IFRS 9: Credit Risk Modeling 2.0

Fermac Risk White Paper

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Foreword

The field of credit risk modeling is undergoing a profound transformation, driven by the rapid advancements in artificial intelligence and quantum computing. As financial institutions adapt to the new accounting standard IFRS 9, which requires forward-looking estimates of expected credit losses, the need for sophisticated, predictive models has never been greater.

This course IFRS 9: Credit Risk Modeling 2.0 represents a pioneering effort to harness the power of generative AI and quantum computing for IFRS 9 credit risk modeling. By combining cutting-edge techniques from machine learning, computational finance, and quantum information science, we aim to equip participants with the tools and knowledge needed to develop state-of-the-art models for estimating expected credit losses.

Generative AI, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), offers a powerful framework for learning the complex, non-linear relationships between macroeconomic factors and credit risk parameters. By training on historical data and generating realistic economic scenarios, these models can help institutions stress-test their portfolios and estimate expected credit losses under a wide range of plausible conditions.

Quantum computing, with its ability to perform certain computations exponentially faster than classical computers, holds immense promise for credit risk modeling. From optimization and simulation to machine learning, quantum algorithms can potentially revolutionize how we build, calibrate, and deploy credit risk models. This course will explore the current state-of-the-art in quantum computing for finance and provide hands-on experience with quantum software development kits.

Throughout the course, participants will work on real-world case studies and projects, applying generative AI and quantum computing techniques to IFRS 9 credit risk modeling challenges. They will gain practical skills in data preparation, model development, validation, and interpretation, as well as an understanding of the regulatory landscape and best practices for model risk management.

This course brings together experts from academia and industry, offering a unique opportunity to stay at the forefront of innovation in credit risk modeling. Whether you are a risk professional, data scientist, or quantum computing enthusiast, we invite you to join us on this exciting journey to reshape the future of finance.

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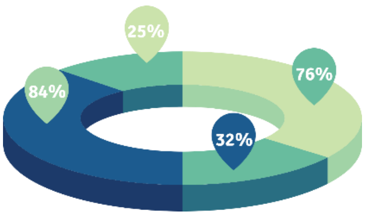
1. Modeling the lifetime Probability of Default (PD) under IFRS 9 for retail portfolios



Estimating the lifetime Probability of Default (PD) under IFRS 9 in retail portfolios is a critical task for financial institutions, involving a variety of methodologies from traditional survival models to advanced machine learning-based survival analyses. These approaches aim to predict the likelihood and timing of default across the lifetime of financial instruments. Here, we'll delve into the traditional survival models like Cox regression and contrast them with survival machine learning approaches like deep learning survival analysis, survival random forests, and survival boosting.

Traditional Survival Models (e.g., Cox Regression)

Cox Proportional Hazards Model is a seminal approach in traditional survival analysis. It's designed to model the time until an event occurs, considering the effect of several covariates on this timing. Key features include:

- **Proportional Hazards Assumption:** Assumes the effect of the covariates on the hazard is multiplicative and constant over time.
- **Semi-parametric:** The Cox model is semi-parametric because it makes no assumptions about the shape of the baseline hazard function, allowing for flexibility in modeling the time-to-event data.
  - **Interpretability:** Provides hazard ratios for each covariate, offering insights into the relative risk of

default associated with different borrower or loan characteristics.

- **Limitations:** The assumption of proportional hazards may not hold in all datasets, and the model may struggle with complex nonlinear relationships or high-dimensional data.

Survival Machine Learning Approaches

Survival Machine Learning models extend traditional survival analysis by Incorporating machine learning techniques to handle more complex relationships and interactions among covariates, without some of the restrictive assumptions of traditional models.

Deep Learning Survival Analysis

- **Architecture**: Utilizes neural networks to model survival data. The flexibility of neural networks allows for modeling complex, non-linear relationships, and interactions among high-dimensional data.
- **Example Models:** DeepSurv, a deep learning model inspired by the Cox model but capable of capturing more complex relationships without the proportional hazards assumption.
- **Strengths**: Can handle large and complex datasets, including unstructured data such as text or images, potentially improving prediction accuracy.
- **Limitations:** Less interpretable than traditional models and requires large amounts of data and computational resources.

Survival Random Forests

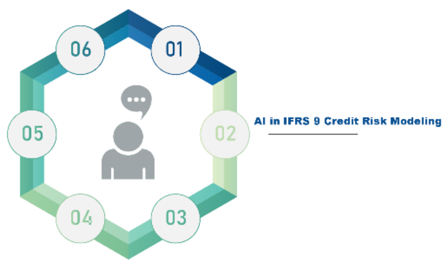
- **Extension of Random Forests:** This approach applies the concept of random forests to survival analysis, creating an ensemble of survival trees that can accommodate censoring.
- **Advantages**: More flexible and capable of capturing complex interactions and non-linear relationships without assuming proportional hazards.
- **Interpretability**: Offers some level of interpretability through variable importance measures but is less transparent than Cox regression.

Comparison and Considerations

- **Accuracy vs. Interpretability**: Machine learning-based survival models often provide higher accuracy by capturing complex patterns in the data but at the cost of reduced interpretability compared to traditional models like Cox regression.
- **Computational Resources**: Advanced machine learning models require more computational power and data to train effectively, which might be a limitation for some institutions.
- **Regulatory and Business Considerations**: The choice of model might also be influenced by regulatory requirements for model transparency and explainability. Traditional models like Cox regression are well-understood and accepted in regulatory contexts, while machine learning models may require additional justification.
- **Data Requirements:** Machine learning models, especially deep learning, benefit from large datasets to learn complex patterns. However, this might not be necessary for traditional survival analysis models, which perform well with smaller, structured datasets.

In conclusion, the choice between traditional survival models and survival machine learning approaches depends on specific needs, including the complexity of the dataset, regulatory requirements, desired model interpretability, and available computational resources. While traditional models like Cox regression provide a solid foundation with good interpretability, survival machine learning approaches offer enhanced flexibility and performance at the cost of greater complexity and reduced transparency.

1. AI in IFRS 9 Credit Risk Modeling



AI techniques have revolutionized the IFRS 9 credit risk modeling approach, offering sophisticated tools to predict credit risk more accurately and efficiently. IFRS 9, with its focus on expected credit losses (ECL), demands models that can assess current and future credit risk, incorporating a wide range of economic scenarios. Here's how AI and machine learning (ML) are applied:

Data Preparation and Management

- Big Data Integration: AI models can handle vast datasets from diverse sources, including nontraditional ones like social media, transaction patterns, and even satellite images, providing a richer basis for risk assessment.

- Data Cleaning and Processing: Automated tools and algorithms can preprocess data, handle missing values, and ensure the data fed into models is clean and relevant.

Feature Engineering and Selection

- Automated Feature Engineering: AI can automate the creation of new features that better capture the nuances of credit risk, significantly improving model performance.
- Dimensionality Reduction: Techniques like PCA (Principal Component Analysis) are used to reduce the number of variables, focusing on those most relevant to predicting credit risk.

Predictive Modeling

- Advanced ML Algorithms: Models like Gradient Boosting, Neural Networks, and Ensemble Methods have been employed to predict the probability of default (PD), loss given default (LGD), and exposure at default (EAD) with higher accuracy.
- Deep Learning for Complex Patterns: Deep learning models can capture complex nonlinear relationships and interactions between variables that traditional models might miss.

Incorporating Forward-looking Information

- Scenario Analysis and Simulations: AI models can incorporate multiple economic scenarios and forecast their impact on ECL, allowing for dynamic adjustment of credit risk provisions.
- Natural Language Processing (NLP): AI can analyze news articles, financial reports, and other textual data to extract sentiment and indicators that forecast economic trends impacting credit risk.

Model Validation and Back-testing

- Automated Model Testing: AI can automate the process of model validation, including back-testing against historical data and stress testing under various scenarios.
- Continuous Learning and Adaptation: AI models can continuously learn from new data, improving their accuracy over time and adjusting to emerging risk factors.

Regulatory Compliance and Reporting

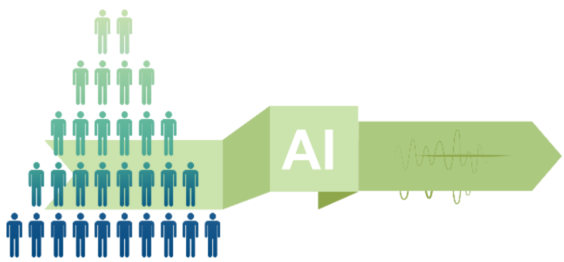
- Transparency and Explainability: Despite their complexity, AI models for IFRS 9 need to be interpretable to satisfy regulatory requirements, employing techniques like SHAP (Shapley Additive explanations) to explain predictions

Automated Reporting

- AI can streamline the generation of regulatory reports, ensuring compliance with IFRS 9 requirements through detailed documentation of risk assessments and provisions.

AI for IFRS 9 credit risk modeling is not just about employing the most advanced technology. It's about integrating these technologies into the financial institution's ecosystem to enhance decision-making, ensure regulatory compliance, and, ultimately, manage credit risk more effectively in an ever-changing economic landscape.

2. AI for Stress Testing Credit Risk



AI can be used in several ways to conduct stress testing for credit risk. Here are some key steps and considerations:

Data preparation: Gather historical data on credit portfolios, including loan characteristics, borrower information, and macroeconomic variables. Ensure the data is clean, consistent, and covers a sufficient period, including both normal and stressed economic conditions.

Scenario generation: To create realistic stress scenarios, use AI techniques like generative adversarial networks (GANs) or variational autoencoders (VAEs). These models can learn from historical data and generate new, plausible economic scenarios that capture potential downturns or shocks.

Feature selection: Apply machine learning techniques such as decision trees, random forests, or regularized regression to identify the most relevant variables that impact credit risk. This helps focus the stress testing on the key drivers of portfolio performance.

Model development: Build AI models to estimate the relationship between macroeconomic variables and credit risk parameters such as the probability of default (PD), loss given default (LGD), and exposure at default (EAD). Techniques like neural networks, support vector machines, or gradient boosting can capture complex, non-linear relationships.

Model validation: Assess the performance and stability of the AI models using techniques like cross-validation, backtesting, and sensitivity analysis. Ensure the models are robust, interpretable, and align with domain knowledge.

Stress testing: Apply the AI models to the generated stress scenarios to estimate the potential impact on credit portfolios. This includes calculating expected losses, capital requirements, and other risk metrics under each scenario.

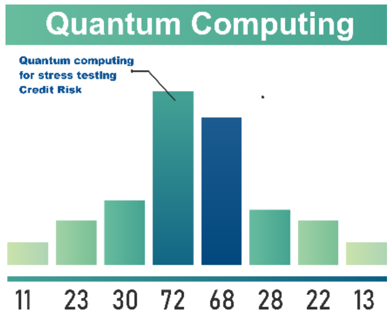
Interpretation and reporting: Analyze the stress testing results to identify vulnerabilities, assess portfolio resilience, and inform risk management decisions. Use data visualization and natural language generation to create clear, actionable reports for stakeholders.

Some benefits of using AI for credit risk stress testing include:

- Handling large, complex datasets and capturing non-linear relationships
- Generating a wide range of plausible stress scenarios beyond historical experience
- Automating and accelerating the stress testing process, allowing for more frequent or ad-hoc analyses
- Providing explainable insights into the drivers of credit risk under stress

However, using AI responsibly is important, ensuring models are transparent, fair, and aligned with regulatory requirements. Human oversight and judgment remain crucial in validating models, interpreting results, and making risk management decisions.

3. Quantum computing for stress testing Credit Risk



Quantum computing has the potential to revolutionize Monte Carlo simulations for stress testing credit risk. By leveraging the principles of quantum mechanics, quantum computers can perform certain computations exponentially faster than classical computers. Here's how quantum computing can be applied to Monte Carlo simulations for credit risk stress testing:

Quantum random number generation:

- Quantum computers can generate true random numbers using the inherent randomness of quantum systems
- This can enhance the quality and efficiency of random number generation required for Monte Carlo simulations
- Quantum random number generators can produce large volumes of high-quality random numbers quickly, improving the accuracy and speed of simulations

Quantum amplitude estimation:

- Quantum amplitude estimation (QAE) is a technique that can estimate the probability of rare events more efficiently than classical Monte Carlo methods
- In credit risk stress testing, QAE can be used to estimate the probability of default (PD) or other rare credit events with higher precision and fewer simulations
- QAE leverages the quantum superposition principle to encode and manipulate probability amplitudes, enabling faster convergence to accurate estimates

Quantum optimization for scenario generation:

- Quantum optimization algorithms, such as quantum annealing or variational quantum eigensolvers (VQE), can be used to generate optimal stress testing scenarios

- These algorithms can efficiently explore a vast space of possible scenarios and identify the most relevant and impactful ones for credit risk assessment
- Quantum optimization can help uncover hidden patterns and dependencies in the data, leading to more comprehensive and realistic stress testing scenarios

Quantum machine learning for credit risk modeling:

- Quantum machine learning algorithms, such as quantum neural networks or quantum support vector machines, can be integrated into credit risk models
- These algorithms can potentially learn complex patterns and relationships in credit data more efficiently than classical machine learning methods
- Quantum machine learning can enhance the predictive power and generalization ability of credit risk models used in stress testing simulations

Quantum speedup for large-scale simulations:

- Quantum computers can potentially perform certain calculations, such as matrix operations and linear system solving, much faster than classical computers
- This quantum speedup can significantly reduce the computational time required for large-scale Monte Carlo simulations in credit risk stress testing
- Quantum algorithms, such as the HHL algorithm for linear systems or the quantum Fourier transform, can be leveraged to accelerate key components of the simulation pipeline

Hybrid quantum-classical approaches:

- In the near term, hybrid quantum-classical approaches that combine the strengths of both quantum and classical computing are likely to be the most practical
- Quantum circuits can be used to perform specific computations within the Monte Carlo simulation, while classical computers handle the overall simulation framework and data processing
- Hybrid approaches can take advantage of the current state of quantum hardware while leveraging the maturity and scalability of classical computing infrastructure

It's important to note that quantum computing for credit risk stress testing is still an emerging field, and practical implementations may face challenges related to quantum hardware limitations, algorithm development, and integration with existing risk management systems. However, as quantum technologies continue to advance, they hold significant promise for enhancing the efficiency, accuracy, and insights obtained from Monte Carlo simulations in credit risk stress testing.

4. Our Experience in IFRS 9: Credit Risk Modeling 2.0

In 2016, we were among the pioneers in training credit risk models for the IFRS 9 directive. Since then, we have trained many bank participants from all over the world. Our IFRS 9: Credit Risk Modeling course covers various econometric models and classical approaches for estimating lifetime PD, such as logistic regressions, survival models like Cox regression, Bayesian regression, and panel data regression.

We utilize transition matrices and advanced models such as the Multi-State Markov Model to estimate Lifetime PD. Another interesting actuarial model that we use is the Exogenous Maturity Vintage (EMV) derived from the age-period-cohort methodology. Additionally, we make use of the Asymptotic Single Risk Factor (ASRF) model which is used to compute Basel IV regulatory capital and can also be used to estimate Lifetime PD.

In 2018, we integrated machine learning models for PD and LGD estimation. These models included neural network models, random forests, and support vector machines. To ensure a comprehensive understanding of the course, we have included numerous Python, R, and Excel exercises.

To estimate the Expected Credit Losses (ECL), we included Forward-Looking Information (FLI), which

involves macroeconomic scenarios. Initially, we used a method that created 3 or 5 scenarios to estimate the probability-weighted outcome. However, we later explored more scenarios using Monte Carlo simulation. We employ various traditional econometric models such as ARIMA, Vector Autoregressive (VAR), Vector Error-Correction (VEC), and Bayesian vector autoregression (BVAR), among others, and explain the statistical tests involved in the use of these models. These tests include multicollinearity, heteroscedasticity, serial autocorrelation, detection of stationary series, normality, and outliers.
The courses are designed to address issues related to implementation, lack of data, methodologies for determining significant increases in credit risk (SICR), and the typology of overlays used by financial institutions. These overlays can include those used during the COVID-19 crisis as well as overlays used to mitigate data deficiencies. The courses will also cover the challenges posed by the new definition of default (DoD) in EBA, lifetime in credit cards, transition matrices of S1, S2, and S3 exposures, backtesting, and other related topics.

With the emergence of new technologies, we have introduced the IFRS 9: Credit Risk Modeling 2.0 course, where we incorporate the use of AI models and quantum computing to calculate risk parameters like PD and LGD. For developing retail credit scoring models, we now use convolutional neural network models instead of classical logistic regression models, which have resulted in a 15-percentage point increase in ROC. Similarly, for creating satellite models, we have started comparing Cox regression models with 68% ROC to deep learning survival models with 89% ROC.

Having high discriminant power is crucial for achieving quality results in backtesting.

We compared multinomial regression to SVM and deep learning models that use softmax activation functions. The ML models exhibit a multiclass ROC that is 18 percentage points higher than that of multinomial regression.

We observed significant improvements in modeling LGD using machine learning instead of econometric models. Neural networks, random forest regression, and SVC/SVR significantly reduced RSME-type errors between estimated and observed values.

We have been exploring different methods to forecast PD and have started using econometric models like ARIMA, SARIMA, VAR, VEC, and VARMAX. We also compared them against machine learning models such as the traditional Long Short-Term Memory (LSTM), and we found that the latter is more accurate than the traditional models.

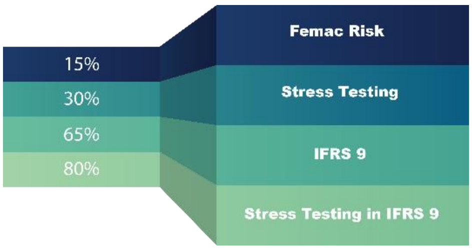
We have implemented more sophisticated models like the Bayesian Long Short-Term Memory. This model enables us to establish confidence intervals based on prior distributions estimated by experts. Combining expert judgment and empirical data allows for better control over the adjustments made by experts.

The quantum LSTM is a hybrid quantum model that enables fast convergence, achieving better accuracy.

Generative artificial intelligence models, such as Transformers, enable forecasting through parallel processing and long-term dependency capturing.

Transformers and Quantum LSTM models have outperformed traditional LSTM models in backtesting. Despite requiring large volumes of data, they can allow banks to make better decisions.

5. Our Experience in Stress Testing in IFRS 9



We use credit risk stress testing methods, such as the Bank of Finland model, which is based on the Credit Portfolio Views economic capital model. This helps us create scenarios of PD (Probability of Default) and macroeconomic variables using Monte Carlo simulation. Additionally, we create PD-LGD dependency models, inspired by the Vasicek model. These models help us create scenarios of PD and LGD with macroeconomic variables.
We are discovering that quantum computing techniques like Quantum amplitude estimation (QAE) can be used to estimate the probability of default (PD) with higher precision and fewer simulations than Classical Monte Carlo simulations. Quantum Monte Carlo provides quadratic speed-up in comparison with

classical Monte Carlo, i.e., to get some accuracy of result, we need n operations on a classical computer, while only $\sqrt{n}$ operations on a quantum computer.

Another advanced option that we are working on is Simulated Annealing, a probabilistic technique for approximating the global optimum of a given function. This technique provides a robust framework for stress testing credit portfolios. Simulating extreme market conditions and evaluating their impact on credit risk helps assess portfolio resilience and identify potential vulnerabilities.

Another way to create realistic stress scenarios is using Gen AI techniques like generative adversarial networks (GANs) or variational autoencoders (VAEs). These models can learn from historical data and generate new, plausible economic scenarios that capture potential downturns or shocks.

The results obtained with these new models show significant improvements over traditional models, greater speed, accuracy, and extension of plausible and robust scenarios.

Stress testing is an important aspect of IFRS 9, which deals with the accounting for financial instruments. Stress testing under IFRS 9 involves assessing the impact of adverse economic scenarios on the expected credit losses (ECL) of financial assets. Here are the key points we explained during the course to consider when conducting stress testing under IFRS 9:

Scenario design:

- Develop a range of plausible adverse economic scenarios that could impact credit risk
- Consider macroeconomic factors such as GDP growth, unemployment rates, interest rates, and sector-specific stresses
- Incorporate forward-looking information and expert judgment in scenario design
- Using quantum and gen AI techniques, define the severity and duration of stress scenarios based on historical data and future expectations.

ECL modeling:

- Use the existing IFRS 9 ECL models as a starting point for stress testing
- Assess the sensitivity of ECL estimates to changes in macroeconomic variables and other risk drivers
- Modify the ECL models to incorporate stress scenarios and their impact on credit risk parameters (PD, LGD, EAD)
- Consider the segmentation of the portfolio and apply stress factors at an appropriate level of granularity

Data and assumptions:

- Ensure the availability and quality of data required for stress testing, including historical data and forward-looking information
- Review and validate the assumptions used in ECL models, such as risk parameter estimates, cure rates, and collateral values
- Assess the impact of stress scenarios on key assumptions and make necessary adjustments to reflect the severity of the stress

Staging and migration:

- Evaluate the potential migration of financial assets between IFRS 9 stages (Stage 1, Stage 2, Stage 3) under stress scenarios
- Consider the triggers for significant increase in credit risk (SICR) and how they may be impacted by stress conditions
- Assess the effect of stress on the coverage ratios and the proportion of assets in each stage

Overlay and management adjustments:

- Consider the need for overlay adjustments to capture risks not adequately reflected in the ECL models
- Apply management judgment and qualitative adjustments to ensure the stress testing results are reasonable and aligned with expert expectations
- Document and justify any overlay adjustments made to the stress testing outcomes

Reporting and governance:

- Present the stress testing results to senior management and relevant committees, including the impact on ECL, regulatory capital, and key performance metrics
- Provide clear and concise explanations of the stress testing methodology, assumptions, and limitations

- Establish a robust governance framework for stress testing, including model validation, independent review, and approval processes
- Use the stress testing results to inform risk management decisions, such as risk appetite setting, limit monitoring, and contingency planning

Sensitivity analysis and benchmarking:

- Conduct sensitivity analysis to assess the impact of alternative stress scenarios and assumptions on ECL estimates
- Compare the stress testing results with industry benchmarks and regulatory expectations to ensure reasonableness
- Perform reverse stress testing to identify the scenarios that could lead to breaches in risk appetite or capital adequacy

Effective stress testing under IFRS 9 requires a combination of quantitative modeling, expert judgment, and robust governance. It is an iterative process that should be regularly reviewed and updated to reflect changes in the economic environment, portfolio characteristics, and evolving best practices. The insights gained from stress testing can help financial institutions understand better and manage their credit risk exposures, maintain adequate capital buffers, and ensure the resilience of their business models under adverse conditions.