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How is Artificial Intelligence transforming Credit Risk Management? Opportunities & Challenges

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The management of AI / ML risks is gaining importance due to rising public and regulatory attention

Big potential - Big challenges

- AI / ML usage is widespread and becoming the norm for many industries
- An increasing use of AI / ML can be observed in Banking, focusing on credit scoring & credit risk management, fraud detection, loan approvals, deep hedging
- Use of AI / ML comes with both advantages and specific risks
- The specific risks must be taken into account when using machine learning

Increasing relevance for Banking and Financial Risk Management

- Increased use of AI/ML in various areas: Pricing, Customer acquisition, risk management across various types (credit, market, operational, liquidity risk), fraud detection, portfolio optimization, trading strategies, RegTech.
- Applications can be found in less regulated areas due to large regulatory uncertainties

Increasing public interest

- Machine learning is increasingly used with direct relation to the customer.
- AI decisions might increase the risk of negative and harmful impact on private persons

Increasing Regulatory requirements

- Many regulatory publications at European and national level – However, only recently regulatory requirements have been materializing with EU AI Act
- Specific and additional regulation w. r. t. governance and Model Risk Management (MRM) can be expected

AI Specifics

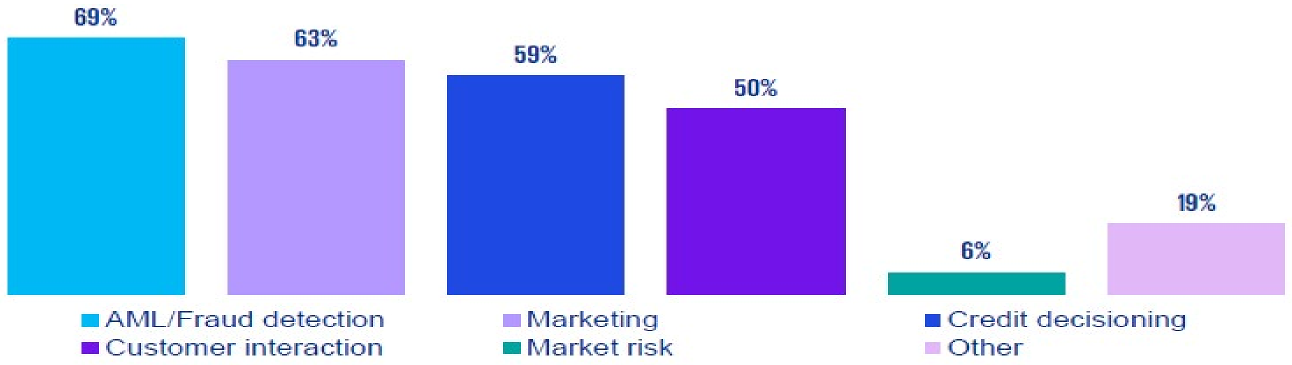
- Traditional MRM processes are often not capable to address specific risks of AI / ML models and regulatory requirements
- In particular model choice, parametrization / feature engineering, explainability, validation, and are challenging

How are European Banks using AI/ML technologies?

76% of Banks use AI/ML methodologies for model development

19% of Banks use AI/ML methodologies for model validation

65% of Banks have implemented a model risk framework adapted to the inherent nature of AI/ML models



- Banks continue to explore the application of AI / ML methodologies for model development, while at the same time acknowledging the challenges that lie ahead: explainability, complexity, and fairness.
- Banks focus on the end-to-end enhancement of the MRM lifecycle to account for the risks associated with these new methodologies
- Despite the EU's AI Act publication, financial institutions have identified a lack of specific regulatory guidelines, and hence mostly focus on the development of challenger models at this time.

Source: Models Management Global Benchmarking Survey, KPMG International, 2023

Benefits of a well-structured incorporation of AI in Credit Risk Management

Performance Improvement

Improve accuracy, speed and efficiency in strategic, operational and tactical decisions through data-driven information.

Risk Management

Identify and mitigate potential risks associated with AI implementation by establishing clear guidelines, review processes and monitoring mechanisms.

Compliance with Regulation

Comply with legal and industry-specific requirements, minimizing risks associated with data privacy, security and bias.

Promotion of the Public Trust

Adopt responsible AI practices, demonstrating the company's commitment to upholding user rights and ensuring that technology benefits all members of society.

Optimal use of AI Applications

Frequently evaluate AI systems and algorithms to ensure continuous improvement, taking into account user feedback and changing business objectives

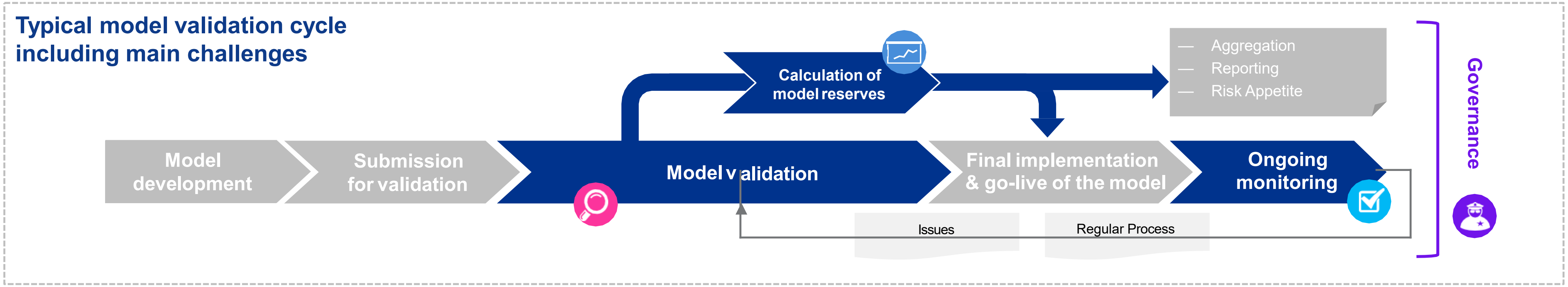
Ethical use of AI

Monitor and control the ethical implications of AI applications, guaranteeing transparency, fairness and responsibility.

Focus Areas for AI Governance in Credit Risk Management

	Requirement	Newness	Complexity
Adequacy	**Similar requirement as traditional models, but:** AI / ML models require new approaches to validation, stronger focus on data and stronger ongoing monitoring	BCBS (e.g. risk data aggregation & risk reporting), Basel Core Principles, CRR II/III, TRIM	Due to high complexity of the model and specific model cycle
Transparency / explainability	**Explainability of the method is one of the most critical issues in AI / ML:** Application of new methods is necessary. Approaches require know-how building and new technical solutions	Only a few requirements in existing regulations (CRRII/III)	Machine Learning Algorithms i.e. black boxes
Fairness, ethics	**High social relevance - Currently not sufficiently taken into account:** Intensive research and further developments in the topic to be observed. Requires a new approach to data, methods and results	No consideration in previous regulatory framework for banks.	Front-to-back to be considered, no empirical values, imprecise specifications.
Accountability	**Additional requirements in addition to those on traditional models:** **Human-in-the-Loop:** Human influence in decision-making **Human-on-the-Loop:** Human influence in design and review	BCBS (Corporate governance principles for banks), Basel Core Principles, CRR II/III	Processual effort with resource utilization incl. documentation
Data privacy, third party	• **Data privacy:** Ensuring privacy in all steps of the processing, if necessary, enquiry about the use of the data for training • **Third party:** Same requirements as for in-house applications	Extensive detail and regulation through DSVGO	New customer communication and data protection concepts necessary

The validation approach for Credit Risk models needs to be adapted to AI / ML idiosyncrasies



Challenges for the different validation components

Model Validation

- Underlying data
- Model choice
- Parametrization / Feature Engineering
- Fairness
- Explainability

Ongoing Monitoring

- Re-Training
- Model changes
- Explainability
- Fairness

Model reserves

- Benchmark models
- Risk approximation
- Monitoring

Governance

- Responsibilities
- Documentation
- Certificates
- Open-Source / third party
- Fairness

Challenges of validating Credit Risk models that incorporate AI / ML techniques...

Model validation	Challenges
Underlying data	• Larger data sets, different data structure and content - validation regarding bias and fairness necessary • Ensuring representativeness of training and test sets for productive data
Model choice Parametrization / Feature Engineering	• Review the appropriateness of the model in terms of model performance, explanatory power, fairness and data basis. • Validation feature selection from the raw data incl. "business backgrounds". • Higher importance and larger number of hyperparameters in ML algorithms – "Nature" of parameter difference compared to classical models
Explainability	• Explainability of machine learning models not given or challenging for certain approaches. • Use of Explainable AI required
Fairness	• Fairness is partly a completely new topic for validation without defined responsibilities and know-how • Application of new methods required • How is fairness quantified?

Fairness is one of the biggest challenges in the application of ML algorithms besides XAI and requires a high level of attention and the application of new approaches.

... Nevertheless, Evaluation & Explainability techniques for AI/ML-based Credit Risk Models open the “Black Box”

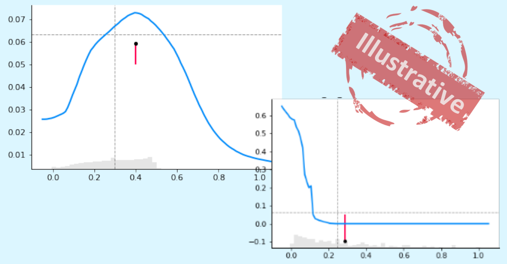
With regards to the risk model evaluation, several tests/metrics can be employed. In relation to model explainability, various approaches can be used, such as the Partial dependence plots (PDPs) and the Shapley Additive explanations (SHAP) algorithm

Model evaluation

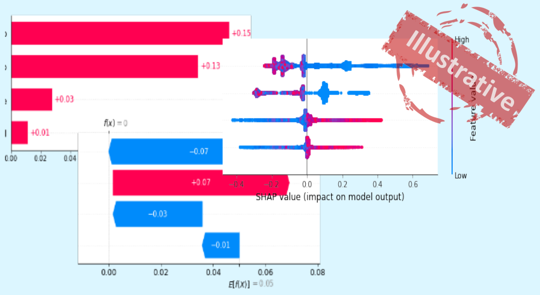
The models’ evaluation can be performed under all optimization metrics employed during model development (e.g. Gini, F1 approach), based on metrics commonly used for the assessment of the performance of the models (e.g. Gini coefficient, F1 score, AUROC, Precision, Recall), as well as applicable validation metrics as per Banks’ Validation Standards.

Model interpretation

- ***Partial dependence plots (PDPs)*** aid in model interpretation by revealing relationships, interactions, and non-linearities within the model, enabling better insights into feature importance and behavior.
- These visual tools are used to understand how a specific feature or variable influences the predictions of any machine learning model and show how the model's output changes as one feature varies while keeping all others constant.



- ***Shapley Additive explanations (SHAP)*** algorithm is used to explain how each feature affects the model allowing for insights into the relationship between features and predictions.
- ML technique that quantifies the impact of each feature on the model's output.
- The algorithm works either at a local (per record) or global (full dataset) level.



AI Target Operating Model (TOM)

Operationalization of AI Governance forms the basis of our proposed Target Operating model for an AI program, establishing core principles and procedures that direct the effective and ethical utilization of AI within the broader operational framework.

Proposed AI Target Operating Model

Governance

Establish Gen AI principles, policies, standards, guidelines, risk management and organizational structure; prioritize data privacy, model security, and regulatory compliance.

Functional Processes

Establish business objectives and a scalable framework to leverage Gen AI technology, prioritize opportunities for technology improvements, protect organizational data, and business unit adoption.

Performance insights and data

Define, monitor, and optimize critical success factors (CSFs), key risk indicators (KRIs) and key performance indicators (KPIs) for Gen AI technology performance

People

Cultivate collaboration between participating business units and functions, track key values and activities that support Gen AI adoption, maintain training plans for all populations adopting Gen AI technologies.

Technology

Technology and tools to enable data supply chain, build LLM, create, quickly tune or adjust Gen AI models, user interfaces, seamlessly integrate Gen AI solutions into existing systems

Service delivery model

Optimize end-to-end Gen AI service management, ensuring seamless integration and optimal performance to revolutionize employee and customer experiences and drive growth and efficiency.

Our Proof Of Concept – Overview

The scope of this POC is to conduct a comparative analysis between conventional credit risk methodologies typically employed in developing Probability of Default (PD) models and alternative Machine Learning methodologies.

Traditional PD model

Create a PD model utilizing conventional credit risk methodologies (i.e., Logistic Regression).

Challenger ML models

Develop challenger PD models by leveraging cutting-edge machine learning methodologies, including Neural Networks, Random Forest, Decision Trees, XGBoost, and Gradient Boosting.

Benchmarking

Conduct a comparative analysis between the machine learning methodologies and the traditional approach to assess and validate the obtained results.

Interpretability

Showcase the interpretability and transparency of machine learning algorithms, highlighting that they are not invariably "black boxes“.

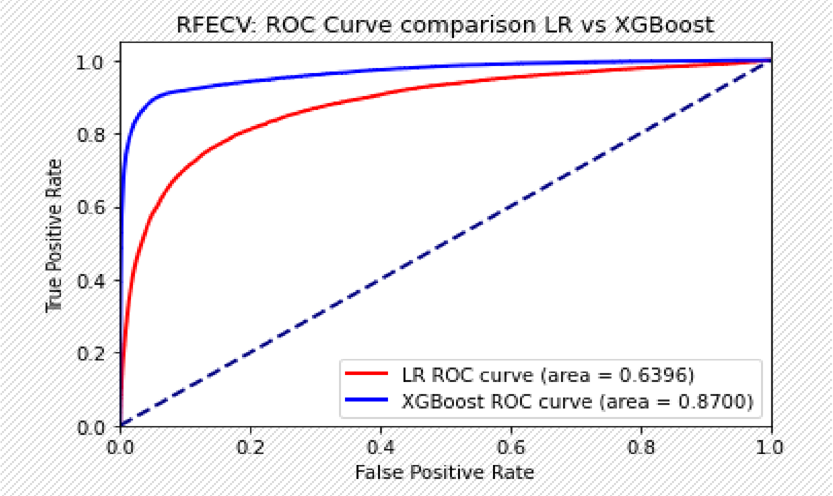
Summary of Dataset

- **Data source:** Kaggle platform, an online data science community platform which contains numerous free datasets for ML projects.
- **Dataset:** Lending Club dataset which contains real customer’s behavioral data for Credit Cards portfolio.
- **Dataset shape:** The dataset contained 151 variables related to real customer data for ~500K customers.

Our Proof of Concept - Model Evaluation (1/3)

The table below summarizes the model performance under various methodologies considered.

	Precision	Recall	F1	AUC	Gini
Logistic Regression	0.84	0.64	0.69	0.63962	0.279239
Decision Tree	0.88	0.82	0.85	0.820425	0.64085
XGBoost	**0.93**	**0.87**	**0.9**	**0.870024**	**0.740049**
Random Forest	0.89	0.77	0.81	0.768174	0.536347
Gradient Boosting	0.88	0.77	0.81	0.766061	0.532121
Neural Networks	0.86	0.73	0.77	0.72592	0.451841



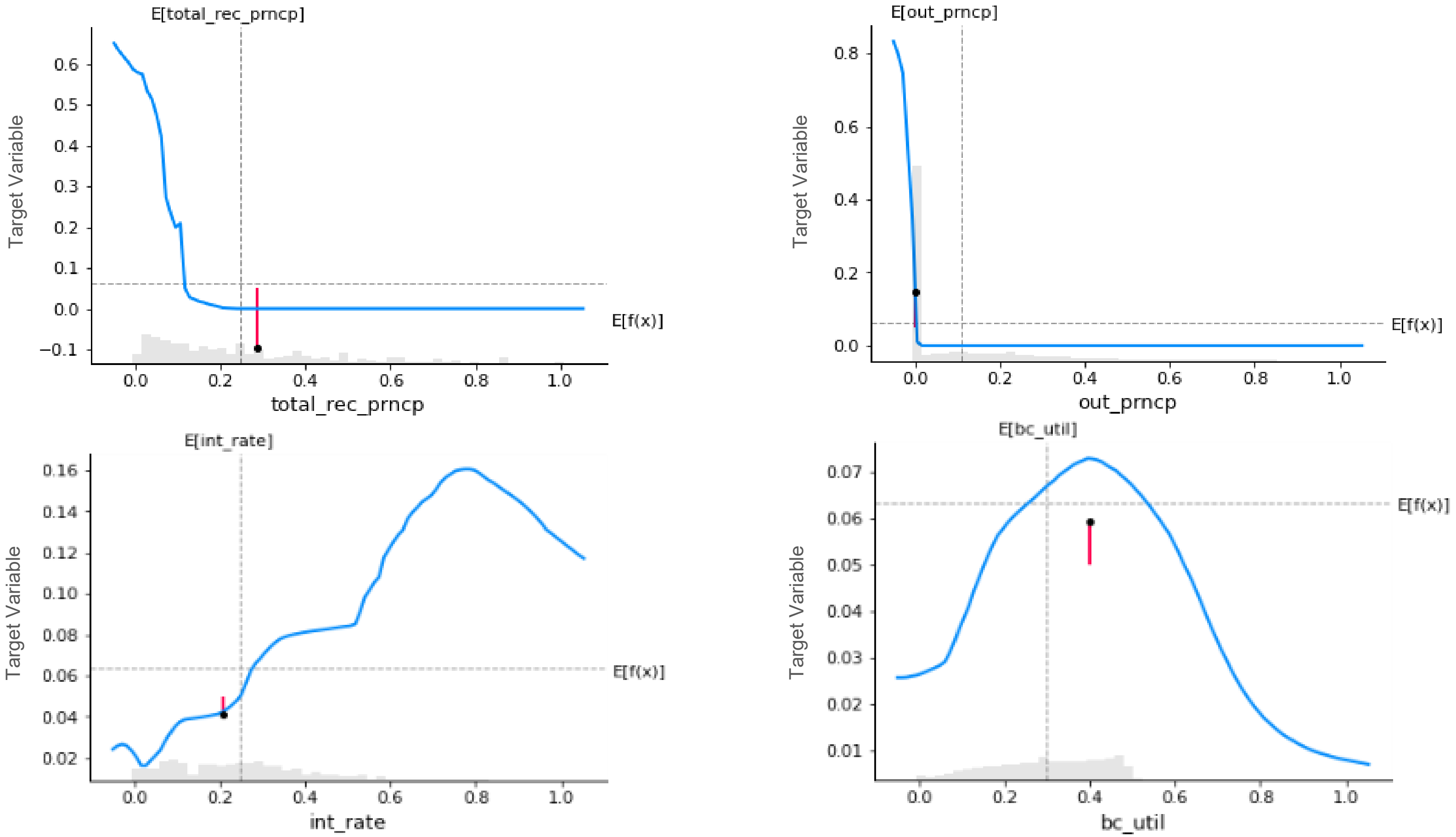
Our accelerator

The **"Greedy Forward Selection Algorithm"** constitutes an internally developed approach, with low computational requirements, that focuses on selecting the **most effective** feature combination leading to **superior model accuracy**. It encompasses a flexible technique for selecting variables, designed to effectively work for a **multitude of objective functions and accuracy metrics** (F1, Gini, Kolmogorov-Smirnov (KS)) based on the Bank's needs, ensuring **compatibility** across a wide range of evaluation criteria.

Our Proof of Concept - Model Evaluation (2/3)

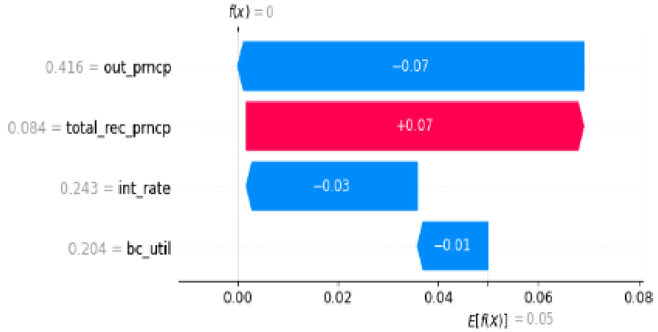
Partial dependence plots (PDPs) is a useful tool for gaining insights into the relationship between features and predictions. Neural networks for example are widely considered a black box algorithm that cannot be interpreted easily. The PDPs for algorithm 4 / Neural Network are provided below.

On these plots, the vertical axis shows the predicted probability and the horizontal one shows the feature's values. The blue line captures how average predicted probability changes as the feature's values change while the red lines indicate the average Shapley value.

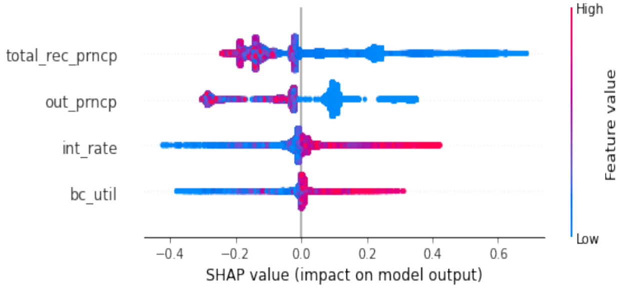


Our Proof of Concept - Model Evaluation (3/3)

Shapley Additive explanations (SHAP) algorithm, used to explain how each feature affects the model allowing for insights into the relationship between features and predictions.

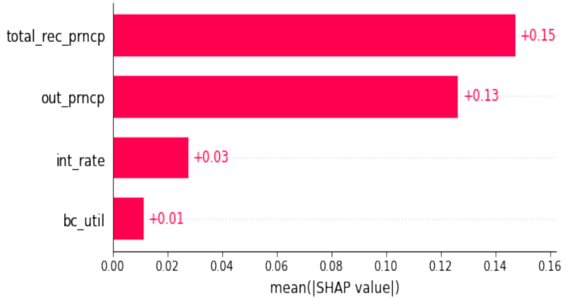


The waterfall diagram illustrates the impact of the explanatory variables values on a customer's PD, as predicted by the Neural Network model. It demonstrates whether each variable has a positive or negative influence on the customer's PD, based on an observation that was randomly selected from the dataset.



The plot shows how each feature is affecting the PD.

- *total_rec_prncp: Lower loan repayment percentages correspond to higher PD*
- *out_prncp: Lower total outstanding loan amounts increase default likelihood*
- *int_rate: Higher interest rates increase default likelihood*
- *bc_util: High credit card utilization leads to higher PD*



For analysis of the global effect of the features, the bar plot can be used. The features are ordered from the highest to the lowest effect on the prediction. It takes in account the absolute SHAP values, so it does not matter if the feature affects the prediction in a positive or negative way.

Thank you!

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