exploration

November 9, 2023

1 ML for cybersecurity - Exploration

1.1 Project objectives

The goal of the project is to design, deploy and evaluate a data chain for the analysis of cybersecurity data. The data treatment will be performed as batch.

This notebook will be used to explore the data and try to find some interesting insights.

1.1.1 Data description

This paper presents a dataset to support researchers in the validation process of solutions such as Intrusion Detection Systems (IDS) based on artificial intelligence and machine learning techniques for the detection and categorization of threats in Cyber Physical Systems (CPS). To this end, data were acquired from a hardware-in-the-loop Water Distribution Testbed (WDT) which emulates water flowing between eight tanks via solenoid-valves, pumps, pressure and flow sensors. The testbed is composed of a real subsystem that is virtually connected to a simulated one. The proposed dataset encompasses both physical and network data in order to highlight the consequences of attacks in the physical process as well as in network traffic behaviour. Simulations data are organized in four different acquisitions for a total duration of 2 hours by considering normal scenario and multiple anomalies due to cyber and physical attacks.

1.1.2 Importing libraries

[3]:
```
from preprocess_data import get_HITL, clean_HITL
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

random_state = 42
```

1.1.3 Loading data

As both types of datasets have different structures, we will load them separately.

[4]:
```
hitl_dict = get_HITL("../../data/HardwareInTheLoop/", small=True)
df_network, df_physical = clean_HITL(hitl_dict)  # Clean-up helper function

print("Network dataset shape: ", df_network.shape)
```

```python
print("Physical dataset shape: ", df_physical.shape)
```

```
Network dataset shape:  (243065, 17)
Physical dataset shape:  (9206, 44)
```

1.2 Network dataset exploration

[5]:
```python
df_network.head()
```

[5]:
```
           time              mac_s              mac_d          ip_s  \
0  1.617993e+09  74:46:a0:bd:a7:1b  e6:3f:ac:c9:a8:8c   84.3.251.20
1  1.617993e+09  e6:3f:ac:c9:a8:8c  74:46:a0:bd:a7:1b  84.3.251.101
2  1.617993e+09  74:46:a0:bd:a7:1b  fa:00:bc:90:d7:fa   84.3.251.20
3  1.617993e+09  fa:00:bc:90:d7:fa  74:46:a0:bd:a7:1b  84.3.251.103
4  1.617993e+09  e6:3f:ac:c9:a8:8c  74:46:a0:bd:a7:1b  84.3.251.101

           ip_d    sport    dport   proto    flags  size  \
0  84.3.251.101  56666.0    502.0  Modbus  11000.0    66
1   84.3.251.20    502.0  56666.0  Modbus  11000.0    64
2  84.3.251.103  56668.0    502.0  Modbus  11000.0    66
3   84.3.251.20    502.0  56668.0  Modbus  11000.0    65
4   84.3.251.20    502.0  56666.0  Modbus  11000.0    65

                         modbus_fn  n_pkt_src  n_pkt_dst modbus_response  \
0           Read Holding Registers       50.0       15.0             NaN
1              Read Coils Response       15.0       50.0             [0]
2           Read Holding Registers       50.0       15.0             NaN
3  Read Holding Registers Response       15.0       50.0             [0]
4  Read Holding Registers Response       15.0       50.0             [0]

   label_n   label  attack
0        0  normal       1
1        0  normal       1
2        0  normal       1
3        0  normal       1
4        0  normal       1
```

[6]:
```python
df_network.columns
```

[6]:
```
Index(['time', 'mac_s', 'mac_d', 'ip_s', 'ip_d', 'sport', 'dport', 'proto',
       'flags', 'size', 'modbus_fn', 'n_pkt_src', 'n_pkt_dst',
       'modbus_response', 'label_n', 'label', 'attack'],
      dtype='object')
```

The `attack` column come from the cleanup of the dataset to differentiate between normal and attack datasets.

Dtypes of the columns:

[7]:
```
df_network.dtypes
```

[7]:
```
time                float64
mac_s                object
mac_d                object
ip_s                 object
ip_d                 object
sport               float64
dport               float64
proto                object
flags               float64
size                  int64
modbus_fn            object
n_pkt_src           float64
n_pkt_dst           float64
modbus_response      object
label_n               int64
label                object
attack                int64
dtype: object
```

Let's look at the proportion of nan values per column:

[8]:
```
df_network.isna().sum() / df_network.shape[0] * 100
```

[8]:
```
time                 0.000000
mac_s                0.000000
mac_d                0.000000
ip_s                 0.003703
ip_d                 0.003703
sport               14.194146
dport               14.194146
proto                0.000000
flags               14.194146
size                 0.000000
modbus_fn           16.644108
n_pkt_src            0.003703
n_pkt_dst            0.003703
modbus_response     58.290169
label_n              0.000000
label                0.000000
attack               0.000000
dtype: float64
```

`modbus_response` is made out of more than half of nan values, trying to remove this column later on might be a good idea to reduce the dimensionality of the dataset.

`sport`, `dport` and `flags` are all numerical columns so we can interpolate some values to fill the nan values later on. Theses columns seem to be interesting to play with/without to see how they impact the model.

A PCA could be interesting to reduce the dimensionality of the dataset as 5 columns contain lots of nan values.

1.2.1 Labels

Let's take a quick detour to see what are the labels like.

[9]:
```
network_dataset_labels = df_network[["label_n", "label", "attack"]]
df_network = df_network.drop(columns=["label_n", "label", "attack"])
```

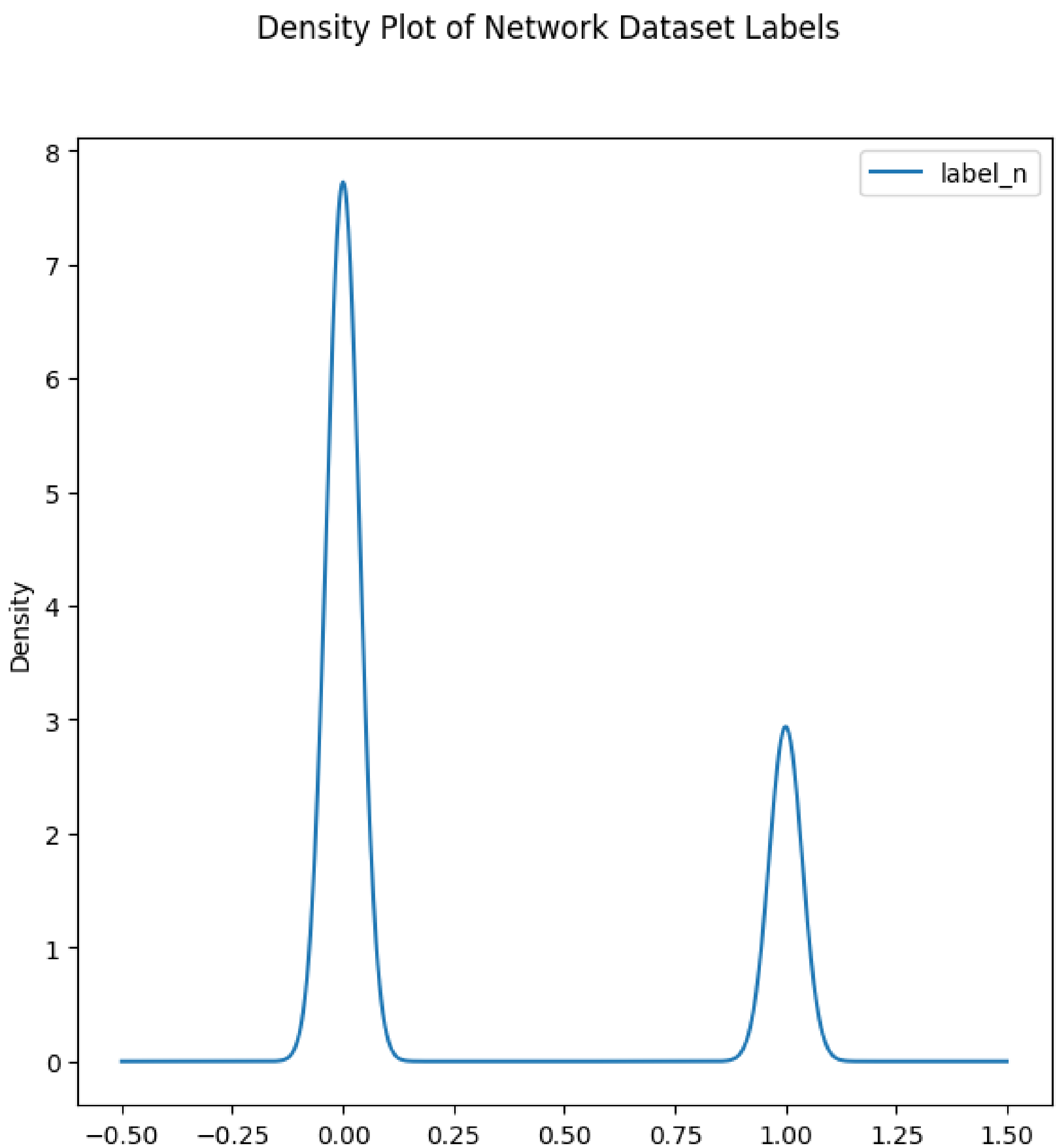
[10]:
```
network_dataset_labels.head(3)
```

[10]:
```
   label_n   label  attack
0        0  normal       1
1        0  normal       1
2        0  normal       1
```

[11]:
```
network_dataset_labels["label_n"].value_counts()
```

[11]:
```
label_n
0    176087
1     66978
Name: count, dtype: int64
```

[12]:
```
network_dataset_labels.loc[:, ["label_n"]].plot(
    kind="density",
    subplots=True,
    layout=(1, 1),
    sharex=False,
    figsize=(7, 7),
    title="Density Plot of Network Dataset Labels",
)
plt.show()
```



Our dataset is unbalanced, the ratio seems to be 1/3.

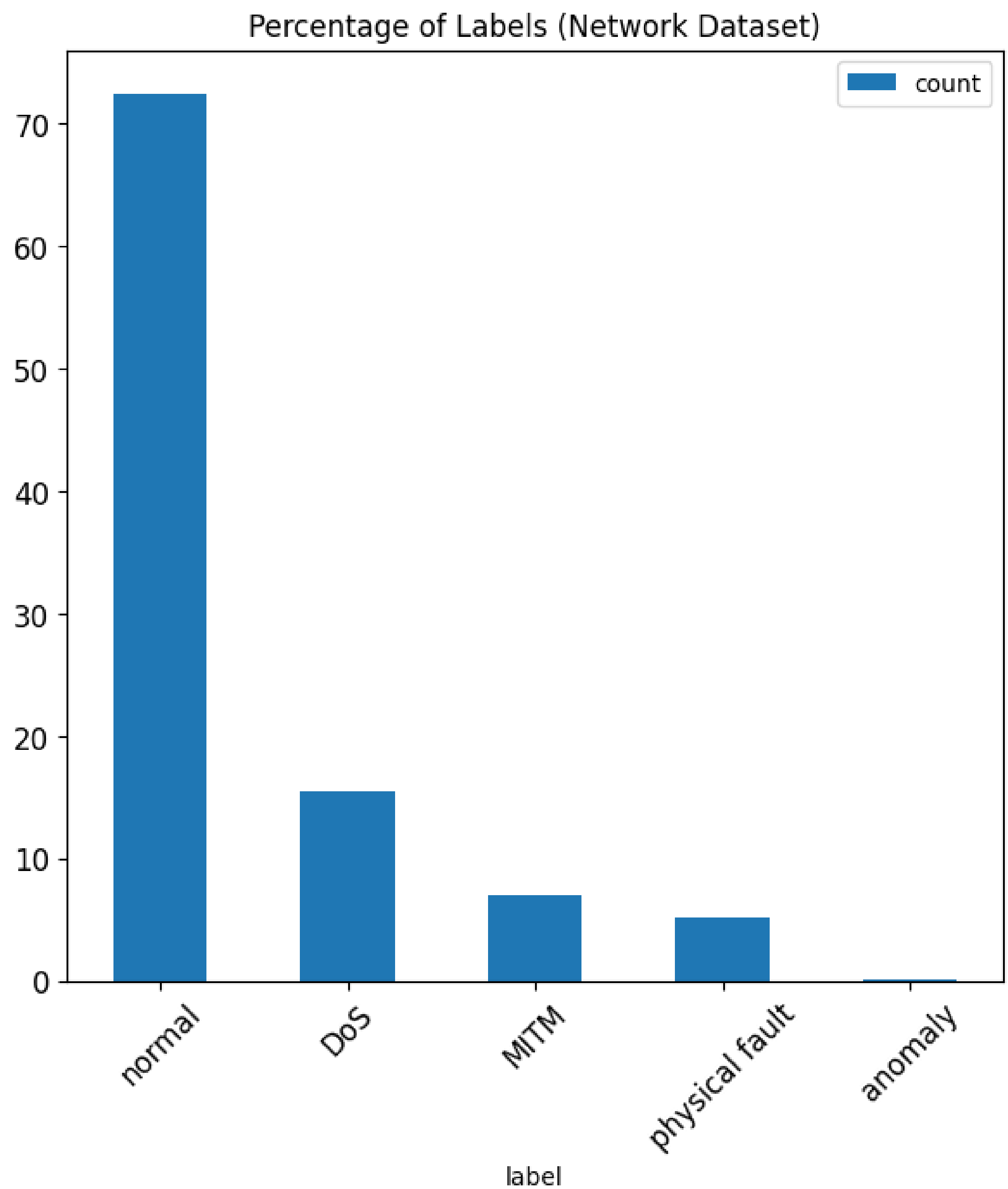
[13]:
```
network_dataset_labels["label"].value_counts()
```

[13]:
```
label
normal            176087
DoS                37665
MITM               16841
physical fault     12469
anomaly                3
```

```
Name: count, dtype: int64
```

We have 5 labels: normal, DoS, MITM, physical fault, anomaly. More imporantly the data is also split is normal (label_n=0) or not normal (label_n=1).

[14]:
```python
# Get dataset labels value counts
network_dataset_labels_value_counts = network_dataset_labels["label"].
 ↪value_counts()

# Ratio of each label
network_dataset_labels_value_counts = (
    network_dataset_labels_value_counts
    / network_dataset_labels_value_counts.sum()
    * 100
)

# Bar plot of the dataset labels
network_dataset_labels_value_counts.plot(
    kind="bar",
    title="Percentage of Labels (Network Dataset)",
    figsize=(7, 7),
    rot=45,
    legend=True,
    fontsize=12,
)
plt.show()
```



1.2.2 Features

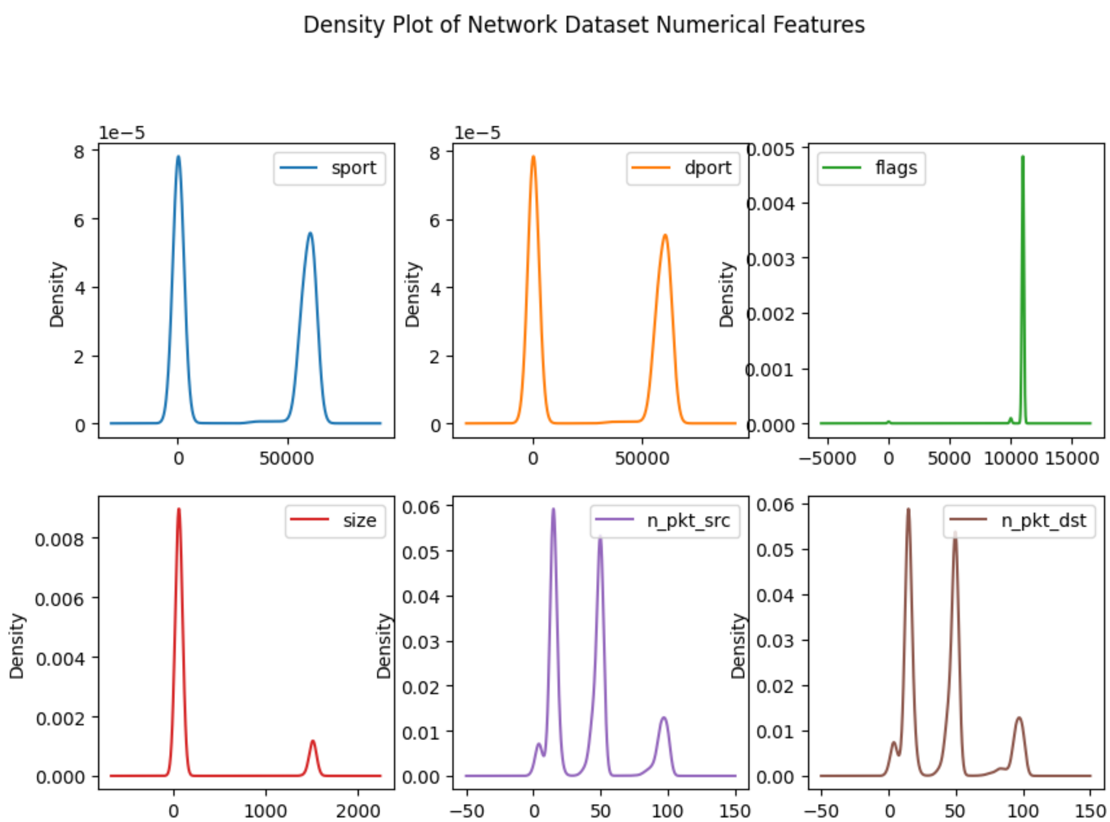
Numbers columns:

[15]:
```
network_number_cols = df_network.select_dtypes(
    include=["number"]
).columns.values.tolist()
```

```python
network_number_cols.remove("time")  # Timestamp column
network_number_cols
```

[15]: ['sport', 'dport', 'flags', 'size', 'n_pkt_src', 'n_pkt_dst']

[16]:
```python
df_network[network_number_cols].plot(
    kind="density",
    subplots=True,
    layout=(3, 3),
    sharex=False,
    figsize=(10, 10),
    title="Density Plot of Network Dataset Numerical Features",
)
plt.show()
```



Let's quickly analyse the density of the numerical columns: - `sport` and `dport`: two density spikes around 0 and 60000 - `flags`: a huge spike around 11000 and very few data around 10000 and 0 - `size`: two main spikes, the first one around 60 and the second one is around 1500, but 10x less dense - `n_pkt_src` and `n_pkt_dst`: closer data with more dominant spikes, the two main ones are around 15 and 50

[17]:
```
df_network.describe()
```

[17]:
```
               time          sport          dport          flags  \
count  2.430650e+05  208564.000000  208564.000000  208564.000000
mean   1.618168e+09   29935.053614   29827.705903   10902.935909
std    3.528267e+05   29495.006844   29513.480383     928.439179
min    1.617968e+09     502.000000     502.000000      10.000000
25%    1.617971e+09     502.000000     502.000000   11000.000000
50%    1.617995e+09   33321.000000     502.000000   11000.000000
75%    1.617998e+09   61317.000000   61317.000000   11000.000000
max    1.618849e+09   61646.000000   61646.000000   11000.000000

                size      n_pkt_src      n_pkt_dst
count  243065.000000  243056.000000  243056.000000
mean      236.671434      39.752514      39.561961
std       467.620917      28.052526      27.835061
min        60.000000       0.000000       0.000000
25%        65.000000      15.000000      15.000000
50%        66.000000      44.000000      44.000000
75%        66.000000      50.000000      50.000000
max      1514.000000     100.000000     100.000000
```

Let's quickly analyse this: - `n_pkt` columns range from 0 to a 100. Combined to what we saw on the density plot, we might be able to cluster them and reduce the dimensionality of the dataset. - `flags` flags has a median of 10902 which is extremely close of the max value (which represents most of the density). - `ports` look the same (density wise and range wise) but on a different scale. We might be able to cluster them as well.

Object columns:

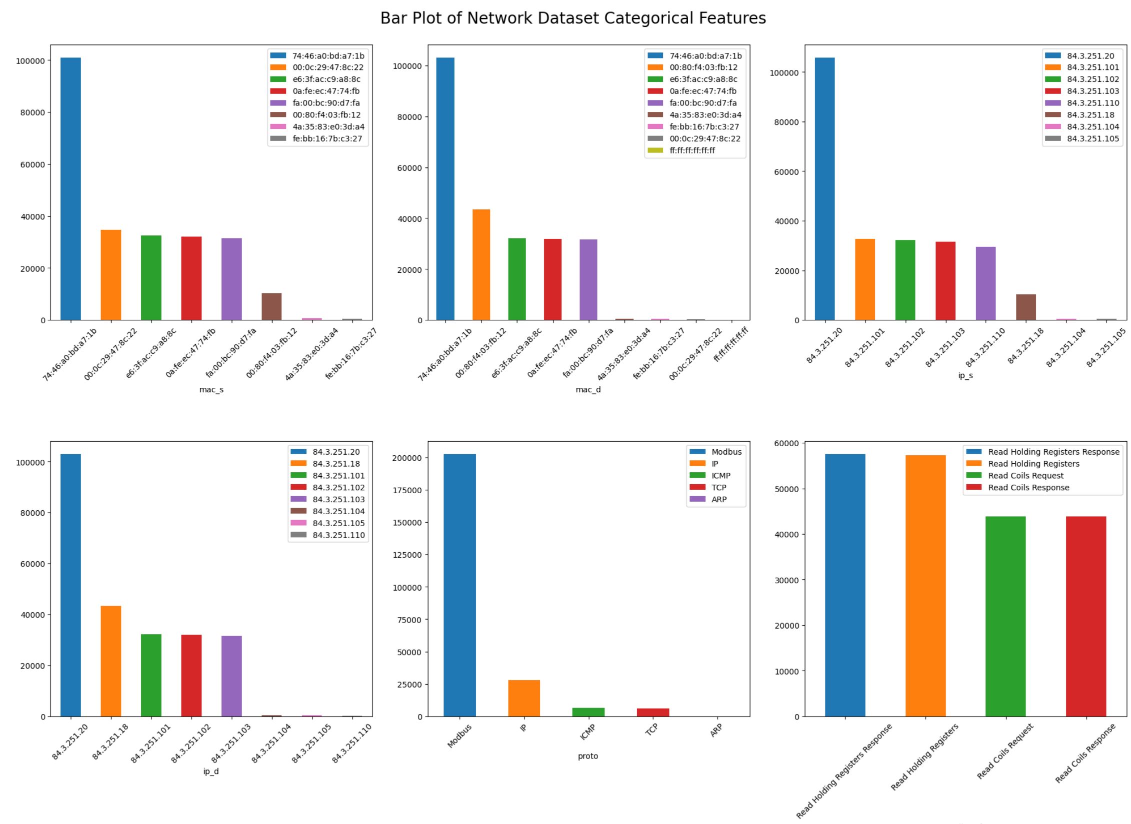
[18]:
```
network_categorical_cols = df_network.select_dtypes(
    include=["object"]
).columns.values.tolist()
network_categorical_cols
```

[18]:
```
['mac_s', 'mac_d', 'ip_s', 'ip_d', 'proto', 'modbus_fn', 'modbus_response']
```

Let's look at the distribution of the object columns:

[19]:
```
cols = [
    col for col in network_categorical_cols if col not in ["modbus_response",␣
 ↪"Time"]
]  # Remove modbus_response (too many NaNs) and Time columns (not fit for this␣
 ↪analysis)

fig = plt.figure(figsize=(20, 20))
fig.suptitle("Bar Plot of Network Dataset Categorical Features", fontsize=20)
for i, col in enumerate(cols):
    ax = fig.add_subplot(3, 3, i + 1)
```

```
    value_count = df_network[col].value_counts()
    lines = value_count.plot(kind="bar", ax=ax)
    for j, patch in enumerate(ax.patches):
        patch.set_facecolor(f"C{j}")
        patch.set_label(value_count.index[j])
    ax.legend(handles=ax.patches)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
fig.tight_layout()
fig.subplots_adjust(top=0.95)
plt.show()
```



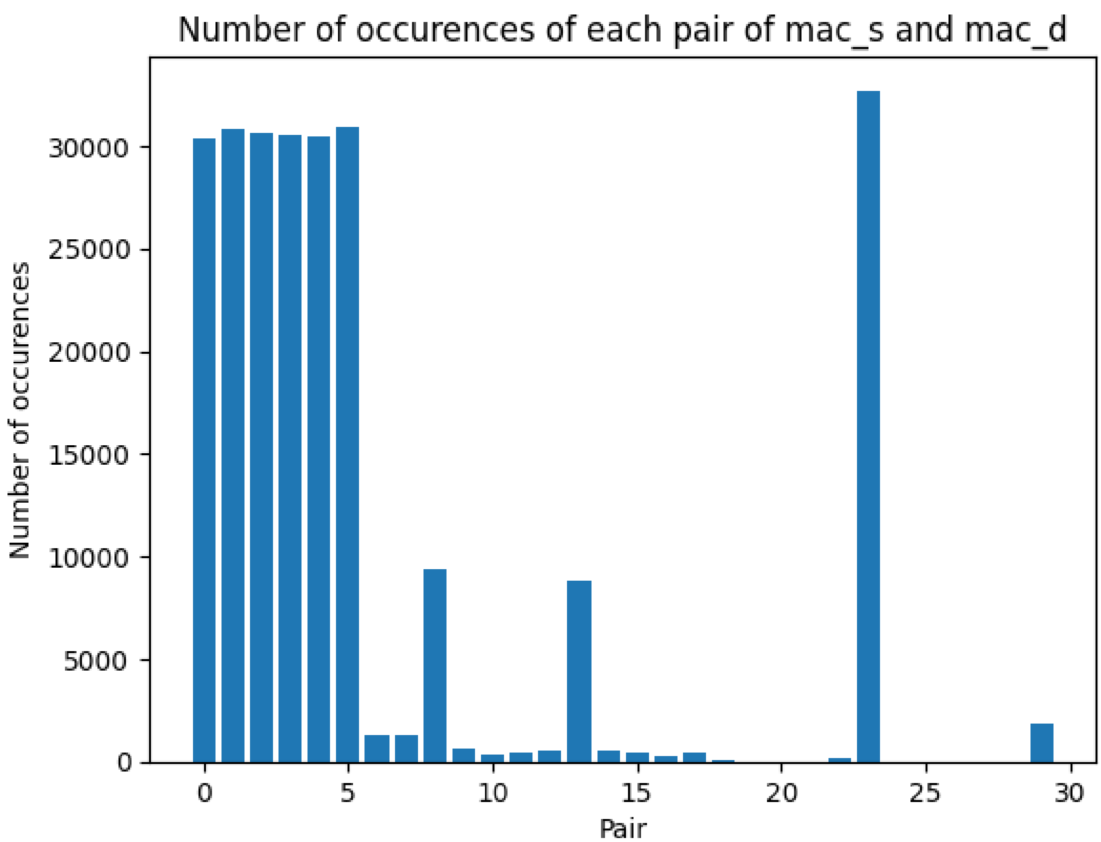
It is hard to deduce anything from the distributions, but we make the following observations: - the distribution of `mac_s`, `mac_d`, `ip_s` and `ip_d` are very similar: one address is more frequent than the 7 others - the distribution of `proto` is very unbalanced, with the "Modbus" protocol being 10x more frequent than the others. This column might be irrelevant for the classification - the `modbus_response` data is very balanced between the 4 values.

We can see that most of our categorical features have <10 unique values.

[20]:
```
def get_hist_pairs_per_column(dataset, col_name_1, col_name_2):
    # Sum each identical pair of ip addresses
    ip_pairs_count = {}
```

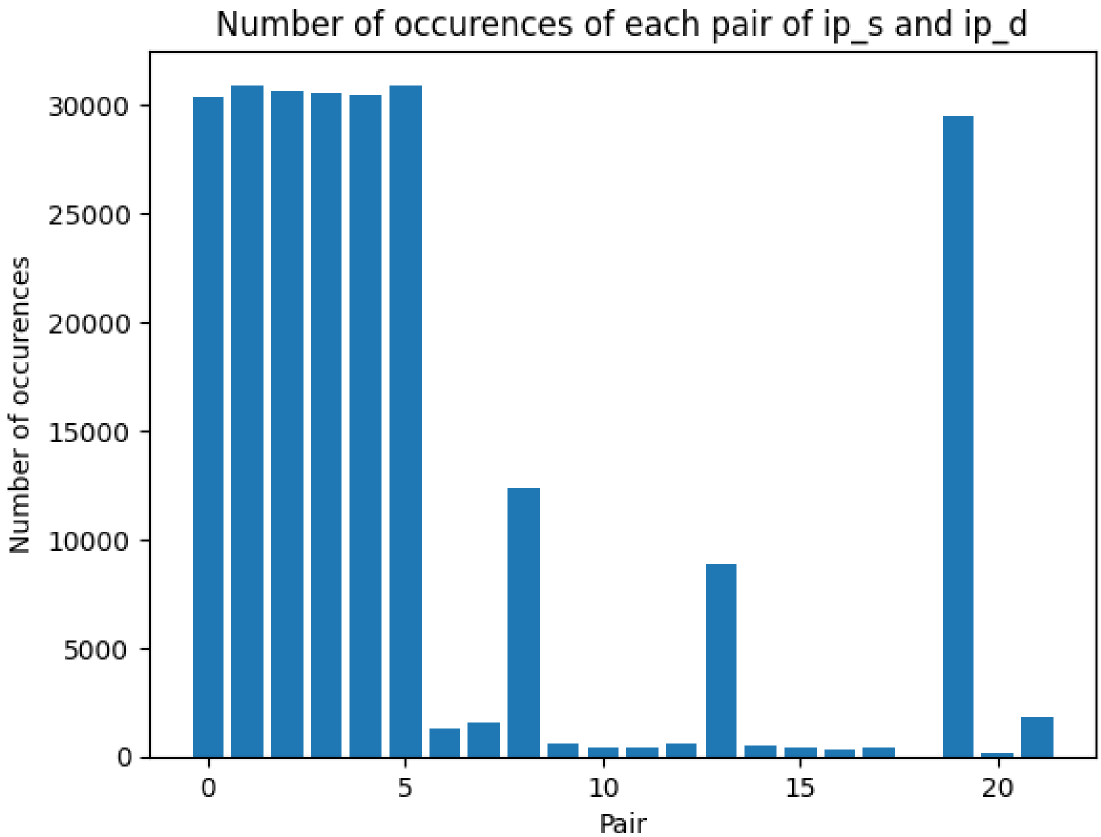
```
    for i, row in dataset.iterrows():
        ip_pair = (row[col_name_1], row[col_name_2])
        if ip_pair in ip_pairs_count:
            ip_pairs_count[ip_pair] += 1
        else:
            ip_pairs_count[ip_pair] = 1

    # Numerize each pair to print it on a graph
    ip_pairs_count_numerized = {}
    for i, (key, value) in enumerate(ip_pairs_count.items()):
        ip_pairs_count_numerized[i] = value

    # Plot the histogram
    plt.bar(ip_pairs_count_numerized.keys(), ip_pairs_count_numerized.values())
    plt.title(f"Number of occurences of each pair of {col_name_1} and␣
↪{col_name_2}")
    plt.xlabel("Pair")
    plt.ylabel("Number of occurences")
```

[21]:
```
get_hist_pairs_per_column(df_network, "mac_s", "mac_d")
```



We have around 30 pairs of (mac_s, mac_d) that are unique. There are mostly 7-9 pairs that are mostly used.

[22]:
```
get_hist_pairs_per_column(df_network, "ip_s", "ip_d")
```



We have around 21 pairs of (ip_s, ip_d) that are unique. The repartition here is also a bit shallow as there are 7-9 pairs that are also mostly used. The repartition of the ip addresses is very similar to the mac addresses.

1.2.3 Correlation between features

We'll first take a look at the correlation between the features that are the same types (numerical or categorical).

And then'll we'll broaden our analysis to all the features together to try and catch some interesting insights like maybe the correlation between the packets size and the port used.

[23]:
```
from mlsecu.data_exploration_utils import (
    get_number_column_names,
    get_object_column_names,
)
```

```python
from mlsecu.data_preparation_utils import (
    get_one_hot_encoded_dataframe,
    remove_nan_through_mean_imputation,
)

# We'll remove the modbus_response column as it is has too many NaN values
# it would be hard to impute as we have so much categorical data
df_network = df_network.drop(columns=["modbus_response"])

# Get the number columns
number_cols = get_number_column_names(df_network)
number_cols.remove("time")  # Timestamp column
# Get the object columns
object_cols = get_object_column_names(df_network)
```

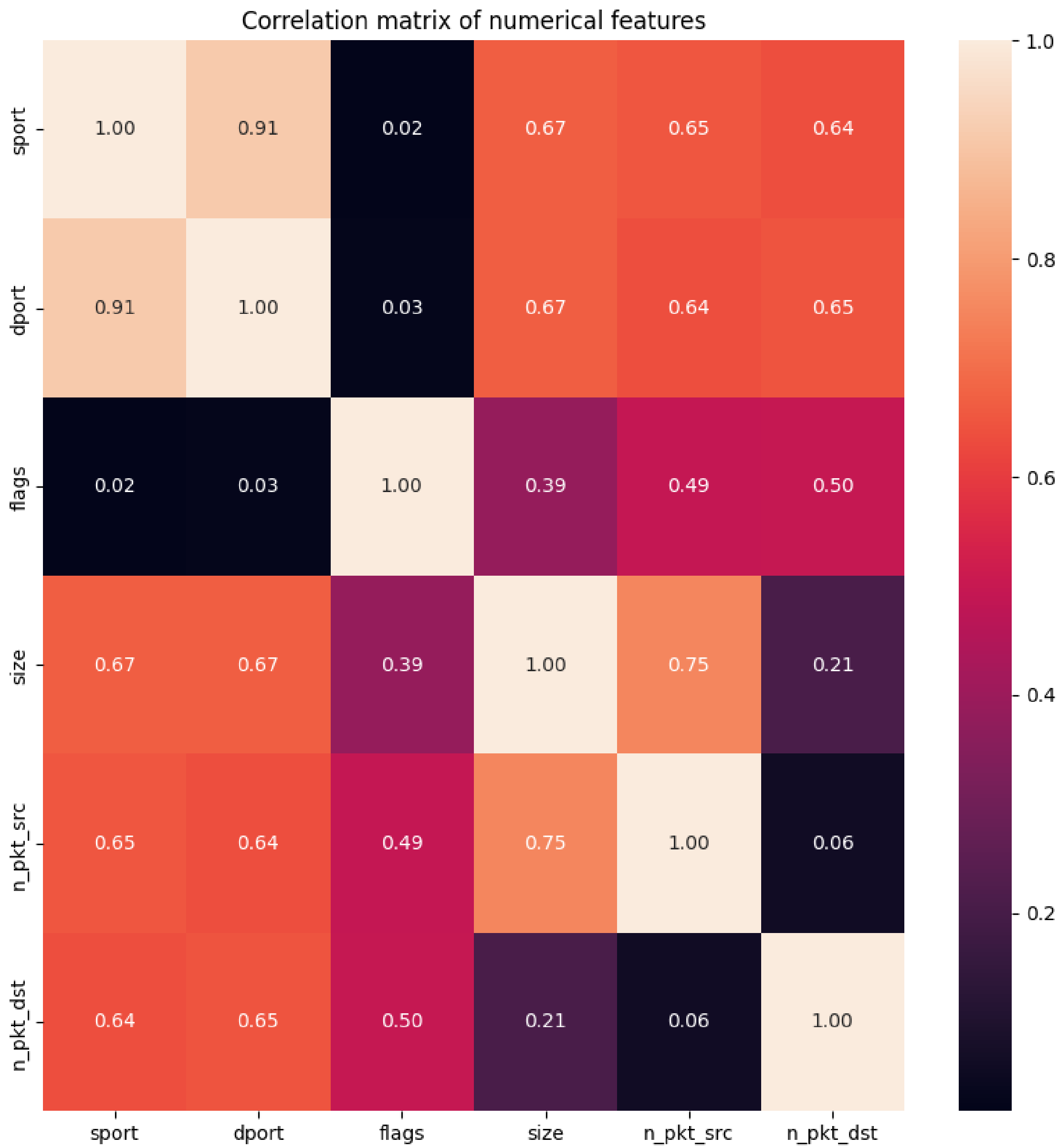
Let's compute and display the correlation matrix of the numbers columns first:

[24]:
```python
df_network[number_cols] =␣
 ↪remove_nan_through_mean_imputation(df_network[number_cols])

corr_matrix = df_network[number_cols].corr(method="spearman").abs()
corr_matrix
```

[24]:

	sport	dport	flags	size	n_pkt_src	n_pkt_dst
sport	1.000000	0.913909	0.018213	0.667260	0.653485	0.636953
dport	0.913909	1.000000	0.029246	0.667895	0.638175	0.650308
flags	0.018213	0.029246	1.000000	0.385702	0.493689	0.495567
size	0.667260	0.667895	0.385702	1.000000	0.752641	0.207100
n_pkt_src	0.653485	0.638175	0.493689	0.752641	1.000000	0.062721
n_pkt_dst	0.636953	0.650308	0.495567	0.207100	0.062721	1.000000

[25]:
```python
# Plot correlation matrix with sns
import seaborn as sns

plt.figure(figsize=(10, 10))
plt.title("Correlation matrix of numerical features")
sns.heatmap(corr_matrix, annot=True, fmt=".2f")
plt.show()
```



The analysis reveals the following relationships between the different variables:

1. **`sport` and `dport`**:
   - These two variables continue to show a strong positive correlation ((0.913909)), indicating that the values of `sport` and `dport` tend to increase or decrease together.
2. **`sport`, `dport`, and `size`**:
   - `sport` and `size` exhibit a moderate positive correlation ((0.667260)).
   - `dport` and `size` also show a moderate positive correlation ((0.667895)).
   - These correlations suggest that increases in the values of `sport` and `dport` are generally associated with increases in the packet size (`size`).
3. **`size` and `n_pkt_src`**:

- These two variables have a relatively strong positive correlation ((0.752641)), indicating that increases in packet size are often associated with increases in the number of packets originating from the source.

4. **flags**:
   - `flags` shows moderate positive correlations with `n_pkt_src` ((0.493689)) and `n_pkt_dst` ((0.495567)), and a weaker correlation with `size` ((0.385702)).
   - This suggests that increases in the values of `flags` are generally associated with increases in the number of packets originating from the source, the number of packets destined, and the packet size.
5. **n_pkt_src and n_pkt_dst**:
   - These two variables show a very weak positive correlation ((0.062721)), indicating that the number of packets originating from the source and the number of packets destined are not strongly linked.
6. **sport, dport, n_pkt_src, and n_pkt_dst**:
   - These variables show moderate positive correlations among themselves, suggesting some relationship in their movements.

In summary, the strongest relationships are observed between `sport` and `dport`, as well as between `size` and `n_pkt_src`. The other correlations are more moderate or weak, indicating less direct relationships between these variables.

Now let's take a look at the correlation between the categorical features:

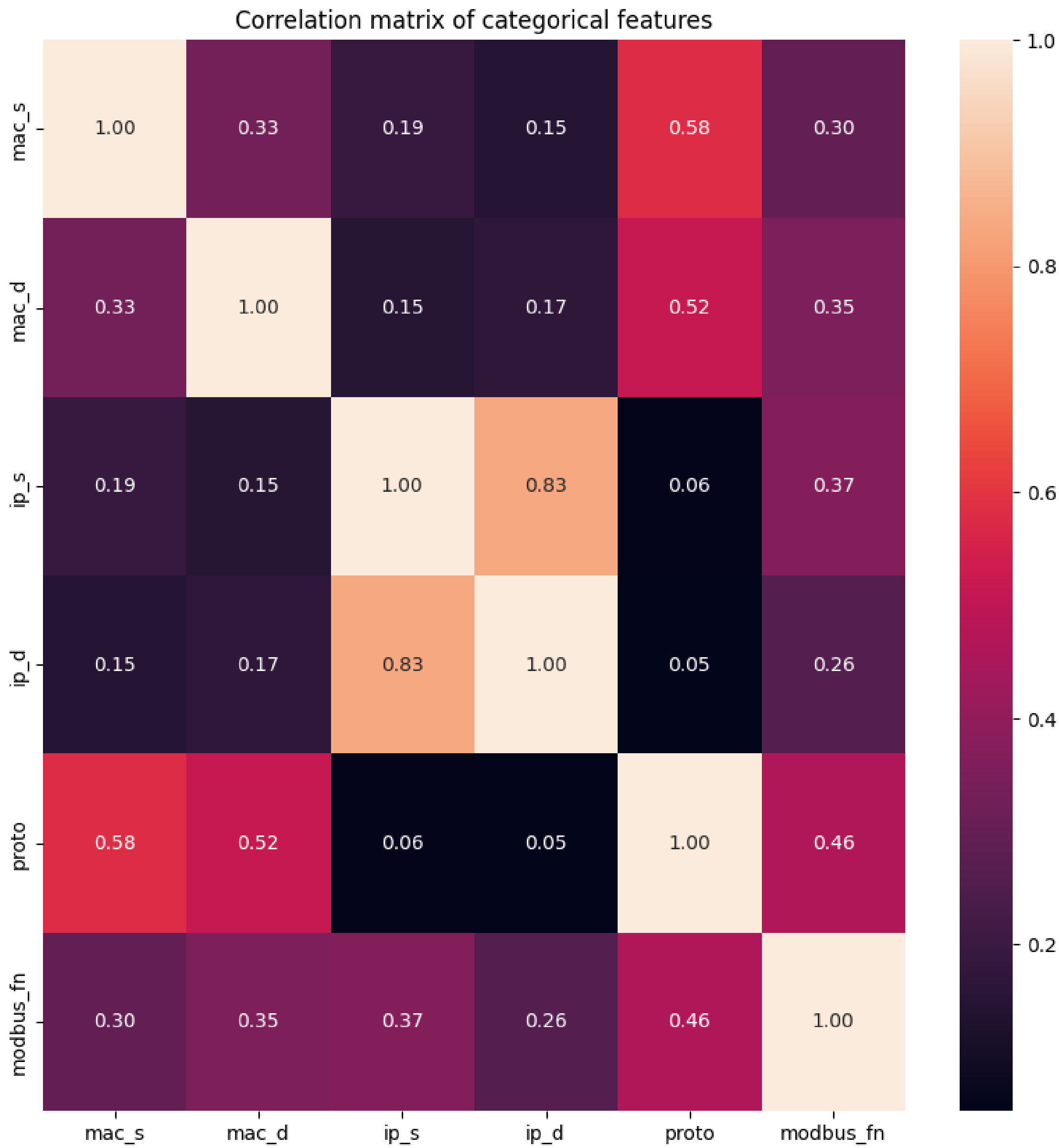
[26]:
```python
# Apply label encoding to all object columns
# If we use one-hot encoding, we will have a correlation matrix with almost␣
↪1000+ columns and lines
from sklearn.preprocessing import LabelEncoder

cpy_df_network = df_network.copy()
label_encoder = LabelEncoder()
for col in object_cols:
    cpy_df_network[col] = label_encoder.fit_transform(df_network[col])
cpy_df_network[object_cols].head()

cpy_df_network = remove_nan_through_mean_imputation(cpy_df_network)
```

[27]:
```python
corr_matrix = cpy_df_network[object_cols].corr(method="spearman").abs()
corr_matrix
```

[27]:

	mac_s	mac_d	ip_s	ip_d	proto	modbus_fn
mac_s	1.000000	0.331400	0.193150	0.148599	0.578621	0.295003
mac_d	0.331400	1.000000	0.149861	0.170083	0.516733	0.353727
ip_s	0.193150	0.149861	1.000000	0.834745	0.059539	0.369480
ip_d	0.148599	0.170083	0.834745	1.000000	0.052825	0.263606
proto	0.578621	0.516733	0.059539	0.052825	1.000000	0.463579
modbus_fn	0.295003	0.353727	0.369480	0.263606	0.463579	1.000000

[28]:
```
import seaborn as sns

plt.figure(figsize=(10, 10))
plt.title("Correlation matrix of categorical features")
sns.heatmap(corr_matrix, annot=True, fmt=".2f")
plt.show()
```



The analysis of the provided correlation matrix reveals the following insights:

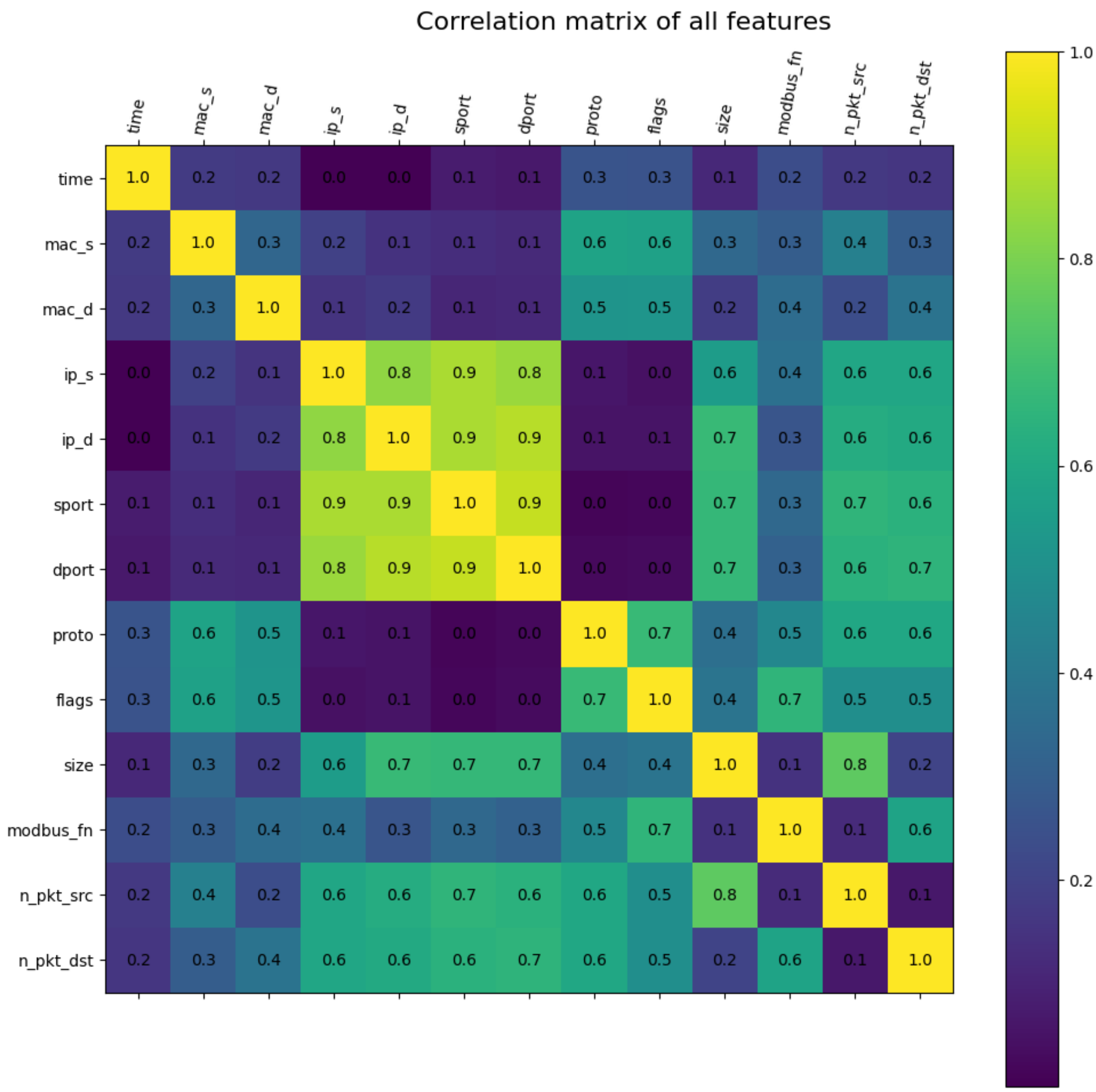
1. **ip_s and ip_d**:
   - These variables show a strong positive correlation ((0.834745)), suggesting that the

source and destination IP addresses are often related.
2. **proto**:
   - `proto` exhibits moderate positive correlations with `mac_s` ((0.578621)) and `mac_d` ((0.516733)), and a slightly lower correlation with `modbus_fn` ((0.463579)).
   - This indicates that changes in the `proto` value are somewhat associated with changes in the source and destination MAC addresses, as well as the Modbus function code.
3. **modbus_fn**:
   - `modbus_fn` shows moderate positive correlations with `ip_s` ((0.369480)) and `mac_d` ((0.353727)), suggesting that the Modbus function code tends to change with variations in these values.
4. **mac_s and mac_d**:
   - These variables have a moderate positive correlation ((0.331400)), indicating that there is some relationship between the source and destination MAC addresses.
5. **Other Correlations**:
   - The other pairs of variables show weak correlations, suggesting that there are no strong linear relationships between them.

Overall, the most significant relationship is observed between `ip_s` and `ip_d`, while other variables have moderate or weak correlations.

Finally let's look at the correlation between all the features:

[29]:
```
corr_matrix = cpy_df_network.corr(
    method="spearman"
).abs()  # All the features columns are already enocded

fig, ax = plt.subplots(figsize=(10, 10))
fig.suptitle("Correlation matrix of all features", fontsize=16)
fig.tight_layout()
im = ax.matshow(corr_matrix)
fig.colorbar(im)
ticks = np.arange(0, len(corr_matrix.columns))
ax.set_xticks(ticks)
ax.set_yticks(ticks)
ax.set_xticklabels(cpy_df_network.columns.tolist(), rotation=80)
ax.set_yticklabels(cpy_df_network.columns.tolist())

for (i, j), z in np.ndenumerate(corr_matrix):
    ax.text(j, i, "{:0.1f}".format(z), ha="center", va="center")
plt.show()
```



The whole correlation matrix is very hard to read, so we'll focus on the most interesting parts. We can see the same anaylysis as before, from the two separated kinds of features but we can also see that the algorithm is struggling to find any correlation between the two types of features. This is surely due to how we encoded our categorical features.

1.2.4 Let's try to go a bit deeper and plot the labels as a time series

[30]:
```
df_network[network_dataset_labels.columns] = network_dataset_labels

df_network_sorted = df_network.sort_values(by=["time"])
df_network_sorted["time_minute"] = pd.to_datetime(
    df_network_sorted["time"], unit="s"
).dt.strftime("%m-%d %H:%M")
```

```
df_network_sorted.head()
```

```
[30]:                 time              mac_s              mac_d         ip_s  \
165493  1.617968e+09  fa:00:bc:90:d7:fa  74:46:a0:bd:a7:1b  84.3.251.103
165494  1.617968e+09  74:46:a0:bd:a7:1b  0a:fe:ec:47:74:fb   84.3.251.20
165495  1.617968e+09  fa:00:bc:90:d7:fa  74:46:a0:bd:a7:1b  84.3.251.103
165496  1.617968e+09  0a:fe:ec:47:74:fb  74:46:a0:bd:a7:1b  84.3.251.102
165497  1.617968e+09  e6:3f:ac:c9:a8:8c  74:46:a0:bd:a7:1b  84.3.251.101

                ip_d    sport    dport   proto    flags  size  \
165493   84.3.251.20    502.0  61516.0  Modbus  11000.0    65
165494  84.3.251.102  61517.0    502.0  Modbus  11000.0    66
165495   84.3.251.20    502.0  61516.0  Modbus  11000.0    65
165496   84.3.251.20    502.0  61517.0  Modbus  11000.0    65
165497   84.3.251.20    502.0  61515.0  Modbus  11000.0    64

                                 modbus_fn  n_pkt_src  n_pkt_dst  label_n  \
165493  Read Holding Registers Response       15.0       49.0        0
165494               Read Coils Request       49.0       15.0        0
165495  Read Holding Registers Response       18.0       43.0        0
165496  Read Holding Registers Response       18.0       44.0        0
165497              Read Coils Response       15.0       50.0        0

         label  attack  time_minute
165493  normal       0  04-09 11:30
165494  normal       0  04-09 11:30
165495  normal       0  04-09 11:30
165496  normal       0  04-09 11:30
165497  normal       0  04-09 11:30
```

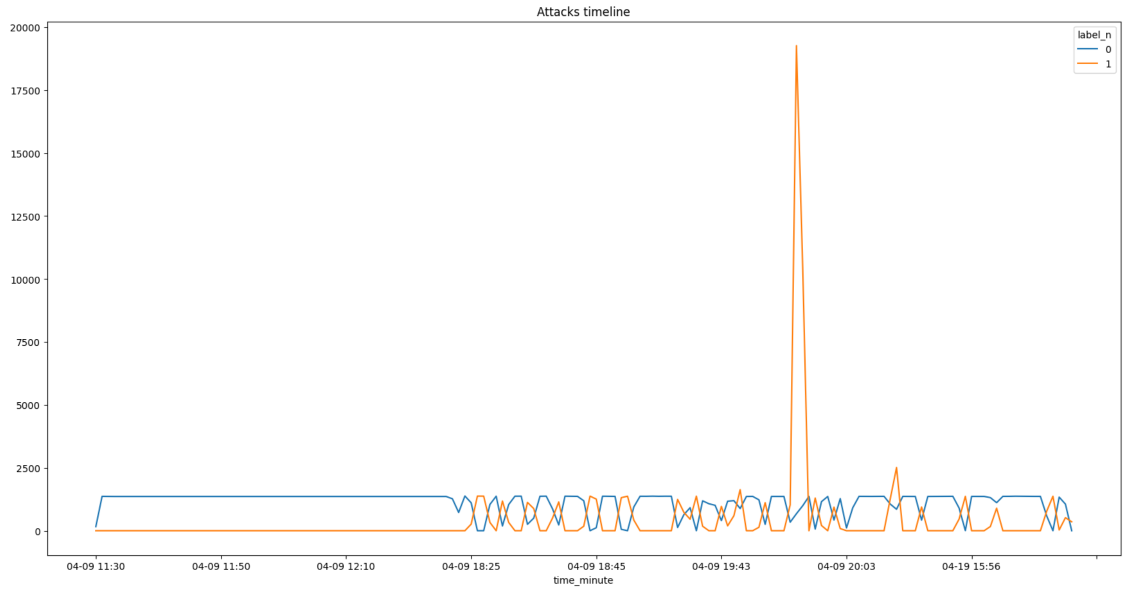
```
[31]: df_grouped = (
          df_network_sorted.groupby(["time_minute", "label_n"]).size().unstack().
       ↪fillna(0)
      )
      df_grouped
```

```
[31]: label_n           0       1
time_minute
04-09 11:30    164.0     0.0
04-09 11:31   1365.0     0.0
04-09 11:32   1362.0     0.0
04-09 11:33   1360.0     0.0
04-09 11:34   1360.0     0.0
…                …     …
04-19 16:08    593.0   772.0
04-19 16:09      0.0  1368.0
04-19 16:10   1334.0    30.0
```

```
04-19 16:11  1057.0   519.0
04-19 16:12     0.0   355.0

[157 rows x 2 columns]
```

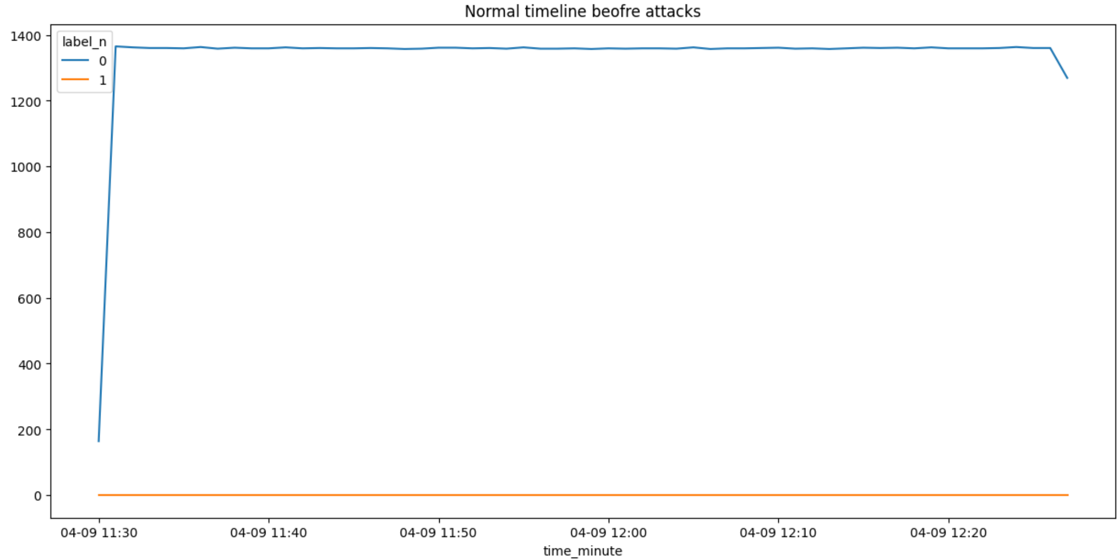
[32]:
```python
df_grouped.loc[:].plot(figsize=(20, 10), title="Attacks timeline")
```

[32]:
```
<Axes: title={'center': 'Attacks timeline'}, xlabel='time_minute'>
```



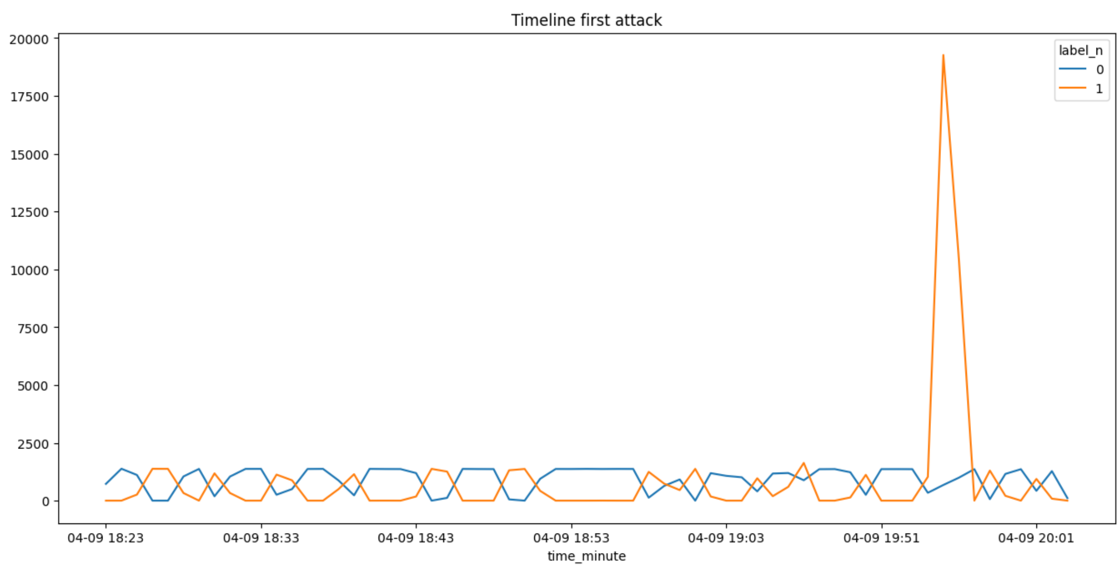
Firstly, let's see the number of anormal data per minute for the "normal" dataset

[33]:
```python
df_grouped.loc["04-09 11":"04-09 13"].plot(
    figsize=(15, 7), title="Normal timeline beofre attacks"
)
plt.show()
```



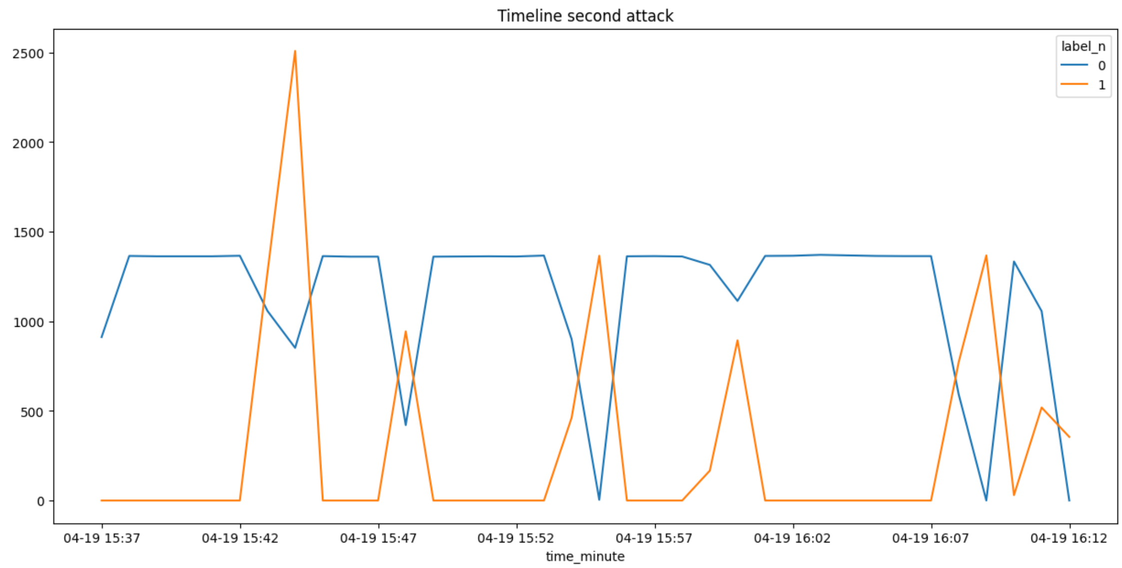
As expected, there is no 1 label in the normal dataset. Let's check for 2020-04-09 (first day of recorded anomalies)

[34]:
```
df_grouped.loc["04-09 18":"04-09 22"].plot(
    figsize=(15, 7), title="Timeline first attack"
)
plt.show()
```



We see way more fluctuation in the data. There is anormal activity for some time, then it stops, then it starts again with a huge peak

[35]:
```
df_grouped.loc["04-19":"04-20"].plot(figsize=(15, 7), title="Timeline second␣
↪attack")
plt.show()
```



Finally, let's have a look at our timeline but from a multi-class perspective.

[36]:
```
df_grouped = df_network_sorted.groupby(["time_minute", "label"]).size().
↪reset_index()

# Value encode the label column
label_encoder = LabelEncoder()
df_grouped["label"] = label_encoder.fit_transform(df_grouped["label"])
df_grouped.head()
```

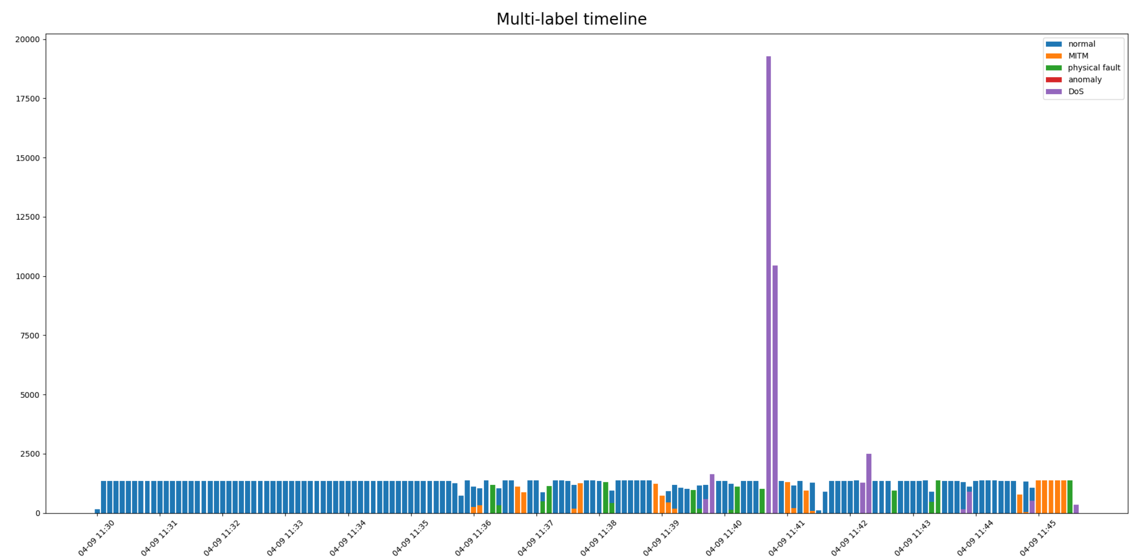
[36]:

	time_minute	label	0
0	04-09 11:30	3	164
1	04-09 11:31	3	1365
2	04-09 11:32	3	1362
3	04-09 11:33	3	1360
4	04-09 11:34	3	1360

[37]:
```
fig, ax = plt.subplots(figsize=(20, 10))
fig.suptitle("Multi-label timeline", fontsize=20)


for label in df_grouped["label"].unique():
    df_grouped_label = df_grouped[df_grouped["label"] == label]
    ax.bar(
```

```
        df_grouped_label["time_minute"],
        df_grouped_label[0],
        label=label_encoder.inverse_transform([label])[0],
    )


ax.legend()
ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
ax.set_xticks(ax.get_xticks()[::10])

fig.tight_layout()
plt.show()
```

```
/tmp/ipykernel_1088213/2337235685.py:11: UserWarning: FixedFormatter should only
be used together with FixedLocator
  ax.set_xticklabels(ax.get_xticklabels(), rotation=45)
```



We can see that the peaks of attacks correspond to `DoS` attacks, `Man in the Middle` attacks occur in bursts but last only a short time, and finally, there are often `physical faults` following an attack, regardless of its type.

1.3 Physical dataset exploration

[38]:
```
df_physical.head()
```

[38]:

	time	tank_1	tank_2	tank_3	tank_4	tank_5	tank_6	tank_7	\
0	1.630780e+09	0	0	0	0	0	0	0	
1	1.630780e+09	0	0	0	0	0	0	0	
2	1.630780e+09	0	0	0	0	0	0	0	

```
3  1.630780e+09      0      0      0      0      0      0      0
4  1.630780e+09      0      0      0      0      0      0      0

   tank_8  pump_1  …  valv_16  valv_17  valv_18  valv_19  valv_20  valv_21  \
0       0       0  …        0        0        0        0        0        0
1       0       0  …        0        0        0        0        0        0
2       0       0  …        0        0        0        0        0        0
3       0       0  …        0        0        0        0        0        0
4       0       1  …        0        0        0        0        0        0

   valv_22  label_n   label  attack
0        0      0.0  normal       1
1        0      0.0  normal       1
2        0      0.0  normal       1
3        0      0.0  normal       1
4        0      0.0  normal       1

[5 rows x 44 columns]
```

[39]:
```python
df_physical.columns
```

[39]:
```
Index(['time', 'tank_1', 'tank_2', 'tank_3', 'tank_4', 'tank_5', 'tank_6',
       'tank_7', 'tank_8', 'pump_1', 'pump_2', 'pump_3', 'pump_4', 'pump_5',
       'pump_6', 'flow_sensor_1', 'flow_sensor_2', 'flow_sensor_3',
       'flow_sensor_4', 'valv_1', 'valv_2', 'valv_3', 'valv_4', 'valv_5',
       'valv_6', 'valv_7', 'valv_8', 'valv_9', 'valv_10', 'valv_11', 'valv_12',
       'valv_13', 'valv_14', 'valv_15', 'valv_16', 'valv_17', 'valv_18',
       'valv_19', 'valv_20', 'valv_21', 'valv_22', 'label_n', 'label',
       'attack'],
      dtype='object')
```

Dtypes of the columns:

[40]:
```python
df_physical.dtypes
```

[40]:
```
time                float64
tank_1                int64
tank_2                int64
tank_3                int64
tank_4                int64
tank_5                int64
tank_6                int64
tank_7                int64
tank_8                int64
pump_1                int64
pump_2                int64
pump_3                int64
pump_4                int64
```

```
pump_5              int64
pump_6              int64
flow_sensor_1       int64
flow_sensor_2       int64
flow_sensor_3       int64
flow_sensor_4       int64
valv_1              int64
valv_2              int64
valv_3              int64
valv_4              int64
valv_5              int64
valv_6              int64
valv_7              int64
valv_8              int64
valv_9              int64
valv_10             int64
valv_11             int64
valv_12             int64
valv_13             int64
valv_14             int64
valv_15             int64
valv_16             int64
valv_17             int64
valv_18             int64
valv_19             int64
valv_20             int64
valv_21             int64
valv_22             int64
label_n           float64
label              object
attack              int64
dtype: object
```

Let's look at the proportion of nan values per column:

[41]:
```
df_physical.isna().sum() / df_physical.shape[0] * 100
```

[41]:
```
time              0.0
tank_1            0.0
tank_2            0.0
tank_3            0.0
tank_4            0.0
tank_5            0.0
tank_6            0.0
tank_7            0.0
tank_8            0.0
pump_1            0.0
pump_2            0.0
```

```
pump_3          0.0
pump_4          0.0
pump_5          0.0
pump_6          0.0
flow_sensor_1   0.0
flow_sensor_2   0.0
flow_sensor_3   0.0
flow_sensor_4   0.0
valv_1          0.0
valv_2          0.0
valv_3          0.0
valv_4          0.0
valv_5          0.0
valv_6          0.0
valv_7          0.0
valv_8          0.0
valv_9          0.0
valv_10         0.0
valv_11         0.0
valv_12         0.0
valv_13         0.0
valv_14         0.0
valv_15         0.0
valv_16         0.0
valv_17         0.0
valv_18         0.0
valv_19         0.0
valv_20         0.0
valv_21         0.0
valv_22         0.0
label_n         0.0
label           0.0
attack          0.0
dtype: float64
```

Surprinsigly, coming from a dataset that has been made from physical data capture, this dataset has no NaN values.

1.3.1 Labels

Let's take a quick detour to see what are the labels like.

[42]:
```
physical_dataset_labels = df_physical[["label_n", "label"]]
df_physical = df_physical.drop(columns=["label_n", "label"])
```

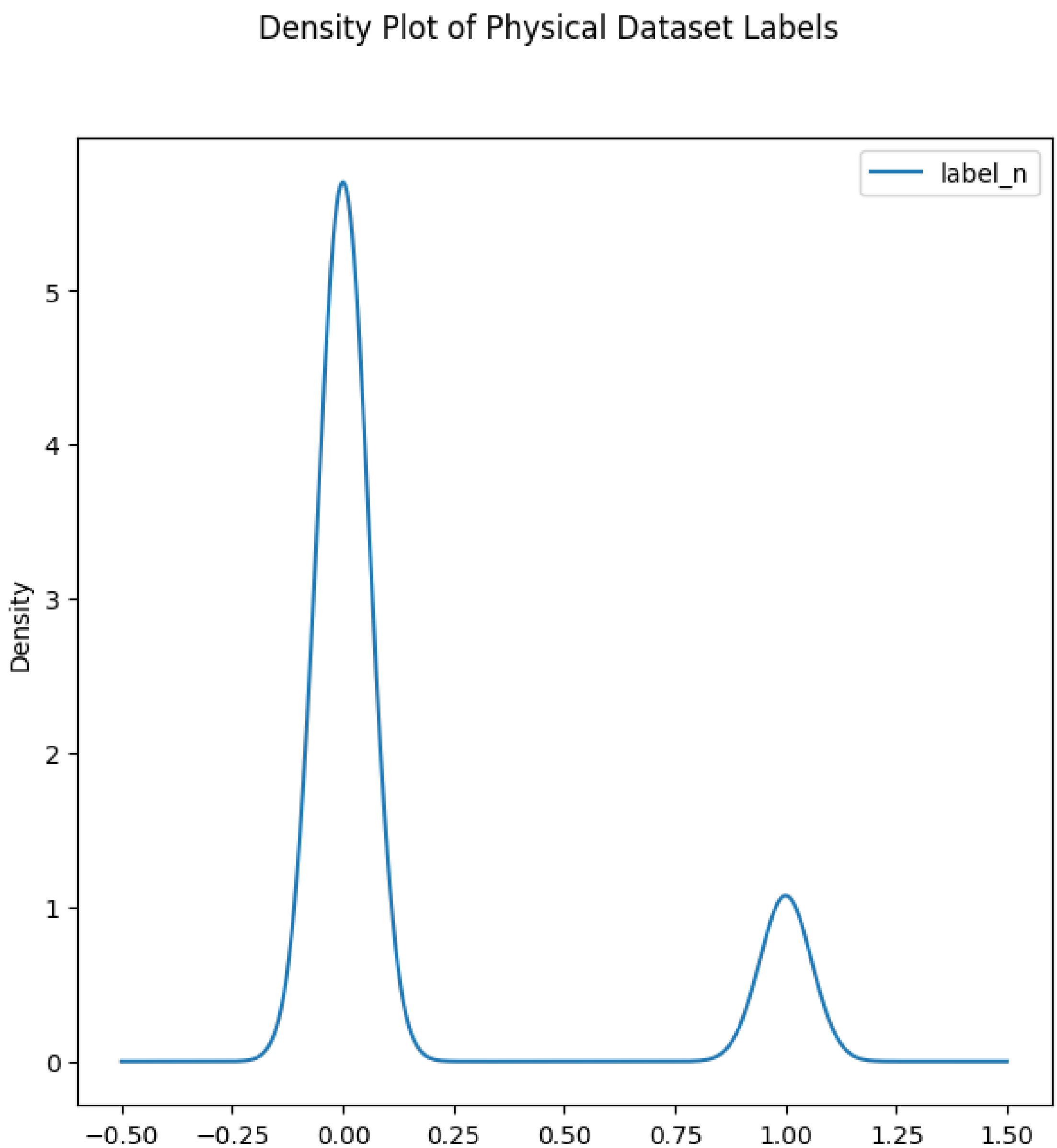
[43]:
```
physical_dataset_labels.head(3)
```

[43]:
```
   label_n   label
0      0.0  normal
1      0.0  normal
2      0.0  normal
```

[44]:
```python
physical_dataset_labels["label_n"].value_counts()
```

[44]:
```
label_n
0.0    7747
1.0    1459
Name: count, dtype: int64
```

[45]:
```python
physical_dataset_labels.plot(
    kind="density",
    subplots=True,
    layout=(1, 1),
    sharex=False,
    figsize=(7, 7),
    title="Density Plot of Physical Dataset Labels",
)
plt.show()
```



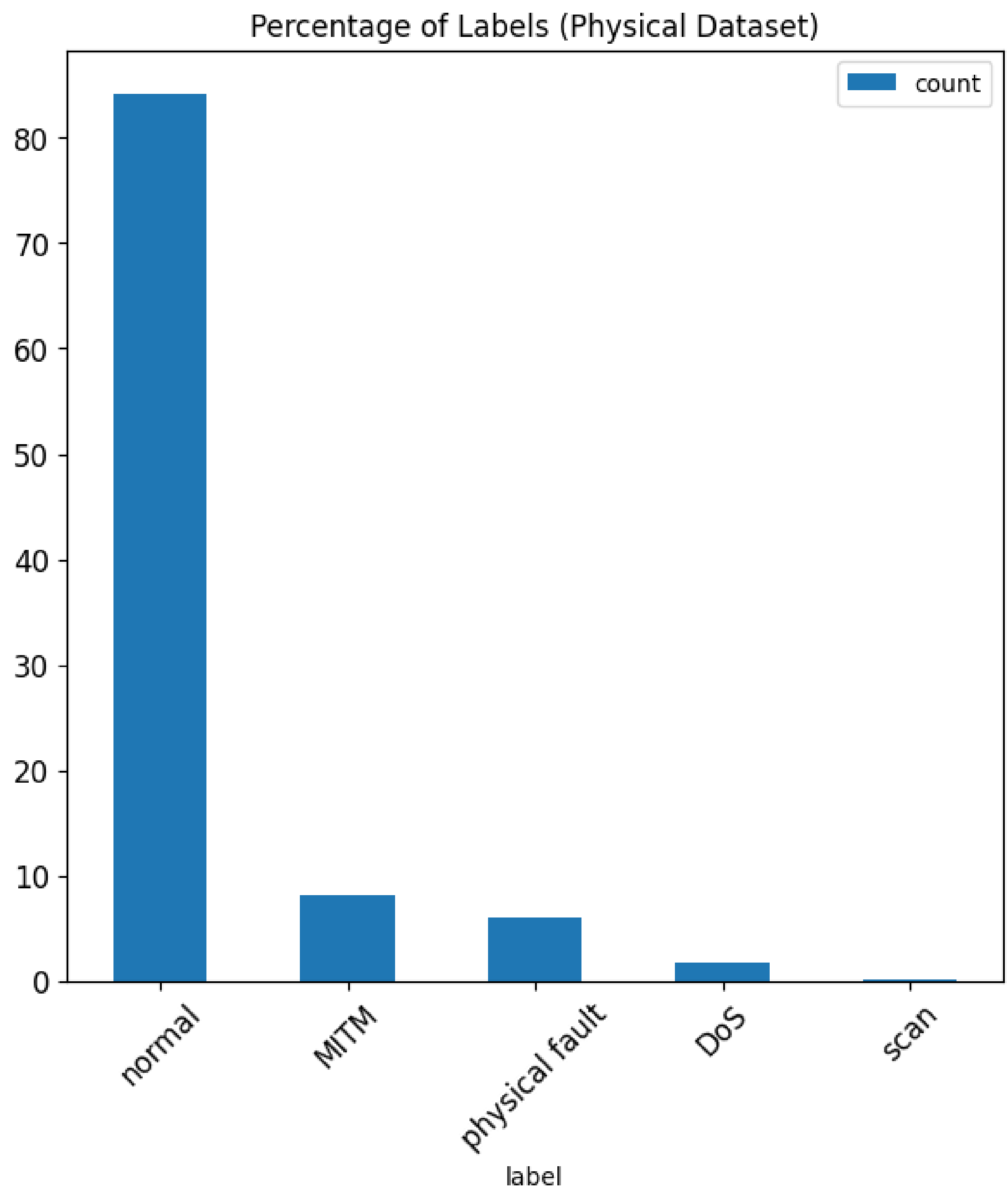
Our dataset is unbalanced, the ratio seems to be 1/4.

[46]:
```
physical_dataset_labels["label"].value_counts()
```

[46]:
```
label
normal            7747
MITM               743
physical fault     552
DoS                157
scan                 7
```

```
Name: count, dtype: int64
```

[47]:
```
# Get dataset labels value counts
physical_dataset_labels_value_counts = physical_dataset_labels["label"].
    ↪value_counts()

# Ratio of each label
physical_dataset_labels_value_counts = (
    physical_dataset_labels_value_counts
    / physical_dataset_labels_value_counts.sum()
    * 100
)

# Bar plot of the dataset labels
physical_dataset_labels_value_counts.plot(
    kind="bar",
    title="Percentage of Labels (Physical Dataset)",
    figsize=(7, 7),
    rot=45,
    legend=True,
    fontsize=12,
)
plt.show()
```



We have 5 labels: normal, DoS, MITM, physical fault, anomaly. More imporantly the data is also split is normal (label_n=0) or not normal (label_n=1).

This is the same as our network dataset.

However, the most noticeable thing is that the physical dataset has less than a hundred samples.

1.3.2 Features

[48]:
```
assert np.all([t in [int, float] for t in df_physical.dtypes])
len(df_physical.columns)  # 42
df_physical.columns
```

[48]:
```
Index(['time', 'tank_1', 'tank_2', 'tank_3', 'tank_4', 'tank_5', 'tank_6',
       'tank_7', 'tank_8', 'pump_1', 'pump_2', 'pump_3', 'pump_4', 'pump_5',
       'pump_6', 'flow_sensor_1', 'flow_sensor_2', 'flow_sensor_3',
       'flow_sensor_4', 'valv_1', 'valv_2', 'valv_3', 'valv_4', 'valv_5',
       'valv_6', 'valv_7', 'valv_8', 'valv_9', 'valv_10', 'valv_11', 'valv_12',
       'valv_13', 'valv_14', 'valv_15', 'valv_16', 'valv_17', 'valv_18',
       'valv_19', 'valv_20', 'valv_21', 'valv_22', 'attack'],
      dtype='object')
```

All of our features are numbers.

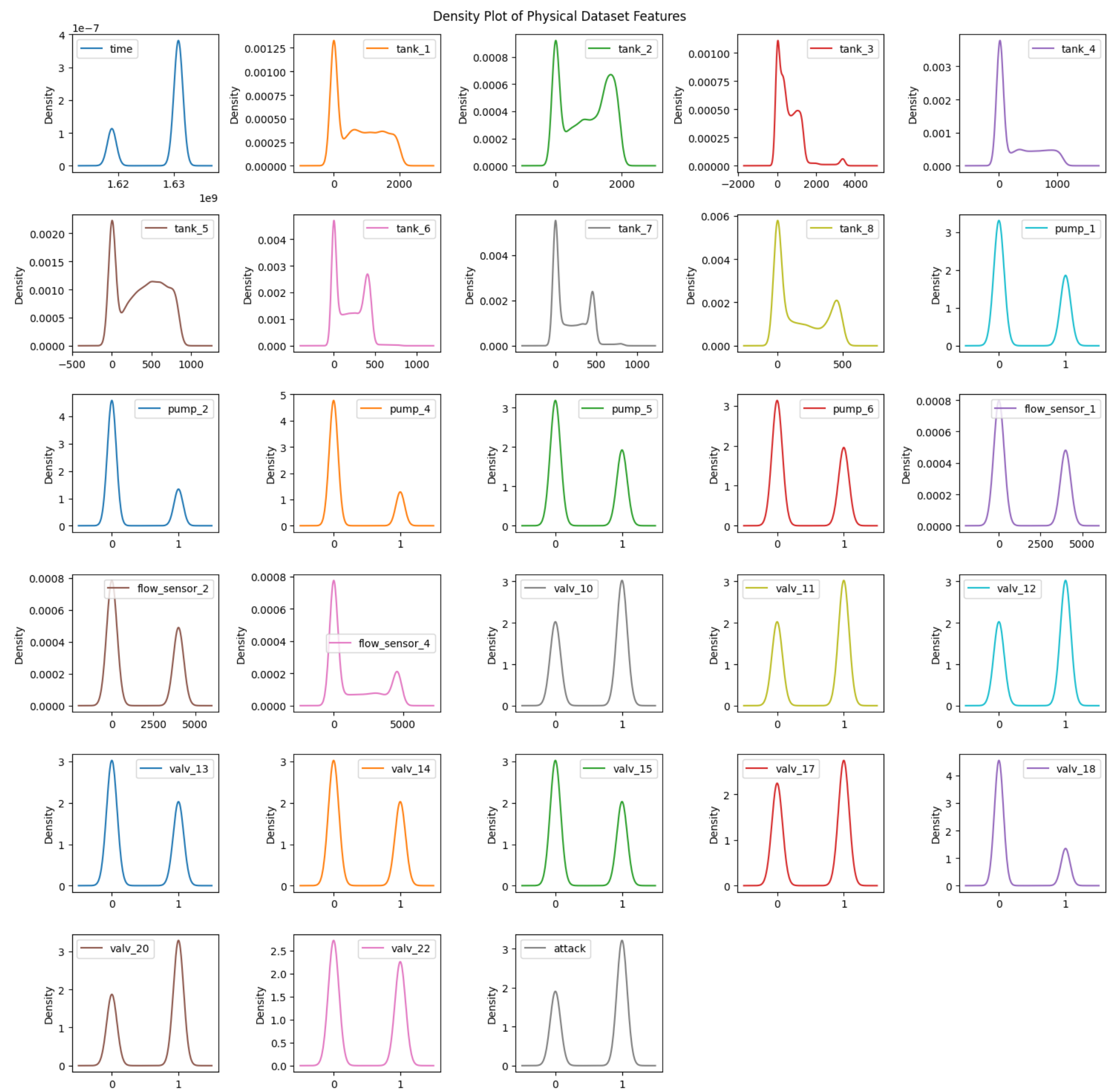
[49]:
```
df_physical.plot(
    subplots=True,
    layout=(6, 7),
    sharex=False,
    figsize=(20, 20),
    title="Plot of Physical Dataset Features",
)
plt.tight_layout()
plt.show()
```

We can see that some features are constrant troughout the dataset, let's remove them and look at the density of the rest of the features.

[50]:
```
n_removed_cols = 0
for col in df_physical.columns:
    unique_values = df_physical.loc[:, col].value_counts()
    if len(unique_values) == 1:
        df_physical.drop(columns=col, inplace=True)
        n_removed_cols += 1
print("Number of columns removed: ", n_removed_cols)
```

```
Number of columns removed:  14
```

```
[51]: # Let's plot the density to have a better look at the data repartition
df_physical.plot(
    kind="density",
    subplots=True,
    layout=(6, 5),
    sharex=False,
    figsize=(15, 15),
    title="Density Plot of Physical Dataset Features",
)
plt.tight_layout()
plt.show()
```

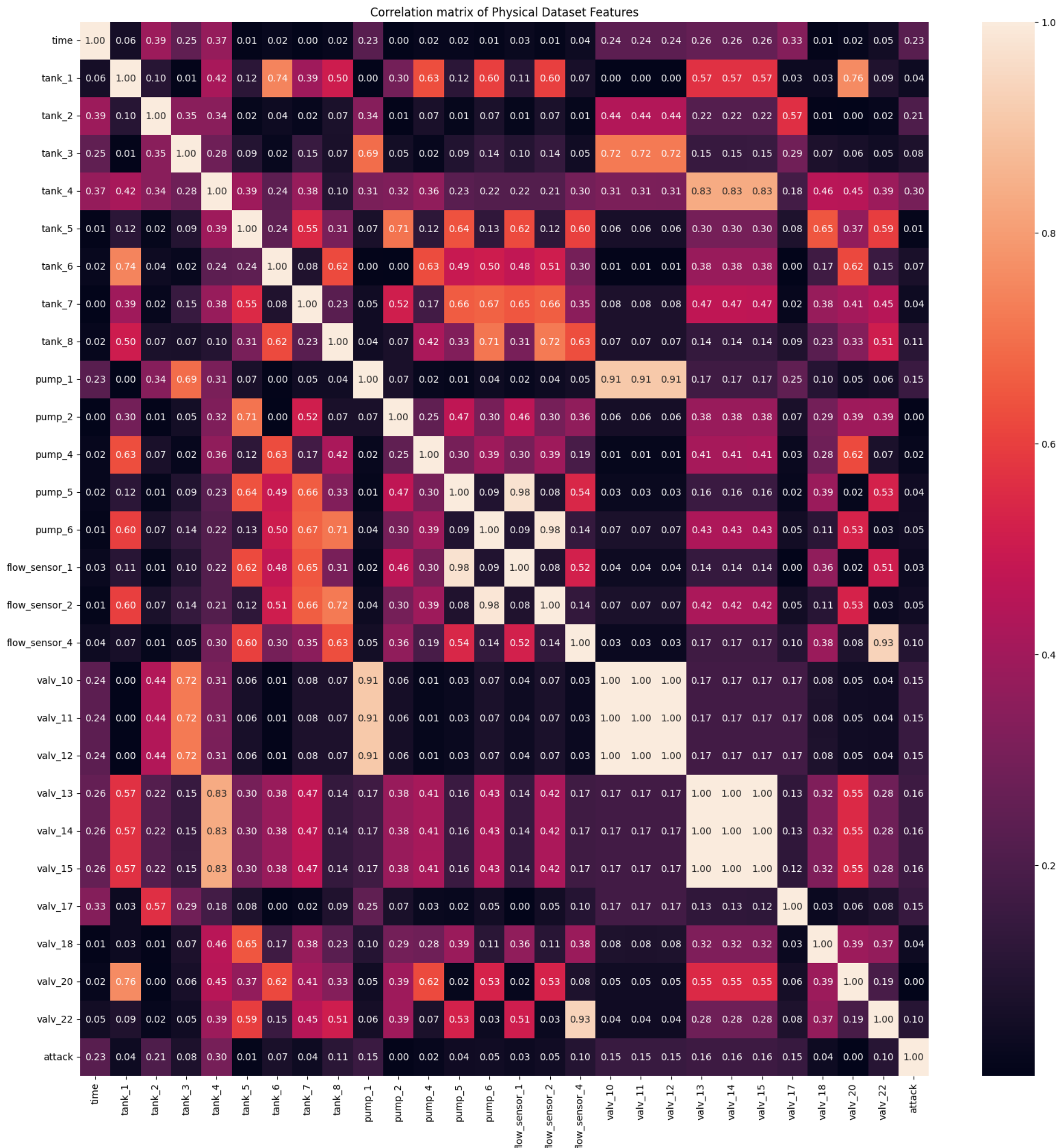


Let's quickly analyse the density of the numerical columns: - `tank`: most of the data is around 0. The sensors 2, 5 and 6 have non-zero values that are proportionnaly bigger or on par with the 0 values. - `pump`: boolean, 0 or 1. 0 is 2x/3x more dense than 1. - `flow_sensor`: int, between 0 and 6000. Most of the data is 0, all sensors have a spike around 4000. - `valv`: boolean, 0 or 1. The distribution between the two values differ a lot between the sensors.

Now, let's look at the correlation between the features:

[52]:
```python
# Correlation matrix
corr_matrix = df_physical.corr(method="spearman").abs()
```

[53]:
```python
# Plot correlation matrix with sns
plt.figure(figsize=(20, 20))
plt.title("Correlation matrix of Physical Dataset Features")
sns.heatmap(corr_matrix, annot=True, fmt=".2f")
plt.show()
```



As we can see the matrix is way to big to be read easily. There doesn´t seem to be any correlation between the four sensors.

As expected, we can see that some groups of the same sensors are correlated together.

1.3.3 Side note: Time series

The data is recorded at two points in time. Let’s cluster them to see what we can find.

[54]:
```
# Cluster the time column
from sklearn.cluster import KMeans
```

```python
from sklearn.preprocessing import StandardScaler

time_col = df_physical["time"].values.reshape(-1, 1)
scaler = StandardScaler()
time_col_scaled = scaler.fit_transform(time_col)

kmeans = KMeans(n_clusters=2, random_state=random_state)

kmeans.fit(time_col_scaled)

df_physical["time_cluster"] = kmeans.labels_
```

```
/home/arnaudb/Documents/EPITA/ING3/ml-secu/.venv/lib/python3.11/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

Here we can see that we have two clusters. Is is the same for the network dataset. We can see that in the density plot of the number values of the network dataset.

Back to our physical dataset, let's look at the time series of the sensors.

Let's try to scatter plot the data of each sensor category combined relative to the timestep of each cluster.

[55]:
```python
def print_scatter_chart(df, sensor_list, logx=False, logy=False):
    subplot_size = int(np.sqrt(len(sensor_list)))
    fig, axs = plt.subplots(subplot_size, subplot_size, figsize=(20, 20))
    fig.suptitle("Scatter chart of each sensor type", fontsize=20)

    # For each sensor type, plot the scatter chart
    for sensor_prefix in sensor_list:
        columns = df.columns[df.columns.str.startswith(sensor_prefix)]

        # Create a scatter chart with each column in columns with a different␣
 ↪color
        ax = axs.flatten()[sensor_list.index(sensor_prefix)]
        is_bool = True
        for i, col in enumerate(columns):
            if len(np.unique(df[col])) > 2:
                is_bool = False
                break

        for i, col in enumerate(columns):
            df.plot(
                kind="scatter",
                x="time_readable",
                y=col,
```

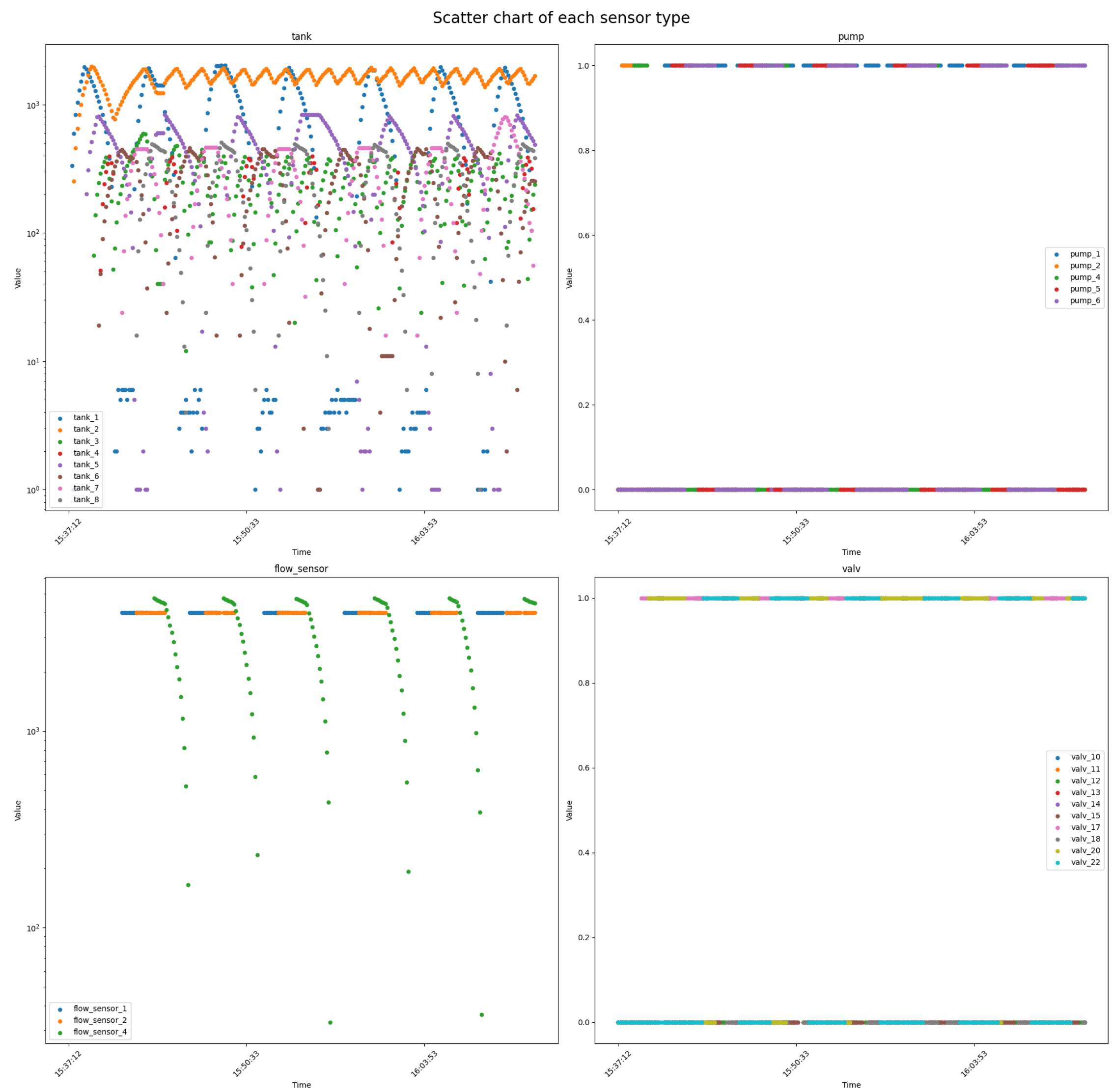
```
                color=f"C{i}",
                ax=ax,
                label=col,
                logx=logx,
                logy=logy if not is_bool else False,
            )

        # Plot it
        ax.tick_params(axis="x", labelrotation=45)  # Better readability
        ax.set_title(sensor_prefix[:-1])
        ax.set_xlabel("Time")
        ax.set_ylabel("Value")
        ax.set_xticks(ax.get_xticks()[::100])

        fig.tight_layout()
        fig.subplots_adjust(top=0.95)

    # Show the plot
    plt.show()
```

[56]:
```
first_cluster = df_physical[df_physical["time_cluster"] == 0]

# Compute the max span of time col in readable format
max_span = first_cluster.loc[:, "time"].max() - first_cluster.loc[:, "time"].
 ↪min()
max_span_readable = pd.to_datetime(max_span, unit="s").strftime("%H:%M:%S")
print("Max span of time col in First cluster: ", max_span_readable)

# Get the time in MM:SS format
x_axis_time = pd.to_datetime(first_cluster.loc[:, "time"], unit="s").dt.
 ↪strftime(
    "%H:%M:%S"
)
```

```
Max span of time col in First cluster:  00:35:04
```

[57]:
```
# Plot a scatter chart for every type of sensor in the first cluster
sensor_list = ["tank_", "pump_", "flow_sensor_", "valv_"]
first_cluster.loc[:, "time_readable"] = x_axis_time
print_scatter_chart(first_cluster.loc[::8], sensor_list, logy=True)
```

```
/tmp/ipykernel_1088213/1869177305.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  first_cluster.loc[:, "time_readable"] = x_axis_time
```



- There seem to be a pattern in the values for `tank_2` ,`tank_3`, `tank_5` and `tank_7`. Very few values are low.
- `pump` has 7 occurences where none of them are True.
- `flow_sens_4` seems to be the one that varies the most.
- `valv`s have only one occurence where none of them are False. This is surely due to the amount of sensors we had in this category

Second Cluster

[58]:
```
second_cluster = df_physical[df_physical["time_cluster"] == 0]

# Compute the max span of time col in readable format
max_span = second_cluster["time"].max() - second_cluster["time"].min()
max_span_readable = pd.to_datetime(max_span, unit="s").strftime("%H:%M:%S")
```

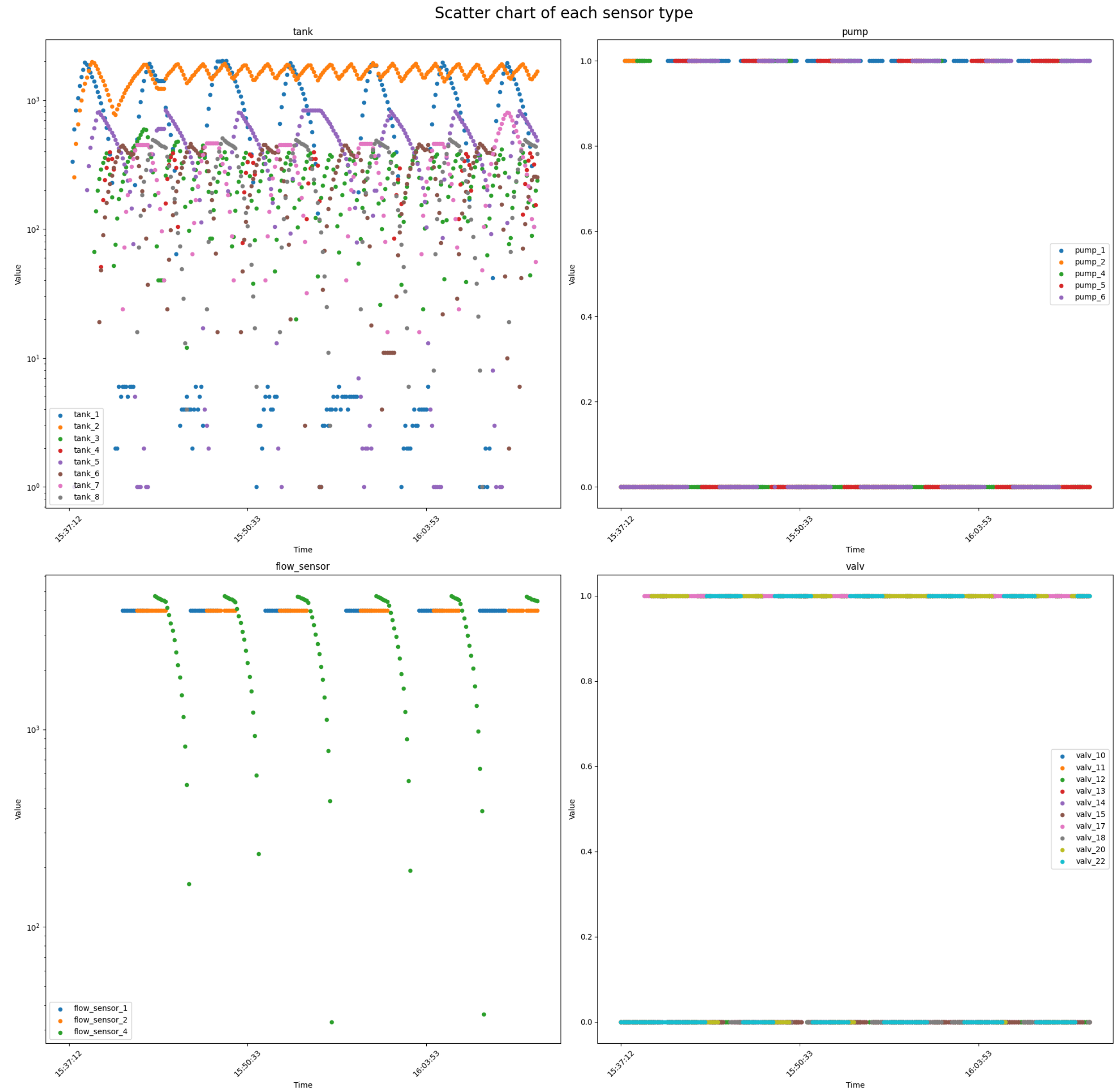
```
print("Max span of time col in First cluster: ", max_span_readable)

# Get the time in MM:SS format
x_axis_time = pd.to_datetime(second_cluster.loc[:, "time"], unit="s").dt.
↪strftime(
    "%H:%M:%S"
)
```

```
Max span of time col in First cluster:  00:35:04
```

[59]:

```
# Plot a scatter chart for every type of sensor
sensor_list = ["tank_", "pump_", "flow_sensor_", "valv_"]
second_cluster.loc[:, "time_readable"] = x_axis_time
print_scatter_chart(second_cluster.loc[::8], sensor_list, logy=True)
```

```
/tmp/ipykernel_1088213/1153993981.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  second_cluster.loc[:, "time_readable"] = x_axis_time
```



The behavior of the second cluster is very similar to the first one.

1.4 Conclusion

The dataset, originating from the Water Distribution Testbed, encompasses both physical and network data, essential for understanding the impact of attacks on the physical process and network traffic. In the network dataset analysis, we examined feature distributions, laying the foundation for feature engineering and model building.

Subsequently, in the physical dataset, we were pleasantly surprised to find no missing values, albeit with label imbalance issues. Our features underwent density analysis, highlighting patterns in the different system points of capture: tanks, pumps, flow sensors, and valves.

In addition, we delved into the dataset's time series aspects, clustering the data for in-depth examination.

Overall, these analyses provide crucial insights for our ongoing project, aiding in feature selection, preprocessing, and subsequent modeling.