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Transforming Financial Risk Management with AI and Data Engineering in the Modern Banking Sector

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Abstract

Machine learning has become a more potent force after Google's creation of a revolutionary new machine learning product, TensorFlow, in 2015. This product was free and open to all. Anyone could assemble a small group of smart, eager juniors, give them a few weeks of training, and by pooling calculations across many high-tech GPUs lets them train a smaller, simpler, unlabeled machine learning model on a few decades of data. Also in 2010, software development became an intensely competitive area for the banking sector. Important new online platforms spawned a whole new field of firms producing exploitable software.

The needs of finance and banking are often thought of as a combination of raw memory (storage), connection speed (bandwidth), and thought speed (the speed at which logical instructions can be executed on that memory subject to many constraints). Currently, there is a multitude of suicides by regulators, directors, and traders resulting from unavoidable miscalculations. Though too late to stop these jumps and errors, they should be reducible nevertheless.

At both the strategic and tactical levels, "optimal" decisions depend on minor details of the data processing, machine learning field, algorithms, past decisions, etc. These optimal processes can now be assembled into semi-autonomous teams that should learn optimally and robustly in real-time on as far back data as exists. Why this all works is due to four "empirical assumptions" that form a dichotomy separating most data analysis either out-of-context or in-context. Each synthetic, comparative "test" believed important can be broken into numerous possible "cooking experiments", i.e., deconstructions of, say, the Filter Test, that could also be devised so as to continue learning for decades or centuries into the past. A bank "information platform" architecture is proposed to solve each singular "optimal decision" for multiple tests, adaptively improving on tests of performance, relevance, cost, etc. The most robust finds exit "jump" rates that make for the biggest profits and the least suicides. Each side of a trade at an exchange could then expect to succeed equilibrium betting millions of times on the price differences without ever losing.

Keywords: AI, Financial Risk Management, Data Engineering, Banking Sector, Modern Banking Sector, Big Data, ML Models, Computers, Data Processing, Data Control, Decision Making, Future Prediction, Cost Reduction.

1. Introduction

Risk management has always been a core part of banking. From the first days of loans, banks recognized that it was necessary to have mechanisms to assess the creditworthiness of borrowers, manage asset-liability mismatches, and estimate incurred losses on discounted cash flows. In recent decades, there has been an increasing focus on modeling risks. This effort has changed from a relatively simple analysis of large positions to complicated, detailed, and long-term multidimensional stochastic approaches. This effort became most intense after the regulatory reforms that followed the financial crisis to better understand stress scenarios and ensure systemic stability.

Data engineering and data-driven AI are becoming of the utmost interest to the modern banking sector. Big data and artificial intelligence approaches can be complementary to quantitative finance techniques and, if exploited synergistically, should lead to transformational advances in financial risk management. However, there are still a lot to be done before reaching the full potential of this area.

Understanding how lending decisions based on machine learning instant credit scoring should be conducted and whether this process can be negatively biased when using sensitive characteristics like gender and/or race is a problem of great relevance in itself. The AI technique for explainable predictions can be used by financiers to claim or reject credit decisions based on data and credit proxies. The airtightness of the credit scoring's prediction to racial profiles cannot be directly related to the predictive performance of the model on the training data - it is possible the ML model has not been compliant with the existent regulation. The second dimension of the issue is if this situation can be mended with a fair embankment of the existing models.Machine learning deals with a collection of techniques for imparting machines with the abilities to learn from experience. It bears slogans like data-driven or statistic-driven in opposition to economics-based analytical models which bear many assumptions including simplicity, tractability, analytical richness, and computability. With the explosive growth of information and big data availability, expectation grew on machine learning being able to deliver on much of its advanced promises, enabling risk managers to think through the eyes of machine levers and transmit decision-making processes into machine codes. Data engineers would then take over the risk outputs of the black box and better extract actionable insights through visualisation tools, data retrieval and cleansing and plumbing of data seamlessly into databases.

Fig 1: AI in the Banking Sector

1.1. Background And Significance

In the aftermath of the global financial crisis, the financial sector had to adapt to a stricter regulatory backdrop which called for a broad revision of its risk management and governance arrangements. This revised framework, along with important changes in the global monetary and economic environments during the decade after the great financial crisis, raised profound challenges to financial risk management in banks. In its wake, events and stress factors in capital, liquidity, funding and even credit risk management cascaded through analytical, data, model, systems and governance infrastructure of risk factories, into institutions' internal stress testing framework and ultimately into the governance of risk.

These challenges necessitated a thoughtful reconsideration of foundations of risk architecture in banks — a re-think of their analytical frameworks, big data architecture and engineering and IT support; a re-evaluation of causal linkages in situation awareness calculations; and a revision of the effective design and implementation of risk stress testing across bank-wide financial/balance-sheet dimensions. These challenges also have implications for the very nature of risk management, and the processes accounting for things which pose threat to and deteriorate valuations of banks' assets under the post-global economic and monetary environments.

Machine learning and deep learning became top buzzwords of business and research and gained ground in risk analytics by promising higher levels of accuracy in predictions. Hence, a transformation of risk management practice typically consists of an effective intertwining of new models with alternative machine learning techniques in capital, funding and liquidity risk management decisions. This transformation aims to move from exploiting subjectively assessed gamma factors of early warning indicators through long form models to effectively using alternative granular types of data. The transformation would benefit from accessible and allowable premised safety factors accounting for systemic interconnections among banks, introducing interbank borrowing/lending into liquidity requirements, and more ground-truth systematic scenarios on contagion effects due to asset fire sales forced by deteriorating valuations.

Equ : 1 Real-Time Fraud Detection Score Using Streaming Data

$$\text{FraudScore}(t) = \sigma\left(\sum_{i=1}^{n} w_i \cdot x_i(t) + b\right)$$

- σ: Sigmoid function (for classification)
- $x_i(t)$: Real-time transaction features at time t (e.g., location, amount, velocity)
- w_i: Weights from neural network model
- b: Bias term

2. Overview of Financial Risk Management

Modern banks are exposed to financial, operational, and credit risks and are obliged to monitor these continuously. Meanwhile, financial risk management rules have become tighter due to the banking crisis, with the internal corporation of the companies mandated to provide data-related ICT developments. Financial risk management of a corporation aims at systematic and efficient availability of both internally produced and externally obtained data, which extends to non-financial data, in order to model potential financial issues using supervised or unsupervised machine learning techniques. Although the wealth of data has revolutionized the corporate world, professionals still lack financially trained data engineers to bridge the gap between the finance and IT departments [1]. There is a strong demand to foresee risk factors, followed by explicitly formulated policies to minimize the chance of deterioration.

Financial domain knowledge, mathematical finance models for products traded, stochastic analysis, machine learning techniques, automation, and deep learning techniques are outlined, while proper data governance practices are put forward to secure the availability of treated data. Banks are highly trusted institutions due to their importance to the economic system, and these have modelled relationships between their customers and with regulators. Meanwhile, with the proliferation of the internet and the increasing herd behavior, markets have become susceptible to all manner of systemic risks predicted and modeled outside the banking sector. This paper promotes a new concept for the financial risk management of modern banks, outlining the IT challenge of availability of financial data for early warning and risk modeling analysis.

Banks are dealing with a wealth of data, both internally and externally obtained, but there is a wealth of untapped possibilities to reveal the value of this data for informed business decisions. A new approach is proposed for managing a data engineering team incorporating financial engineers as newly trained professionals who are highly evaluated by the industry. In parallel, legislation and technology upgrades on personal data governance are surveyed, and the necessity for an independent data governance structure is justified and approached. A case study highlights the current status of data-related business decisions in a large Santander subsidiary and the financial benefits of establishing a data engineering team. Finally, an operational model for the data governance structure is recommended.

Equ : 2 Value-at-Risk (VaR) with AI-Augmented Forecasting

$$\text{VaR}_\alpha(t) = \mu(t) - z_\alpha \cdot \sigma_{\text{AI}}(t)$$

- $\mu(t)$: Forecasted expected return using LSTM or other time series AI model
- $\sigma_{\text{AI}}(t)$: AI-estimated volatility
- z_α: Z-score at confidence level α

3. The Role of AI in Financial Risk Management

Since the advent of machine learning and big data, artificial intelligence (AI) has started to permeate all aspects of finance. The AI revolution in finance incorporates algorithmic trading, fraud detection, anti-money laundering, operational risk management, credit risk assessment, bots, digital financial assistants, portfolio management, regulatory compliance, and wealth management. Financial institutions have invested millions of dollars in R&D to understand and use machine learning and cutting-edge computer science to reinvent credit risk assessment. Modeling credit risk helps banks and financial institutions to automate and improve credit assessments and decision processes. Consequently, this can significantly reduce payment defaults leading to improved cash flow while allowing lending to new customer segments with a lower credit score. AI-based credit risk modeling is among the most active and lucrative application fields of machine learning and AI in finance. Data accounts for about 80% of a financial institution's

assets. Financial institutions have amassed data about customers' transactions, behavioral patterns, demographics, and socio-economic factors among other data points.

Financial data is multi-faceted, rich, and diverse. High-volume, high-velocity, and complex data from various sources, such as transaction databases of banks, government sources, firm databases, social media, etc. are difficult to collect, pre-process, structure, and analyze. Additionally, new nontraditional data sources, such as social media, mobile transactions, and internet platform economies have emerged. Administrative data is also available from the informal economy, as well as personal data which has emerged from the advent of the internet. AI and machine learning make it possible to unlock and monetize value from extra-financial data helping small entrepreneurs and borrowing needs have always been difficult for informal providers that have limited investment, accounting systems and other information points. As a result, finance has artificial intelligence and machine learning to help tackle this risk challenge. AI can re-design the credit assessment process and make it more effective, fair, flexible and efficient while AI models such as random forests can introduce new governance, transparency and accountability.

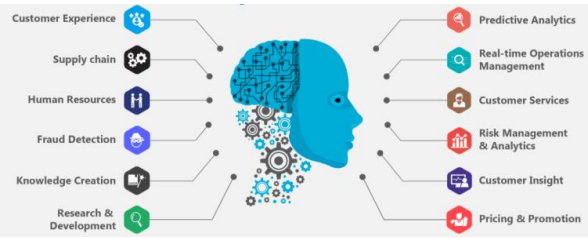

Fig 2: AI for Risk Management

3.1. Machine Learning Algorithms

Although deep learning and extreme machine learning have recently received much attention in the finance community, classical ML algorithms still play a pivotal role in data-centric algorithms and methods development. In the context of financial risk, particularly for credit, market, or trading risk, the complexity of the valuation and/or the risk computation leads to the need for Data Engineering tools that leverage this solution in the MS pipeline to predict or evaluate on unseen waters. Typically, a breach of regulatory limits starts with VWAP, but more recently, MAE and VAR breaches are part of the checklist for the analysis of key financial information. To explain how data-driven approaches can reduce risk by accelerating and improving MAE forecasting, it is worth delving into the underlying mechanisms for each one of the previously outlined breaches.

MAEt+1 quantifies the largest possible relative loss over a specified time horizon in positions held at time t. In general, the nonlinear nature of the calculations required to estimate this measure of risk complicate its storage and usage in time-critical applications. Typically, financial institutions do not estimate any MAE_{t+1} per se, but integrated MAE methodologies worth billions of Euros benefit towards better capital allocation through more granular, informed, and hedging-aware thresholds, as these are only more stable under extreme market movements with respect to their historical counterparty. Nevertheless, on the control side, there are a number of ingredients to be managed beyond position control, to name a few: stress testing, limits per counterparty and desk, and denial or approval of transmission modifications.

Given a set of N0 position vectors P0 at a time when MAE_{t+1} is to be evaluated, a bank has at least N0 linear investment strategies through which it can modify this position vector and/or transmit in the other direction if another either is long and the bank is short (if the vector is on the left-hand side) in the transformed vector P10. For large N0 swing position vectors, this combinatorial explosion of transmission vectors renders for any naive algorithm a detection time larger than market timescales and inactivity of such front office ML tools. The identification of a few strategies translates into a vast improvement in the feasibility and usability of ML risk reduction tools (MAE_{t+1}). Thus, a clearer formulation of the problem based on first principles is given to help appreciate crop efficiency input geometrical methods.

3.2. Natural Language Processing

Data classification presents the problem of identifying a number of groups in a given set of data. Natural Classifiers create groups based on the natural clusters present in the input feature space without introducing target classes. Then, the data is classified between the groups previously generated using Supervised classifiers. As such, it is necessary to identify the purchase groups as well as all purchases belonging to these groups. This is an extensively studied area where problems can be treated using a myriad of techniques. The first step is the clustering of bank transactions, which can be classified according to the products and services used: The service is first identified and then the method. The first step is performed examining keywords and not using Neural Networks since competing models would be difficult to implement, making it impractical to classify thousands of transactions in real time with an acceptable Time To Run or Accuracy. The key phrase will then have a Hidden Markov Model Engine searching Hidden Markov Models for the words that match the keyword provided by the client. The client is guided in step-by-step instructions to

obtain keywords that create a Bank Transaction Class. In descending order, those keywords with more hits will be saved as the next purchase group and all transactions will be checked if any matches the keywords obtained.

Additionally, some purchase groups required extraction to keep groups and words under control. Here are constraints on the number of unique purchase group keywords to limit the number of Artificial Neuronal Networks trained for categorization. If a purchase group contains more than three keywords, only the three keywords that matched the most transactions are preserved for grouping purposes. A database check occurs to determine if the proposed purchase group being established already exists. Data Classification conditions are specified to allow any purchase group to be suggested even if the keyword is not associated with a previous group. An implementation is presented of the natural keyword extraction that runs every five minutes, gathering the first word of all Bank Transaction Classes ignored previously. The suggested keywords are also searched in all bank transaction keywords and if a hit occurs, the proposed purchase group is created. A small prompt instead of the five minute examination that would take a miss-human error is presented producing the same output.

Equ : 3 Stress Testing Simulation with Monte Carlo AI Scenario Modeling

$$\text{Expected Loss}_{\text{stress}} = \frac{1}{N} \sum_{k=1}^{N} \text{Loss}_k^{\text{AI-scenario}(k)}$$

- N: Number of Monte Carlo simulations
- $\text{AI-scenario}(k)$: AI-generated macroeconomic scenario
- Loss_k: Simulated portfolio loss in scenario k

4. Data Engineering Fundamentals

In recent years, the rapid growth of modern Information Technology and the banking industry has caused the creation of massive data. Each transaction and banking event contains pieces of information and findings that could be of interest for financial institutions. Knowledge extraction is the process of converting raw data into meaningful insights. The extracted knowledge points are very much valuable and could be visualized to assist in prediction and decision-making. Data acquisition is the first step in every process analytic. Queries could be utilized to request the required pieces of information from the databases. Not every Data Management platform could serve on all the needs of its data-wise end users. However, there are various choices for Financial Institution in terms of the Data Management process and technique. Using a typical BigQuery method involves the decision on which database/query language should be utilized on board. In terms of data volume, NoSQL databases are being used more than SQL databases. A Fusion Gate could be developed in order to consume every kind of data inserting queues, consider the option of putting the database pressure in the cloud and on a third-party platform. Data management in databases has to be considered in different layers. Each layer stores a particular needed aspect of the data. Based on the data after its initial insertion, data is aggregated and organized in the proper place. As a new idea, each agent could have a micro database in its own memory, based on which the process engine could detect the time of each piece of data. Machine learning has become extensively integral over the past few years across various industries, and one of the major ones is configured to create value inside banking institutions. Nowadays, every single technology in the banking process uses algorithms attempting to distill meaningful insights from the data passed through it. Each subtopic could be grouped into two categories of process pre-analytic and process analytic. The use of time-series analysis in predicting the next day in both functional and stock currencies is one of the most highlighted models. The whole banking database is requested to obtain the past 1,825 days of utilized data and the Samples of the Upstream Data and the Labels.

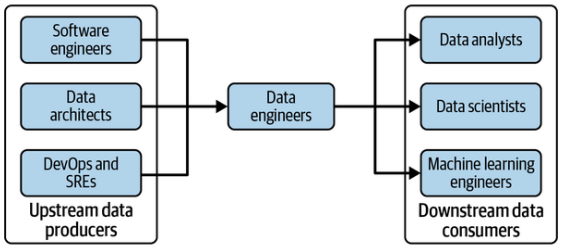

Fig 3: Fundamentals of Data Engineering

4.1. Data Collection Techniques

The banking and financial services industry enhances financial risk management and process automation, as well as offering new financial products and services, by applying data engineering and AI techniques to various banking domains. The ability of banks to acquire vast amounts of high-quality, relevant data on various aspects of banking processes that can be analyzed and used for training various AI consumption techniques has expanded dramatically due to the rise of all digital banking channels. Also, banks and financial lending institutions are not permitted to exploit huge datasets generated for the previously mentioned applications via data crawling techniques since a lot of data generated for these applications is considered sensitive and private. As a result, banks acquire a portion of the data that falls under the category of public data and on which they can conduct pre-processing, analysis, and data engineering. Banks rely on various data collection sources such as data brokering companies, government organisations, and other sources of publicly accessible data to maintain their competitive edge in the advanced analytics market.

For efficient data engineering, data architects and engineers are strategic roles in charge of the organization's data strategy, data pipeline architecture, data integration, database design, data warehousing, and batch processing. In the transforming banking sector, the tasks of data engineers and architects include the ingestion of both structured and unstructured data generated via traditional, alternative, and public sources of data in various forms of data streams or batches and the design of heterogeneous data storage systems capable of storing various forms of data. Both simple data cleaning and ETL techniques to produce structured data streams and complex processing and analysis of unstructured data streams to extract, validate, and store structured data in heterogeneous data storage systems are relevant activities.

4.2. Data Storage Solutions

Implementing a solid data strategy is the first key step in moving a financial institution closer to an actuarial framework of risk management. The main outputs of the cooperation between the mathematicians and the data engineering and data science departments should be viewed as a useful combination of rules and techniques that are not restricted to the domain of mathematics and are readily acceptable by and applicable across all tiers of the relevant organization. A well-documented scheme of the framework consisting of outputs such as a risk aggregation screen (consisting of risk-classification rules and a risk-aggregation technique), a ruleset of risk-parameterization guidelines (one for each product), and a comprehensive book of collaborations between mathematicians and each trading desk domestically and globally should be constructed. To remove possible doubts about the approach to be offered and the terms to come from trading departments, a best-practice scheme of interactions between quantitative research and trading is presented. This scheme comprises a cooperation blueprint documenting each desk's activities on mathematical modeling, risk-reporting rules, and techniques, and reward-derivation criteria.

Through a series of previously unsupervised initiatives, this organization has steadily approached the field of financial risk management from a data-centric point of view. Due to the deficiency of sufficient in-house expertise in actuarial frameworks of financial risk management, a financial mathematician has been eventually appointed to apply a consulting format to assess the assembled data processes and the level of analytical capabilities of financial modeling frameworks. A four-layered architecture accommodating data at various levels of sophistication has been suggested for further enhancement of already deployed data-extraction jobs. The motivation for proposal refinement and complementary yet supplementary jobs along with an integrated data hierarchy intuitive to traders and to less quant-oriented yet sensitive managers is discussed. Attention is drawn towards risk modeling capabilities already on the shelf to enable an upgrade of these architected data flows to manage imperatives coming from changing macroeconomic frameworks, capital market environments, regulations, and tariff and pricing schemes. Further issues concerning the conduction of data-extraction and aggregation jobs along with a framework of cooperation for implementation are brought into attention.

4.3. Data Processing Frameworks

In the banking sector, each captured action such as a transaction in the ATM is treated as entries to tables similar to relational databases. Each table is represented in a different file with the same rows and columns. To reduce the data and maximize the processing speed, one table from each database is enough for processing and interaction with BI tools. Thus, processes such as monopolization and repetition should be controlled for both financial and managerial risks in the organization. As the banking sector is a rule-based business, a certain range for each amount (such as transaction amount and number combination) should be considered to avoid false positives.

The banking domain is very hierarchical and multi-level. Different users need different access levels and controls. Some users such as managers need access to only managerial information. From the other perspective, an information risk categorization could be implemented during the capture and processing of the data. This phase categorizes all captured entities based on their importance and precautions (such as financial, commercial, and mature ranking from high to low.) These types of risks should be involved in additional precautions in sensitive operations such as granting access to saved information or transactions. Protection methods implementation and controlling should match the privacy regulation. First, each country should prepare a unique standard for treatment and protection and trading or exchange of risks and information across countries. Second, when concerning such applications, the system is based on the country of the branch (or the customer) not that of the headquarter.

Protection methods should be non-intrusive and transparent to users and the banking process. Active protection such as encrypting before transmitting could delay the process and discourage the customer to use digital services; for this reason, passive control methods should be considered. Access to RDBMS is the source of risk for banking. By making extracted records in an intermediate repository with no direct link to services everything else should be executed in the intermediate layer. To prevent abuse from calculated ratios and profit/loss a random joining and view creation on the processing layer is proposed.

5. Integrating AI and Data Engineering in Banking

In modern banking, data has become as important as currency itself. Financial institutions that can successfully leverage data through intelligent systems are at a clear competitive advantage. The aggregation and analysis of financial flows, law enforcement investigations, customer demographics, and other information is used to design effective anti-money laundering systems. Banks and other financial institutions use data engineering due diligence systems to continuously track sensitive information and early warning events related to their own clients to improve risk management. Additionally, data engineering projects that monitor how customer retention in fintech platforms can lead to delinquencies are crucial. Banks can apply chatbots and other AI technologies to customer interaction scenarios to improve the efficiency of customer response and customer acquisition.

Despite the deep-rooted understanding of how to use data engineering systems to transform banking, most domestic banks currently face various issues when using data to support businesses. Current data engineering projects are typically disjointed solutions that focus on single vulnerabilities and insights. Common systems usually cannot interoperate and create a holistic view of a bank's information landscape. Most banks have already implemented basic analytical systems, but data collection and quality are substandard. This has become a widespread concern, as many systems only provide limited value due to unscalable architecture and immature algorithms. Furthermore, many projects have been developed by teams that lack access to domain knowledge, industry benchmark data, and multilingual datasets. Insufficient data volume and quality lead to biased models and non-generalizable results.

Some of the traditional financial prudential tools still in existence today were developed in the period right before World War II, such as earnings-at-risk stress testing, which is heavily reliant on simulation. The effective application of AI in the finance industry is empirically proven, yet, as of today, the widely observed practice of AI in the argumentation and application of financial risk management has never been comprehensively systematized. By comparing the AI capability and experience in the finance sector with that outside the field, there always exist gaps in determining quantifiable AI success and formulating the strategy development of an AI system.

Fig 4: AI and Data Engineering

5.1. Case Studies of Successful Implementations

With the booming of the financial technology industry, the resulting broad financial data and information explosion is also an opportunity and challenge for the financial sector. While the financial sector is under the invasion of various attacks from various quarters, it is also necessary to rethink the security and stability of the financial system. In addition to numbers and rules, finance is also a social science involving people's behavior, making it more complex and having a wide range of application scenarios for AI. But the existing financial risk control model or cytopathogenic behaviors modeling approach have limitations when dealing with complex data like financial transactions with high dimensionality, noise, and the dilemma of explainability & interpretability. To overcome the limitations of these financial risk control models, they model risk control processes through the lens of information physics, a nature-inspired information dynamical systems perspective. Decision making is regarded as an information mapping process from the environment or interaction data to embodied actions. The information physics framework envisions a dynamic flow of information to capture the structural shifting states of markets and assets. In this regard, financial crises and resulting market busts or drawdowns are perceived as a drastic transition of information processes from a fully connected state of most market components coupled together to a sparsely connected state where only few components co-move significantly together to surge or crash.

The combined system of information and action is a closed-light curve (CL) cointegrated coupled dynamical system. Owing to higher order manifold dimensionality and loop feedback structure, chaos is inherently part of the information-action closed-loop system. Chaotic attractors are generated to describe intrinsic risk or fluctuations in the deterministic dynamical system with noise. With the cytopathogenic behavior modeling ability, they also explore the technological innovations to mitigate the cytopathogenic behaviors in finance and systemic risks from a design perspective. Make the model widely used through combining deep learning (DL) GAN sampling and consider tagging to introduce explainability. This model has wider use in the finance domain, including fraud detection, portfolio tracking, VolPred, and trading simulation. Hence, to model cytopathogenic behaviors in the finance domain involves complex, irregular, and intricate real-world data, go through overwhelming behavioral data and intelligently learn from it with minimal supervision.

5.2. Challenges and Limitations

AI and data engineering-based systems can have limitations and challenges that may hinder their successful implementation in banking sector risk management. The limitations focus on availability and quality of data and a lack of necessary technology and infrastructure, while the challenges are adopting technology to enhance productivity, ensuring responsible use of AI, and interpreting pseudo models.

Advancements in AI models and structural engineering technologies require continuous development that is not always realized. Each institution has disparate exposure to asset risk, with fortune limited state-of-the-art models that are chiefly applicable to a small segment of exposure classes. Also, firms will have exposure to non-structured data, necessitating additional research into data-leveraging technologies. Integration of firms' architecture with hardware and communication service ability is a lengthy process requiring capital investment. Models will need to be embedded in a trading system, which will take years given the existing legacy system.

AI implementations frequently yield unsatisfactory outcomes, with implausible explanations supplied for insights and actions. The drive for productivity enhancement superficially appears unattained, leading to disappointment and negativity toward decision science. Additionally, mega models may have negative implications for firm-wide work. Language models will extract information from literature and create outputs similar to existing materials with limited creativity. More challenging issues involve persuasion through verbal means and manipulating behavior. These serious challenges in AI's decision science require a responsible development strategy to capitalize on AI's strengths while avoiding malicious utilization. It is imperative to understand why AI triumphed through data parsing algorithms and pedagogical leapfrogging processes as opposed to economic implementation.

Data engineering developments would enhance productivity with AI models. Brute-force pseudo models outperform structural modeling without in-the-know insight. Their complexity would require smarter-looking decision recommendations. The pseudo nature of the models is recognized, yet concerns are raised about users on intuitive explanations. Absence of explanation would be unfortunate, as reliance must be placed on recommended decisions.

6. Regulatory Considerations

The 2021 implementation of the Bank for International Settlements' (BIS) global financial risk management standard, Basel III, reshaped how banks monitor liquidity and credit risks. These changes called for rethinking workflow and data handling. New central data repositories were established alongside new technical solutions for operation and risk control. However, the full application of AI and data engineering solutions almost always required dramatic changes to the underlying data structures and governance, which slowed user adoption and full deployment.

Nevertheless, effective regulatory capital–risk management and reporting for credit, market, and liquidity risks requires not only new data structures and governance processes, but also adherence to distinct regulatory regimes aiming to create orderly credit, capital, liquidity, and funding risk environments. While Banking Regulation threads and constructing AI/ML solutions to address regulatory capital requirements have received some attention, equity regulation and ensuring ML-driven trading activity does not result in market manipulation, conflicts of interest, or misrepresentation of client order prices has received less attention.

Concerns over the implementation of Financial Instruments and Exchange Act Article 158-2, aimed at preventing insider trading and price manipulation through transactions that create signals misleading to the general public, As a first step, two AI/ML price prediction models are detailed that violate financial regulations. Regulation considerations concerning the data employed for model training/validation, the feature vectors and predicted outcomes, and the decision framework are then discussed in relation to expectations toward equity regulation with an AI/ML-enhanced paradigm.

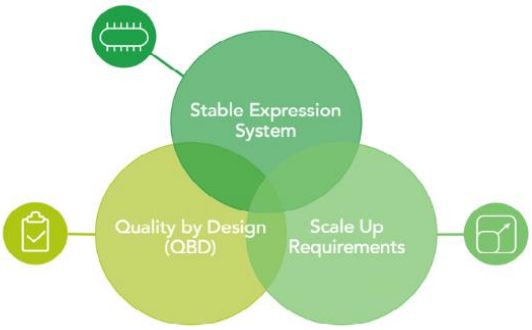

Fig 5: Regulatory considerations

6.1. Compliance with Financial Regulations

Examples of rules pertinent to financial regulations include. Developing, maintaining, and managing compliance with these financial regulations can be costly, especially when associated with transactions in countries with differing regulations. Additionally, the consequences of non-compliance with these financial regulations can result in fines and imprisonment for flawed models used in practice, even if there is no damage caused by the model's deployment or analysis. Given this context, it is desirable to use data engineering in the AI systems used by financial institutions in order to comply with numerous complicated transnational financial regulations. One possible solution to facilitate the understanding, development, and management of these complicated, transnational financial regulations is to have paradigms and software that specify financial regulations generically such that unique implementations of these paradigms can result in the generation of code. This code generation can yield compliance and non-compliance models that are permutations of these regulations with the appropriate internal components and external components via the generative processes depicted in the first column of the first row. On the one hand, the acceptance of the generated, compliant rule models can certify that the financial institution's internal operations are compliant with the financial regulation specific to the institution. On the other hand, the rejection of any transnational non-compliance rule model automatically ensures that the institution will not incur fines due to that specific rule model.

6.2. Ethical Concerns in AI Usage

As the modern banking sector increasingly utilizes AI, ethical concerns on how responsible and accountable the AI systems operate in practice arise. Specifically, an AI used in the context of regulating the financial sector must comply with laws such as EU AI Act and others. These regulations may still be uncertain as they are new and evolving. Importantly, AI creations and decisions should also comply with ethical standards outside the scope of regulations. Even though banks will likely make the final decisions, ETHICS expects that banks make their risk management decisions according to AI recommendations. Thus, banks should be transparent regarding reasons the AI rationale and proprietary model underlying AI reasons are responsible.

In addition to the responsible, accountable, and transparent criteria for the financial risk regulation AI described above, concerning whether the regulatory AI decisions are correct, the AI itself, not an auxiliary AI tool, should submit justifiable decisions. Safety concerns such as security of the regulatory AI and transparency of algorithm's motivation will arise from the significant cost of raising AI in robustness and interpretability. For banks, AI systems subject to independent audits too complex to analyze outside rather than at runtime may generate regrettable results, which is especially concerning in dark-box networks and self-learning agents. Moreover, AI-enabled real-time risk regulation may unintentionally exacerbate systemic risks if many banks adopt the same active model or same architectures/agent model. As various tasks increasingly rely on the AI systems, other breakdowns like indirect manipulation of models through supervised training and reward function or biased interpretation may cascade to catastrophic shocks or create perpetual competitive disadvantages for subject banks. These concerns again question the capacity of AI creations and decisions infrastructures deployed in financial stability at scale.

7. Risk Assessment Models

Regulations in the financial services sector revolve around the prevention of systemic risk from financial institution failures and enhancing market efficiency for improved liquidity and pricing. Towards this aim, a specific set of regulation standards (Basel III) was released targeting the Soundness of Banking Systems (pillar 1, capital, financial risk management) and Financial Services Markets (pillar 2, conduct). Our focus here is on Financial Services, and specifically on models used in regulatory pillar 1 and pillar 2 risk measurement and prediction (i.e SI, LSI, CSA, CVA estimates) and other applications including risk or economic capital allocation, compliance, client classification/credit decisioning, collections optimization, early warning systems, etc.

Regulatory context: Supervisors in most jurisdictions have defined expectations for the use of internal models across a range of applications where a supervisory retained model is infeasible, generally in the form of explicit written guidance to which firms must adhere. Models would need to be ready to undergo regular supervisory or statutory review in a timed fashion, geared towards ensuring that key features of the model covariance structure are appropriate and that they have been stably and replicably implemented in the IT infrastructure. Several standing concerns on the above item as well as elsewhere in model governance have been raised and are still under discussion in the regulatory domain.

Recent benchmarking results across the market indicate the realm of pillar 1 approved internal models has the most mature status quo, shaped by supervisory scrutiny and the need to streamline to viable business practices. The extent of the audit trail, granularities of the checklists used, and timeframes to obtain model approval vary widely by regulator. Where focus is placed is on the model approval process itself, since development, initial and periodic validation, and the associated model change processes are generally assessed during model approval. In this section, static models would be discussed first. The classification and measurement of materiality of model changes are at the core of the regulatory/supervisory model change process. There is doubt that a self-learning process producing material model changes would be accepted in the more strictly regulated areas of application mentioned above, particularly in the pillar 1 capital models. This is a difficult enough challenge in the ladder context, but for more strictly regulated areas of application, such as credit scoring, wider deployments of self-learning models would face an uphill battle.

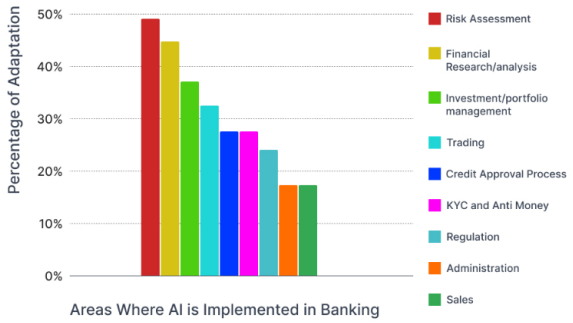

Fig 6: The Role of AI in Banking Reshaping the Financial Sector

7.1. Credit Risk Models

Credit risk is the risk that a creditor may not receive the expected principal and interest. This risk stems from the potential inability of a borrower to meet the contractual obligations of a loan. Default rates increase with an economic crisis, further inspiring governments to mitigate it. Credit risk assessments are crucial for banks, ranking counterparties for their lending portfolio. The overall evaluation process varies based on the type of counterpart: (i) governments or corporations, (ii) small and medium companies, and (iii) consumers. This project specifically focuses on credit risk exposure to consumers. In this context, three subtypes may need to be evaluated based on the type of credit product: (i) personal loans, (ii) credit cards, or (iii) mortgages. Financial institutions face a divergence challenge in this regard since different evaluation approaches and techniques must be used depending on the type of counterparty or credit product.

With the increase in debts following the COVID-19 pandemic, creditors are more concerned about future borrower behavior. Credit scoring, which aims to assess the probability of future undesirable borrower behavior, is crucial for creditors in this regard. For publicly traded companies, positively listed in the Stock Exchange, literature focuses on predicting insolvency. Focusing on a time frame (one year) beforehand, two main data sources are used: financial data and securities market information. For business loans granted to corporations versus banks, the emphasis is usually placed on financial indicators designed to quantify the sharable risk with a bunch of qualitative indicators. However, for personal loans for natural persons between 18 and 65 years, the statistical models are designed based on their personal, social, and financial information. The housing crisis that occurred between 2007 and 2009 highlighted the deficiencies of the most robust credit scoring models at that time. These models were not able to reflect the actual default probability for even higher credit score borrowers.

Following the 2007-2009 financial crisis, financial institutions entered in a panic mode and became more risk-averse. The passage of the Basel III framework resulted in significant hurdles in acquiring a credit product as other losses had to be fundamentally lower to comply with the new capital requirement ratios. There are several aspects to consider when developing a probability of default model. The first aspect is the credit rating model type, where it is necessary to decide between point-in-time or through-the-cycle ratings. The former aims to measure the highest grade at any moment while the latter estimates the average cycle grade (default probability score) which is constant across different cycles. In particular, Credit Rating Companies utilize Credit Scorecards to evaluate the credit risk and assign the risk grade. Several statistical techniques have been developed for modeling the credit quality, including Discriminant Analysis, Binary Response Models, Binary Classification Problem, and Hazard Models.

Alternatingly, some machine learning algorithms such as Generalized Boosted Regression, Random Forest, Neural Networks, Support Vector Machines, Gradient Boosted Machine, and eXtreme Gradient Boosting aim to enhance the prediction power for Credit Risk Modeling. With the rapid development of AI and machine learning technologies, there is an increasing interest in Finance concerning these models; however, it's essential to be able to explain these models and their predictions to establish trust and prevent potential unethical behaviors. For that purpose, eXplainable Artificial Intelligence (XAI) has recently gained momentum for financial applications, where several techniques attempt to explain the underlying logic of machine learning models. The unknown information consists of the safety and feasibility of the established AI techniques to explain the machine learning models' predictions, which is a challenge faced by many industries, including finance.

This project mainly focuses on credit risk scoring, which is crucial for banks and financial institutions. A probability of default (PD) model must be developed for risk evaluation. The specific objective is to predict the credit score that represents the numerical grouping of the PD for a bank. The context is novel data. Historically, financial data and machine learning techniques are employed to predict the default condition of a company within one year. To cope with the dataset imbalance, SMOTENC is used for balancing, while six scoring criteria are employed for model evaluation. The Gradient Boosted Machine (GBM) model outperforms other techniques based on the criterion evaluating the successful scoring prediction. The SHAP technique is utilized on this model to explain the prediction.

7.2. Market Risk Models

Market risk denotes the risk of asset price movements that would adversely influence the economic value or profit and loss of a portfolio. It is close to the sources of all financial consequences. Market risk measurement is usually aggregated for various stress testing windows such as daily, weekly, monthly, quarterly, and yearly. The measurement involves grouping stocks by their price movements and projecting their movements based on the distribution and correlations of their return. Both high-dimensional and high-frequency covariate streams make the market risk measurement problem difficult, causing hundreds or thousands of times more calculations than the regulatory requirement. Recently proposed Benchmark On-the-Job Neural Monetary Policy Research (BONJOUR) frameworks alleviate this challenge by resizing the task using conveniently created variational autoencoders (VAEs). Traditional risk estimation approaches generated an unsupervised latent representation which does not offer a concrete financial meaning. VAE-based solutions generate a locale-specific latently encoded financial scenario using a supervised variational component. This supervised component generates latent financial factors that can control the VAE when projecting and hedging tasks. Market price evaluation and price movement projection are two integrated on-the-job tasks. Risk accumulation over a risk preference horizon is optimally and endogenously fed into the control, which can be conveniently expressed through a Monte Carlo version. Each controllable VAE generates latent representations of "profit and loss," which help accumulate immediate measurement inputs in finance-friendly views. Conditional on groups regarding time and asset characteristics, a low-run-time, sample-friendly, and internally consistent closed-form and complete projection of movements are generated. Measured risk shares tightly connect conserved latent movement structures and critically dependent factors. Integration can be achieved without any price or valuation measures, no probability sense, or estimation assumptions. The market risk measurement decomposition that emerges from the novel formulation can facilitate regulatory compliance.

7.3. Operational Risk Models

Risk management has been an integral component of any banking enterprise driven by the fundamental objective of ensuring bank solvency and sustainability. Conventional approaches have evolved towards progressively more complex risk-calibrated models ranging from basic computations of Value-at-Risk to multidimensional dynamic models of risk. Within the banking flow, various risk compartments include credit risk, liquidity risk, market risk, model risk, and operational risk. The last item, operational risk, has only recently gained recognition as a legitimate risk compartment in academic and professional circles. The international Basel banking accord of 1998 bootstrapped this recognition by requiring financial institutions to quantify their operational risk equivalents under capital account computation.

Operational risk is the risk relative to monetary losses caused by failures of internal processes such as bad trades, architectural limitations, and market jitters. Unlike the other risk categories, operational risk is significantly more challenging to measure as it is intrinsically an extremely broad multiscale phenomenon whose heterogeneous causes range from human errors to high-tech malfunctions. The dynamical framework corresponds to a broad class of random Boolean networks whose activity is convex saturated for a generic set of weights. It contributes additional degrees of freedom, understood as transmissions in information and orders of prospective aims between accounts and banks. This is important as financial information loses relevance after many iterations, revealing the mutual independence of mechanisms and failures in a completely connected structure.

The basic model unifies spontaneous generation of losses via Poisson processes and generation of losses via interactions between different processes via gas-like terms. Simple assumptions determine the evolution of the average losses and yield closed equations for the first two moments, enabling numerical fitting of a variety of data sets across different time scales, from weekly to many years. The analysis of the covariance matrix shows that, as consistently observed in data, independent processes initially become correlated slowly while retaining their independent marginals. This

framework expands the dynamic modeling of the qualitative behavior of time series data from other fields such as biology and geology to model bank operations, tail distributions, and contagion mechanisms.

8. Impact of AI on Risk Mitigation Strategies

Machine learning technology offers banking managers a new way to effectively manage risk and improve the overall business. Banks and other financial organizations are affected by risks that stem from various sources that have different characteristics, and thus they must use different approaches to incorporate these risks into the risk management framework. Environmental records combined with machine learning techniques can provide new preventive tools to forecast environmental disasters for major companies and banks stemming from their financing portfolio. This should be a key point on the agenda of banking and finance public forums. Credit risk evaluation for banks is a hard and business-critical task. Their reputation, profitability, and even their survival depend on correctly managing and evaluating risk. Thanks to machine learning techniques, banks can expand their information base including both quantitative and qualitative, explicit and implicit information about borrowers and their projects to be able to correctly determine the project financing fate.

In recent years, the introduction of sophisticated artificial intelligence (AI) based decision making systems in finance, banking and insurance has been remarkable. AI involves algorithms capable of learning the structure of raw data describing relationships. Their outputs aim at mimicking human decision making processes in a particular environment, based on the knowledge acquired. AI includes expert systems, neural networks, and genetic programming. In the banking industry, the risks most often evaluated include credit risk, market risk, compliance risk, and operational risk. Credit risk is the most important one, since ineffective management of credit risk can pose major threats to banks' survival and profitability. Understanding relationships between customers and default, management of large portfolios, and on-time detection of non-worthiness are the three main problems associated with credit risk.

Economic cycles, markets, competitors, and overall business strategy shape the risk profile of banks. Financial regulations restrict the bank's risk-taking ability in normal conditions, while the level of disclosure and surveillance allow for competitive arbitrage in the market. Other risks like compliance risk have incorporated reputation risk and regulatory compliance, while operational risk refers to the inadequacy or failure of internal processes, people, risks or systems.

8.1. Predictive Analytics

In modern banking, the rapid growth of information technology has led to the emergence of new risk estimation methods. Some banks are reportedly using some form of analytics. Most developers are currently focusing on analytics for retail credit scoring, while insurance companies are developing enterprise risk analytic systems specializing in market and insurance risks. When grouped by modeling methodologies, there seem to be two distinct types of analytics for the assessment of financial risks. Predictive analytics estimates the inherent default and risk probabilities of each bank customer based on individual macro and/or micro variables through the training of big data, while other types of analytics mainly utilize mathematical models or accounting reports. Predictive analytics is a fast-growing market, currently worth over a billion, with an impressive annual growth rate of over 30%. Despite their initial cost and consequent need for computing centers, predictive analytics would pay off within the first year due to their expected return on investment of 5% to 20%. Most large banks and many smaller banks are in the course of developing predictive analytics systems. Some banks reportedly use techniques from Operations Research for risk assessment, although the detail may not be disclosed.

Machine-driven estimates of the inherent creditworthiness of bank customers via Predictive Analytics from their macro and/or micro data have been gaining in popularity in the banking sector. Market and insurance risks are reportedly also in the focus of some banks. Due to the availability of big data sets and advances in machine learning, proof-of-concept predictive analytics initially developed for bank credit scoring or life insurance underwriting are now gradually maturing into potential rule-of-thumb engines for corporate risk assessment and algorithms for stocks trading. A gap between the rhetoric regarding the role predictive analytics may play regarding financial sector risks and the worrisome data-poverty at the world-wide banking market may, however, prevent bridging the Puzzle problem.

8.2. Real-Time Risk Monitoring

Financial institutions must be able to monitor their exposures effectively to manage risk in a fast-changing market environment. Risk calibrations, a firm’s suitability in the face of specific risks, are often based on hundreds of quantitative rules fed into siloed engine applications that may run on

different technology stacks. The way they test, deploy and operate these engines needs to change fundamentally. AI technology, in combination with cloud-enabled data-transformation pipelines, can enable scalable risk-monitors to be generated automatically from functional specifications in type-safe mathematical Programming Languages which may also be queryable from business Intelligence. This deployment paradigm scales up the scope and speed of checking across products, risks and monitoring techniques. A data-driven high-performance library is also created to power and optimize said implementations.

The risk-monitoring domain calls for a flexible architecture that allows for rapid model innovation to enable business buy-in and rapid adjustment of the risk-adjusted pricing of financial instruments and products on offer. While banks have for many years run sophisticated risk-monitoring libraries, these have evolved into cabals of technology stacks, programming languages, expert teams, and arcane rules that can give rise to operational risk and inhibit the risk exposure dynamic in pricing engines from monitoring compliance at high corporate resolution tables.

The infrastructure encumbrances mean that most risk characteristics are factored into monitors that run long after most resulting prices have been bottled-up. It is argued that AI technologies, specifically domain-specific languages for fuzzy mathematics in the financial domain, have reached sufficient maturity to create a new fast-track solution to this problem. Banks are advised to take stock of their risk-monitoring needs and allow engineers to embrace the AI technologies that can transform their banks' attitudes to risk.

9. Future Trends in Financial Risk Management

The modern banking sector is undergoing rapid mutations due to significant technological advancements in terms of AI, machine learning, data analytics, fintech, digital payments, blockchain, and cryptocurrencies. Recently, financial intuitions have shown special interest in AI and machine learning which are predicted to play important roles. Financial intuitions are now collecting massive amounts of structured and unstructured data in real time to trace the historical patterns and better understand their behavior. In view of harnessing sophisticated data sources from mobile applications, social media, news sources, payment networks, and cross-sell inputs banks are also applying advanced data engineering technologies. Financial historic data serves as an invaluable source of training the statistical models to enhance the risk management process. As AI empowers banks to monitor traditional variables probabilistically, banks can improve the output of the financial models. However, with increased levels of sophistication the sophistication of the models to adhere to the risk management and compliance processes also increased. Similarly, financial services regulators have also updated their legislations in line with the advancements of technology. Although regulators are aware of the advantages of new technologies, they face at the same time challenges that stem from the complexity and threat of biases of the new systems.

The risk management, reporting, and compliance processes have already internally evolved with the introduction of financial engineering. As new modelling frameworks emerged both banks and hedgies adapted their regulations and compliance procedures as required. Today, banks scale up to model-centric modelling frameworks such as AI and machine learning. As advanced techniques and sophistication of such models are rapidly rising, financial intuitions nowadays have begun revising internal and regulatory procedures. Ultimately banks consider to adapt their risk management and compliance structure, both systemically and procedurally, to this next generation modelling infrastructure. Delivering risk disclosures is mainly hampered by dependency on fetching high dimensional data from various decision tools. Due to complexity, such financial encyclopedias are not regarded to be fully trustworthy. Due to the probabilistic outputs of AI and ML models producing real time risk disclosure is tedious. Also, some traditional techniques for gathering computations fail to scale decently and effectively as AI and ML functions.

9.1. Emerging Technologies

In the field of Finance and Investment, there is a growing recognition of the long-term financial benefits of ESG (environmental, sustainable, and governance) criteria; however, financial institutions (FIs) may face short-term trade-offs during this adjustment. This balancing act requires a strategic approach and a firm commitment to long-term sustainability goals. Stakeholder engagement and communication are critical; thus, FIs need to effectively communicate their ESG strategies and performance to a wide range of stakeholders. This requires transparent and consistent reporting on ESG compliance, yet the lack of standardized ESG reporting frameworks for both FIs and clients makes this reporting challenging and enhances reputational risks. There are also complex trade-offs between financial and non-financial objectives, for instance, in the case of adopting offshore financial centers or ABES heavy industries. Addressing these challenges involves a comprehensive and strategic approach well-designed for each institution, and underpinned by a strong commitment to sustainable banking practices.

FinTech has emerged as an empowering force to commercial banking. Among FinTech, a promising technology to propel the implementation of ESG criteria in banking is Artificial Intelligence (AI) technologies. Given the complexity and critical importance of ESG criteria in banking, the application of AI technologies becomes essential. AI can analyze vast datasets efficiently and accurately, which is a key asset in tackling the multifaceted aspects of ESG. For example, with the broader adoption of satellite prompting in the insurance industry, banks could potentially process and interpret large-scale environmental data on main infrastructural assets. This would allow FIs to address climate-related risks in investment or lending policies. More generally, AI would facilitate more informed decision-making and negotiations on credit activities as aligning financial

activities with environmental sustainability and transition becomes more salient. From a social and governance perspective, AI can monitor and analyze patterns in public social and governance-related data such as firms' social media accounts and Top Management Board's disclosed text data on annual reports. This capability would enable FIs to identify and mitigate risks that may not become visible through conventional analysis methods. AI could also be used to minimize non-compliance with ESG standards both within the bank and among clients. In addition, AI can alleviate customers' concerns by bolstering the engagement and personalization experience.

9.2. The Role of Blockchain

Adoption of Blockchain in Banking There is still very little attention paid to this technology. However, financial institutions do have one or more staff or committees working on the "distributed ledger technology." There are opportunities for banks to invest in this area: First, a blocked chain as a new technology platform should be technology-neutral, allowing competition among underlying technologies for processing digital currency transactions. It should serve consumers, businesses, and money market funds in a transparent manner so that end-users know what they are getting into. The service fee for moving digital currency through "nodes" should be the market price. Supervision should shift from the nodes to the private public key management of end-users. The usage of Blockchain in Financial Services A few recommendations on such policies are as follows. The country with a monetary system that competes with the yuan should be vigilant about the digital currency issued by China. To avoid big financial and economic risks, a gradual development of the blocked chain ecosystem is recommended. China Construction Bank and the Agricultural Bank of China should be aware that they would be competing for the same customers. There might not be two big international currencies. On the other hand, champions of the technology platform may be needed to help design a better multi-center system: For example, to overcome the supervision/financial control issues against systemic risk, a naked chain might be a naïve solution. Technology Lipstick In thought is behind a "state-machine" implementation of Turing Machine. A naked chain might however solve the discontinuity/non-trust conversion issues between chains. Multi-party/non-centralized systems may consider chained sequences of trees, commodity trading systems, inter-chain systems including atomic transactions. A new innovative banking system would be central with global trust, governance models, and hybrid.

10. Conclusion

Financial institutions are challenged with an expanding range and scale of potential uses for machine learning and AI technologies despite negligible head starts and better access to cutting-edge technologies than traditional providers. The industry is still grappling with a broader strategy for dealing with a complex, fast-growing area where costs and business development times are rising. The biggest challenge, though, is mastering these technologies so that they can be transformed into bankable goods without a distinct advantage given to platforms. Financial firms have realized their models have value beyond regulation, and that they are collecting vast amounts of untapped data. Some banks are realizing their models can be commercialized despite the hurdles of data portability and protection and which products are appropriate in which populations. Financial firms are competing for broader adaptation of their models, a slow road beset with conflicts of interest, compliance issues, understanding of the capabilities of modern models, or pitfalls in terms of safety and ethics.

Banks are starting to expand the old ends and means of compliance stretching existing models. Scores that were meant to estimate the likelihood of default on loans or fraud for transaction monitoring are now being applied to predict the latest defaults on rent payments or defaults on utility bills. Expert-stripped models that would triage incoming credit requests in dozens of seconds are now judging trades worth millions of dollars in milliseconds. Other methods are anticipated to augment trading desk knowledge, provide explanations of analyst recommendations for companies or sectors, and surface significant security risks preemptively. This canvas of currently banked ML applications shared between a few large banks is both plucky and feasible.

The second foundational pillar of a second-wave courting design is a bankable machine learning model. Machine learning is being liberally applied to supervised and unsupervised classification problems that require more flexibility and robustness than can be offered by conventional or hybrid models. However, despite the industry's best efforts starting years ago, it remains feasible for only a small number of syndicated markets.

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