A cheaper Rectified-Nearest-Feature-Line-Segment classifier based on safe points

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Introduction

- A commonly used baseline algorithm is the well-known *Nearest Neighbor* (1-NN) rule.
- There are several proposals aimed at solving the weaknesses of 1-NN, e.g. condensing and editing (García et al., 2012).
- Other alternatives build continua between pairs of points belonging to the same class (Chien and Wu, 2002).
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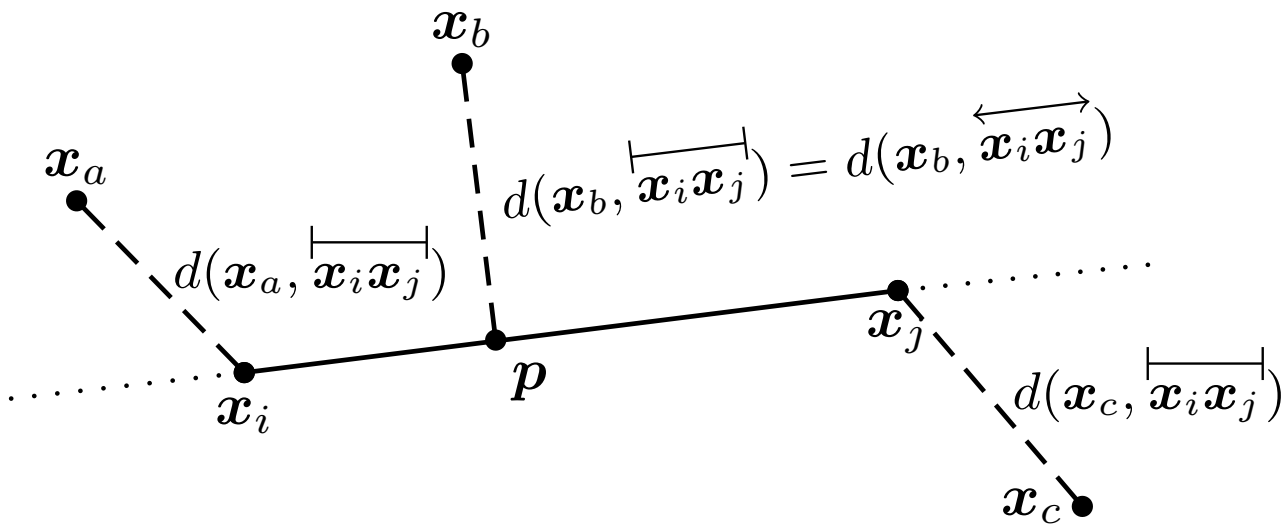
The RNFLS classifier

The Rectified-Nearest-Feature-Line Segment (RNFLS) classifier (Du and Chen, 2007) improves over NFL (Li and Lu, 1999) by solving two drawbacks of the latter: *interpolation* and *extrapolation* inaccuracies.



The RNFLS classifier

Two processes allow to solve those drawbacks:

- **Segmentation:** Distances on the extrapolating part of the feature line are replaced with the distance to the nearest endpoint.
- **Rectification:** Feature lines segments crossing the territory of other classes are removed. Very costly!
- Degenerated lines are also considered. So, RNFLS includes 1-NN as a special case.

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Typification according to the 5-nearest neighbors

According to the proportion *{Same class}:{Different class}* among its 5-nearest neighbors, a point **x** is categorized as (Napierala and Stefanowski, 2016):

- *s* (safe) if 5:0 or 4:1;
- *b* (borderline) if 3:2 or 2:3;
- *r* (rare) if 1:4 but, only if its nearest neighbor from the same class has, in turn, a proportion or either 0:5 or 1:4. Otherwise, **x** is *b* (Sáez et al., 2016);
- *o* (outlier) if 0:5.

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Proposed typification of feature line segments

- We propose to categorize each feature line segment according to the types of its endpoints: *s2s*, *s2b*, *s2r*, *s2o*, *b2b*, *b2r*, *b2o*, *r2r*, *r2o*, *o2o*.
- The most preserved category after the rectification process is *s2s*. In addition, most of the class labels are assigned by them.
- Hypothesis: removing of all non-safe examples, prior the building of the feature line segments, allows to avoid many computations without significantly deteriorating the classification performance of the original RNFLS.

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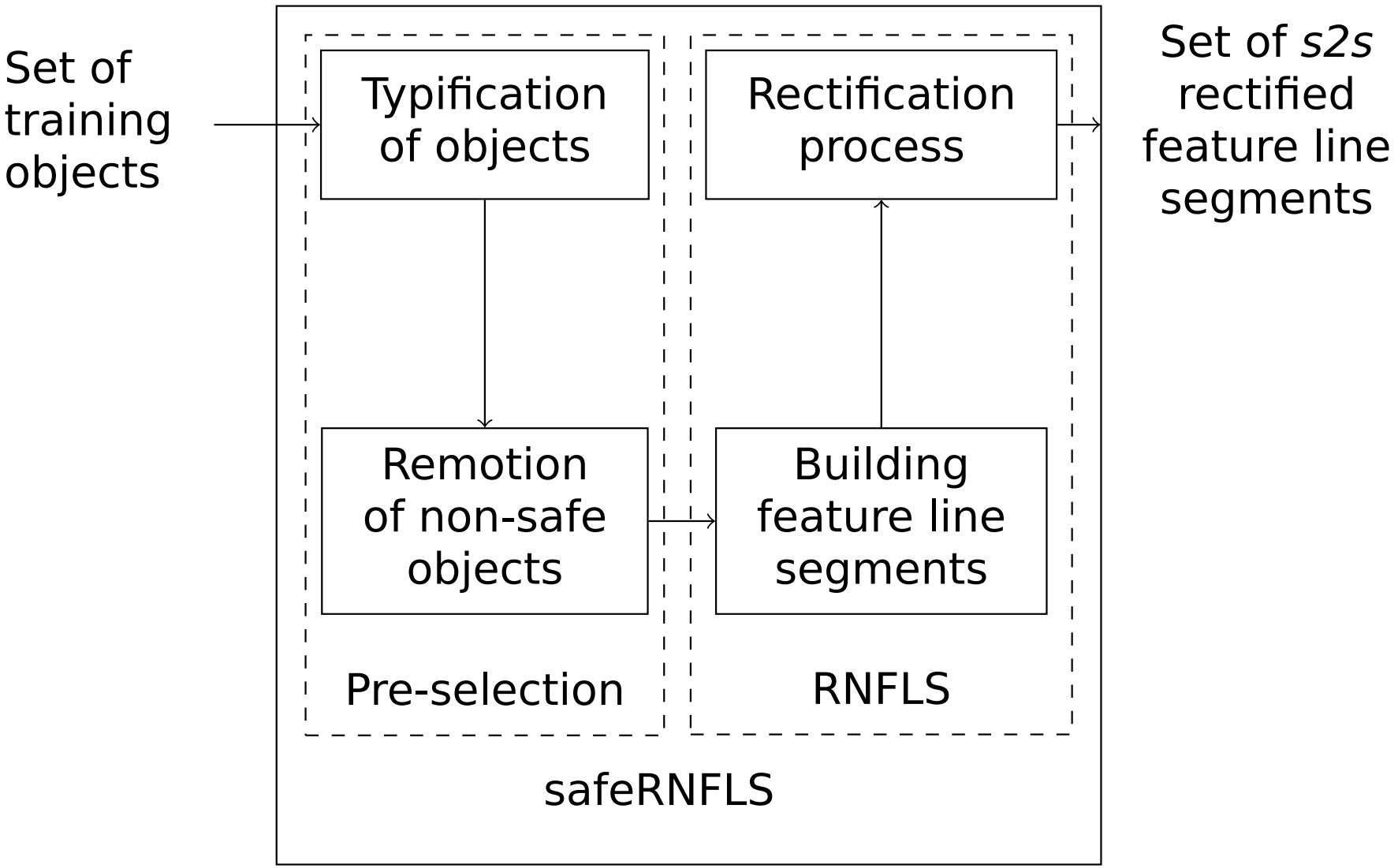
safeRNFLS: the cheaper proposal



Classification accuracies

- Setup: 20 repetitions, 50-50 random training-test.
- Safe variants of 1-NN and NFL were also studied: safeNN and safeNFL, respectively.

	(a) 1-NN vs. safeNN		(b) RNFLS vs. safeRNFLS		(c) NFL vs. safeNFL	
Dataset	1-NN	safeNN	RNFLS	safeRNFLS	NFL	safeNFL
Hepatitis	92.25±0.95	87.75±1.16	91.50±0.99	91.38±0.99	93.62±0.86	93.00±0.90
Iris	93.40±0.64	93.67±0.63	94.87±0.57	94.80±0.57	87.07±0.87	87.47±0.85
Pima	70.29±0.52	72.93±0.51	74.14±0.50	74.44±0.50	68.05±0.53	68.31±0.53
Wine	94.33±0.55	94.27±0.55	95.45±0.49	95.34±0.50	95.73±0.48	95.62±0.49
Liver	59.83±0.83	58.32±0.84	63.67±0.82	62.86±0.82	61.16±0.83	61.04±0.83
Ionosphere	84.49±0.61	77.50±0.70	90.43±0.50	89.38±0.52	83.89±0.62	83.38±0.63
WDBC	94.88±0.29	95.61±0.27	96.47±0.24	96.53±0.24	94.77±0.29	94.88±0.29
WPBC	65.46±1.08	75.36±0.98	72.99±1.01	74.33±0.99	72.16±1.02	71.75±1.02
Glass	66.40±1.02	58.41±1.07	68.36±1.01	67.10±1.02	62.90±1.04	60.28±1.06
Gastro	52.11±1.81	49.08±1.81	55.66±1.8	45.53±1.81	58.55±1.79	51.97±1.81

- safeRNFLS is, in general, not significantly different from RNFLS.

Execution times (in seconds) and percentage of savings

- Setup: HP laptop: AMD A9-9420 proc., 3GHz, 8GB RAM, Windows 10, timing with the `time.perf_counter()` Python 3.4.1 function.

	(a) 1-NN vs. safeNN			(b) RNFLS vs. safeRNFLS			(c) NFL vs. safeNFL		
Dataset	1-NN	safeNN	Saving	RNFLS	safeRNFLS	Saving	NFL	safeNFL	Saving
Hepatitis	0.03	0.02	7.27%	0.44	0.40	8.53%	0.49	0.46	6.78%
Iris	0.14	0.10	26.20%	1.56	1.38	11.56%	1.41	1.26	10.56%
Pima	2.03	0.91	55.11%	127.74	96.19	24.70%	334.62	134.60	59.78%
Wine	0.11	0.08	21.17%	1.74	1.69	2.90%	2.59	2.08	19.85%
Liver	0.34	0.11	69.49%	4.71	1.72	63.54%	28.85	2.82	90.22%
Ionosphere	0.35	0.27	21.35%	17.62	14.77	16.12%	33.67	27.08	19.59%
WDBC	0.91	0.87	4.21%	101.81	98.03	3.71%	135.29	117.02	13.51%
WPBC	0.11	0.06	45.63%	2.64	1.78	32.54%	6.24	1.21	80.53%
Glass	0.13	0.05	61.60%	1.08	0.42	61.12%	3.55	0.88	75.31%
Gastro	0.02	0.005	78.90%	0.06	0.01	81.14%	0.34	0.004	98.89%

- safeRNFLS is, in general, much cheaper than RNFLS.

Conclusions

- *s2s* feature line segments are typically the ones providing the class label assignments for the RNFLS classifier (see the paper).
- safeRNFLS is, in general, not significantly different from RNFLS but much cheaper (saved computations and excecution times, in most cases, are outstanding).
- safeRNFLS is not recommended for complicated compositions along with very sparse representations (few examples in very high-dimensional feature spaces); c.f. `Gastro`.

Contact information

Thanks for your attention.

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References

Chien, J.-T. and Wu, C.-C. (2002). Discriminant waveletfaces and nearest feature classifiers for face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(12):1644–1649.

Du, H. and Chen, Y. Q. (2007). Rectified nearest feature line segment for pattern classification. *Pattern Recognition*, 40(5):1486 – 1497.

García, S., Derrac, J., Cano, J. R., and Herrera, F. (2012). Prototype selection for nearest neighbor classification: Taxonomy and empirical study. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(3):417–435.

Li, S. Z. and Lu, J. (1999). Face recognition using the nearest feature line method. *IEEE Transactions on Neural Networks*, 10(2):439–443.

Napierala, K. and Stefanowski, J. (2016). Types of minority class examples and their influence on learning classifiers

from imbalanced data. *Journal of Intelligent Information Systems*, 46(3):563–597.

Sáez, J. A., Krawczyk, B., and Woźniak, M. (2016). Analyzing the oversampling of different classes and types of examples in multi-class imbalanced datasets. *Pattern Recognition*, 57:164 – 178.