17TH BANKING CREDIT RISK MANAGEMENT SUMMIT

Credit scoring models:
Which performance metrics for optimal financial decision-making?

VIENNA, 7 FEBRUARY 2024

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ORIGINAL PAPERS

- Dessain, J., Bentaleb, N., & Vinas, F. (2023). Cost of Explainability in AI: An Example with Credit Scoring Models. In L. Longo (Ed.), Explainable Artificial Intelligence. xAI 2023. Springer, Cham. https://doi.org/10.1007/978-3-031-44064-9_26

- Dessain, J. (2023). Credit scoring models: which performance metrics for optimal financial decision-making?. SSRN preprint. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4624501

AGENDA

IMPORTANCE OF THE CREDIT RISK MODEL ASSESSMENT

Why is it so important to correctly assess a credit risk model predicting the probability of default (PD) ?

In the EU/EEA area, credit risk of credit institutions represents, on average, roughly 84% of their Risk Weighted Assets*.

With recent advancements in AI, a wide range of ML models have been adopted to perform credit scoring and PD prediction tasks.

=> Important to assess the **accuracy and effectiveness of PD prediction models:**

- Importance of **reliable and robust models**** :
    - **Predictive ability** => PD estimates are a reliable forecast of effective default rates
    - **Discriminatory power** => Model separates riskier borrowers from less riskier ones
    - **Stability** => Stability of the model:
- With the objective to :
    - **Reduce the cost of risk** within the limits of the risk appetite framework
    - **Improve RoE**

*EBA: *Report on the role of environmental and social risks in the prudential framework*, 2023.

*** ECB Instructions for reporting the validation results of internal models (2019 02) provides a detailed list of statistical tests.*

INTRODUCTION

How to assess a credit risk model predicting the probabilty of default (PD) or performing credit scoring ?

The accuracy and effectiveness of PD prediction models must be assessed thoroughly. This can be approached from two distinct perspectives:

Statistical metrics

- Use statistical tests to compare the predicted PD distribution with the actual observed values.
- The 9 statistical measures used in our analysis are: AUROC, Accuracy, Precision, Recall, F1 Score, KS, Gini, Brier Score and Lift.

ECB tests*, most model owners and uttermost academic papers use statistical tests as main tool to assess PD prediction models

Financial metrics

- "Real-world oriented", they assume a lending strategy and operating environment.
- Pragmatic approach to compute tangible outcomes, (ROI or ROE), thus considering the required amount of capital that the lender has set aside as a reserve for the credit.

Infrequent approach from model owners (and rare academic papers), with RoI, **standard ROE** or **IRB ROE**

- **Can "easy-to-implement" statistical metrics adequately assess the financial performance of ML models ?**
- **What metric is best to identify best model for predicting future PDs ?**
- **To what extent does the regulatory framework influence the model assessment: Standard or IRB ?**

** ECB Instructions for reporting the validation results of internal models (2019 02) provides a detailed list of statistical tests*

AGENDA

METHODOLOGY : CONTEXTUAL BACKGROUND AND RATIONALE

Is there a disconnect between statistical metrics and financial performance ?

Statistical Metrics

Major challenges arising for practitioners and researchers:

1. **Class imbalance:** scarcity of default events for learning.
2. **The spectrum of risk appetite**: varying risk appetite thresholds in financial institutions.
3. **The imbalance in the costs of prediction errors**: asymmetric costs of false positives (opportunity costs) and false negatives (significant loss in the event of default).

Financial Metrics

Financial metrics encompass

1. **the exposure at default (EAD),**
2. **the loss given default (LGD),**
3. **the risk appetite and the coupon rate.**

➔Computation of the performance can prove to be more complex to perform

➔No systematic analysis of the correlation or relationship between these two distinct sets of metrics.

Can statistical metrics provide a fair representation of financial performance that is utmost important for lenders?
Do they have the ability to identify the best models for credit scoring prediction?

METHODOLOGY FOR MEASURING THE FINANCIAL PERFORMANCE

Measuring statistical and financial performance to ensure profitability of a credit risk activity

1	2	3	4
Probability of Default (PD) computation	**Risk appetite threshold (RAT) determination**	**Statistical performance metrics computation**	**Financial performance metrics computation**
Computation of the PD for each proposed credit with each ML model*.	Loans with PDs equal or below RAT are approved, and those above are declined.	Statistical metrics are computed for each RAT, based on the estimated PDs by each model.	Financial performance for each RAT is measured through the computation of ROE.

** See Appendix 5.1. Methodology that describes the 510 different models that are used to compare statistical and financial performance*

METHODOLOGY FOR MEASURING THE FINANCIAL PERFORMANCE

Measuring statistical and financial performance to ensure profitability of a credit risk activity

1. Probability of Default (PD) computation
2. Risk appetite threshold (RAT) determination
3. Statistical performance metrics computation
4. **Financial performance metrics computation**

The **financial result** includes a dynamic coupon rate that varies based on the loan's riskiness as assessed by each model. It includes the following building blocks:

- i. The **risk-free rate**
- ii. A margin for funding and liquidity

$\}$ **Fund Transfer Pricing FTP**

- iii. A **credit risk premium cs_{ij}** equal to the PD determined for a loan i, by each model j, times the LGD
- iv. A **commercial margin** to remunerate the capital, commercial and back-offices departments

Defaulted loans

Result = - EAD * LGD

Non-defaulted loans

Result = credit spread cs_{ij}+ commercial margin

The financial performance-based metrics we have used cover 3 capital requirement scenario's:

1) **ROI** for unregulated lender assumed to borrow 100% of the lent amount
2) **Standard ROE** for regulated lender that apply the standard approach with a defined target equity ratio
3) **IRB ROE** for regulated lender operating with an IRB approach and the same target equity ratio

* See Appendix 2. Methodology that describes the 510 different models that are used to compare statistical and financial performance

METHODOLOGY – A ZOOM ON HOW WE FILL THE GAP

Ex-post & ex-ante comparative analysis of statistical and financial metrics

Ex-Post analysis

"What was the best model based on statistical measures?" &
"Does the best-performing model in terms of statistical measures ensure the best financial performances?".

Quality assessment of PDs generated using multiple algorithms and assess their quality using both statistical and financial metrics.

Ex-post interconnections between those metrics are explored through **correlation analysis, univariate linear regression and ANOVA.**

Ex-Ante analysis

"Does the best ex-post model (determined by a metric X, translate in the best model for future financial performance predictions? ".

This question is answered by selecting the best ex-post performing algorithm for each statistical metric on the validation set & **evaluating** its **financial performance** on a **test set**.

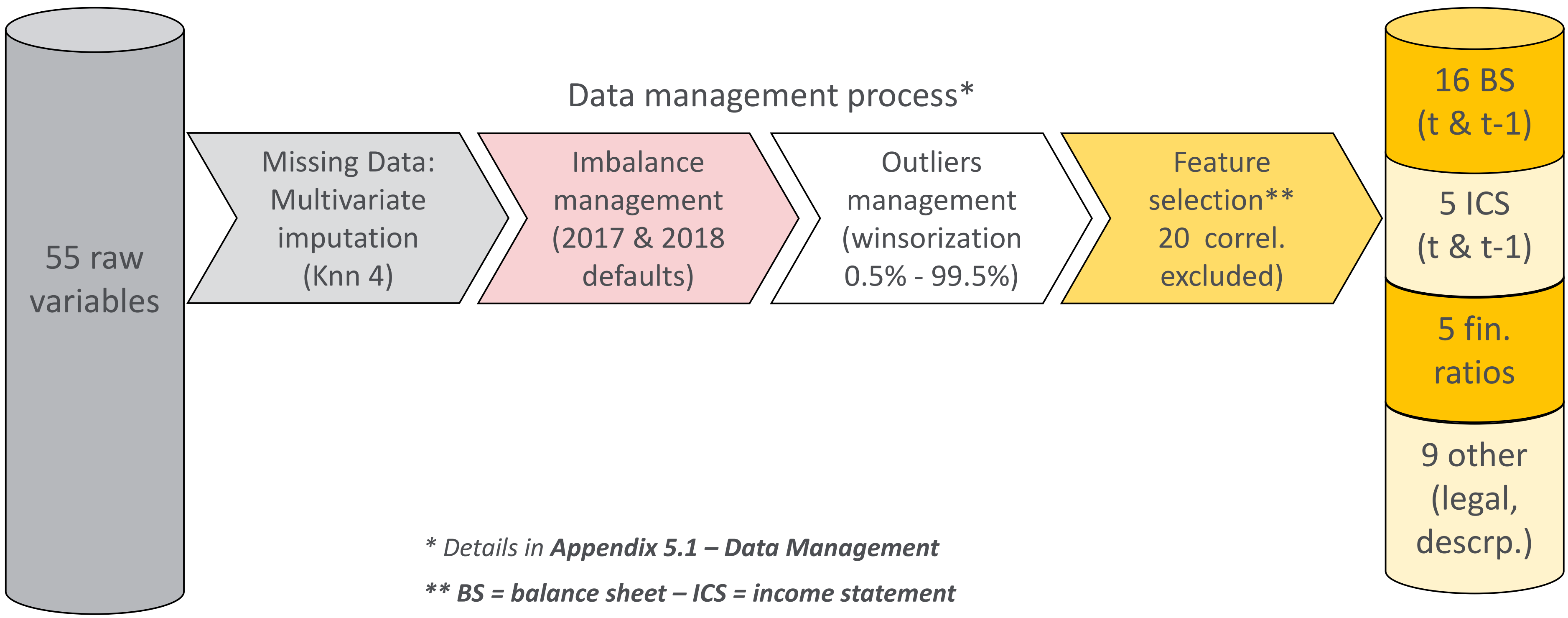
To evaluate **metric effectiveness in selecting the optimal model** for the future, the realized financial performance of each algorithm is compared to the best-performing one.

AGENDA

WE USE REAL-LIFE 1-YEAR CORPORATE CREDIT DATA

- Anonymized **real-life 1-year corporate credit exposures**, with 55 explanatory variables *(confidential and proprietary dataset)*

	Period	# Obs	# Defaults	Default rate
Training set	*2019*	*76,089*	*608*	*0.80%*
Enhanced training set	2019++	77,435	1,954	2.52%
Test set 1	2020	44,151	582	1.32%
Test set 2	2021	61,406	335	0.55%
Test set 3	2022	59,074	275	0.47%



** Details in **Appendix 5.1 – Data Management***

***** BS = balance sheet – ICS = income statement***

NO STATISTICAL METRIC CONSISTENTLY EMERGES AS A ROBUST PROXY FOR FINANCIAL PERFORMANCE

Correlation analysis of performance metrics for Grades 7 and 11* over a 3-year period

Correlations of performance metrics for grade 7

	Average ROE_STD	*Min ROE_STD*	*Max ROE_STD*	Average ROE_IRB	*Min ROE_IRB*	*Max ROE_IRB*
ROE_STD	1,00	*1,00*	*1,00*	0,97	*0,94*	*0,99*
ROE_IRB	0,97	*0,94*	*0,99*	1,00	*1,00*	*1,00*
accuracy	0,35	*0,11*	***0,55***	0,34	*0,08*	***0,55***
auroc	0,39	*0,26*	*0,47*	0,42	*0,32*	*0,49*
brier	0,20	*0,14*	*0,23*	0,17	*0,12*	*0,22*
f1	0,40	***0,35***	*0,46*	0,49	*0,46*	*0,51*
precision	0,40	***0,35***	*0,46*	**0,49**	***0,46***	*0,51*
recall	0,22	*0,16*	*0,25*	0,31	*0,29*	*0,33*
gini	0,39	*0,26*	*0,47*	0,42	*0,32*	*0,49*
lift	0,22	*0,16*	*0,25*	0,31	*0,29*	*0,33*
ks	**0,44**	*0,35*	*0,50*	0,48	*0,39*	*0,53*

Correlations of performance metrics for grade 11

	Average ROE_STD	*Min ROE_STD*	*Max ROE_STD*	Average ROE_IRB	*Min ROE_IRB*	*Max ROE_IRB*
ROE_STD	1,00	*1,00*	*1,00*	0,69	*0,31*	*0,89*
ROE_IRB	0,69	*0,31*	*0,89*	1,00	*1,00*	*1,00*
accuracy	**-0,45**	***-0,55***	***-0,37***	**-0,45**	***-0,59***	***-0,22***
auroc	0,07	***-0,21***	*0,27*	0,19	***-0,02***	*0,39*
brier	0,02	***-0,08***	*0,11*	0,13	*0,05*	*0,18*
f1	-0,43	***-0,49***	*-0,33*	**-0,33**	***-0,56***	***-0,18***
precision	-0,56	***-0,61***	*-0,49*	**-0,48**	***-0,65***	***-0,23***
recall	0,42	*0,21*	*0,66*	0,55	*0,38*	*0,79*
gini	0,07	***-0,21***	*0,27*	0,19	***-0,02***	*0,39*
lift	0,42	*0,21*	*0,66*	0,55	*0,38*	*0,79*
ks	**-0,53**	***-0,65***	***-0,45***	**-0,40**	***-0,63***	***-0,18***

Findings: Ex-Post analysis

For both grade levels, the **average correlations are less than 0,50**.

Correlation tends to decrease as the risk appetite threshold increases.

- **A significant gap exists regardless of whether lenders operate under unregulated, standard or IRB regulations. This disparity becomes more pronounced as risk appetite increases.**
- The Regression & ANOVA analysis further support the **unreliableness** of proxying financial performance with statistical measures.
- Moreover, volatility of correlations over the years remains high.

*Scale with 16 grades. Grade 7 =0.68% PD & Grade 11 last grade below 7.66% PD.

FINANCIAL METRICS EMERGE AS THE SUPERIOR OUT-OF-TIME PREDICTORS OF FUTURE FINANCIAL PERFORMANCE

Predictive ability of all metrics in identifying the best performing models

Average ROE_STD underperformance of the models selected per metric and per RAT versus best model

ROE_STD	7	8	9	10	11	12
ROE_STD	**-0,11%**	**-0,05%**	**-0,12%**	-0,73%	**0,000%**	**-0,04%**
accuracy	**-0,11%**	-0,46%	-2,23%	-1,84%	-3,20%	-2,95%
auroc	-0,50%	-0,19%	-0,20%	-0,76%	-1,09%	-0,70%
brier	-1,04%	-0,65%	-0,64%	-1,08%	-1,41%	-0,87%
f1	-0,50%	-0,15%	-0,20%	**-0,40%**	-2,12%	-2,95%
precision	-0,50%	-0,15%	-0,20%	**-0,40%**	-3,20%	-2,95%
recall	-0,50%	-0,15%	-0,20%	-0,79%	-1,22%	-0,75%
gini	-0,50%	-0,19%	-0,20%	-0,76%	-1,09%	-0,70%
lift	-0,50%	-0,15%	-0,20%	-0,79%	-1,22%	-0,75%
ks	**-0,11%**	-0,46%	-2,23%	-1,84%	-3,20%	-0,75%
LR	-0,95%	-0,57%	-0,50%	-0,91%	-1,08%	-0,42%

Methodology Ex-ante

Methodology:

- Models are selected based on their performance in year 0 following each metric
- Average performance in years 1 and 2 of the selected model is compared with the best performing model for years 1 and 2

=> Best possible result is 0%, the lower the number, the more efficient the metric to predict future performance

The historically most common model logistic regression (LR) significantly underperforms the other ML models identified with financial metrics.

FINANCIAL METRICS EMERGE AS THE SUPERIOR OUT-OF-TIME PREDICTORS OF FUTURE FINANCIAL PERFORMANCE

Predictive ability of all metrics in identifying the best performing models

Average ROE_IRB underperformance of the models selected per metric and per RAT versus best model

ROE_IRB	7	8	9	10	11	12
ROE_IRB	**-1,39%**	**-0,33%**	**-0,03%**	-0,97%	**-0,41%**	**-0,29%**
accuracy	**-1,39%**	-1,19%	**-0,03%**	**-0,53%**	-0,53%	-0,37%
auroc	-1,88%	-0,44%	-4,34%	-1,29%	-0,64%	-0,75%
brier	-3,68%	-1,40%	-4,95%	-1,57%	-0,86%	-0,77%
f1	-1,88%	-0,40%	-4,37%	-1,22%	-1,98%	-0,37%
precision	-1,88%	-0,40%	-4,37%	-1,22%	-0,53%	-0,37%
recall	-1,88%	-0,40%	-4,37%	-1,38%	-0,80%	-0,66%
gini	-1,88%	-0,44%	-4,34%	-1,29%	-0,64%	-0,75%
lift	-1,88%	-0,40%	-4,37%	-1,38%	-0,80%	-0,66%
ks	**-1,39%**	-1,19%	**-0,03%**	**-0,53%**	-0,53%	-0,66%
LR	-3,77%	-1,60%	-5,06%	-1,72%	-0,85%	-0,65%

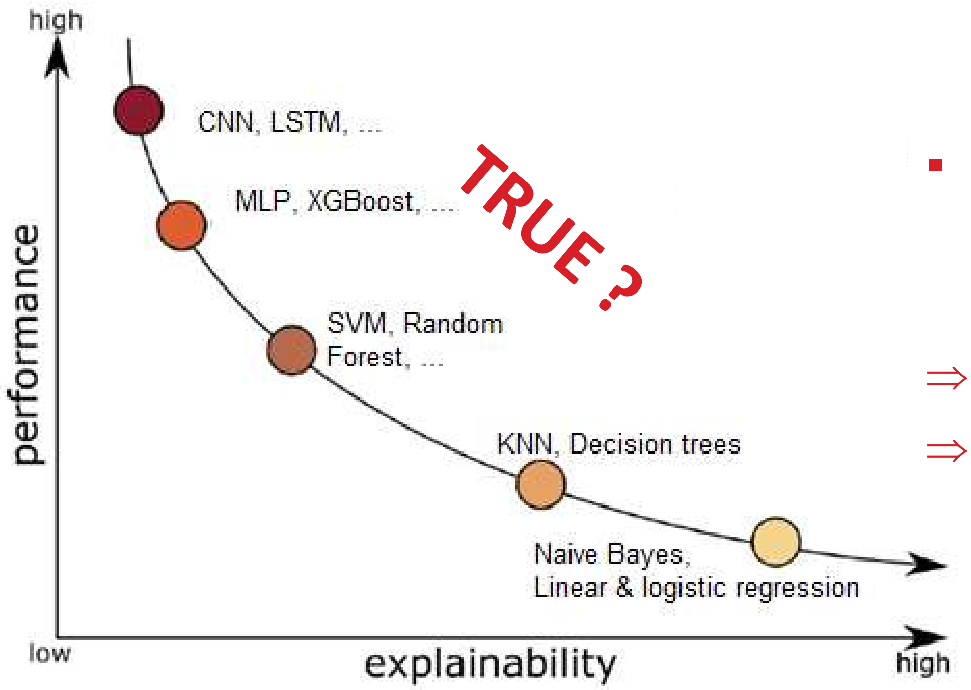
Findings: Ex-ante analysis

- **Financial metrics consistently outperform all statistical metrics across the risk appetite framework.**

The predictive capacity is particularly robust for predicting standard ROE.

AGENDA

IS THERE A TRADE-OFF BETWEEN PERFORMANCE AND EXPLAINABILITY ?



- Popular wisdom expects a **trade-off between performance and explainability**

⇒ Is it true ?

⇒ How to measure explainability and performance ?

- Difference between :
  - **White box:** **"inherently explainable"*** statistical inference models (linear and logistic regressions, Naïve Bayes and more generally GLM** and GAM)
  - **Black box** **"ex-post interpretable"** algorithms can benefit from ex-post local explanatory techniques (neural networks, complex decision trees, SVM, etc)

** For this presentation, we consider "inherently explainable" and "intrinsically explainable" as synonyms)*

*** Full article Dessain et al. Cost of Explainability in AI: An Example with Credit Scoring Models,* https://doi.org/10.1007/978-3-031-44064-9_26

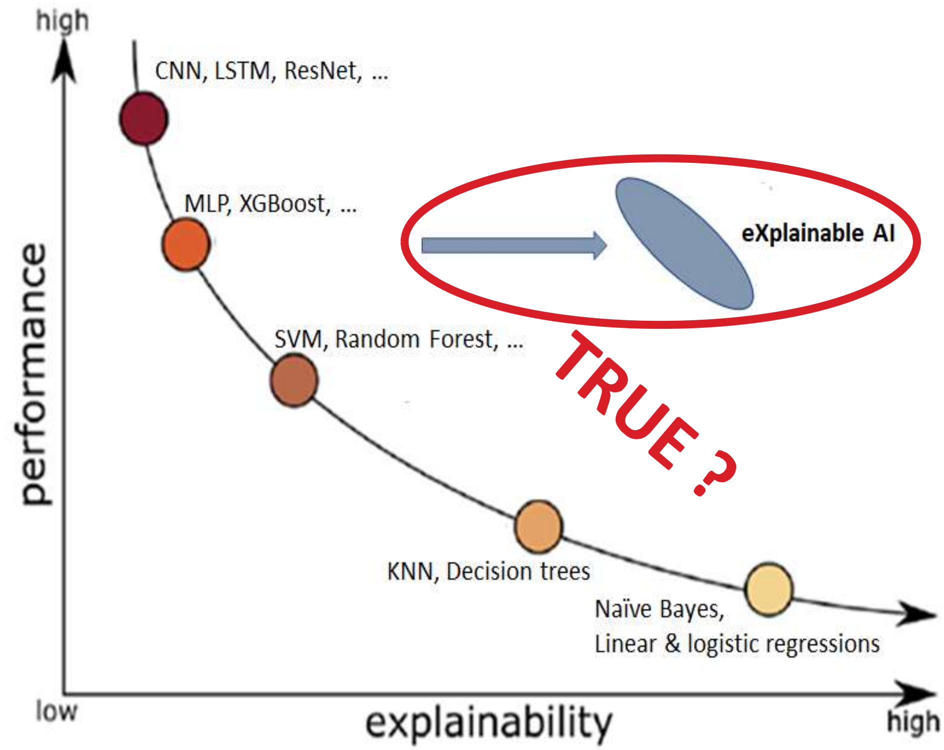
IF THERE IS A TRADE-OFF, CAN EXPLAINABLE AI DISRUPT IT ?

- Recent **"eXplainable AI"** algorithms ("**XAI**"):
  - Rely on black-box algorithms (XGB, MLP, …)
  - Produce a GAM

=> more acceptable for the regulators

⇒ Inherently explainable GAM*

⇒ As powerful as black-box algorithm ?



* GAM = Generalized Additive Model. It is like a "linear model" $y = a_i X_i + b$ where each a_i is not a single value but **each a_i is function of the value of X_i**

NOT ALL MODELS ARE ROBUST ENOUGH TO MATCH ECB REQUIREMENTS

- **11 out of 14 models succeed with ECB requirements**
- Naïve Bayes, SVM and Random Forest fail to provide at least 7 non-defaulted grades and are excluded from the analysis
- LDA delivers weak results for the predictive ability but is kept

Model	# grades	Predictive ability	Discriminat. power	Stability*	*Explainability*
Logistic regression	Yes	Yes	Yes	Yes	*Yes*
ElasticNet	Yes	Yes	Yes	Yes	*Yes*
Naïve Bayes	No	NR	NR	NR	*Yes*
Linear Discriminant Analysis	Yes	Weak	Yes	Yes	*Yes*
Explainable Boosting Machine	Yes	Yes	Yes	Yes	*Yes*
GamiNet	Yes	Yes	Yes	Yes	*Yes*
Isotonic EBM	Yes	Yes	Yes	Yes	***Yes +***
Isotonic GAMI	Yes	Yes	Yes	Yes	***Yes +***
Support Vector Machine	No	NR	NR	NR	*NR*
Random Forest	No	NR	NR	NR	*NR*
Gradient Boosting	Yes	Yes	Yes	Yes	*NR*
eXtreme Gradient Boosting	Yes	Yes	Yes	Yes	*NR*
Light GBM	Yes	Yes	Yes	Yes	*NR*
Multi-Layer Perceptron	Yes	Yes	Yes	Yes	*NR*

** Stability has been tested on a small sample (2 transitions) during an unusual period marked by covid-19*
All algorithms succeed with HI test and MWB, but most face minor issues with z-tests

- All other models succeed with the ECB tests
- General requirement but **no specific ECB test for the explainability**

11 MODELS, FROM WHITE-BOX TO BLACK-BOX, ARE TESTED

Models

- **11 models* in total** (among the most common):
  - 3 inherently explainable models
  - 2 explainable AI models
  - *2 Isotonic versions of the explainable AI models, based on **expert judgment to "force" the shape of the GAMs***
  - 4 black-box models whose interpretation can be done locally and ex-post
- Hyper-parameters tuning with a 2-step grid search

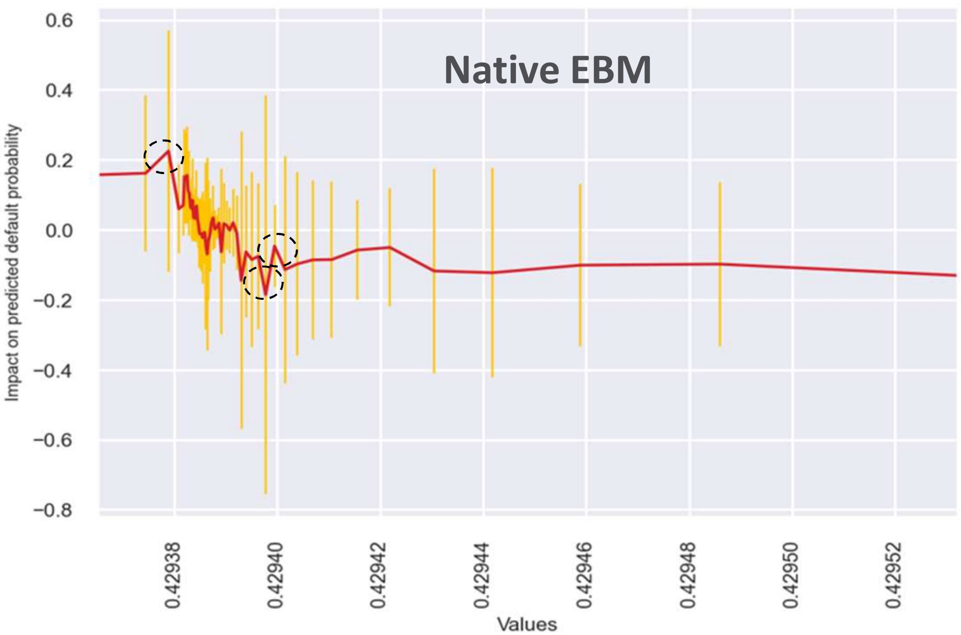
Model	Abbrev.	Type	Expert judgment(*)	
Logistic regression	LR	IE	No	Explainable
ElasticNet	EL	IE	No	Explainable
Linear Discriminant Analysis	LDA	IE	No	Explainable
Explainable Boosting Machine	EBM	XAI	**Yes**	Explainable
GamiNet	GAMI	XAI	**Yes**	Explainable
Gradient Boosting	GB	BB	No	Black-box
eXtreme Gradient Boosting	XGB	BB	No	Black-box
Light GBM	LGBM	BB	No	Black-box
Multi-Layer Perceptron	MLP	BB	No	Black-box

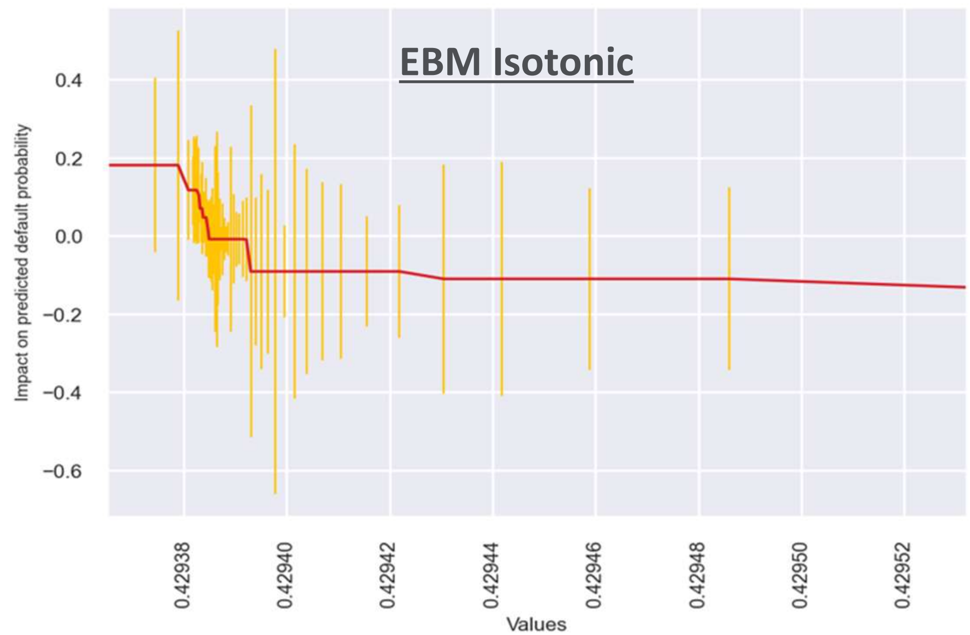
IE = inherently explainable
XAI = explainable AI, classified as inherently explainable
BB = Black-box, interpretable locally and ex-post
(*) Isotonicity of the GAM forced according to financial expert judgment

** The format of the data does not allow to apply more complex neural networks as CNN, LSTM or ResNet. While these models tend to overperform MLPs, they would require longer historical data for a reliable analysis*

EXPLAINABLE MODELS CAN BE IMPROVED WITH EXPERT JUDGMENT

- **Expert judgment improves the explainability** of EBM and GAMI, making the GAM-shapes easier to understand. Example with bs_012 feature (normalized amount of retained earnings) for which a monotonic negative correlation with the PD is expected:





- Monotonizing the shape of the GAMs:
  - ⇒ **Increased explainability** with a GAM shape that follows market expectation
  - ⇒ **Reduced risk of overfitting**
  - ⇒ **Possible outliers'** impact eliminated

ALL MODELS ADD VALUE, SOME MUCH MORE THAN OTHERS…

Financial results 2020

All ML models significantly improve the credit portfolio management compared to the standard LR

	RAT Grade 7			RAT Grade 11		
Model	Accepted	RoE_STD	RoE_IRB	Accepted	RoE_STD	RoE_IRB
LR	39.93%	7.25%	12.24%	93.16%	12.73%	16.13%
ELN	40.26%	7.12%	12.00%	93.21%	12.68%	16.11%
LDA	41.53%	7.64%	13.26%	92.95%	12.61%	16.20%
EBM	40.62%	**8.33%**	**14.79%**	94.21%	12.81%	16.31%
EBM Isotonic	*40.65%*	***8.33%***	***14.79%***	*94.22%*	***12.83%***	*16.32%*
GAMI	40.40%	8.12%	14.16%	92.94%	**12.83%**	**16.34%**
GAMI Isotonic	*40.38%*	*8.13%*	*14.17%*	*92.92%*	*12.82%*	*16.33%*
XGB	40.27%	8.52%	15.13%	94.40%	12.97%	16.44%
LGBM	38.88%	8.44%	14.88%	94.09%	13.21%	16.58%
GB	40.40%	8.41%	14.85%	93.79%	12.93%	16.40%
MLP	41.49%	**8.76%**	**15.57%**	93.46%	**13.43%**	**16.85%**

Explainable

Black-box

- EBM and GAMI are best performer for inherently explainable model, far ahead of the 3 other "standard" models
- **MLP significantly over-performs** the other black-box models
- **Isotonic XAI models** that integrate expert judgment **come at virtually no cost**, compared to native XAI models
- *Risk appetite impacts the rejection rate. Therefore, low risk appetite might create commercial issues*
- *2021 and 2022 results are very similar. Please refer to corresponding author for further details*

TRADE-OFF BETWEEN EXPLAINABILITY AND PERFORMANCE EXISTS BUT EXPLAINABLE AI REDUCES THE COST OF EXPLAINABILITY

- From the analysis for a risk appetite threshold at grade 7 and 11 respectively, we can deduct a cost of explainability :

		RoE_STD	RoE_IRB
RAT Grade 7	Best XAI model	8.33%	14.79%
	Best model	8.76%	15.57%
	Cost of explainability	0.43%	*0.78%*
RAT Grade 11	Best XAI model	12.83%	16.34%
	Best model	13.43%	16.85%
	Cost of explainability	0.60%	0.51%

- The **cost of explainability is around 0.50% :**
  - **RoE_IRB**: is most significant with low-risk appetite threshold, and decreases as the risk appetite increase
  - RoE_STD: increases with the risk appetite from just above 0.4% towards 0.6%

- The **purpose of the model** (pricing and underwriting, risk management, capital consumption, …) might **influence the importance of the cost of explainability** and should drive the preference for the best model or for the best explainable model, rather than for traditional explainable algorithms

AGENDA

5.1 METHODOLOGY

Research details

- The dataset consists of:
  - 9,180 loan portfolios of one-year corporate credit exposures from anonymized data on European borrowers with assets over €1 Million.
    - Generated by 510 different models over 3 years (2019-2022) and,
    - 6 different Risk Appetite Thresholds (RATs), going from grade 7 to 12.
- To assign a credit score and PD estimation to each proposed credit, a wide range of models were used:
  - Logistic Regression (LR), ElasticNet, Linear Discriminant Analysis (LDA), Gradient Boosting, XGBoost*, LGBM*, GamiNet*, EBM* and 15 different neural networks*.

    Where "" represents models ran with several hyperparameters to diversify the outcome.*
- Once the PD is estimated, the performance of the model is evaluated using statistical and financial metrics.
  - 9 statistical metrics (Auroc, Accuracy, Recall, Precision, Brier, F1, Gini, Lift and KS)
  - 3 financial metrics (ROI, ROE based on Standard Approach and ROE based on IRB Approach)
- Finally, for each year and RAT, the relationship between statistical and financial metrics is assessed through:
  1. **Correlation analysis**
  2. **Univariate linear regression**
  3. **ANOVA**

5.1 METHODOLOGY : AI MODELS USED

Various models matching ECB requirements have been applied to evaluate performance metrics

- We run 23 different models with various hyperparameters to obtain 510 models predicting PDs.
- Models are trained. They produce then PDs for 3 years OOT.
- PDs are graded on a scale of 16 grades.
- 6 different risk appetite thresholds (RAT) are considered, from grade 7 to grade 12.

=> 9180 different portfolios are therefore generated: 510 models * 3 years * 6 RAT

Tests are performed on these 9180 portfolios.

*Ran with various hyperparameters to diversify the outcome. These models are described in Dessain et al., 2023. We aim to capture a broad range of model performance outcomes and do not focus on the best performing models.

5.2 FINANCIAL RESULTS ARE USED TO ASSESS MODELS' PERFORMANCE

Financial Performance analysis

- Financial data:

Financial parameter	Abbrev.	Value	Comment
Risk-free rate	rfr	3.25%	1-year government bond yield
Fund-transfer pricing	ftp	0.75%	for funding & liquidity costs, set by ALM
Credit spread	cs_i	model-based	capped per grade at reference masterscale's PD* LGD
Commercial margin	cm	0.50%	to remunerate commercial and BO departments and capital
Loss-given default	LGD	45.00%	IRB value for senior unsecured credit to corporates in foundation IRB (CRE 32.5)

- Actual **financial result per accepted loan for each model** is equal to:
  - Loan paid-back: $\mathbf{cs_i + cm}$ = credit spread + commercial margin
  - Defaulted loan: $\mathbf{-\,(1 + rfr + ftp + cs_i + cm\,) * LGD}$ = total exposure at risk * the LGD

- Risk appetite threshold: based on the grades provided by the algorithms with:
  - low threshold : below grade 6 => lot of loans rejected as too risky
  - Base case: threshold for acceptance set at grade 7
  - High threshold : grades 11 => most loans accepted, only limited rejections

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Estimates given in this presentation are based on our current knowledge, they can be based upon our previous experience within the Undertaking, as well as taking into account similar projects in the same context as the Undertaking, either locally, within majority of the EU countries as well as overseas.

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