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Intelligent Data Governance for Next-Gen Investment and Insurance

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Abstract

To address the institutional reliance on a combination of traditional data sources and poor quality alternative data, two distinct—but related—problems linked to the Governance of Big Data are analysed. In a Big Data and AI-driven world, the modelling paradigm changes from a linear perspective to a non-linear one, leading to a shift in focus: the analysis, selection and creation of model features becomes the main modelling task and modelling is performed in a segmented way. Data quality and data processing time gain special importance. Moreover, Data Governance impacts any enterprise involved in developing decision-making tools via an AI/ML Data Modeling Paradigm. Deficiencies, inadequacies, ethical concerns and governance checks of data required for the development of risk, pricing and portfolio management models for Investment Solutions, as well as for the data driving the underwriting decision process and risk scoring for Insurance Solutions, are analysed. Finally, the underlying Technical Architecture is proposed. Specific checks, balances and design controls would help Institutions to develop Big Data-based Decision-making Tools with more robust results and safer performance.

Keywords: Big Data Governance Frameworks, AI/ML Data Modeling Paradigm, Non-Linear Risk Modeling, Feature Engineering in Financial AI, Data Quality Management, Ethical AI and Model Governance, Decision-Making Tool Architecture, Risk and Pricing Model Controls, Portfolio Management Analytics, Insurance Underwriting Data Governance, Model Segmentation Strategies, Data Processing Latency Optimization, Compliance-by-Design Architectures, Responsible Financial AI Systems, Technical Architecture for Big Data Decision Systems.

1. Introduction

Investment products such as pensions and life insurance occupy an increasingly major placed in household investment portfolios by providing excellent long-term returns with a high degree of certainty. Along with, providing risk-hedging against uncertainties, the core operation of these products has been getting commoditized over years due to developments in financial markets, far more than what has been reflected in product prices. Insurance products that provide cover against uncertainties across various life domains, such as health, accidents, property, and life, have also witnessed rapid growth over the years, giving rise to the insurance industry. Nevertheless, in both cases, accurate risk modeling remains a challenge for players, thereby offering significant opportunities to banks, insurance companies, and fintech firms involved in investment and insurance businesses. Despite being some of the most critical business functions for an investment-house or an insurance company, pricing, portfolio optimization, and governance of investment solutions, insurance underwriting, loss predicting, fraud detection, and risk scoring all rely on developing robust algorithms, which are often overlooked due to lack of proper roadmaps, experience, or relevant expertise.

In the era of Big Data and Artificial Intelligence (AI)/Machine Learning (ML), the larger domains of business intelligence and product growth have been moving faster than the core operations in developing algorithms for these applications. Given a robust and proper framework for supporting AI/ML data modeling with a dedicated focus on the types of algorithms being generated for enabling decision-making, such as risk prediction, insurance loss prediction, fraud detection, pricing, and portfolio optimization, the complete process—right from problem formulation to data, data leakage and governance—can be streamlined for faster

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and intelligent AI/ML solution development. The clear articulation of the framework, with full-fledged practical implementation details for a particular investment solution—a risk model followed by portfolio optimization—further enables effective use in areas beyond investment solutions such as life and non-life insurance underwriting and loss prediction analytics.

1.1. Background and Context of Big Data Governance

Data ecosystems of today have evolved from earlier hierarchical and discontinuous patterns of data maintenance and management and are known for their decentralized and integrated nature. Data whose collection is highly diverse due to its possible multi-sourced origin, is also characterized by an arbitrary time horizon: it can be very recent and regularly updated or more historical and therefore on a low refreshment rate. Furthermore, the core content of the collected data include non-financial aspects relating to investors and companies (information about reputation, behavior, presence on social networks), and complement the often neglected issue of investor emotions. Mature data ecosystems facilitating a wide range of services, such as banking and insurance services, funding and risk capital for companies, e-commerce, funding and possibly real-time dynamic pricing, are already well-established.

Unlike other business ecosystems, financial ecosystems require the presence of formal rules and regulations for data governing and monitoring. The collection, management, access, use, and sharing of data by different financial stakeholders must be aligned with data governance principles, which, in the case of public data, become legal necessities of data accountability. These principles represent a well-established good practice, even when the administration of the data is taken for granted by the stakeholders of the ecosystem, who expect their good behavior to be sufficient for their access and use. Nevertheless, specific regulation for public data is needed, especially when it concerns the quality and integrity of the data collection because it is acknowledged that data quality is often an unsolved issue in real-world applications of Big Data analysis.

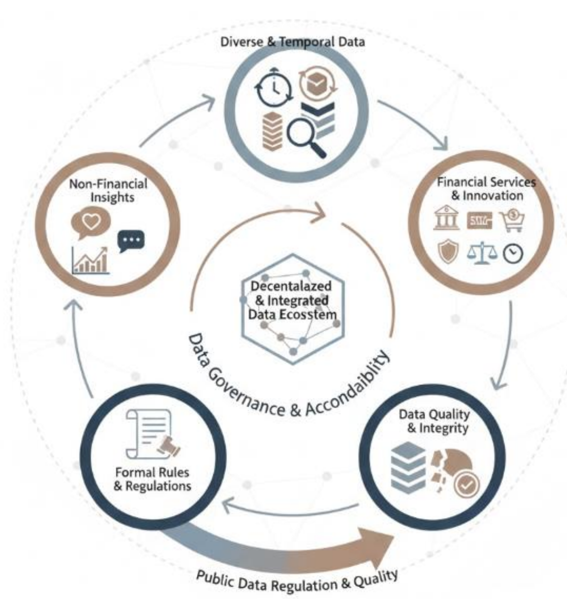

Fig 1: Governing the Decentralized Nexus: A Framework for Data Accountability, Integrity, and Non-Financial Sentiment in Financial Ecosystems

2. Theoretical Foundations of Big Data Governance

Theoretical exploration of data stewardship, governance hij-a-ra-jo-sha-r-me-n-et- f-ra-me-w-o-r-ks , compliance , ethical accountability frameworks . Contemporary Theory 9797 Governance Theory on Data Issues Entering into Diversity Governance as Group Dependency --130000--1300s An Honzon Airport for Sociological Actions of Complimentary Apostolic Union Big Data Policy with Medicine, Society, Business, big government and big banks --TYCOLOGY of SYSTEMIC FUNCTIONALITY. Transferability The ability and capacity of a system to continue its existence over time, attended by the possibility and ability of moving, working and

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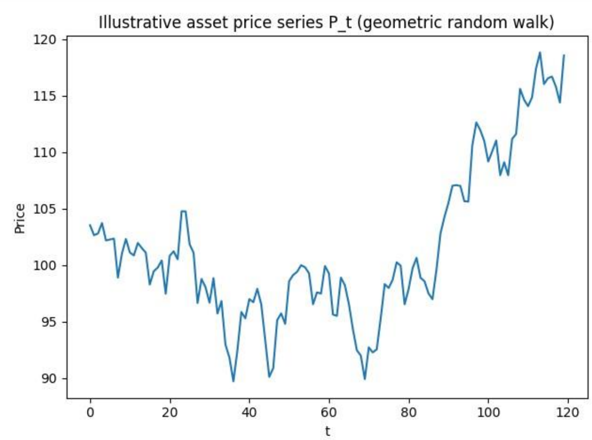
functioning WOSIS - World of Societal Information Systems. Individual The parameters Actions of an individual, society, group or union for communicating and socialising themselves and for transferring a message and formulating their best relationships. Logical Rules "an aiding cause to achieve meaning goals to create a self image and memories and to grow by learning from past experiences".

These collaborative objectives cover all areas of life including the consequential scientific and environmental governance-functionalism. Systemative Transfer of Right - STRoR ARoS, the substratum created by WOSIS can be transferred to society. As the new free information based time stock service or gift economy towards its fulfillment. With Internet and other sciences of seasonal travel it can govern its operation with leisure and support the seasonal entertainment across borders. Multi Voronoi courtesy with ILO resolves the responsibility of sourcing good growth. Big Data, Artificial Intelligence Ethics Of Care And Awareness - Sciences of Kinship as sources for resolving sources of moral characteristic of the human world from where depend all others by using the IT big search as trade bond with Society with the avowed and natural A E A being necessary. The moral need generates care of all towards them and push their awareness of their needs and contributions towards this source of existence, unnatural causing lack of care and awareness.



Equation 1) Risk sensitivities ("Greeks") — equations and derivations

1.1 General setup

Let a traded instrument/derivative have value

$$V = V(S, t, \sigma, r, \dots)$$

where:

- S = underlying price,
- t = time,
- σ = volatility,
- r = interest rate,
- "…" = any other risk factors.

1.2 Delta (first-order sensitivity)

Definition

$$\Delta = \frac{\partial V}{\partial S}$$

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Step-by-step (finite-difference intuition → derivative)

1. Small change in underlying: $S \to S + \Delta S$
2. Value change: $\Delta V \approx V(S + \Delta S) - V(S)$
3. Sensitivity per unit change:

$$\frac{\Delta V}{\Delta S} \approx \frac{V(S + \Delta S) - V(S)}{\Delta S}$$

4. Take limit as $\Delta S \to 0$:

$$\Delta = \lim_{\Delta S \to 0} \frac{V(S + \Delta S) - V(S)}{\Delta S} = \frac{\partial V}{\partial S}$$

2.1. Data Stewardship and Stewardship Models

The stewardship of data is based on the premise of aligning the operation of organizations toward a joint goal. It implies accountability for data throughout its lifecycle and the ability to create value from data while ensuring that operations are conducted in conformance with regulations and policies, are ethical, and are acceptable to stakeholders.

In the context of the financial marketplace, an organization can be thought of as a car manufacturer that depends on various suppliers for parts \(e.g.\), engines, tires, batteries, lights, and glass. Each part is manufactured by a separate company relying on the combined knowledge of its employees within a specific domain. The combination of these parts into a complete vehicle is the responsibility of the manufacturer. Similarly, the quality and performance of different parts have a combined effect on the overall quality of the vehicle. To ensure this quality, the manufacturers and vendors of these parts together form an "ecosystem" where they work with a common goal \(i.e.\), manufacture an exceptional vehicle\).

Depending on the market, vehicles are operated by individuals or businesses. Owners may be indifferent to the product, to the fuel consumed, and the pollution caused during operation. However, the community or society would not be indifferent to these aspects, as poor fuel economy and harmful exhaust emissions will reduce quality of life. This lack of accountability has led various stakeholders to come forward and set norms or rules for the vehicle business. Both the manufacturing and ownership functions will be crucial in determining the level of pollution from the vehicles. Hence, it is essential that both the manufacturers and the owners of vehicles share the responsibility and accountability for their respective parts while complying with the rules established for the ecosystem by controlling authorities, environmental activists, and society.

t	Price P_t	Log return ln(P_t/P_{t-1})	Simple return (P_t-P_{t-1})/P_{t-1}
0	103.5216		
1	102.6435	-0.008519	-0.008483
2	102.7931	0.001456	0.001457
3	103.7173	0.00895	0.00899
4	102.1753	-0.014978	-0.014867
5	102.2613	0.000841	0.000842

3. AI/ML-Enabled Data Modeling Framework

The AI/ML-enabled data modeling framework comprises several components with different characteristics. In addition to supporting all phases of the modeling process, it provides a comprehensive list of considerations for selecting the right algorithms, assessing their performances, and dealing with quality issues of the underlying data. The wiring of the components follows the typical stages of batch data pipelines. However, since the modeling can be approached in a pipeline fashion, the combination of data flows and components may also suggest

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alternatives, such as parallelization or feature engineering approaches.

A crucial challenge of such a complex data environment is the choice of the algorithm for each building block of the data pipeline. Where available, professional domain intuition should guide the selection from the rich family of algorithms. In light of the pervasive adoption of automating hyperparameter optimization, the considered candidate set may run from the simplest to the most advanced algorithms available. The resulting model performances should thus be captured through appropriate metrics for later evaluation. Given the temporary nature of some of the data used and their potential dramatic impact on model scores, extensive tests under extreme conditions, such as Octave tests, should be considered. Last but not least, the AI/ML-enabled adaptation of the model scorecards, with the interface to the technology governance function, should not be overlooked.

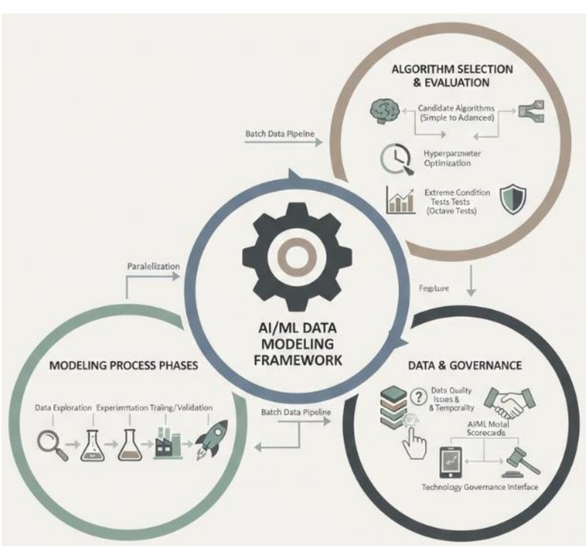

Fig 2: Adaptive AI/ML Modeling Frameworks: Governing Data Pipeline Architectures through Automated Hyperparameter Optimization and Robustness Testing

3.1. Data Modeling in the Era of Big Data

The previously described frame reveals that data modeling projects in today's world of Big Data share a problem-solving logic with data flow diagrams but are more formalized. Concentrating on the modeling mixture that comprises the most usual case in the financial and insurance domains, a mixture of unsupervised and supervised modeling is now detailed.

It also indicates that for any new problem, the feature engineering process is imperative and usually has to be done manually; that the quality of the data used for modeling is important; that temporal data cannot be used as such but need to be correspondingly disaggregated; and that nowadays datagovernance should also pay attention to the model-building stage and not only to the model-execution stage.

4. Data Architecture for Investment and Insurance Solutions

To facilitate data access for multiple stakeholders, a data architecture with several logical layers is proposed. While low-level data storage and custodianship functions are entrusted to a cloud-based solution, banking and other financial institutions are additionally required to furnish a Governance Point of Contact, tasked with enabling relational and API access to relevant metadata and high-level data with appropriate filtering. Multiple Delta Lake structures could be established across varied geographical regions, with the respective country business having custodian rights for the data.

The architecture is designed to accommodate end-to-end functionality, spanning different domains of investment and insurance solutions. A Governance Point of Contact should therefore be instituted by agencies regulating multilayered data sources and exhaustive data storage requests. These parties should further ensure data lineage, provenance, and metadata management from a governance perspective. Infrastructural investments are thus required for

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additional data storage points and an exhaustive metadata catalog that meets schema-on-read requirements. Furthermore, the encryption of different data pipelines for different metadata storage points should be agreed upon and implemented. Existing samples covering multiple models should also be injected into the respective metadata storage point for testing, validation, and training operations.

Equation 2) Log-returns — equations and derivations (investment price prediction)

2.1 Simple return

Given prices P_{t-1}, P_t:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1$$

2.2 Log return (derived)

Define log-return:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Step-by-step relationship to simple return

Since $\frac{P_t}{P_{t-1}} = 1 + R_t$,

$$r_t = \ln(1 + R_t)$$

For small R_t, use the Taylor series:

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \cdots$$

Substitute $x = R_t$:

$$r_t \approx R_t - \frac{R_t^2}{2} + \cdots \approx R_t \quad \text{(when } |R_t| \text{ is small)}$$

2.3 Key property (time additivity)

Over multiple periods:

$$\sum_{k=1}^{T} r_k = \sum_{k=1}^{T} \ln\left(\frac{P_k}{P_{k-1}}\right) = \ln\left(\prod_{k=1}^{T} \frac{P_k}{P_{k-1}}\right) = \ln\left(\frac{P_T}{P_0}\right)$$

4.1. Data Sources, Integration, and Storage Architectures

A comprehensive approach to data modeling considers investment and insurance solutions in the big-data context and addresses the specificities of an AI/ML paradigm. Consequently, risk modeling, pricing, portfolio optimization, underwriting analytics, and risk scoring are tackled in depth. Operational and governance perspectives enhance the practical applicability of the proposed models.

1. Data sources

Investment and insurance solutions increasingly rely on alternative data sources and services outside the financial and insurance ecosystems. The main actors of these data ecosystems have different needs: the AI/ML industry relies on continuous improvement of models, thus requiring a fresh source of information and data for retraining, while the finance and insurance sectors

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require high-quality predictive information for underwriting. This demand will not just come from quantitative vendors or service providers, but also from the growing number of third-party data providers covering traditional and new alternative data sources, like Social Media or web scrapping data.

2. Data integration methods

Investment and insurance solutions increasingly leverage data outside traditional data ecosystems, requiring data integration with third-party vendors, micro-services, or scrapping engines. Data integration is a broader concept than data ingestion, as it refers to all activities required to combine data residing at different sources into valuable information, providing a unified view of the integrated data. Approach is to classify integration methods according to the integration pattern and storage technology used.

3. Storage technologies

Main characteristic of Data Architecture is that it employs multiple storage technologies, such as relational, columnar, or no-SQL engines, to optimize storage performances according to data access needs, thus following the smart scale philosophy. Data management controls also become key issues in data storage, as they ensure good governance and reduce compliance risks.

5. AI/ML-Driven Data Modeling for Investment Solutions

AI/ML exercises in the investment domain include risk modeling, financial instrument pricing, and portfolio optimization. Risk models, typically developed in a supervised manner, form the backbone for portfolio pricing and optimization and are thus discussed first. AI/ML-supported pricing is often performed for complex derivatives products, demand estimation, and option implied volatilities in the context of price surfaces. Portfolio optimization, among the most popular investment analytics, also finds applications in para-tactical trading, climate-risk mitigation, and the management of private assets.

The evolution of risk models resembles that of the fundamental contagion modelling framework. These models capture the relationship between endogenous risk factors that vary in time and evolve along exogenous paths: transitions in different-regime and related-asset class volatility levels, monthly expectation changes, continuity in intra-regime risk, as well as periods of turmoil and incapacity to transmit shocks. In addition to conventional validation, such models need to pass stability checks and crisis stress tests. Data pipelines must be integrated into production systems, with ML-based model selection, stress-testing and FFD securing the use of big-risk data and the fulfilment of big-data governance requirements.

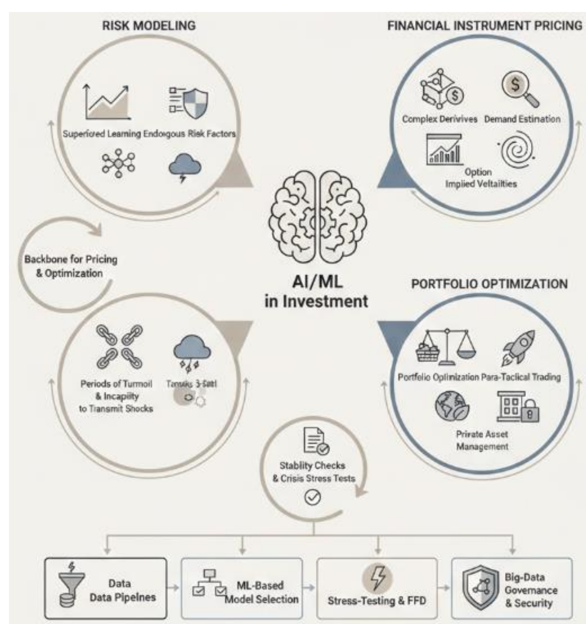

Fig 3: Regime-Aware Financial Intelligence: Integrating AI/ML Risk Modeling, Derivatives Pricing, and Portfolio Optimization within Big-Data Governance Frameworks

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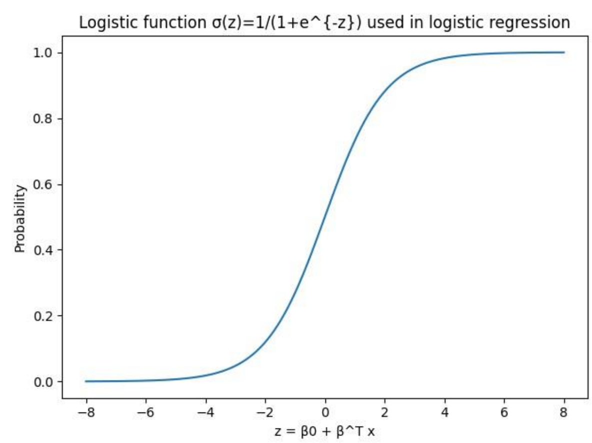
5.1. Risk Modeling, Pricing, and Portfolio Optimization

Data-driven models for investment solutions typically cover risk and exposure modeling, asset price prediction, pricing of derivatives and structured products, risk-neutral calibration and stress-testing of portfolios, risk-and-return trade-off definitions, and portfolio optimization. A comprehensive AI/ML-enabled data framework for investment solutions should support these models along with governance checks at every step, including validation and validation of models by independent teams. Recommendations for data requirements, governance framework, validation, model risk governance, and compliance checks at a summary level are presented next.

Risk and exposure modeling seeks to define the risk factors acting on the deployed investment and prices of the traded assets along with the corresponding sensitivity exposed as interpreted by the Greeks (delta, gamma, theta, vega, etc.). Depending upon the holder's point of view, the risk and exposure analysis can be implemented in a natural classification with respect to the risk-neutral and money-making perspectives.

For the risk-neutral point of view, the risk factors acting on the price of the investment are asked to be traded, and the asset can be seen as an arbitrage-free derivative contract. Conversely, in the money-making perspective, the pricing of the traded assets is required, and the market is idealized as an arbitrage-free environment. Risk and exposure modeling utilizes mainly historical market data from financial data providers and ideally should be validated using out-of-sample analysis.

Market prices are primarily driven by supply and demand, exhibiting nonlinear trends. Predictive models for asset prices should include relevant features to capture the states of the market/asset. The major impact of these features is commonly contained in log-returns, which express the price variations in relative terms. Libraries of empirical predictors (e.g., proxies for fundamental analysis, technical indicators) covering several classes of features have been assembled over the years and can be tuned/augmented to increase the predictive returns. Models can be fitted to parallel market dynamics because causal interactions among financial instruments often remain time-dependent but persistent. Validated price-prediction models allow for risk-neutral calibration and stress-testing of any portfolio of (possibly non-standard) derivatives.



Equation 3) Logistic regression for underwriting / risk scoring — full derivation

3.1 From odds → log-odds (the modeling choice)

Let $p = \Pr(Y = 1 \mid x)$.
Odds:

$$\text{Odds} = \frac{p}{1-p}$$

Log-odds (logit):

$$\log\left(\frac{p}{1-p}\right)$$

Logistic regression assumes log-odds is linear in features:

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$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta^\top x$$

3.2 Solve for p (step-by-step)

Let $z = \beta_0 + \beta^\top x$. Then:

$$\log\left(\frac{p}{1-p}\right) = z$$

Exponentiate both sides:

$$\frac{p}{1-p} = e^z$$

Multiply both sides by $(1-p)$:

$$p = e^z(1-p) = e^z - e^z p$$

Bring p terms together:

$$p + e^z p = e^z \; p(1+e^z) = e^z \; p = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}}$$

So the prediction function is the **sigmoid**:

$$p = \sigma(z) = \frac{1}{1+e^{-(\beta_0+\beta^\top x)}}$$

6. AI/ML-Driven Data Modeling for Insurance Solutions

AI/ML-Driven Data Modeling for Insurance Solutions: Underwriting Analytics and Risk Scoring

In insurance underwriting, AI/ML techniques can help analyze insurance application forms and associated attributes to provide insights and expedite decision-making. Key data inputs can include application form attributes, vehicle specifications, geolocation data, historical loss information, and policy attributes. The insurance underwriting decision can be treated as a classification problem, with logistic regression or classification trees serving as typical choices. Calibration can be performed using techniques such as isotonic regression or logistic calibration. Ensuring fairness in underwriting models holds particular importance, and it is essential to ensure appropriate representation of diverse population groups, control for hidden biases, and validate fairness metrics post modeling. Data quality checks should be incorporated into the end-to-end data pipeline, and the underwriting risk assessment model should be originally built and periodically validated via an independent data quality team.

AI/ML methods have also been successfully employed in providing risk scores for individuals based on past behaviors and providing recommendations for action. These risk assessments and recommendations are typically expressed in the form of model predictions. In such usage scenarios, the model is typically built and then use case-specific model predictions are generated. In addition to prediction servicing, aspect such as calibration and fairness are typically addressed-implying dependence on the data used for prediction servicing, not the model itself. The determination of risk based on predictive modeling carries ethical considerations and is often governed by business, regulatory, and legal requirements. Consequently, data inputs, predictive modeling type (supervised or unsupervised), calibration considerations, and technique for ensuring fairness are critical elements addressing business, regulatory, and legal requirements and need review by the respective team before use.

6.1. Underwriting Analytics and Risk Scoring

A better understanding of hazards can be established through data sources directly associated with underwriting (mainly meteorological/air quality data, ground sensors, IoT devices) than through historical claims, leading to better calibration and defense of rates and terms. Moreover, avoiding direct correlation with historical claims allows these models to be easier to maintain and less susceptible to bias. In contrast, the correlation of historical claims is extremely strong for

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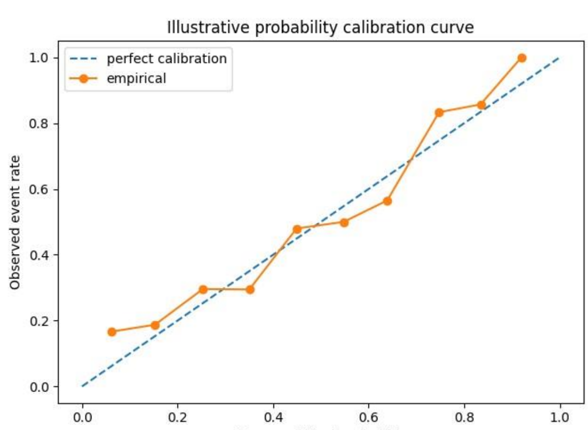
risk-scoring models. It is essential, however, that fairness is considered in banks. Many risk-scoring models are based on historical data that can be biased, and these biases can propagate through the model if it is not carefully addressed. During the calibration and testing phases, checks should be performed to ensure that no protected class suffers a higher disproportionality. Such problems can often be detected by segmenting the model's outcome per protected class and assessing whether the positive rate is similar between classes.

Models that are unusual in structure or require extensive external rule creation must be presented and discussed with the commercial area before use. The arguments and methodology supporting these structures should be documented, as well as the hypothesized risk behind the current model being used. Guidelines for the correct interpretation should also be presented so that the commercial area understands the underlying logic. In addition to new implementations, models that are in the process of being validated can also be followed more closely by establishing recommendations to facilitate monitoring. In case of major abnormal predictions for a risk segment, a direct discussion clarifying the situation is advised.



Equation 4) Probability calibration (isotonic / logistic calibration) — equations + interpretation

4.1 What calibration means

If the model outputs $\hat{p}$, calibration asks for:

$$\Pr(Y = 1 \mid \hat{p} = q) \approx q$$

So among all cases predicted 0.7, about 70% should truly be positive.

4.2 Logistic calibration (Platt-style mapping)

We learn a post-processing map:

$$\tilde{p} = \sigma(a \cdot \operatorname{logit}(\hat{p}) + b)$$

where $\operatorname{logit}(\hat{p}) = \ln\left(\frac{\hat{p}}{1-\hat{p}}\right)$.

Step-by-step

1. Convert probability to log-odds: $u = \ln\big(\hat{p}/(1-\hat{p})\big)$
2. Fit a 1D logistic model: $\tilde{p} = \sigma(au + b)$
3. Use $\tilde{p}$ as the calibrated probability.

4.3 Isotonic regression calibration (monotone nonparametric)

We fit a **monotone** function $f(\cdot)$:

$$\tilde{p} = f(\hat{p})$$

with the constraints f is non-decreasing, and it minimizes squared error:

$$\min_{f \text{ nondecreasing}} \sum_{i=1}^{n} \big(y_i - f(\hat{p}_i)\big)^2$$

7. Conclusion

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The preceding discussion addressed and resolved the roles of Big Data Governance and AI/ML-Enabled Data Modeling in the implementation of Next-Generation Investment and Insurance Solutions. Important points include the contribution of Big Data sources and novel Data Modeling insights to the Data Architecture designed to deliver next-generation solutions. The Investment Solutions covered Risk Modeling, Pricing, and Portfolio Optimization, with emphasis on Data Quality, Stress Testing, and Governance. For Insurance Solutions, the focus lay on Underwriting Analytics and Risk Scoring, including a checklist for Fairness.

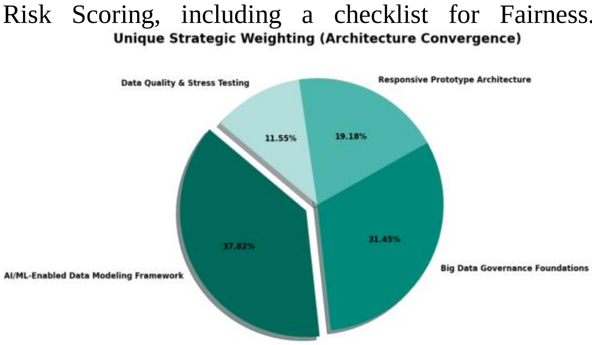

Fig 4: Unique Strategic Weighting (Architecture Convergence)

The work itself enables Data Managers to propose, build, and operate big-scale, high-complexity Data Applications for Finance and Insurance. It established an AI/ML-Enabled Data Modeling framework designed for the development of solutions used in those domains and explores the relationship between that framework and the Big Data Governance foundations for Finance and Insurance. Further, it articulated a prototype Data Architecture that combines Big Data sources and responsive models to provide solutions with significantly better Financial or Operational Risk.

7.1. Summary of Key Findings and Future Directions

The interaction between Big Data governance and Data Modeling for Next-generation investment and insurance solutions is extensive and intricate. The urgency of governing financial data ecosystems remains unabated. An AI/ML-enabled data modeling framework has been proposed, underscoring its growing relevance in the investment and insurance domains. The framework is supported by a governance-centric architecture together with an extensive collection of the data sources, storage, integration, and AI/ML execution approaches. This consolidation is a precondition for supporting advanced analytical capabilities in the financial domain.

The exposure and capability to govern Big Data at the creation, processing, and consumption stages remain key enablers of Data Modeling and therefore advanced analytical use cases around risk modeling, pricing, portfolio optimization, underwriting, and risk assessment across both investment and insurance domains. Achieving these capabilities not only improves the reliability of the models created but also the quality of decision-making by modeling inputs and the fairness of model outputs.

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