Network Dataset Quality Problem

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Motivation

- The Network Management area needs innovative solutions
- Expansion of Machine Learning
- Challenge of creating an ML model that works in production (algorithms, GIGO)
- Lack of the high quality datasets
- Model quality rather than the dataset quality
- High quality data is the cornerstone for evidence-based decision making
- Assessing the quality of the network dataset is an overlooked area

Dataset quality – what does it mean?

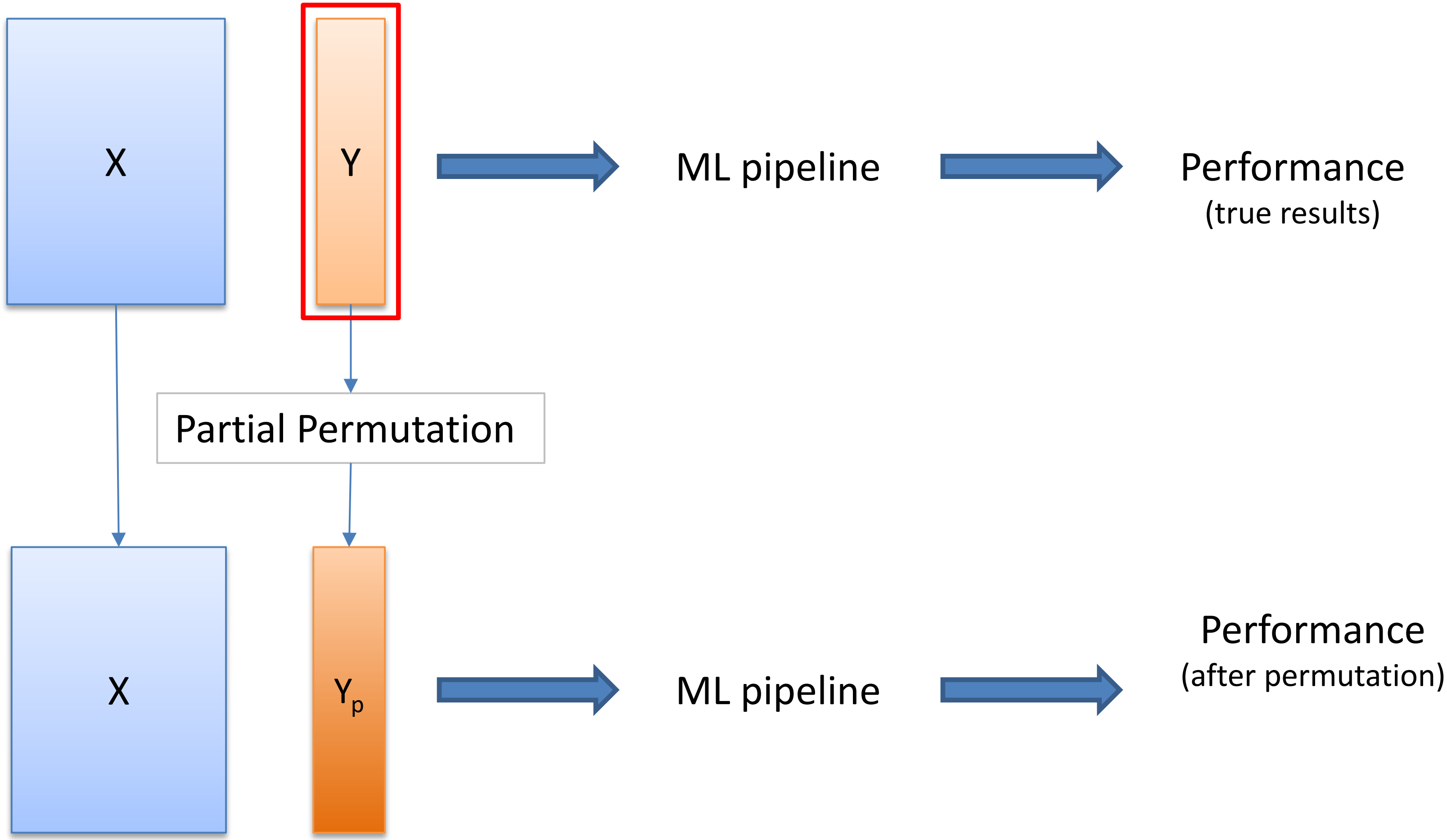
A dataset is said to be of high quality if it meets the requirements for its intended use

- Validity
- Accuracy
- Consistency
- Integrity
- Precision
- Correctness
- Uniqueness
- Reliability
- Completeness
- Representativeness
- Timeliness
- …

- Errors (technical, human)
- Invalid data
- Types, formats
- Missing values
- Noisy labels
- Class overlapping
- Data homogeneity
- Outliers
- Duplicates
- Feature correlation
- Imbalanced datasets
- Curse of dimensionality
- …

Approaches: entropy based methods, metamorphic testing, crowdsourcing, …

PerQoDA - Dataset Quality Assesment with Permutation Testing



Camacho J., Wasielewska K. (2022), **Dataset Quality Assessment in Autonomous Networks with Permutation Testing**, *NOMS IEEE/IFIP Network Operations and Management Symposium*, Budapest, Hungary, doi: 10.1109/NOMS54207.2022.9789767

Wasielewska, K., Soukup, D., Čejka, T., Camacho, J. (2023), **Evaluation of the Limit of Detection in Network Dataset Quality Assessment with PerQoDA**. In: *et al.* Machine Learning and Principles and Practice of Knowledge Discovery in Databases. *ECML PKDD 2022*. Communications in Computer and Information Science, vol 1753. Springer. doi: 10.1007/978-3-031-23633-4_13

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PerQoDA - Methodology

1. Train a pool of classifiers using the original dataset (X, Y)
2. Evaluate each model using the selected performance metric
3. Permute selected percentage of the labels Y to get new labels Yp and new dataset (X, Yp)
4. Train the pool of classifiers on the dataset (X, Yp)
5. Evaluate each model with the same performance metric
6. For Yp and Y, compute the correlation coefficient
7. Repeat the steps 3 through 6, P times, where P is the number of permutations
8. Calculate p-value
9. Repeat the steps 7 and 8 for each value of percentage (for example for 50%, 25%, 10%, 5%, 1% labels)

PerQoDA

- Let's define a null hypothesis:

$$XY = XY_p$$

- For each (M, multiple M*), p-values are calculated as follows

$$\text{p-value} = \frac{\text{No. of } (M* \geq M) + 1}{\text{Total no. of } M* + 1}$$

where M refers to the performance metric value computed from the original dataset and M^* stands for the performance after a certain number of permutations

- If p-value ≤ α, there is evidence of statistical significance in M
- If p-value > α, it means that null hypothesis cannot be rejected

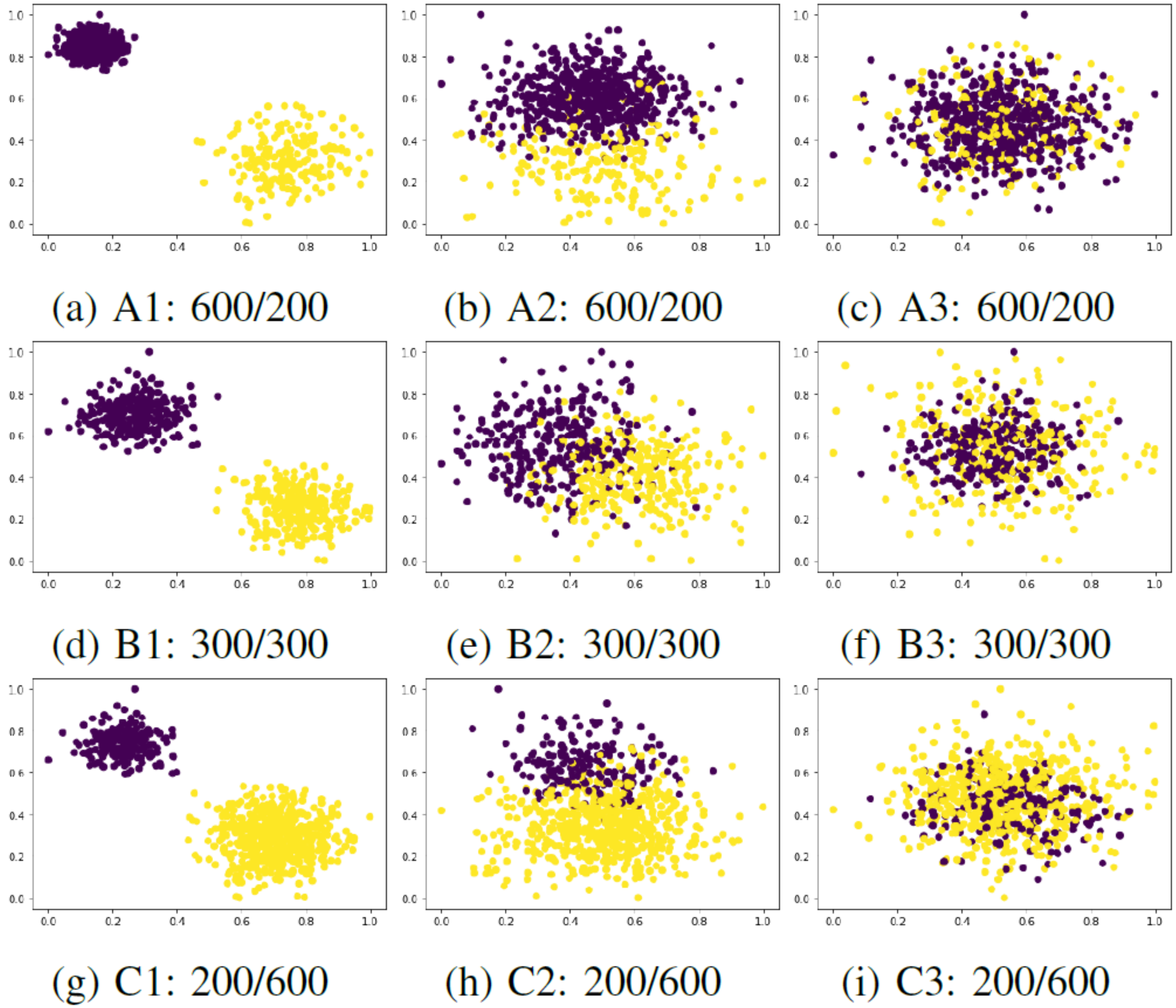
Experiments

- Classifiers: KNN, SVM, Decision Tree, Random Forest, GNB, AdaBoost, DT, RF, MLP
- Metrics: Recall, F1, Balanced Accuracy, …
- Subsets of labels (percentages): 50%, 25%, 10%, 5%, 1%
- 100 permutations
- α=0.05

Interpretation:

- If all models perform bad (non-significance) => dataset is bad
- If some models perform good (significance) => dataset is good

Balanced and imbalanced toy datasets



(a) A1: 600/200 (b) A2: 600/200 (c) A3: 600/200

prev=0.25

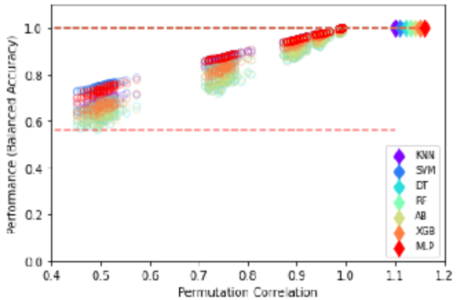
(d) B1: 300/300 (e) B2: 300/300 (f) B3: 300/300

prev=0.5

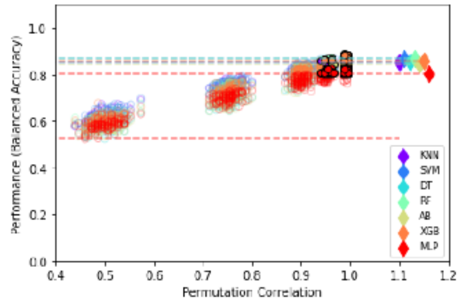
(g) C1: 200/600 (h) C2: 200/600 (i) C3: 200/600

prev=0.75

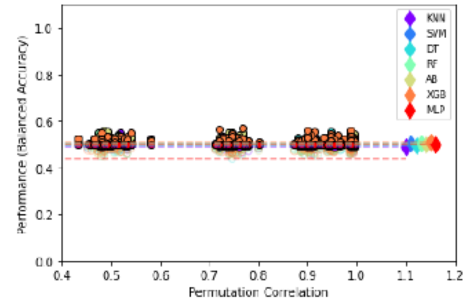
Results for Balanced Accuracy (1/2)



(a) A1

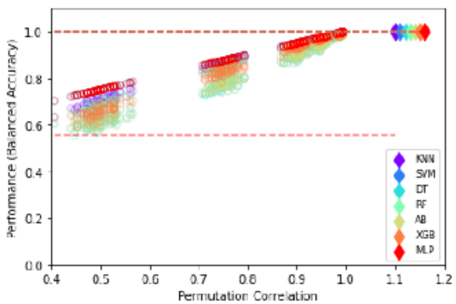


(b) A2

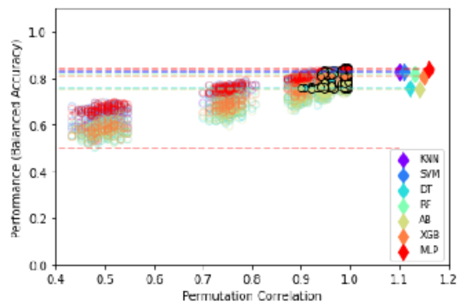


(c) A3

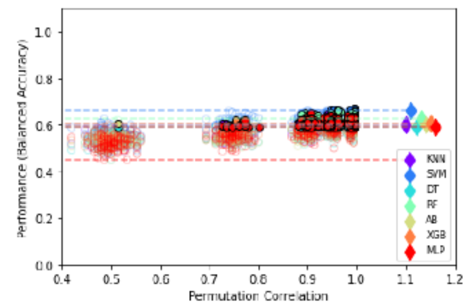
prev=0.25



(d) B1

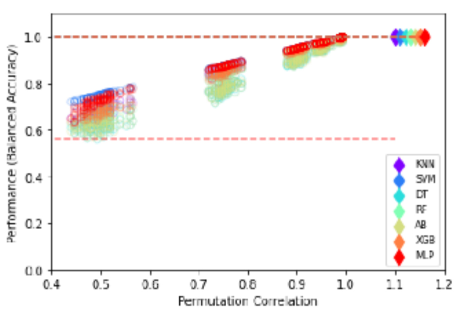


(e) B2

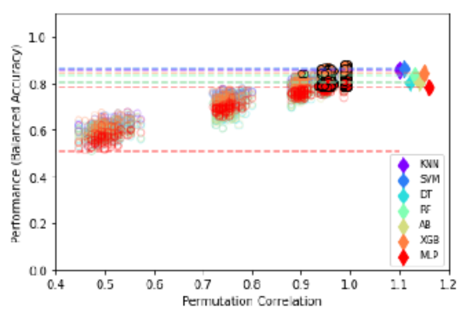


(f) B3

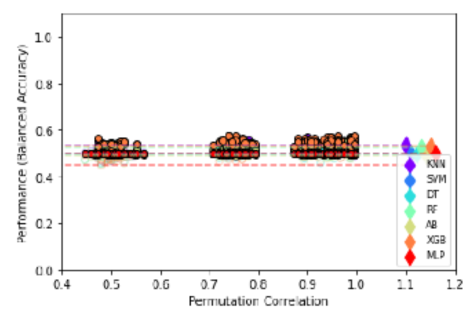
prev=0.5



(g) C1



(h) C2



(i) C3

prev=0.75

Results for Balanced Accuracy (2/2)

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(a) A1

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.158416	0.663366
SVM	0.009901	0.009901	0.009901	0.009901	0.455446
DT	0.009901	0.009901	0.009901	0.009901	0.168317
RF	0.009901	0.009901	0.009901	0.039604	0.297030
AB	0.009901	0.009901	0.009901	0.039604	0.306931
XGB	0.009901	0.009901	0.009901	0.079208	0.564356
MLP	0.009901	0.009901	0.009901	0.326733	0.851485

(b) A2

	50%	25%	10%	5%	1%
KNN	0.732673	0.673267	0.732673	0.772277	0.821782
SVM	0.168317	0.297030	0.504950	0.633663	0.772277
DT	0.534653	0.485149	0.475248	0.524752	0.495050
RF	0.475248	0.376238	0.415842	0.425743	0.485149
AB	0.465347	0.376238	0.396040	0.386139	0.386139
XGB	0.346535	0.336634	0.277228	0.376238	0.346535
MLP	1.000000	1.000000	1.000000	1.000000	1.000000

(c) A3

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(d) B1

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.138614
SVM	0.009901	0.009901	0.009901	0.069307	0.663366
DT	0.009901	0.009901	0.029703	0.217822	0.683168
RF	0.009901	0.009901	0.009901	0.079208	0.366337
AB	0.009901	0.009901	0.039604	0.227723	0.782178
XGB	0.009901	0.009901	0.009901	0.049505	0.297030
MLP	0.009901	0.009901	0.009901	0.009901	0.128713

(e) B2

	50%	25%	10%	5%	1%
KNN	0.009901	0.049505	0.267327	0.475248	0.386139
SVM	0.009901	0.009901	0.009901	0.059406	0.099010
DT	0.019802	0.039604	0.227723	0.336634	0.366337
RF	0.009901	0.009901	0.128713	0.217822	0.287129
AB	0.019802	0.009901	0.089109	0.168317	0.158416
XGB	0.009901	0.029703	0.148515	0.306931	0.277228
MLP	0.009901	0.148515	0.425743	0.633663	0.693069

(f) B3

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(g) C1

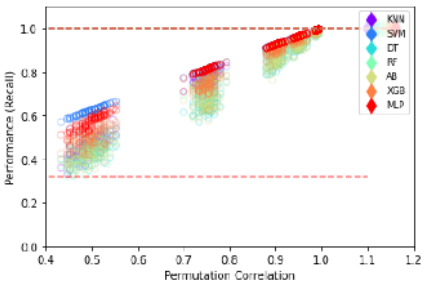
	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.019802	0.198020
SVM	0.009901	0.009901	0.009901	0.009901	0.376238
DT	0.009901	0.009901	0.009901	0.217822	0.762376
RF	0.009901	0.009901	0.019802	0.277228	0.801980
AB	0.009901	0.009901	0.009901	0.138614	0.732673
XGB	0.009901	0.009901	0.019802	0.326733	0.772277
MLP	0.009901	0.009901	0.009901	0.495050	0.871287

(h) C2

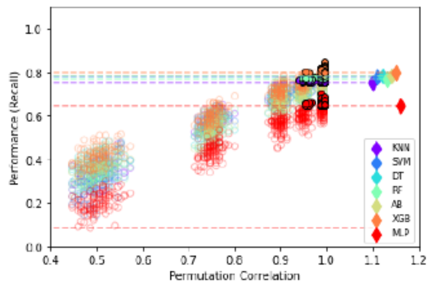
	50%	25%	10%	5%	1%
KNN	0.118812	0.227723	0.346535	0.386139	0.514851
SVM	0.970297	0.950495	0.920792	0.930693	0.920792
DT	0.782178	0.920792	0.940594	0.950495	0.960396
RF	0.148515	0.217822	0.386139	0.326733	0.514851
AB	0.732673	0.861386	0.881188	0.930693	0.950495
XGB	0.158416	0.376238	0.524752	0.435644	0.554455
MLP	1.000000	1.000000	1.000000	0.990099	0.990099

(i) C3

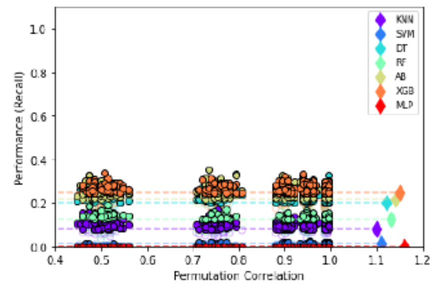
Results for Recall (1/2)



(a) A1, Recall

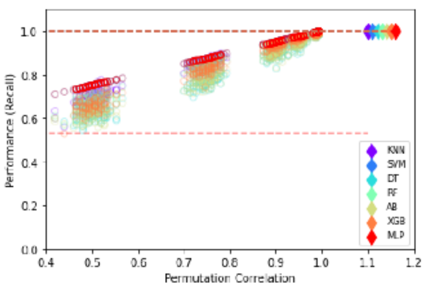


(b) A2, Recall

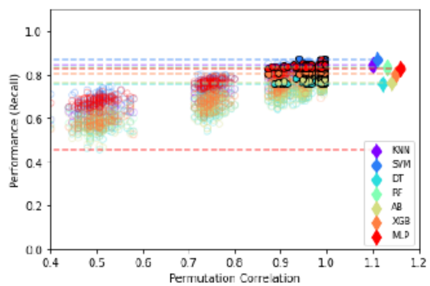


(c) A3, Recall

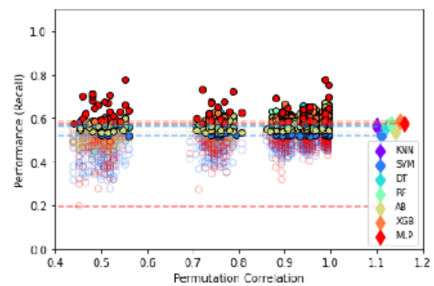
prev=0.25



(g) B1, Recall

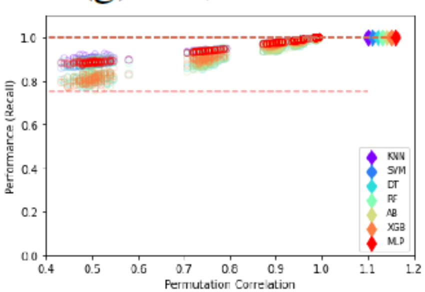


(h) B2, Recall

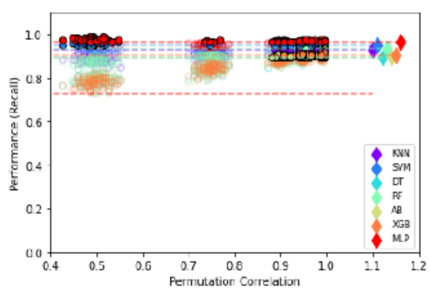


(i) B3, Recall

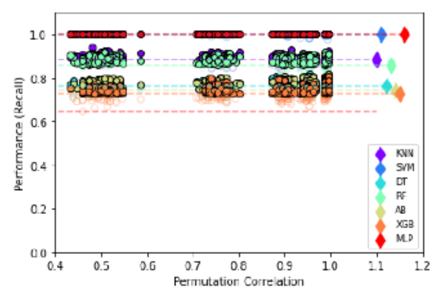
prev=0.5



(m) C1, Recall



(n) C2, Recall



(o) C3, Recall

prev=0.75

Results for Recall (2/2)

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(a) A1, Recall

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.188119	0.712871
SVM	0.009901	0.009901	0.009901	0.009901	0.336634
DT	0.009901	0.009901	0.009901	0.009901	0.188119
RF	0.009901	0.009901	0.009901	0.118812	0.633663
AB	0.009901	0.009901	0.009901	0.009901	0.148515
XGB	0.009901	0.009901	0.009901	0.029703	0.336634
MLP	0.009901	0.009901	0.009901	0.089109	0.336634

(b) A2, Recall

	50%	25%	10%	5%	1%
KNN	0.801980	0.801980	0.900990	0.881188	0.881188
SVM	0.039604	0.099010	0.148515	0.108911	0.178218
DT	0.861386	0.910891	0.960396	0.920792	0.930693
RF	0.336634	0.247525	0.267327	0.227723	0.237624
AB	0.762376	0.801980	0.881188	0.861386	0.821782
XGB	0.514851	0.534653	0.594059	0.475248	0.534653
MLP	1.000000	1.000000	1.000000	1.000000	1.000000

(c) A3, Recall

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(g) B1, Recall

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.039604	0.158416
SVM	0.009901	0.009901	0.009901	0.019802	0.089109
DT	0.009901	0.009901	0.079208	0.217822	0.603960
RF	0.009901	0.009901	0.009901	0.029703	0.079208
AB	0.009901	0.009901	0.049505	0.158416	0.455446
XGB	0.009901	0.009901	0.029703	0.148515	0.534653
MLP	0.009901	0.009901	0.108911	0.574257	0.970297

(h) B2, Recall

	50%	25%	10%	5%	1%
KNN	0.089109	0.128713	0.267327	0.297030	0.366337
SVM	0.059406	0.138614	0.138614	0.089109	0.158416
DT	0.128713	0.396040	0.663366	0.742574	0.871287
RF	0.029703	0.247525	0.386139	0.485149	0.673267
AB	0.267327	0.653465	0.900990	0.900990	0.970297
XGB	0.039604	0.158416	0.415842	0.544554	0.594059
MLP	0.257426	0.168317	0.099010	0.128713	0.128713

(i) B3, Recall

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.009901	0.009901	0.009901
SVM	0.009901	0.009901	0.009901	0.009901	0.009901
DT	0.009901	0.009901	0.009901	0.009901	0.009901
RF	0.009901	0.009901	0.009901	0.009901	0.009901
AB	0.009901	0.009901	0.009901	0.009901	0.009901
XGB	0.009901	0.009901	0.009901	0.009901	0.009901
MLP	0.009901	0.009901	0.009901	0.009901	0.009901

(m) C1, Recall

	50%	25%	10%	5%	1%
KNN	0.009901	0.009901	0.059406	0.128713	0.356436
SVM	0.237624	0.019802	0.049505	0.128713	0.138614
DT	0.009901	0.009901	0.188119	0.623762	0.920792
RF	0.009901	0.009901	0.009901	0.019802	0.059406
AB	0.009901	0.009901	0.128713	0.524752	0.841584
XGB	0.009901	0.009901	0.039604	0.168317	0.287129
MLP	0.722772	0.089109	0.247525	0.405941	0.504950

(n) C2, Recall

	50%	25%	10%	5%	1%
KNN	0.792079	0.712871	0.554455	0.574257	0.623762
SVM	0.871287	0.891089	0.881188	0.900990	0.900990
DT	0.465347	0.425743	0.524752	0.455446	0.603960
RF	0.960396	0.910891	0.881188	0.861386	0.851485
AB	0.792079	0.811881	0.891089	0.782178	0.910891
XGB	0.554455	0.594059	0.574257	0.584158	0.722772
MLP	1.000000	1.000000	1.000000	0.970297	0.970297

(o) C3, Recall

Permutation slope

For each classifier and each permutation percentage, we compute:

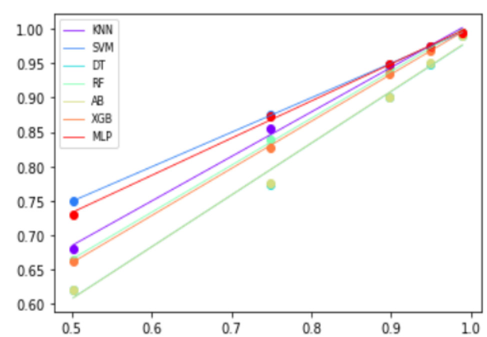
- the mean of correlation coefficient *r*,
- and the mean of performance score.

Then, we compute the **slope** as the maximum abs(intercept) of all regression lines computed for each classifier (using regression line we minimize the sum of squared residuals).

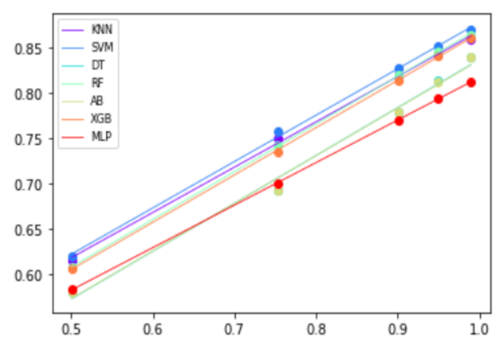
Example:

A1, A2, A3 datasets (prev=0.25), Balanced Accuracy

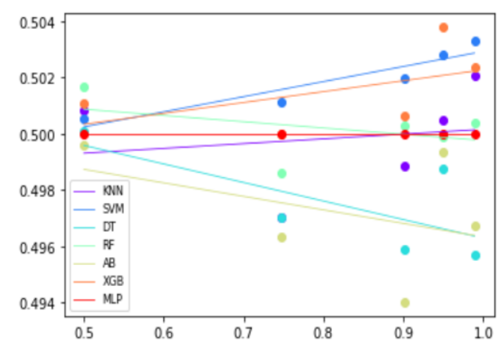
```
KNN = 0.6473834243218128
SVM = 0.5018185022465786
DT = 0.7529240320972793
RF = 0.6833829086587506
AB = 0.7543691867051512
XGB = 0.6853261584364769
MLP = 0.540553620135657
Slope: 0.7543691867051512 - AB
```




```
KNN = 0.5013234866326473
SVM = 0.5129416245213057
DT = 0.529453992010826
RF = 0.5277622380369938
AB = 0.5274511411217867
XGB = 0.5230397552862625
MLP = 0.4703306522394924
Slope: 0.529453992010826 - DT
```




```
KNN = 0.0016955610875442864
SVM = 0.005371807316245113
DT = -0.006596210510203646
RF = -0.002225722667557547
AB = -0.004807503506193736
XGB = 0.0038706404350221752
MLP = 3.5597713425436314e-16
Slope: 0.006596210510203646 - DT
```



9 toy datasets – Slopes
(max percentage: 50%)

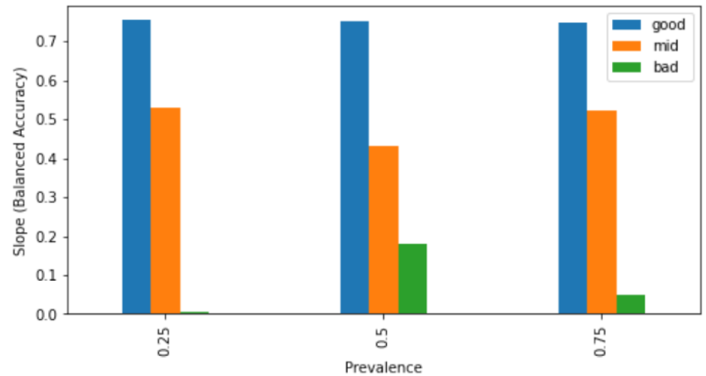
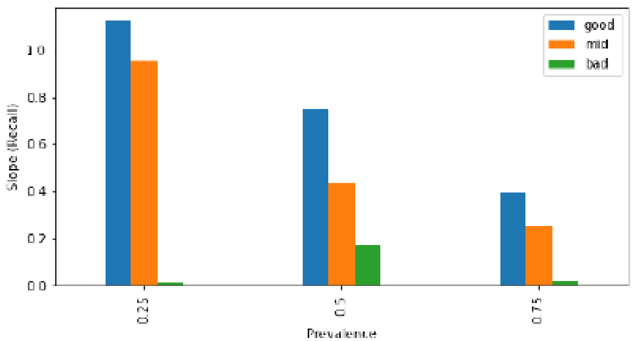
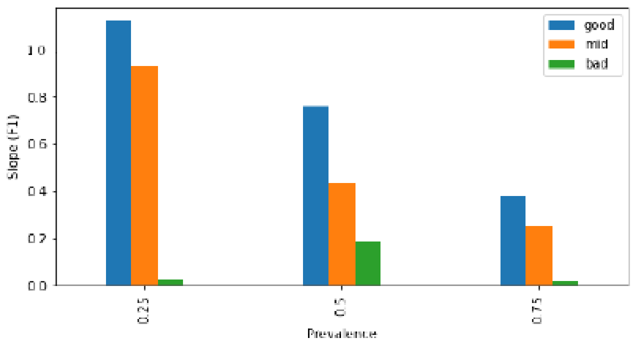


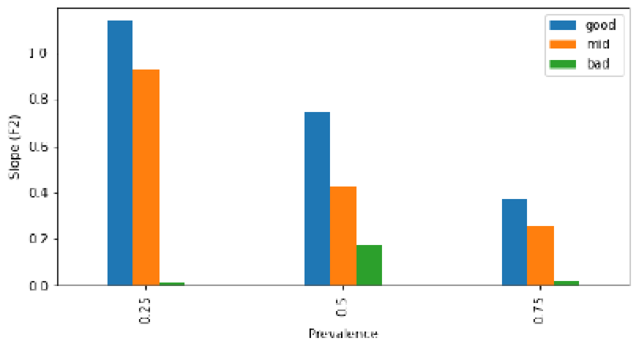
Fig. 4: Slopes, Balanced Accuracy



(a) Slopes, Recall



(b) Slopes, F1



(c) Slopes, F2

Limits of detection

- Dataset examples:

X = 1000 obs, 1% of labels = 10 labels

X = 10000000 obs, 1% of labels = 100000 labels

Since we want to detect all relationship problems in the dataset, intuitively, we should permute the smallest possible number of labels.

For example: 100, 50, 25, 10, 5, 1 obs – regardless of dataset size

Experiment

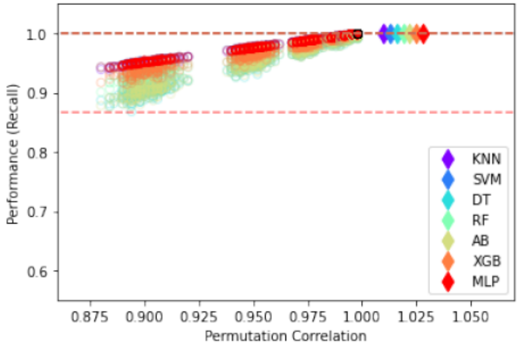
- inSDN dataset - public dataset with 68,424 normal and 275,465 attack data (DoS, Probe, brute force attacks (BFA), password-guessing (R2L), web application attacks, and Botnet), 83 features

- We considered Probe attacks
- We created balanced datasets with 2000, 10,000 and 20,000 obs (prev = 0.5)
- To the original datasets we introduced 5% and 10% mislabels

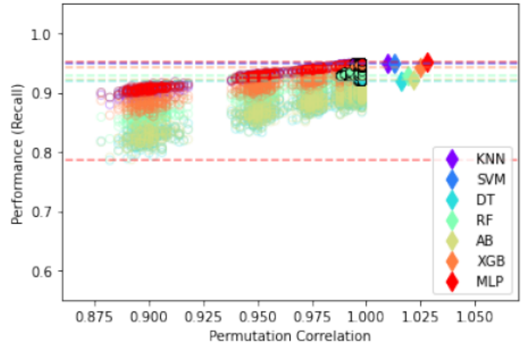
- Permutation policy: 100, 50, 25, 10, 5, 2, 1 obs
- Pool of classifiers: KNN, SVM, Decision Tree, Random Forest, AdaBoost, XGBoost, Multi-Layer Perceptron (default hyperparameters)
- Stratified 2-fold CV with shuffling
- Recall metric

	Flow Duration	Tot Fwd Pkts	Tot Bwd Pkts	TotLen Fwd Pkts	TotLen Bwd Pkts	Fwd Pkt Len Max	Fwd Pkt Len Min	Fwd Pkt Len Mean	Fwd Pkt Len Std	Bwd Pkt Len Max	Bwd Pkt Len Min	Bwd Pkt Len Mean	Bwd Pkt Len Std	Flow Byts/s	Flow Pkts/s	Flow IAT Mean	Flow
0	506706	11	12	1067	31337	517	0	97.0000	196.5645	16900	0	2611.4167	4920.5026	63950.2986	45.3912	2.3032e+04	9.0809e
1	62435590	20	33	6365	21205	1644	0	318.2500	539.2679	4304	0	642.5758	1242.9272	441.5751	0.8489	1.2007e+06	7.2460e
2	6192375	21	19	3119	5524	708	0	148.5238	216.8358	2600	0	290.7368	697.0737	1395.7488	6.4596	1.5878e+05	8.0322e
3	22428	4	2	31	0	31	0	7.7500	15.5000	0	0	0.0000	0.0000	1382.2008	267.5227	4.4856e+03	9.8245e
4	15147441	8	10	2281	928	1713	0	285.1250	604.0209	756	0	92.8000	237.1731	211.8510	1.1883	8.9103e+05	2.5312e

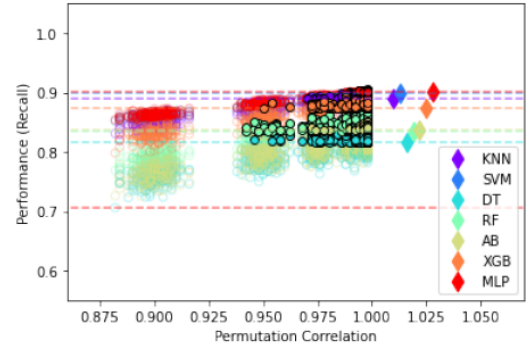
inSDN - Permutation charts



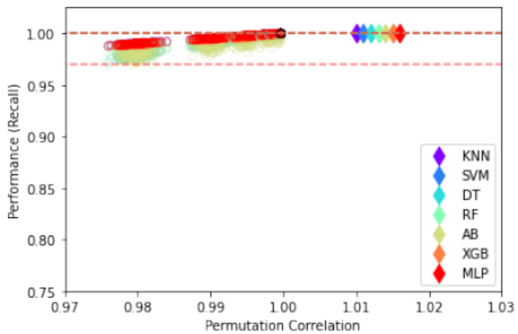
(a) 2000 obs, 0% mislabels



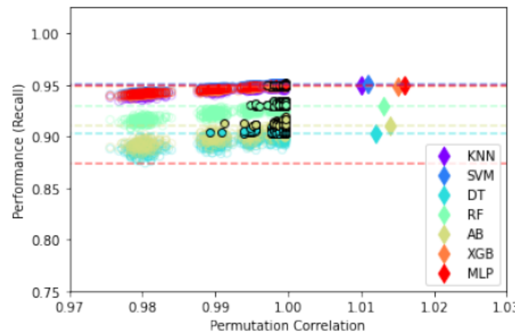
(b) 2000 obs, 5% mislabels



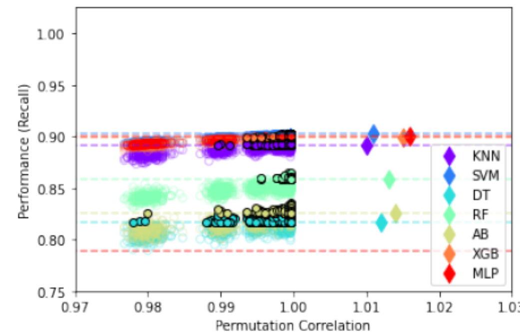
(c) 2000 obs, 10% mislabels



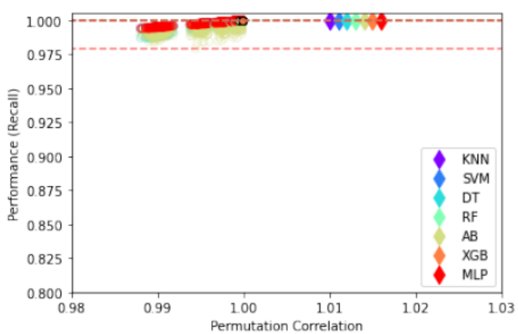
(d) 10,000 obs, 0% mislabels



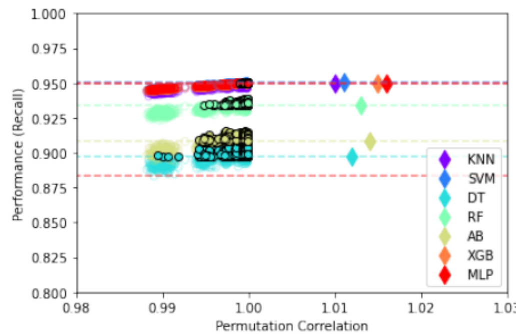
(e) 10,000 obs, 5% mislabels



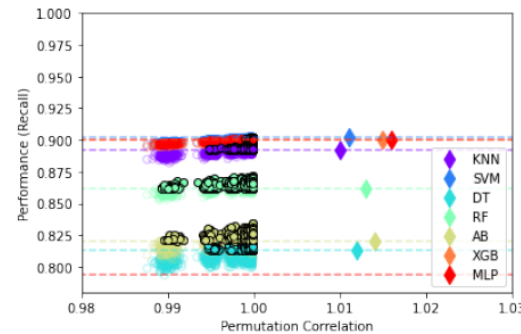
(f) 10,000 obs, 10% mislabels



(g) 20,000 obs, 0% mislabels



(h) 20,000 obs, 5% mislabels



(i) 20,000 obs, 10% mislabels

inSDN
p-value tables

	2000 obs 0% mislabels							2000 obs 5% mislabels							2000 obs 10% mislabels						
	100	50	25	10	5	2	1	100	50	25	10	5	2	1	100	50	25	10	5	2	1
KNN	.	.	.	.	.	.02	.02	.	.	.	.	.01	.08	.16	.	.	.	.05	.13	.18	.14
SVM	.	.	.	.	.	.02	.02	.	.	.	.	.02	.13	.15	.	.	.	.	.07	.25	.31
DT	.	.	.	.	.	.	.	.	.	.02	.18	.21	.33	.38	.	.04	.26	.51	.66	.62	.64
RF	.	.	.	.	.	.	.	.	.	.12	.66	.81	.91	.89	.	.	.10	.32	.51	.52	.56
AB	.	.	.	.	.	.	.	.	.	.01	.13	.17	.24	.32	.	.06	.26	.52	.70	.68	.68
XGB	.	.	.	.	.	.	.	.	.	.42	.86	.94	.95	.97	.	.	.05	.23	.38	.43	.41
MLP	.	.	.	.	.	.03	.01	.	.	.	.	.02	.17	.21	.	.	.	.12	.34	.74	.74

	10,000 obs 0% mislabels							10,000 obs 5% mislabels							10,000 obs 10% mislabels						
	100	50	25	10	5	2	1	100	50	25	10	5	2	1	100	50	25	10	5	2	1
KNN	.	.	.	.	.	.	.	.	.	.	.06	.15	.28	.30	.	.	.06	.17	.21	.22	.30
SVM	.	.	.	.	.	.02	.05	.	.	.	.	.02	.11	.10	.	.	.	.	.03	.15	.19
DT	.	.	.	.	.	.	.	.	.	.01	.05	.06	.10	.12	.01	.12	.35	.53	.56	.53	.55
RF	.	.	.	.	.	.	.	.	.	.	.08	.13	.10	.15	.	.	.	.05	.07	.05	.04
AB	.	.	.	.	.	.	.	.	.	.02	.03	.07	.06	.07	.	.02	.08	.20	.17	.14	.16
XGB	.	.	.	.	.	.	.	.	.	.	.01	.05	.11	.10	.	.	.01	.09	.15	.17	.19
MLP	.	.	.	.	.03	.19	.21	.	.	.	.	.03	.19	.22	.	.	.	.02	.06	.21	.26

	20,000 obs 0% mislabels							20,000 obs 5% mislabels							20,000 obs 10% mislabels						
	100	50	25	10	5	2	1	100	50	25	10	5	2	1	100	50	25	10	5	2	1
KNN	.	.	.	.	.	.	.	.	.	.10	.47	.60	.66	.69	.	.	.07	.17	.20	.23	.25
SVM	.	.	.	.	.05	.22	.24	.	.	.	.02	.09	.27	.24	.	.	.	.02	.16	.48	.48
DT	.	.	.	.	.05	.26	.27	.	.06	.26	.46	.46	.49	.56	.11	.38	.55	.68	.67	.68	.68
RF	.	.	.	.	.18	.46	.50	.	.	.05	.15	.15	.16	.18	.04	.21	.42	.55	.60	.61	.61
AB	.	.	.	.	.08	.30	.44	.	.05	.12	.28	.36	.32	.39	.14	.41	.54	.61	.73	.68	.68
XGB	.	.	.	.01	.30	.59	.65	.	.	.	.02	.13	.43	.33	.	.	.15	.63	.80	.80	.81
MLP	.	.	.	.03	.03	.57	.56	.	.	.	.	.04	.19	.24	.	.	.	.08	.27	.67	.65

inSDN
true scores - recall

	2000 obs 0% mislabels	2000 obs 5% mislabels	2000 obs 10% mislabels
KNN	1.0	0.951	0.899
SVM	1.0	0.95	0.9
DT	1.0	0.907	0.814
RF	1.0	0.921	0.852
AB	1.0	0.908	0.816
XGB	1.0	0.926	0.881
MLP	1.0	0.95	0.9
	10,000 obs 0% mislabels	10,000 obs 5% mislabels	10,000 obs 10% mislabels
KNN	1.0	0.948	0.891
SVM	1.0	0.951	0.902
DT	1.0	0.901	0.814
RF	1.0	0.93	0.854
AB	1.0	0.909	0.822
XGB	1.0	0.949	0.902
MLP	1.0	0.95	0.9
	20,000 obs 0% mislabels	20,000 obs 5% mislabels	20,000 obs 10% mislabels
KNN	1.0	0.948	0.893
SVM	1.0	0.95	0.902
DT	1.0	0.9	0.809
RF	1.0	0.936	0.864
AB	1.0	0.91	0.82
XGB	1.0	0.95	0.9
MLP	1.0	0.95	0.901

Permutation slopes

Max percentage: 5%, 1%, 0.5% respectively

Dataset	0% mislabels		5% mislabels		10% mislabels	
2000 obs	0.97279	DT	0.78068	DT	0.60636	RF
10,000 obs	1.04494	AB	0.82356	DT	0.70278	AB
20,000 obs	1.04837	DT	0.85276	DT	0.63686	DT

Limitations

- PerQoDA does not detect all dataset problems
- Labeled datasets are required
- PerQoDA is affected by the quality and adaptation possibilities of classifiers
- Computational cost

Conclusions

- We need high-quality datasets
- Suitable assessment of the dataset quality is critical for building reliable high-quality models that can be put into real autonomous networks
- PerQoDA can be useful method in the DQA process

Thank you very much