Optimal Risk Scores

Cristina Molero-Río¹, Claudia D'Ambrosio¹

LIX, CNRS, École Polytechnique, Institut Polytechnique de Paris, France {dambrosio, molero}@lix.polytechnique.fr

Keywords : Risk Scores, Scoring Systems, Mixed-Integer Non-Linear Optimization, Interpretability, Sparsity

1 Introduction

With the widespread use of Machine Learning applications, in relevant fields such as Criminal Justice, Health Care and Risk Management, interpretability has become essential for trust on them [3]. This is supported by the so-called right-to-explanation in algorithmic decision-making, imposed by the European Union since 2018 [1], that encourages to design models that are understandable and enable explanation to the users. Mathematical Optimization has been shown to be a flexible enough tool for dealing with this necessity and creating Interpretable Machine Learning models.

One of the fundamental forms of Interpretable Machine Learning models is Risk Scores [2, 4]. Risk Score models are logistic regression models applied to scoring systems. A scoring system consists of a linear classifier that requires the user to perform simple and few calculations with integer numbers in order to make a prediction. Figure (1) shows an example of a risk score for an application in healthcare. The user can easily determine whether the risk of malignancy of a breast lesion by adding points for its shape, its margin and the patient's age. If the score is above a threshold, the patient would be recommended to further tests.

 Ova Irre Circ Circ Spid Age 	-2 points 4 points -5 points 2 points 3 points		+ + + +	···· ··· ···			
SCORE	-3	-2		-1			
RISK	6.0%	10.6%	13.8%	17.9%	22.8%	6	28.6%
SCORE	0	1	2	3	4		\geq 5
RISK	35.2%	42.4%	50.0%	57.6%	64.8%	6	71.4%

FIG. 1: Risk score from FasterRisk [2] on the well-known mammo dataset, which consits of a sample of biopsy patients. The model tries to predict the risk of malignancy of a breast lesion.

2 Our proposal

In this work, we propose a novel Mixed-Integer Non-Linear Optimization formulation to construct a risk score. A trade-off between prediction accuracy and sparsity is sought. Previous approaches are typically designed to handle binary datasets, where numerical predictor variables are discretized in a preprocessing step by using arbitrary thresholds, such as the corresponding deciles. In contrast, we allow the model decide for each continuous predictor variable the particular threshold that is critical for prediction. The resulting optimization problem is tested in real-world datasets, and compared with state-of-the-art benchmarks.

3 Perspectives

Some extensions of our approach are of interest. First, including in risk scores desirable properties such as cost-sensitivity or fairness is appealing. Second, tailoring risk scores to other kinds of complex data that are not captured appropriately by standard implementations of these models such as text, image or network data is also an attractive research avenue. Third, this methodology can be extended to other kind of Interpretable Machine Learning models, such as rule sets, where thresholds of numerical predictor variables are discovered on the go.

References

- [1] Bryce Goodman, and Seth Flaxman. European Union regulations on algorithmic decisionmaking and a "right to explanation". *AI Magazine*, 38(3):50–57, 2017.
- [2] Jiachang Liu, Chudi Zhong, Boxuan Li, Margo Seltzer, and Cynthia Rudin. FasterRisk: fast and accurate interpretable risk scores. Advances in Neural Information Processing Systems, 35:17760–17773, 2022.
- [3] Cynthia Rudin, Chaofan Chen, Zhi Chen, Haiyang Huang, Lesia Semenova, and Chudi Zhong. Interpretable machine learning: Fundamental principles and 10 grand challenges. *Statistics Surveys*, 16:1–85, 2022.
- Berk Ustun, and Cynthia Rudin. Learning Optimized Risk Scores. Journal of Machine Learning Research, 20(150):1–75, 2019.