FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

Evaluating the Stability of Model Explanations in Instance-dependent Cost-sensitive Credit Scoring

Matteo Ballegeer, Matthias Bogaert, Dries F. Benoit

August 28th, 2025

GHENT UNIVERSITY - RESEARCH GROUP DATA ANALYTICS

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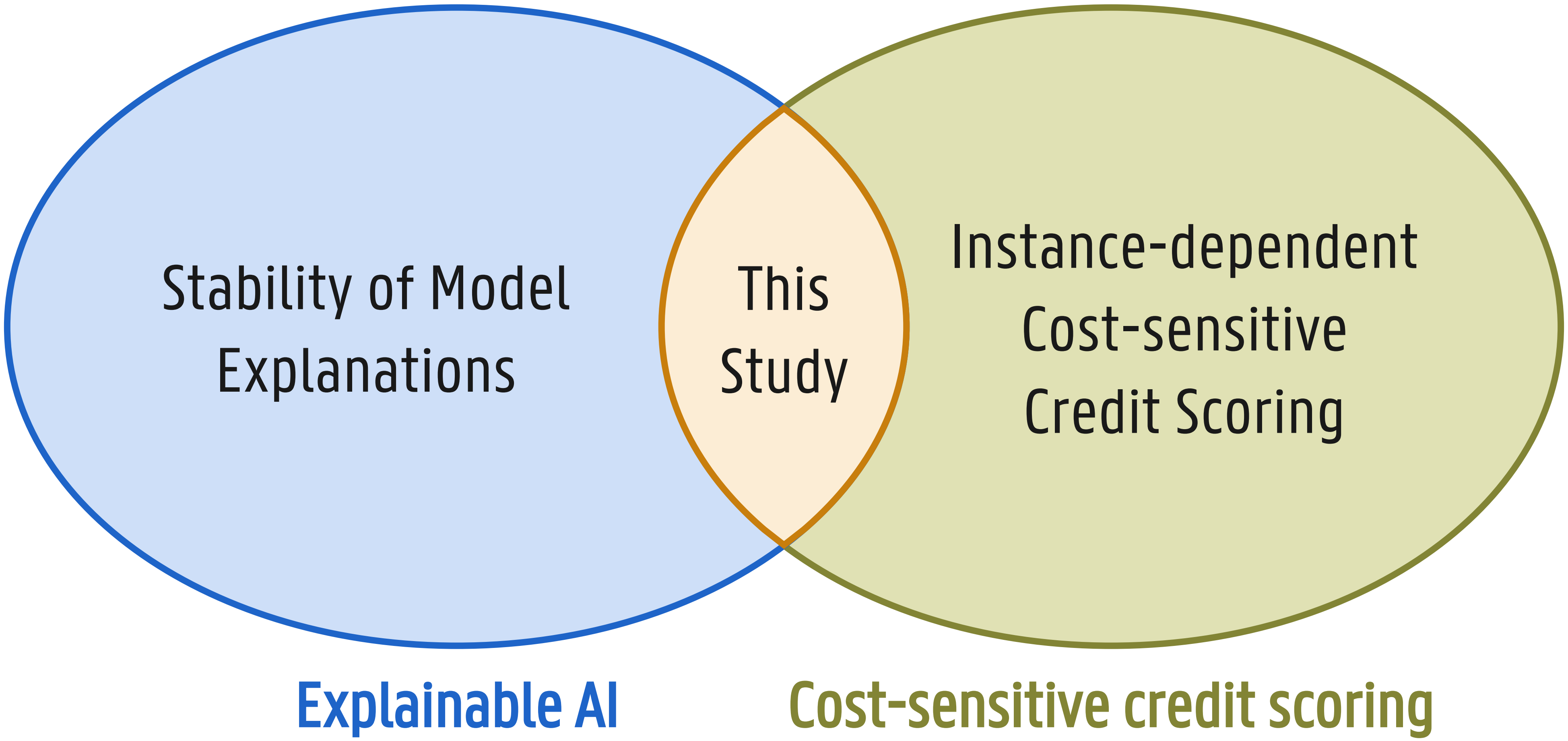
Credit Research Centre

FLANDERS MAKE
DRIVING INNOVATION IN MANUFACTURING

Research Positioning and Contributions

A bridge between model explainability and cost-sensitive learning



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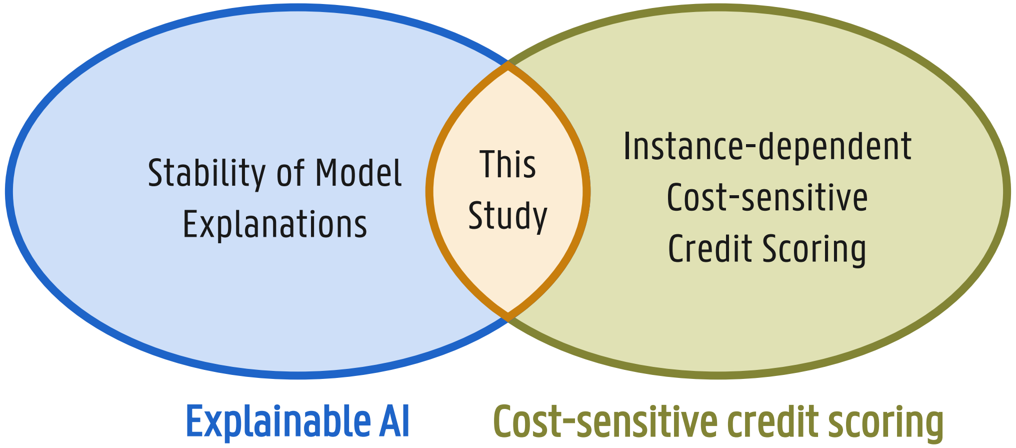

Main Contributions

1. First credit scoring study relating explainable AI to cost-sensitive learning.
2. Demonstrate the impact of IDCS classifiers on the stability of post-hoc explainable AI techniques.
3. Show that a known negative impact of class imbalance on explanation stability[1] is amplified when using IDCS classifiers.
4. Introduce a novel, cross-dataset comparable evaluation metric for cost-sensitive learning.

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[1] Chen, Y., Calabrese, R., Martin-Barragan, B., 2024. Interpretable machine learning for imbalanced credit scoring datasets.

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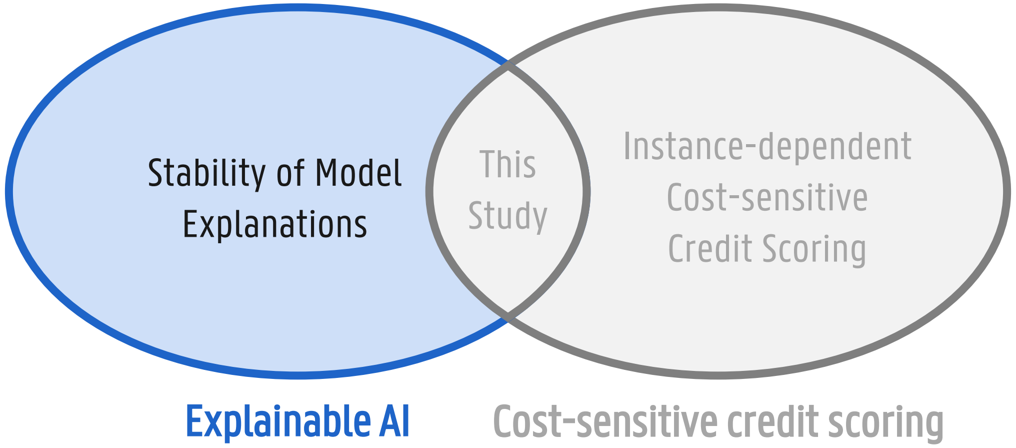

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Explainable AI

An increasing focus on regulating the use of black-box machine learning models


EBA DISCUSSION PAPER ON MACHINE LEARNING FOR IRB MODELS

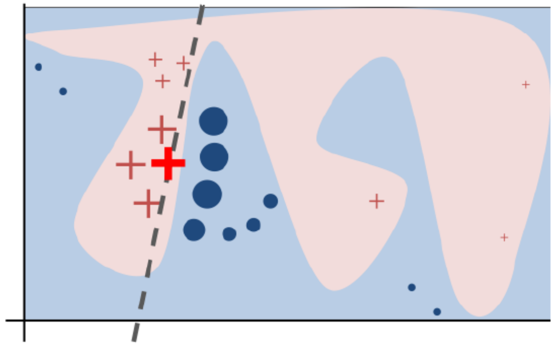
EBA/DP/2021/04

11 NOVEMBER 2021

Explainable AI

In response, XAI techniques to explain black-box models are rising in popularity

SHAP



LIME

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Explainable AI

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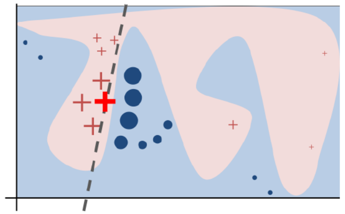

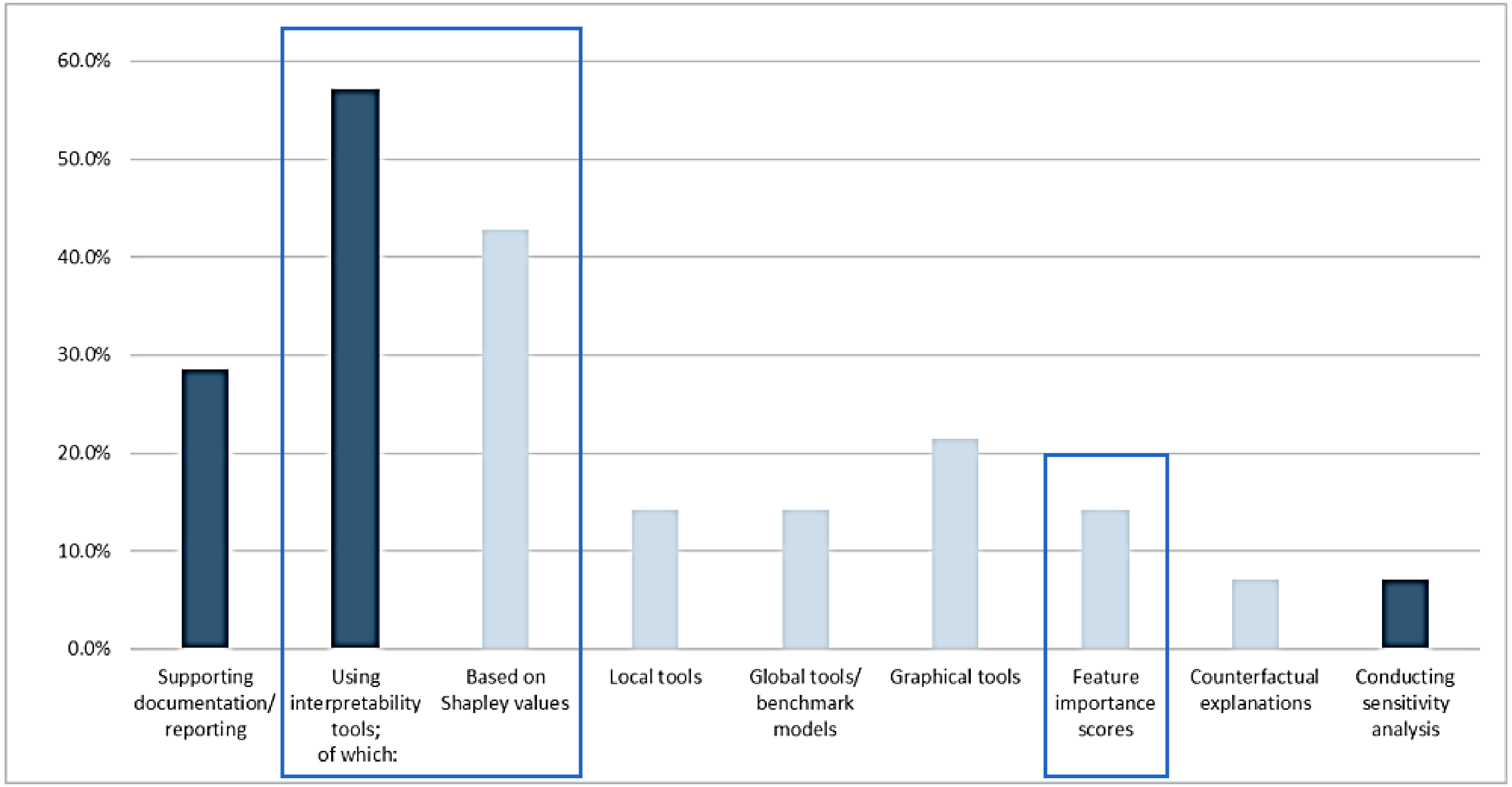

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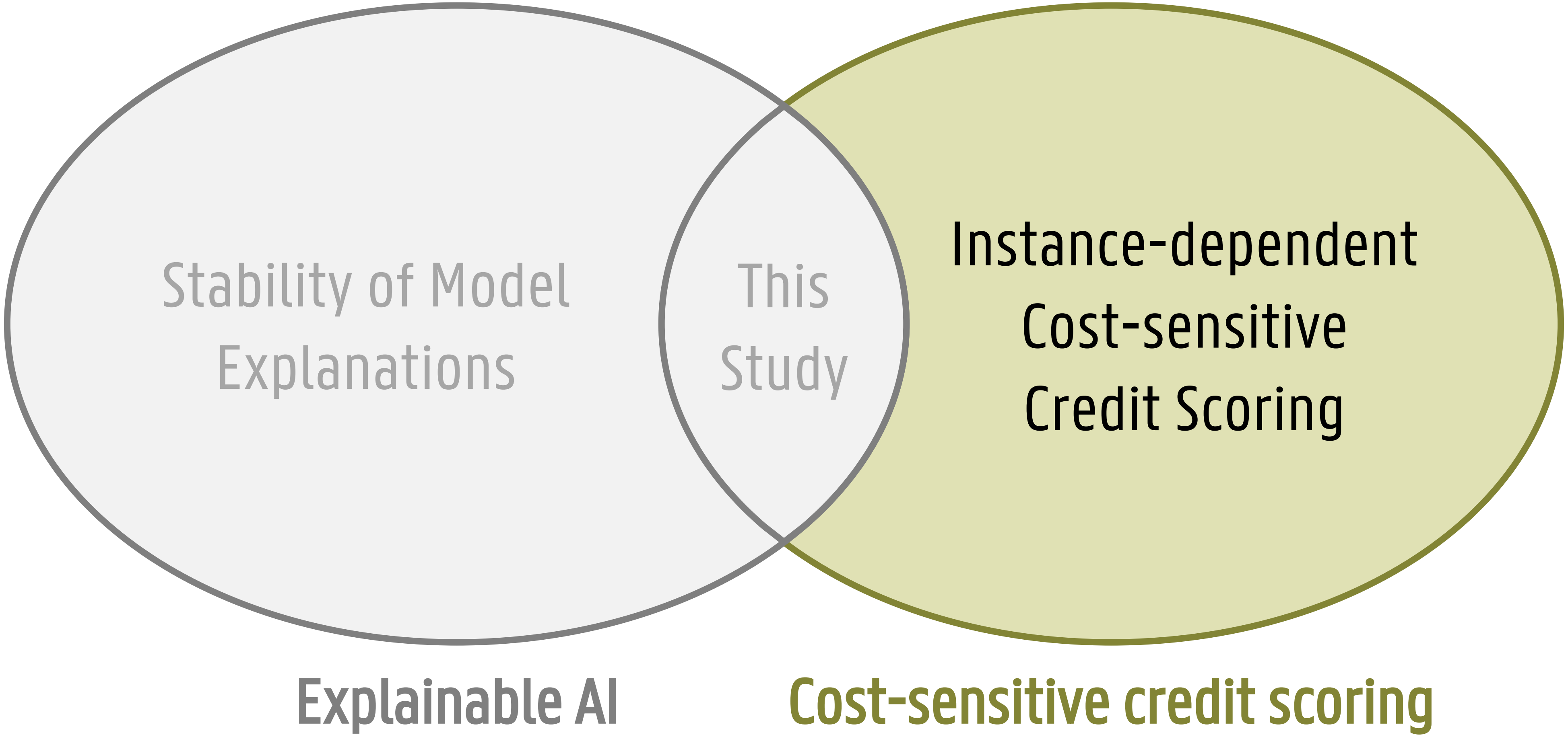
European Banking Authority, 2023. Machine Learning for IRB Models: Follow-up Report from the Consultation on the Discussion Paper on Machine Learning for IRB Models.

Research Positioning and Contributions

A bridge between model explainability and cost-sensitive learning



Cost-sensitive Learning

Different misclassifications do not result in equal costs

Predicted \ Actual	No Default	Default
No Default	True negative	False negative
Default	False positive	True positive

Symmetrical misclassification costs

Predicted \ Actual	No Default	Default
No Default	Cost (0|0)	Cost (0|1)
Default	Cost (1|0)	Cost (1|1)

Asymmetrical at the class level

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Instance-dependent Cost-sensitive Learning

The requested loan amounts (and associated cost) between customers can vary a lot

		Actual	
		No Default	Default
Predicted	No Default	Cost (0|0)	Cost (0|1)
	Default	Cost (1|0)	Cost (1|1)

Asymmetrical at the class level

		Actual	
		No Default	Default
Predicted	No Default	$Cost_i(0\|0)$	$Cost_i(0\|1)$
	Default	$Cost_i(1\|0)$	$Cost_i(1\|1)$

Asymmetrical at the instance level

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Vanderschueren, T., Verdonck, T., Baesens, B., Verbeke, W., 2022a. Instance-dependent cost-sensitive learning: do we really need it?.

Instance-dependent Cost-sensitive Credit Scoring

The most popular credit scoring cost matrix from literature is used

		Actual	
		No Default	Default
Predicted	No Default	$Cost_i(0\|0)$	$Cost_i(0\|1)$
	Default	$Cost_i(1\|0)$	$Cost_i(1\|1)$

Asymmetrical at the instance level

		Actual	
		No Default	Default
Predicted	No Default	0	$Amount_i \cdot LGD$
	Default	$\boldsymbol{r_i} + Cost_{alt}$	0

$$Cost_{alt} = -\bar{r} \cdot \pi_0 + \overline{Amount} \cdot LGD \cdot \pi_1$$

Bahnsen, A. C., Aouada, D., & Ottersten, B. (2014). Example-dependent cost-sensitive logistic regression for credit scoring.

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Instance-dependent Cost-sensitive Credit Scoring

Cost-efficient decision-making comes down to minimizing the AEC

		Actual	
		No Default	Default
Predicted	No Default	$Cost_i(0\|0)$	$Cost_i(0\|1)$
	Default	$Cost_i(1\|0)$	$Cost_i(1\|1)$

		Actual	
		No Default	Default
Predicted	No Default	0	$Amount_i \cdot LGD$
	Default	$r_i + Cost_{alt}$	0

$$Cost_{alt} = -\bar{r} \cdot \pi_0 + \overline{Amount} \cdot LGD \cdot \pi_1$$

$$\begin{aligned} Average\ Expected\ Cost\ (AEC)_i \ &= y_i \cdot [(1 - s(default)_i) \cdot (Amount_i \cdot LGD)] \\ &+ (1 - y_i) \cdot \left[s(default)_i \cdot \left(r_i + (-\bar{r} \cdot \pi_0 + \overline{Amount} \cdot LGD \cdot \pi_1)\right)\right] \end{aligned}$$

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Bahnsen, A. C., Aouada, D., & Ottersten, B. (2014). Example-dependent cost-sensitive logistic regression for credit scoring.

Instance-dependent Cost-sensitive Credit Scoring

Relative AEC is introduced as dimensionless adaptation of AEC

$$\begin{aligned} \mathit{Average\ Expected\ Cost\ (AEC)}_i = {} & y_i \cdot [(1 - s(default)_i) \cdot (Amount_i \cdot LGD)] \\ & + (1 - y_i) \cdot \left[s(default)_i \cdot \left(r_i + (-\bar{r} \cdot \pi_0 + \overline{Amount} \cdot LGD \cdot \pi_1) \right) \right] \end{aligned}$$

$$\boldsymbol{Relative}\ \mathit{Average\ Expected\ Cost}\ (\boldsymbol{rel}AEC)_i = 1 - \frac{AEC(yi, s(default)_i, Amount_i)_i}{AEC(yi, \pi_1, Amount_i)}$$

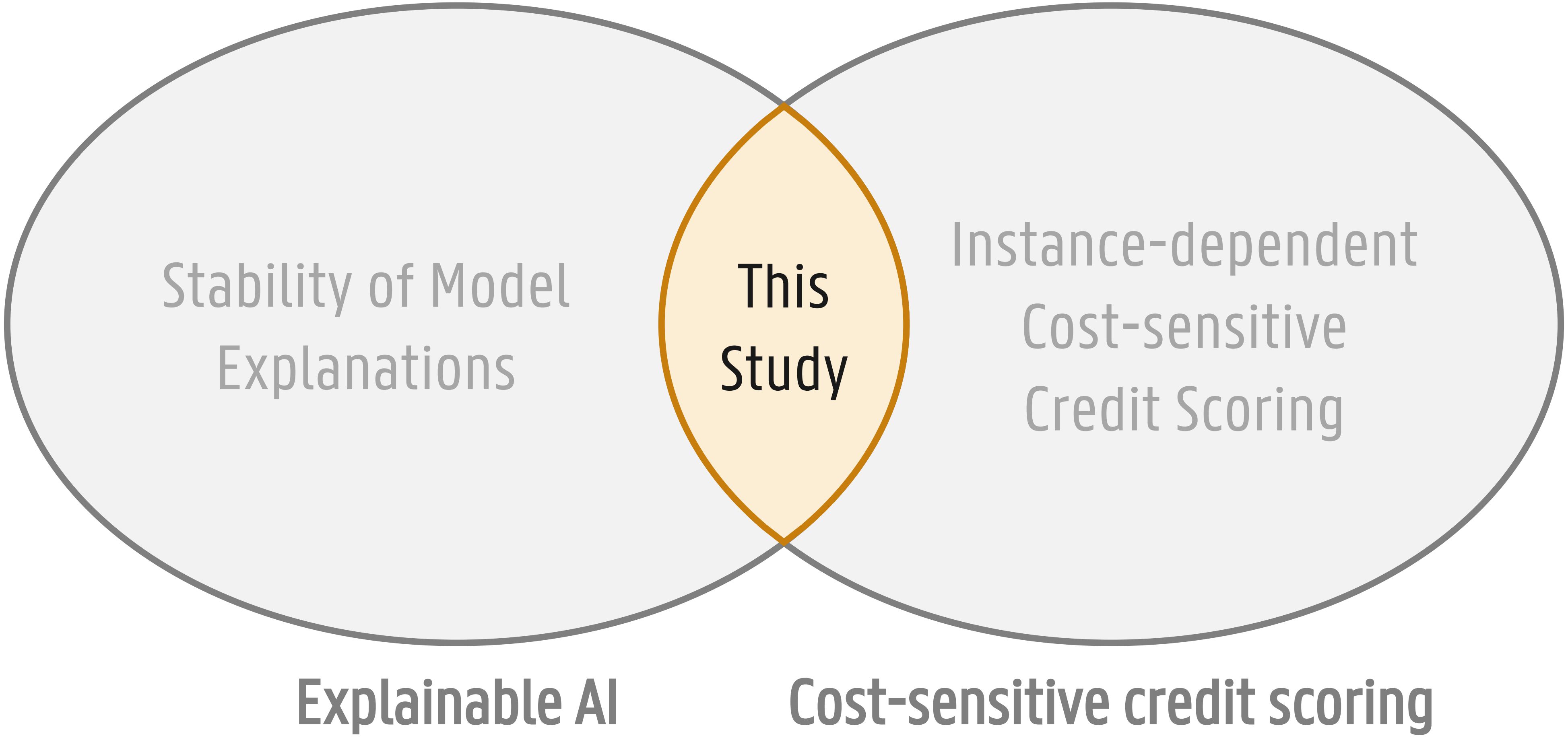
Worse than no model | Value

$-\infty$ 0 1

Similar interpretation as the savings metric!

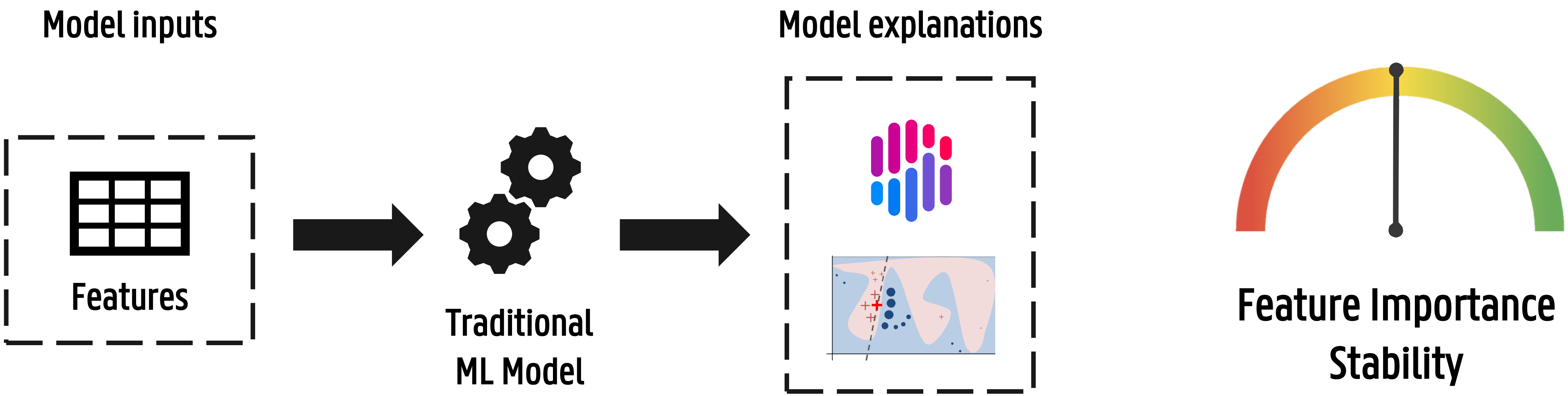
Research Positioning and Contributions

A bridge between model explainability and cost-sensitive learning



Explanation Stability in IDCS Credit Scoring

Does optimizing for an IDCS loss function impact the stability of model explanations?



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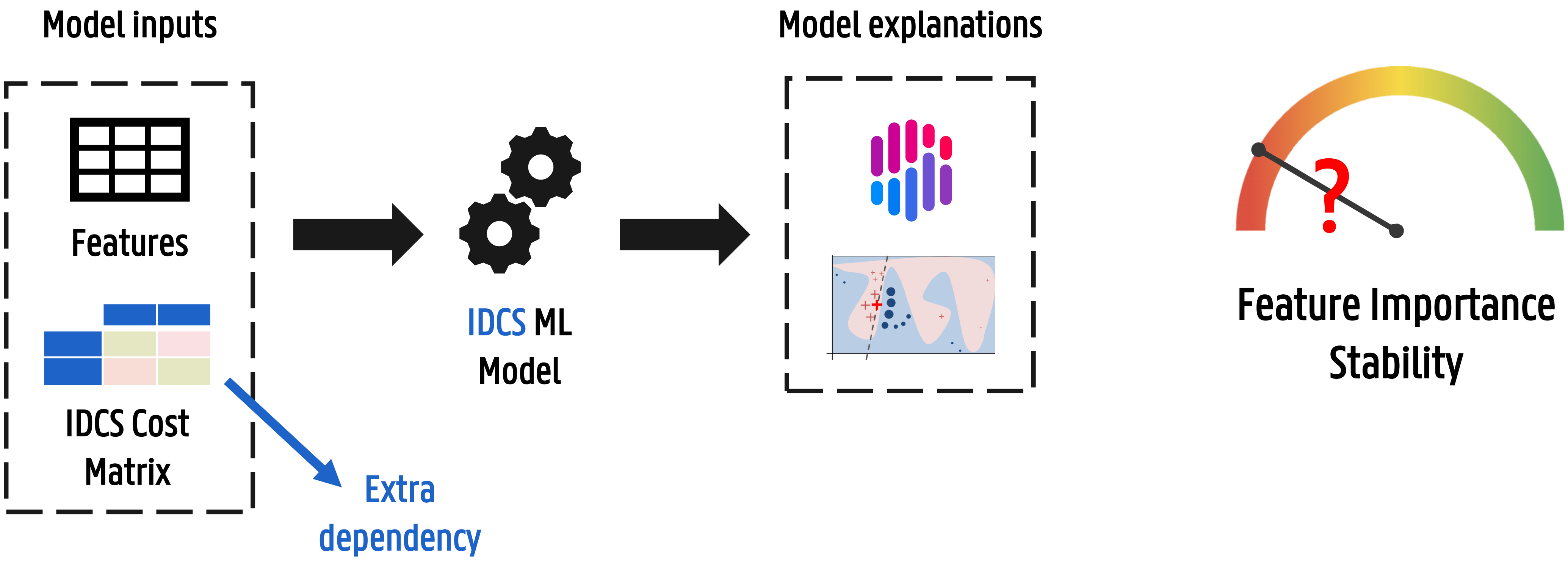
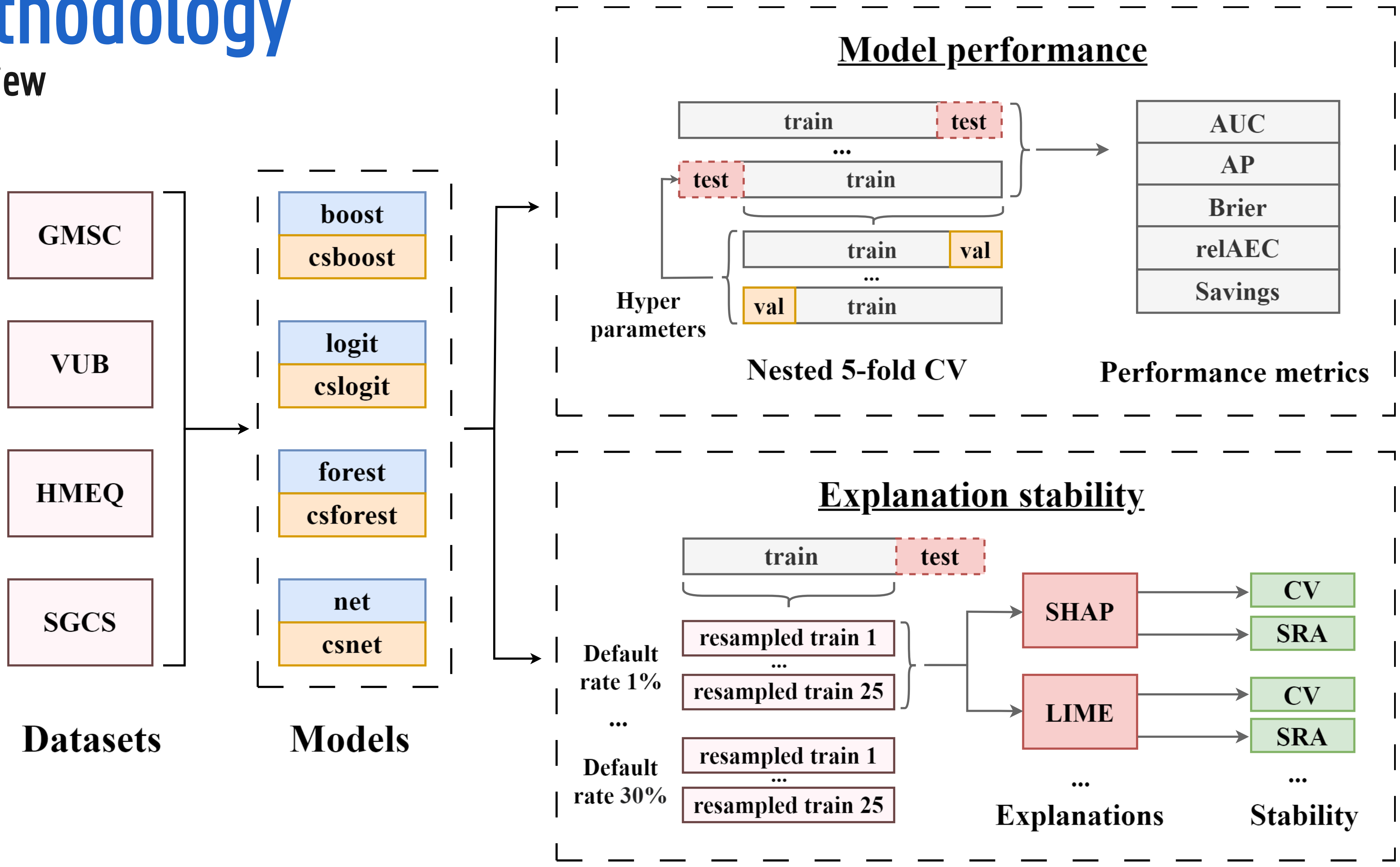


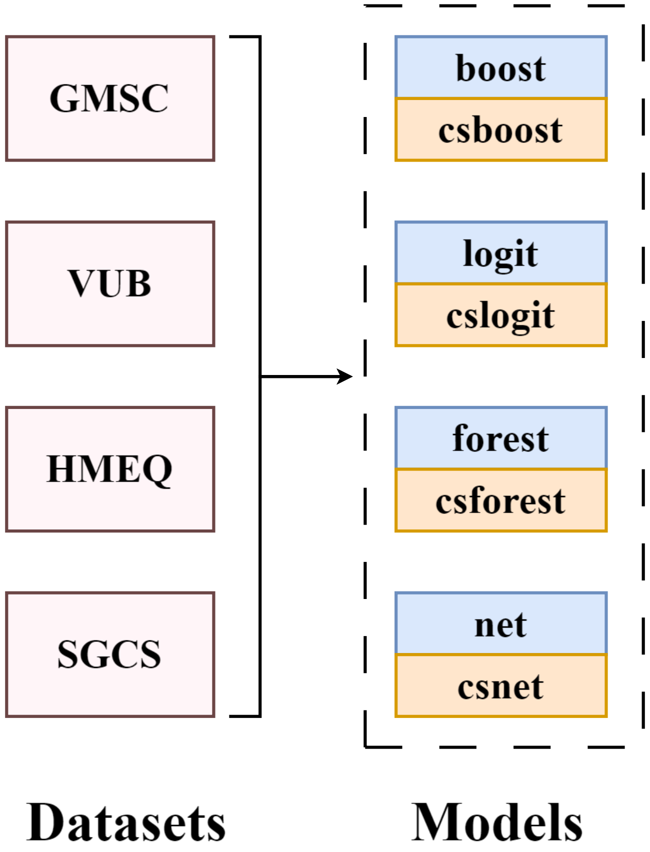
De Vos, S., en, T., Verdonck, T., Verbeke, W., 2023. Robust instance-dependent cost-sensitive classification

Methodology
Overview



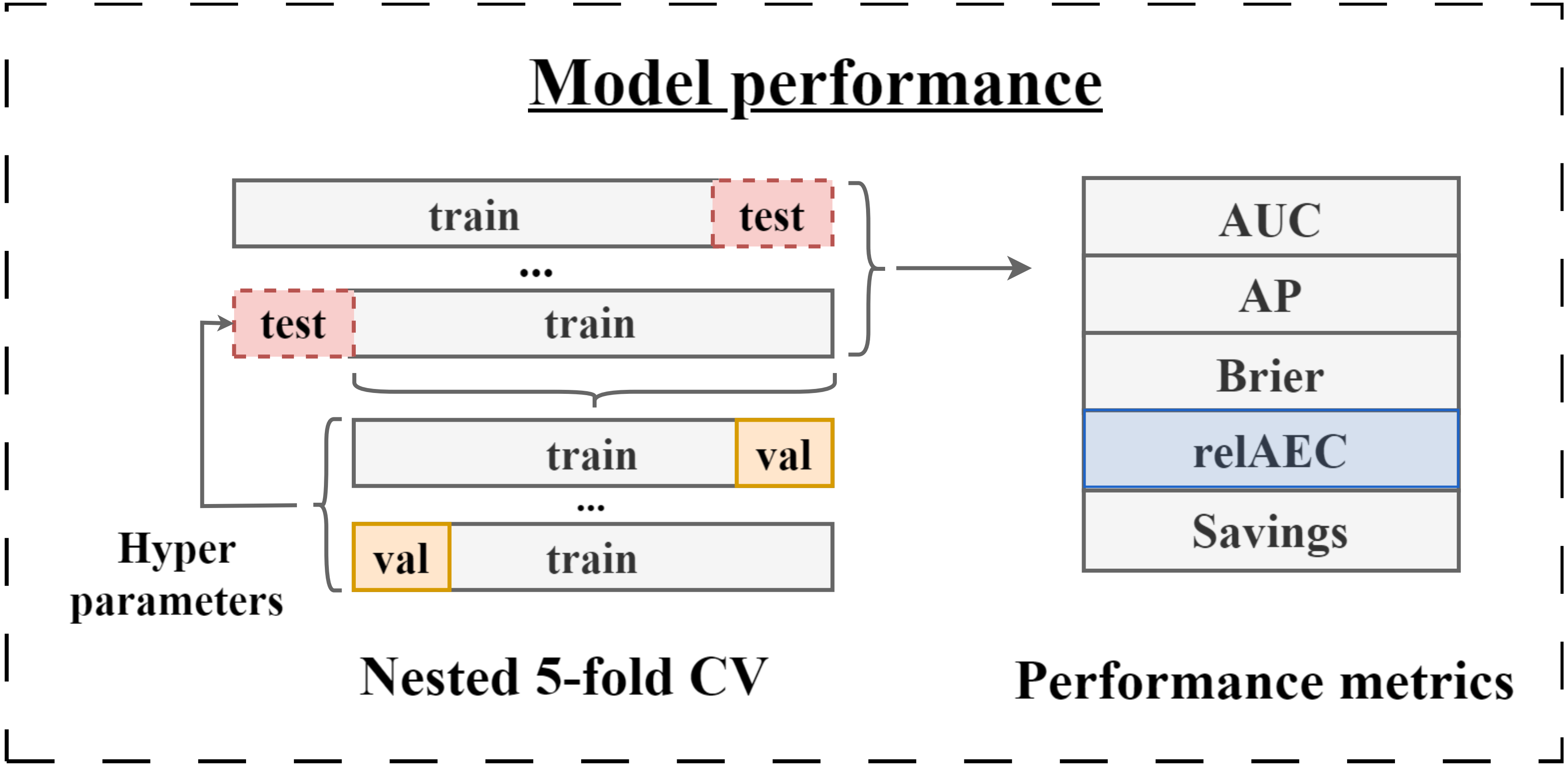
Methodology

Datasets and models



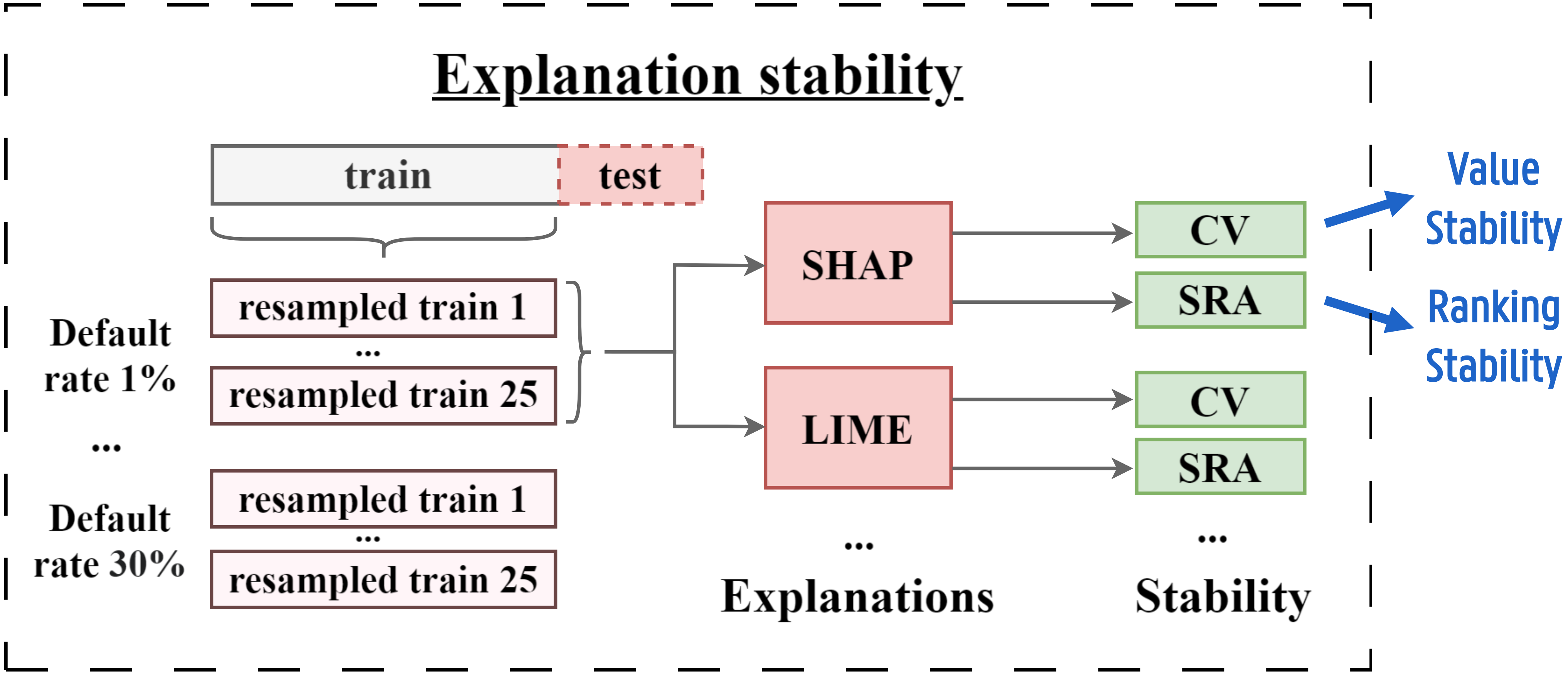
Methodology

Model performance



Methodology

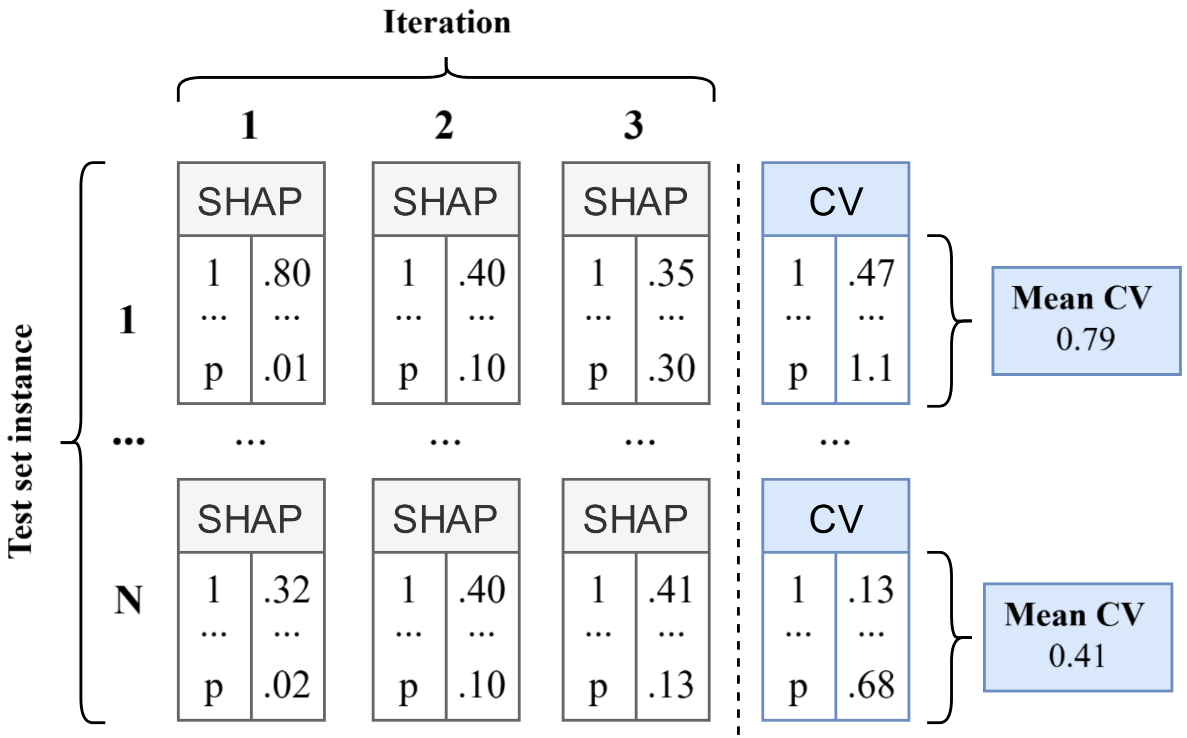
Explanation stability



Chen, Y., Calabrese, R., Martin-Barragan, B., 2024. Interpretable machine learning for imbalanced credit scoring datasets.

Methodology

Stability metrics



Xp	Φ_1	Φ_2	Φ_3
A	0.20	0.21	0.36
B	0.84	0.22	0.28
C	0.55	0.33	0.89
D	0.93	0.65	0.77
E	0.12	0.10	0.11

Value Stability

Coefficient of Variation (CV)

Ranking Stability

Sequential Rank Agreement (SRA)

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Ekstrøm, C.T., Gerds, T.A., Jensen, A.K., 2018. Sequential rank agreement methods for comparison of ranked lists. Biostatistics 20, 582598.

Methodology

Stability metrics

Xp	Φ_1	Φ_2	Φ_3
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C	0.55	0.33	0.89
D	0.93	0.65	0.77
E	0.12	0.10	0.11

→

Xp	R_1	R_2	R_3	Var_L
A	4	4	3	0.33
B	2	3	4	1
C	3	2	1	1
D	1	1	2	0.33
E	5	5	5	0

Ranking Stability

Sequential Rank Agreement (SRA)

Ekstrøm, C.T., Gerds, T.A., Jensen, A.K., 2018. Sequential rank agreement methods for comparison of ranked lists. Biostatistics 20, 582598.

Methodology

Stability metrics

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A	4	4	3	0.33
B	2	3	4	1
C	3	2	1	1
D	1	1	2	0.33
E	5	5	5	0

Depth	S(d)	SRA
1	{C, D}	0.67
2	{B, C, D}	0.77
3	{A, B, C, D}	0.67
4	{A, B, C, D}	0.67
5	{A, B, C, D, E}	0.53

Ranking Stability

Sequential Rank Agreement (SRA)

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Methodology

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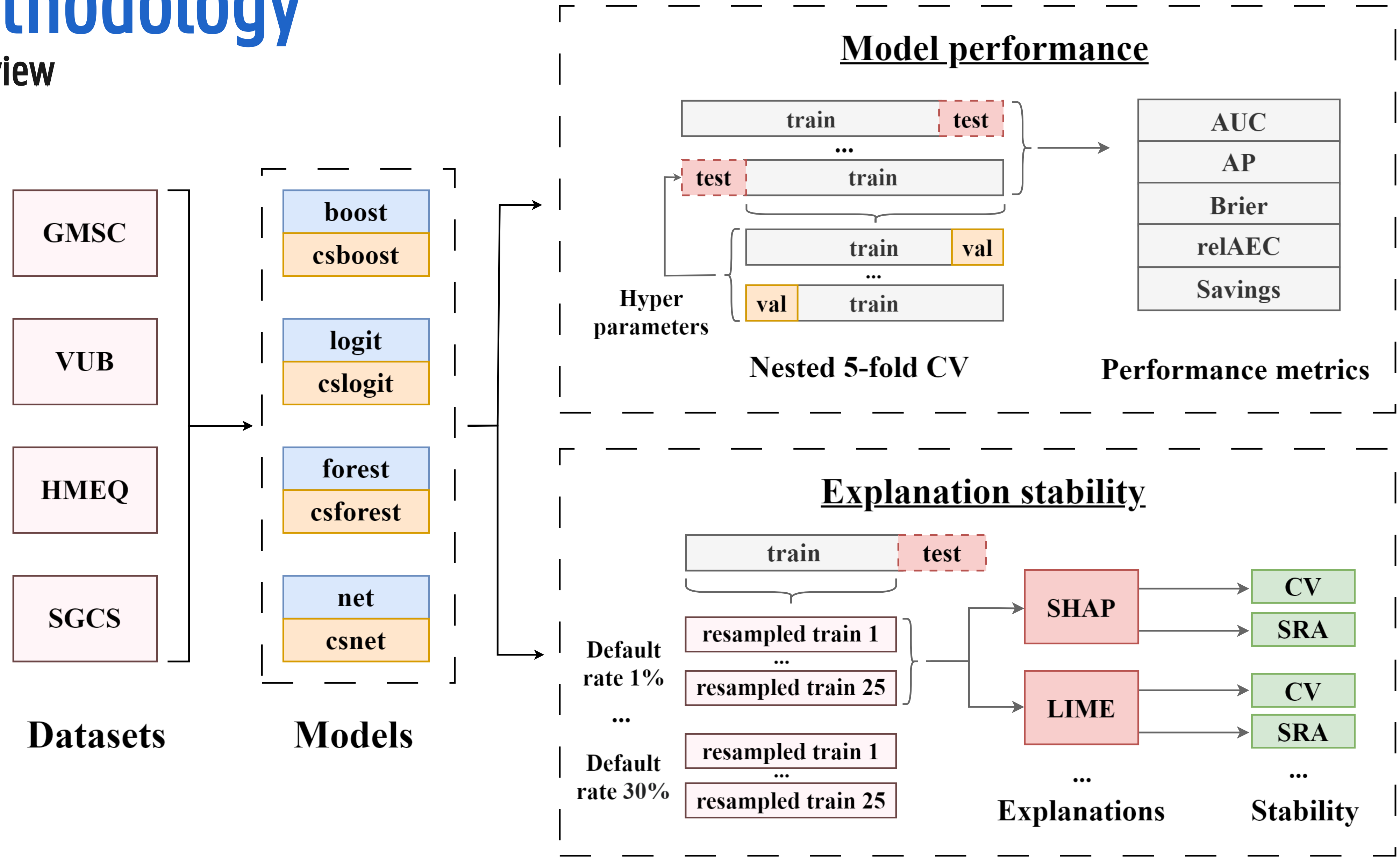

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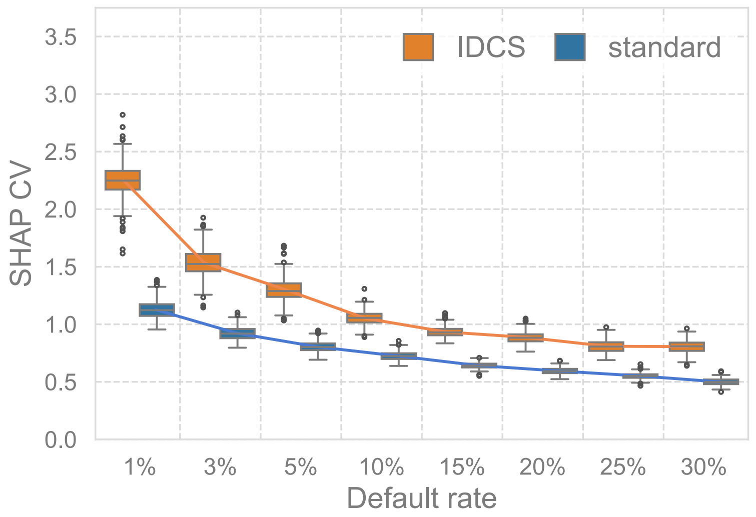
Explanation Stability Results

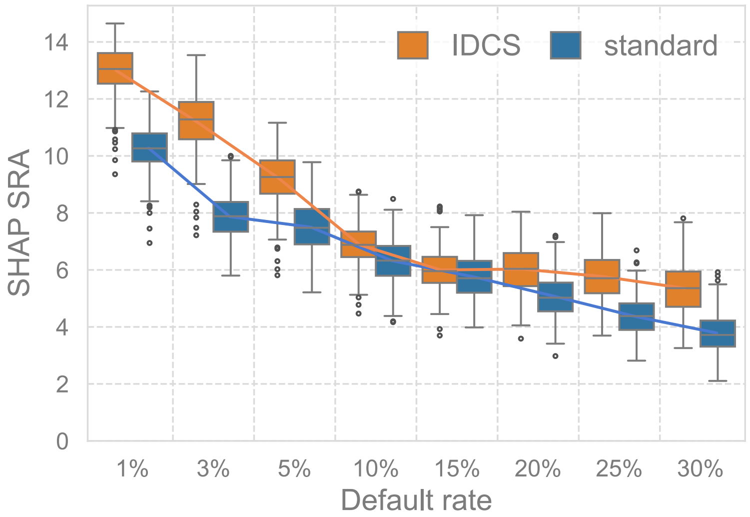
HMEQ dataset

CV

SRA

SHAP





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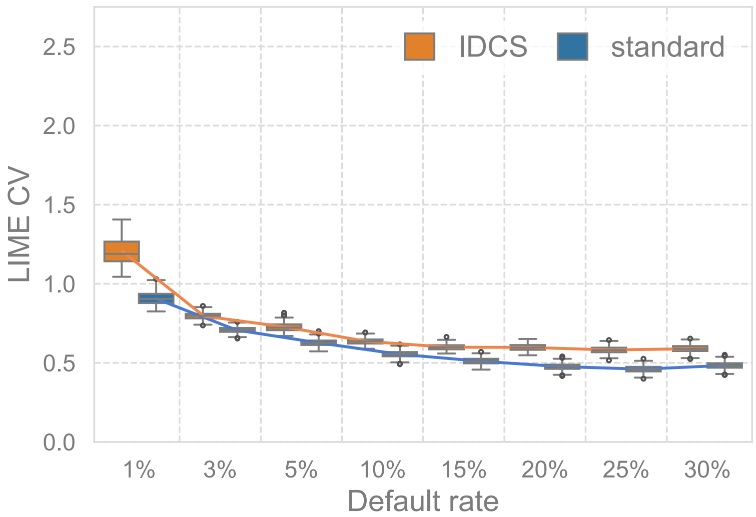

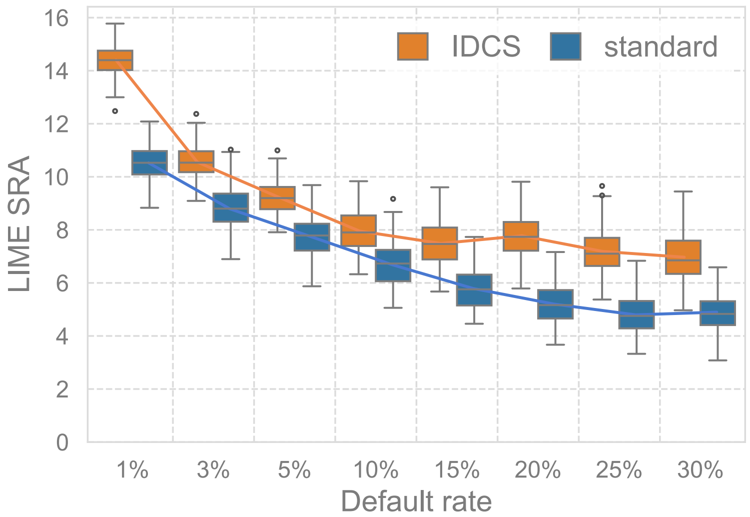

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HMEQ dataset

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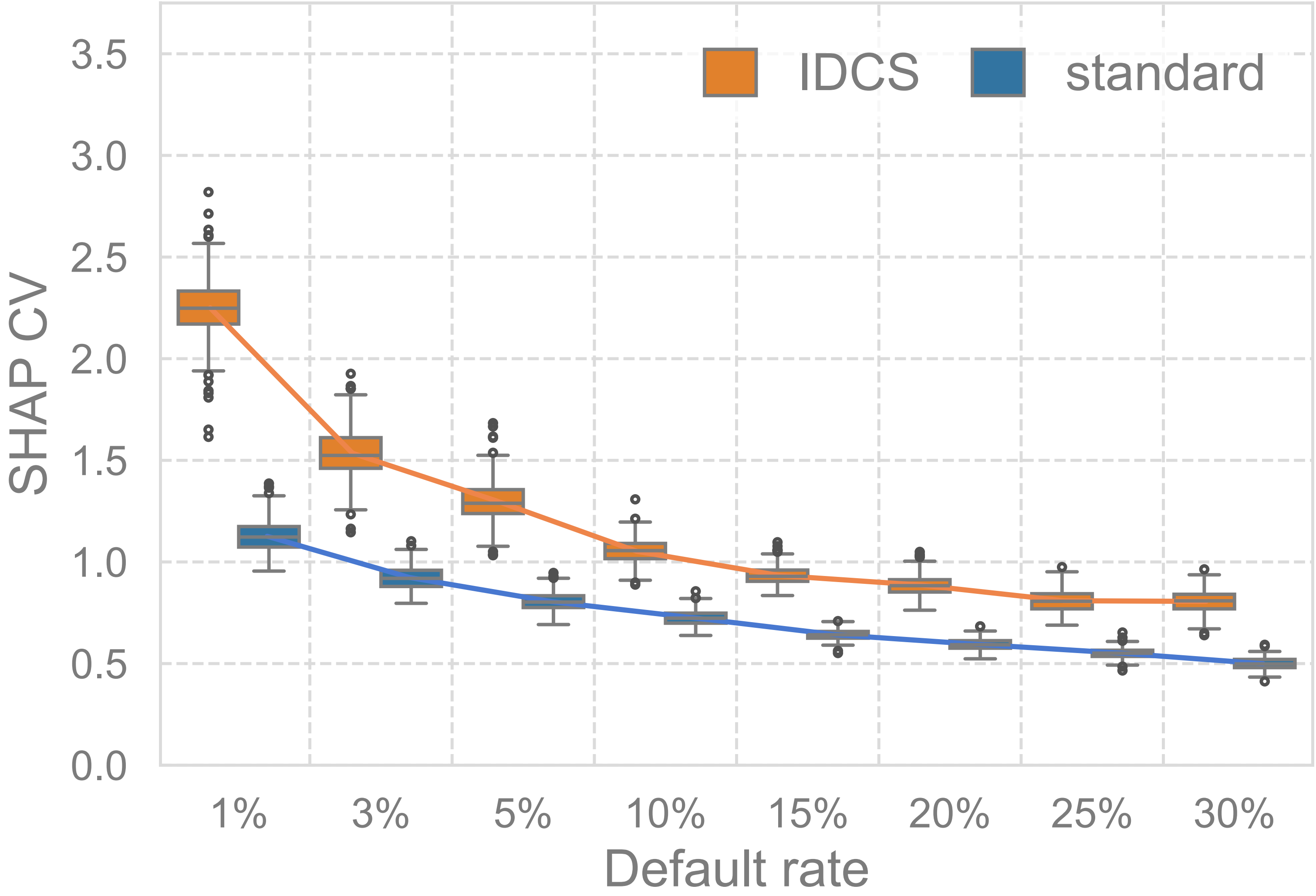

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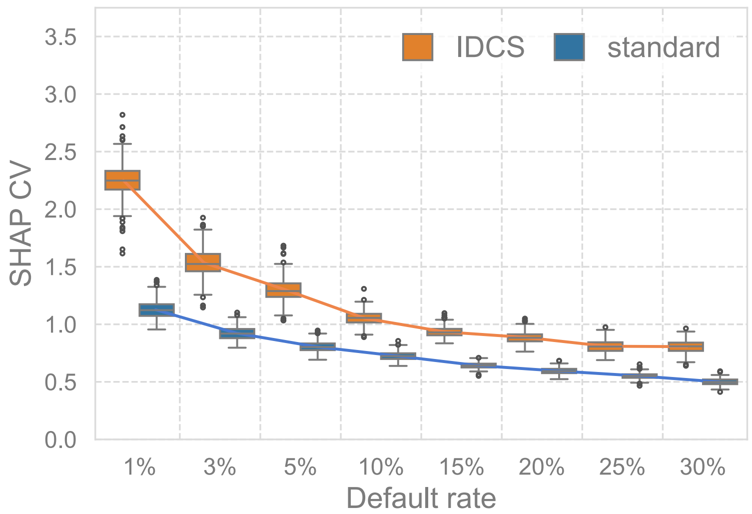

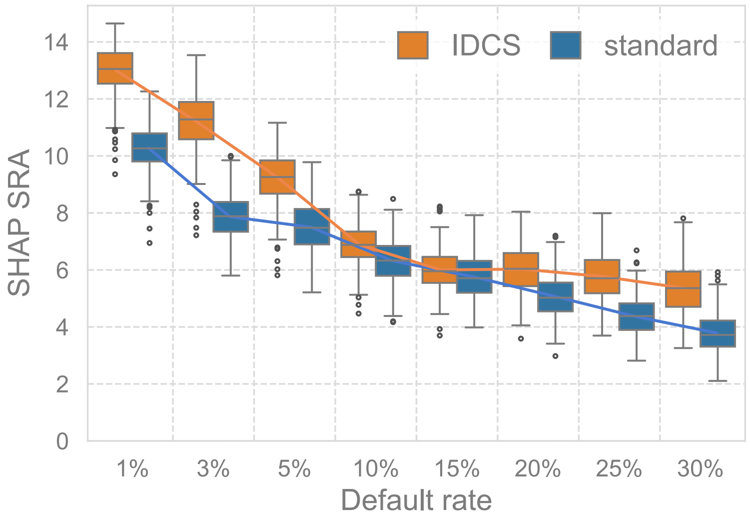

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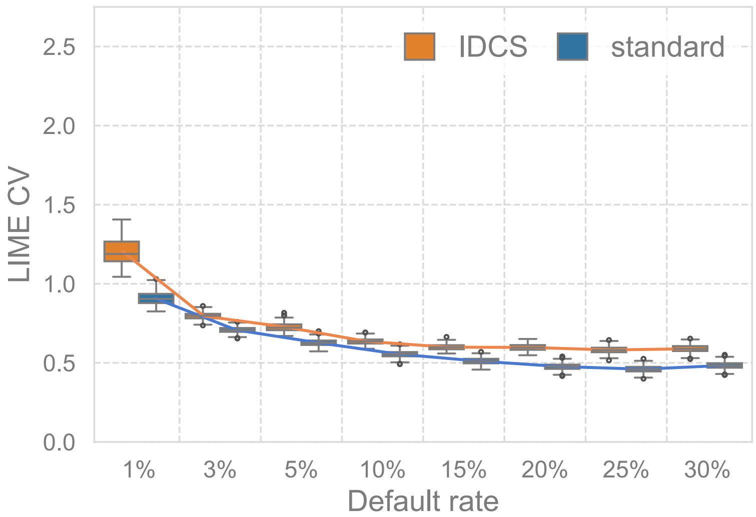

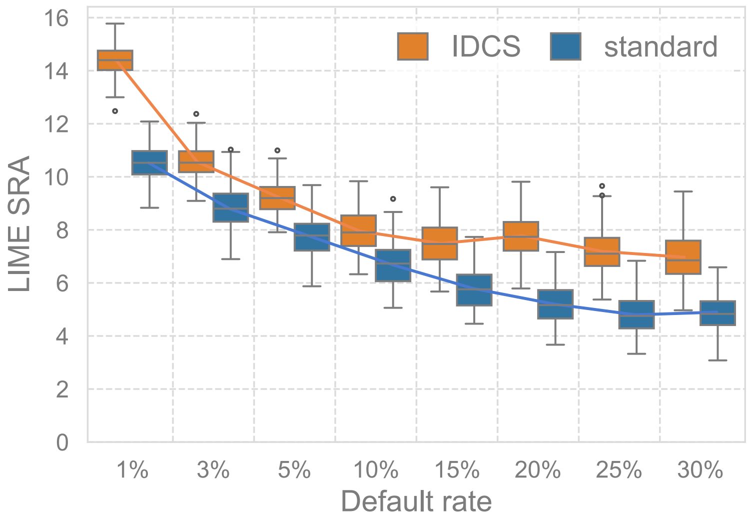

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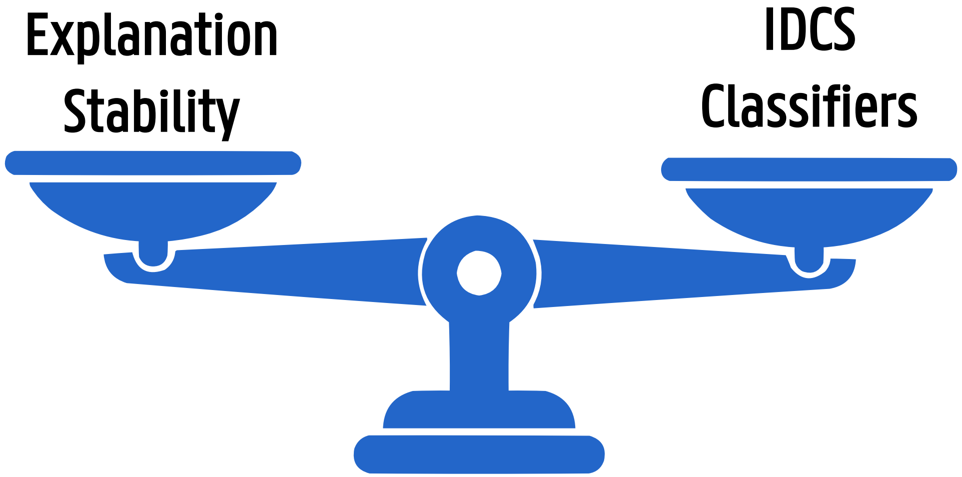
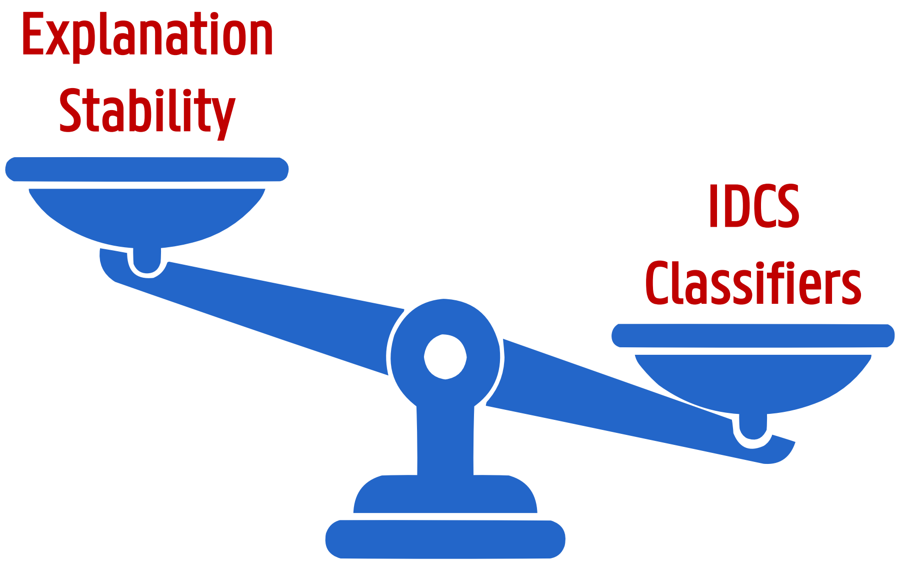
Conclusions

1. There is a trade-off between directly optimizing for costs and providing stable explanations.



Conclusions

1. There is a trade-off between directly optimizing for costs and providing stable explanations.
2. In their current state, IDCS classifiers will fail to meet the regulatory XAI standards to be used in practice.
3. Further research should explore safety measures or remediations to make IDCS model explanations more stable.



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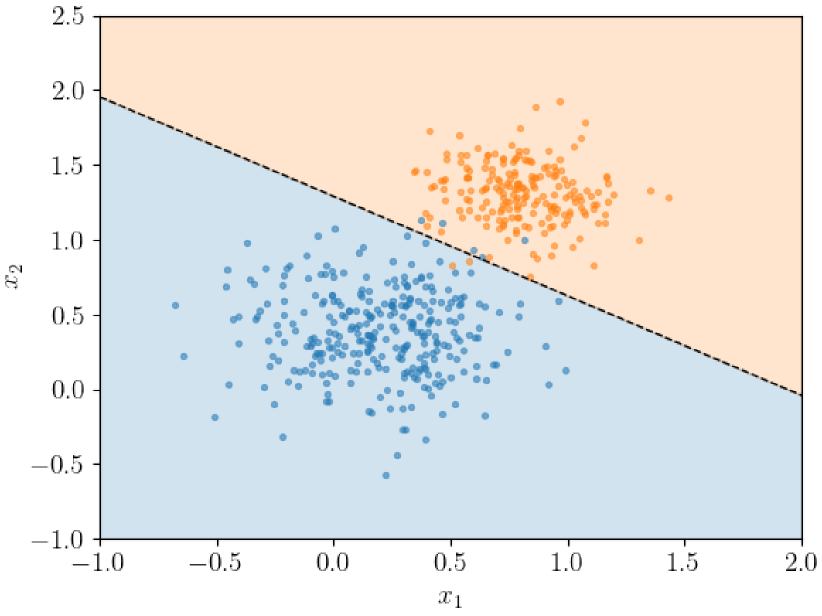
Discussion: the importance of a training sample

Traditional ML models: $s(\boldsymbol{x}) = \mathbb{E}\,(\mathrm{Y} \mid \boldsymbol{x})$

- Feature distribution
- Class imbalance (cfr Chen et al.)

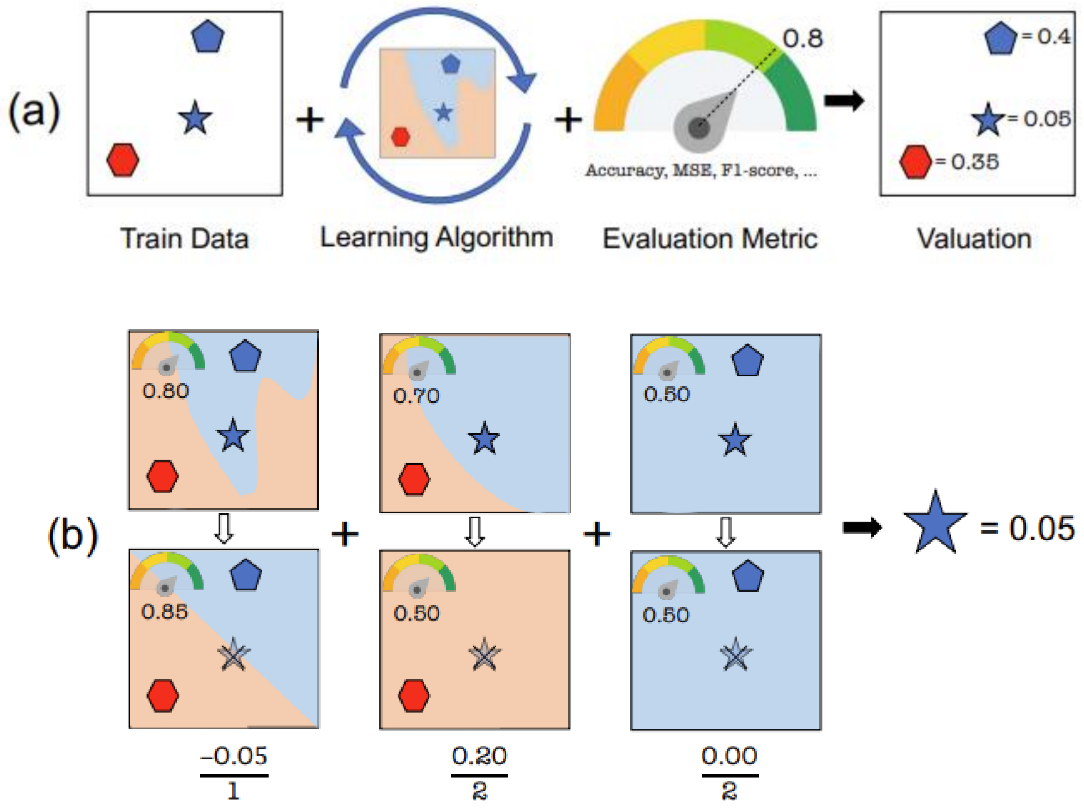
IDCS ML models: $\mathrm{AEC}(\mathrm{Y}, s(\boldsymbol{x}), \mathrm{C})$

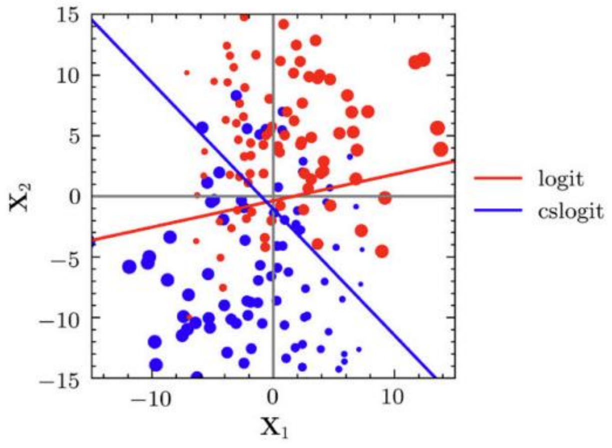
- Feature distribution
- Class imbalance
- **COST**



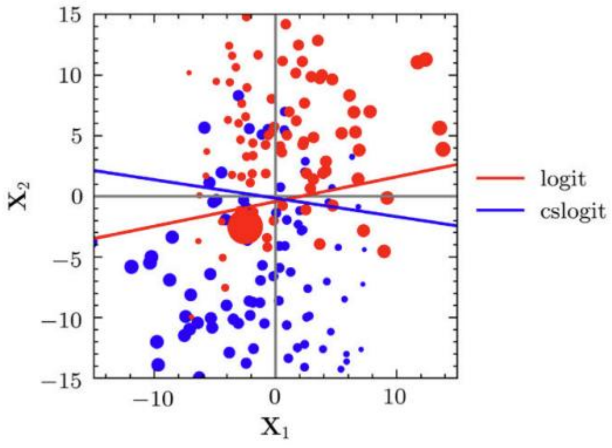
Chen, Y., Calabrese, R., Martin-Barragan, B., 2024. Interpretable machine learning for imbalanced credit scoring datasets.

Discussion: IDCSL and data valuation





(a) Example on synthetic data:
Optimal behavior of logit and cslogit



(b) Example on synthetic data:
Influence of outliers on cslogit

Ghorbani, A., & Zou, J. (2019). Data shapley: Equitable valuation of data for machine learning. In International conference on machine learning (pp. 2242-2251). PMLR.
De Vos, S., Vanderschueren, T., Verdonck, T., & Verbeke, W. (2023). Robust instance-dependent cost-sensitive classification. Advances in data analysis and classification, 17(4), 1057-1079.

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Read the study here

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FlandersMake@UGent—Corelab CVAMO, Tweekerkenstraat 2, 9000 Gent, Belgium

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