

# Index Who we are What is XAI Challenges and solutions A use case Management Solutions Making things happen



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#### A global and international company



50+ countries



customers



+ 600 F.I (1)

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Reference consultant accredited by supervisory authorities and supranational bodies (ECB, FCA, PRA, BoS, DNB, GNB, SNB, MNB, SBIF, SBS, BCCR, SSN, EIOPA, MEDE/ESM, WB, EIB, etc.)

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+3.300consultants



A multidisciplinary team with 1/3 "quant" profiles

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Through its 44 offices, MS regularly serves clients operating in 50 countries in Europe, America, Asia and Africa

# What is XAI Challenges of advanced modelling

The need to understand AI decisions stems from the widespread use of advanced modelling, and its critical impact on human and societal decisions

# Recommender Systems Clustering Customer Retention Structure Discovery Classification Classification Classification Diagnostics Classification Diagnostics Classification Diagnostics Advertising Popularity Prediction Learning Customer Forecasting Forecasting Customer Forecasting Customer Segmentation Customer Retention Classification Diagnostics Advertising Popularity Prediction Carning Regression Market Forecasting Estimating Infe expectancy Reinforcement Learning Robot Navigntion Customer Retention Classification Diagnostics Advertising Popularity Prediction Forecasting Scanne Al Reinforcement Learning Robot Navigntion Skill Acquisition

#### Context

- **Digital transformation** has made available a massive amount of structured and unstructured data.
- Increased appetite for modelling and technological infrastructures that provide greater computational capacity.
- The proliferation of the use of machine learning has generated the need to explain its results.

Can we understand well enough the decisions made by Al algorithms...

... especially when they have a critical impact on human, moral, or social decisions?

- 1 Since 2012, Deep Learning methods have dominated benchmarks of model predictive power and yield better results in business cases 1.
- There is a trade-off between the predictive power of Machine Learning models, and their ability to produce explainable and interpretable predictions.
- 3 This has led to the emergence of Explainable Artificial Intelligence (XAI), a field of AI that focuses on understanding and interpreting it.



# What is XAI Why XAI?

Explainable Artificial Intelligence (XAI) can prevent and mitigate risks that affect all sectors, and is increasingly found in all proposed regulatory frameworks for AI adoption







#### XAI Framework: What elements make up an XAI Framework?

#### **Interpretability of AI models**

Interpretability of results

Interpretability of the model design

Other aspects: biases, monitoring



#### **Model Risk Management (MRM)**

Explain the results to different users during development

Question the design during the validation and internal audit

BAU users in the monitoring and use of the model

Assess the risks arising from poor interpretability

Operational: data, implementation and documentation

Data free of biases

Implementation should ensure the replicability of the model Documentation should enable understanding of the model

#### **Technological support**

Tools available to implement interpretability techniques

**Model governance tools** 



#### **Challenges in XAI: Main challenges and proposed solutions**

	Challenges	
Interpretability of the model	The modelling process must be reproducible	Randomisation control
	Interpretability explanations may not be unique	Comparison of interpretability techniques, verifying consistency in similar data. Creation of interpretability reports
	The sequence of most likely model predictions may not be consistent	Include specific sensitivity analyses when revising the model.
	There is no mathematical formalism to describe the properties of many ML models	Comprehensive documentation on models and their mathematical basis
Model risk	There are no <b>globally accepted measures of evaluation</b> for ML models, nor of interpretability.	Application of a diverse and comprehensive testing framework throughout the model lifecycle.
	Model users must be able to access the interpretability modules to understand the predictions	Implementation of XAI modules
Data, documentation and implementation	There is implementation variance in certain Al algorithms.	Adequate documentation and implementation controls.
	The level of documentation should reflect the complexity	Include in detail the results of the interpretability tests,

of the algorithm.

guaranteeing their replication by a third party.

Interpretability of an intake model with ModelCraft® (1/2)

#### **Problem: Intake**

Objective: apply the ModelCraft® interpretability module to explain and detail the predictions made by an advanced Machine Learning model

- Find the best Machine Learning model that fits the data in a credit admission portfolio using ModelCraft®.
- Application of the ModelCraft® interpretability module for the Machine Learning model to be developed.
- Generate ModelCraft® automatic reporting of model development and interpretability information explaining the average weights of the model over the entire portfolio and the specific weights of the variables on each prediction.

#### **Approach**

#### Two phases:

- Application of the ModelCraft® interpretability module and analysis of the results
- Customisation and automatic report generation of the development and interpretability process.

#### **Benefits**

- Advanced XgBoost model with 94% hit rate
- Interpretability module that allows to know the influences of the variables in the prediction of a specific client.

#### **Applied strategy**

#### Using ModelCraft® as an accelerator

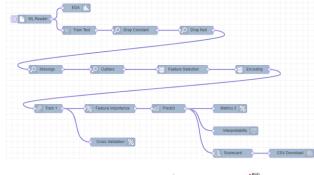
Implementation of various development algorithms to test the best accuracy:

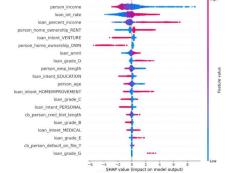
- XgBoost (94% Accuracy 87% AUC 94% F1 Score)
- LightGBM (94% Accuracy 86% AUC 94% F1 Score)
- R. Forest (94% Accuracy 86% AUC 93% F1 Score)
- Logistics (87% Accuracy 76% AUC 86% F1 Score)

#### **Interpretability module:**

- Obtain, on average, the weights that the variables have for the model's decision on any prediction.
- To be able to analyse, for each prediction, the influence of each variable on the admission decision.

In order to cover both concerns, the SHAP algorithm is applied.





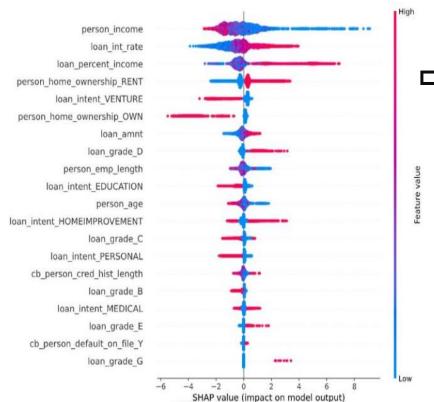
### A use case

Interpretability of an intake model with ModelCraft® (2/2)

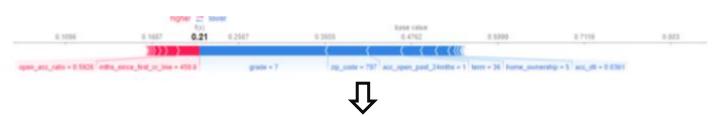


Objective: apply the ModelCraft® interpretability module to explain and detail the predictions made by an advanced Machine Learning model

#### Results



- Income turns out to be the most important variable in the model.
- People with low incomes (blue observations) show a positive correlation with default.
- The second characteristic identified as most important: interest rate of the loan.



- The influences of each variable in the model are also obtained.
- Owning a real estate property has a great impact on the admission,

