notebook

May 8, 2022

0.1 Imports

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import ipaddress

from IPython.display import display
from sklearn.covariance import EllipticEnvelope
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn.metrics import precision_score, recall_score, accuracy_score,␣
↪confusion_matrix, average_precision_score, ConfusionMatrixDisplay,␣
↪roc_curve, auc, PrecisionRecallDisplay

rng = np.random.RandomState(42)
```

0.2 Data loading

[ ]:
```
col_names = ['end_epoch', 'duration', 'src_ip', 'dst_ip', 'src_port',␣
↪'dst_port', 'protocol', 'flags', 'status', 'service_type', 'packets',␣
↪'bytes', 'attack']

def load_dataframe(name):
    return pd.read_csv(f"data/training/{name}_flows_cut.csv", header = None,␣
↪names = col_names)

def load_test_dataframe(name):
    return pd.read_csv(f"data/test/{name}_flows_cut.csv", header = None, names␣
↪= col_names)
```

[ ]:
```
# Load training datasets
background = load_dataframe("background")
blacklist  = load_dataframe("blacklist")
sshscan    = load_dataframe("sshscan")
spam       = load_dataframe("spam")
```

```
# Load tests datasets
test_background = load_test_dataframe("background")
test_blacklist  = load_test_dataframe("blacklist")
test_sshscan    = load_test_dataframe("sshscan")
test_botnet     = load_test_dataframe("botnet")
test_scan11     = load_test_dataframe("scan11")
test_scan44     = load_test_dataframe("scan44")
test_spam       = load_test_dataframe("spam")
test_dos        = load_test_dataframe("dos")

# We regroup all attacks of each dataset in lists to have a cleaner code latter
attacks_dataframes = [blacklist, sshscan, spam]
test_attacks_dataframes = [test_blacklist, test_sshscan, test_botnet,␣
 ↪test_scan11, test_scan44, test_spam, test_dos]
```

[ ]:
```
def get_dataframes(outlier_ratio, num_samples):
    """
    This function allow us to get two proper datasets of training and tests␣
 ↪with the given size and outlier ratio.
    """
    # Set offsets of each dataset depending on poor sized sub-datasets
    train_offset = len(spam) % num_samples * outlier_ratio
    test_offset = len(test_sshscan) % num_samples * outlier_ratio

    # Get the number of attack sample our datasets will contains
    nb_train_attack = int((num_samples * outlier_ratio - train_offset) //␣
 ↪(len(attacks_dataframes) - 1))
    nb_test_attack  = int((num_samples * outlier_ratio - test_offset) //␣
 ↪(len(test_attacks_dataframes) - 1))

    # Get the correct number of sample for each attack sub-dataset
    train_dataframes = [df.head(nb_train_attack) for df in attacks_dataframes]
    test_dataframes = [df.head(nb_test_attack) for df in␣
 ↪test_attacks_dataframes]

    # The remaining of space allowed is fill with background flows for each␣
 ↪dataset
    train_dataframes.append(background.head(num_samples - sum(len(df) for df in␣
 ↪train_dataframes)))
    test_dataframes.append(test_background.head(num_samples - sum(len(df) for␣
 ↪df in test_dataframes)))

    # Concat each lists to get our dataframes
    train_df = pd.concat(train_dataframes, ignore_index=True)
    test_df = pd.concat(test_dataframes, ignore_index=True)
```

```
    return train_df, test_df
```

[ ]:
```
outlier_ratio = 0.1
train_df, test_df = get_dataframes(outlier_ratio, 10000)
train_df.head()
```

[ ]:

	end_epoch	duration	src_ip	dst_ip	src_port	dst_port	protocol	flags	status	service_type	packets	bytes	attack
0	2016-04-18 00:02:16	0.996	42.219.158.242	60.56.180.24	33421	80	TCP	.AP.SF	0	0	6	437	blacklist
1	2016-04-18 00:02:16	0.852	42.219.158.242	60.56.180.24	35297	443	TCP	.AP.SF	0	0	52	3030	blacklist
2	2016-04-18 00:02:17	0.936	60.56.180.24	42.219.158.242	80	33421	TCP	.AP.SF	0	0	4	565	blacklist
3	2016-04-18 00:02:17	0.804	60.56.180.24	42.219.158.242	443	35297	TCP	.AP.SF	0	0	72	86267	blacklist
4	2016-04-18 00:02:30	0.000	42.219.152.242	88.205.102.190	38531	25	TCP	…S.	0	0	1	60	blacklist

0.3 Data analysis

As described in the scientific paper, we know that our 'background' data may contain unlabeled attacks.
Because we cant know for sure which exchanges are attacks we'll consider them as geniune exchanges for now.
Same goes for blacklist flows, we cant know for sure if they are attacks we'll consider them as fraudulent exchanges for now.

0.3.1 Training dataset observations

[ ]:
```
print(f'The training dataset size is: {len(train_df)}\n')

print(f'The number of unknown attacks / background exchanges is:␣
 ↪{len(train_df[train_df.attack == "background"])}')
print(f'The number of known attacks is: {len(train_df[train_df.attack !=␣
 ↪"background"])}\n')

print(f'The types of attack are: {train_df[train_df.attack != "background"].
 ↪attack.unique()}')
for attack in train_df[train_df.attack != "background"].attack.unique():
    print(f'The number of {attack} is: {len(train_df[train_df.attack ==␣
 ↪attack])}')
print()

print(f'Number of source IP used in known attacks: {len(train_df[train_df.
 ↪attack != "background"].src_ip.unique())}')
```

```
print(f'Number of source IP used in othe exchanges: {len(train_df[train_df.
  ↪attack == "background"].src_ip.unique())}')
print(f'Number of destination IP used in known attacks: {len(train_df[train_df.
  ↪attack != "background"].dst_ip.unique())}')
print(f'Number of destination IP used in other exchanges:␣
  ↪{len(train_df[train_df.attack == "background"].dst_ip.unique())}\n')

print(f'Number of source port used in known attacks: {len(train_df[train_df.
  ↪attack != "background"].src_port.unique())}')
print(f'Number of source port used in othe exchanges: {len(train_df[train_df.
  ↪attack == "background"].src_port.unique())}')
print(f'Number of destination port used in known attacks:␣
  ↪{len(train_df[train_df.attack != "background"].dst_port.unique())}')
print(f'Number of destination port used in othe exchanges:␣
  ↪{len(train_df[train_df.attack == "background"].dst_port.unique())}\n')

print(f'Protocols used during known attacks: {train_df[train_df.attack !=␣
  ↪"background"].protocol.unique()}')
print(f'Protocols used during other exchanges: {train_df[train_df.attack ==␣
  ↪"background"].protocol.unique()}\n')
```

```
The training dataset size is: 10000

The number of unknown attacks / background exchanges is: 8965
The number of known attacks is: 1035

The types of attack are: ['blacklist' 'anomaly-sshscan' 'anomaly-spam']
The number of blacklist is: 497
The number of anomaly-sshscan is: 497
The number of anomaly-spam is: 41

Number of source IP used in known attacks: 251
Number of source IP used in othe exchanges: 2018
Number of destination IP used in known attacks: 227
Number of destination IP used in other exchanges: 1537

Number of source port used in known attacks: 451
Number of source port used in othe exchanges: 4363
Number of destination port used in known attacks: 495
Number of destination port used in othe exchanges: 3939

Protocols used during known attacks: ['TCP' 'UDP' 'ICMP']
Protocols used during other exchanges: ['TCP' 'UDP' 'GRE' 'ESP' 'ICMP' 'IPv6']
```

```
[ ]: print(f'Flags used during known attacks: {train_df[train_df.attack !=␣
      ↪"background"]["flags"].unique()}')
     print(f'Flags used during other exchanges: {train_df[train_df.attack ==␣
      ↪"background"]["flags"].unique()}\n')

     print(f'Types of service used during known attacks: {train_df[train_df.attack !
      ↪= "background"].service_type.unique()}')
     print(f'Types of service used during other exchanges: {train_df[train_df.attack␣
      ↪== "background"].service_type.unique()}\n')

     print(f'Number of different status in the dataset: {len(train_df.status.
      ↪unique())}\n')

     print('Details of quantitative features of known attacks:')
     display(train_df[train_df.attack != "background"][['duration', 'packets',␣
      ↪'bytes']].describe())
     print()
     print('Details of quantitative features of other exchanges:')
     display(train_df[train_df.attack == "background"][['duration', 'packets',␣
      ↪'bytes']].describe())
```

```
Flags used during known attacks: ['.AP.SF' '…S.' '.A.R..' '.AP.S.' '.A…F'
'.A…' '.A..SF' '.APRSF'
 '.A..S.' '.AP..F' '.AP…' '.APR.F' '…R..' '.APRS.' '…RS.']
Flags used during other exchanges: ['.A…' '.A..S.' '.AP.S.' '.AP…' '…S.'
'.A…F' '.A.R.F' '.APR..'
 '.A.R..' '.AP..F' '…R..' '.AP.SF' '.A..SF' '.APRS.' '.APRSF' '.A.RSF'
 '.APR.F' '.A.RS.']

Types of service used during known attacks: [ 0 40 72  8]
Types of service used during other exchanges: [  0  64  40  72   2   8 192  26
24 200  80  42 184  16 104  20  75]

Number of different status in the dataset: 1

Details of quantitative features of known attacks:
```

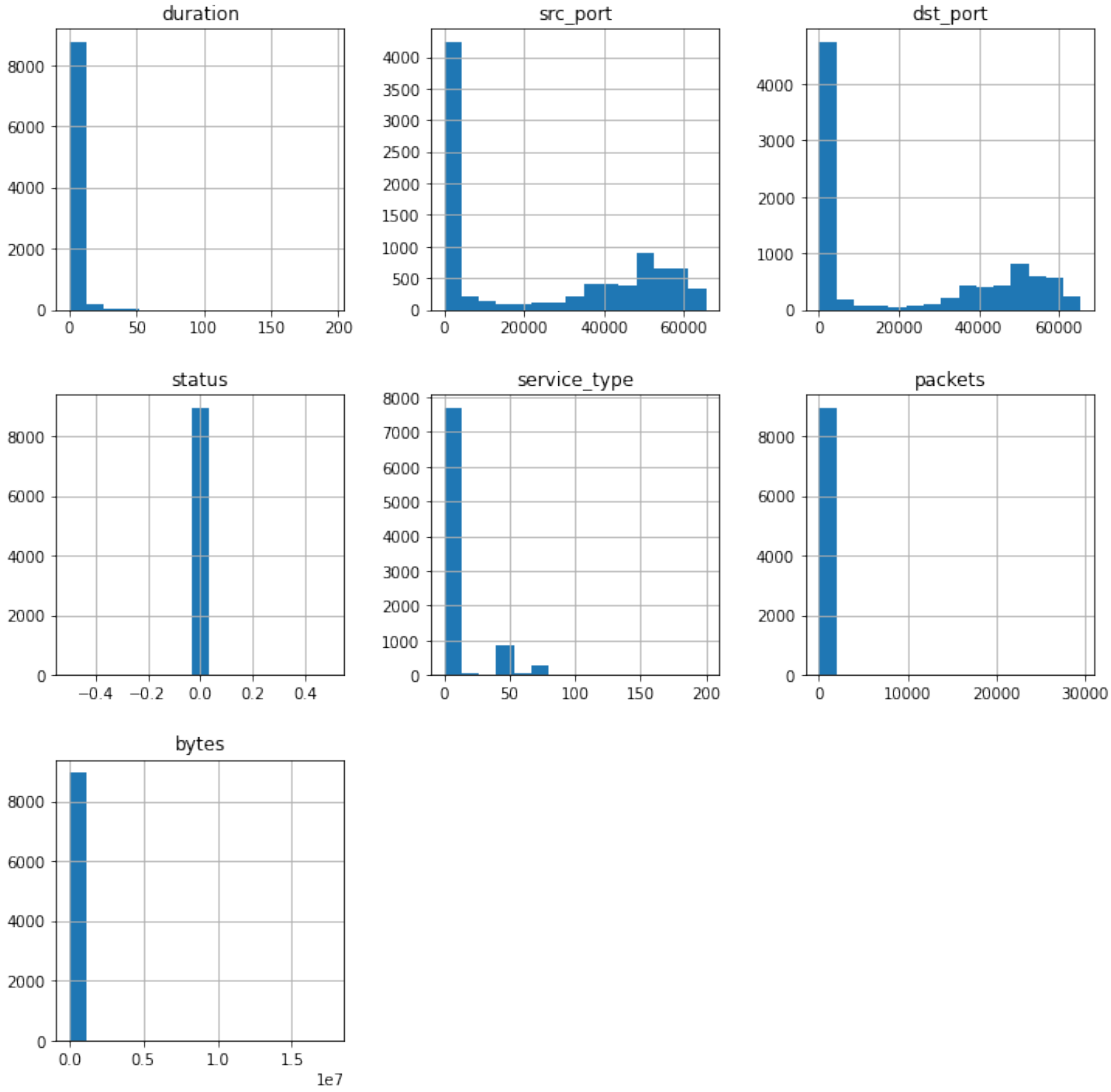
	duration	packets	bytes
count	1035.000000	1035.000000	1.035000e+03
mean	4.668881	24.860870	1.485774e+04
std	5.745437	63.051175	7.601059e+04
min	0.000000	1.000000	4.000000e+01
25%	0.888000	5.000000	5.650000e+02
50%	3.540000	12.000000	1.373000e+03
75%	5.040000	15.000000	1.954000e+03
max	54.712000	782.000000	1.118209e+06

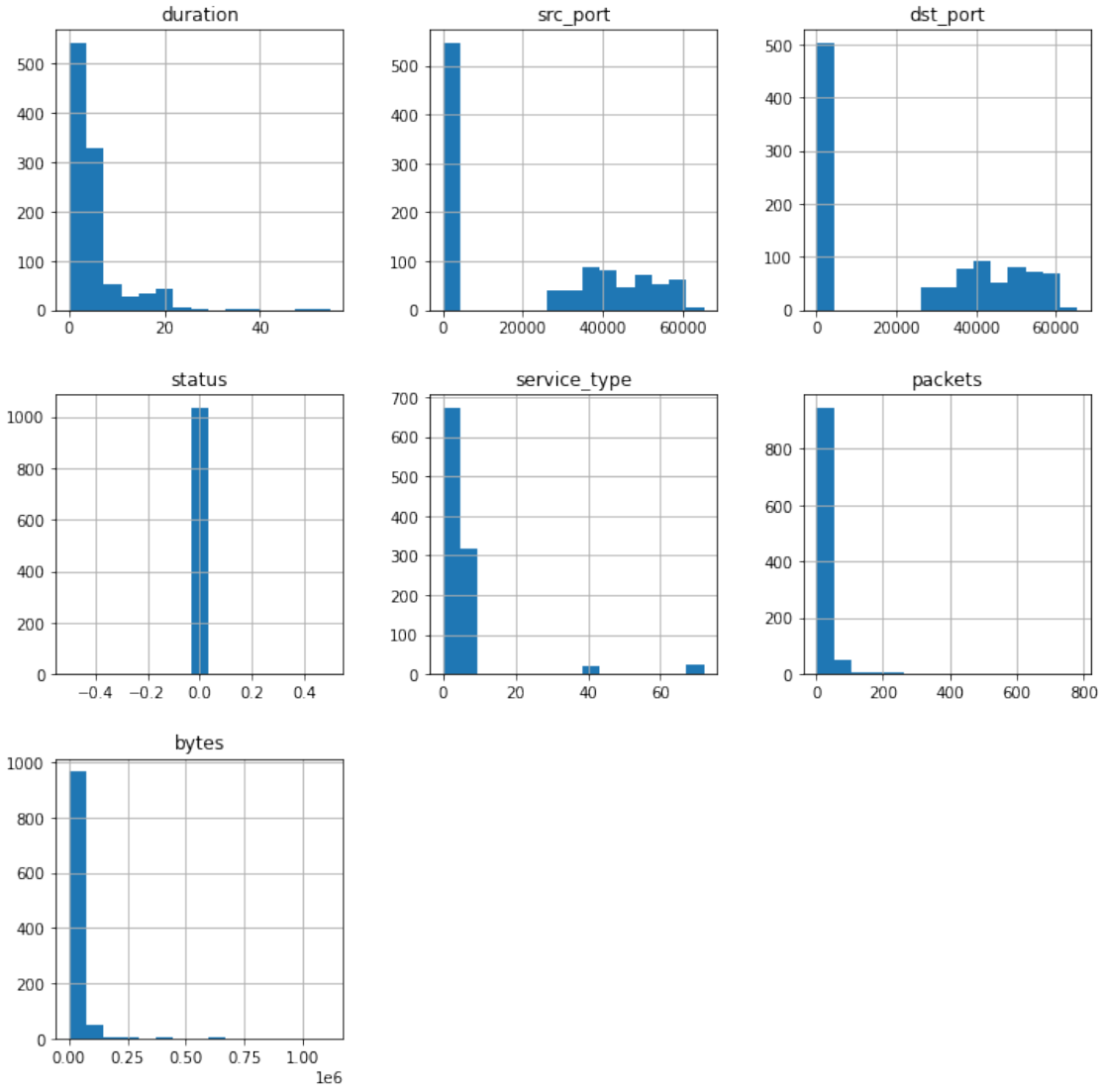
Details of quantitative features of other exchanges:

	duration	packets	bytes
count	8965.000000	8965.000000	8.965000e+03
mean	1.109757	15.008589	7.854498e+03
std	5.411496	374.938073	2.400408e+05
min	0.000000	1.000000	3.100000e+01
25%	0.000000	1.000000	7.600000e+01
50%	0.000000	1.000000	1.310000e+02
75%	0.324000	6.000000	7.280000e+02
max	194.796000	29544.000000	1.765682e+07

[ ]:
```
train_df[train_df.attack == "background"].hist(bins=15, figsize=(12, 12))
train_df[train_df.attack != "background"].hist(bins=15, figsize=(12, 12))
```

[ ]:
```
array([[<AxesSubplot:title={'center':'duration'}>,
        <AxesSubplot:title={'center':'src_port'}>,
        <AxesSubplot:title={'center':'dst_port'}>],
       [<AxesSubplot:title={'center':'status'}>,
        <AxesSubplot:title={'center':'service_type'}>,
        <AxesSubplot:title={'center':'packets'}>],
       [<AxesSubplot:title={'center':'bytes'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```


duration
src_port
dst_port
status
service_type
packets
bytes
1e7



0.3.2 Test Dataset observations

```
[ ]: print(f'The test dataset size is: {len(test_df)}\n')

print(f'The number of unknown attacks / background exchanges is:␣
  ↪{len(test_df[test_df.attack == "background"])}')
print(f'The number of known attacks is: {len(test_df[test_df.attack !=␣
  ↪"background"])}\n')

print(f'The types of attack are: {test_df[test_df.attack != "background"].
  ↪attack.unique()}')
for attack in test_df[test_df.attack != "background"].attack.unique():
```

```
    print(f'The number of {attack} is: {len(test_df[test_df.attack ==␣
 ↪attack])}')
print()

print(f'Number of source IP used in known attacks: {len(test_df[test_df.attack !
 ↪= "background"].src_ip.unique())}')
print(f'Number of source IP used in othe exchanges: {len(test_df[test_df.attack␣
 ↪== "background"].src_ip.unique())}')
print(f'Number of destination IP used in known attacks: {len(test_df[test_df.
 ↪attack != "background"].dst_ip.unique())}')
print(f'Number of destination IP used in other exchanges: {len(test_df[test_df.
 ↪attack == "background"].dst_ip.unique())}\n')

print(f'Number of source port used in known attacks: {len(test_df[test_df.
 ↪attack != "background"].src_port.unique())}')
print(f'Number of source port used in othe exchanges: {len(test_df[test_df.
 ↪attack == "background"].src_port.unique())}')
print(f'Number of destination port used in known attacks: {len(test_df[test_df.
 ↪attack != "background"].dst_port.unique())}')
print(f'Number of destination port used in othe exchanges: {len(test_df[test_df.
 ↪attack == "background"].dst_port.unique())}\n')

print(f'Protocols used during known attacks: {test_df[test_df.attack !=␣
 ↪"background"].protocol.unique()}')
print(f'Protocols used during other exchanges: {test_df[test_df.attack ==␣
 ↪"background"].protocol.unique()}\n')
```

```
The test dataset size is: 10000

The number of unknown attacks / background exchanges is: 8999
The number of known attacks is: 1001

The types of attack are: ['blacklist' 'anomaly-sshscan' 'nerisbotnet' 'scan11'
'scan44'
 'anomaly-spam' 'dos']
The number of blacklist is: 166
The number of anomaly-sshscan is: 5
The number of nerisbotnet is: 166
The number of scan11 is: 166
The number of scan44 is: 166
The number of anomaly-spam is: 166
The number of dos is: 166

Number of source IP used in known attacks: 131
Number of source IP used in othe exchanges: 1603
Number of destination IP used in known attacks: 50
Number of destination IP used in other exchanges: 3311
```

```
Number of source port used in known attacks: 515
Number of source port used in othe exchanges: 4455
Number of destination port used in known attacks: 274
Number of destination port used in othe exchanges: 3838

Protocols used during known attacks: ['TCP' 'UDP' 'ICMP']
Protocols used during other exchanges: ['ICMP' 'TCP' 'UDP']
```

[ ]:
```
print(f'Flags used during known attacks: {test_df[test_df.attack !=␣
 ↪"background"]["flags"].unique()}')
print(f'Flags used during other exchanges: {test_df[test_df.attack ==␣
 ↪"background"]["flags"].unique()}\n')

print(f'Types of service used during known attacks: {test_df[test_df.attack !=␣
 ↪"background"].service_type.unique()}')
print(f'Types of service used during other exchanges: {test_df[test_df.attack␣
 ↪== "background"].service_type.unique()}\n')

print(f'Number of different status in the dataset: {len(test_df.status.
 ↪unique())}\n')

print('Details of quantitative features of known attacks:')
display(test_df[test_df.attack != "background"][['duration', 'packets',␣
 ↪'bytes']].describe())
print()
print('Details of quantitative features of other exchanges:')
display(test_df[test_df.attack == "background"][['duration', 'packets',␣
 ↪'bytes']].describe())
```

```
Flags used during known attacks: ['.APRS.' '.AP.S.' '.APR..' '.AP.SF' '.A..SF'
'…S.' '.APRSF' '.A.R..'
 '.A…' '.A.RSF' '…R..' '.AP..F' '.A..S.' '…RS.']
Flags used during other exchanges: ['.A…' '.A..S.' '…S.' '.A…F' '.A.R..'
'.APR..' '.AP…' '…R..'
 '.AP.S.' '.A.RS.' '.A..SF' '.AP.SF' '.APR.F' '.APRSF' '.AP..F' '.APRS.'
 '.A.R.F' '…RS.']

Types of service used during known attacks: [40  0 72  8 74]
Types of service used during other exchanges: [192   0 200  26   2  64  24  72
40   4   8  20  16]

Number of different status in the dataset: 1

Details of quantitative features of known attacks:

          duration      packets         bytes
```

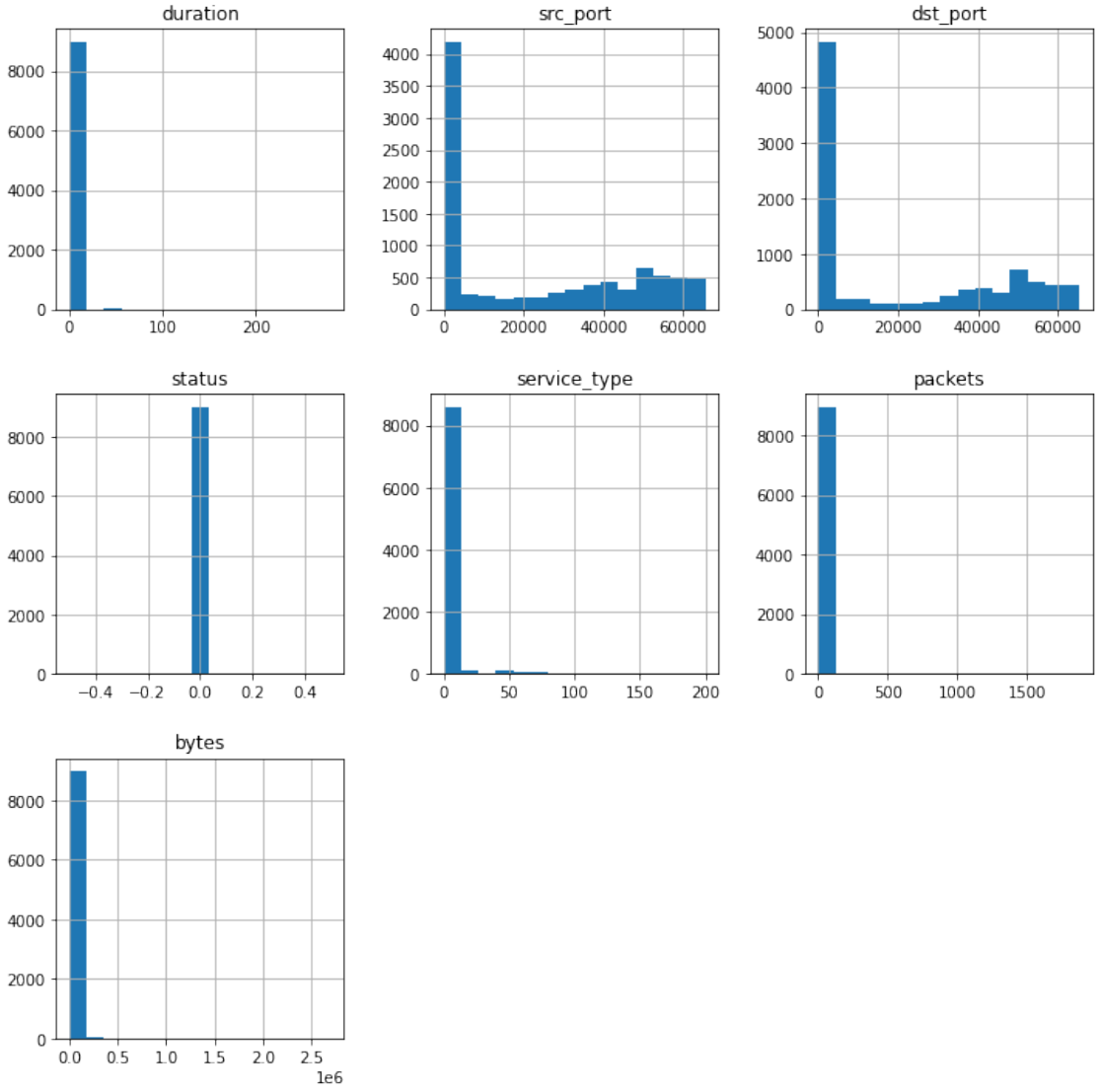
```
count  1001.000000  1001.000000   1001.000000
mean      0.779888     3.335664    634.646354
std       2.593195     3.860987   2776.405061
min       0.000000     1.000000     28.000000
25%       0.000000     1.000000     44.000000
50%       0.000000     2.000000    197.000000
75%       0.576000     6.000000    441.000000
max      21.060000    27.000000  36132.000000
```

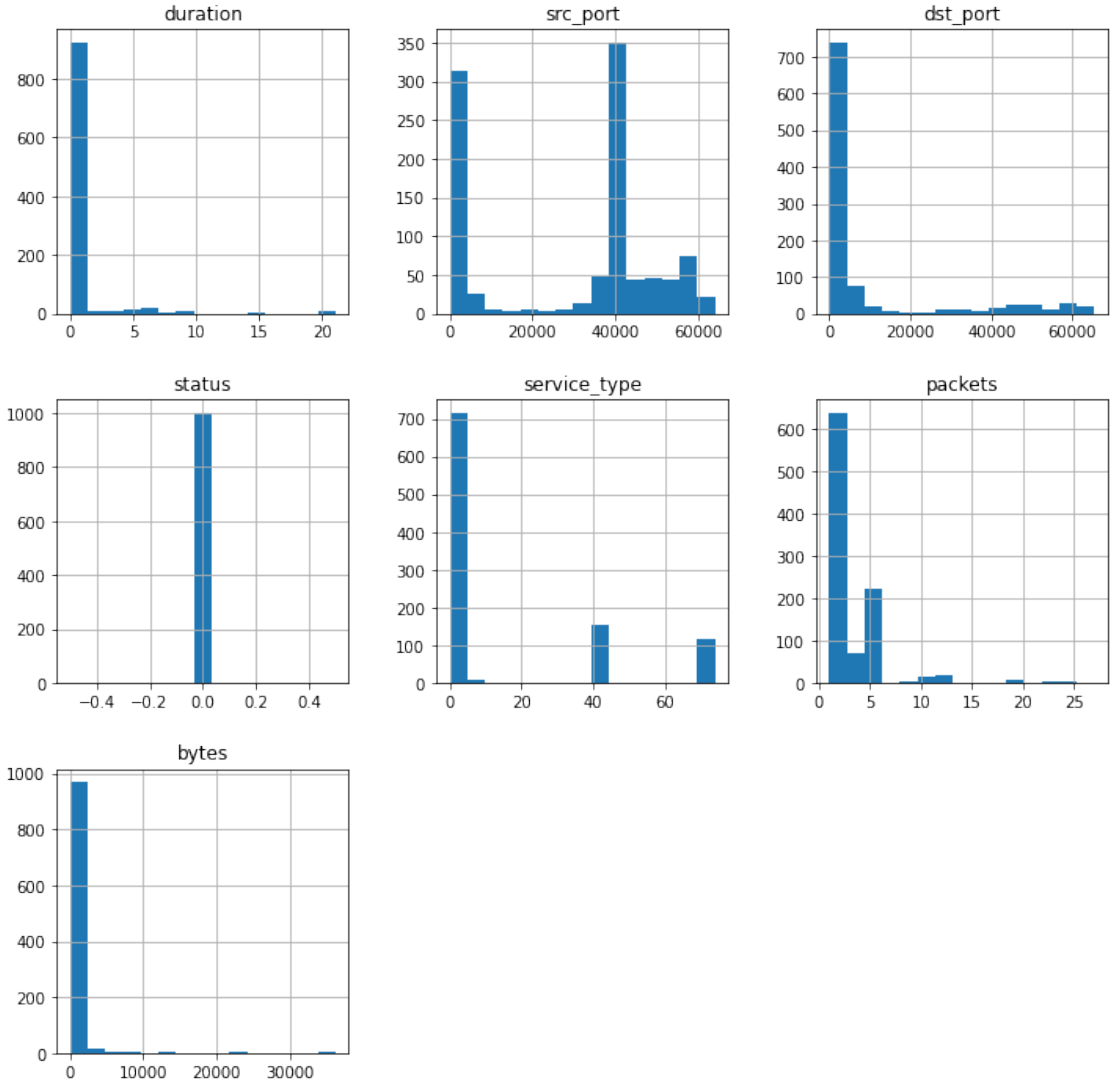
Details of quantitative features of other exchanges:

```
          duration      packets         bytes
count  8999.000000  8999.000000  8.999000e+03
mean      1.431335     7.270252  4.047749e+03
std       5.636508    31.983570  4.009776e+04
min       0.000000     1.000000  2.800000e+01
25%       0.000000     1.000000  9.600000e+01
50%       0.200000     2.000000  1.640000e+02
75%       1.828000     7.000000  1.081500e+03
max     280.620000  1879.000000  2.703238e+06
```

[ ]:
```
test_df[test_df.attack == "background"].hist(bins=15, figsize=(12, 12))
test_df[test_df.attack != "background"].hist(bins=15, figsize=(12, 12))
```

[ ]:
```
array([[<AxesSubplot:title={'center':'duration'}>,
        <AxesSubplot:title={'center':'src_port'}>,
        <AxesSubplot:title={'center':'dst_port'}>],
       [<AxesSubplot:title={'center':'status'}>,
        <AxesSubplot:title={'center':'service_type'}>,
        <AxesSubplot:title={'center':'packets'}>],
       [<AxesSubplot:title={'center':'bytes'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```


duration
src_port
dst_port
status
service_type
packets
bytes
1e6



0.4 Data Cleaning

[ ]:
```
# We drop 'status' column as we saw that there is only one value accepted all␣
 ↪datasets
# We also drop 'packets' column as it is redoundant with the 'bytes' column

train_df.drop(['status'], axis=1, inplace=True)
test_df.drop(['status'], axis=1, inplace=True)

print(f'Number of missing values in the train dataset: {train_df.isnull().
 ↪values.sum()}')
print(f'Number of missing values in the test dataset: {test_df.isnull().values.
 ↪sum()}')
```

```
Number of missing values in the train dataset: 0
Number of missing values in the test dataset: 0
```

[ ]:
```python
def encode_dataframes(train_df, test_df):
    """
    Encode the training and testing dataframes to have better performance in our algorithms.
    """
    train_df = train_df.drop(['attack'], axis=1)
    test_df = test_df.drop(['attack'], axis=1)

    # Convert timestamp to epoch integer, we dont keep the date values to not have biaised models later
    train_df.end_epoch = pd.to_datetime(train_df.end_epoch).apply(lambda x: x.strftime('%H%M%S')).astype(np.int64)
    test_df.end_epoch = pd.to_datetime(test_df.end_epoch).apply(lambda x: x.strftime('%H%M%S')).astype(np.int64)

    # Convert IPs to int, for optimization purpose only
    train_df.src_ip = train_df.src_ip.apply(lambda x: np.int64(ipaddress.IPv4Address(x)))
    train_df.dst_ip = train_df.dst_ip.apply(lambda x: np.int64(ipaddress.IPv4Address(x)))
    test_df.src_ip = test_df.src_ip.apply(lambda x: np.int64(ipaddress.IPv4Address(x)))
    test_df.dst_ip = test_df.dst_ip.apply(lambda x: np.int64(ipaddress.IPv4Address(x)))

    encoded_train_df = pd.get_dummies(train_df)
    encoded_test_df = pd.get_dummies(test_df)

    # Add missing columns to each dataset for consistency
    for column in encoded_train_df.columns:
        if column not in encoded_test_df.columns:
            encoded_test_df[column] = 0

    for column in encoded_test_df.columns:
        if column not in encoded_train_df.columns:
            encoded_train_df[column] = 0

    # Reorder columns order, also for consistency
    encoded_test_df = encoded_test_df[encoded_train_df.columns]

    return encoded_train_df, encoded_test_df

encoded_train_df, encoded_test_df = encode_dataframes(train_df, test_df)
encoded_train_df.head()
```

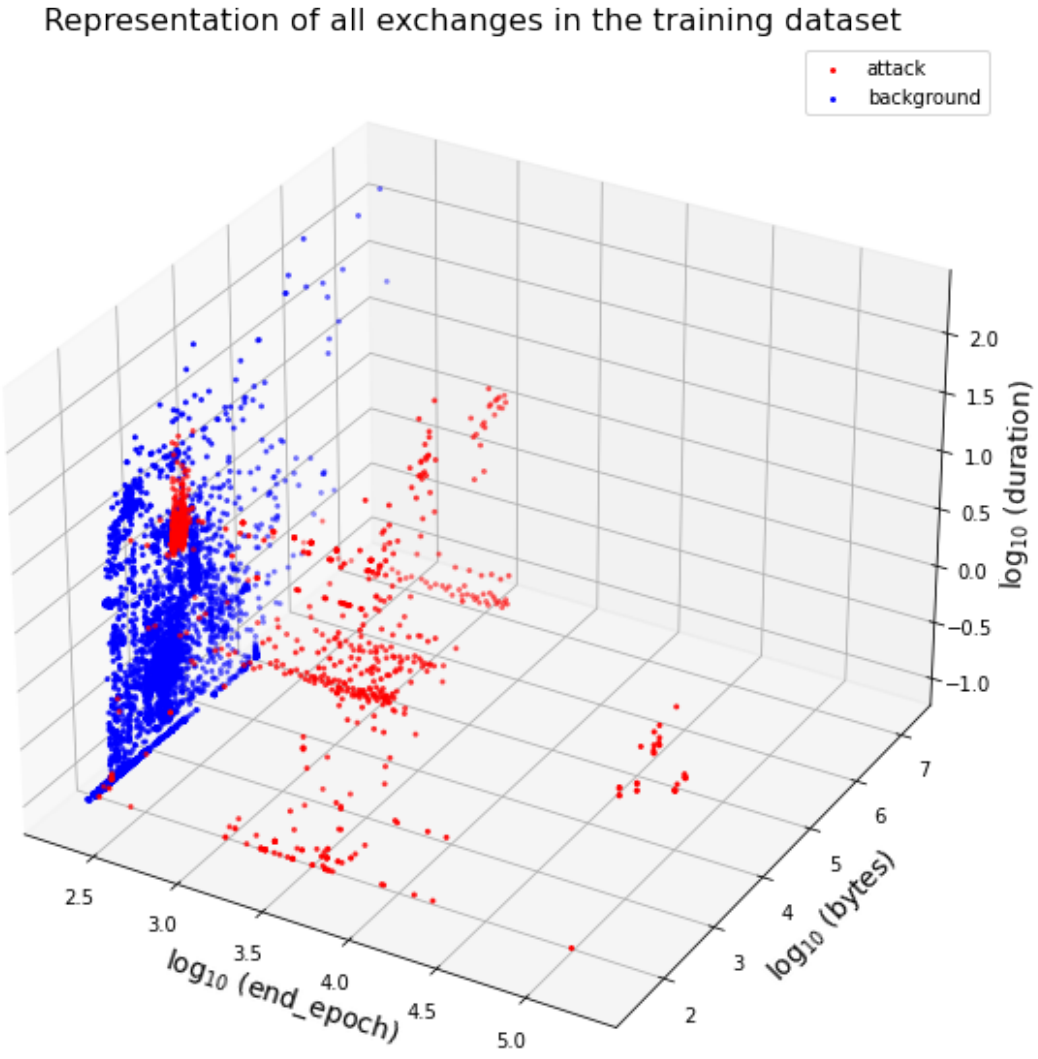
[ ]:
```
   end_epoch  duration      src_ip      dst_ip  src_port  dst_port  \
0        216     0.996   719036146  1010349080     33421        80
1        216     0.852   719036146  1010349080     35297       443
2        217     0.936  1010349080   719036146        80     33421
3        217     0.804  1010349080   719036146       443     35297
4        230     0.000   719034610  1489856190     38531        25

   service_type  packets  bytes  protocol_ESP  …  flags_.A.RS.  \
0             0        6    437             0  …             0
1             0       52   3030             0  …             0
2             0        4    565             0  …             0
3             0       72  86267             0  …             0
4             0        1     60             0  …             0

   flags_.A.RSF  flags_.AP…  flags_.AP..F  flags_.AP.S.  flags_.AP.SF  \
0             0           0             0             0             1
1             0           0             0             0             1
2             0           0             0             0             1
3             0           0             0             0             1
4             0           0             0             0             0

   flags_.APR..  flags_.APR.F  flags_.APRS.  flags_.APRSF
0             0            0             0             0
1             0            0             0             0
2             0            0             0             0
3             0            0             0             0
4             0            0             0             0

[5 rows x 34 columns]
```

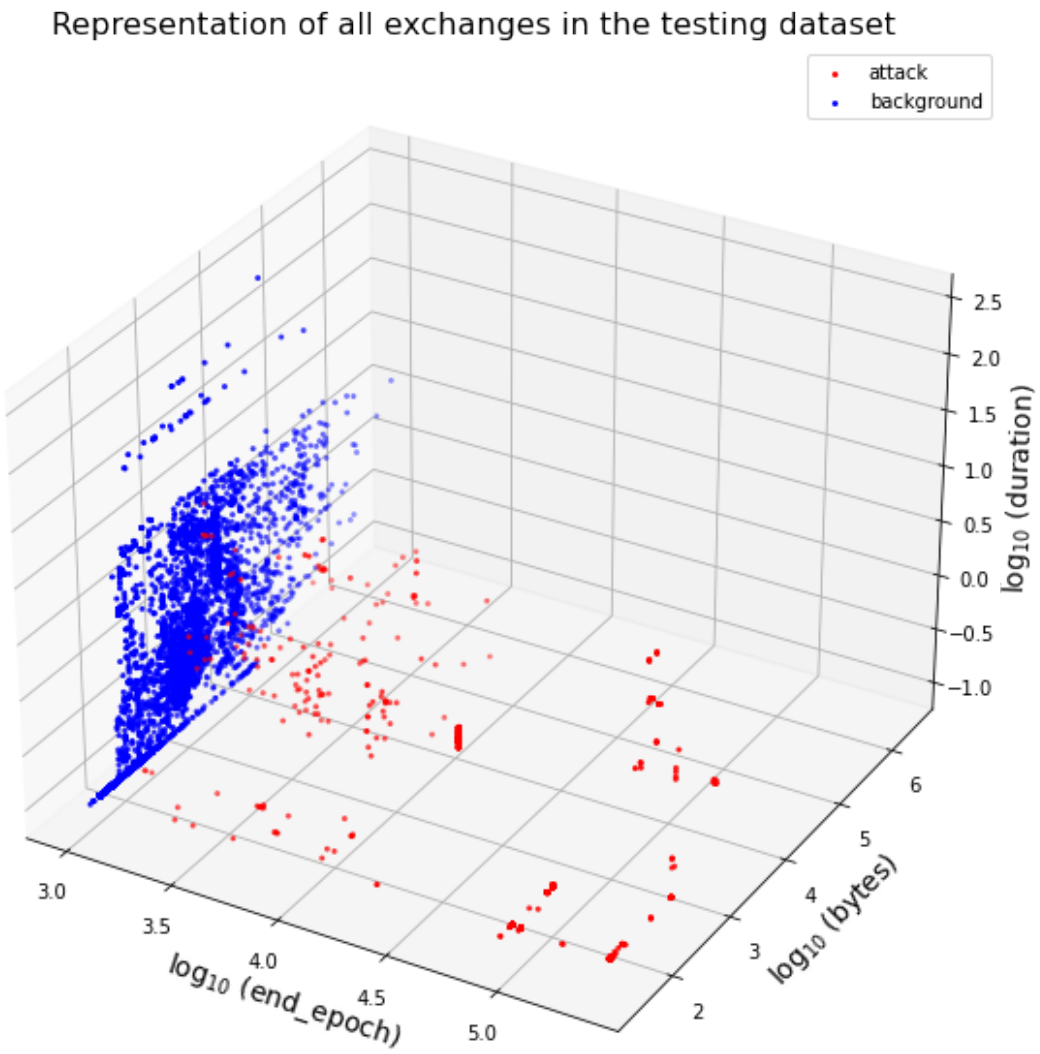
0.5 Dataset Visualisation

[ ]:
```
def show_flow_exchanges_3d(df, df_attack, x_axis, y_axis, z_axis, title):
    fig = plt.figure(figsize=(10,10))
    ax = fig.add_subplot(111, projection='3d')

    df_attacks = df[df_attack != "background"]
    xa = df_attacks[x_axis]
    ya = df_attacks[y_axis]
    za = df_attacks[z_axis]

    ax.scatter3D(np.log10(xa + 0.1), np.log10(ya + 0.1), np.log10(za + 0.1),␣
 ↪label="attack", color="r", marker=".", s=15)

    df_genuines = df[df_attack == "background"]
    xg = df_genuines[x_axis]
    yg = df_genuines[y_axis]
```

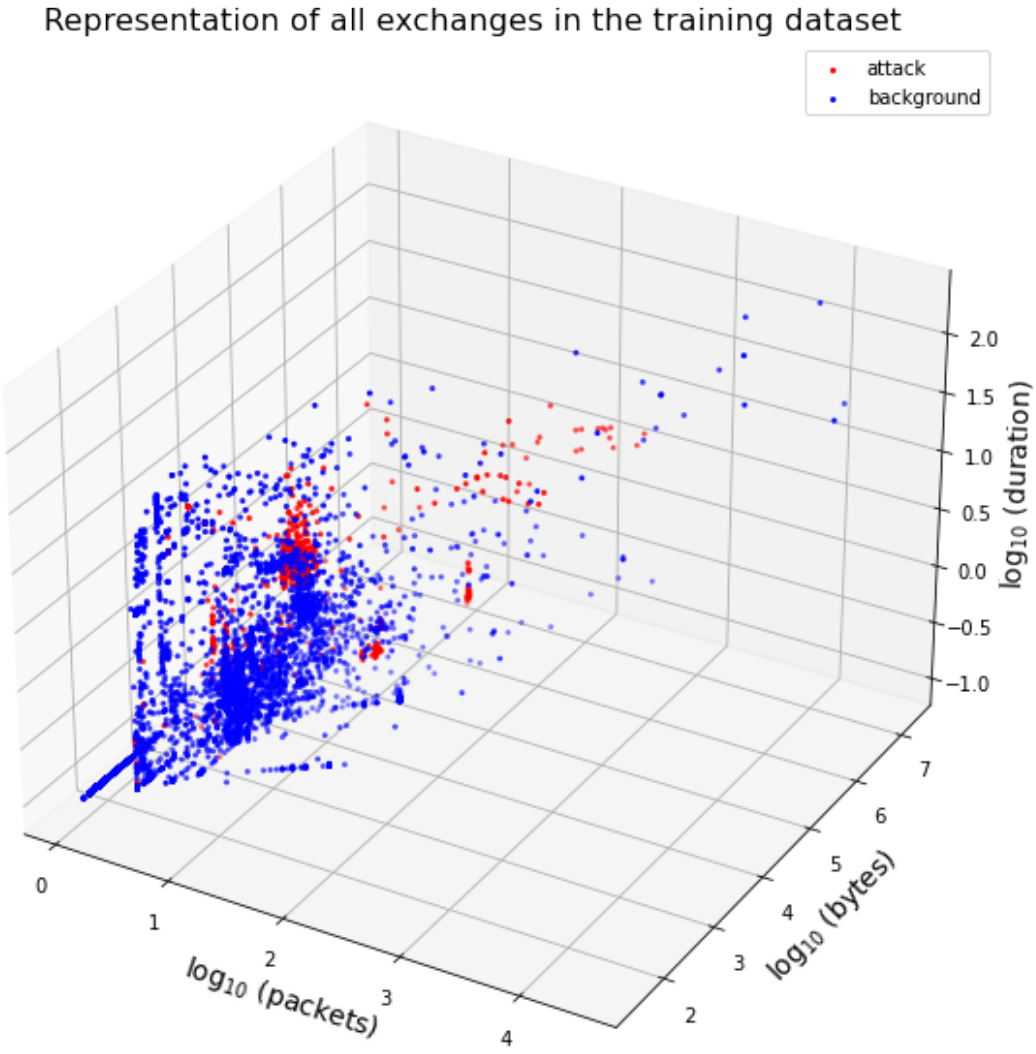
```
    zg = df_genuines[z_axis]

    ax.scatter3D(np.log10(xg + 0.1), np.log10(yg + 0.1), np.log10(zg + 0.1),␣
 ↪label="background", color="b", marker=".", s=15)

    ax.set_title(title, size=16)
    ax.set_xlabel('log$_{10}$ (' + x_axis + ')', size=14)
    ax.set_ylabel('log$_{10}$ (' + y_axis + ')', size=14)
    ax.set_zlabel('log$_{10}$ (' + z_axis + ')', size=14)

    plt.legend()
```

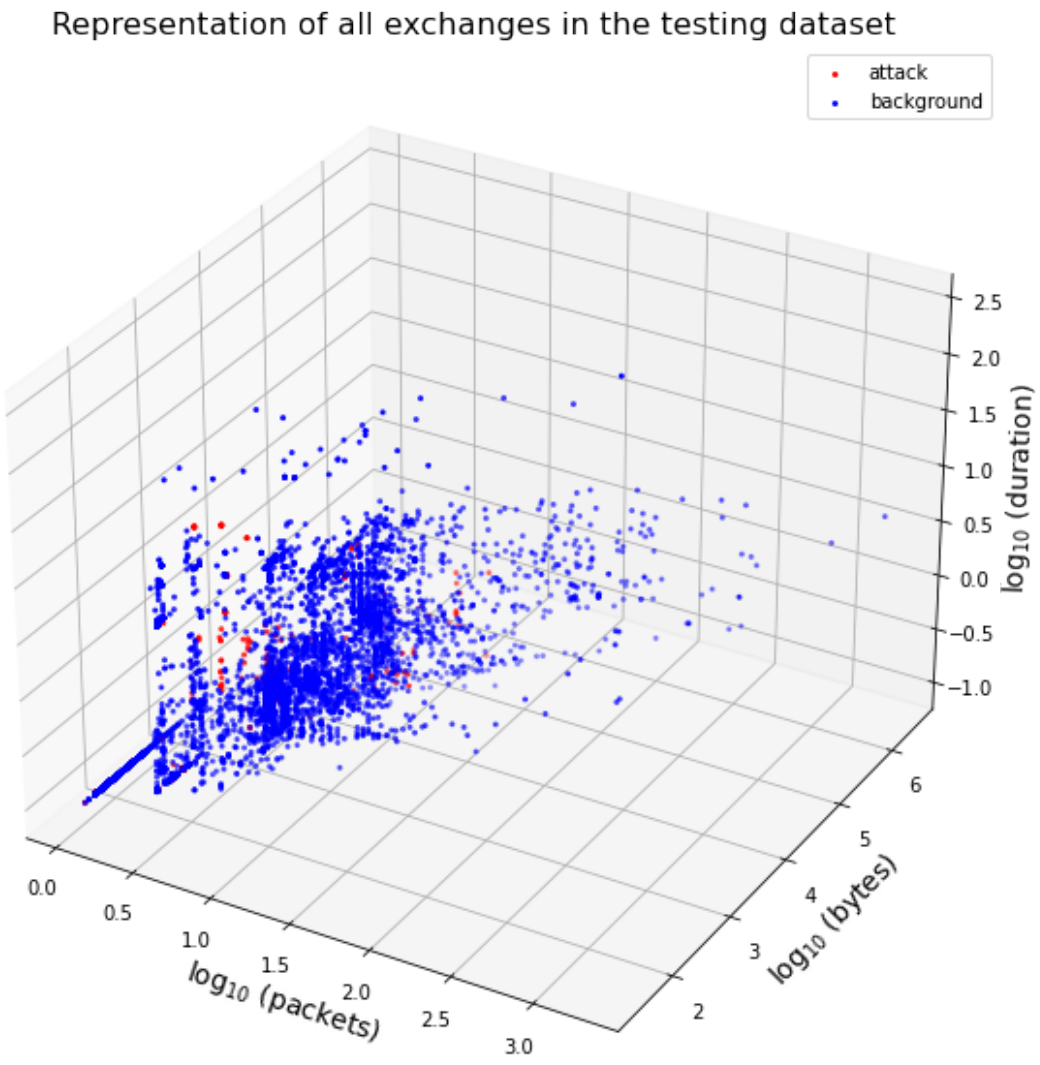
[ ]:
```
# End epoch differs a lot between attacks and normal flows
show_flow_exchanges_3d(encoded_train_df, train_df["attack"], 'end_epoch',␣
 ↪'bytes', 'duration', 'Representation of all exchanges in the training␣
 ↪dataset')
show_flow_exchanges_3d(encoded_test_df, test_df["attack"], 'end_epoch',␣
 ↪'bytes', 'duration', 'Representation of all exchanges in the testing␣
 ↪dataset')
```


Representation of all exchanges in the training dataset
attack
background
log10 (end_epoch)
log10 (bytes)
log10 (duration)
2.5
3.0
3.5
4.0
4.5
5.0
2
3
4
5
6
7
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0

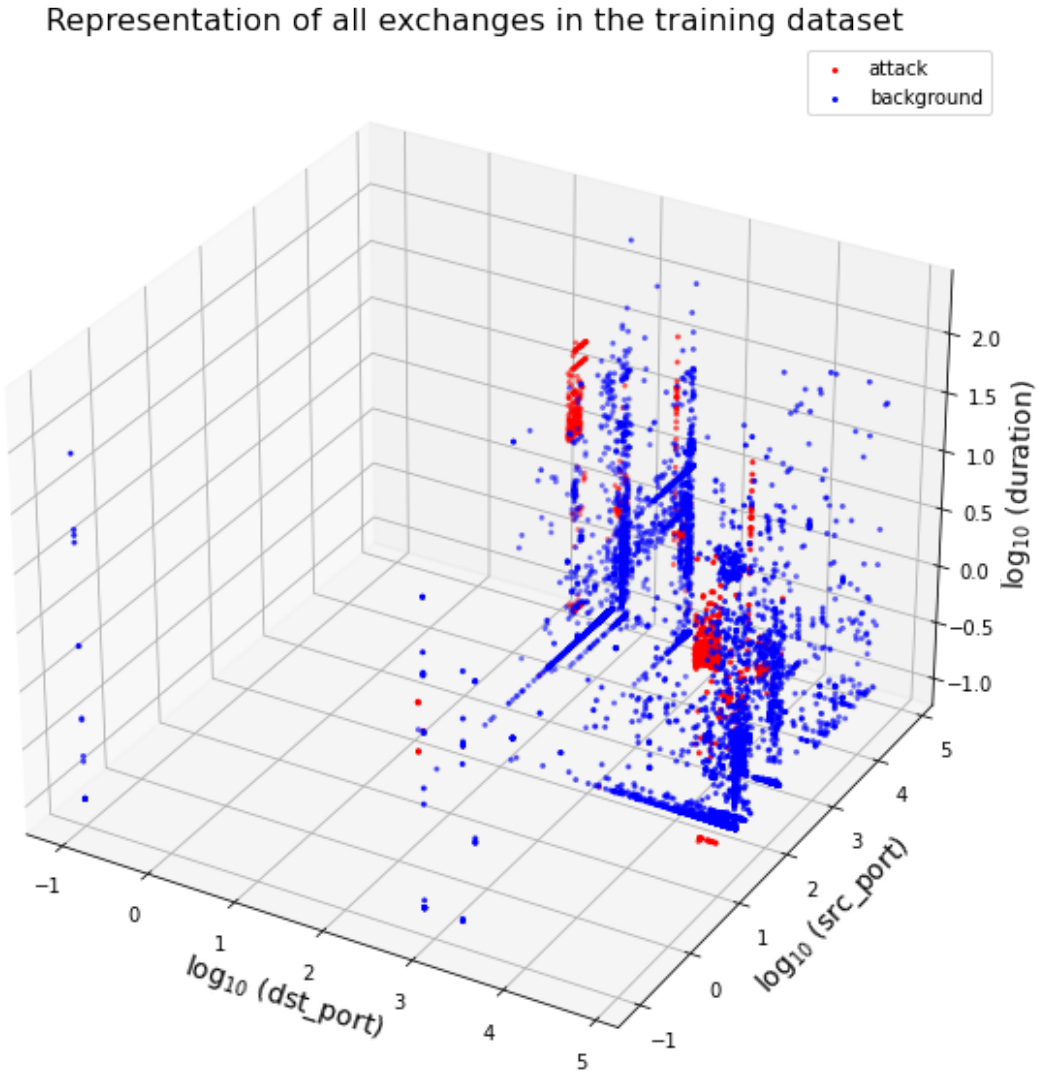


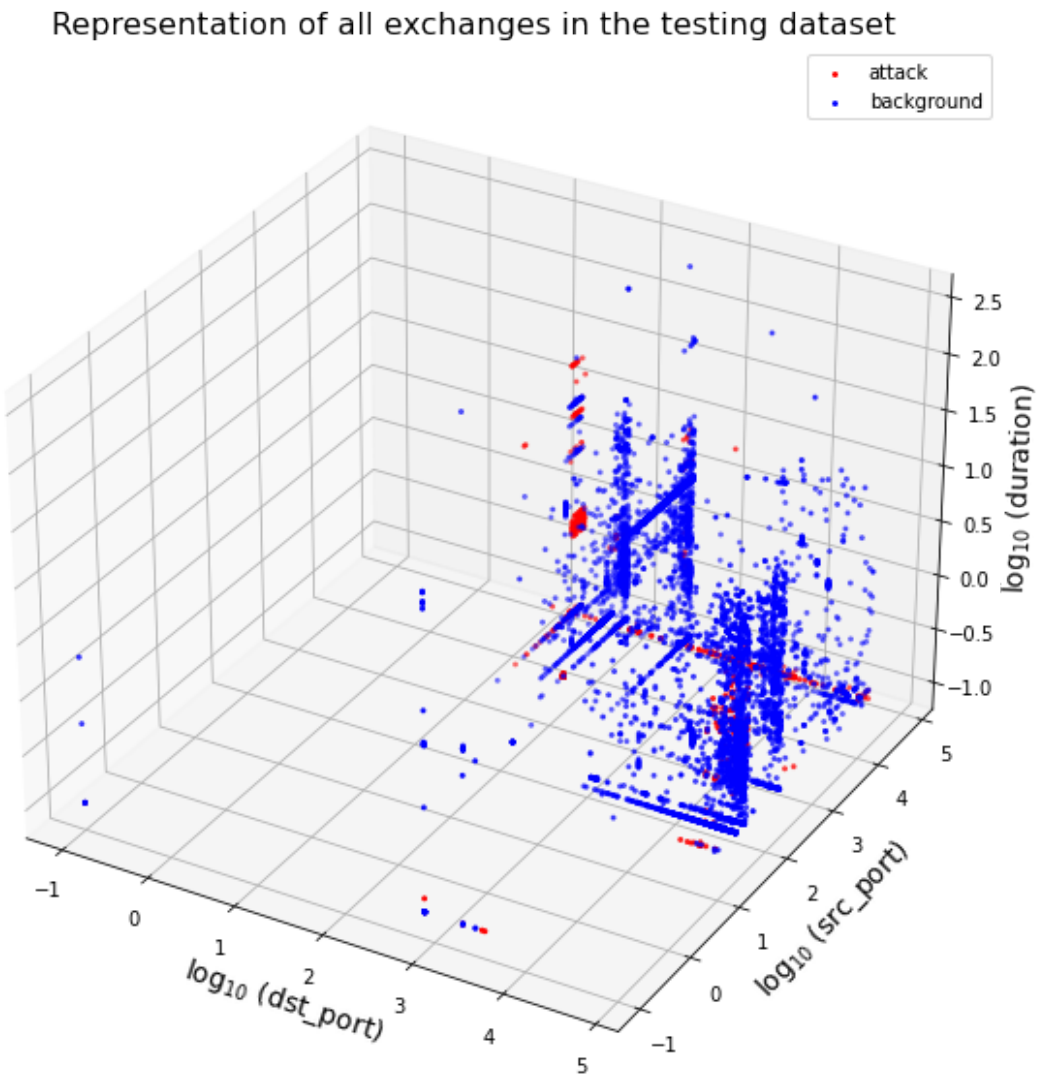
[ ]:
```
# Packets differs a bit between attacks and normal flows
show_flow_exchanges_3d(encoded_train_df, train_df["attack"], 'packets',␣
 ↪'bytes', 'duration', 'Representation of all exchanges in the training␣
 ↪dataset')
show_flow_exchanges_3d(encoded_test_df, test_df["attack"], 'packets', 'bytes',␣
 ↪'duration', 'Representation of all exchanges in the testing dataset')
```


Representation of all exchanges in the training dataset
attack
background
log10 (duration)
log10 (packets)
log10 (bytes)



[ ]:
```
# Attacks seems to be focused on a reduced set of source / destination ports.
show_flow_exchanges_3d(encoded_train_df, train_df["attack"], 'dst_port',␣
 ↪'src_port', 'duration', 'Representation of all exchanges in the training␣
 ↪dataset')
show_flow_exchanges_3d(encoded_test_df, test_df["attack"], 'dst_port',␣
 ↪'src_port', 'duration', 'Representation of all exchanges in the testing␣
 ↪dataset')
```


Representation of all exchanges in the training dataset
attack
background
log10 (duration)
log10 (dst_port)
log10 (src_port)



[ ]:
```
# Matrix de correlation
corr = train_df.corr()
corr.style.background_gradient(cmap="coolwarm")
```

[ ]:
```
<pandas.io.formats.style.Styler at 0x7f21e1db1a90>
```

0.6 Outlier detection

[ ]:
```
def display_metrics(y_true, y_pred):
    fig, axes = plt.subplots(1, 3, figsize=(20, 5))

    # Display the confusion matrix
    cm = confusion_matrix(y_true, y_pred)
```

```
    tn, fp, fn, tp = cm.ravel()
    ConfusionMatrixDisplay(confusion_matrix=cm).plot(ax=axes[0])

    # Display classifier metrics
    print(f'AUPRC: {round(average_precision_score(y_true, y_pred) * 100, 2) }%')
    print(f'Precision: {round(precision_score(y_true, y_pred) * 100, 2) }%')
    print(f'Recall: {round(recall_score(y_true, y_pred) * 100, 2) }%')
    print(f'True Negative Rate: {round( tn * 100 / (tn + fp), 2) }%')
    print(f'Accuracy: {round(accuracy_score(y_true, y_pred) * 100, 2) }%\n')

    # Plot ROC curve
    fpr, tpr, _ = roc_curve(y_true, y_pred)
    roc_auc = round(auc(fpr, tpr), 2)
    axes[1].plot([0, 1], [0, 1], color="navy", linestyle="--")
    axes[1].plot(fpr, tpr, color='darkorange', label=f'Roc curve (area =␣
↪{roc_auc})')

    axes[1].set_xlim([0.0, 1.0])
    axes[1].set_ylim([0.0, 1.5])
    axes[1].set_xlabel('False Positive Rate')
    axes[1].set_ylabel('True Positive Rate')
    axes[1].set_title('Receiver operating characteristic curve')
    axes[1].legend(loc="lower right")

    # Plot Precision-Recall curve
    PrecisionRecallDisplay.from_predictions(y_true, y_pred, ax=axes[2])
    axes[2].set_title('Precision-Recall Curve')
```

Isolation Forests

[ ]:
```
classifier = IsolationForest(contamination=outlier_ratio, n_estimators=1000,␣
↪random_state=rng).fit(encoded_train_df.values)
y_pred = classifier.predict(encoded_test_df.values)

df_outliers = encoded_test_df.copy()
df_outliers["attack"] = test_df.attack != "background"
df_outliers['if_outliers'] = [i == -1 for i in  y_pred]
df_outliers.head()
```

[ ]:

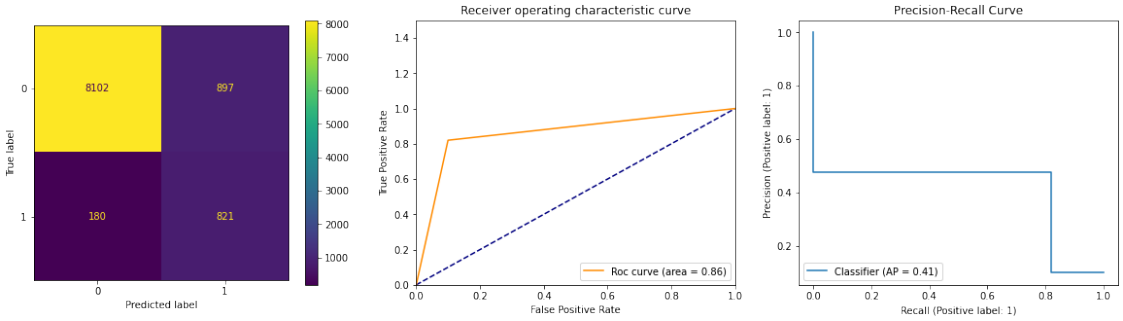
	end_epoch	duration	src_ip	dst_ip	src_port	dst_port	\
0	1103	8.152	1167153979	719035603	38490	443	
1	1107	4.372	1167153979	719035603	40516	443	
2	1132	0.000	1167153979	719035603	40516	443	
3	1136	4.464	1167153979	719035603	51560	443	
4	1149	0.000	1167153979	719035603	51560	443	

	service_type	packets	bytes	protocol_ESP	…	flags_.AP…	\

```
0             40        13   1620              0  …              0
1             40        11   1502              0  …              0
2             40         2    135              0  …              0
3             40        10   1439              0  …              0
4             40         2    135              0  …              0

   flags_.AP..F  flags_.AP.S.  flags_.AP.SF  flags_.APR..  flags_.APR.F  \
0             0             0             0             0             0
1             0             1             0             0             0
2             0             0             0             1             0
3             0             1             0             0             0
4             0             0             0             1             0

   flags_.APRS.  flags_.APRSF  attack  if_outliers
0             1             0    True         True
1             0             0    True        False
2             0             0    True        False
3             0             0    True         True
4             0             0    True         True

[5 rows x 36 columns]
```

[ ]:
```
display_metrics(df_outliers.attack, df_outliers.if_outliers)
```

```
AUPRC: 40.99%
Precision: 47.79%
Recall: 82.02%
True Negative Rate: 90.03%
Accuracy: 89.23%
```



Elliptic Envelope

[ ]:
```
robustCovariance = EllipticEnvelope(contamination=outlier_ratio,␣
↪random_state=rng).fit(encoded_train_df.values)
```

```
rc_outliers = robustCovariance.predict(encoded_test_df.values)

df_outliers['rc_outliers'] = [i == -1 for i in  rc_outliers]
df_outliers.head()
```

```
/home/leiyks/.local/lib/python3.8/site-
packages/sklearn/covariance/_robust_covariance.py:738: UserWarning: The
covariance matrix associated to your dataset is not full rank
  warnings.warn(
```

[ ]:

	end_epoch	duration	src_ip	dst_ip	src_port	dst_port	\
0	1103	8.152	1167153979	719035603	38490	443	
1	1107	4.372	1167153979	719035603	40516	443	
2	1132	0.000	1167153979	719035603	40516	443	
3	1136	4.464	1167153979	719035603	51560	443	
4	1149	0.000	1167153979	719035603	51560	443	

	service_type	packets	bytes	protocol_ESP	…	flags_.AP..F	\
0	40	13	1620	0	…	0	
1	40	11	1502	0	…	0	
2	40	2	135	0	…	0	
3	40	10	1439	0	…	0	
4	40	2	135	0	…	0	

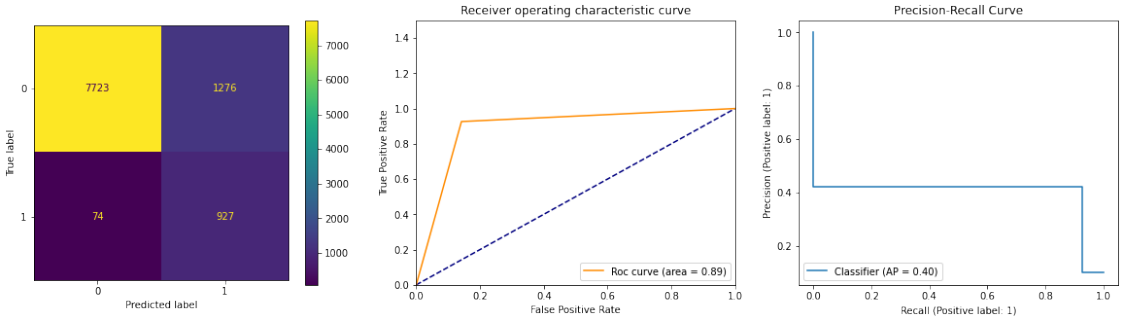
	flags_.AP.S.	flags_.AP.SF	flags_.APR..	flags_.APR.F	flags_.APRS.	\
0	0	0	0	0	1	
1	1	0	0	0	0	
2	0	0	1	0	0	
3	1	0	0	0	0	
4	0	0	1	0	0	

	flags_.APRSF	attack	if_outliers	rc_outliers
0	0	True	True	False
1	0	True	False	False
2	0	True	False	False
3	0	True	True	False
4	0	True	True	False

[5 rows x 37 columns]

[ ]:
```
display_metrics(df_outliers.attack, df_outliers.rc_outliers)
```

```
AUPRC: 39.71%
Precision: 42.08%
Recall: 92.61%
True Negative Rate: 85.82%
Accuracy: 86.5%
```



Local Outlier Factor

[ ]:
```
localOutlierFactor = LocalOutlierFactor(contamination=outlier_ratio,␣
↪n_neighbors=1000, n_jobs=-1)

lof_outliers = localOutlierFactor.fit_predict(encoded_test_df.values)

df_outliers['lof_outliers'] = [i == -1 for i in lof_outliers]
df_outliers.head()
```

[ ]:

	end_epoch	duration	src_ip	dst_ip	src_port	dst_port	\
0	1103	8.152	1167153979	719035603	38490	443	
1	1107	4.372	1167153979	719035603	40516	443	
2	1132	0.000	1167153979	719035603	40516	443	
3	1136	4.464	1167153979	719035603	51560	443	
4	1149	0.000	1167153979	719035603	51560	443	

	service_type	packets	bytes	protocol_ESP	…	flags_.AP.S.	\
0	40	13	1620	0	…	0	
1	40	11	1502	0	…	1	
2	40	2	135	0	…	0	
3	40	10	1439	0	…	1	
4	40	2	135	0	…	0	

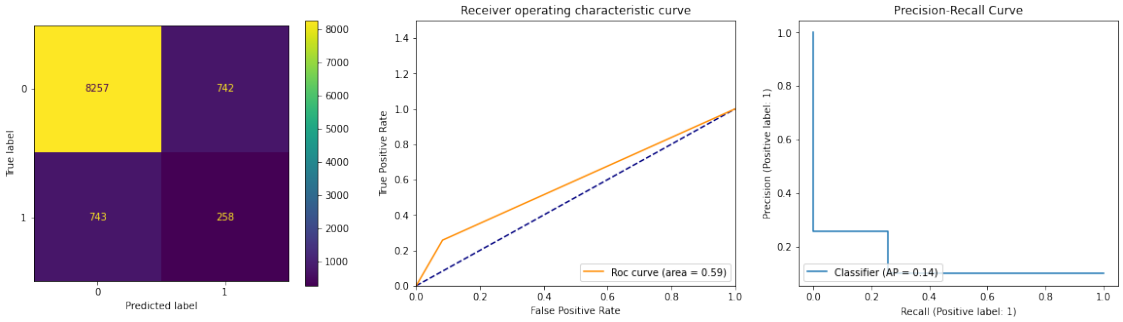
	flags_.AP.SF	flags_.APR..	flags_.APR.F	flags_.APRS.	flags_.APRSF	\
0	0	0	0	1	0	
1	0	0	0	0	0	
2	0	1	0	0	0	
3	0	0	0	0	0	
4	0	1	0	0	0	

	attack	if_outliers	rc_outliers	lof_outliers
0	True	True	False	True
1	True	False	False	True
2	True	False	False	True

```
3    True          True         False          True
4    True          True         False          True

[5 rows x 38 columns]
```

[ ]:
```
display_metrics(df_outliers.attack, df_outliers.lof_outliers)
```

```
AUPRC: 14.08%
Precision: 25.8%
Recall: 25.77%
True Negative Rate: 91.75%
Accuracy: 85.15%
```



0.7 Algorithm comparison

0.7.1 Number of attacks detected as outliers by all algorithms

[ ]:
```
len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['if_outliers']␣
↪== True) & (df_outliers['lof_outliers'] == True) &␣
↪(df_outliers['rc_outliers'] == True)])
```

[ ]: 202

0.7.2 Number of attacks detected as outliers by LOF and RC

[ ]:
```
len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['lof_outliers']␣
↪== True) & (df_outliers['rc_outliers'] == True)])
```

[ ]: 203

0.7.3 Number of attacks detected as outliers by RC and IF

```
[ ]: len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['if_outliers']␣
      ↪== True) & (df_outliers['rc_outliers'] == True)])
```

```
[ ]: 770
```

0.7.4 Number of attacks detected as outliers by LOF and IF

```
[ ]: len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['if_outliers']␣
      ↪== True) & (df_outliers['lof_outliers'] == True)])
```

```
[ ]: 244
```

0.7.5 Number of attacks detected as outliers by LOF

```
[ ]: len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['lof_outliers']␣
      ↪== True)])
```

```
[ ]: 258
```

0.7.6 Number of attacks detected as outliers by IF

```
[ ]: len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['if_outliers']␣
      ↪== True)])
```

```
[ ]: 821
```

0.7.7 Number of attacks detected as outliers by RC

```
[ ]: len(df_outliers[(df_outliers['attack'] == True) & (df_outliers['rc_outliers']␣
      ↪== True)])
```

```
[ ]: 927
```

0.7.8 Number of background detected as outliers by all algorithms

```
[ ]: len(df_outliers[(df_outliers['attack'] == False) & (df_outliers['if_outliers']␣
      ↪== True) & (df_outliers['lof_outliers'] == True) &␣
      ↪(df_outliers['rc_outliers'] == True)])
```

```
[ ]: 68
```