# Deep Learning for Network Intrusion Detection System

CSC 11910 Spring 2023 Temidayo Akinyemi, Pushpen Bikash Goala, Ivan Miller Professor: Michael Grossberg

#### Motivation

- Huge volume of network traffic to be analyzed
- Quick identification of malicious attack traffic is a challenge in cybersecurity
- Lots of detection systems are signature-based
- Security analysts are usually overwhelmed by the volume of data traffic they have to look through
- Lots of false positives eventually causing alert fatigue
- Aim to create intrusion detection system to identify attack patterns with a high detection rate
- UNSW-NB15 Dataset 9 attack classes, 49 features, 2mill records

#### Intended Experiments

#### Part 1: Data preprocessing

- Data cleaning
- Feature Selection
- Class Imbalance

#### **Part 2: Baseline Methods**

- Random Forest
- Logistic Regression
- KNN
- Simple Sequential Model

#### Part 3: Deep Learning Methods

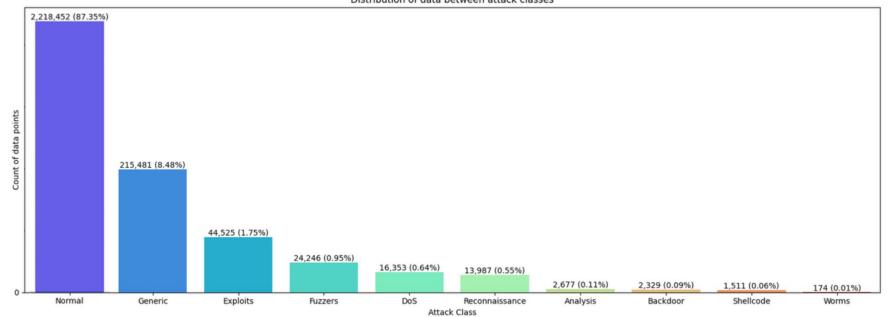
- Larger Sequential Model
- Autoencoder & Variational Autoencoder

Part 1: Data preprocessing

#### NB-15 Dataset

- Data Cleaning
- Feature Importance (VIF, Pearson correlation, RF)
- Visualization of classes





#### Dataset: Pearson Correlation + VIF + Random Forest

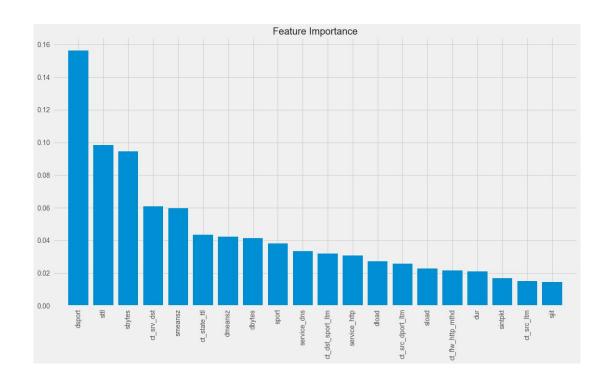
Pearson Correlation

• Variance Inflation Factor (VIF) is given by

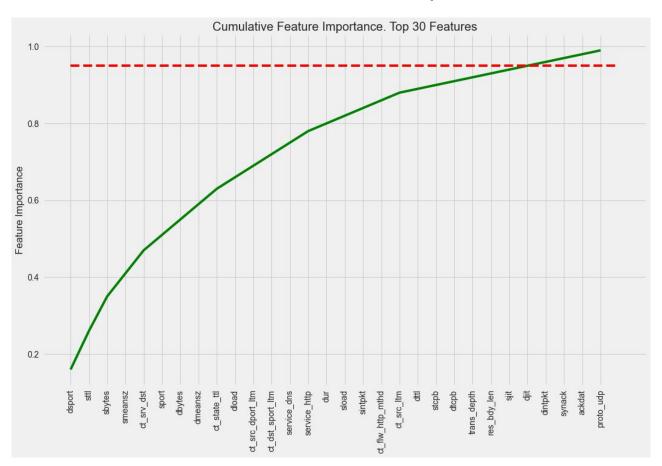
$$VIF_{i} = \frac{1}{1-R_{i}^{2}}$$
 , where  $R^{2}$  is the coefficient of determination

Random Forest

#### Dataset: Feature Importance with Random Forest



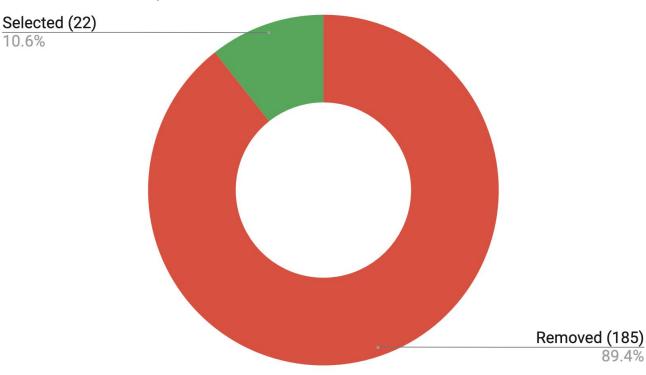
#### Dataset: Cumulative Feature Importance



#### Dataset: Removed 89% of Features

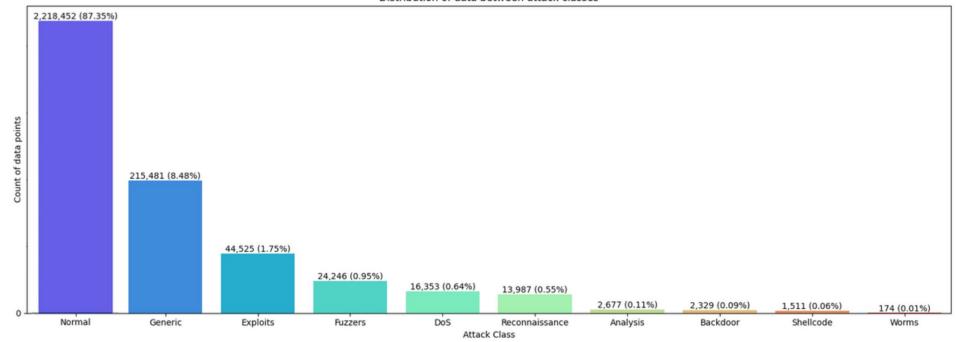
- sttl
- sbytes
- smeansz
- sload
- dmeansz
- dbytes
- dsport
- ct\_srv\_src
- dintpkt
- sport
- o ct\_dst\_sport\_ltm
- o tcprtt
- 。 dur
- o dttl
- $_{\circ}$  sintpkt
- 。ct\_src\_ltm
- spkts
- 。 sjit
- 。 djit
- 。stcpb
- o res\_bdy\_len
- trans\_depth

Feature Selection. Kept vs Removed Features

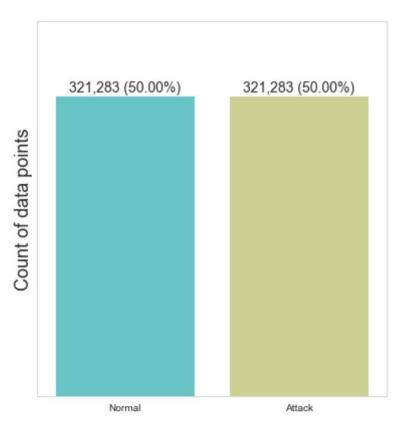


#### Class Imbalance





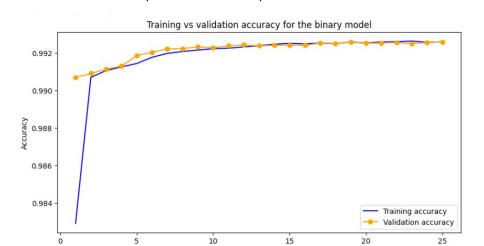
#### Binary Classification: Undersampling Majority Class

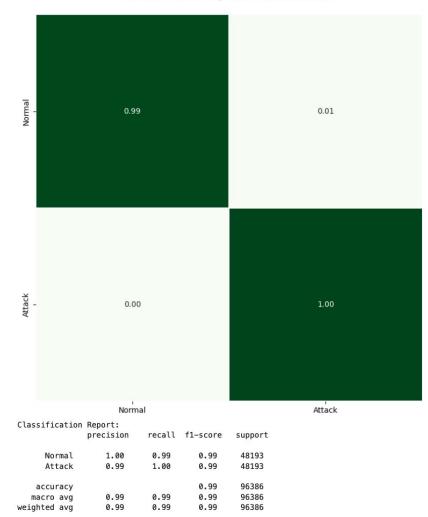


Part 2: Baseline Methods

#### Binary Classification: Results

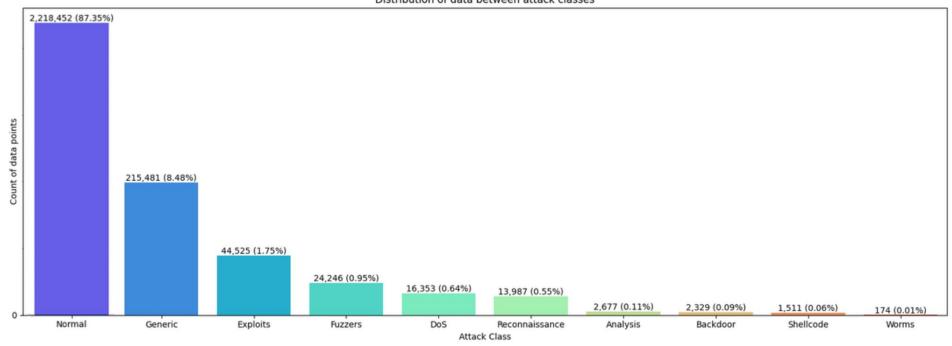
- Random Forest: 99.32%
- Logistic Regression: 98.93%
- K-Nearest Neighbors (KNN): 99.19%
- Neural Network: 99.30%
  - 2 hidden layers (256 >> 128 units)
  - o 40k params & 25 epochs





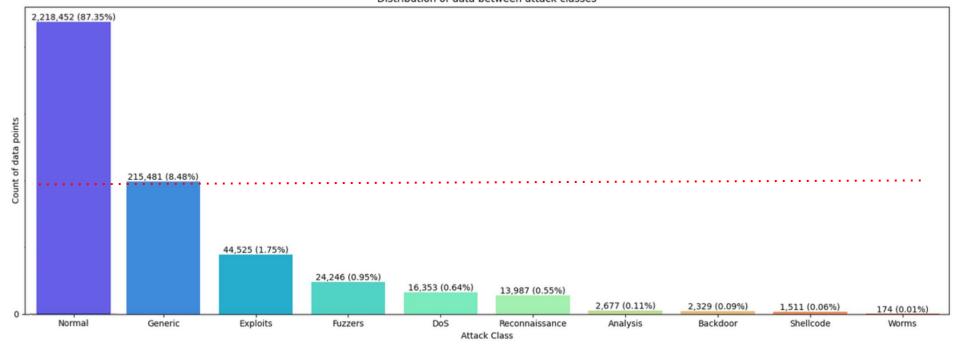
#### Multi-class. Addressing Imbalance with SMOTE





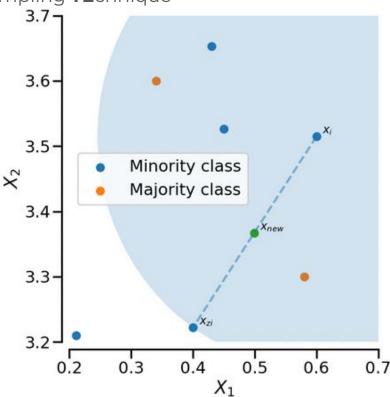
#### Class Imbalance





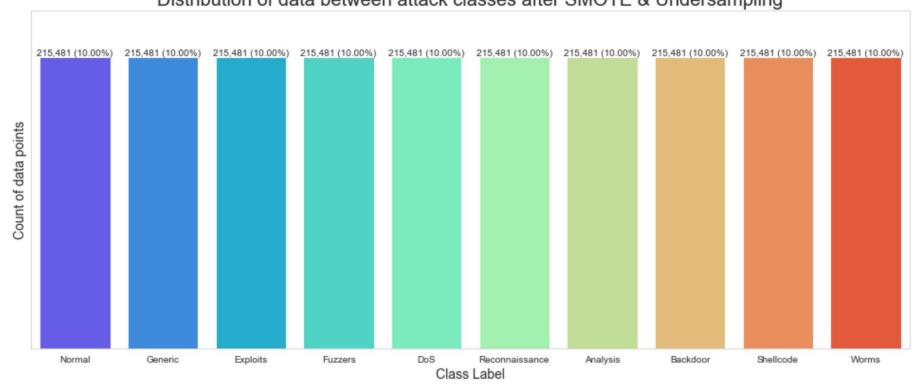
#### Class Imbalance: SMOTE & undersampling

Synthetic Minority Oversampling TEchnique



#### Class Imbalance: SMOTE & Undersampling

Distribution of data between attack classes after SMOTE & Undersampling



#### Cross-validation and Grid Search with SMOTE

#### Steps:

- Subsampled imbalanced data
- 5-Fold Cross-Validation
- Applied SMOTE & Undersampling on TRAIN folds
- Grid Search (80 combinations):
  - 300 trees
  - Min 3 samples to split a node
  - 10 nodes max
  - Min 2 samples per leaf

Trained Random Forest on the full balanced train set

#### Multi-class: Random Forest

Balanced Accuracy on Test Set: 72.68%

Normal	0.99	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Generic	0.00	0.97	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Exploits	0.00	0.00	0.44	0.05	0.24	0.04	0.02	0.13	0.02	0.05
Fuzzers	0.00	0.00	0.00	0.87	0.05	0.01	0.00	0.06	0.00	0.01
DoS	0.00	0.00	0.11	0.03	0.53	0.01	0.02	0.26	0.01	0.02
Reconnaissance	0.00	0.00	0.00	0.00	0.11	0.82	0.00	0.05	0.00	0.01
Analysis	0.00	0.00	0.00	0.00	0.42	0.00	0.25	0.32	0.00	0.00
Backdoor	0.00	0.00	0.01	0.01	0.44	0.01	0.03	0.48	0.01	0.01
Shellcode	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.98	0.00
Worms	0.00	0.00	0.00	0.04	0.00	0.04	0.00	0.00	0.00	0.92
	Normal	Generic	Exploits	Fuzzers	DoS	naissance	Analysis	Backdoor	Shellcode	Worms

inference time: 13.509408955000254

Accuracy:0.97

Balanced accuracy:0.73

Precision: 0.98 Recall: 0.97 F1-score: 0.97

Report:			
precision	recall	f1-score	support
1.00	0.99	0.99	332768
1.00	0.97	0.99	32322
0.82	0.44	0.58	6679
0.42	0.87	0.56	3637
0.34	0.53	0.41	2453
0.81	0.82	0.81	2098
0.12	0.25	0.16	402
0.08	0.48	0.13	349
0.49	0.98	0.66	227
0.04	0.92	0.07	26
		0.97	380961
0.51	0.73	0.54	380961
0.98	0.97	0.97	380961
	1.00 1.00 0.82 0.42 0.34 0.81 0.12 0.08 0.49 0.04	1.00 0.99 1.00 0.97 0.82 0.44 0.42 0.87 0.34 0.53 0.81 0.82 0.12 0.25 0.08 0.48 0.49 0.98 0.04 0.92	precision         recall         f1-score           1.00         0.99         0.99           1.00         0.97         0.99           0.82         0.44         0.58           0.42         0.87         0.56           0.34         0.53         0.41           0.81         0.82         0.81           0.12         0.25         0.16           0.08         0.48         0.13           0.49         0.98         0.66           0.04         0.92         0.07           0.51         0.73         0.54

#### Multi-class: Random Forest

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Fuzzers	0.00	0.00	0.00	0.87	0.05	0.01	0.00	0.06	0.00	0.01
DoS	0.00	0.00	0.11	0.03	0.53	0.01	0.02	0.26	0.01	0.02
Reconnaissance	0.00	0.00	0.00	0.00	0.11	0.82	0.00	0.05	0.00	0.01
Analysis	0.00	0.00	0.00	0.00	0.42	0.00	0.25	0.32	0.00	0.00
Backdoor	0.00	0.00	0.01	0.01	0.44	0.01	0.03	0.48	0.01	0.01
Shellcode	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.98	0.00
Worms	0.00	0.00	0.00	0.04	0.00	0.04	0.00	0.00	0.00	0.92
	Normal	Generic	Exploits	Fuzzers	Dos	naissance	Analysis	Backdoor	Shellcode	Worms

inference time: 13.509408955000254

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Classification	Report:			
	precision	recall	f1-score	support
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Exploits	0.82	0.44	0.58	6679
Fuzzers	0.42	0.87	0.56	3637
DoS	0.34	0.53	0.41	2453
Reconnaissance	0.81	0.82	0.81	2098
Analysis	0.12	0.25	0.16	402
Backdoor	0.08	0.48	0.13	349
Shellcode	0.49	0.98	0.66	227
Worms	0.04	0.92	0.07	26
accuracy			0.97	380961
macro avg	0.51	0.73	0.54	380961
weighted avg	0.98	0.97	0.97	380961

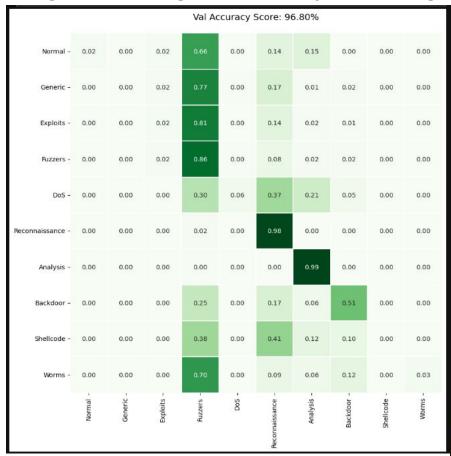
#### Logistic Regression (multiclass)(Test)

				Test A	ccuracy	Score: 9	6.81%			
Normal -	0.99	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Generic -	0.00	0.98	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Exploits -	0.00	0.01	0.43	0.04	0.31	0.01	0.04	0.05	0.02	0.10
Fuzzers -	0.00	0.00	0.01	0.80	0.07	0.05	0.01	0.03	0.00	0.03
DoS -	0.00	0.01	0.13	0.03	0.66	0.02	0.04	0.07	0.01	0.04
Reconnaissance -	0.00	0.00	0.01	0.02	0.15	0.68	0.00	0.01	0.00	0.13
Analysis -	0.00	0.00	0.04	0.01	0.57	0.00	0.28	0.09	0.00	0.00
Backdoor -	0.00	0.00	0.05	0.04	0.55	0.01	0.12	0.18	0.03	0.02
Shellcode -	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.95	0.03
Worms -	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.06	0.82
	Normal -	Generic -	Exploits -	Fuzzers -	- DOS -	Reconnaissance -	Analysis -	Backdoor -	Shellcode	Worms -

	precision	recall	f1-score	support
Normal	1.00	0.99	0.99	221846
Generic	1.00	0.98	0.99	21548
Exploits	0.77	0.43	0.55	4452
Fuzzers	0.43	0.80	0.56	2425
DoS	0.33	0.66	0.44	1635
Reconnaissance	0.65	0.68	0.66	1399
Analysis	0.10	0.28	0.15	268
Backdoor	0.07	0.18	0.10	233
Shellcode	0.54	0.95	0.69	151
Worms	0.02	0.82	0.03	17
accuracy			0.97	253974
macro avg	0.49	0.68	0.52	253974
weighted avg	0.98	0.97	0.97	253974

Dataset	No. of the contract of the con		Balanced Accuracy		
	Logistic Regression			0.98%	31 10 27 10 10

#### Logistic Regression (after log transformation)



	column	range	std_dev
0	dur	8786.637695	12.790263
1	sbytes	13677393.000000	59568.237445
2	dbytes	14655417.000000	160579.679925
3	sttl	255.000000	74.598099
4	dttl	254.000000	42.903800
5	sload	5640000000.000000	118277920.527573
6	dload	128761904.000000	4228217.689794
7	spkts	10200.000000	77.736579
8	swin	255.000000	125.460743
9	stcpb	4294958913.000000	1421676319.890164
10	dtcpb	4294953724.000000	1422227817.896179
11	smeansz	1504.000000	152.161292
12	dmeansz	1500.000000	335.562090
13	trans_depth	172.000000	0.325749
14	res bdy len	6558056.000000	47617.334730
15	sjit	1483830.917000	17040.869328
16	djit	781221.118300	3383.518124
17	stime	2334691.000000	1134350.896264
18	sintpkt	60009.992000	2783.993022
19	dintpkt	57739.240000	1428.959277
20	tcprtt	10.037506	0.046891
21	synack	4.525272	0.026429
22	ackdat	5.512234	0.024193
23	is_sm_ips_ports	1.000000	0.040646
24	ct_state_ttl	6.000000	0.683346
25	ct_flw_http_mthd	36.000000	0.556569
26	is_ftp_login	1.000000	0.130179
27	ct_ftp_cmd	8.000000	0.184054
28	ct_srv_src	66.000000	10.830274
29	ct_dst_ltm	66.000000	8.160660
30	ct_src_ ltm	66.000000	8.204105
31	ct_dst_sport_ltm	59.000000	6.176511
32	total_bytes	14725649.000000	173750.649661

Dataset		F1-score	Accuracy	Balanced Accuracy	Precision   Recall	ij
Val	Logistic Regression	0.96%	0.97%	0.35%	0.97% 0.97%	İ

#### Exploring LIME for binary classification

```
In [33]: import lime
          from lime import lime tabular
In [36]: import numpy as np
In [37]: explainer = lime tabular.LimeTabularExplainer(
                       training data = np.array(x train ssc),
                       feature names = pd.DataFrame(x train ssc).columns,
                       class_names=['normal', 'attack'],
                       mode='classification'
In [49]: exp = explainer.explain instance(
                   data row = pd.DataFrame(x test ssc).iloc[44452],
                   predict fn = model.predict proba
In [50]: exp.show_in_notebook(show_table=True)
                                                                         attack
                                                  normal
            Prediction probabilities
                                                                                         Feature Value
                                                                 16 > -0.11
                   normal 0.00
                                                        160 \le -0.01
                                       1.00
                    attack
                                                        181 \le -0.01
                                                        98 \le -0.01
                                                       202 \le -0.02
                                                        142 \le -0.01
                                                         0.29
                                                        121 \le -0.01
                                                         0.28
                                                        106 \le -0.01
                                                        111 \le -0.01
                                                        123 \le -0.01
```

#### **Cross Validation & Grid Search**

- Subsampled 20 percent of the imbalanced train data (all features) to use for cross-validation
- Reduced the feature number to 20 using Autoencoder
- Perform 5 fold cross-validation with upsampling using SMOTE on TRAIN folds
   ONLY
- Loop to find the best parameters considering balanced accuracy as the main metric

#### Cross Validation & Grid Search

```
[{'n neighbors': 49, 'balanced accuracy': 0.5508148051162506}.
 {'n neighbors': 50, 'balanced accuracy': 0.5511920811605482},
 {'n_neighbors': 51, 'balanced_accuracy': 0.5523819275900327},
 {'n_neighbors': 52, 'balanced_accuracy': 0.5557178600589406},
 {'n_neighbors': 53, 'balanced_accuracy': 0.5556471417887272},
 {'n_neighbors': 54, 'balanced_accuracy': 0.551750839937972},
  'n neighbors': 55, 'balanced accuracy': 0.5599760683814748}
 {'n_neighbors': 56, 'balanced_accuracy': 0.5573045869512194},
  'n neighbors': 57, 'balanced accuracy': 0.5569417807182738},
 ['n neighbors': 58, 'balanced_accuracy': 0.5560335307225059];
  'n neighbors': 59, 'balanced accuracy': 0.5630037411254806},
 'n neighbors': 60, 'balanced accuracy': 0.561005063642477},
 'n neighbors': 61, 'balanced accuracy': 0.5677061492385941},
  'n_neighbors': 62, 'balanced_accuracy': 0.5653395355553826},
 {'n_neighbors': 63, 'balanced_accuracy': 0.566290560405714},
 {'n_neighbors': 64, 'balanced_accuracy': 0.5647718505852728},
 {'n_neighbors': 65, 'balanced_accuracy': 0.5643503723158758},
 {'n neighbors': 66, 'balanced accuracy': 0.5665008392798578},
 {'n neighbors': 67, 'balanced accuracy': 0.5669077215489262},
 {'n neighbors': 68, 'balanced accuracy': 0.5643401813505488},
  'n neighbors': 69. 'balanced accuracy': 0.5649583175224001}.
 {'n neighbors': 70, 'balanced accuracy': 0,5600643302747267},
 {'n neighbors': 71, 'balanced accuracy': 0.5617432271889845}.
 {'n neighbors': 72, 'balanced accuracy': 0.5674144299502444}.
 {'n_neighbors': 73, 'balanced_accuracy': 0.5630399576800995},
 {'n_neighbors': 74, 'balanced_accuracy': 0.5678219393440977},
 {'n neighbors': 75, 'balanced accuracy': 0.5655973678758706},
 {'n neighbors': 76, 'balanced accuracy': 0.5663929771522259}.
 {'n neighbors': 77, 'balanced_accuracy': 0.5683476918573426},
 {'n_neighbors': 78, 'balanced_accuracy': 0.5649599016050691},
 {'n neighbors': 79, 'balanced accuracy': 0.5703037967766694},
 'n_neighbors': 80, 'balanced_accuracy': 0.5697340315202826},
 ['n neighbors': 81, 'balanced accuracy': 0.5702264107092452},
  'n neighbors': 82, 'balanced accuracy': 0.564277279996679},
  'n neighbors': 83, 'balanced accuracy': 0.5673289434214377}.
  'n neighbors': 84, 'balanced accuracy': 0.5689585643743597},
 'n_neighbors': 85, 'balanced_accuracy': 0.5722217154031973},
 {'n neighbors': 86, 'balanced accuracy': 0.5649246007014843},
 {'n neighbors': 87, 'balanced accuracy': 0.5701193226449313},
 {'n neighbors': 88, 'balanced accuracy': 0.5702827576946465},
 {'n neighbors': 89, 'balanced accuracy': 0.5683590433240072}.
 {'n neighbors': 90, 'balanced accuracy': 0.5688847766877598},
 {'n_neighbors': 91, 'balanced_accuracy': 0.5689720163302273},
  'n neighbors': 92, 'balanced accuracy': 0.5696620910448992},
 {'n_neighbors': 93, 'balanced_accuracy': 0.5719220548252297},
 ['n neighbors': 94, 'balanced accuracy': 0.5721098872392114},
 {'n neighbors': 95, 'balanced accuracy': 0,5727270922342399},
  'n neighbors': 96, 'balanced accuracy': 0.5708056959099765}.
 {'n neighbors': 97, 'balanced accuracy': 0.5700645614486193}.
  'n_neighbors': 98, 'balanced_accuracy': 0.5730734125876973},
 ['n neighbors': 99, 'balanced accuracy': 0.5714835320094052},
 {'n neighbors': 100. 'balanced accuracy': 0.5710996858021758}]
```

#### n\_neighbours=95

Model: "model 4"

	Output Shape	Param #
<pre>input_3 (InputLayer)</pre>	[(None, 207)]	0
dense (Dense)	(None, 414)	86112
batch_normalization_6 (Batc hNormalization)	(None, 414)	1656
leaky_re_lu (LeakyReLU)	(None, 414)	0
dense_1 (Dense)	(None, 207)	85905
batch_normalization_7 (Batc hNormalization)	(None, 207)	828
leaky_re_lu_1 (LeakyReLU)	(None, 207)	Ø
dense_2 (Dense)	(None, 20)	4160
dense_3 (Dense)	(None, 207)	4347
batch_normalization_8 (Batc hNormalization)	(None, 207)	828
leaky_re_lu_2 (LeakyReLU)	(None, 207)	0
dense_4 (Dense)	(None, 414)	86112
batch_normalization_9 (Batc hNormalization)	(None, 414)	1656
leaky_re_lu_3 (LeakyReLU)	(None, 414)	Ø
dense_5 (Dense)	(None, 207)	85905
otal params: 357,509		
Trainable params: 355,025		
Non-trainable params: 2,484		

None

#### KNN (Multi-Class)

Accuracy:0.96
Balanced accuracy:0.63
Precision:0.98
Recall:0.96
F1-score:0.97



#### KNN (Multi-Class)

Classification	Report:			
	precision	recall	f1-score	support
Normal	1.00	0.98	0.99	221846
Generic	1.00	0.97	0.99	21548
Exploits	0.70	0.40	0.51	4452
Fuzzers	0.39	0.75	0.51	2425
DoS	0.31	0.55	0.40	1635
Reconnaissance	0.54	0.62	0.58	1399
Analysis	0.07	0.29	0.11	268
Backdoor	0.03	0.07	0.04	233
Shellcode	0.42	0.89	0.57	151
Worms	0.02	0.82	0.03	17
accuracy			0.96	253974
macro avg	0.45	0.63	0.47	253974
weighted avg	0.98	0.96	0.97	253974

#### LIME For Multiclass

#### Prediction probabilities

#### **NOT** Generic

service\_dns > -0.38 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.04 | 0.059 < proto\_udp <=... | 0.01 | ct\_dst\_ltm > -0.16 | 0.01 | ct\_src\_ltm > -0.02 | 0.01 | 0.58 < ct\_state\_ttl <=...

0.01

Generic

#### Feature Value

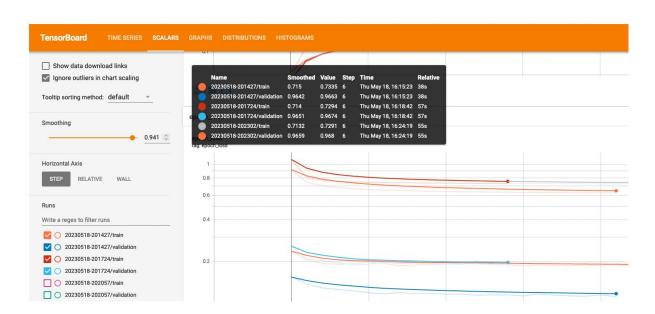
service_dns	2.64
service_http	-0.40
proto_udp	1.70
ct_dst_ltm	2.76
ct_src_ltm	2.28
ct_state_ttl	

### Part 3: Deep Learning

Baseline Neural Network for Multi-Class Case

#### Sequential Model: KerasTuner + TensorBoard

- Simple Architecture (6 hidden layers)
- Relu activation on hidden layers
- Train data upsampled w/SMOTE
- Adam optimizer
- 1024 batch size
- 0.001 learning rate



#### Sequential Model: KerasTuner + TensorBoard

- Simple Architecture (6 hidden layers)
- L2 regularization
- Tanh activation on hidden layers
- Train data upsampled w/SMOTE
- Adam optimizer

Model: "model"

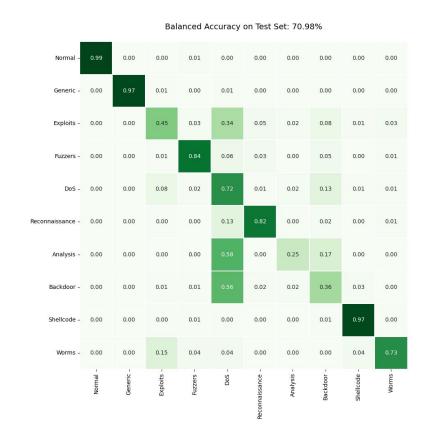
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 22)]	0
dense (Dense)	(None, 512)	11776
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 512)	262656
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 256)	131328
dropout_2 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 256)	65792
dropout_3 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 128)	32896
dropout_4 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 128)	16512
dropout_5 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 10)	1290

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Total params: 522,250 Trainable params: 522,250 Non-trainable params: 0

#### Sequential Model: KerasTuner + TensorBoard

- Simple Architecture (6 hidden layers)
- L2 regularization
- Tanh activation on hidden layers
- Train data upsampled w/SMOTE
- Adam optimizer



#### Ensemble of One vs All Classifiers

- 10 Small Neural Nets for each class
- Weighted Voting Classifier

Accuracy:0.97

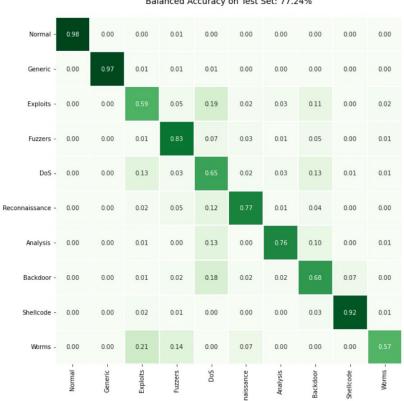
Balanced accuracy:0.77

Precision:0.98 Recall:0.97 F1-score:0.98

Classification Report:

C COSSITICATION I	20 Table 20			
	precision	recall	f1-score	support
Normal	1.00	0.98	0.99	135296
Generic	1.00	0.97	0.99	13285
Exploits	0.79	0.59	0.67	2719
Fuzzers	0.41	0.83	0.55	1466
DoS	0.42	0.65	0.51	981
Reconnaissance	0.78	0.77	0.77	857
Analysis	0.25	0.76	0.38	157
Backdoor	0.12	0.68	0.21	133
Shellcode	0.30	0.92	0.46	91
Worms	0.06	0.57	0.12	14
accuracy			0.97	154999
macro avg	0.51	0.77	0.56	154999
weighted avg	0.98	0.97	0.98	154999

Balanced Accuracy on Test Set: 77.24%



### Part 3: Deep Learning

Variational Autoencoder

#### Variational Autoencoder

Model: "model\_2"

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 207)]	0	[]
batch_normalization_4 (BatchNo rmalization)	(None, 207)	828	['input_2[0][0]']
encoder_hidden (Dense)	(None, 25)	5200	['batch_normalization_4[0][0]']
batch_normalization_5 (BatchNormalization)	(None, 25)	100	['encoder_hidden[0][0]']
z_mean (Dense)	(None, 20)	520	['batch_normalization_5[0][0]']
z_log_var (Dense)	(None, 20)	520	['batch_normalization_5[0][0]']
z_sampled (Lambda)	(None, 20)	0	['z_mean[0][0]', 'z_log_var[0][0]']
decoder_hidden (Dense)	(None, 25)	525	['z_sampled[0][0]']
decoded_mean (Dense)	(None, 207)	5382	['decoder_hidden[0][0]']

Total params: 13,075 Trainable params: 12,611 Non-trainable params: 464

Test Accuracy Score: 95.27%

## KNN With Variational Autoencoder

Accuracy:0.95

Balanced accuracy:0.634

Precision:0.97

Recall:0.95

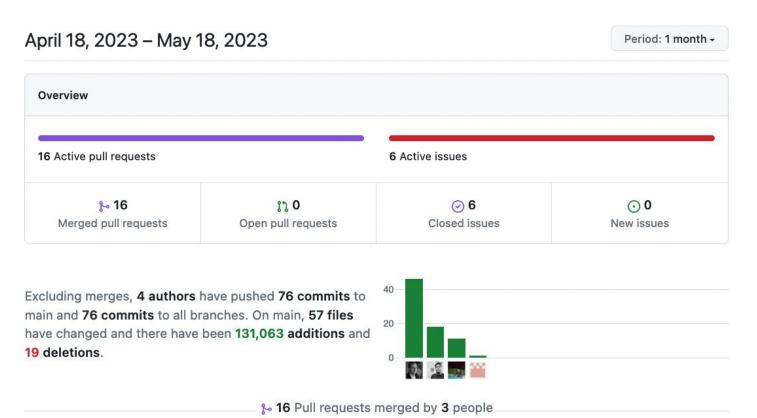
F1-score:0.96

Normal -	0.97	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Generic -	0.00	0.97	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Exploits -	0.01	0.00	0.41	0.05	0.27	0.03	0.07	0.06	0.02	0.09
Fuzzers -	0.00	0.00	0.02	0.66	0.07	0.13	0.02	0.03	0.02	0.06
DoS -	0.00	0.00	0.13	0.02	0.54	0.02	0.10	0.13	0.01	0.04
Reconnaissance -	0.00	0.00	0.01	0.05	0.13	0.66	0.02	0.03	0.00	0.11
Analysis -	0.00	0.00	0.03	0.00	0.51	0.00	0.27	0.18	0.00	0.01
Backdoor -	0.00	0.00	0.05	0.05	0.55	0.03	0.17	0.09	0.05	0.02
Shellcode -	0.00	0.00	0.00	0.07	0.00	0.04	0.00	0.00	0.89	0.01
Worms -	0.00	0.00	0.06	0.00	0.00	0.06	0.00	0.00	0.00	0.88
	Normal -	Generic -	Exploits -	Ruzzers -	- Sog	nnaissance -	Analysis -	Backdoor -	Shellcode -	Worms -

#### KNN With Variational Autoencoder

Classification	Report:			
	precision	recall	f1-score	support
Normal	1.00	0.97	0.99	221846
Generic	0.99	0.97	0.98	21548
Exploits	0.38	0.41	0.39	4452
Fuzzers	0.35	0.66	0.45	2425
DoS	0.30	0.54	0.38	1635
Reconnaissance	0.52	0.66	0.58	1399
Analysis	0.07	0.27	0.11	268
Backdoor	0.03	0.09	0.05	233
Shellcode	0.30	0.89	0.44	151
Worms	0.01	0.88	0.03	17
accuracy			0.95	253974
macro avg	0.40	0.63	0.44	253974
weighted avg	0.97	0.95	0.96	253974

#### Contributions. Repository on GitHub. Commits



#### Contributions. Repository on GitHub. Commits

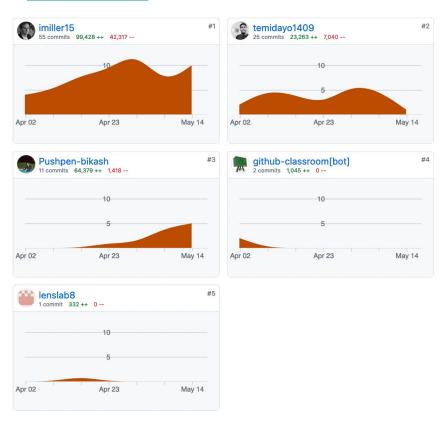
Apr 2, 2023 – May 18, 2023

Contributions: Commits -

Contributions to main, excluding merge commits and bot accounts



### Repository on GitHub. Individual Contributions



#### Repository on <u>GitHub</u>. New Code Over Time





