


Intrusion Detection with Machine Learning



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Data 606

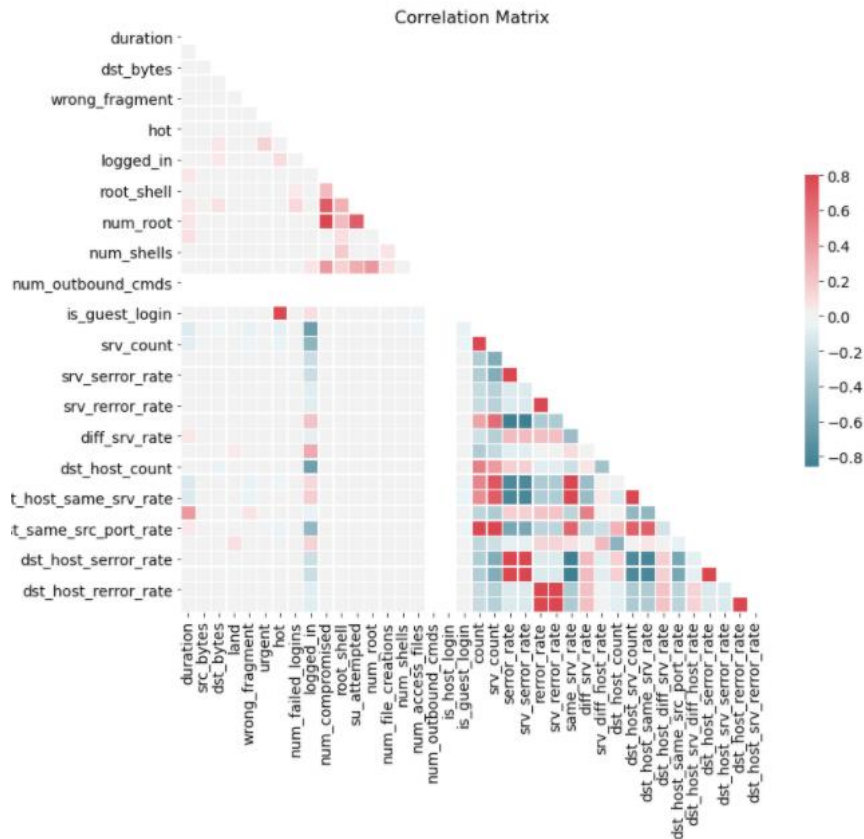


RECAP

- Intrusion Detection System using KDD-CUP 99 Dataset
- Neural Network that can work with the dataset
- Dataset is 75MB CSV File
- Dataset contains 41 unique features
- No nulls or missing values

Creation of a Correlation Matrix

- Correlation of one column to another column in our dataset
- Dataset do not have a lot correlation



Data Exploration

- Dataset contains 42 unique features including the label
- 39 features are numerical values
- 4 features columns are object types
 - Service has 64 unique categories
 - Flag has 11 unique categories
 - Protocol Type has 3 unique categories
 - Label(attack) has 23 unique categories

```
Column: flag has 11 unique categories
Distribution for flag
SF      302903
S0      49526
RE3     23430
R5T6    710
R5T0    466
SH       81
S1      43
S2       10
S3       10
R5T0S0   9
OTH       6
Name: flag, dtype: int64
```

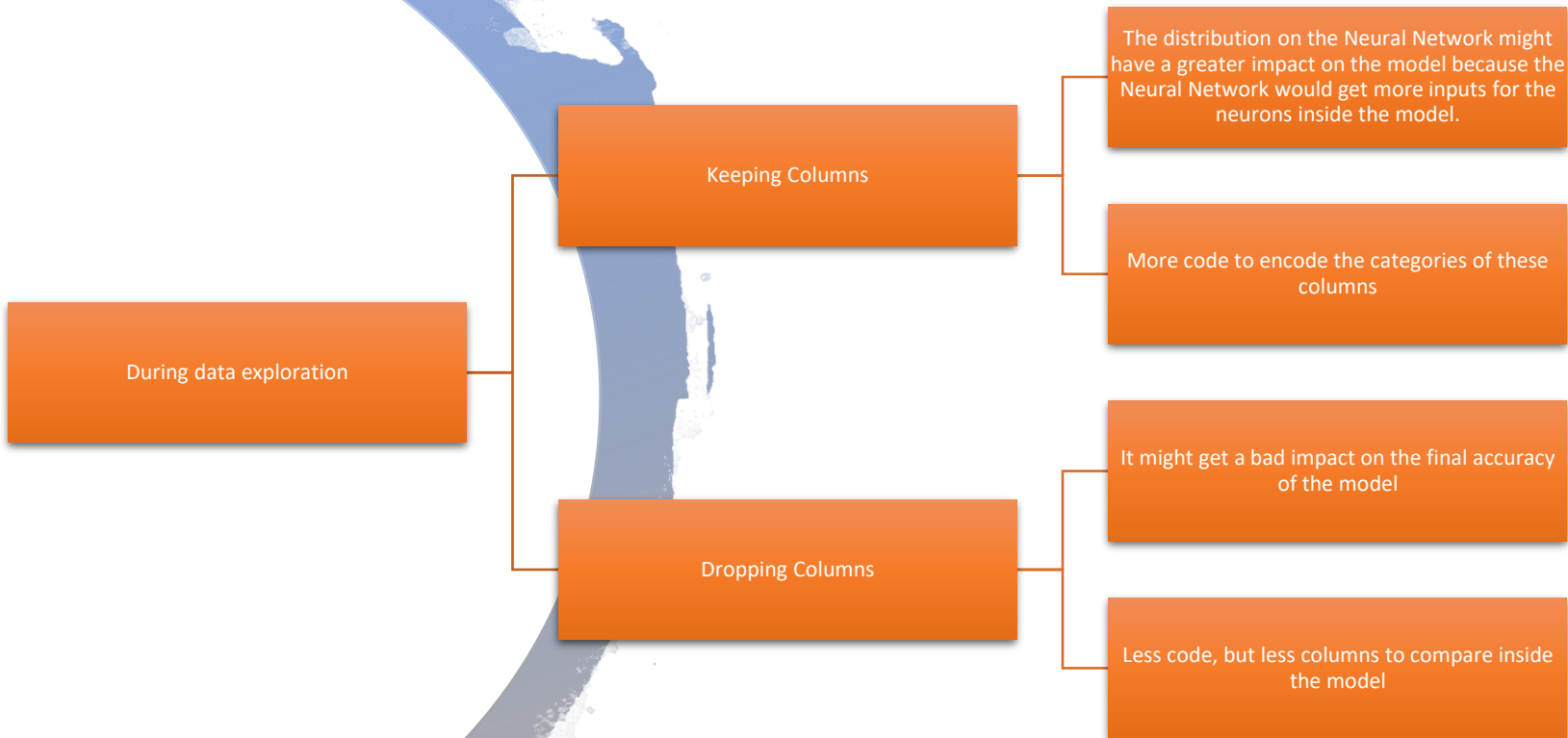
```
Column: service has 65 unique categories
Distribution for service
ecr_i    225258
private  88632
http     51347
smtp     7765
other    5827
```

```
urh_i    13
X11      9
tim_i     6
pm_dump   1
red_i     1
Name: service, Length: 65, dtype: int64
```

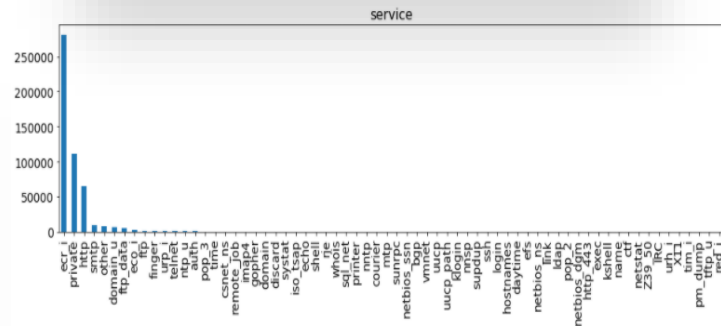
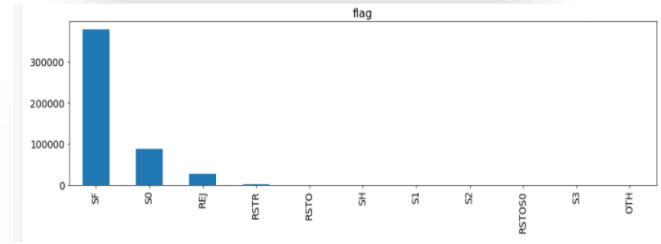
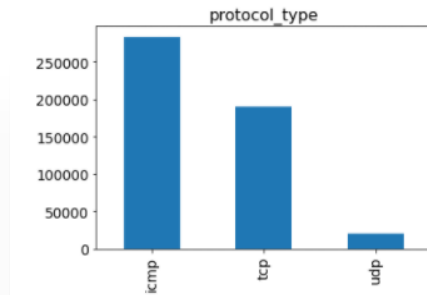
```
Column: label has 23 unique categories
Distribution for label
smurf.    224761
neptune.  85659
normal.   77761
back.     1777
satan.    1298
ipsweep.  988
portsweep. 824
warezclient. 815
teardrop.  800
pod.      210
nmap.     183
guess_passwd. 44
buffer_overflow. 21
land.     19
warezmaster. 15
imap.     9
rootkit.  7
loadmodule. 7
multihop. 6
phf.      4
ftp_write. 4
perl.     3
spy.      1
Name: label, dtype: int64
```

```
Column: protocol_type has 3 unique categories
Distribution for protocol_type
icmp    226997
tcp     151889
udp     16330
Name: protocol_type, dtype: int64
```

Decisions ?



Distributions of these Columns



Dataset after keeping the Categories

- After encoding the categories, we ended up with a new database that contains 119 columns which is almost twice as large than the original
- Use `labelEncoder()` with `oneHotEncoder()` to transform the string values

Before Encoding

Out[31]:

	service	flag	protocol_type
288190	ecr_i	SF	icmp
338941	ecr_i	SF	icmp
138802	http	SF	top
271063	ecr_i	SF	icmp
342685	ecr_i	SF	icmp

After Encoding

Out[32]:

	service	flag	protocol_type
288190	14	9	0
338941	14	9	0
138802	22	9	1
271063	14	9	0
342685	14	9	0

Before Adding the New Categories

```
In [78]: #printing the shape of all Datasets
print(f'Original Dataset: {df.shape}, Train Dataset: {dfTrain.shape}, Test Dataset: {dfTest.shape}')
Original Dataset: (494021, 42), Train Dataset: (395216, 42), Test Dataset: (98805, 42)
```

After Adding the New Categories

```
In [79]: #printing the shape of all Datasets after
print(f'Original Dataset: {df.shape}, Train Dataset Encoded: {dfTrainFinal.shape}, Test Dataset Encoded: {dfTestFinal.shape}')
Original Dataset: (494021, 42), Train Dataset Encoded: (395216, 119), Test Dataset Encoded: (98805, 119)
```

Lessons



Scaling the data is very important?



For neural network, scaling the features can create a balance between the different columns.



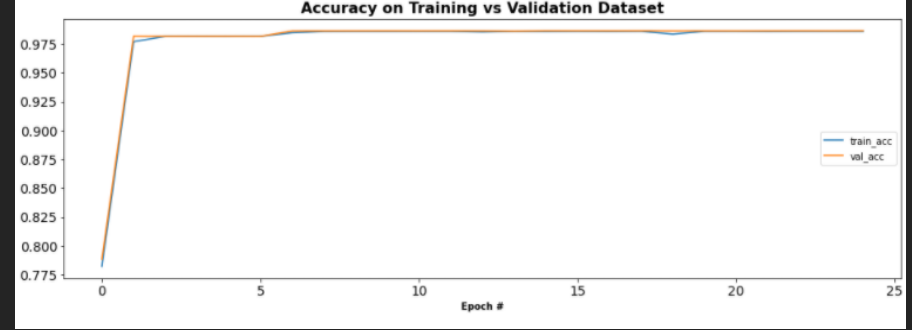
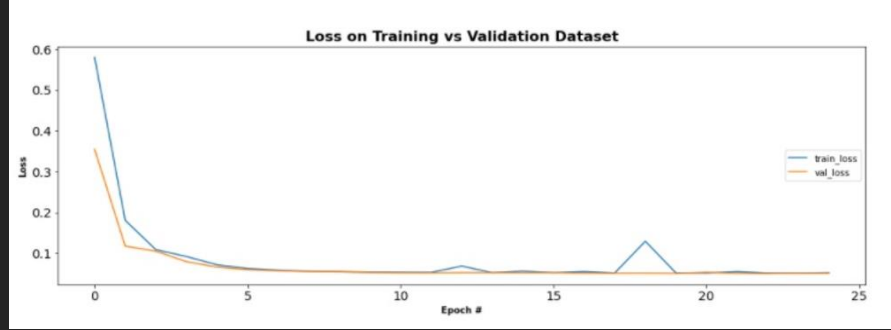
Better performance



Differences in the scales across input variables may increase the difficulty of the problem being modeled.

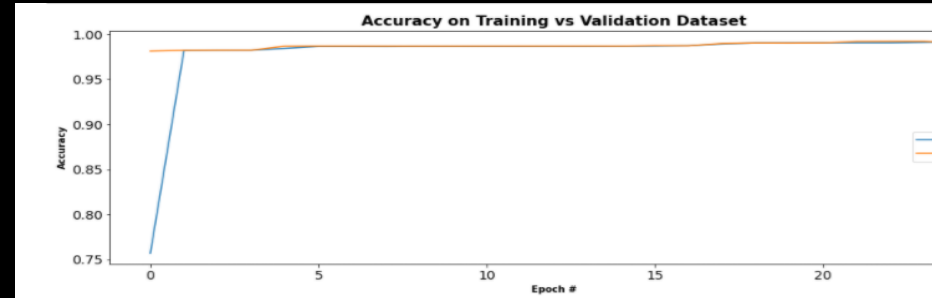
```
Epoch 23/25
17785/17785 [=====] - 12s 668us/step - loss: 1.7766 - accuracy: 0.4093 - val_loss: 1.6932 - val_accuracy: 0.4212
Epoch 24/25
17785/17785 [=====] - 12s 668us/step - loss: 1.2961 - accuracy: 0.5321 - val_loss: 1.2481 - val_accuracy: 0.5592
Epoch 25/25
17785/17785 [=====] - 12s 668us/step - loss: 1.1561 - accuracy: 0.5878 - val_loss: 1.2366 - val_accuracy: 0.5559
```


3 Layers



Neural Network models?

5 Layers



Coming Next

Create a complex Neural Network

- Create model that can have an early stopper for overfitting
- More layers vs More epochs
- Create a second Model using Random Forest
 - Compare Results
 - Advantages and Disadvantages of both models



Code Overview

```
mirror_ob.select=1  
mirror_mod.mirror_object  
operation = "MIRROR_X"  
mirror_mod.use_x = True  
mirror_mod.use_y = False  
mirror_mod.use_z = False  
operation = "MIRROR_Y"  
mirror_mod.use_x = False  
mirror_mod.use_y = True  
mirror_mod.use_z = False  
operation = "MIRROR_Z"  
mirror_mod.use_x = False  
mirror_mod.use_y = False  
mirror_mod.use_z = True
```

```
selection at the end - add  
mirror_ob.select=1  
mirror_ob.select=1
```

```
context.scene.objects.active
```

```
("Selected" + str(modifier
```

```
mirror_ob.select = 0
```

```
bpy.context.selected_ob
```

```
data.objects[one.name].se
```

```
print("please select exactly
```

```
OPERATOR CLASS
```

```
MODE OK
```

New Sources

- Brownlee, J. (2020, August 25). How to use Data Scaling Improve Deep Learning Model Stability and Performance. Retrieved October 28, 2020, from <https://machinelearningmastery.com/how-to-improve-neural-network-stability-and-modeling-performance-with-data-scaling/>
- Valkov, V. (2019, Jul 01). Build your first Neural Network in TensorFlow 2: TensorFlow for Hackers (Part I). Retrieved October 28, 2020, from <https://towardsdatascience.com/building-your-first-neural-network-in-tensorflow-2-tensorflow-for-hackers-part-i-e1e2f1dfe7a0>
- Lolico, R. (2020, July 06). Creating a Vanilla Neural Network with Tensorflow. Retrieved October 28, 2020, from <https://towardsdatascience.com/creating-a-vanilla-neural-network-with-tensorflow-96fec241e369>

