instance, any particular loan should either default or not default on a given date, independent from its past track record on the remaining assets in the bank's portfolio. The volatility of the financial market at some date does not depend on the volatility of the market a year ago. Consequently, the relationship among the input and output variables can be captured by the architecture synchronously. Observations across multiple instances can thencapture the underlying relationship, which can be extrapolated into situations yet to be observed.

As such, FNNs can be used in credit risk modeling, market risk measurement, credit portfolio loss estimation, and fraud detection problems, among others. Such problems have been tackled using different flavors of FNNs in the last years, incorporating ideas such as convolutions, bottleneck architectures, autoencoders, or deep ensembles. The testing conditions have differed in terms of data sets, modeling choices, performance measures, training/testing approaches, and benchmark methods.

3.3.2. Recurrent Neural Networks and Temporal Dependencies

Recurrent Neural Networks (RNNs) and their variations are other sets of architectures that have been utilized in addressing risk modeling problems, particularly those that contain temporal dependencies. Unlike feedforward neural networks, RNNs possess recurring cycles in their connectivity, which allows them to process and retain data over time. Formally, given an input sequence $X = [x_1, x_2, x_3, \ldots x_T]$, RNNs leverage several shared parameters to transform input x_i as follows:

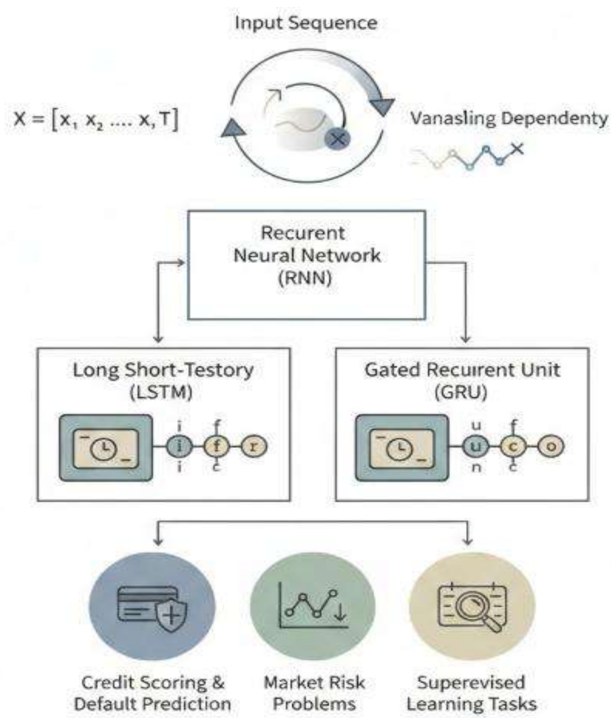

Fig 3.2: Temporal Gating Mechanisms in Financial Risk Modeling: A Comparative Analysis of LSTM and GRU Architectures for Sequential Default Prediction

RNN architectures, however, suffer from substantial difficulties in capturing long-term dependency data because of the exponential decay in stored information, a problem known as vanishing gradients. To address this shortcoming, a wide range of architectures that add a dedicated short- and long-term memory mechanism have been proposed. Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) are such architectures built from one or more recurrent cells that include a memory element (the cell state) with the capacity to store information for long times, and input, output, and forget gates that control the information stored and released.

These types of networks have become the mainstay of many supervised learning tasks with temporal sequences in sequential data and have been also exploited for credit scoring and default prediction and market risk problems.

3.4. Feature Engineering and Data Considerations

Data plays a vital role in deep learning and related models, as successful techniques require considerable amounts of it. Predictable dependency on quantity, however, is accompanied by less predictable dependence on quality. Indeed, feeding irrelevant or erroneous data to a model may yield poorer results than using a simpler approach with less data. Nevertheless, increasing the quantity of good data remains a primary challenge. Part of this can be addressed through representation—transforming the business and natural language problems earlier discussed into a format more amenable to a model. Thus, companies typically apply techniques like one-hot encoding, linear hashing, or word embeddings to bootstrap deep learning models. Word embeddings (GloVe, Word2Vec, FastText) can also generate representations that preserve similarity structure embedded in the original data.

Proper preparation of both the features used by the model and on the target data being predicted remains of paramount importance. Temporal considerations must also factor into the model development process. For example, suppose that all available data up to the end of 2018 are used to predict 2019 default rates, hold-out data up to the end of 2019 are used to predict 2020 rates, and so on. Following similar principles as test set approaches, a real world validation set can be similarly constructed. Hyperparameter selection, validation and model selections rely upon a dedicated validation set that preserves the sequential nature of the data, typically based on a rolling-window analysis to assess different hyperparameter conditions across a temporal dimension.

3.4.1. Data Preprocessing and Quality

Two steps are necessary prior to the deployment of any machine learning or deep learning technique. First, the data quality must be carefully addressed, as it has a meaningful impact on the learning process. This leads to a substantial amount of tasks aimed at identifying and treating data quality problems, including outliers, missing values, and noise detection. In the second step, a preliminary analysis of the data can usher to the definition of a feature engineering strategy. The findings from this analysis may suggest the need for creating new input patterns that offer a better description of the problem at hand. Once the focus has been identified, the data acquisition process can start. When acquiring the data, one should keep in mind requirements for data quality. Given that, it is recommended to check the collected data for outliers, missing values, and noise.

Data quality can be assessed by dimensions such as trustworthiness, completeness, and noise. Trustworthiness refers to the data source and indicates the origin of the data. Completeness indicates whether all the relevant information is present. Data quality problems in this dimension can be related to physical failures with sensors, such as the malfunctioning of a stock price quotation machine. Noise refers to random modification of the values in the data set, resulting from inaccuracy in the measurement system. During the acquisition phase, it is suggested to avoid the introduction of patterns in the data that require excessive feature engineering for their treatment. Once the data are stored in the learning environment, the focus can shift toward detecting and treating data quality problems.

3.4.2. Feature Extraction and Representation

Sufficient characterization of the data is essential for risk modeling. In traditional modeling, domain experts analyze the data and construct relevant features to feed an input layer. Feature engineering can also improve the predictive power of deep learning models, at the expense of added complexity. In risk settings, the characteristics of the underlying data, rather than the model architecture, generally define an appropriate feature representation. Consequently, there exists no universally “best” feature representation for risk modeling.

Within structured data, where each attribute corresponds to an independent input, the most common approach is to use the raw attribute values directly. These correspond to static features whose relative importance is noticeable across different historical data samples. Within graph-structured data, such as in operational risk modeling, the representation of individual graph objects is often carried out by applying a message-passing neural network to extract embeddings that capture neighborhood information;

the entire graph is then represented by a corresponding pooling layer. Within text data, domain knowledge can guide text preprocessing, such as stop-word removal or aggregation at the document level, which is then combined with representation-learning techniques (e.g., word2vec or Doc2Vec) to produce an embedding that captures semantic information. Finally, in image data, convolutional neural networks (CNNs) can serve as a dedicated architecture to jointly learn the appropriate representation and risk model from labeled samples.

3.5. Model Training, Evaluation, and Validation

Model training is a critical process in project development within various fields, including risk modeling. As opposed to traditional statistical models, most DNNs attempt to learn mappings from input to output by directly using original features, thereby requiring sufficient training data. Data networks can be distinguished based on the number of observations and features available for training. For example, fraud-discrimination architectures usually have a larger number of observations than features, allowing the model to learn the feature representations through many learning iterations and obtain useful relations. In such scenarios, decisions need to be made regarding the optimum ratio of observations to model parameters.

The considered paradigms encompass supervised, unsupervised, and self-supervised learning—all perspectives from artificial intelligence. Once the model is defined, training becomes a process where adjustments are made to weights with back-propagation. Training can be viewed as a minimization problem in which a regularization term is added to prevent overfitting. The definition of relevant performance metrics is a complex task faced by practitioners; what is considered acceptable performance depends on the context of the analysis being conducted and is seldom dictated by a general rule.

In risk models, special attention should be given to the definition of false-negative and false-positive costs. In the case of credit risk, the cost associated with misclassifying a good client is much lower than that of misclassifying a bad client. Consequently, the penalization given for the classification of bad clients as good must be higher than the opposite situation. In prediction problems, a common metric is the area under the receiver operating characteristic curve, which can be interpreted as the probability that the model ranks a random positive observation higher than a random negative one.

In a risk context, the average true positive rate over different regularization levels gives a measure of risk-adjusted model performance. For temporal risk analysis, it is also important to determine the model's ability to follow the underlying dynamics of the data. In other words, at any point in time, how well does the model rank clients in relation to the danger of defaulting? The prediction should also depend on the time distance to the event. Indeed, the risk of making mistakes increases when the model is used to evaluate clients in a shorter (or longer) time horizon than was assumed in the development of the model.

3.5.1. Training Paradigms and Regularization

Many neural networks are trained using a supervised paradigm, in which pairs of input samples and the desired target values are processed during model training. Backpropagation is frequently used to minimize the loss between the predicted and target values. In applications of risk modeling, training a model through supervised learning requires labelled risk data. However, it is often infeasible or very expensive to acquire such labelled risk data, especially in operational risk areas.

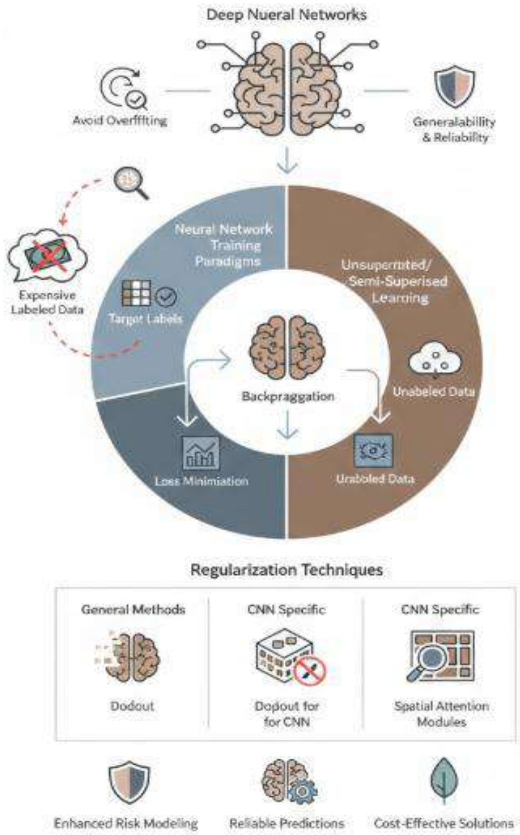

Fig 3.3: Robust Deep Learning for Operational Risk: Leveraging Semi-Supervised Paradigms and Advanced Regularization to Overcome Data Scarcity

Despite this, deep learning methods are still being used to model risk through unsupervised and semi-supervised training paradigms, which can utilize unlabelled samples, either alone or in conjunction with supervised learning. The regularization of deep neural networks aims to ensure the generalizability and reliability of the hidden representations so that overfitting to the training set can be avoided. Various methods, which include dropout, weight decay, and early stopping, have emerged either from theoretical constructions or empirical effectiveness. Alongside dropout, other methods for Convolutional Neural Networks (CNN) such as dropout for CNN, convolutional block attention module distortion (CABD), and other spatial attention module-based techniques have recently been introduced to address overfitting in models that fall prey to the large number of parameters.

3.5.2. Evaluation Metrics for Risk

Evaluation of a risk model should not be performed using general-purpose metrics like accuracy or ROC AUC. Risk quantification should adhere to the principles of financial mathematics; that is, money is measured in a ratio, so prediction of risk is a regression problem predicting a real-valued quantity, rather than a classification task where predicting the wrong class incurs the same cost for all classes. Failures should not be evaluated equally; operational risk must be evaluated for its ability to distinguish between diff erent magnitudes of failure accurately and precisely. A model predicting a $1m loss, when the actual loss was $100m, is clearly a failure. It is equally important to capture and predict the small, but numerous events (e.g. a million $1k failures makes for a loss of $1bn). The only acceptable metric for a risk model is using financial metrics, such as Sharpe Ratio, P&L or Metropolitan Arithmetic Mean. These metrics should be enriched with standard deviation, skewness, and tail loss ratios (where a lower ratio represents better prediction) for a more descriptive assessment.

Risk survival analysis moves the focus from the frequency of category A, B and C losses to the amount of money lost for each category. A better improvement to the usual approach allocated by Frequencies-Financial Cost Matrix is the addition of Risk-Cost Index that properly weight failure of category C as highly undesirable and costive to the bank sustainability and share holders. Risk–Customer Relation explores the impact of money lost through operational loss on actual customers. It defines the probability of customer attrition based on the economic impact of the loss and matches operational event with changes in bank customers' portfolio (e.g. losses of bank money as consequence of Bank Robberies through the risk–customer relation can affect all customers of the bank and not just the ones who has suffered a loss directly).

3.6. Applications in Risk Modeling

Numerous application areas can draw upon the methodologies and architectures covered so far. Traditional risk modeling has focused, in particular, on credit risk, market risk, and operational risk. Credit risk modeling can be traced back to Altman's Z-score model of bankruptcy prediction, predicting the ratio of actual data, considering financial reports. Market risk forecasting has developed since the introduction of value-at-risk modeling. The growing amount of data, enhancements in databases and computing power, and the availability of methods to measure frequencies and time separation of rare events have revived interest in operational risk quantification. Advanced data mining techniques apply to practical problems of operational risk and, in particular, for fraud detection.

Credit risk forecasting involves predicting when a borrower will default or be late on a scheduled payment. For charged-off loans, the time to default may be known, but exact time to default data is sparse. Neural networks have been used in survival analysis with censored data. An alternative modeling strategy employs a simpler formulation with only a binary indication of default: whether or not the loan was ultimately charged off. The risk modeling community is cautious with the use of machine-learning methods due to the domination of traditional methods that have been in use for decades despite many shortcomings. They are, nevertheless, useful for developing competing models especially when a lot of risk data is available.

3.6.1. Credit and Market Risk

In credit risk modeling, significant advances have been achieved using deep learning, particularly in the analysis of credit scoring, default prediction, default time prediction, and credit portfolio risk management. Early work in credit scoring relied on FFNN with raw data fed into a single-layer NN, especially in the analysis of literature on neural network applications to credit scoring problems. Subsequently, deep structured methods achieved state-of-the-art accuracy but were less interpretable than FFNN. Prediction of the likelihood of credit default is a core issue in finance, with penalized logistic regression the prevalent method in practice due to theoretical properties and ease of interpretation.

More recent research has employed deep learning models for this task, drawing on similarly heterogeneous risk factors (demographic, macroeconomic, and strategic/operational) specially labeled as in out-of-time real-world tests, and proposed integrating FFNN and deep embedded decision tree architectures with complementary strengths into a unified framework. Deep learning has also extended to prediction of the expected time-to-default, even in applications with considerable label noise, where label corruption could potentially mislead neural networks. Strong performance on U.S. corporate sample data relative to existing benchmarks supported the approach. Risk-sensitive credit portfolio management based on convolutional neural networks has also been tackled. These advances show that effective feature engineering and careful structure design can help overcome the well-known interpretability problems of deep models even for the most critical and sensitive problems in credit risk management.

Application effort in market risk modeling is more recent and still limited in volume, with promising early results using RNN to predict real exchange rates. Market risk management is one of the key sectors in financial security, and informed judgment of the possible change trend and rule of exchange rate risk fluctuation is a practical issue for enterprises with foreign investment. Low-dimensional dynamic modeling methods have been utilized and combined with a broad family of neural topologies to construct a TT-RNN and TT-QRNN. The established TT-RNN process model achieves competitive forecasting performance over various benchmarks. The combined use of all available sources of information of the target process through a recently proposed neuro-informative fusion approach greatly improves the predictive capability of the original TT-RNN.

3.6.2. Operational Risk and Fraud Detection

Fraud detection and operational risk management are key areas in which Deep Learning models are finding increased application. Traditionally, statistical techniques such as various Generalized Linear Models (GLMs) and their extensions, support vector machines (SVMs) and random forests have been employed. Popular detection patterns include bank transactions revealing abnormal customer behavior, credit cards activity indicating fraud, IRS tax returns through asymmetric distributions, telecommunication calls patterns signaling possible fraud, detection of phishing webpages, among many others. One notable approach consists of training an extra classifier over the correctly classified observations of the first one, in an iterative manner, done until an explicitly predetermined cut-off level of the second classifier is achieved. Label noise in fraud detection is known to be an important concern. Recent efforts aimed to address it include semi-supervised neural networks and the adaptation of the Generative Adversarial Networks (GANs) in a semi-supervised fashion to a credit card fraud detection problem.

However, despite the general perception that the performance of neural networks would be low due to small amounts of data pertaining to each label, these models are being successfully applied. Recently, a Convolutional Neural Network (CNN)-based transfer learning method was successfully employed for detecting Credit Card Fraud Detection. Other applications in operational risk comprise the potential use of recurrent Deep

Learning models to both detect and predict financial fraud and phishing websites, respectively.

3.7. Conclusion

The research explored both the foundational concepts of risk modeling and predictive analytics and potential applications using deep learning techniques. Risk modeling comprises different types of predictive models either for the measure of risk for highly predictive risk stratification. Modeling risk and risk-sensitive variables has inherent challenges in data quality, sample size, nonlinear relationships, and temporal dependencies. While practical approaches have been developed, the risk measure itself can suggest better modeling choices such as feedforward neural networks incorporated smoothing and can be represented very effectively by recurrent neural networks.

The multitude of practical implementations of predictive analytics suggests many types of problems are solvable. Success, however, requires careful choices in the underlying data as well as the predictive modeling techniques themselves. Any predictive modeling analysis must carefully consider the data characteristics and provide features for the predictive model with appropriate representation, smoothing, and temporal considerations to adequately support a predictive function. Further, in order to avoid bias in the results, proper model training, validation, and testing efforts are essential and should be reflected in the choice of underlying predictive models.

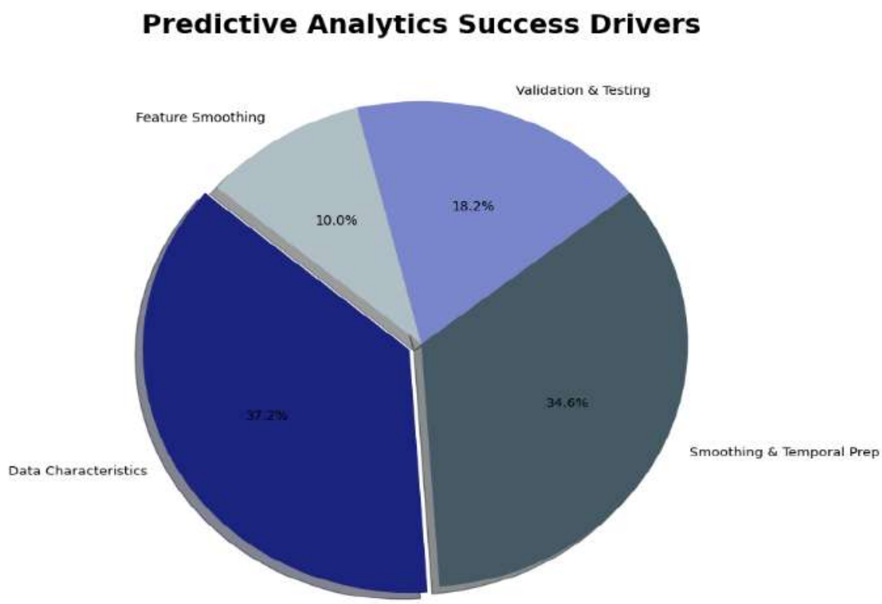

Fig 3.4: Predictive Analytics Success Drivers

3.7.1. Final Thoughts and Future Directions in Risk Modeling

The facets of risk can be approached in many ways, as different forms of predictive modeling have been conceived to form smarter credit models, better detect fraud, provide clearer guidelines regarding money laundering risks, or improve the forecasting of stock market fluctuations. Such multiperspective models can serve to inspire a richer understanding of risk and therefore form more complete models. Indeed, risk modeling and prediction can be seen as a growing field, even when traditional methods employed in economics are not abandoned. Risk modeling techniques for formal systems are therefore gaining ground at all levels.

A recent explorative and comparative study in this domain has signaled word embeddings and other state-of-the-art machine learning techniques as possible candidates for modeling money laundering, terrorism financing, and sanctions risks in a single model, TruthFinder, the first capable of detecting all types of Elmer Lee Transactions in one process while also being trained under a formally structured system. A system specifically constituted to manage operational risk and enhance fraud-detection and prevention mechanisms has moreover blended the traditional use of formal systems with deep learning techniques, applying convolutional layers for detection, recurrent layers for prediction, and a shallow Learning Fishbone Backpropagation Network for training on Elmer Lee Transactions.

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