Performing anomaly detection on UNSW_NB15_1 dataset

1.1 Loading the dataset

Connecting to the google drive where dataset is stored

```
## Mouting the google drive in which datasets are stored
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount
```

> Loading the necessary libraries

```
## Loading the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
```

> Loading the dataset

```
## Loading the dataset
data = pd.read_csv('drive/MyDrive/netSecurity/UNSW-NB15_1.csv', sep=',',
                   low_memory = False, header= None)
```

```
## Checking the shape of UNSW-NB15_1 dataset
data.shape
```

```
(700001, 49)
```

```
## Getting the overview of the loaded data
data.head()
```

	0	1	2	3	4	5	6	7	8	9	...	39	40	41	42	43	44	45	46	47	48
0	59.166.0.0	1390	149.171.126.6	53	udp	CON	0.001055	132	164	31	...	0	3	7	1	3	1	1	1	NaN	0
1	59.166.0.0	33661	149.171.126.9	1024	udp	CON	0.036133	528	304	31	...	0	2	4	2	3	1	1	2	NaN	0
2	59.166.0.6	1464	149.171.126.7	53	udp	CON	0.001119	146	178	31	...	0	12	8	1	2	2	1	1	NaN	0
3	59.166.0.5	3593	149.171.126.5	53	udp	CON	0.001209	132	164	31	...	0	6	9	1	1	1	1	1	NaN	0
4	59.166.0.3	49664	149.171.126.0	53	udp	CON	0.001169	146	178	31	...	0	7	9	1	1	1	1	1	NaN	0

5 rows × 49 columns

```
## Getting the feature names for above loaded dataset
featuresNames = pd.read_csv('drive/MyDrive/netSecurity/NUSW-NB15_features.csv',
                            encoding='latin-1')
## printing the feature names
featuresNames
```

	No.	Name	Type	Description
0	1	srcip	nominal	Source IP address
1	2	sport	integer	Source port number
2	3	dstip	nominal	Destination IP address
3	4	dsport	integer	Destination port number
4	5	proto	nominal	Transaction protocol
5	6	state	nominal	Indicates to the state and its dependent proto...
6	7	dur	Float	Record total duration
7	8	sbytes	Integer	Source to destination transaction bytes
8	9	dbytes	Integer	Destination to source transaction bytes
9	10	sttl	Integer	Source to destination time to live value
10	11	dttl	Integer	Destination to source time to live value
11	12	sloss	Integer	Source packets retransmitted or dropped
12	13	dloss	Integer	Destination packets retransmitted or dropped
13	14	service	nominal	http, ftp, smtp, ssh, dns, ftp-data ,irc and ...
14	15	Sload	Float	Source bits per second
15	16	Dload	Float	Destination bits per second
16	17	Spkts	integer	Source to destination packet count
17	18	Dpkts	integer	Destination to source packet count
18	19	swin	integer	Source TCP window advertisement value
19	20	dwin	integer	Destination TCP window advertisement value
20	21	stcpb	integer	Source TCP base sequence number
21	22	dtcpb	integer	Destination TCP base sequence number
22	23	smeansz	integer	Mean of the ?ow packet size transmitted by the...
23	24	dmeansz	integer	Mean of the ?ow packet size transmitted by the...
24	25	trans_depth	integer	Represents the pipelined depth into the connec...
25	26	res_bdy_len	integer	Actual uncompressed content size of the data t...
26	27	Sjit	Float	Source jitter (mSec)
27	28	Djit	Float	Destination jitter (mSec)
28	29	Stime	Timestamp	record start time
29	30	Ltime	Timestamp	record last time
30	31	Sintpkt	Float	Source interpacket arrival time (mSec)
31	32	Dintpkt	Float	Destination interpacket arrival time (mSec)
32	33	tcprtt	Float	TCP connection setup round-trip time, the sum ...
33	34	synack	Float	TCP connection setup time, the time between th...
34	35	ackdat	Float	TCP connection setup time, the time between th...
35	36	is_sm_ips_ports	Binary	If source (1) and destination (3)IP addresses ...
36	37	ct_state_ttl	Integer	No. for each state (6) according to specific r...
37	38	ct_flw_http_mthd	Integer	No. of flows that has methods such as Get and ...
38	39	is_ftp_login	Binary	If the ftp session is accessed by user and pas...
39	40	ct_ftp_cmd	integer	No of flows that has a command in ftp session.

1.2 Overlaying feature names on the dataset

42	43	ct_dst_ltm	integer	No. of connections of the same destination add...

```
## Assigning features names to the repective columns using the features names
## dataset
feaNames= np.array(featuresNames['Name'])
data.columns = feaNames
data.head()
```

	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	ct_ftp_cmd	ct_srv_src	ct_srv_dst
0	59.166.0.0	1390	149.171.126.6	53	udp	CON	0.001055	132	164	31	...	0	3	7
1	59.166.0.0	33661	149.171.126.9	1024	udp	CON	0.036133	528	304	31	...	0	2	4
2	59.166.0.6	1464	149.171.126.7	53	udp	CON	0.001119	146	178	31	...	0	12	8
3	59.166.0.5	3593	149.171.126.5	53	udp	CON	0.001209	132	164	31	...	0	6	9
4	59.166.0.3	49664	149.171.126.0	53	udp	CON	0.001169	146	178	31	...	0	7	9

> Since, the attack_cat feature contains NaN's in place of normal datapoints. We are checking the shape to get a view how many of these occurances are there.

```
data[pd.isna(data['attack_cat']) & (data['Label'] == 0)].shape
```

```
(677786, 49)
```

```
# Initial no. anomalous cases
data[data['Label'] == 1].shape
```

```
(22215, 49)
```

```
## Replacing NaN with normal in attack_cat column
data['attack_cat'].fillna('normal', inplace=True)
```

```
## Checking the modified shape which is same as above i.e. 677785
data[(data['attack_cat']=='normal')].shape
```

```
(677786, 49)
```

```
print(data.dtypes)
```

```
srcip                object
sport                object
dstip                object
dsport               object
proto                object
state                object
dur                 float64
sbytes                int64
dbytes                int64
sttl                  int64
dttl                  int64
sloss                 int64
dloss                 int64
service              object
Sload               float64
Dload               float64
Spkts                 int64
Dpkts                 int64
swin                  int64
dwin                  int64
stcpb                 int64
dtcpb                 int64
smeansz               int64
dmeansz               int64
trans_depth           int64
res_bdy_len           int64
Sjit                float64
Djit                float64
Stime                 int64
Ltime                 int64
Sintpkt             float64
Dintpkt             float64
tcprtt              float64
synack              float64
ackdat              float64
is_sm_ips_ports       int64
ct_state_ttl          int64
ct_flw_http_mthd      int64
is_ftp_login          int64
ct_ftp_cmd            int64
ct_srv_src            int64
ct_srv_dst            int64
ct_dst_ltm            int64
ct_src_ ltm           int64
ct_src_dport_ltm      int64
ct_dst_sport_ltm      int64
ct_dst_src_ltm        int64
attack_cat           object
```

```
Label                 int64
dtype: object
```

1.3 Checks for Missing data values

```
## Checking for missing values
print(data.isna().sum())
```

```
srcip               0
sport               0
dstip               0
dsport              0
proto               0
state               0
dur                 0
sbytes              0
dbytes              0
sttl                0
dttl                0
sloss               0
dloss               0
service             0
Sload               0
Dload               0
Spkts               0
Dpkts               0
swin                0
dwin                0
stcpb               0
dtcpb               0
smeansz             0
dmeansz             0
trans_depth         0
res_bdy_len         0
Sjit                0
Djit                0
Stime               0
Ltime               0
Sintpkt             0
Dintpkt             0
tcprtt              0
synack              0
ackdat              0
is_sm_ips_ports     0
ct_state_ttl        0
ct_flw_http_mthd    0
is_ftp_login        0
ct_ftp_cmd          0
ct_srv_src          0
ct_srv_dst          0
ct_dst_ltm          0
ct_src_ ltm         0
ct_src_dport_ltm    0
ct_dst_sport_ltm    0
ct_dst_src_ltm      0
attack_cat          0
Label               0
dtype: int64
```

1.4 Checks for Duplicate data

```
## checking for duplicated Rows
data.loc[data.duplicated(), :]
## Shape of the data does not remain same, we have duplicate rows
```

	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	ct_ftp_cmd	ct_srv_src	ct_s
11	10.40.170.2	0	10.40.170.2	0	arp	INT	0.000000	46	0	0	...	0	2	
12	10.40.182.3	0	10.40.182.3	0	arp	INT	0.000000	46	0	0	...	0	2	
72	59.166.0.6	15807	149.171.126.7	53	udp	CON	0.001118	132	164	31	...	0	12	
122	10.40.85.1	0	224.0.0.5	0	ospf	INT	50.004341	384	0	1	...	0	2	
699649	59.166.0.0	46785	149.171.126.2	5190	tcp	FIN	0.004181	1064	2260	31	...	0	16	

Since, there are duplicate rows which can be dropped and we are just keeping the first occurance of those and dropping duplicate one's.

```
## keeping the first occurance and dropping the duplicates
data.drop_duplicates(keep='first',inplace=True)

## Printing the shape of the dataset after removing duplicates
print(data.shape)
```

```
(640788, 49)
```

```
dup = 700001-640788
print(dup)
```

```
59213
```

```
## Checking for NA's in rows of modified data
print("No. of NA's present in the given Dataset:",data.isnull().values.
      ravel().sum())
```

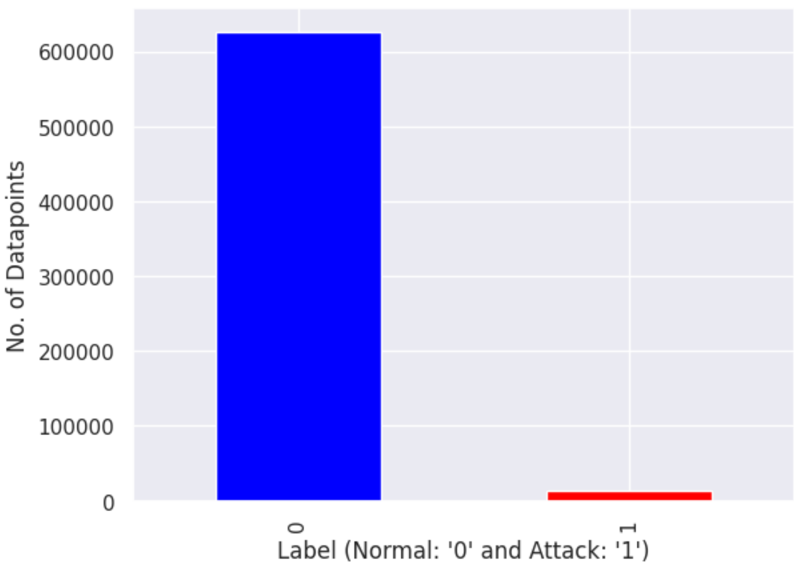
```
No. of NA's present in the given Dataset: 0
```

```
## Now checking for duplicate columns
dupColumns = data.columns[data.columns.duplicated()]

# Print the duplicate columns
print("No. of Duplicate columns:",len(dupColumns))
## As return is empty we can say that all features are unique
```

```
No. of Duplicate columns: 0
```

1.5 Distribution of the UNSW_NB dataset

```
## Checking for normal and anomalous data distribution
## (Normal: '0' and Attack: '1')
sns.set(style="darkgrid")

data['Label'].value_counts().plot.bar(color=['blue', 'red'])

plt.xlabel("Label (Normal: '0' and Attack: '1')")
plt.ylabel("No. of Datapoints")
plt.show()
```



Data Preprocessing

2.1 Checking for hexadecimal data:

```
## Checking for features that contains hexadecimal values
hexCols = []
for col in data.columns:
  count = data[col].astype(str).str.contains('0x').sum()
  if count>0:
    hexCols.append(col)
  print("{0} feature contains {1} hexadecimal values".format(col, count))
```

```
srcip feature contains 0 hexadecimal values
sport feature contains 6 hexadecimal values
dstip feature contains 0 hexadecimal values
dsport feature contains 56 hexadecimal values
proto feature contains 0 hexadecimal values
state feature contains 0 hexadecimal values
dur feature contains 0 hexadecimal values
sbytes feature contains 0 hexadecimal values
dbytes feature contains 0 hexadecimal values
sttl feature contains 0 hexadecimal values
dttl feature contains 0 hexadecimal values
sloss feature contains 0 hexadecimal values
dloss feature contains 0 hexadecimal values
service feature contains 0 hexadecimal values
Sload feature contains 0 hexadecimal values
Dload feature contains 0 hexadecimal values
Spkts feature contains 0 hexadecimal values
Dpkts feature contains 0 hexadecimal values
swin feature contains 0 hexadecimal values
dwin feature contains 0 hexadecimal values
stcpb feature contains 0 hexadecimal values
dtcpb feature contains 0 hexadecimal values
smeansz feature contains 0 hexadecimal values
dmeansz feature contains 0 hexadecimal values
trans_depth feature contains 0 hexadecimal values
res_bdy_len feature contains 0 hexadecimal values
Sjit feature contains 0 hexadecimal values
Djit feature contains 0 hexadecimal values
Stime feature contains 0 hexadecimal values
Ltime feature contains 0 hexadecimal values
Sintpkt feature contains 0 hexadecimal values
Dintpkt feature contains 0 hexadecimal values
tcprtt feature contains 0 hexadecimal values
synack feature contains 0 hexadecimal values
ackdat feature contains 0 hexadecimal values
is_sm_ips_ports feature contains 0 hexadecimal values
ct_state_ttl feature contains 0 hexadecimal values
ct_flw_http_mthd feature contains 0 hexadecimal values
is_ftp_login feature contains 0 hexadecimal values
ct_ftp_cmd feature contains 0 hexadecimal values
ct_srv_src feature contains 0 hexadecimal values
ct_srv_dst feature contains 0 hexadecimal values
ct_dst_ltm feature contains 0 hexadecimal values
ct_src_ ltm feature contains 0 hexadecimal values
ct_src_dport_ltm feature contains 0 hexadecimal values
ct_dst_sport_ltm feature contains 0 hexadecimal values
ct_dst_src_ltm feature contains 0 hexadecimal values
attack_cat feature contains 0 hexadecimal values
Label feature contains 0 hexadecimal values
```

```
## printing the columns with hexadecimal values
print('Features with hexadecimal values are:',hexCols)
```

```
Features with hexadecimal values are: ['sport', 'dsport']
```

```
## Removing the hexadecimal rows based on their index
hexRows = []

for col in hexCols:
    mask = data[col].astype(str).str.contains('0x')
    hexRows.extend(mask[mask].index.tolist())

hexRows = list(set(hexRows))
## Removing the rows that contains these hexadecimal values
data = data.drop(hexRows)

print("Dimensions of the data after modification are:", data.shape)
```

```
Dimensions of the data after modification are: (640726, 49)
```

2.2 Identify categorical and numerical features

Getting the names of the features which are categorical and which are numeric

```
## Getting the categorical columns
catCols = data.select_dtypes('object').columns
catCols = catCols.tolist()

## Getting the numeric columns
numCols = data._get_numeric_data().columns
numCols = numCols.tolist()


print("Categorical columns are:",catCols, '\n')
print("Numerical columns are:", numCols)
```

```
Categorical columns are: ['srcip', 'sport', 'dstip', 'dsport', 'proto', 'state', 'service', 'attack_cat']

Numerical columns are: ['dur', 'sbytes', 'dbytes', 'sttl', 'dttl', 'sloss', 'dloss', 'Sload', 'Dload', 'Spkts', 'Dpkts',
```

```
## Dropping the attack_cat column(Because we don't want to encode it)
catCols.remove('attack_cat')
print(catCols)
```

```
['srcip', 'sport', 'dstip', 'dsport', 'proto', 'state', 'service']
```

```
## function for checking unique data in columns
def uniq(data, fea):
  uniq = len(np.unique(data[fea]))
  # Printing the results
  print("Unique {0} feature data values are {1}".format(fea, uniq))

## Checking no. of unique values in each columns of the dataset
for col in data.columns:
  uniq(data, col)
```

```
Unique srcip feature data values are 40
Unique sport feature data values are 64539
Unique dstip feature data values are 44
Unique dsport feature data values are 62220
Unique proto feature data values are 134
Unique state feature data values are 14
Unique dur feature data values are 243827
Unique sbytes feature data values are 7947
Unique dbytes feature data values are 11898
Unique sttl feature data values are 13
Unique dttl feature data values are 11
Unique sloss feature data values are 275
Unique dloss feature data values are 572
Unique service feature data values are 13
Unique Sload feature data values are 391838
Unique Dload feature data values are 403499
Unique Spkts feature data values are 715
Unique Dpkts feature data values are 1086
Unique swin feature data values are 12
Unique dwin feature data values are 4
Unique stcpb feature data values are 441843
Unique dtcpb feature data values are 441640
Unique smeansz feature data values are 1288
Unique dmeansz feature data values are 1356
Unique trans_depth feature data values are 6
Unique res_bdy_len feature data values are 543
Unique Sjit feature data values are 426219
Unique Djit feature data values are 454152
Unique Stime feature data values are 27568
Unique Ltime feature data values are 27566
Unique Sintpkt feature data values are 350428
Unique Dintpkt feature data values are 351748
Unique tcprtt feature data values are 17050
Unique synack feature data values are 15769
Unique ackdat feature data values are 13690
Unique is_sm_ips_ports feature data values are 2
Unique ct_state_ttl feature data values are 7
Unique ct_flw_http_mthd feature data values are 13
Unique is_ftp_login feature data values are 2
Unique ct_ftp_cmd feature data values are 8
Unique ct_srv_src feature data values are 43
Unique ct_srv_dst feature data values are 40
Unique ct_dst_ltm feature data values are 41
Unique ct_src_ ltm feature data values are 45
Unique ct_src_dport_ltm feature data values are 34
Unique ct_dst_sport_ltm feature data values are 32
Unique ct_dst_src_ltm feature data values are 33
```

```
Unique attack_cat feature data values are 10
Unique Label feature data values are 2
```

Since, the service feature contains '-' as unique value. We are removing it and None in it's place. There may other columns present which will encounter the same problem. So, doing this for every feature present in the dataset.

```
data['service'].unique()
idx_rm = np.array(data[data['service'] == '-'].index)
## no. of rows associated with '-'
print("No. of rows with '-':", len(idx_rm))
```

```
No. of rows with '-': 388508
```

```
def rmValues(data, fea):
  data[fea] = np.where(data[fea]=='-', 'other', data[fea])
  return data
data = rmValues(data, data.columns)
```

```
## Checking if our function has done the job
data['service'].unique()
```

```
array(['dns', 'other', 'http', 'smtp', 'ftp-data', 'ftp', 'ssh', 'pop3',
       'snmp', 'ssl', 'irc', 'radius', 'dhcp'], dtype=object)
```

```
## ct_state_ttl is also a categorical feature
data['ct_state_ttl'].unique()
```

```
array([0, 2, 1, 3, 4, 6, 5], dtype=object)
```

```
## trans_depth is also a categorical feature in our dataset
data['trans_depth'].unique()
```

```
array([0, 1, 2, 3, 4, 8], dtype=object)
```

```
## Checking the no. of unique ports susceptible to attack
susceptible_sports = data[data['Label'] == 1]['sport']
susceptible_dsports = data[data['Label'] == 1]['dsport']
print("No. of unique ports on which attack happended:",len(susceptible_sports.unique()))
```

```
No. of unique ports on which attack happended: 9607
```

Creating a new feature time difference 'TimeDiff' based on difference between starting and loading time.

```
## Creating a new feature based on time
data['TimeDiff'] = data['Ltime'] - data['Stime']
data = data.drop(['Stime', 'Ltime'], axis=1)
print("Dimensions of the modified dataset are:", data.shape)
```

```
Dimensions of the modified dataset are: (640726, 48)
```

```
## Adding integer categorical columns to the catCols
catCols.append('ct_state_ttl')
catCols.append('is_ftp_login')
catCols.append('is_sm_ips_ports') ## Binary feature
catCols.append('trans_depth')

## Adding TimeDiff as new
numCols.append("TimeDiff")

## Dropping the categorical columns from numCols
numCols.remove("Label")
numCols.remove("is_ftp_login")
numCols.remove("is_sm_ips_ports")
numCols.remove("trans_depth")
numCols.remove('Stime')
numCols.remove('Ltime')
```

```
## Printing the arrays
print("Categorical columns are:",catCols, '\n')
print("Numerical columns are:", numCols)
```

```
Categorical columns are: ['srcip', 'sport', 'dstip', 'dsport', 'proto', 'state', 'service', 'ct_state_ttl', 'is_ftp_logi

Numerical columns are: ['dur', 'sbytes', 'dbytes', 'sttl', 'dttl', 'sloss', 'dloss', 'Sload', 'Dload', 'Spkts', 'Dpkts',
```

```
## Final shape of the data after remving the rows
data.shape
```

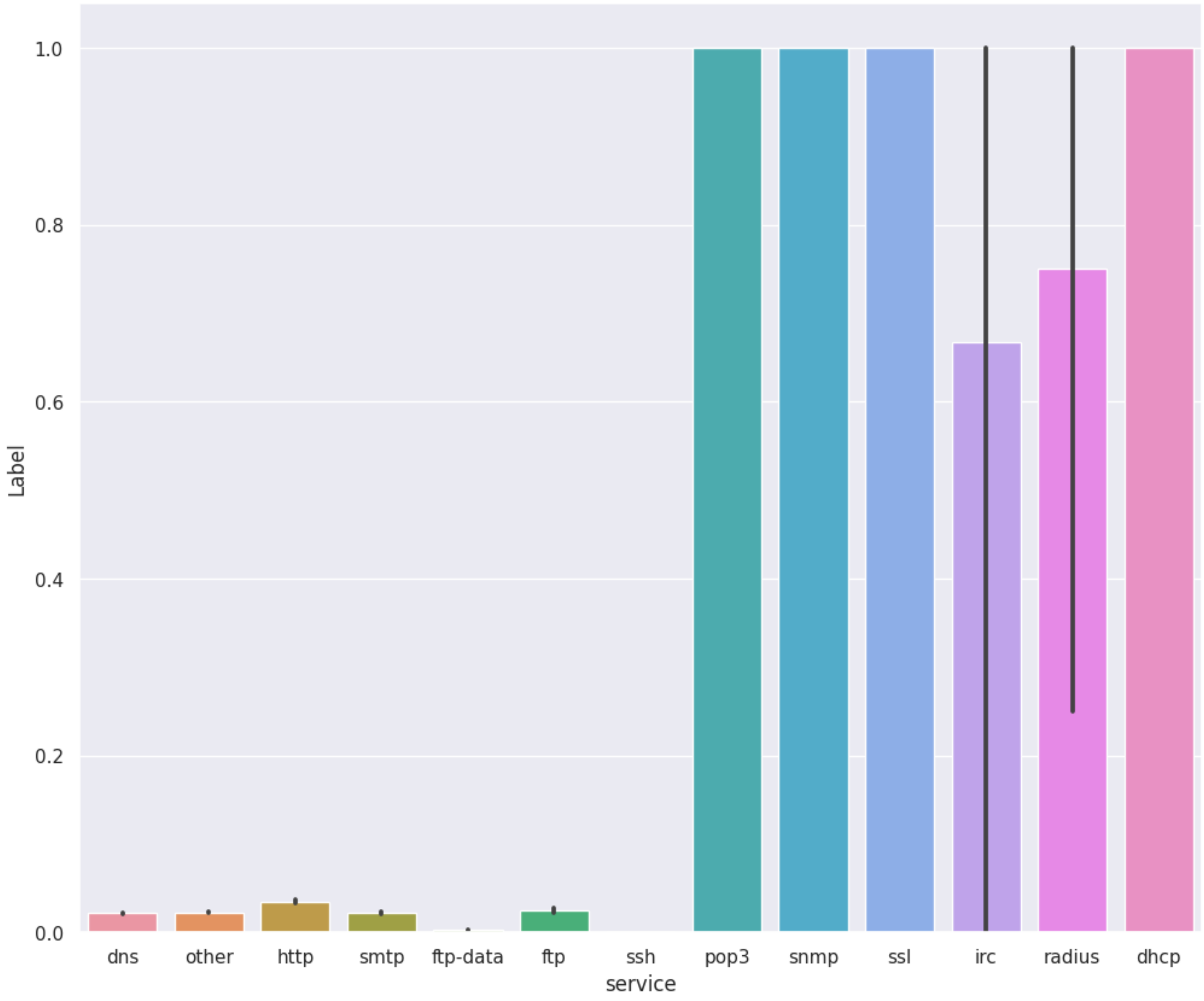
```
(640726, 48)
```

```
## No. of attacks after modifications
data[data['Label'] == 1].shape
```

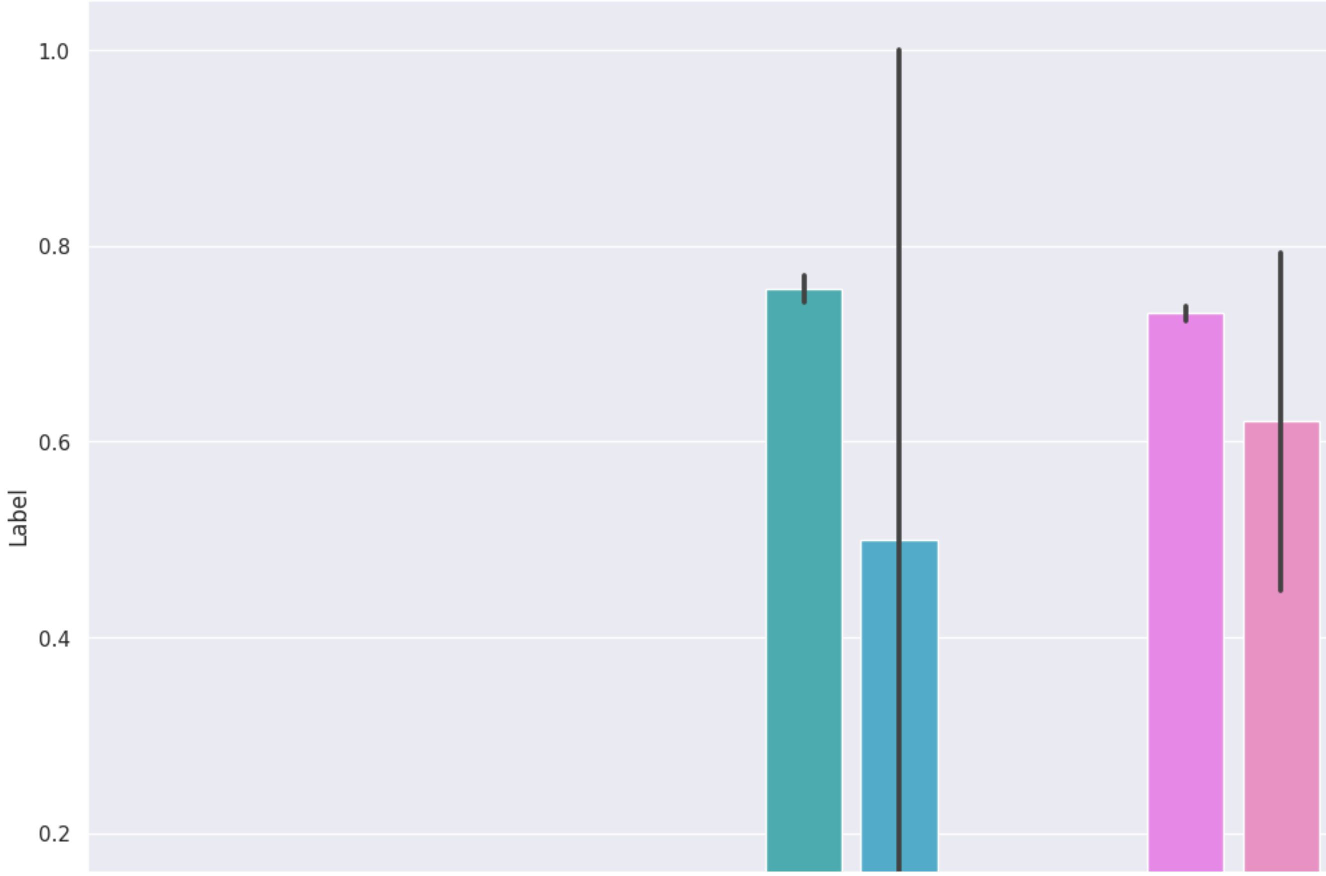
```
(14278, 48)
```

2.3 Checking relation between indepent and dependent variables

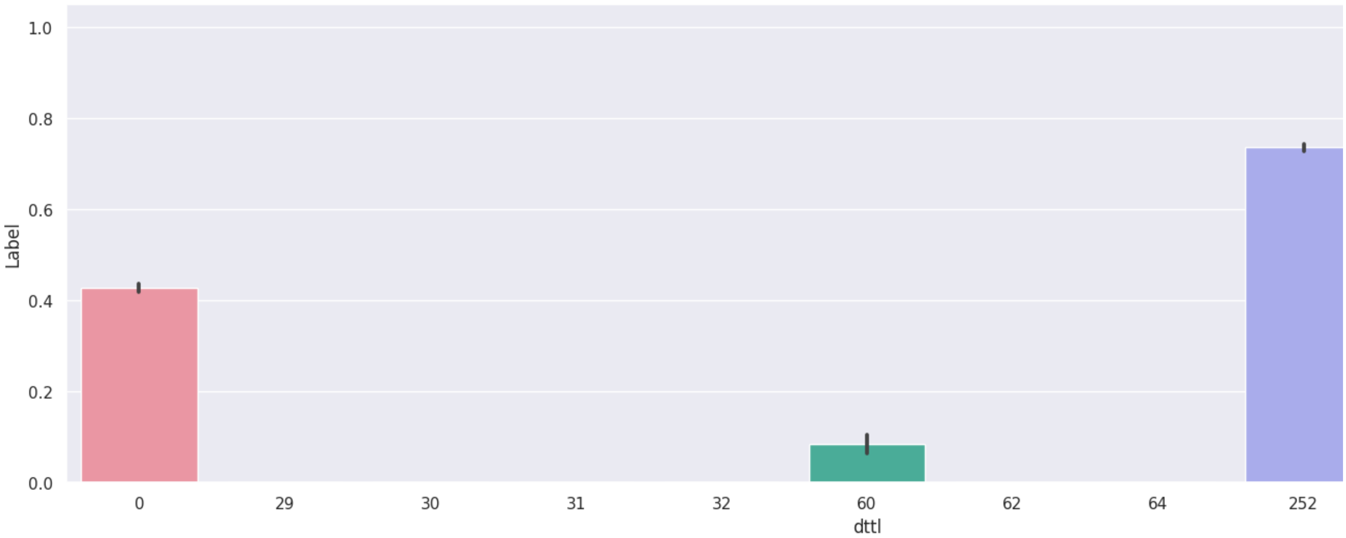
```
## Checking the relation between the label and servie types
plt.figure(figsize=(12, 10))
sns.barplot(x='service', y="Label", data=data)
plt.show()
```




```
## Checking the relation between the label and sttl types
plt.figure(figsize=(12, 10))
sns.barplot(x="sttl", y="Label", data=data)
plt.show()
```




```
## Checking the relation between the label and dttl

plt.figure(figsize=(20, 6))
sns.barplot(x="dttl", y="Label", data=data)
plt.show()
```



Tried one-hot encoding method for some of the features but the results were not good as expected

```
## For categorical data which has less than 20 unique values,
## we will one hot encode them and on others we will encode differently to
## load on our system
#oneHotcols = []
#for col in catCols:
  #if len(data[col].unique())<=20:
    #oneHotcols.append(col)
#print('Columns on which one hot encoding to use:', oneHotcols)

#catCols = [col for col in catCols if col not in oneHotcols]

#print("Features on which we intend to do label encoding:",catCols)
```

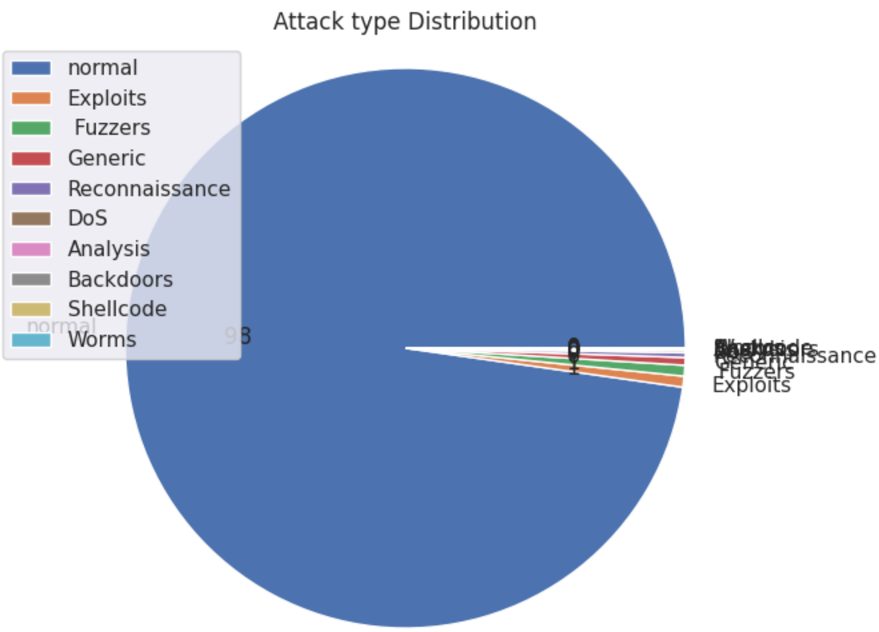
> Getting the indicies of rows where this is happening and removing them from the dataset.

```
data.describe()
```

	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	ct_srv_src	ct_srv_dst	ct_
count	640726	640726	640726	640726	640726	640726	640726.0	640726	640726	640726	...	640726	640726	
unique	40	64539	44	62220	134	14	243827.0	7947	11898	13	...	43	40	
top	59.166.0.2	0	149.171.126.4	53	tcp	FIN	0.0	146	178	31	...	1	1	
freq	62850	4369	62883	122578	457028	450611	2207.0	82522	82391	612562	...	87057	87956	

4 rows × 48 columns

```
catCounts = data['attack_cat'].value_counts()

# Create a pie chart
plt.figure(figsize=(8, 6))
plt.pie(catCounts, labels = catCounts.index, autopct='%1.0f')
plt.title("Attack type Distribution")
plt.axis('equal')
plt.legend(labels= catCounts.index)
# Display the chart
plt.show()
```




```
## Getting the no. of attacks in each category
for i in range(len(catCounts)):
  print(" {} cases are :{}".format(catCounts.index[i], catCounts[i]))
```

```
normal cases are :626448
Exploits cases are :4042
 Fuzzers cases are :3991
Generic cases are :2833
Reconnaissance cases are :1740
DoS cases are :825
Analysis cases are :301
Backdoors cases are :299
Shellcode cases are :223
Worms cases are :24
```

```
## Total no. of attacks
data[data['Label'] == 1].shape
```

```
(14278, 48)
```

```
## Dimension of the whole data
data.shape
```

```
(640726, 48)
```

2.4 Feature Engineering

```
## Installing the category-encoder library
!pip install category_encoders
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting category_encoders
  Downloading category_encoders-2.6.1-py2.py3-none-any.whl (81 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 81.9/81.9 kB 7.6 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.22.4)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.10.1)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (1.5.3)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (0.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->cat
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_enco
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->category_encoders) (1.1
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0->categ
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.0
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.9.0->categ
Installing collected packages: category_encoders
Successfully installed category_encoders-2.6.1
```

> One-hot encoding didn't work as expected so dropped the idea.

```
#data[oneHotcols] = data[oneHotcols].astype('object')
#Onehot_data = pd.get_dummies(data[oneHotcols])
#data_mod = Onehot_data.join(data[np.concatenate((catCols, numCols, ['Label', 'attack_cat']))])
#data_mod.shape
```

```
## Using sklearn Labelencoder to convert into categorical features
from sklearn.preprocessing import LabelEncoder

## Using sklearn libary to convert nominal features into categorical features
## Defining a function so we don't have to repeat again
def convertToCategorical(s, data):
  encoder = LabelEncoder()
  encoded = encoder.fit_transform(data[s])
  return encoded

## Converting dataset features into categorical
for col in catCols:
  data[col] = convertToCategorical(col, data)

## Frequency encoding the label encoded features
from sklearn.preprocessing import OneHotEncoder
from category_encoders import CountEncoder

## using frequency encoding to encode categorical variables
data = CountEncoder(cols = catCols, normalize = True).fit(data).transform(data)
```

2.5 Splitting the Dataset

```
## Dividing data into normal and abnormal attacks
normalData = np.array(data[data['Label']==0])
abnormalData = np.array(data[data['Label'] == 1])
```

```
## Splitting the dataset (70% training, 15% validation, 15% testing)
## Validation will contain normal cases, which is used for tuning the threshold.
## Getting an estimate of number of Rows to get from normal data

nRows = int(np.round(normalData.shape[0]*.70))
print("No. of rows to get for training data: ",nRows)
```

```
No. of rows to get for training data:  474450
```

```
## Shape of anomalous data
abnormalData.shape
```

```
(22215, 49)
```

```
## getting the required data at random using numpy
indices = np.random.choice(normalData.shape[0], size = nRows,
                           replace = False)
X_train = normalData[indices,:]


## Print the shape of the modified data
print(X_train.shape)
```

```
(438514, 48)
```

```
## Getting the remaining normal data
mask = np.logical_not(np.isin(np.arange(normalData.shape[0]), indices))
normalData = normalData[mask,:]

## Printing the dimension after modification
normalData.shape
```

```
(187934, 48)
```

```
## Creating a validation set of normal cases i.e. 0
nRows = (normalData.shape[0])// 2
print("No. of Rows to get for Validation data:", nRows)

indices = np.random.choice(normalData.shape[0], size = nRows,
                           replace = False)
X_val = normalData[indices,:]


## Print the shape of the modified data
print("Dimension of the Validation set:", X_val.shape)
```

```
No. of Rows to get for Validation data: 93967
Dimension of the Validation set: (93967, 48)
```

```
## Getting the remaining normal data
mask = np.logical_not(np.isin(np.arange(normalData.shape[0]), indices))
normalData = normalData[mask,:]

## Printing the dimension after modification
normalData.shape
```

```
(93967, 48)
```

```
## Combining remaining normal with abnormal cases
remainingData = np.concatenate((normalData, abnormalData), axis=0)

## Shuffling the combined data
np.random.shuffle(remainingData)

## Storing the data for testing
X_test = remainingData


## Print the shape of test data
print("Dimension of the test set:", X_test.shape)
```

```
Dimension of the test set: (108245, 48)
```

2.6 Removing the Labels and unwanted features

```
############### Removing the unwanted columns of the Dataset #################

## Converting back to pandas dataFrame for preprocessing
feaNames = data.columns
X_train = pd.DataFrame(X_train, columns = feaNames)
X_val = pd.DataFrame(X_val, columns = feaNames)
X_test = pd.DataFrame(X_test, columns = feaNames)

## Dropping columns named record start time and end time as well as Labels

y_train = X_train["Label"].tolist()


X_train = X_train.drop("Label", axis=1)
X_train = X_train.drop("attack_cat", axis=1)
```

```
y_val = X_val["Label"].tolist()
X_val = X_val.drop("Label", axis=1)
X_val = X_val.drop("attack_cat", axis=1)


y_test = X_test["Label"].tolist()
X_test = X_test.drop("Label", axis=1)
X_test = X_test.drop("attack_cat", axis=1)


## Checking the changes are made
X_train.head()
```

	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	is_ftp_login	ct_ftp_cmd	ct_srv
0	0.094018	0.000014	0.093197	0.043532	0.713297	0.703282	0.602904	37218	3276	31	...	0.983161	0	
1	0.097397	0.000017	0.092984	0.000179	0.713297	0.703282	0.223248	8928	320	31	...	0.983161	0	
2	0.097118	0.000012	0.098143	0.000016	0.713297	0.703282	0.49512	4688	3080	31	...	0.983161	0	
3	0.097408	0.000016	0.092887	0.000009	0.279784	0.278024	0.455122	536	304	31	...	0.983161	0	
4	0.097118	0.000014	0.094287	0.000005	0.713297	0.703282	0.060399	998	9069	31	...	0.983161	0	

5 rows × 46 columns

2.7 Min-max Scaling of the features

```
################### Min_max features in the dataset ############################

from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
## Doing Min-max scaling
X_train[numCols] = scaler.fit_transform(X_train[numCols])

## Doing Min-max scaling on validation and test data
X_val[numCols] = scaler.transform(X_val[numCols])

X_test[numCols] = scaler.transform(X_test[numCols])


## Checking if the Min-max scaling is as expected
X_train.head()
```

	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	is_ftp_login	ct_ftp_cmd	c
0	0.094018	0.000014	0.093197	0.043532	0.713297	0.703282	0.000069	0.024961	0.001996	0.121569	...	0.983161	0.0	
1	0.097397	0.000017	0.092984	0.000179	0.713297	0.703282	0.000025	0.005988	0.000195	0.121569	...	0.983161	0.0	
2	0.097118	0.000012	0.098143	0.000016	0.713297	0.703282	0.000057	0.003144	0.001876	0.121569	...	0.983161	0.0	
3	0.097408	0.000016	0.092887	0.000009	0.279784	0.278024	0.000052	0.000359	0.000185	0.121569	...	0.983161	0.0	
4	0.097118	0.000014	0.094287	0.000005	0.713297	0.703282	0.000007	0.000669	0.005525	0.121569	...	0.983161	0.0	

5 rows × 46 columns

```
## Getting the shape of the dataset
print("Shape of the training data:", X_train.shape)
print("Shape of the validation data:", X_val.shape)
print("Shape of the test data:", X_test.shape)
```

```
Shape of the training data: (438514, 46)
Shape of the validation data: (93967, 46)
Shape of the test data: (108245, 46)
```

Autoencoder

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

```
from tensorflow import keras
from tensorflow.keras import Model
from tensorflow.keras import layers
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import KFold

# Set the seed for TensorFlow to make results reproducible
tf.random.set_seed(42)


## Converting the arrays to tensor
X_train = tf.convert_to_tensor(X_train, dtype = tf.float32)
X_val = tf.convert_to_tensor(X_val, dtype = tf.float32)
X_test = tf.convert_to_tensor(X_test, dtype = tf.float32)
```

3.1 Model Architecture

```
## Building an autoEncoder using(https://www.tensorflow.org/tutorials/generative/)
class autoEncoder(Model):
  def __init__(self):
        super(autoEncoder, self).__init__()
        self.encoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(8, activation="LeakyReLU")])

        self.decoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(46, activation="sigmoid")])


  def call(self, input):
    encoded = self.encoder(input)
    decoded = self.decoder(encoded)
    return decoded
```

3.2 Doing k-fold cross validation:

```
## Built an autoencoder using this
## tutorial https://www.tensorflow.org/tutorials/generative/autoencoder
## Concatenating training and validation data
X = np.concatenate((X_train, X_val), axis=0)
kf = KFold(n_splits=5)  ## Defining the number of folds for cross-validation

fold_scores = []  # To store the scores for each fold

# Perform cross-validation
for train_index, val_index in kf.split(X):
    # Split the data into training and validation sets for the current fold
    X_train_fold, X_val_fold = X[train_index], X[val_index]
    class autoEncoder(Model):
       def __init__(self):
        super(autoEncoder, self).__init__()
        self.encoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(8, activation="LeakyReLU")])

        self.decoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(46, activation="sigmoid")])


       def call(self, input):
        encoded = self.encoder(input)
        decoded = self.decoder(encoded)
        return decoded
    # Initialize a new instance of the autoEncoder model for each fold
    autoEncoder = autoEncoder()
    # Compile the model
    autoEncoder.compile(optimizer='adam', loss='mae')

    # Fit the model to the current fold's training data
    fittedModel = autoEncoder.fit(X_train_fold, X_train_fold, epochs=11,
      batch_size=128, validation_data=(X_val_fold, X_val_fold), shuffle=True)

    # Evaluate the model on the current fold's validation data and store the score
    fold_score = autoEncoder.evaluate(X_val_fold, X_val_fold)
```

```
    fold_scores.append(fold_score)

# Calculate the average score across all folds
average_score = np.mean(fold_scores)

# Print the average score
print("Average score:", average_score)
```

```
3329/3329 [==============================] - 8s 3ms/step - loss: 0.0096 - val_loss: 0.0106
Epoch 7/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0093 - val_loss: 0.0099
Epoch 8/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0091 - val_loss: 0.0093
Epoch 9/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0090 - val_loss: 0.0100
Epoch 10/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0088 - val_loss: 0.0098
Epoch 11/11
3329/3329 [==============================] - 16s 5ms/step - loss: 0.0087 - val_loss: 0.0089
3328/3328 [==============================] - 11s 3ms/step - loss: 0.0089
Epoch 1/11
3329/3329 [==============================] - 10s 2ms/step - loss: 0.0260 - val_loss: 0.0138
Epoch 2/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0120 - val_loss: 0.0115
Epoch 3/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0111 - val_loss: 0.0120
Epoch 4/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0109 - val_loss: 0.0115
Epoch 5/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0102 - val_loss: 0.0110
Epoch 6/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0097 - val_loss: 0.0106
Epoch 7/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0095 - val_loss: 0.0107
Epoch 8/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0093 - val_loss: 0.0095
Epoch 9/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0091 - val_loss: 0.0099
Epoch 10/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0090 - val_loss: 0.0097
Epoch 11/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0090 - val_loss: 0.0093
3328/3328 [==============================] - 5s 2ms/step - loss: 0.0093
Epoch 1/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0261 - val_loss: 0.0132
Epoch 2/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0120 - val_loss: 0.0120
Epoch 3/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0114 - val_loss: 0.0118
Epoch 4/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0108 - val_loss: 0.0108
Epoch 5/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0105 - val_loss: 0.0114
Epoch 6/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0099 - val_loss: 0.0095
Epoch 7/11
3329/3329 [==============================] - 9s 3ms/step - loss: 0.0085 - val_loss: 0.0097
Epoch 8/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0081 - val_loss: 0.0085
Epoch 9/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0078 - val_loss: 0.0087
Epoch 10/11
3329/3329 [==============================] - 10s 3ms/step - loss: 0.0075 - val_loss: 0.0078
Epoch 11/11
3329/3329 [==============================] - 8s 2ms/step - loss: 0.0074 - val_loss: 0.0078
3328/3328 [==============================] - 6s 2ms/step - loss: 0.0078
Average score: 0.0087802080437541
```

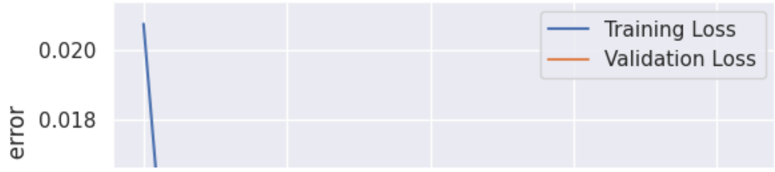
3.3 Training the AutoEncoder

```
## Our define model architecture for autoencoder
class autoEncoder(Model):
  def __init__(self):
        super(autoEncoder, self).__init__()
        self.encoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(8, activation="LeakyReLU")])

        self.decoder = tf.keras.Sequential([
         layers.Dense(36, activation="LeakyReLU"),
         layers.Dense(46, activation="sigmoid")])


  def call(self, input):
    encoded = self.encoder(input)
    decoded = self.decoder(encoded)
    return decoded
```

```
    return decoded
autoEncoder = autoEncoder()


## Fitting the training data into model above and using adam optimizer and
## using mean square logarithmic loss function


# Defining early stopping criteria for regularisation
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)

## Using the adam optimizer and mean absolute error loss function
autoEncoder.compile(optimizer = 'adam', loss = 'mae')
fittedModel = autoEncoder.fit(X_train, X_train, epochs = 22, batch_size = 64,
               validation_data=(X_val, X_val), shuffle=True, callbacks=[early_stopping])
```

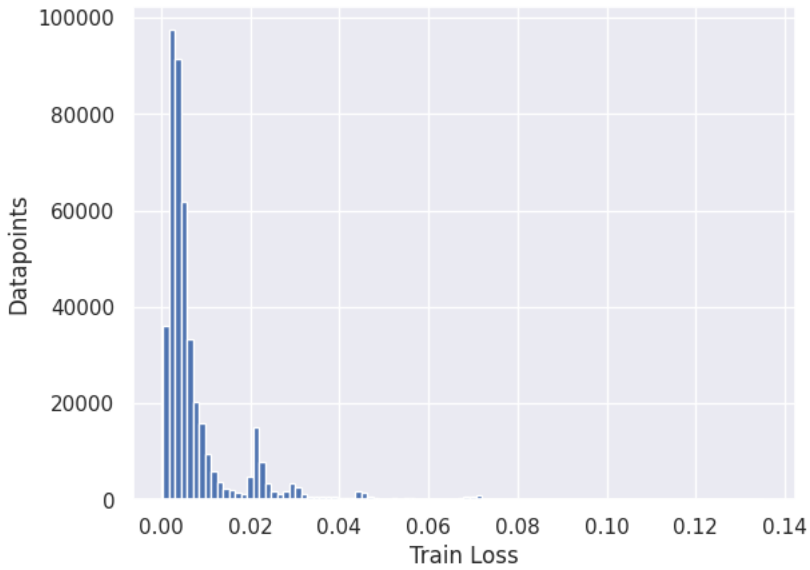
```
Epoch 1/22
6852/6852 [==============================] - 19s 3ms/step - loss: 0.0207 - val_loss: 0.0115
Epoch 2/22
6852/6852 [==============================] - 17s 3ms/step - loss: 0.0110 - val_loss: 0.0106
Epoch 3/22
6852/6852 [==============================] - 20s 3ms/step - loss: 0.0105 - val_loss: 0.0101
Epoch 4/22
6852/6852 [==============================] - 17s 3ms/step - loss: 0.0100 - val_loss: 0.0099
Epoch 5/22
6852/6852 [==============================] - 20s 3ms/step - loss: 0.0096 - val_loss: 0.0093
Epoch 6/22
6852/6852 [==============================] - 19s 3ms/step - loss: 0.0091 - val_loss: 0.0089
Epoch 7/22
6852/6852 [==============================] - 20s 3ms/step - loss: 0.0089 - val_loss: 0.0088
Epoch 8/22
6852/6852 [==============================] - 19s 3ms/step - loss: 0.0088 - val_loss: 0.0087
Epoch 9/22
6852/6852 [==============================] - 19s 3ms/step - loss: 0.0086 - val_loss: 0.0085
Epoch 10/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0086 - val_loss: 0.0084
Epoch 11/22
6852/6852 [==============================] - 19s 3ms/step - loss: 0.0085 - val_loss: 0.0084
Epoch 12/22
6852/6852 [==============================] - 17s 2ms/step - loss: 0.0084 - val_loss: 0.0083
Epoch 13/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0083 - val_loss: 0.0083
Epoch 14/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0083 - val_loss: 0.0082
Epoch 15/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0083 - val_loss: 0.0082
Epoch 16/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0082 - val_loss: 0.0083
Epoch 17/22
6852/6852 [==============================] - 17s 2ms/step - loss: 0.0082 - val_loss: 0.0082
Epoch 18/22
6852/6852 [==============================] - 17s 2ms/step - loss: 0.0082 - val_loss: 0.0081
Epoch 19/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0081 - val_loss: 0.0080
Epoch 20/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0080 - val_loss: 0.0079
Epoch 21/22
6852/6852 [==============================] - 18s 3ms/step - loss: 0.0080 - val_loss: 0.0079
Epoch 22/22
6852/6852 [==============================] - 26s 4ms/step - loss: 0.0079 - val_loss: 0.0079
```

```
## Plotting the training and validation loss
plt.plot(fittedModel.history["loss"], label="Training Loss")
plt.plot(fittedModel.history["val_loss"], label="Validation Loss")
plt.xlabel("Epochs (No. of Iterations)")
plt.ylabel("Mean reconstruction error")
plt.legend()

plt.savefig('/content/drive/MyDrive/autoEncoderTrainLoss.png')
```




```
## Deciding a threshold based on the training set
reConstruction = autoEncoder.predict(X_train)
trainLoss = tf.keras.losses.mae(reConstruction, X_train)

## Plotting the loss
plt.hist(trainLoss[None, :], bins= 100)
plt.xlabel("Train Loss")
plt.ylabel("Datapoints")
```

```
13704/13704 [==============================] - 21s 2ms/step
Text(0, 0.5, 'Datapoints')
```




```
## Getting test Statistics for reConstruction training Loss
mean = np.mean(trainLoss.numpy())
maxVal = np.max(trainLoss.numpy())
minVal = np.min(trainLoss.numpy())
std = np.std(trainLoss.numpy())
perInt = np.percentile(trainLoss.numpy(), [2.5, 97.5])

## Printing train Loss statistics
print("Mean:", mean)
print("Max:", maxVal)
print("Min:", minVal)
print("Standard Deviation:", std)
print("95% confidence interval is:", perInt)
```

```
Mean: 0.0079395035
Max: 0.13549843
Min: 0.0003615392
Standard Deviation: 0.010259468
95% confidence interval is: [0.00118454 0.03896145]
```

```
## Used this as refrence (https://www.tensorflow.org/tutorials/generative/)
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, roc_auc_score, precision_recall_curve


def predictModel(model, XX, threshold):
  reConstruction = model(XX)
  loss = tf.keras.losses.mae(reConstruction, XX)
  return tf.math.greater(loss, threshold)

def Stats(predictions, labels):
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  print("F1-score = {}".format(f1_score(labels, predictions, zero_division=1)))
  print("Precision = {}".format(precision_score(labels, predictions, zero_division=1)))
```

```
  print("Recall = {}".format(recall_score(labels, predictions, zero_division=1)))
  print("AUC-ROC = {}".format(roc_auc_score(labels, predictions)))


## Taken plotting code from following book:
## Beginning Anomaly Detection Using Python-Based Deep Learning:
## With Keras and PyTorch by by Sridhar Alla (Author), Suman Kalyan Adari(Author)
def plot_anomaly(y, error, best_threshold):
  Df = pd.DataFrame({'error': error, 'true':y }).groupby('true')
  figure, axes = plt.subplots(figsize=(10, 6))

  for name, group in Df:
    axes.plot(group.index, group.error, marker='*' if name==1 else 'x', linestyle='',
              color= 'crimson' if name==1 else 'limegreen', label="Anomaly" if name==1
              else "Normal")
  axes.hlines(best_threshold, axes.get_xlim()[0], axes.get_xlim()[1],
              color = 'darkblue', zorder = 100, label = 'Threshold')
  axes.legend()
  plt.title("Anomaly detection")
  plt.ylabel("Reconstruction Error")
  plt.xlabel("Observations")
  plt.show()
def plot_confusion_matrix(confusion_matrix, labels):
    figure, axes = plt.subplots(figsize=(8, 6))
    heatmap = sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Blues",
                          cbar=False)
    heatmap.set_xticklabels(labels, rotation=45, ha='right')
    heatmap.set_yticklabels(labels, rotation=0)
    axes.set_xlabel('Predicted')
    axes.set_ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()


## Getting rough idea of threshold
#threshold = np.mean(trainLoss) + 1.96 * np.std(trainLoss)
threshold_train = perInt[1]
print("Threshold is:", threshold_train)
```

```
Threshold is: 0.03896144600585101
```

```
## Stats based on this threshold=0.020
preds = predictModel(autoEncoder, X_test,  threshold_train)
Stats(preds, y_test)
```

```
Accuracy = 0.978594854265786
F1-score = 0.9248678621226369
Precision = 0.8611194976148784
Recall = 0.9988093570528085
AUC-ROC = 0.9871663395350562
```

```
## Reconstruction for validation data
reConstructionVal = autoEncoder.predict(X_val)
LossVal = tf.keras.losses.mae(reConstructionVal, X_val)

## Plotting the loss
plt.hist(LossVal[None, :], bins=100)
plt.axvline(threshold_train, color='red')
plt.xlabel("Validation Loss")
plt.ylabel("Datapoints")
```

```
2937/2937 [==============================] - 5s 2ms/step
Text(0, 0.5, 'Datapoints')
```

```
## Getting test Statistics for reConstruction validation Loss
mean = np.mean(LossVal.numpy())
maxVal = np.max(LossVal.numpy())
minVal = np.min(LossVal.numpy())
std = np.std(LossVal.numpy())
perInt = np.percentile(LossVal.numpy(), [2.5, 97.5])

## Printing train Loss statistics
print("Mean:", mean)
print("Max:", maxVal)
print("Min:", minVal)
print("Standard Deviation:", std)
print("95% confidence interval is:", perInt)
```

```
Mean: 0.007877302
Max: 0.112033926
Min: 0.00038319486
Standard Deviation: 0.010207352
95% confidence interval is: [0.00118696 0.03839385]
```

Validation Loss

```
## Getting the threshold based on validation set
threshold_val = perInt[1]
print("Threshold based on validation is:", threshold_val)
```

```
Threshold based on validation is: 0.03839385099709031
```

```
## Stats based on this threshold of validation
preds = predictModel(autoEncoder, X_test,  threshold_val)
Stats(preds, y_test)
## Getting the classification report
print(classification_report(y_test, preds))
```

```
Accuracy = 0.9781791306757818
F1-score = 0.9235252217833323
Precision = 0.858742774566474
Recall = 0.9988793948732315
AUC-ROC = 0.9869565916654407
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     93967
           1       0.86      1.00      0.92     14278

    accuracy                           0.98    108245
   macro avg       0.93      0.99      0.96    108245
weighted avg       0.98      0.98      0.98    108245
```

```
## Getting recosntruction loss for test set
reConstructionTest = autoEncoder.predict(X_test)
Loss_test = tf.keras.losses.mae(reConstructionTest, X_test)
```

```
3383/3383 [==============================] - 8s 2ms/step
```

```
## Plotting the reconstruction error of test set and the threshold separating
## normal and anomalous cases
plot_anomaly(y_test, Loss_test, threshold_val)
```


```
## Doing a grid serch to select the threshold based on validation set
def find_best_threshold(model, X_val, y_val):
  max_error = -9999999
  for i in range(0,30):


    reConstruction = autoEncoder.predict(X_val)
    loss = tf.keras.losses.mae(reConstruction, X_val).numpy()
    # Calculate maximum construction error
    meanconstruction_error = np.max(np.mean(loss)+ np.std(loss))

    # Update best threshold and maximum construction error if necessary
    if meanconstruction_error > max_error:
        max_error = meanconstruction_error


  return max_error
  ## Getting the best threshold
bestThreshold = find_best_threshold(autoEncoder, X_val, y_val)
print("Best Threshold:", bestThreshold)
```

```
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
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2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
Best Threshold: 0.018084655
```

```
## Metrics for the best threshold
predsTest = predictModel(autoEncoder, X_test,  bestThreshold)
Stats(predsTest, y_test)
```

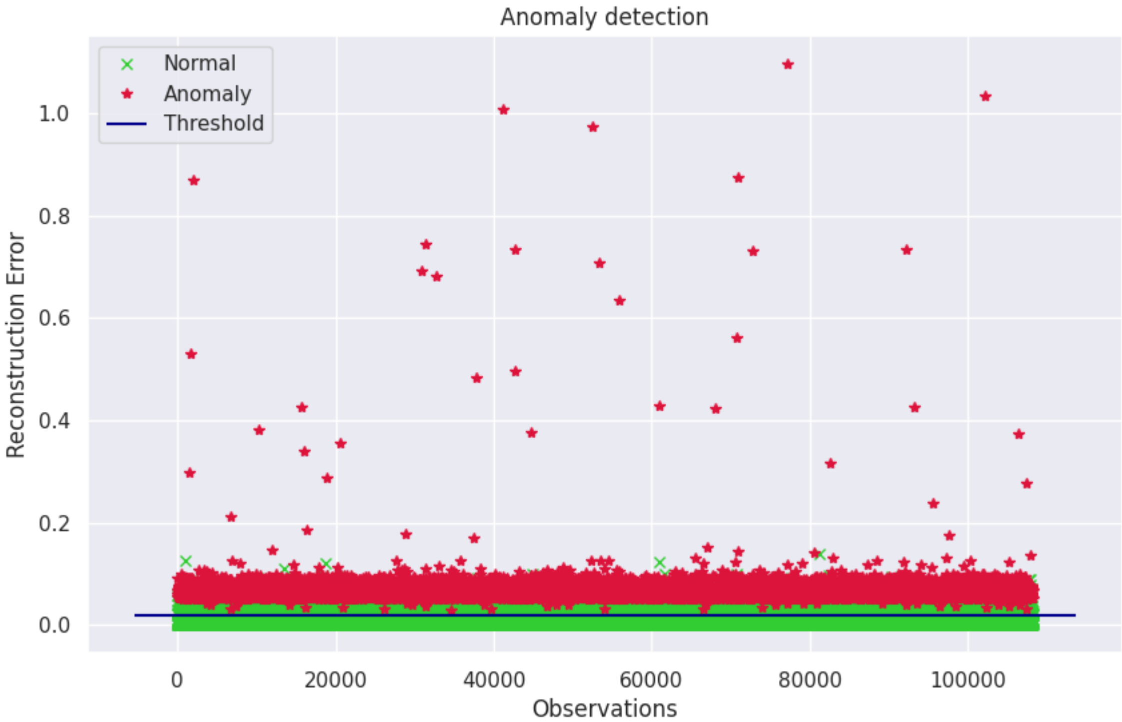
```
Accuracy = 0.8853711487828537
F1-score = 0.6970998925886144
Precision = 0.5350370981038747
Recall = 1.0
AUC-ROC = 0.9339768216501538
```

```
## Getting error for test set
reConstructionTest = autoEncoder.predict(X_test)
Loss_test = tf.keras.losses.mae(reConstructionTest, X_test)
```

```
3383/3383 [==============================] - 5s 1ms/step
```

3.4 Visualizing the anomaly detection using AE

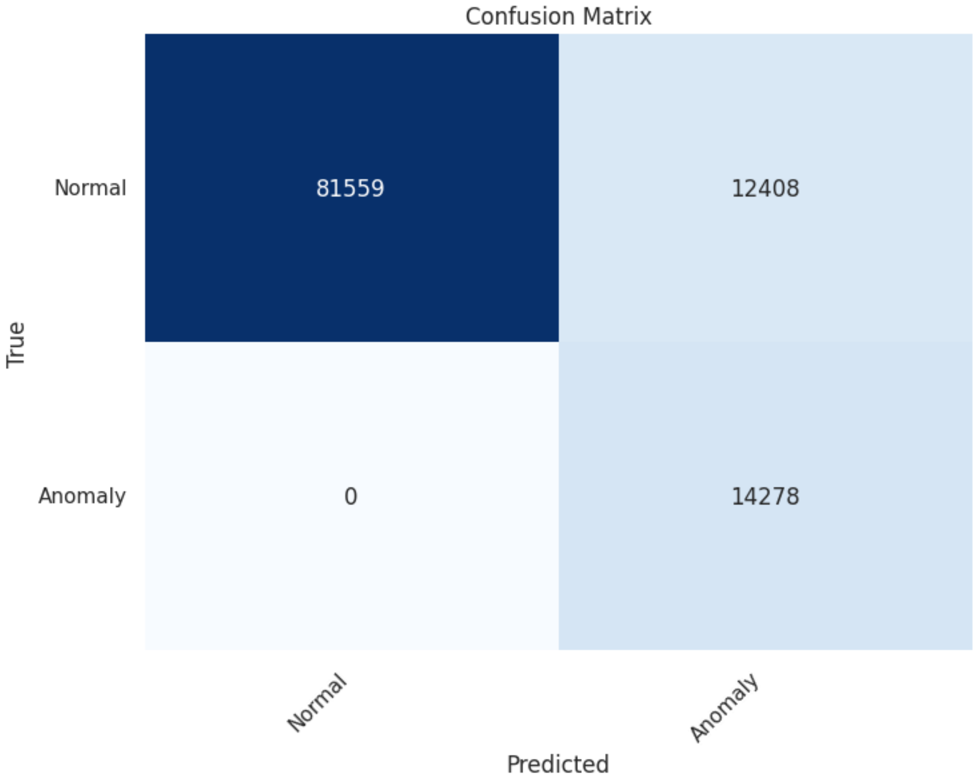
```
## Visualizing the results for reconstruction error on test set
plot_anomaly(y_test, Loss_test, bestThreshold)
```



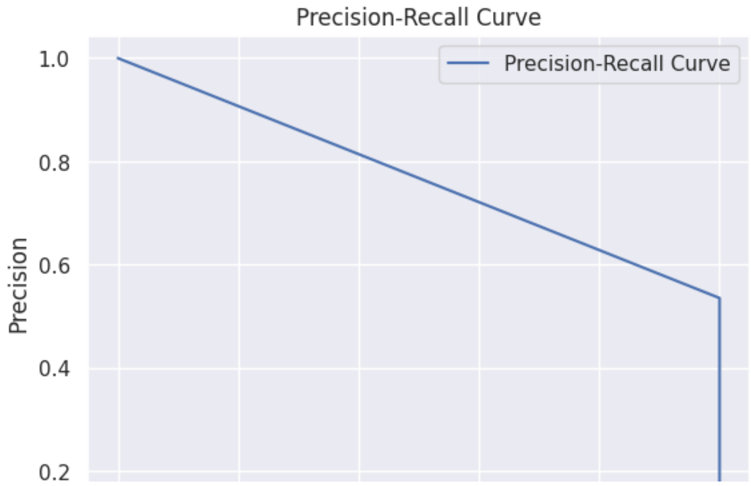
3.5 Confusion matrix

```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, predsTest)
print("Confusion Matrix:")
print(cm)

## Created function to create confusion matrix takes matrix as input returns the
## plot
def plot_confusion_matrix(confusion_matrix, labels):
    figure, axes = plt.subplots(figsize=(8, 6))
    heatmap = sns.heatmap(confusion_matrix, annot=True, fmt="d", cmap="Blues",
                          cbar=False)
    heatmap.set_xticklabels(labels, rotation=45, ha='right')
    heatmap.set_yticklabels(labels, rotation=0)
    axes.set_xlabel('Predicted')
    axes.set_ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()

## plotting the confusion matrix
plot_confusion_matrix(cm, np.array(['Normal', 'Anomaly']))


# Calculate the AUC-ROC score
auc_roc = roc_auc_score(y_test, predsTest)
print("AUC-ROC Score:", auc_roc)

# Calculate precision and recall values for plotting the precision-recall curve
precision, recall, thresholds = precision_recall_curve(y_test, predsTest)

# Plot the precision-recall curve
plt.plot(recall, precision, label='Precision-Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.show()
```

```
Confusion Matrix:
[[81559 12408]
 [    0 14278]]
```




```
AUC-ROC Score: 0.9339768216501538
```



Variational Autoencoder

4.1 Fitting an Variational autoencoder

```
## Taken code refrence from following book:
## Beginning Anomaly Detection Using Python-Based Deep Learning:
## With Keras and PyTorch by by Sridhar Alla (Author), Suman Kalyan Adari(Author)
## Loading the required libraries
## Loading the required libraries
from re import VERBOSE
from keras import optimizers
from keras.layers import Input, Dropout, Embedding, LSTM, Lambda
from keras.losses import mse
from keras.optimizers import Adam
from keras import backend as B
from keras.models import Sequential, Model


## Creating an class for variational autoencoder(VAE)
class VariationalAutoencoder():
    def __init__(self, input_dim, encoder_dim, latent_dim, decoder_dim):
        self.input_dim = input_dim
        self.encoder_dim = encoder_dim
```

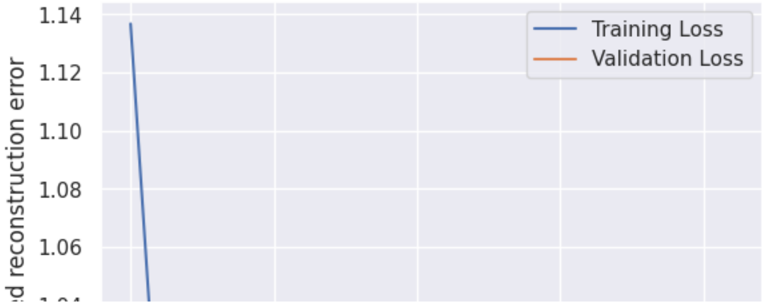
```
        self.latent_dim = latent_dim
        self.decoder_dim = decoder_dim
        self.vae = None
    ## function for Reparameterisation trick to do sampling
    def sample(self, args):
      ## Getting the arguments
        zMean, zLogVar = args
        ## Getting the batch size
        batch = B.shape(zMean)[0]
        dim = B.int_shape(zMean)[1]
        ## Getting the epsilon from standard normal
        epsilon = B.random_normal(shape=(batch, dim))
        return zMean + B.exp(0.5 * zLogVar) * epsilon
    ## function to build the VAE
    def build(self):
      ## Getting the input shapes
        inputs = Input(shape=(self.input_dim,), name='encoderInput')
        Encoder = Dense(self.encoder_dim, activation='LeakyReLU')(inputs)
        zMean = Dense(self.latent_dim, name='zMean')(Encoder)
        zLogVar = Dense(self.latent_dim, name='zLogVar')(Encoder)

        z = Lambda(self.sample, output_shape=(self.latent_dim,), name='z')([zMean, zLogVar])

        ## Encoder
        encoder = Model(inputs, [zMean, zLogVar, z], name='encoder')
        encoder.summary()


        ## Latent-space representation
        latent_inputs = Input(shape=(self.latent_dim,), name='zSampling')
        Code = Dense(self.decoder_dim, activation='LeakyReLU')(latent_inputs)
        outputs = Dense(self.input_dim, activation='sigmoid')(Code)

        ## Decoder
        decoder = Model(latent_inputs, outputs, name='decoder')
        decoder.summary()

        outputs = decoder(encoder(inputs)[2])
        vae = Model(inputs, outputs, name='vae')


        ## Reconstruction Loss(=MSE - KL divergence)
        reconstructionLoss = mse(inputs, outputs)
        reconstructionLoss *= self.input_dim

        ## Calculating the KL-divergence loss
        kLloss = 1 + zLogVar - B.square(zMean) - B.exp(zLogVar)
        kLloss = B.sum(kLloss, axis=1)
        kLloss *= -0.5

        vae_loss = B.mean(reconstructionLoss + kLloss)
        vae.add_loss(vae_loss)

        ## Compiling the model
        vae.compile(optimizer='adam', metrics=['accuracy'])
        vae.summary()
        self.vae = vae

    def fit(self, X_train, X_val, batch_size, epochs):
        self.vaeFit = self.vae.fit(X_train, X_train, batch_size=batch_size, epochs=epochs,
                    verbose=1, shuffle=True, validation_data=(X_val, X_val))
    def plotLoss(self):
      plt.plot(self.vaeFit.history["loss"], label="Training Loss")
      plt.plot(self.vaeFit.history["val_loss"], label="Validation Loss")
      plt.xlabel("Epochs (Iterations over entire training set)")
      plt.ylabel("Mean squared reconstruction error")
      plt.legend()
      plt.show()
    def predict(self, XX):
      return self.vae.predict(XX)
    def evaluate(self, XX):
      return self.vae.evaluate(XX, XX, verbose= True)


## Initializing the model parameters
input_dim = X_train.shape[1]
inputShape = (input_dim,)

## Encoder dimension
encoderDim = 36
## Latent space dimension
latentDim = 8
## Decoder dimesions
```

```
decoderDim = 36

## Creating an instance of VariationalAutoencoder(VAE) Class
vae = VariationalAutoencoder(input_dim, encoderDim, latentDim, decoderDim)
## Calling the build inside the class to build an VAE
vae.build()

## Fitting the mode with 22 training iterations and batch_size = 64
vae.fit(X_train, X_val, batch_size=64, epochs = 22)
```

```
 Layer (type)                Output Shape         Param #     Connected to
==================================================================================================
 encoderInput (InputLayer)   [(None, 46)]         0           []

 dense_24 (Dense)            (None, 36)           1692        ['encoderInput[0][0]']

 zMean (Dense)               (None, 8)            296         ['dense_24[0][0]']

 zLogVar (Dense)             (None, 8)            296         ['dense_24[0][0]']

 z (Lambda)                  (None, 8)            0           ['zMean[0][0]',
                                                               'zLogVar[0][0]']

==================================================================================================
Total params: 2,284
Trainable params: 2,284
Non-trainable params: 0
__________________________________________________________________________________________________
Model: "decoder"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 zSampling (InputLayer)      [(None, 8)]               0

 dense_25 (Dense)            (None, 36)                324

 dense_26 (Dense)            (None, 46)                1702

=================================================================
Total params: 2,026
Trainable params: 2,026
Non-trainable params: 0
_________________________________________________________________
Model: "vae"
__________________________________________________________________________________________________
 Layer (type)                Output Shape         Param #     Connected to
==================================================================================================
 encoderInput (InputLayer)   [(None, 46)]         0           []

 encoder (Functional)        [(None, 8),          2284        ['encoderInput[0][0]']
                              (None, 8),
                              (None, 8)]

 decoder (Functional)        (None, 46)           2026        ['encoder[0][2]']

 dense_24 (Dense)            (None, 36)           1692        ['encoderInput[0][0]']

 zLogVar (Dense)             (None, 8)            296         ['dense_24[0][0]']

 zMean (Dense)               (None, 8)            296         ['dense_24[0][0]']

 tf.__operators__.add (TFOpLamb  (None, 8)        0           ['zLogVar[0][0]']
 da)

 tf.math.square (TFOpLambda)  (None, 8)           0           ['zMean[0][0]']

 tf.convert_to_tensor (TFOpLamb  (None, 46)       0           ['decoder[0][0]']
 da)
```

4.2 Plotting Train loss and Validation Loss

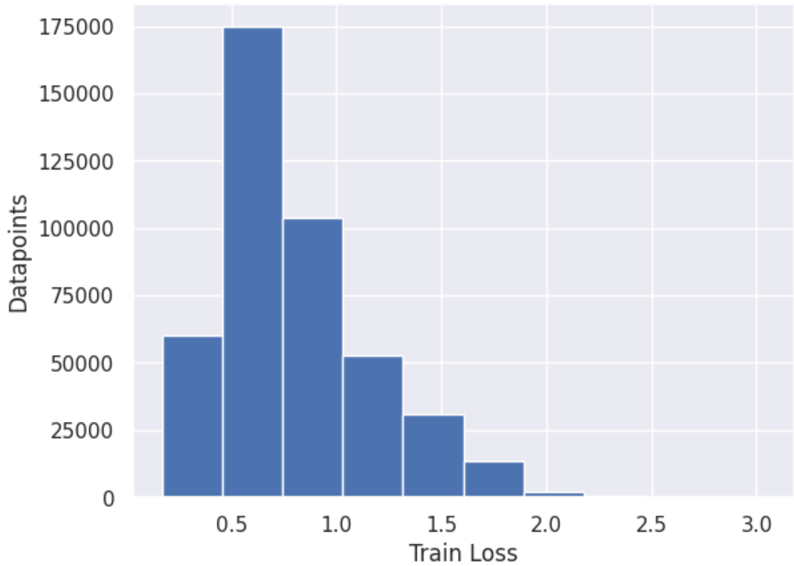
```
## Plotting the loss
vae.plotLoss()
```



4.3 Deciding threshold based on Train Loss

```
## Deciding a threshold
reConstruction = vae.predict(X_train)
trainLoss = np.linalg.norm(X_train - reConstruction, axis=-1)

## Plotting the loss
plt.hist(trainLoss)
plt.xlabel("Train Loss")
plt.ylabel("Datapoints")
```

```
13704/13704 [==============================] - 22s 2ms/step
Text(0, 0.5, 'Datapoints')
```




```
## Getting test Statistics for reConstruction training Loss
mean = np.mean(trainLoss)
maxVal = np.max(trainLoss)
minVal = np.min(trainLoss)
std = np.std(trainLoss)
perInt = np.percentile(trainLoss, [2.5, 97.5])

## Printing train Loss statistics
print("Mean:", mean)
print("Max:", maxVal)
print("Min:", minVal)
print("Standard Deviation:", std)
print("Spread range interval is:", perInt)
```

```
Mean: 0.8002387
Max: 3.0346656
Min: 0.17263745
Standard Deviation: 0.36259854
Spread range interval is: [0.29143052 1.67166655]
```

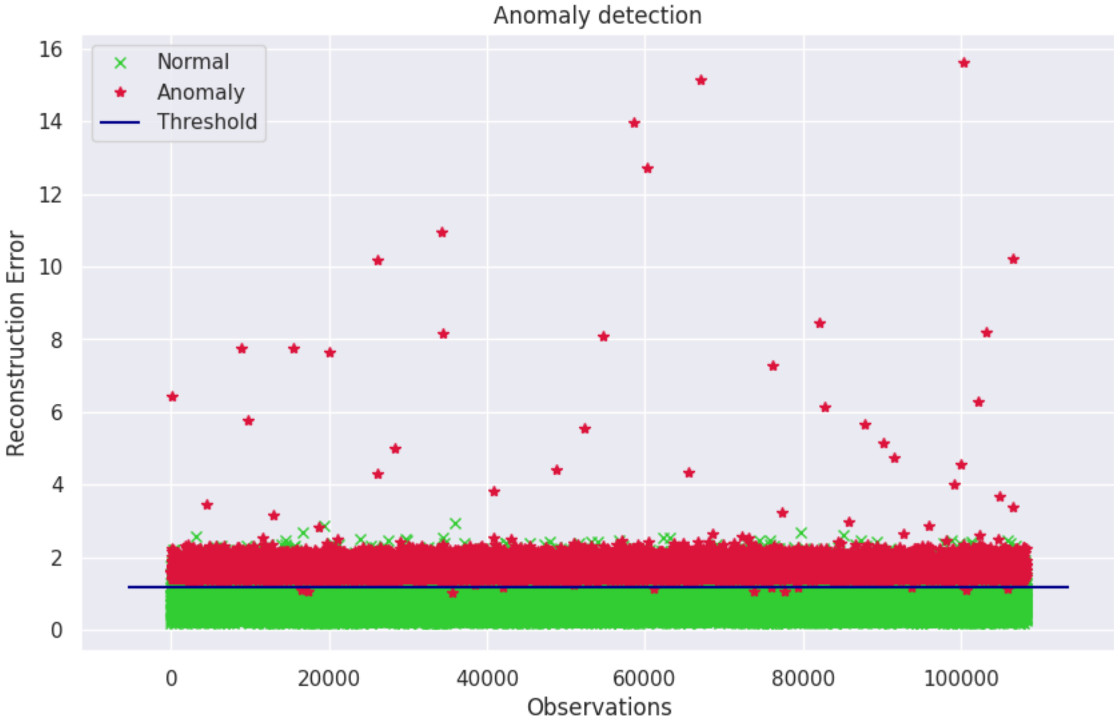
> Threshold based on trainLoss

```
## Taken plotting code refrence from following book:
## Beginning Anomaly Detection Using Python-Based Deep Learning:
## With Keras and PyTorch by by Sridhar Alla (Author), Suman Kalyan Adari(Author)

## Based on the threshold detecting the anomalies and printing the Stats
threshold = mean + std
```

```
print('Threshold is:', threshold)
yy_pred = vae.predict(X_test)
yyDist = np.linalg.norm(X_test - yy_pred, axis =-1)
zz = zip(yyDist >= threshold, yyDist)
yLabel = []
testReconsError = []
for idx, (anomaly, yyDist) in enumerate(zz):
  if anomaly:
    yLabel.append(1)
  else:
    yLabel.append(0)
  testReconsError.append(yyDist)
Stats(yLabel, y_test)
```

```
Threshold is: 1.1628373
3383/3383 [==============================] - 6s 2ms/step
Accuracy = 0.8561503995565615
F1-score = 0.6470041486250595
Precision = 0.4783293668085677
Recall = 0.9994396974366158
AUC-ROC = 0.9169088618825039
```

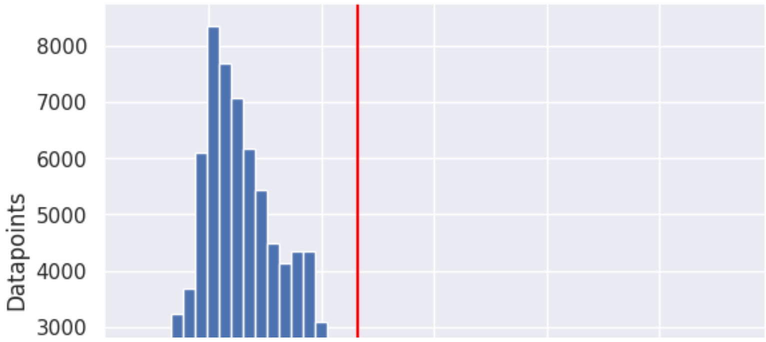
```
##Threshold is: 1.1652662
plot_anomaly(y_test, testReconsError, threshold)
```



4.4 Deciding threshold based on Validation Loss

```
## Calculating the validation loss
reConstructionVal = vae.predict(X_val)
trainLossVal = np.linalg.norm(X_val - reConstructionVal, axis=-1)

## Plotting the loss
plt.hist(trainLossVal, bins=50)
plt.axvline(threshold, color='red')
plt.xlabel("Validation Loss")
plt.ylabel("Datapoints")
```

```
2937/2937 [==============================] - 4s 1ms/step
Text(0, 0.5, 'Datapoints')
```




```
from matplotlib.transforms import interval_contains
## Getting test Statistics for reConstruction validation Loss
mean = np.mean(trainLossVal)
maxVal = np.max(trainLossVal)
minVal = np.min(trainLossVal)
std = np.std(trainLossVal)
perint = np.percentile(trainLossVal, [2.5, 97.5])

## Printing train Loss statistics
print("Mean:", mean)
print("Max:", maxVal)
print("Min:", minVal)
print("Standard Deviation:", std)
print("Spread range interval is:", perint)
```

```
Mean: 0.8004719
Max: 2.8398159
Min: 0.17434429
Standard Deviation: 0.36317518
Spread range interval is: [0.2913793  1.67519702]
```

```
## Taken code refrence from following book:
## Beginning Anomaly Detection Using Python-Based Deep Learning:
## With Keras and PyTorch by by Sridhar Alla (Author), Suman Kalyan Adari(Author)


## Threshold based on the validation data=0.060
threshold = perint[1]
print("Threhold is:", threshold)
yy_pred = vae.predict(X_test)
yyDist = np.linalg.norm(X_test - yy_pred, axis =-1)
zz = zip(yyDist >= threshold, yyDist)
yLabel = []
testReconsError = []
for idx, (anomaly, yyDist) in enumerate(zz):
  if anomaly:
    yLabel.append(1)
  else:
    yLabel.append(0)
  testReconsError.append(yyDist)
## Getting the Stats
Stats(yLabel, y_test)
```

```
Threhold is: 1.163647
3383/3383 [==============================] - 6s 2ms/step
Accuracy = 0.8581828259965818
F1-score = 0.6502631399084137
Precision = 0.4818841803140301
Recall = 0.9995097352570388
AUC-ROC = 0.9181091835053699
```

4.5 Loss for test data

```
## Evaluating loss for test data using VAEs
res = vae.evaluate(X_test)
print("Loss using vae:",res[0])
print("Accuracy using vae:",res[1])
```

```
3383/3383 [==============================] - 6s 2ms/step - loss: 1.2895 - accuracy: 0.0535
Loss using vae: 1.2895125150680542
Accuracy using vae: 0.0534990057349205
```

4.6 Tuning the Threshold

```
## Tuning the threshold based on the validation set
max_error = -float('inf')

for i in range(0,50):
    yy_pred = vae.predict(X_val)
    yyDist = np.linalg.norm(X_val - yy_pred, axis=-1)

    # Calculate maximum construction error
    meanconstruction_error = np.max(np.mean(yyDist))

    # Update best threshold and maximum construction error if necessary
    if meanconstruction_error > max_error:
        max_error = meanconstruction_error
print("Maximum Construction Error:", max_error)
```

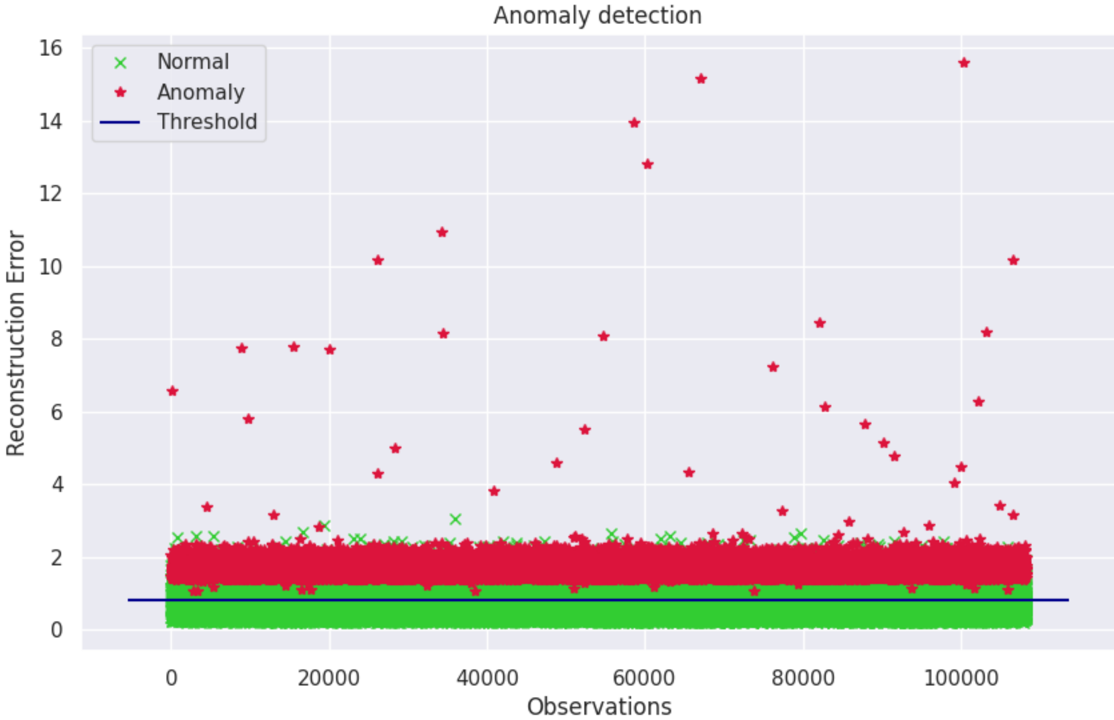
```
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 8s 3ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 7s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 7s 2ms/step
2937/2937 [==============================] - 8s 3ms/step
2937/2937 [==============================] - 8s 3ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 7s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 7s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 6s 2ms/step
2937/2937 [==============================] - 4s 2ms/step
2937/2937 [==============================] - 5s 2ms/step
2937/2937 [==============================] - 4s 1ms/step
2937/2937 [==============================] - 5s 2ms/step
Maximum Construction Error: 0.80286324
```

4.7 Visualising the anomaly detection using VAE

```
## Taken plotting code refrence from following book:
## Beginning Anomaly Detection Using Python-Based Deep Learning:
## With Keras and PyTorch by by Sridhar Alla (Author), Suman Kalyan Adari(Author)


## Calculates the reconstruction error and detect anomaly
## based on threshold
threshold = max_error
yy_pred = vae.predict(X_test)
yyDist = np.linalg.norm(X_test - yy_pred, axis =-1)
zz = zip(yyDist >= threshold, yyDist)
```

```
yLabel = []
testReconsError = []
for idx, (anomaly, yyDist) in enumerate(zz):
  if anomaly:
    yLabel.append(1)
  else:
    yLabel.append(0)
  testReconsError.append(yyDist)
## Printing Stats
Stats(yLabel, y_test)
## Plotting the results
plot_anomaly(y_test, testReconsError, max_error)
```

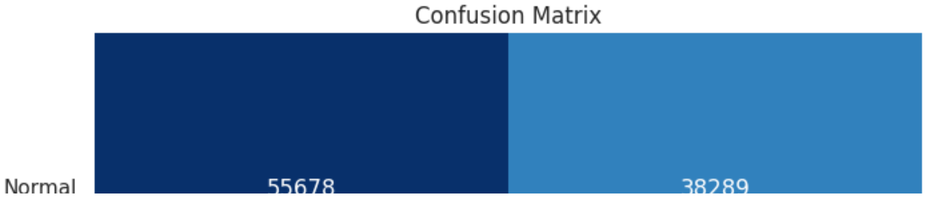
```
3383/3383 [==============================] - 5s 2ms/step
Accuracy = 0.6462746547184628
F1-score = 0.4271972473633032
Precision = 0.27161527193866875
Recall = 1.0
AUC-ROC = 0.796263581895772
```



Confusion matrix

```
## Plotting the confusion matrix
cm = confusion_matrix(y_test, yLabel)
print("Confusion Matrix:")
plot_confusion_matrix(cm, np.array(["Normal", "Anomaly"]))
```

```
Confusion Matrix:
```



Explainability of Autoencoder predictions

```
!pip install lime shap
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting lime
  Downloading lime-0.2.0.1.tar.gz (275 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 275.7/275.7 kB 10.9 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Collecting shap
  Downloading shap-0.41.0-cp310-cp310-manylinux_2_12_x86_64.manylinux2010_x86_64.whl (572 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 572.6/572.6 kB 44.9 MB/s eta 0:00:00
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from lime) (3.7.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from lime) (1.22.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from lime) (1.10.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from lime) (4.65.0)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.10/dist-packages (from lime) (1.2.2)
Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/python3.10/dist-packages (from lime) (0.19.3)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from shap) (1.5.3)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.10/dist-packages (from shap) (23.1)
Collecting slicer==0.0.7 (from shap)
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-packages (from shap) (0.56.4)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-packages (from shap) (2.2.1)
Requirement already satisfied: networkx>=2.2 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.12->lime) (
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,!=8.3.0,>=6.1.0 in /usr/local/lib/python3.10/dist-packages (from sci
Requirement already satisfied: imageio>=2.4.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.12->lime)
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.12->l
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image>=0.12->lin
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.18->lime) (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.18->
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (1.1.(
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (4.4(
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (1.4.
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (3.1.(
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->lime) (2
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba->shap) (
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from numba->shap) (67.7.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2022.7.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib
Building wheels for collected packages: lime
  Building wheel for lime (setup.py) ... done
  Created wheel for lime: filename=lime-0.2.0.1-py3-none-any.whl size=283839 sha256=00a273082dc1d1041ac1c459d9ba1e50825d7
  Stored in directory: /root/.cache/pip/wheels/fd/a2/af/9ac0a1a85a27f314a06b39e1f492bee1547d52549a4606ed89
Successfully built lime
Installing collected packages: slicer, shap, lime
Successfully installed lime-0.2.0.1 shap-0.41.0 slicer-0.0.7
```

5.1 LIME

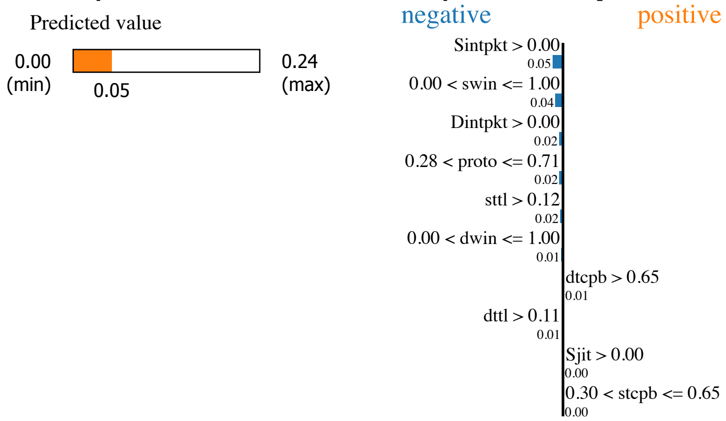
```
## Getting the index of anomaly in the test set
idx = np.where(np.array(yLabel) == 1)[0]
test_point = idx[50]
print("Index to test:", test_point)
```

```
Index to test: 317
```

```
## Code take from lime github page(https://github.com/thomasp85/lime)
## Imporing lime library
import lime
from lime import lime_tabular

instance = lime_tabular.LimeTabularExplainer(
    training_data = np.array(X_train),
    feature_names = feaNames,
    mode = 'regression'
)

X_test_Dummy = np.array(X_test)
exp = instance.explain_instance(data_row = X_test_Dummy[test_point, :],
```

```
predict_fn = autoEncoder.predict)

exp.show_in_notebook(show_table=True)
```

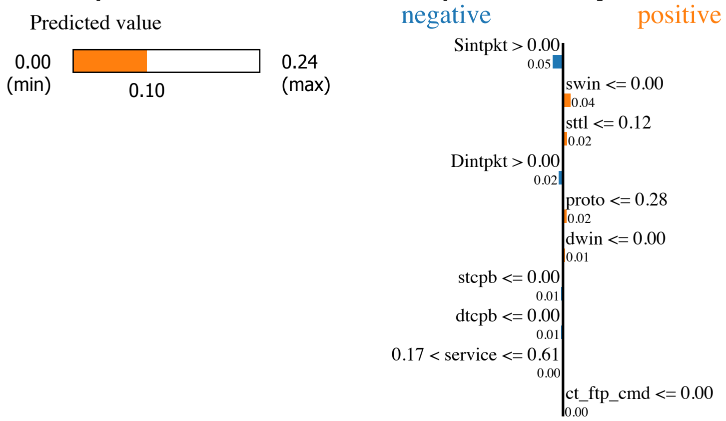
```
157/157 [==============================] - 0s 2ms/step
```



Feature	Value
Sintpkt	0.00
swin	1.00
Dintpkt	0.01
proto	0.71
sttl	1.00
dwin	1.00
dtcpb	0.70
dttl	0.99
Sjit	0.02
stcpb	0.31

```
## Explaination for normal instance
exp = instance.explain_instance(data_row = X_test_Dummy[0, :],
predict_fn = autoEncoder.predict)

exp.show_in_notebook(show_table=True)
```

```
157/157 [==============================] - 1s 4ms/step
```



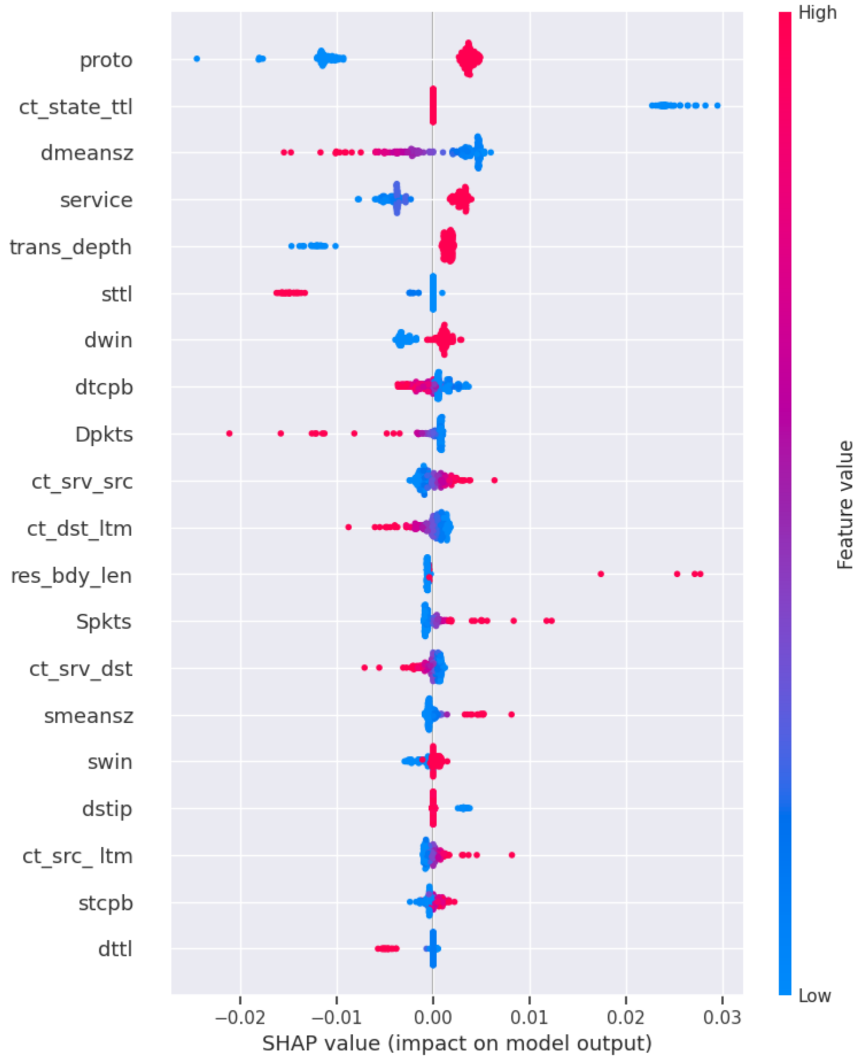
Feature	Value
Sintpkt	0.00
swin	0.00
sttl	0.12
Dintpkt	0.00
proto	0.28
dwin	0.00
stcpb	0.00
dtcpb	0.00
service	0.61
ct_ftp_cmd	0.00

5.2 SHAP

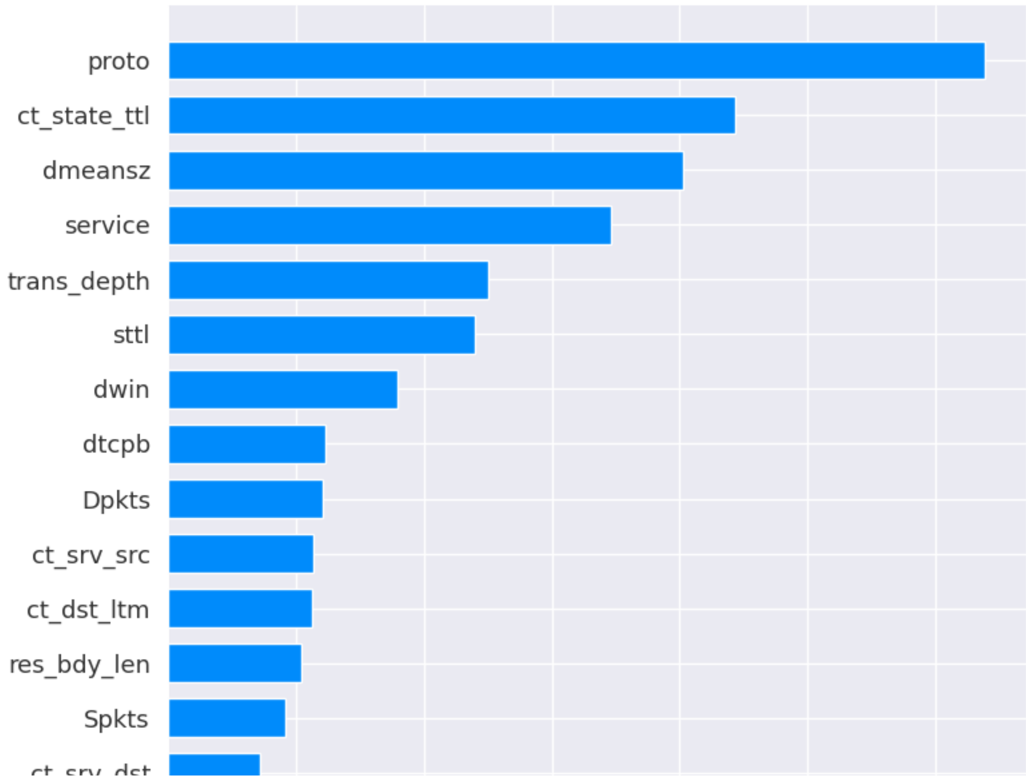
```
## Dropping the features that we didn't want on training sets
feaNames = feaNames.drop('Label')
feaNames = feaNames.drop('attack_cat')


## Converting back to DataFrame
X_train = pd.DataFrame(X_train, columns = feaNames)
X_val = pd.DataFrame(X_val, columns = feaNames)
X_test = pd.DataFrame(X_test, columns = feaNames)


## Code taken from SHAP github page (https://github.com/slundberg/shap)

import shap
import tensorflow.keras.backend
shap.initjs()


## Redefining our model beacuse shap expects this kind of structure on the class
autoencoder = tf.keras.Sequential([
    layers.Dense(36, activation="LeakyReLU", input_shape=(46,)),
    layers.Dense(8, activation="LeakyReLU"),
    layers.Dense(36, activation="LeakyReLU"),
    layers.Dense(46, activation="sigmoid")
])

## Modifying our data as numpy array because shap uses that and
## Creating qn explainer object for that
explainer = shap.DeepExplainer(autoencoder, X_train.iloc[150:250,:])

# Compute SHAP values for the test set
```

```
shap_values = explainer.shap_values(X_test.iloc[300:500,:])


## Getting the summary plot
shap.summary_plot(shap_values[0], X_test.iloc[300:500,:])
```

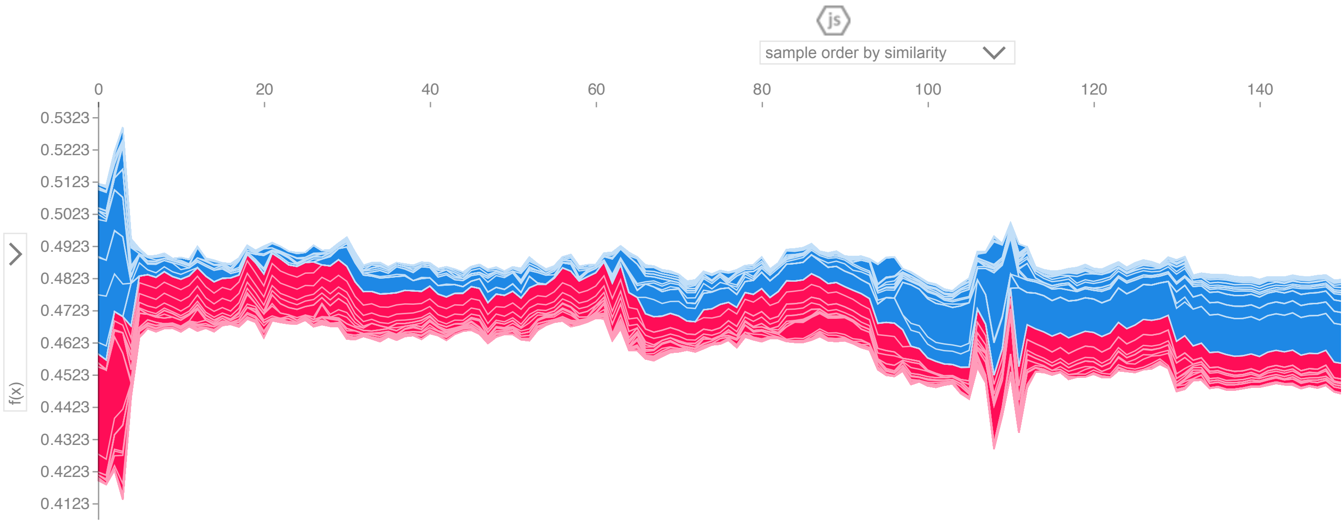
100% 200/200 [13:54<00:00, 3.89s/it]




```
shap.initjs()
## Summary plot
shap.summary_plot(shap_values[0], X_test.iloc[300:500,:], plot_type='bar')
```




```
shap.initjs()
## Force plot
shap.plots.force(explainer.expected_value[0], shap_values[0])
```



One Class SVM

> Training one-class SVM on the subset of the dataset

```
## Importing the necessary libraries for SVM
import pandas as pd
from sklearn.svm import OneClassSVM
from sklearn import svm
## Used this as refrence
## https://towardsdatascience.com/support-vector-machine-svm-for-anomaly
## -detection-73a8d676c331
## Creating a model but due to compuation power trained on half of the data
model = OneClassSVM(kernel = 'rbf', gamma = 0.5,
                    nu = 0.02).fit(X_train.iloc[:200000, :])
## Getting the predictions
y_pred = model.predict(X_test)

## Getting the outlier indicies
outlierIndicies = np.where(y_pred == -1)
```

```
yy_pred = np.zeros(X_test.shape[0])

# Marking the outliers as 1 in y_pred
yy_pred[outlierIndicies] = 1

## Printing the stats for predictions
Stats(yy_pred, y_test)
```

```
Accuracy = 0.9615132338676151
F1-score = 0.851859753929308
Precision = 0.8652123663681017
Recall = 0.8389130130270346
AUC-ROC = 0.9095274888796671
```

Isolation Forest

> trained on the normal data.

```
## Used chatgpt as refrence
## Importing the Isolation forest
from sklearn.ensemble import IsolationForest

# Create an instance of the Isolation Forest model
clf = IsolationForest(n_estimators=100, contamination=0.03, random_state=42)

# Fit the model to your data
clf.fit(X_train)

# Predict the anomalies (outliers)
predicted_labels = clf.predict(X_test)
# Map the predicted labels to 0 for normal and 1 for anomaly
yy_pred = np.where(predicted_labels == 1, 0, 1)


# Getting Stats for your model
Stats(yy_pred, y_test)
```

```
Accuracy = 0.9687098711256871
F1-score = 0.8892594409024032
Precision = 0.8339363463543263
Recall = 0.9524443199327637
AUC-ROC = 0.9618128460583077
```

Unsupervised K-Nearest Neighbours

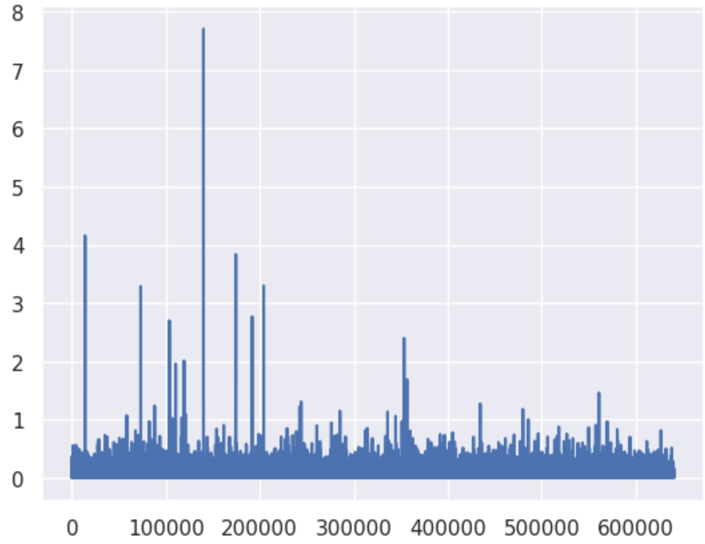
```
## Converting tensor back to numpy arrays for better performance

## Concatenating
data = np.concatenate((X_train, X_val, X_test), axis=0)
y_data = np.concatenate((y_train, y_val, y_test), axis=0)


## Combining the dataFrame
combData = np.concatenate((data, y_data.reshape(-1, 1)), axis=1)

## Reshuffling the data
np.random.shuffle(combData)


## Storing the Labels
yy = combData[:,-1]


## Removing the lables
data = combData[:, :-1]
```

Implementing K nearest neighhours with K=7.

```
## Refrence taken from
##https://towardsdatascience.com/k-nearest-neighbors-knn-for-anomaly-detection-fdf8ee160d13

## Importing the necessary libraries
from sklearn.neighbors import NearestNeighbors
```

```
from sklearn.datasets import make_blobs
import numpy as np
from sklearn.cluster import KMeans

## Initializing the model
nb = NearestNeighbors(n_neighbors = 7)

# fitting the model
nb.fit(data)

## getting the distance and indexex from the model
dist, indices = nb.kneighbors(data)

# plot mean of k-distances of each observation
plt.plot(dist.mean(axis = 1))
```

```
[<matplotlib.lines.Line2D at 0x7f16e7954eb0>]
```




```
# visually determine the threshold
outlierIndices = np.where(dist.mean(axis = 1) > 0.4)
## getting the indicies for outliers
#outlierIndices


confidenceInterval_knn = np.percentile(dist.mean(axis = 1), [2.5, 97.5])

## Getting the outliers based on the threshold
outlierThreshold = confidenceInterval_knn[1]
print("Threshold for unsupervised KNN is(based on 95% confidence interval):", outlierThreshold)
```

```
Threshold for unsupervised KNN is(based on 95% confidence interval): 0.1353089258002197
```

```
## Getting the indicies of the anomalies
outlierIndices = np.where(dist.mean(axis = 1) > 0.05)


y_pred = np.zeros(data.shape[0])

# Marking the outliers as 1 in y_pred
y_pred[outlierIndices] = 1

## Printing the stats for predictions
Stats(y_pred, yy)
```

```
Accuracy = 0.7177405006196096
F1-score = 0.08873279888743885
Precision = 0.04780571496826526
Recall = 0.6166830088247653
AUC-ROC = 0.6683634056715455
```

Accuracy above is misleading because there are few anomalies, which are not correctly indentied by this unsupervised model.