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The influence of the dataset bias on the accuracy of the NIDS systems

Franciszek Pelc

supervisor: dr hab. inż. Marcin Iwanowski

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Motivation

The goal of our research was to measure the impact of training datasets on accuracy of machine learning Network Intrusion Detection System (NIDS) models.



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Datasets

- UNSW-NB15

- BoT-IoT

- ToN-IoT

- CIC-CSE-IDS2018

Klasa	ВоТ %	IDS2018 %	NB15 %	ToN %
Analysis	0	0	0.0962	0
Backdoor	0	0	0.0907	0.0992
Benign	0.3576	88.0482	96.0233	36.0053
Bot	0	0.7574	0	0
Brute Force	0	0.6562	0	0
DDoS	48.5438	7.3584	0	11.9608
DoS	44.1516	2.5617	0.2424	4.2065
Exploits	0	0	1.32	0
Fuzzers	0	0	0.9334	0
Generic	0	0	0.6928	0
Infilteration	0	0.6158	0	0
Reconnaissance	6.9406	0	0.5346	0
Shellcode	0	0	0.0596	0
Theft	0.0063	0	0	0
Worms	0	0	0.0069	0
injection	0	0.0023	0	4.0404
mitm	0	0	0	0.0456
password	0	0	0	6.8081
ransomware	0	0	0	0.0202
scanning	0	0	0	22.3218
xss	0	0	0	14.4919

Percentage of datasets consisting of particular class.



Features

- Originaly there have been 43 derived from flow and other data.
- Some features have been discarded
- Ultimately 32 features were considered for each record.



Classifiers

- Decision Tree Classifier
- Random Forest Classifier
- Extra Trees Classifier

Test have been conducted both on default

as well as optimized hiperparameters

gini
entropy
log_loss
log_loss
entropy

OPTIMIZED PARAMETERS FOR RANDOM FOREST CLASSIFIER

Dataset / Hyperparameter	criterion	max_features	bootstrap		
Default	gini	sqrt	False		
BoT	entropy	None	True		
IDS2018	log_loss	log2	True		
NB15	log_loss	None	True		
ToN	entropy	None	True		
	TABLE V				
OPTIMIZED PARAMETERS FOR EXTRA TREES CLASSIFIER					

Dataset / Hyperparameter	criterion
Default	gini
BoT	log_loss
IDS2018	entropy
NB15	entropy
ToN	log_loss

OPTIMIZED PARAMETERS FOR DECISION TREE CLASSIFIER





Experiments

1. Training each classifier on every dataset

2. Tests for each model on every dataset

3. Accuracy measured separately for each class

4. Accuracy = (TP + TN)/(All records)

Benign
DDoS
DoS
Reconnaissance
Backdoor
All classes







Results

		1	rained on d	ataset BoT				
Accuracy for class [%] \	IDS2018	IDS2018	NB15	NB15	ToN	ToN	BoT	ВоТ
tested on dataset		optimized		optimized		optimized		optimized
Benign	55.4610	57.2694	28.6710	24.7427	55.5062	58.145	99.9855	99.984
DDoS	92.5474	92.64	99.9802*	99.998*	87.9844	87.9911	99.874	99.87
DoS	98.4526	97.5279	98.7986	99.179	90.6257	89.4078	99.6704	99.6709
Reconnaissance	52.5663*	49.7831*	28.624	24.2688	14.9694*	20.5188*	99.774	99.7825
Backdoor	100.0*	100.0*	99.9093	99.9093	99.9008	99.9008	100.0*	100.0*
All classes	41.182	46.7863	26.7328	22.3717	3.3359	3.8008	99.6505	99.6525
Trained on dataset IDS2018								
Accuracy for class [%] \	ВоТ	ВоТ	NB15	NB15	ToN	ToN	IDS2018	IDS2018
tested on dataset		optimized		optimized		optimized		optimized
Benign	51.807	7.0542	90.5869	93.7148	44.2014	41.8339	55.423	99.5255
DDoS	51.4062	51.4368	99.9993*	99.9990*	87.8835	88.0384	92.5904	99.9755
DoS	55.8207	57.2276	97.7408	99.7512	76.7222	83.2694	98.4299	99.9985
Reconnaissance	93.0594	93.0594	99.4654	99.4654	100.0*	100.0*	52.535*	100.0*
Backdoor	100.0*	100.0*	99.9093	99.9093	99.9008	99.9008	100.0*	100.0*
All classes	0.2438	1.6812	94.0112	93.1099	26.2241	25.7695	41.2095	99.5015
		Т	rained on da	ataset NB15			•	
Accuracy for class [%] \	ВоТ	ВоТ	IDS2018	IDS2018	ToN	ToN	NB15	NB15
tested on dataset		optimized		optimized		optimized		optimized
Benign	41.6776	2.75089	61.4127	52.1712	48.3047	53.6949	28.773	99.6695
DDoS	51.4561	51.4561	92.6416	92.6416	88.0391	88.0391	99.9805*	100.0*
DoS	55.6830	55.8262	66.0998	90.2995	91.1191	86.9492	98.812	99.655
Reconnaissance	84.8808	93.0594	99.5719*	99.9984*	99.9956*	99.9944*	28.7	<i>99.818</i>
Backdoor	99.9994*	99.9986*	99.991*	99.9864*	99.8944	99.8803	99.911	99.842
All classes	0.3282	0.3308	45.1172	41.5032	33.5194	33.2048	26.8510	98.8225
Trained on dataset ToN								
Accuracy for class [%] \	ВоТ	ВоТ	IDS2018	IDS2018	NB15	NB15	ToN	ToN
tested on dataset		optimized		optimized		optimized		optimized
Benign	53.3776	17.221	58.9632	77.2498	58.062	75.1247	55.5845	99.2205
DDoS	51.413	51.4047	94.5719	98.2498	95.7979*	88.7531*	87.89	99.681
DoS	55.8401	55.846	95.5346	97.2593	99.1569	99.7511	90.728	99.181
Reconnaissance	93.0594	93.0594	99.4654*	99.4654*	99.4654	99.4654	14.915*	100.0*
Backdoor	99.9975*	99.9995*	99.8862*	99.9058*	99.909	99.9093	99.9035	99.9995
All classes	0.3215	0.3236	57.5044	76.4519	69.878	74.4936	3.3655	97.3485

Results for Decision Tree Classifier

Results

- 1. Results in tests may vary greatly between testing on dataset model was trained on and testing on other datasets.
- 2. Optimizing classifiers improves performance on datasets training was perfomed but may decrease for others.
- 3. The greatest variance in results was found in Benign, DDoS and DoS classes



Conclusions

- 1. There is a need to carefully select the training data for IDS models
- 2. The set-up specific properties as well as great diversity of traffic present obstacle in training effective models.
- 3. For IDS model there is a risk of selection bias, sampling bias, exlcusion bias as well as reporting bias.





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Thank you for your attention

Franciszek Pelc

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