Semi-supervised Feature Selection for Efficient Detection of Systemic Deviations to Develop Trustworthy AI

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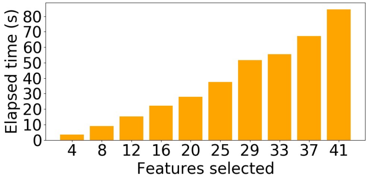
1. Introduction

- Identifying systemic deviations in datasets and model outputs helps to achieve trustworthy AI
- Multiple techniques have been proposed in the state-of-the-art[1] to detect systemic deviations in tabular data, but the computational complexity grows with the dimension of the feature space.

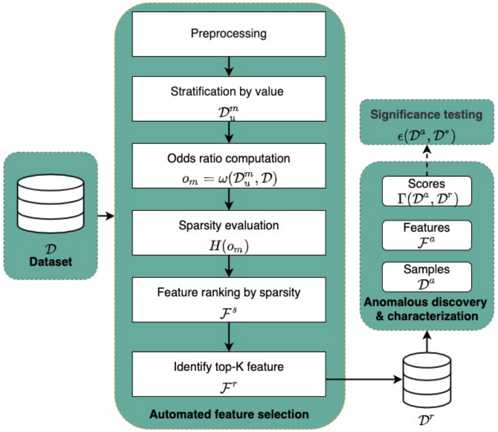


- We propose a **model-free** and sparsity-based automated feature selection (**SAFS**) framework for efficient discovery of anomalous patterns

2. Proposed framework

- SAFS employs sparsity of the odds ratios of feature values
- Deviation across values of a given feature is encoded using Hoyer-based sparsity metric[2]
- Top K features are selected based on sparsity-based ranking and fed into the MDSS-based subgroup discovery technique[1]

$$H(o_m) = \left(\sqrt{C_m} - \frac{\sum_{u=1}^{C_m} o_m^u}{\sum_{u=1}^{C_m} o_m^{2\,u}}\right)\left(\sqrt{C_m} - 1\right)^{-1}$$



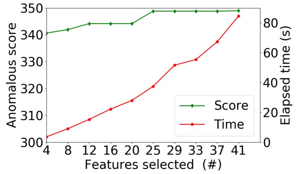
3. Experiments

- **Dataset**: Medical Information Mart for Intensive Care (MIMIC-III)[3]
- Outcome: Patients death within 28 days of the onset of ICU admission
- N=19,658 patients, and M = 41 features

- **Baseline methods**
- Mutual-information based Filter[4]
- Backward-elimination based Wrapper[5], and
- Embedded techniques (XGBoost, CatBoost and Committee)[6]

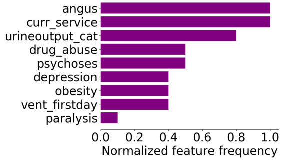
- **Performance metric**
- Computation time and characterization of identified subgroup

Results



Top K	Size	Odds Ratio (95% CI)	P-Value
4	4312	2.48 (2.3, 2.67)	< 0.01
8	2811	3.00 (2.75, 3.26)	< 0.01
12	4383	2.48 (2.31, 2.67)	< 0.01
16	4383	2.48 (2.31, 2.67)	< 0.01
20	4383	2.48 (2.31, 2.67)	< 0.01
25	3078	2.93 (2.7, 3.18)	< 0.01
29	3078	2.93 (2.7, 3.18)	< 0.01
33	3078	2.93 (2.7, 3.18)	< 0.01
37	3078	2.93 (2.7, 3.18)	< 0.01
41	4218	2.54 (2.36, 2.73)	< 0.01

- **3x** reduction in computation time using just **half** of the features
- Consistent subgroup detection
- Superior to the baselines



	Baseline methods					**Proposed**
			Embedded methods			
K	Filter	Wrapper	XGB	CatB	Committee	SAFS
4	337.19	311.27	337.19	339.23	337.19	**340.61**
8	340.61	311.27	337.19	340.61	340.61	**341.90**
12	340.61	311.27	340.61	340.61	340.61	**344.13**
16	340.61	316.09	340.61	**344.13**	340.61	**344.13**
20	340.61	340.86	340.61	**344.13**	**344.13**	**344.13**
25	340.61	346.64	348.53	348.45	348.53	**348.77**
29	344.59	346.64	**348.77**	**348.77**	**348.77**	**348.77**
33	**348.77**	346.64	**348.77**	**348.77**	**348.77**	**348.77**
37	348.45	**348.91**	**348.91**	**348.91**	**348.91**	348.77
41	**348.91**	**348.91**	**348.91**	**348.91**	**348.91**	**348.91**

4. Conclusions

- We proposed a sparsity-based automated feature selection (SAFS) framework for anomalous subgroup discovery **without** training a particular model.
- SAFS outperformed multiple baseline feature selection methods and achieved more than **3×** reduction in computational time but with competitive detection performance using just **half** of the features.
- Future work aims to extend SAFS to select layers and nodes, e.g., for adversarial detection in deep learning frameworks

References

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2. Hurley and Rickard. Comparing measures of sparsity. IEEE Tran. on Info. Theory 55, 10 (2009)
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6. Wanjiru et al. Automated Supervised Feature Selection for Differentiated Patterns of Care. (2021) arXiv preprint arXiv:2111.03495