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Which Algorithm can Detect Unknown Attacks?

Comparison of Supervised, Unsupervised and Meta-Learning Algorithms for Intrusion Detection

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Traditional Intrusion Detectors

- ▶ Typical means to attain security mainly revolve around two main approaches:
 - Rule-based, Invariant-Based or
 - Signature-based



Images from <https://blogs.vmware.com/security/2016/11/next-generation-antivirus-ngav.html>

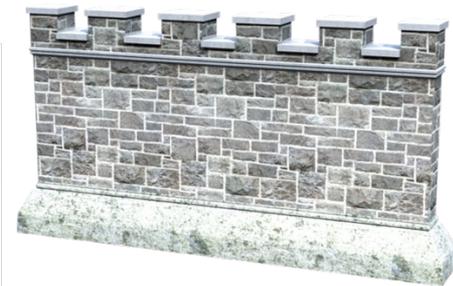
Signature-based Detection

- ▶ Network or host activity is analyzed to seek for matching attack patterns (signatures).
 - If the current behavior of the system matches one or more attack signatures (or rules), an alert is raised



What about Unknown Threats?

- ▶ Research and Practice found ways to defend against specific attacks
 - Mostly rule, signature-based or using supervised learning

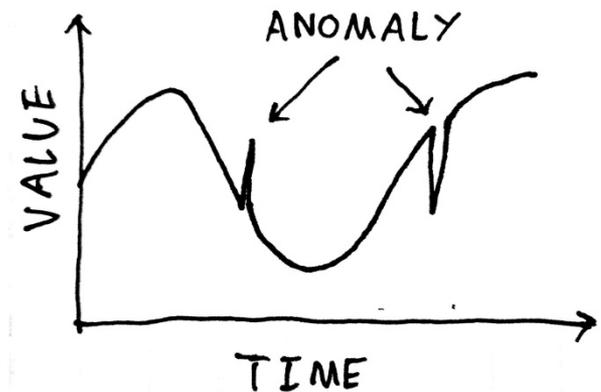
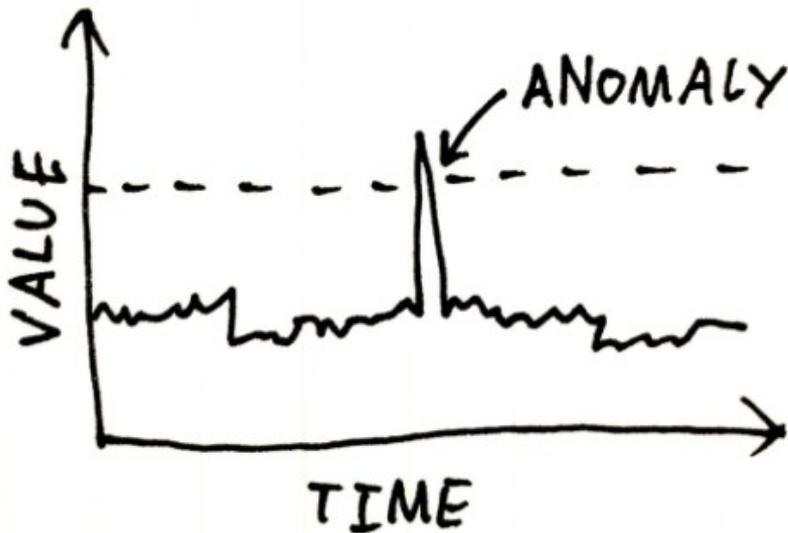


- ▶ But what about unknown attacks or errors?
 - Unknown attacks: no rule / signature available yet



Anomaly-based Detection

- ▶ It allows to identify patterns in data streams and operations which are different from those expected, and label them as anomalies
 - They do not need signatures of anomalies
 - Instead, they characterize what is normal and act accordingly





(Un)Supervised Algorithms

- ▶ ML Algorithms are usually partitioned as (semi)supervised and unsupervised, depending on their need of labels in the training data
 - Supervised Algorithms very well known
 - Unsupervised Algorithms
 - Do not assume any detailed knowledge of anomalous events

	Known Issue	Unknown Issue
Supervised	Very Good!	Potentially Bad
Unsupervised	Average	



Tommaso Zoppi

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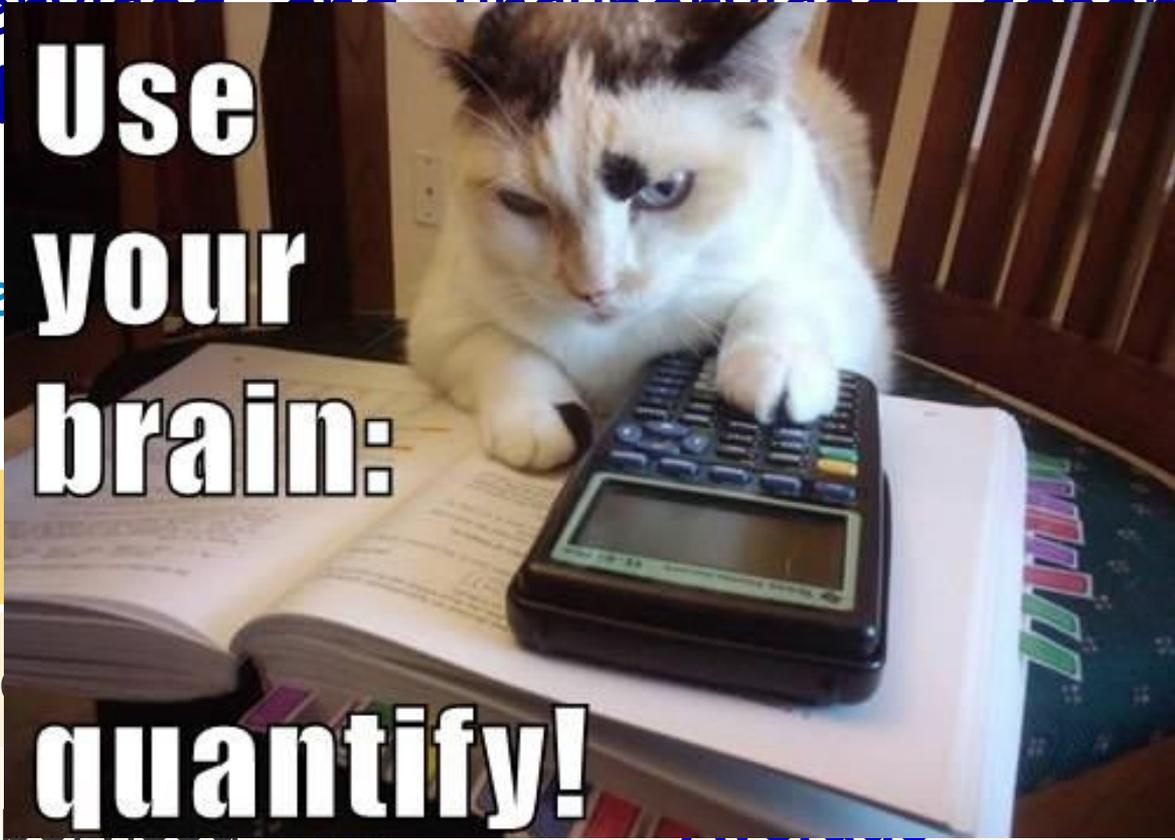
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(Un)Supervised Algorithms

► ML Algorithms are usually partitioned as (semi)supervised and unsupervised depending on their need

- Supervised
- Unsupervised
- Do not assume



is events

Issue

Bad

Sup
Unsu

Bad

Evaluation Plan

- ▶ How to evaluate detection of unknowns?
 - Unknown attack: not in the training set but in the test set
- ▶ Therefore we created variants of each dataset
 - where a given attack is unknown

Name	Training Set	Test Set
ISCX12		Normal Data DoS Attack Data BruteForce Attack Data DDoS Attack Data Infiltration Attack Data
Name	Training Variants	
ISCX12_NO(DoS)		
ISCX12_NO(BruteForce)		
ISCX12_NO(DDoS)		
ISCX12_NO(Infiltration)		



Metrics For Benchmarking

► Accuracy / F-Measure (F1)

- Example: System where 95% of data is normal
 - "Optimistic silly detector": always outputs "normal"
 - $TP = 0$, $TN = 95\%$, $FP = 0$, $FN = 5\%$
 - Accuracy = 95%

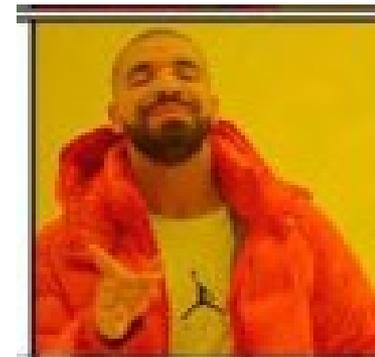


Metrics For Benchmarking

- ▶ Accuracy / F-Measure (F1)
- ▶ Matthews Coefficient (MCC)
 - A bit complex, but fits also unbalanced datasets

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

- ▶ Example: System where 95% of data is normal
 - "Optimistic silly detector": always outputs "normal"
 - $TP = 0$, $TN = 95\%$, $FP = 0$, $FN = 5\%$
 - Accuracy = 95%
 - $MCC = 0$ (random guessing)





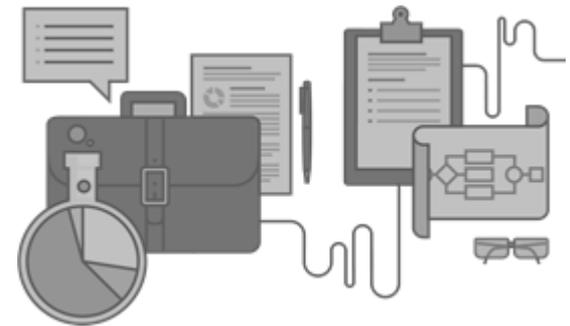
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- ▶ Recall (or Coverage)
- ▶ Recall-Unknown

- Recall, but considering only zero-day attacks





ML Algorithms to be Benchmarked

► Supervised

- Tree-based: Decision Tree, ADABoost, Gradient Boosting, XGBoost, Random Forests
- Statistical: Naive Bayes, LDA, Logistic Regression
- Others: kNN, SVM, MLP

► Supervised - Deep learning

- FastAI, AutoGluon, TabNet, Custom PyTorch

► Unsupervised

- Clustering: K-Means, G-Means, LDCOF
- Distance: ODIN, COF, LOF, SDO, FastABOD
- Others: iForest, HBOS, One-Class SVM, SOM



Evaluation of Supervised Algs. (I)

- ▶ Best MCC scores of supervised algorithms
 - With respect to best unsupervised classifiers
 - Huge difference w.r.t. Unsupervised

Dataset	Supervised Deep Learning	Supervised (Non-Deep)	Unsupervised	Difference Sup - Unsup
ADFANet	0.9943	0.9983	0.9837	0.0146
AndMal	0.3895	0.6458	0.5503	0.0955
CICIDS17	0.9954	0.9996	0.6511	0.3485
CICIDS18	0.9286	0.9281	0.8277	0.1009
CIDDS	0.9924	0.9754	0.8026	0.1898
IoT_IDS	0.9965	0.9998	0.9739	0.0259
ISCX	0.8763	0.8927	0.7921	0.1006
NSLKDD	0.9830	0.9888	0.8384	0.1504
SDN20	0.9994	0.9998	0.8818	0.118
UGR	0.9426	0.9272	0.8161	0.1265
UNSW	0.8904	0.9369	0.8849	0.052

Evaluation of Supervised Algs. (II)

► Now, let's look at Recall-Unk

- Supervised against unsupervised classifiers
- Negative value in the plot means that unsupervised classifiers outperform supervised in detecting unknowns





Need of Unsupervised Meta-Learning

- ▶ Overall, Supervised > Unsupervised
 - Except for Recall-Unk (detection of zero-days)

BUT BUT BUT

- ▶ Top-Performing Supervised Algorithms use complex learning strategies (meta-learning)
 - Random Forests -> Bagging
 - XGBoost -> (extreme) gradient boosting

why shouldn't we apply those to unsupervised algorithms?

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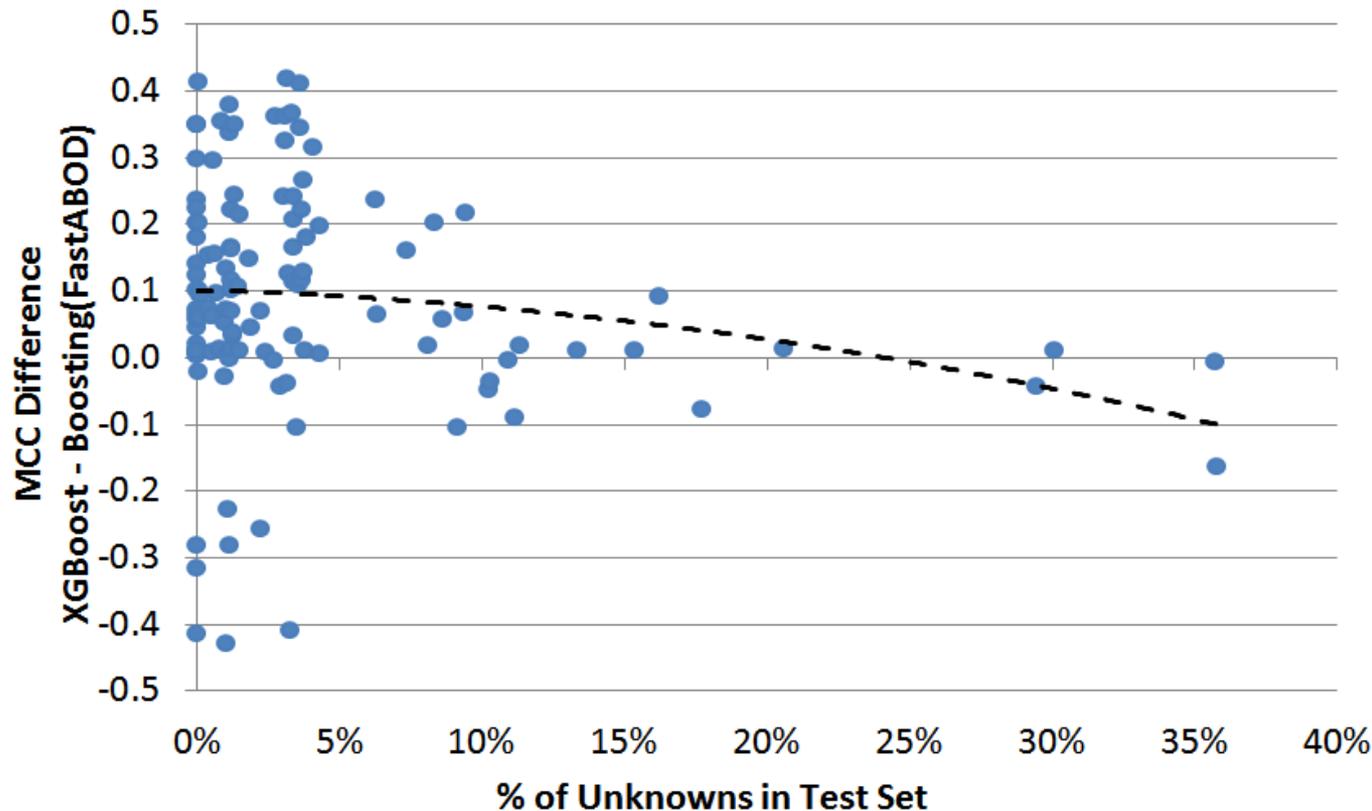
Unsupervised Meta-Learning

- ▶ As such, we built bagging and boosting ensembles of unsupervised algorithms

Dataset	Unsupervised			Improvement w Boosting
	Regular	Bagging	Boosting	
ADFANet	0.9837	0.9867	0.9916	0.0079
AndMal	0.5503	0.4290	0.5277	-0.0226
CICIDS17	0.6511	0.6706	0.8981	0.247
CICIDS18	0.8277	0.8369	0.8460	0.0183
CIDDS	0.8026	0.8234	0.9734	0.1708
IoT_IDS	0.9739	0.9902	0.9896	0.0157
ISCX	0.7921	0.8447	0.8202	0.0281
NSLKDD	0.8384	0.8925	0.9101	0.0717
SDN20	0.8818	0.9441	0.9481	0.0663
UGR	0.8161	0.8445	0.8745	0.0584
UNSW	0.8849	0.8457	0.8927	0.0078

Compare w XGB - MCC

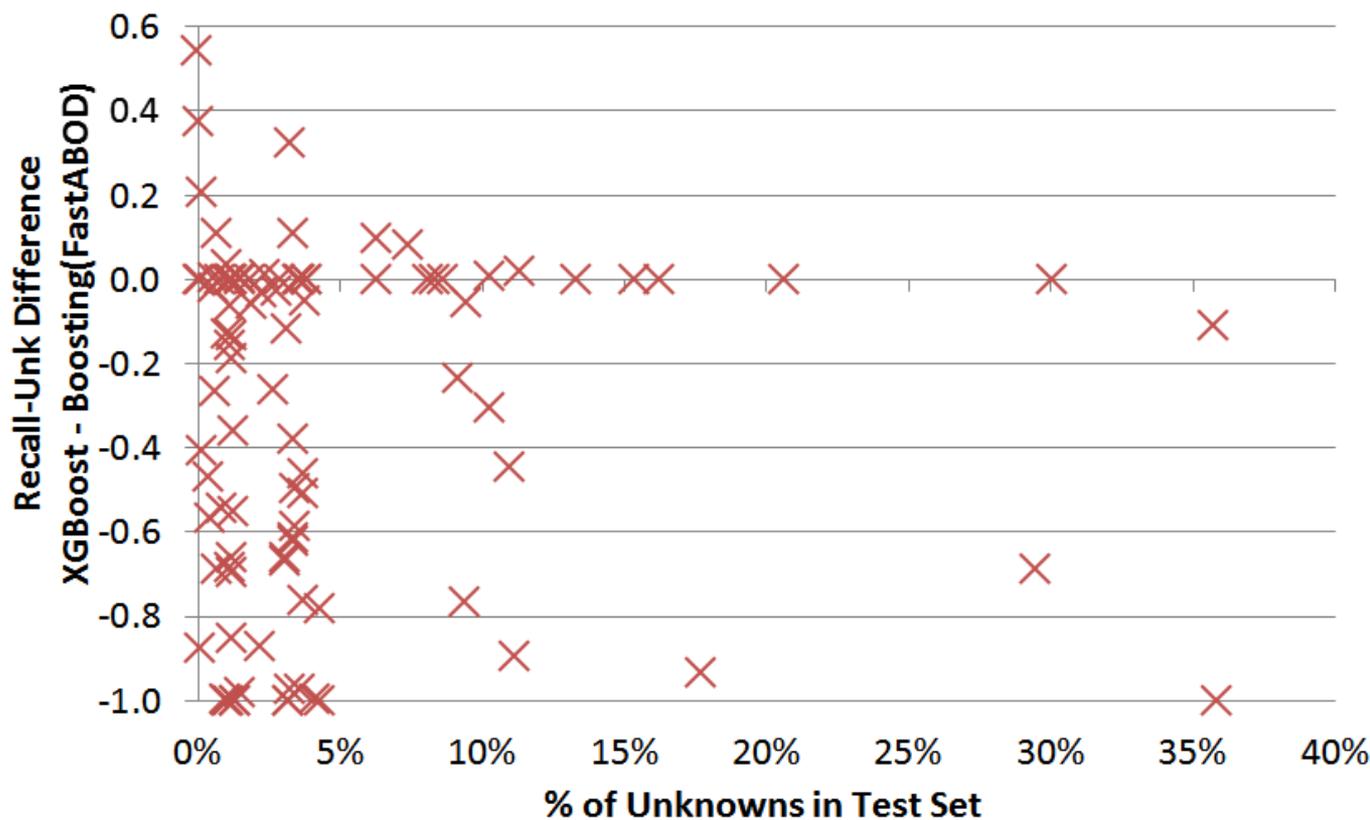
- ▶ Scores of XGB (sup) vs FastABOD (w boosting)
- ▶ MCC of XGB decays the more unknowns happen
 - Up to a point in which Unsup > Sup



VS – Recall-Unk Comparison

► Also, Recall-Unk of FastABOD is far better than those of XGBoost

- And this gets more evident the more zero-days appear





Takeovers

- There is no “silver bullet” algorithm to plug into a system for excellent intrusion detection capabilities
- Deep Learning algorithms do not really fit the analysis of tabular data coming from network monitoring
 - XGBoost > Deep Learners (FastAI, TabNet, Autogluon ...)
- XGBoost (sup) shows good overall detection capabilities
- Applying meta-learning dramatically reduces misclassifications of unsupervised algorithms
 - Up to a point in which FastABOD > XGBoost
 - But only if we expect zero-days to happen very frequently!



