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Intelligent Risk Management in Financial Services Using Cloud-Based Machine Learning Models

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Abstract

Model risk is one of the three largest risk types affecting the financial services industry, in addition to credit risk and market risk. It is particularly relevant concerning Artificial Intelligence (AI) technique-based models, unlike deterministic statistical, mechanical, and engineering models (or freely interpretable rule-based models). The latter three types of models have been long established and accepted for risk and capital measurement; where the interpretation of the mechanisms is more or less clear and comprehensible, it is broader than probability density estimation. Machine learning-based models might not have learned what the human mind believes worth predicting and how this should be done for regulatory purposes to be interpreted, scrutinized, explained, and validated.

Comprehensibility/explainability/interpretability of naturally black-boxed AI and machine learning models, especially deep learning-based ones, are frequently considered as essential constraints for the model approval process. Here, the black box issue must be considered the number of parameters, since even stochastic optimal control and voting factor models' degree of freedom might induce non-comprehensibility (especially in case of many dummy variables). In compliance with the self-extracting effort, propensity score-based non-comprehensibility might successfully be addressed.

Here, it is analyzed how comprehensibility/explainability/interpretability constraints are currently regulated. Accordingly, for AI techniques, it might be deemed astonishing that these points are only sideshows, focused more on documentation than process and praise than well-defined rigor. Hence, it develops a concept to improve this significantly. Last but not least, it analyzes the damned question of who qualifies for generating and approving such models.

Keywords : Financial risk management, intelligent risk management, financial services, explainable artificial intelligence, active monitoring, risk prediction, risk estimation, supervised machine learning, cloud computing, cloud services, scalable machine learning Platforms, financial regulation, financial oversight

1. Introduction

We are living in a world of high uncertainty. Major events such as the COVID-19 pandemic, the financial crisis of 2007/2008, and Russia's invasion of Ukraine have caused abrupt changes in economic and financial conditions. Hence, it is necessary to analyze and quantify these uncertainties regularly, as such high-impact low-probability events have previously contributed to significant consumer losses

and did impact risk management practices in financial services and many real-world businesses.

Recent advances in computing technology provide new opportunities for risk management in financial services, where complex statistical models can be implemented on cloud-based architecture and performed by distributed cloud computing resources. Numerous highly dimensional datasets can now be stored and analyzed for risk measurement and forecasting. Such information can include daily high-frequency economic and multi-asset financial time series, on-chain financial transactions in block chain-based cryptocurrencies, alternative and social media-textual information about firms, countries, and crypto-assets, the web's complex financial network structures, and the global real-economical network that describes the multi-dimensional flow of goods and services among consumers, businesses, and countries.

To keep pace with ever-changing events in high-dimension, the machine learning engines fed by massive daily/real-time data provide intelligent algorithmic risk management systems capable of quickly adjusting the risk measures accordingly. Risk professionals are expected to use a combination of model testing and simple heuristics, such as discounted drift and thresholded sensitivity for model review, validation, and evaluation.

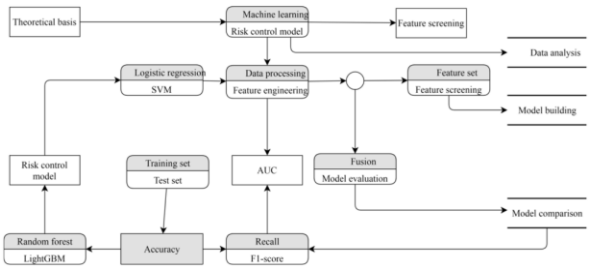

Fig 1: Financial Risk Management

1.1. Background and Significance

Over the last decade, the financial services industry has faced a wave of disruption reminiscent of many prior disruptions across other industries, including retail, media, and travel. Delivering improved services and deflated costs to bank customers, fintechs like Venmo, and Square's Cash App have aggressively attacked banks' retail franchises, and Silicon Valley players with deeper pockets have made early incursions into capital markets and corporate finance. The positive feedback cycle from the first attempted disruption to subsequent attempts is alarming, as new entrants are emboldened not to repeat loyalty mistakes made previously by incumbents. Financial institutions see large sums of money being efficiently transferred into the cloud or cryptocurrency without their involvement, with the state of California now permitting employee wages to be paid in cryptocurrency. In the investment banking space, a company that has never done an IPO, SPAC, or M&A transaction, can now bring the best underwriters and advisors to the table next week and threaten to displace incumbent firms.

Cybersecurity threats are increasing and, lagging many other industries, banks are now recognizing they must act. Global conglomerates with revenues exceeding a billion dollars lose an average of $403 million annually from 130 successful attacks—the cost of these breaches, particularly to small and mid-size firms that lack the budget resources to bolster security controls, can be catastrophic. Cloud vendors both directly by supply chain hacks and indirectly by lack of vigilance must bear a good part of this accountability. Senior banking executives have primarily shown excessive trust in the understanding and vigilance of cloud vendors and have limited accountability placed on their firms despite strict privacy regulations and protocols. Supervision by the OCC and newly formed agencies must first focus on these governance and accountability aspects, as wrapping more tools and technologies that create with less oversight and controls will exacerbate outsourcing governance and risk management issues that are already acute.

With the right knowledge, tools, and procedures banks can attack multivariate fraud, smuggling, insider trading, and other terrifying threats. There are exciting new, cloud-based, initiatives from both start-ups and major technology firms being employed to aid firms in achieving the knowledge needed to see the whole ecosystem and to seize upon

the convergence of Cloud computing, machine intelligence and their savings in big data storage and transfer. Cloud-based machine learning algorithms and software now permit possibilities for instant anomaly detection, prevention of insider trading by mapping and acting on social connections among traders, analyzing whole forest fire events encompassing 27 terabytes of satellite imagery data for detection of illicit logging, and many others.

Equ 1: Anomaly Detection for Fraud Risk

$$\text{AnomalyScore}(X) = \|X - \phi^{-1}(\phi(X))\|_2^2$$

Where:

- ϕ is the encoder
- ϕ^{-1} is the decoder
- A high anomaly score indicates a potential fraud

2. Understanding Risk Management

High-stakes transactions, rapid lateral product market movements, and aggressive competitors and new entrants mean that financial services have one of the highest levels of risk management scrutiny. Business executives and federal regulators spare few resources in ensuring that risk management processes, decision-making models, and risk-reducing technologies are able to support a firm's growth efforts while understanding, guarding against, and isolating risks. Examples include the Sarbanes-Oxley Act, the Basel Committee on Banking Supervision's Capital Accord, the Board of Governors of the Federal Reserve System's Regulation R, and the Office of the Comptroller of the Currency's Guidelines. These statutes promote effective risk management or impose sanctions for shortcomings. Failure to comply triggers a measure of negative publicity or legal action, a cost easily absorbed by a firm. Beyond compliance, risk management can generate competitive advantage through actions that reduce the potential impact of currency or interest rate exposure, enhancing a firm's value dramatically.

Lower-level risks arising from irrelevant costs and decision-making errors abound as well. These can affect a firm's independence or stewardship. They can also prove disastrous: the runaway costs of Rolex watch resources on a doomed guideway to production and the poorly timed helicopter purchases at Oregon's PacificCorp are lessons in the importance of managing risk at all levels. This policy formulation process is referred to as risk management. Determining what risks are sufficiently concerning to warrant management receive senior attention and require prompt resolution. As risks about which a firm needs to be concerned are readily adapted to the context of specific firms, an example from retailing is pressed into service. In this context, it might be a pricing strategy, for instance. Will a firm's prices still be able to cover costs in 6 months' time? How will the entry of an apparel retailer such as H&M or a discount retailer affect discounts, margins, volumes, and costs? Such questions are examples of low-level risk management processes at work.

Like information on big risks, information on small risks, know-how about what a firm's competitors do or plan to do, is also crucial. Such know-how is a function of the quality of processes, information systems/technologies and models enabling it. Trading models for equities, options, debt, and other instruments are simply mathematical models capturing or approximating market pricing and hedge relationships. These models are an initial challenge to audit as they are developed or altered. Treasury import/export programming systems are decision trees capturing the thinking of comparatively few quantitative experts. However, other systems such as earnings estimates, arbitrage program purchase (and discretionarily trading) software, and the appellate processes containing the outputs from fraud detection systems are more complex and less understood. It is difficult to identify errors or concerns as they arise or assess how good a risk they are creating.

2.1. Definition of Risk Management

In a financial services context, risk is defined as "the lack of predictability of outcomes" affecting

financial transactions which form the firm's business. A firm invested in stocks can predict potential gains and losses but cannot know them precisely. Such a firm lacks predictability of the financial risk associated with the stockholdings. Risk has both a positive and negative connotation. It includes the possibility of pleasant surprises and adverse (bad) outcomes. In the latter case, one possible outcome is the capital stock available to undertake business may be drastically reduced (risk of ruin). In markets, there is both up and down movement; in business there may be swings between good and bad income statements (good times or bad times). Risk management is the management of resources and commitments of an organization, firm, or corporation to maximize the value of the organization, taking into account the potential impact of unpredictable outcomes on the performance of the organization. Risk management assumes that a decision maker – and hopefully there is only one - must maximize the firm value effectively or do so in a credible manner. It deals with the uncertain future. A good risk manager is one who could foresee the potential risk and make good decisions to minimize the loss, rather than being caught by surprise. The perception of risk is based on human's judgment of the disagreement among the basis variables forming the perception. Consequently, in a financial market, the risk is largely a function of the magnitude of chaos (variance) existing in its dynamically evolving state.

Risk management requires active and proactive implementation of the infrastructure required for risk identification, risk measurement, risk regulation, risk report, and risk optimization. The ultimate goal is to minimize the losses caused by chaos while maximizing the profits caused by chaos. It deals with the decisions after risk measurement, and can be thought of as a response to risk. Risk management on its own can perform global optimization of the risk management function based on the existing risk profile in the firm.

2.2. Importance in Financial Services

The gap between risk forecasting and the majority of expected losses is a crucial issue in financial services where large, complex and fast trading activities are deployed in an uncertain and dynamic market context. Intelligent Risk Management is the solution at hand here. By blending computational intelligence and cloud-based machine learning models with a real-time integration of market activities, diverse market states can be implicitly clustered and evolution patterns detected for monitoring purposes. Outlier points, for instance unexpected price drops or rapid stock price variations, can be identified live for forecasting and risk prevention. On the financial services industry side, this affords a true time to react to mitigate losses by intelligent mechanisms and alerts automation to assure timely transaction notifications.

Very little research effort has been dedicated to investigating cloud-based models' deployment into production environments in their intelligent context. Nevertheless, they bring something totally different to business than what one would expect from traditional data mining models. In this context, real-time automated monitoring production systems can be achieved to a high level of sophistication by continuously integrating data from hydraulic models with cloud-based and computational intelligence forecasting engines that provide good forecasting even in the most complex and chaotic cases. The models can assimilate human expertise to remain self-refreshing.

Most of the financial services models fitted with machine learning are sometimes a closing set of predictions that computes the probabilities of a set of pre-defined quantiles rather than of a continuous prediction, while some others provide only a fixed number such as the equal variance volatility measure.

3. Cloud Computing in Financial Services

The popularization of the Internet of things and rapid growth of information and communication technology have led to data volume growth at an unprecedented and explosive scale. Traditional data

processing technology has difficulty meeting the financial industry's growing data needs for near real-time processing and complex data analysis. The cloud computing model, which has been hailed as the revolution of information technology, helps organizations provide advanced services to their customers, reduce IT capital costs, and undertake a big change and agile transformation. However, with the increasing use of cloud computing technology in various fields, it has brought opportunities as well as chaos and security risks to the industry development. The financial industry, which pays the most attention to risk control and management, is also facing assessment challenges and significant risk problems against the background of applying cloud computing technology.

This paper analyzes the structure of financial information risk and attributes the assessment variables of the framework. Based on the cloud computing model, it puts forward the prediction and assessment approach of intelligent financial information risk, establishes the predictive model of intelligent financial information risk assessment in cloud computing, and carries out risk assessment experiments. The financial industry, as the core and foundation of national economic operation, plays a crucial role in ensuring the sustainability and stability of the national economy. At the same time, big data is the key to becoming a data-powered intelligent financial service industry and promoting the continuous improvement of financial infrastructure. By comprehensively analyzing and processing the data of various financial sectors, cloud service providers can build intensive cooperation and collaborative security between data, technology, and demand for artificial intelligence scenario applications.

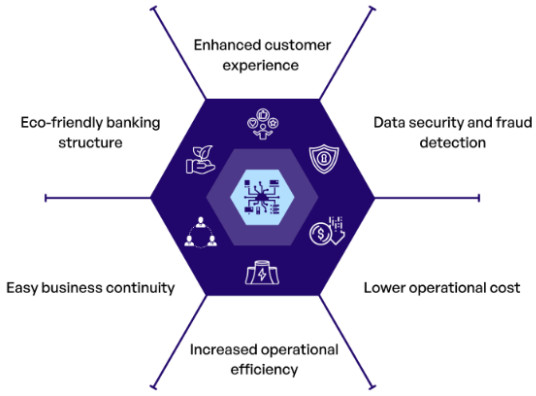

Fig 2: Cloud Computing In Banking

With the rapid development of digital finance, the financial industry's "intelligent" transition needs to be accelerated using advanced intelligent technology. Intelligent risk prediction and assessment methods should be further researched and developed for the finance-facing growing business complexity and emerging occasions. With the increasing use of third-party technology service providers in financial institutions, new risks are emerging in the sector. After the 2008 global financial crisis, new financial infrastructure entities emerged, such as the New York Stock Exchange Arca and algorithmic trading.

3.1. Benefits of Cloud Computing

Among the huge advantages of Cloud Computing is incorporating telephony, applications, servers, storage, security, and web services. As a type of virtualization, Cloud Computing permits access to virtualized computing resources and the ability to network them dynamically and remotely. Data can be stored and transported in the "cloud." It includes web services in accordance with the request, expense, and potential internet access corporations. Cloud Computing is one of those super-fast virtualization and transmission systems in which, based on requirements, resources will be shared among users. Like everything else, the Cloud has its own benefits and drawbacks. Cloud Computing represents two trends: IT efficiency and business agility. IT efficiency enables vendors and users to employ the power of modern computers efficiently. Business agility makes development, parallel

processing, business analysis, and mobile interactive applications accessible for users in real time. It reduces the cost of enterprise IT setups by means of computational tools that can be deployed and scaled rapidly.

Cloud computing is an emerging computing model where IT and computing operations are delivered as services in a highly scalable and cost effective manner. Companies in diverse sectors intend to leverage cloud computing architecture, platforms and applications in order to gain higher competitive advantages. Among the huge advantages of Cloud Computing is incorporating telephony, applications, servers, storage, security, and web services. It includes web services in accordance with the request, expense, and potential internet access corporations. Cloud Computing is one of those super-fast virtualization and transmission systems in which, based on requirements, resources will be shared among users. Public Cloud service providers should implement strong data replication mechanisms to distribute customer's data across the globe in various geographies. The hybrid cloud model is a merger of two or more kinds of cloud deployment models such as private, public or hybrid.

3.2. Challenges of Cloud Adoption

The importance of carefully considering cloud payments in businesses across sectors is steadily increasing. Among the businesses that are migrating to the cloud, the financial services sector is the most inclined to do so. Inconsistent regulatory policies and resistance to automation and new technology have historically hampered the sector's cloud migration pilots. In contrast, technology has advanced rapidly in recent years. As a result, payment systems have been altering, with simple internet payments developing into multi-channel heterogeneous systems. Traditional bank services such as credit, lending, and fund transfer must now adjust to their multi-channel payment counterparts. Banks may be able to alleviate some of their infrastructure and operational obsolescence difficulties by adopting cloud computing technologies.

The importance of all forms of cloud payments in banks is highlighted in this study. New cloud-based models that banks are adopting can allow structural adaptation to the changing payment ecosystem. Models for dealing with a cloud payment architecture are painfully primitive. Furthermore, when banks (or their traditional counterparts acting as IT payment service firms) start several individual semi-cloud computing systems, the overall architecture for cloud payment services may be inefficient. This is why several models for using cloud computing in payments are discussed in detail, classifying both opportunities and threats. In conclusion, the future importance of these models in their partial runtime implementations is anticipated.

The technological advances spurring cloud payment developments are highlighted. An overview of the field of cloud payment services is offered with a definition and classification of cloud payment activities. Important areas of cloud payment service usage followed by listed services in each area that banks worldwide are considering or that are widely used. A thorough research on the possible implications within the cloud payment context and their origin in the financial services area is carried out. Trivial or easily solvable threats are avoided, leaving a detailed description of the cloud-sensitive threats and issues in cloud payment services. The key to the detailed description is a cloud payment state of the art attack vector list that is complemented with research results on the occurrence of the listed attack vectors.

4. Machine Learning Fundamentals

Machine learning (ML) describes the capacity of systems to learn from problem-specific training data to automate the process of analytical model building and solve associated tasks. Examples include detecting fraud, flagging suspicious transactions for AML purposes, forward-looking credit scoring for bond issuance or loan providing, or predicting corporate disasters. Deep learning (DL) is a machine

learning concept based on artificial neural networks in one or multiple layers. For many applications, ML/DL models outperform shallow ML models and traditional data analysis approaches, such as regression or tree-based models.

A clear concept of training data is a precondition for understanding machine learning. The context and training data available for model building set the climate for the corresponding learned models. Similarly, the task to be solved in order to achieve a learning goal is conceptually distinguished. For example, for fraud detection, aspects of the fraudulent transaction may differ from benign transactions, such as their geography, time of day, or the network structure surrounding the purchasing agent. As by definition only a fraction of the feasible data is fraudulent, the learned model for an ML application for fraud monitoring will bias towards detecting fine-grained patterns in the few fraudulent transactions that are not present in more benign ones. Changes in fraud behaviors may render a model learned in one time period infeasible for subsequent periods. For economic questions, control models are often required that compute the optimal decision for each state of the monitored system.

The model learning itself advances in phases of optimization. The corresponding phases are outlined here independently of different processes conceivable under these phases. However, supervision and feasibility are both 0 or 1–based, but the applicability of a model throughout the considered control period can be certainly in between, such as when a model is assumed to be feasible but quickly loses applicability because of changes in market situations. The presented process models are presented with a focus on potential impacts on theoretical models. On the practical side, DA modes, data sources, observations, pre- and post-processing approaches, and implementation and testing aspects are not comprehensively addressed. Transfer of contextual understanding into theoretical representations is legible. Translating such a black box approach into size-specific representations – e.g. payments transmitted across multiple corridors per second. This translates into data input sizes with hundreds of millions of records per second. The task for developing an understanding of very high-frequency multivariate processes such as daily currency conversion rates or no log returns on stocks across several years is indistinct and takes the research domain under scrutiny.

4.1. Overview of Machine Learning

Supervised Learning is a basic machine learning technique that learns complex mathematical functions based on human labelled observations. The models are fitted with a training dataset and make predictions on an unseen testing set. This group aims to predict future events. Predictions can either be numerical values of a quantity or true or false states of a condition. Classification algorithms handle binary states such as default or not default, while regression algorithms estimate continuous quantities such as the probability of default. Popular classifiers include Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Neural Networks.

In supervised machine learning, models fit a function that relates an unlabelled observation (input variables/features) to a labelled human made state (desired output). The learning process is to iteratively modify the function parameters such that the prediction errors on a labelled training dataset are minimized. A trained model can be used on stationary datasets to rapidly make predictions at high speeds. New, unseen observations are assigned to classes or given numerical predictions based on rules learned during the training process. A hugely interesting area of research is the incorporation of alternative data sources with the classical borrower and loan properties traditionally used.

Using smart telemetry devices, alternative data from sensors measuring humidity, sound, light, and atmospheric pressure has been collected in the past decade. Proponents argue that such data can provide valuable insights on borrowers' real life performance. A huge body of research focuses on developing algorithms to utilize the metadata from these

unstructured data to provide additional insight on borrowers that can enhance the prediction of loan delinquency. Unstructured data sources such as business registration locations, reports or social media text exist, leading to new publicly available information. Text is often pre-processed into a bag of words. Existing inferring setups estimate the sentiment of the content and are fed with input vectors. Contour plots showing how the sentiment evolution affects default probabilities can be an attractive avenue of research due to market overreactions to news.

Equ 2: Portfolio Risk via Value-at-Risk (VaR)

$$\mathrm{VaR}_\alpha = \inf\{x \in \mathbb{R} : P(L > x) \leq 1 - \alpha\}$$

Where:

- L is the loss distribution generated using ML models
- α is the confidence level (e.g., 95%, 99%)

4.2. Types of Machine Learning Models

Machine learning models can be categorized as either supervised or unsupervised, depending on whether a target feature is provided to the algorithm. In supervised learning tasks, a machine learning model is developed using historical data that comprises the desired inputs and outputs. These models can then be used to predict the value of an output feature given a new observation of the input features. In unsupervised learning, the training algorithm is provided with only observations of the input features. The goal of unsupervised learning is to extract interesting characteristics of the data that may not be readily apparent. The machine learning models can then be classified further according to their internal structure or methodology.

Machine learning models are divided into two classes — parametric and non-parametric. Parametric models are characterized by a fixed number of parameters and any added data neither adds to the number of parameters nor the complexity of the model. Non-parametric models are characterized by a structure that grows in complexity as more data becomes available, leading to potentially an unbounded number of parameters. Larger models are usually more complex and therefore at higher risk of overfitting. In practice, non-parametric models are often constrained or regularized in order to prevent intractable complexity from arising. Similarly, machine learning models are also categorized as generative or discriminative. Generative models attempt to capture characteristics of the input data and often impose a statistical model on the observed variables. Discriminative models deal only with learning the boundaries between classes.

5. Integration of Machine Learning in Risk Management

The financial services industry faces considerable challenges and costs in risk management due to a lack of effective and immediate models and analytical tools for detecting emerging risk and preventative decision-making. Such systems require a high level of granularity and personalization that not only hinders model performance, but is also difficult to establish due to requirements for input data and the complexity surrounding clients engagement and behaviour. The adoption of machine learning in financial services has been relatively slow also due to the static nature of many machine learning models and the high stakes and costs of risk modelling. The adoption of cloud services for hosting analytical solutions is still in its infancy even though it can provide scalable solutions for the computation wrought by machine learning models. A cloud-based risk management infrastructure for identifying emerging risk and preventative decision-making is developed, and specifically machine learning models for representing and detecting the evolution of risks are investigated.

The reported cloud service is a multi-tenant solution tailored for the needs of the financial services industry. The nature of cloud services brings an opportunity to keep the input data proprietary while creating and deploying a risk management model family tailored for an individual service provider's

needs and infrastructure. It can serve either as a white label option for engagement with clients or a black box solution as a tier of their underlying infrastructure focused on document classification or risk analysis. It offers a SaaS solution for smaller service providers who otherwise can't afford hosting their own application stack and cloud processing power. All elastic features are available also as a step-function pricing model. It is also a more affordable stand-alone option for onboarding a new risk management model.

Simplified graphical representations of the model run on two comparable cloud infrastructures both serving as SaaS platforms tailored for the needs of the financial services sector. One approach is an implementation of a native infrastructure for the cloud and for the model building language using the Google suite of services and processing power to scale on demand and to host dozens of models independently while pooling the adjacent components consequently decreasing the costs. The second solution is built atop an existing cloud analytics solution allowing for their powerful modelling suite and fast implementation. Classical models claim to be able to serve as a higher tier over the underlying cloud for risk management purposes.

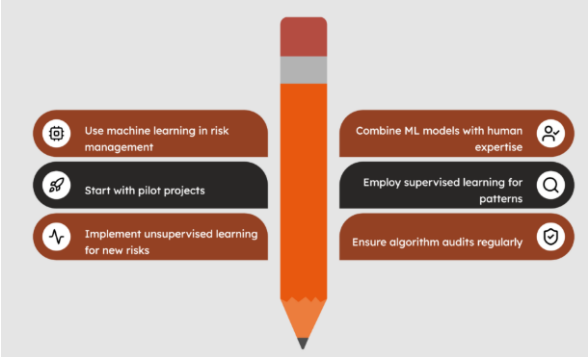

Fig 3: Machine Learning in Risk Management

5.1. Predictive Analytics for Risk Assessment

Risk assessment is one of the main stages in the risk management activities of financial services. The processes, methods, and tools applied in risk assessment significantly affect the efficiency and effectiveness of the overall risk management framework. Risk assessment is carried out mainly through the mining and analyzing of information related to the risk, as data underlies all the risk management processes. These processes comprise the modeling of the risk, the identification of the potential causes and/or triggering events of the risk, and the assessment of the occurrence probability and potential consequences of these causes and/or events. There are many alternative predictive analytics approaches and techniques that can be used for risk assessment from simple statistical ones to sophisticated computational intelligence methods. Risk assessment is performed mostly by credit scoring and rating models or risk scoring models that estimate the risk level of a loan or the borrower based on the analysis of historical default data. In risk modeling, the risk is composed of a set of risk parameters which determine the risk level of a given loan or a loan account. For each risk parameter, a risk scoring model is built based on its historical values and its impact on the loan default probability.

5.2. Real-Time Risk Monitoring

These days, monitoring post-loan risks is getting increasingly important in the accumulated working internet data brought by the development of technology. After over a decade of great improvements in fundamental infrastructure and the explosion of big data in finance, the industry rigorously tests various theories, models, and algorithms that outperform others in terms of credit risk monitoring with a particular focus on microstructures as well as on sequence learning models. Meanwhile, the emergence of streaming and real-time machine learning on continuous-event data brings a second wave of massive change to this domain. Risk monitoring is seen as an important initial and indispensable building block for more complex operations about portfolio management, liquidity risk management, capital allocation, and fraud risk management in finance.

The proposed GMS to interpret sequences of tabular data mainly covers three main scoping findings. Modelling the industry-level parameter trajectory

with cohort and round is important and enough to identify clusters with similar parameter trajectories. Introducing the basin penalty mechanism to jointly identify absolute bull and bear firms helps consistently catch serendipitous risk changes. Market arrestment is shown to be a promising frontier in the practical deployment of this model against incremental prediction. There also remains some important unexplored aspects dealing with more general paradigms to identify episode stages or classes as practical deployments. On a computing parallelization side, the current pipeline employs a designed scheduler for centralized prediction, while it's hard to measure the proper resource allocation on paper. Distributed or edge node computing is also a fruitful and recently proposed research direction in the machine learning domain.

To fill the gap between efficient pre-approved credit services, GMS with input as transaction record sequences is proposed to capture underlying potential abuse targets and simultaneously predict long horizon risks. All these submodels employ common architectures of fully-connected networks. And for a hierarchical parameter structure, the designers are allowed to purify it through the community vision for better interpretability.

6. Cloud-Based Machine Learning Models

The evolution of the World Wide Web and the advent of cloud systems have brought about a host of new labor-saving and sophisticated data management technologies. These technologies enhance the agnostic management of the data life cycle, from inputting information into databases and preserving coherence, to guaranteeing data integrity and confidentiality and extracting useful payback data. Both the analysis of big data and the usage of machine learning and statistics give the fundamental building blocks of advances in this context. Generally, compute agnostic and stochastic cloud-based configurations embrace the existing spectrum of algorithms and enable the education of machine learning models in highly scalable configurations (a cluster of machines of unlimited size).

Cloud-based technologies linked with stochastic computing circuits and machines capable of executing several parallel calculations, or physical micro switches, give a novel insight into the effective utilization of cheap noise in such circuits and software in order to squeeze the massively parallel configure into fixed width fast switchable hardware. This quasi computing approach reveals the link of large and machine learning models, the general notion of a neural net, and the expansion arising from agnostic stochastically switched circuits, such as the well-established Boltzman machine, permitting the education of machine learning models. The newly outlined perspectives, as well as similar ones and physical circuits, all front on an enormous, yet to discover, vista ranging from nanoscopes and nanoseconds hyperfast to astronomic size and slow response time.

6.1. Architecture of Cloud-Based Models

The approaches are structured into five major groups according to proposed characteristics, and distinct review themes are formed, assigning relevant literature to them addressing overall design choices of data analytics solutions for credit scoring. Moreover, important research gaps are identified, and future research directions are proposed. This literature review studies computational approaches and data analytics in financial services by focusing on risk management. The inception, evolution, and structural components of the area of interest are briefly introduced. Statistical approaches, optimization, simulation, and data analytics are recognized as four major research domains of computational approaches used for risk management. Subtypes and representative models from each domain are reviewed. The applications of computational approaches in the context of data acquisition, risk measurement, and risk mitigation for every domain are analyzed. Finally, limitations of the current literature are identified, and future research directions and trends in academia and industry are discussed.

At the 25th European Conference on Operational Research, this study focuses on Financial Services—in a specific risk context. Regulatory demand and economic justification exist for organizations to measure and predict risk, or economic capital, for purposes of accounting, compliance, client classification, credit decisioning, collections, and debt trading. The focus is on models used in this context, rather than on models used for treasury purposes, in trading or for portfolio selection. Models used in measuring, predicting, or calculating Value-at-Risk (VaR), or Conditional VaR, Economic Capital (EC), Credit Valuation Adjustment (CVA) and Counterparty Risk (CR) at all (sub)-portfolios, Discounting, Counterparty Credit Limits (CCL), and concentration risk across assets, banks or clients are covered.

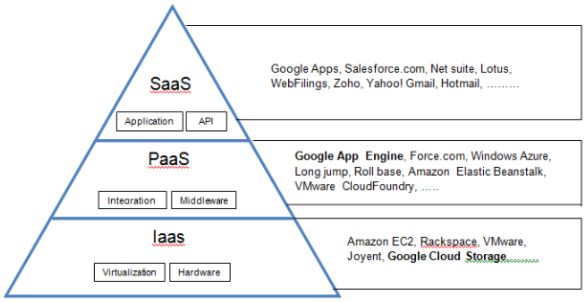

Fig 4: Cloud Computing Service Model Architecture

6.2. Scalability and Flexibility

Without a doubt, cloud-based service and infrastructure are fundamentally about scalability and flexibility. Thanks to the rapid growth of the Internet and connectivity, more and more services and research have come to the cloud. They are no longer isolated and fixed to a specific location, which enables a more vivid collaboration between vendors and remote customers. Already, a lot of viable data collectors, aggregators, and better visualizations and statistics are available. Now is the time to bring finance to the cloud to liberate the financial and big data overages and enhance the interaction with, trading of, and analysis with other cloud services and data sources or vendors. Moreover, the technology is cloud-agnostic and can be ported to other public/private clouds.

As newly available alternative data such as supplier, credit card transactions, job vacancies, search queries, and how and when, this big data has clear value for stock movements but is often considered too immature to be mined and used for trading. Nevertheless, it has different characteristics than traditional big data, such as social, financial, and market data. The availability and structure of the data are more unbalanced which leads to a pull of the bid, i.e., only a handful of players own a major part of the data. The volatility is much higher than market data, especially after certain events, which means more caution in modeling is required. Furthermore, the prediction portion needs to be well assessed which often anti-correlates with the size of records. Incorporating and overcoming these challenges using cloud-based computing power shows promise for broadening the use of these alternative sources.

7. Case Studies

Managing financial service risks requires robust risk management tools utilizing advanced technologies as well as compliance with updated industry regulations. This case study demonstrates the use of Cloud-based Automated Machine Learning (AutoML) for bank lending decision-making, its application in cloud-based credit risk using banking data, and its validation with business data. Cloud-based AutoML supports automated, fast, and integrated lending decision-making processes. Cloud-based credit risk varies for each bank's need and compliance, with model accuracy up to 99%. The demonstration is easily accomplished using cloud service tools by business users without technology background knowledge. As a business analytical tool for financial service industries, it improves better lending decision-making process quality and compliance as well as cost savings using public cloud services.

The market liberalization of financial service industries and technology advancements create diverse and complex service markets and dampening margins. Managing financial service risks is very challenging under economic conditions and regional

regulations. In terms of robust risk management tools using advanced technologies for better risk management decision-making processes, financial service industries require high-quality, speedy, and SLM-compliant risk management solutions for end-to-end and flexible risk management processes. Conducting complex data analytics tasks using effective and powerful machine learning models requires financial service companies' data science background teams. Cloud computing offers a public service environment and environments firms use Cloud service providers (CSPs) to develop production business services without investing which in-house server and/or infrastructure. Banking data networks are huge and vary with each bank lending decision-making process compliance and regulation, thus custom cloud-based tools are necessary to manage end-to-end banking data analytical processes with bank's experts.

Equ 3: Expected Loss (EL) Estimation

$$\mathrm{EL}_i = \mathrm{PD}_i \cdot \mathrm{LGD}_i \cdot \mathrm{EAD}_i$$

Each component can be predicted using separate ML models:

- $\mathrm{PD}_i = f_{PD}(X_i)$
- $\mathrm{LGD}_i = f_{LGD}(X_i)$
- $\mathrm{EAD}_i = f_{EAD}(X_i)$

7.1. Successful Implementations

Risk management measures, including continuous monitoring of financial institutions and financial services, have been introduced in many countries which entail the regulation of certain threshold limits on some activities that are riskier than others, such as limits on the size or nature of these activities, to netout some of this exposure. More effective market risk measures have been suggested which predict potential variation in net income from the current levels over the next 10 days with 95% confidence. These measures can be compared to limit levels and hedged accordingly. A new real-time credit exposure metric which addresses those issues is proposed against which financial services can be credibly limited. Exceeding a limit on this metric signals a high probability of breaching an economic capital limit. Once in breach of this limit, any additional known transaction is guaranteed to result in an increase in the default risk of, and hence credit exposure to, one of the counter-parties. A self-pruning on-line algorithm for non-linear regression provides an attractive basis for such a measure. When applied to simulated OTC derivatives portfolios, it has been shown to produce estimates of credit exposure that rival existing methods, but with a run-time of just a few hundredths of a second for daily Monte Carlo re-pricing of portfolios containing up to 4080 derivatives. This is what makes it possible to implement a performance-aware queue management strategy using a public cloud service.

There have been a number of successful implementations of intelligent risk management systems of the kind described, using cloud based machine learning models. These implementations have typically involved the use of on-premise systems well capable of running the machine learning components but faced with potential losses so large that the systems needed to be scaled up to accommodate this. For performance reasons, this required a switch from cloud based to on-premise storage systems. This is just one example application of the intelligent risk management system, just one application of the self-pruning algorithm. The intelligent risk management system outlined here can handle any number of threshold metrics. For example in the area of market risk, where exposure to interest rate, currency, commodity and equity risks need to be monitored. While the self-pruning algorithm can be invoked on any number of metric/data pairs with arbitrary metric forms, in addition to this there are many other metric/data pairs of interest. Therefore there are many potential extensions to the system outlined here.

7.2. Lessons Learned from Failures

A loss prevention program in retail generally targets protection against a loss of sales revenue, systemic risk, fraud, and theft, but many companies suffer loss in their operations as well. The failure of the credit

risk modeling initiative at a bank resulted from the modeling approach, the lack of consistent and structured data, and lack of staff expertise. The credit risk modeling initiative and the stress testing framework were largely manual processes. Both failure prediction and loss prediction were noted to have manual, labor-intensive, and difficult-to-reproduce approaches that deployed general regression models without version control. A credit risk management initiative was adopted in recognition of credit risk being the largest source of risk; a credit risk model assessment project began in late 2015. The credit risk modeling maturity level was assessed to be an emergent stage below the deployed level in nine of the nine modeling components. Staff were not familiar with statistical modeling beyond analytics, and human resources changed often. Evidence of use was low both internally and externally. In contemporary financial services, the digitization of financial services and the use of intelligent models have proliferated opportunities, ultimately risking financial markets' smooth operation. This led to the opening of research avenues targeting the detection and analysis of failures/risks in financial services and public systems. However, the success and prevalence of intelligent models have not been evenly experienced across financial services and state-controlled public systems such as the nuclear power industry and health care with their inherent societal and economic impact. This research considered the failures of intelligent models in both financial services and other public systems. Lessons learned from these failures are presented along with identifying enabling factors that facilitate the failure of intelligent models and countermeasures aiming at preventing and mitigating these intelligent model failures to guide and intimate both the financial services community and other public systems to architect and govern intelligent systems responsibly.

8. Regulatory Considerations

Model governance, versioning and tracking requirements in line with ownership of business and regulatory responsibility are stringent and widespread. Regulatory expectations, guidelines, standards and templates are coherently outlined by. Conformity with the Basel regulatory framework incorporating the European Union's Capital Requirement Directive IV (CRD IV), for example, has led to a comprehensive, structured, and consistent model documentation and governance strategy and process for models used in the context of monetary capital calculation. The implementation of model governance processes and the documentation of models are similar in other financial services industries. Globally consistent industry participation in the European Community's Joint Research Centre (JRC) database of stress testing models, which includes a comprehensive set of reporting criteria covering all areas of economic and supervisory stress testing models affecting wider Europe and even beyond, exemplifies efforts to comply with expectations, despite potential competitive disadvantages. Internationally, organizational and operational separation of model development, governance and usage is a standard and it is common for model change processes to involve multiple internal stakeholders and departments beyond development teams. This is particularly true for regulatory pillar 1 and associated internal models; by far the majority are of a stress-testing or model-based decision support nature and hence external benchmarking continues to be more common for company- and model-wide governance.

Fig 5: Regulatory Considerations

Business users conservatively implement what models essentially require; the effort to comply with

varied and specific regulatory expectations, on the other hand, has at times led to long-lasting back-logs and inefficiencies that can severely hamper an organization's ability and flexibility to quickly adapt to volatile environments or novel opportunities and risks. In addition, such efforts have led to hundreds of models within financial institutions surviving with minimal, if any, further usage or consideration for the compliant design and staffing of continued development, monitoring or documentation strategies where required. There have also been significant econometric deficits in such efforts, for example, using a too narrow scope of models or metrics needed to accurately assess internal model performance and related risks. Common model training, monitoring, testing and benchmarking for credit risk models is still a rare sight in the industry today, for example, and many examples of out-dated corporate risk models resulting in major losses during the latest financial crises. Of the incorporated variety, scope and granularity of both models and data used in stress-testing further ensure sustainable assessments of stress-testing model performance.

8.1. Compliance with Financial Regulations

Although on a global level this seems relatively few, highly influential financial institutions with countries of jurisdiction with stringent supervision conduct business in many different countries and therefore have a far broader underlying regulatory landscape. The strongest resources are devoted to covering compliance with regulations and subsequent revisions that are already enforced/generated. Some formulations are included in policy documents and the translation of controls in tech specs is based on that. Financial institutions are typically large organizations with siloed and distributed teams mainly organized by asset class, products and countries of jurisdictions. Although large amounts of process information are covered in documents, the understanding of the regulation at high/medium level usually resides within a few experts. The rest of the associates mainly gain their understanding by asking questions. Over time this leads to knowledge bottlenecks and a panic driven response to regulatory deadlines. Therefore, a knowledge elicitation solution to highlight regulation knowledge distributions across organizations and generate training material is proposed here as a high level use case.

The regulatory landscape of financial institutions differs broadly across countries of jurisdiction on a sector specific level enforced by supervisory authorities. Since there are broader transnational and internationally agreed upon principles of conduct, some legislations try to cover regulations in cross-border sectors extensively. The remaining legislations are by far more uneven and a small set of countries of jurisdiction have legislation dictating the daily conduct of the majority of the financial institutions. There is typically an overlapping landscape of legislation, supervisory expectations on control set and tech specs in which the intersection of regulation, tech specs and control is the norm. Therefore, controls are to a large extent a translation of techspecs prescribed by a third party expert input.

8.2. Data Privacy and Security

Abstract: The rising adoption of machine learning in financial services has given rise to numerous cloud-based machine learning platforms. These have opened the floodgates, enabling everyone to create complicated ML models for their purpose. This democratization of ML has raised numerous privacy concerns the practitioners need to contend with once the cloud provider is not trusted. Privacy and security issues in cloud-based ML are many and they come from both the cloud ML clients and providers.

Recent advances in machine learning (ML) have ushered in a wave of new services and applications. The burgeoning deployment of cloud-based ML platforms has given rise to yet another, possibly larger, category of attackers. The nascent area of privacy and security of cloud-based ML services is gaining importance due to the wide adoption of such platforms by organizations all around the world. Organizations must take careful measures when using cloud-based ML services. This paper illustrates

that various privacy and security challenges are posed by cloud-based ML services, reviews and categorizes the existing techniques that tackle these challenges, and outlines possible future directions.

Privacy and Security Threats: Privacy concerns. A recent survey shows a critical gap of understanding between organizations and cloud ML providers on how the latter utilize and protect data, noting a lack of adequate transparency. Organizations' most serious data privacy concern is the cloud application itself, including active attacks by malicious employees or others who may have access to the application. In addition, organizations also worry about the vulnerability of ML models and data drift. There is a clear need for better understanding of privacy and security risks in a cloud-based ML context and corresponding defensive measures.

Intelligent Risk Management in Financial Services Using Cloud-Based Machine Learning Models: Recent advances on making ML both affordable and accessible, especially with the growing number of platform-as-a-service systems, have the potential to democratize AI, giving rise to new broad applications across several domains, including intelligent risk management in financial services. Despite these interesting applications, there exist potential risks and privacy concerns for a risk management practitioner using these systems as a blind user. The purpose of this research is to identify privacy risks, security threats and mitigation strategies for the practitioner.

9. Conclusion

Cloud-based machine learning technology models employed within an intelligent risk management framework can better anticipate losses across more risk domains than statistical models built on historical data and assumes that previously observed events are predictive of future cases. A cloud-based intelligent risk model can leverage information from multiple risk domains to guide credit decisions and enterprise risk management using multiple ML models, trade-off simulations, and sensitivity analysis. This new approach to risk management has immediate marketing, operational, and regulatory implications.

Credit risk comprises some of the primary decisions made by financial services institutions. Cloud-based ML models and IRMFs will allow decisions to leverage data related to factors influencing credit risk across all risk domains, providing an understanding of why decisions differ across entities and resulting in different risk profiles. For instance, comparing risk in two portfolios of loans across countries will be immediate and detailed rather than traditionally static and abstract within credit risk management, which typically uses standard deviation as the only measure of risk.

The CFSS industry consists of large, mid-size, and small institutions that provide both consumer- and corporate-oriented products. Credit, loan, and insurance products across service providers differ in construction, collateralization, pricing, regulation, and monitoring. It is easy for consumers to compare products offered by different service providers and they are often willing to shop for products with lower risk quantification and pricing across different service providers. Large product-generating credit and loan service providers are susceptible to model risk that can lead to severe losses or reputation damage. State-of-the-art research and development programs in service provider ML.

Fig 6: Artificial Intelligence in Risk Management

9.1. Future Trends

Cloud-based machine learning models in credit risk management will require the collection and preprocessing of extensive data prior to utilization. This research shows that it will likely be a further decade before current algorithms can form

sufficiently reliable models for practical implementation in the financial industry.

The greatest obstacle to the proliferation of machine-learning models for credit risk credit analysis concerns data. It is clear that extensive data collection rainfall a deluge rather than a sprinkle is essential. However, quantitative data on occupation is still missing from many credit-decision platforms. Banking systems differ widely in the granularity of property collateral, and unavailability of data on collateralised properties has hampered automated property valuation.

Efforts to harmonize databases, thus making data scours. Where this is the case, in high-retail-banking-penetration countries there have been interesting observations made about non-bank microcredit peer-to-peer lending platforms and competition, as well as trends in declining banking-sector revenue. This argues for the expansion of data to include currency and asset transfers (but leading to reputation/delinquency scoring, not risk models). Due-date poses the greatest challenge to attracting relevant models. One effort underway by a consortium of unbanked providers is to ask partners in payment transactions to disclose their scoring methods. The nearest equivalent is in credit scoring, but historical data needs to be collected on rented accommodation prospective payment and rent loss. Another avenue in low- and non-usage countries is peer-to-peer lending led by non-banks and aggregation of data by a central authority.

10. References

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