Imports necessary for this notebook

```
In [1]: import numpy as np
import pandas as pd
from scipy import stats
import seaborn as sns
```

Let's read the data and take a look

```
In [2]: dataset_path = '../data/dataset_20221127.csv'
df = pd.read_csv(dataset_path)
df
```

Out[2]:		state	c_0	c_1	c_2	c_3	c_4	c_5	c_6	C
	0	0	0.717573	0.714725	0.704585	0.694305	0.687011	0.683188	0.682031	0.6822
	1	0	0.719402	0.717330	0.708022	0.698305	0.691041	0.686480	0.683860	0.6823
	2	0	0.723090	0.721113	0.711632	0.701274	0.692945	0.687295	0.683872	0.6820
	3	0	0.729627	0.726485	0.715613	0.704214	0.695404	0.689836	0.686908	0.6856
	4	0	0.714636	0.714388	0.706626	0.698127	0.691818	0.688184	0.686566	0.6860
	•••						•••		•••	
	495	2	0.722422	0.720920	0.712699	0.704530	0.699261	0.697420	0.698031	0.6996
	496	2	0.726260	0.726227	0.725950	0.725444	0.724643	0.723600	0.722467	0.7214
	497	2	0.726733	0.724837	0.715531	0.705948	0.699105	0.695240	0.693513	0.6929
	498	2	0.747386	0.745534	0.735654	0.724924	0.716467	0.710962	0.708025	0.7069
	499	2	0.740270	0.738251	0.728985	0.719566	0.713096	0.710130	0.709747	0.7105

500 rows × 2001 columns

How many rows do we have for each state?

three times more working engines and an equal number of each type of broken engines

Are there missing or NAN values?

```
In [4]: nan_count = df.isna().sum().sum()
print(nan_count, "nan values found!")
```

23 nan values found!

how many NANs per label?

```
In [5]: na df = df.isna()
        na_df['state'] = df['state']
        na df.groupby('state').sum().sum(axis=1)
Out[5]: state
             13
        0
        1
               3
        2
               7
        dtype: int64
        removing NAN values will get us an uneven quantity of the two type of broken engines
        but for now let just remove this values
In [6]: not na df = df.dropna()
        print(not_na_df.isna().sum().sum(), "nan values found!")
        0 nan values found!
        Some statistical information about the features
        firstly, the label
In [7]: df['state'] = df['state'].astype('category')
        df['state'].describe()
Out[7]: count
                   500
                     3
        unique
                     0
        top
                   300
        freq
        Name: state, dtype: int64
        now for current and tension
In [8]: labels = [0, 1, 2]
        features = ['current', 'voltage']
        label_split = []
        for label in labels:
             feat_df_3d = not_na_df[not_na_df['state'] == label].drop(columns=['state'])
             feat df 3d.columns = pd.MultiIndex.from tuples([(features[c[0] == 't'],
            feat_df = pd.concat([feat_df_3d[c].unstack().reset_index()[0] for c in f
            feat_df.columns = features
            feat df['state'] = label
             feat df['state'] = feat df['state'].astype('category')
             label split.append(feat df)
        label mult index df = pd.concat(label split, axis=1, keys=labels)
        label mult index df.describe()
```

	current	voltage	current	voltage	current	
count	288000.000000	288000.000000	97000.000000	97000.000000	94000.000000	94000.
mean	0.689264	22.044635	0.890812	21.665591	0.702334	22.
std	0.032326	1.025083	0.100502	2.721973	0.041531	2
min	0.622967	0.234658	0.710802	2.365598	0.595338	1.
25%	0.676121	21.379161	0.802473	19.589508	0.678091	21
50%	0.688727	21.863059	0.871379	20.672930	0.708244	21
75%	0.705339	22.533723	0.972040	23.531722	0.730281	22
max	11.554880	111.454900	3.658796	35.565650	7.564789	42

1

here we can see current and voltage details for each label

some data seems off, on label 1 the current has a max value of 1214, it is probably an outlier

on label 0, data seems to be more packed than on the other features

lets do some plotting to better analyze this hypothesis

```
In [9]: label_df = pd.concat(label_split, ignore_index=True)
    label_df['state'] = label_df['state'].astype('category')
    label_df
```

Out[9]:		current	voltage	state
	0	0.717573	24.521245	0
	1	0.719402	24.476110	0
	2	0.729627	24.547889	0
	3	0.714636	24.573959	0
	4	0.709658	24.551453	0
	•••			•••
	478995	0.653173	21.514769	2
	478996	0.692476	20.711599	2
	478997	0.711744	23.732403	2
	478998	0.669758	21.217464	2
	478999	0.721182	22.908746	2

479000 rows × 3 columns

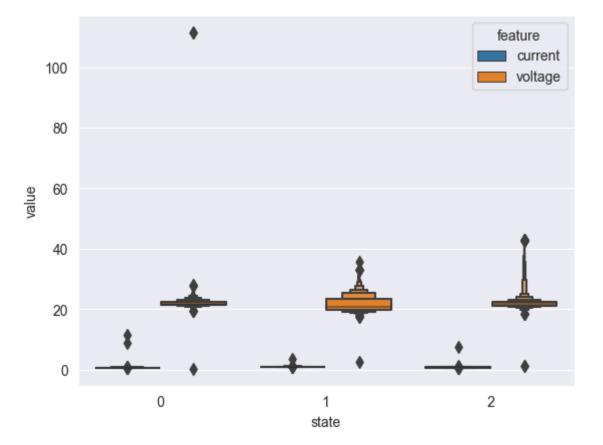
```
In [10]: label_df_melted = label_df.melt(id_vars='state', value_vars=features, var_na
label_df_melted
```

Out[10]: value state feature 0 0 current 0.717573 1 current 0.719402 2 current 0.729627 3 0.714636 current 4 current 0.709658 957995 21.514769 voltage 957996 voltage 20.711599 957997 voltage 23.732403 957998 21.217464 voltage 957999 2 voltage 22.908746

958000 rows × 3 columns



Out[11]: <AxesSubplot: xlabel='state', ylabel='value'>



we can clearly see some outliers

lets remake this plot removing data too far from the standard deviation

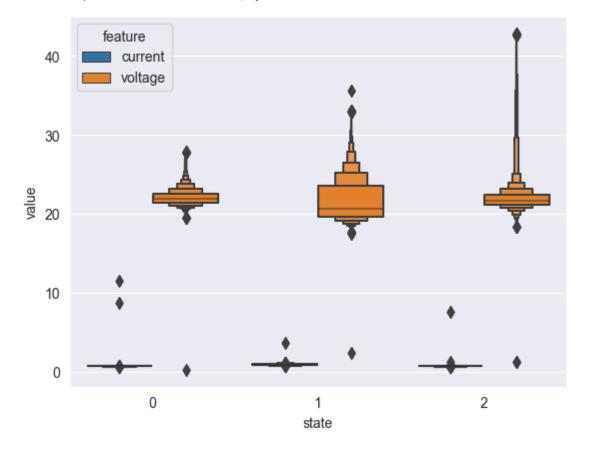
In [12]: label_df_melted_clean = label_df_melted[(np.abs(stats.zscore(label_df_melted_label_df_melted_clean)]

Out[12]:		state	feature	value
	0	0	current	0.717573
	1	0	current	0.719402
	2	0	current	0.729627
	3	0	current	0.714636
	4	0	current	0.709658
	•••	•••	•••	
	957995	2	voltage	21.514769
	957996	2	voltage	20.711599
	957997	2	voltage	23.732403
	957998	2	voltage	21.217464
	957999	2	voltage	22.908746

957998 rows × 3 columns

In [13]: sns.boxenplot(data=label_df_melted_clean, x='state', y='value', hue='feature

Out[13]: <AxesSubplot: xlabel='state', ylabel='value'>



let's check the features separately

In [14]: label_df_clean = label_df[(np.abs(stats.zscore(label_df[features])) < 5).all
label_df_clean</pre>

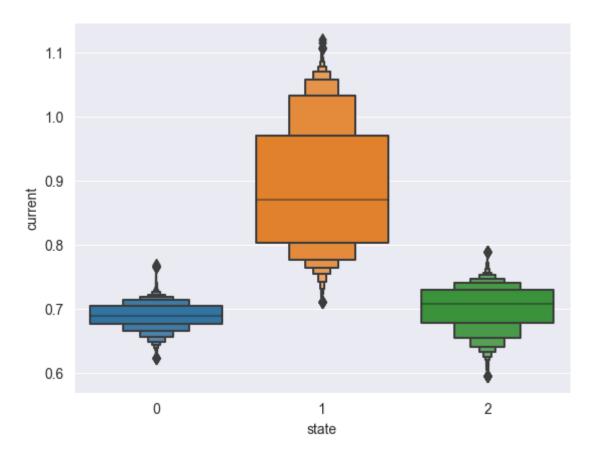
Out[14]:

	current	voltage	state
0	0.717573	24.521245	0
1	0.719402	24.476110	0
2	0.729627	24.547889	0
3	0.714636	24.573959	0
4	0.709658	24.551453	0
•••			
478995	0.653173	21.514769	2
478996	0.692476	20.711599	2
478997	0.711744	23.732403	2
478998	0.669758	21.217464	2
478999	0.721182	22.908746	2

477311 rows × 3 columns

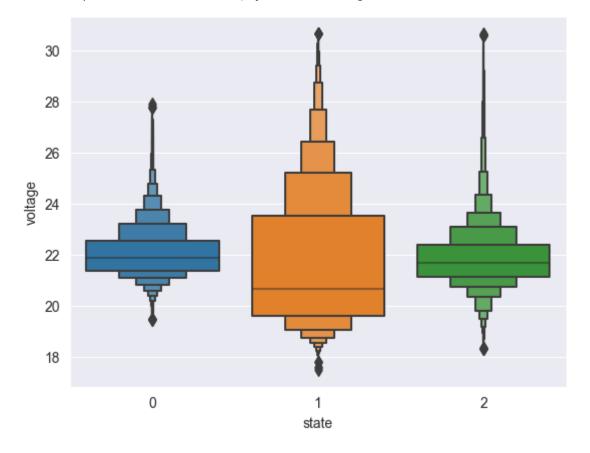
```
In [15]: sns.boxenplot(data=label_df_clean, x='state', y='current')
```

Out[15]: <AxesSubplot: xlabel='state', ylabel='current'>



In [16]: sns.boxenplot(data=label_df_clean, x='state', y='voltage')

Out[16]: <AxesSubplot: xlabel='state', ylabel='voltage'>



we can make several observations based on the above plots

label 0 is the most grouped data

label 2 has similar mean to label 0

label 1 has the greatest std

relation between mean current and mean voltage per line

```
In [18]: mean_feat_df = df.drop(columns=['state'])
    mean_feat_df.columns = pd.MultiIndex.from_tuples([(features[c[0] == 't'], c)
    mean_feat_df = mean_feat_df.groupby(level=0, axis=1).mean()
    mean_feat_df.columns = [f"mean_{c}" for c in mean_feat_df.columns]
    mean_feat_df['state'] = df['state']
    mean_feat_df
```

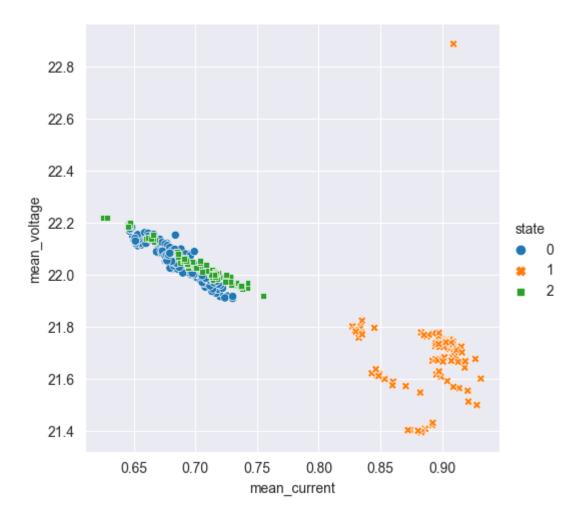
Out[18]: mean_current mean_voltage state

	mean_current	mean_voltage	state
0	0.683705	22.151397	0
1	0.679833	22.066898	0
2	0.690525	22.070464	0
3	0.692794	22.012264	0
4	0.680013	22.076911	0
•••			
495	0.685177	22.086528	2
496	0.692129	22.053290	2
497	0.690922	22.061742	2
498	0.686268	22.079134	2
499	0.708508	22.038410	2

500 rows × 3 columns

```
In [19]: sns.relplot(data=mean_feat_df, x='mean_current', y='mean_voltage', hue='stat
```

Out[19]: <seaborn.axisgrid.FacetGrid at 0x14a19b310>



we can easily see there is a clear distinction on defect type 1

both mean_voltage and mean_average are way off the normal

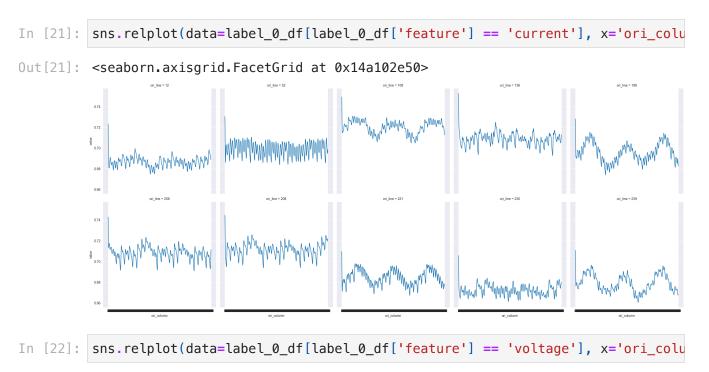
however there is no clear distinction from defect type 2 and normal

Random sample of each feature

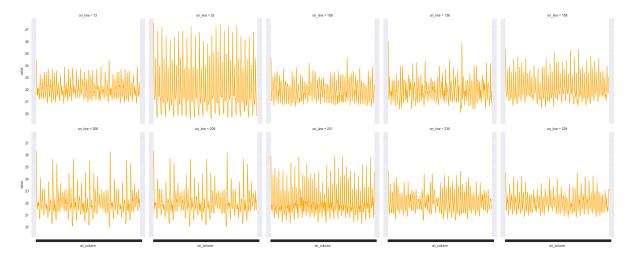
```
In [20]: label_0_df = df[df['state'] == labels[0]].drop(columns=['state']).sample(n=1
label_0_df.columns = pd.MultiIndex.from_tuples([(features[c[0] == 't'], c.sp
label_0_df = label_0_df.transpose()
label_0_df = label_0_df.melt(ignore_index=False, var_name='ori_line')
label_0_df = label_0_df.reset_index(names=['feature', 'ori_column'])
label_0_df
```

Out[20]: feature ori_column ori_line value 0 current 0 208 0.744507 current 208 0.741720 2 current 208 0.731674 3 208 0.721409 current current 4 208 0.713688 19995 voltage 995 108 21.750851 19996 voltage 996 108 21.798354 19997 21.935375 voltage 997 108 19998 998 108 22.162565 voltage 19999 voltage 999 108 22.403317

20000 rows × 4 columns



Out[22]: <seaborn.axisgrid.FacetGrid at 0x14a342c40>



above we can see ten random samples, for each of them we plot the one thousand measurements made

they all belong to label 0 and there doesn't seem to be any pattern