## Final Project: Attack Detection

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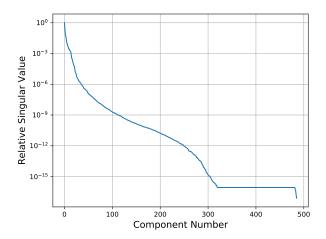
#### Outline

- Introduction
- 2 Input Transformations
- Feature Selection
- Previous Models
- Neural Network
- 6 Novel Learner
- Performance Comparisons
- 8 Conclusion

## Input Transformations

- Transformations only on training data to remove bias.
- Normalization across all samples or samples sharing a time-stamp.
- Available feature-wise normalization techniques:
  - Max: Map X to  $X \in \left[\frac{X_{\min}}{X_{\max}}, 1\right]$ .
  - Standard: Map X to a zero mean and unit variance.
  - Robust: Map X by removing the median and dividing with the IQR.
- Principal Component Analysis (PCA):
  - Dimensionality reduction.
  - Fully decouple the inputs by changing to an orthogonal coordinate system.

## Singular Value Decomposition of Input Data

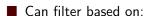


### Feature Selection

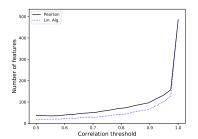
- Correlation filter:
  - Pearson correlation

Pearson correlation 
$$c_{i,j} = \frac{\sum\limits_{k=1}^{N}(x_{i,k}-\bar{x}_i)(x_{j,k}-\bar{x}_j)}{\sqrt{\sum\limits_{k=1}^{N}(x_{i,k}-\bar{x}_i)^2\sum\limits_{k=1}^{N}(x_{j,k}-\bar{x}_j)^2}} \sqrt{\sum\limits_{k=1}^{N}(x_{i,k}-\bar{x}_i)^2\sum\limits_{k=1}^{N}(x_{j,k}-\bar{x}_j)^2}$$
• Linear Algebra correlation

$$c_{i,j} = \frac{x_i \cdot x_j}{||x_i|| ||x_i||},$$



- feature-feature correlation
- feature-label correlation

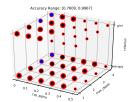


### Previous Model Performance

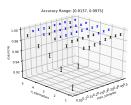
Rank	Model	Accuracy		Domain	Normalization
		Optimized	HW 3	Domain	INOTHIAIIZALIOII
1	Perceptron	(0.9956,	(0.9866,	Global	Any
	Forest	1.0000)	1.0000)		
1 <sup>a</sup>	KNN	(0.9949,	(0.9814,	Global	Standard
		1.0000)	0.9952)		
1	Decision	(0.9871,	(0.9914,	Global	Any
	Tree	1.0000)	1.0000)		
1	Perceptron	(0.9871,	(0.9315,	Global	Standard
		0.9981)	0.9600)		

<sup>&</sup>lt;sup>a</sup>McNemar test [1].

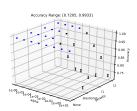
### Grid Search



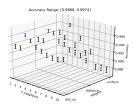
(a) Decision tree.



(c) Perceptron forest.



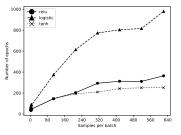
(b) Perceptron.

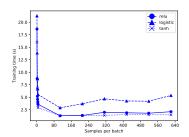


(d) KNN.

## Neural Network Optimizations I

#### ■ Batch/Mini-batch/Stochastic:

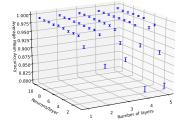


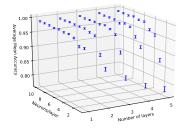


- Number of hidden neurons: 4x7
- Stochastic is the best in number of epochs till convergence
- Stochastic is the worst in terms of training time (due to large number of parameters)
- Both tanh(x) and ReLU(x) activation functions perform better than the sigmoid

## Neural Network Optimizations II

Number of layers, number of neurons per layer:





- (a) Number of features: 486
- (b) Number of features: 101
- Connecting multiple layers with only one neuron is not worth it.
- Above 6-7 neurons per layer, no statistical improvement observed.
- Removing redundant features has little impact on accuracy.

### Best Neural Network Results

Attribute	Value		
Normalization	Global Standardization		
Number of layers	2		
Neurons per layer	9		
Mean Accuracy	0.9936		
Standard Deviation	0.0026		
95.00% Confidence	$0.9936 \pm 0.0051$		
Accuracy Range	(0.9885, 0.9987)		
Best Accuracy	0.9968		
Training Time	7.5350 s		
Classification Time	0.0039 s		

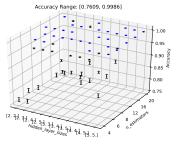
Slow to train and not necessarily better than other learners!

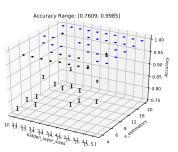
- Training neural networks is expensive.
- Employing a bagger as a filter could reduce the dimensionality of the input data and simplify the target function a neural network must learn.
- Baggers have been shown to be more accurate with unstable weak learners

  - If classifiers within an ensemble have uncorrelated outputs, the output of the ensemble will have higher accuracy than the individual classifiers
  - The author's of [2] show this by comparing unstable decision trees to stable naive Bayes learners.
- An ensemble approach with decision trees is the appropriate design for the novel learner.

## Ensemble Network Architecture Optimization

■ Number of estimators, network architecture:





- Significant reduction in overall size of neural network.
- Optimum number of hidden layers 2.
- Best Configuration:
  - \* Number of estimators: 8
  - \* Architecture: (3, 3)

### Best Ensemble Network Results

Attribute	Value		
Normalization	Global Standardization		
Mean Accuracy	0.9979		
Standard Deviation	0.0015		
95.00% Confidence	$0.9979 \pm 0.0048$		
Accuracy Range	(0.9931, 1.0000)		
Best Accuracy	1.0000		
Training Time	2.5403 s		
Classification Time	0.0242 s		

Greatest mean accuracy of all models and  $\approx 66\%$  reduction in training time compared to the neural network!

# Model Comparisons

Rank	Model	Accuracy		Domain	Normalization
		Optimized	HW 3	Domain	INOTHIAIIZALIUII
1	Perceptron	(0.9956,	(0.9866,	Global	Any
	Forest	1.0000)	1.0000)		
1	KNN	(0.9949,	(0.9814,	Global	Standard
		1.0000)	0.9952)		
1	Ensemble	(0.9931,	_	Global	Any
	Network	1.0000)			
1	Neural	(0.9885,	_	Global	Standard
	Network	0.9987)			
1	Decision	(0.9871,	(0.9914, Global	Any	
	Tree	1.0000)	1.0000)	.0000)	Ally
1	Perceptron	(0.9871,	(0.9315,	Global	Standard
		0.9981)	0.9600)		

#### Conclusions

- For neural networks, tanh(x) and mini-batch learning yield the minimum training times.
- The novel learner yielded comparable to better accuracy to the neural network.
- The novel learner sports a 66% reduction in training time compared to the neural network.
- Further optimizations on the novel learner architecture and exploration of PCA to come!

### References



S. Raschka, "Model evaluation, model selection, and algorithm selection in machine learning."



D. W. A. D. Bazell, "Ensembles of classifiers for morphological galaxy classification," *The Astrophysical Journal*, 2001.