Feature Engineering (Part-1)

The goal of this case study is to build a predictive model that a machine will fail in the next 24 hours due to a certain component failure (component 1, 2, 3, or 4) or not.

During EDA of the data sets it is observed that data sets are having time-stamps.
So, we need to create new features relevant to time series analysis for our predictive model. The first step in predictive model is feature engineering which requires bringing the different data sources together to create features that best describe a machine's health condition at a given point in time. In the next sections, several feature engineering methods will be used to create features based on the properties/attributes/features of each data source.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /content/drive
```

```
#Importing libraries
import os
import sys
import numpy as np
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
matplotlib.style.use("Solarize_Light2")
%matplotlib inline
```

```
#Loading all the dataset using Pandas library from gdrive
import pandas as pd

telemetry = pd.read_csv('/content/drive/MyDrive/AAIC/Case_study_1/PdM_telemetry.csv')
errors = pd.read_csv('/content/drive/MyDrive/AAIC/Case_study_1/PdM_errors.csv')
maint = pd.read_csv('/content/drive/MyDrive/AAIC/Case_study_1/PdM_maint.csv')
failures = pd.read_csv('/content/drive/MyDrive/AAIC/Case_study_1/PdM_failures.csv')
machines = pd.read_csv('/content/drive/MyDrive/AAIC/Case_study_1/PdM_machines.csv')
```

```
# #Loading all the datasets using Pandas library from local PC
# import pandas as pd

# telemetry = pd.read_csv('PdM_telemetry.csv')
# errors = pd.read_csv('PdM_errors.csv')
# maint = pd.read_csv('PdM_maint.csv')
# failures = pd.read_csv('PdM_failures.csv')
# machines = pd.read_csv('PdM_machines.csv')
```

```
# Formating datetime field.
telemetry['datetime'] = pd.to_datetime(telemetry['datetime'], format="%Y-%m-%d %H:%M:%S")

errors['datetime'] = pd.to_datetime(errors['datetime'], format="%Y-%m-%d %H:%M:%S")
errors['errorID'] = errors['errorID'].astype('category')

maint['datetime'] = pd.to_datetime(maint['datetime'], format="%Y-%m-%d %H:%M:%S")
maint['comp'] = maint['comp'].astype('category')

machines['model'] = machines['model'].astype('category')

failures['datetime'] = pd.to_datetime(failures['datetime'], format="%Y-%m-%d %H:%M:%S")
failures['failure'] = failures['failure'].astype('category')
```

Lag Features from Telemetry data

Lag features are the classical way that time series forecasting problems are transformed into supervised learning problems.

Telemetry data comes with time-stamps which makes it suitable for calculating lagging features. A common method is to pick a window size for the lag features to be created and compute rolling aggregate measures such as mean, standard deviation, minimum, maximum, etc. to represent the short term history of the telemetry over the lag window. In the following, we will create only **2 nos features 'min and max' of the telemetry data** over the last 3 hour lag window will be calculated for every 3 hours with pandas's function "resample".

- Reference: https://machinelearningmastery.com/basic-feature-engineering-time-series-data-python/
  #Reference: https://stackoverflow.com/questions/45370666/what-are-pandas-expanding-window-functions
  #Reference: https://towardsdatascience.com/using-the-pandas-resample-function-a231144194c4

```
# Calculate "resample min values" over the last 3 hour lag window for telemetry features.
temp = []
fields = ['volt', 'rotate', 'pressure', 'vibration']
for col in fields:
    temp.append(pd.pivot_table(telemetry,
                               index='datetime',
                               columns='machineID',
                        values=col).resample('3H', closed='left', label='right').min().unstack())

telemetry_min_3h = pd.concat(temp, axis=1)
telemetry_min_3h.columns = [i + '_min_3h' for i in fields]
telemetry_min_3h.reset_index(inplace=True)

telemetry_min_3h.head()
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h
0	1	2015-01-01 09:00:00	162.879223	402.747490	75.237905	34.178847
1	1	2015-01-01 12:00:00	157.610021	346.149335	95.927042	25.990511
2	1	2015-01-01 15:00:00	156.556031	398.648781	101.001083	35.482009
3	1	2015-01-01 18:00:00	160.263954	382.483543	96.480976	38.543681
4	1	2015-01-01 21:00:00	153.353492	402.461187	86.012440	39.739883

```
# Calculate "resample max values" over the last 3 hour lag window for telemetry features.
temp = []
fields = ['volt', 'rotate', 'pressure', 'vibration']
for col in fields:
    temp.append(pd.pivot_table(telemetry,
                               index='datetime',
                               columns='machineID',
                        values=col).resample('3H', closed='left', label='right').max().unstack())

telemetry_max_3h = pd.concat(temp, axis=1)
telemetry_max_3h.columns = [i + '_max_3h' for i in fields]
telemetry_max_3h.reset_index(inplace=True)

telemetry_max_3h.head()
```

	machineID	datetime	volt_max_3h	rotate_max_3h	pressure_max_3h	vibration_max_3h
0	1	2015-01-01 09:00:00	176.217853	527.349825	113.077935	45.087686
1	1	2015-01-01 12:00:00	172.504839	435.376873	111.886648	41.122144
2	1	2015-01-01 15:00:00	175.324524	499.071623	111.755684	45.482287
3	1	2015-01-01 18:00:00	169.218423	460.850670	104.848230	42.675800
4	1	2015-01-01 21:00:00	182.739113	490.672921	93.484954	44.108554

Now, the above new columns of the feature datasets will be merged below to create the final features set from telemetry.

```
# Merge columns of feature sets created earlier
telemetry_feat = pd.concat([telemetry_min_3h,
                            telemetry_max_3h.iloc[:, 2:6]], axis=1).dropna()

telemetry_feat.head()
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	rotate_max_3h
0	1	2015-01-01 09:00:00	162.879223	402.747490	75.237905	34.178847	176.217853	527.349825
1	1	2015-01-01 12:00:00	157.610021	346.149335	95.927042	25.990511	172.504839	435.376873
2	1	2015-01-01 15:00:00	156.556031	398.648781	101.001083	35.482009	175.324524	499.071623
3	1	2015-01-01 18:00:00	160.263954	382.483543	96.480976	38.543681	169.218423	460.850670
4	1	2015-01-01 21:00:00	153.353492	402.461187	86.012440	39.739883	182.739113	490.672921

```
telemetry_feat.describe()
```

	machineID	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	rotate_max_3h
count	292100.000000	292100.000000	292100.000000	292100.000000	292100.000000	292100.000000	292100.000000
mean	50.500000	158.083149	404.146613	92.384876	36.149107	183.473398	489.026431
std	28.866119	11.878952	40.828783	8.783319	4.210114	11.909021	40.802190
min	1.000000	97.333604	138.432075	51.237106	14.877054	134.008631	237.641009
25%	25.750000	150.370836	379.505260	86.862827	33.457643	175.270539	463.319490
50%	50.500000	158.172629	406.891158	92.118675	36.088473	182.769923	489.161104
75%	75.250000	165.846384	432.062323	97.281361	38.667734	190.895306	515.375351
max	100.000000	235.726785	565.962115	160.026994	68.001841	255.124717	695.020984

Lag Features from Errors dataset

Like telemetry data, errors data set comes with timestamps. An important difference is that the error IDs are categorical values and should not be averaged over time intervals like the telemetry measurements. Instead, we count the number of errors of each type in a lagging window. We begin by reformatting the error data to have one entry per machine per time at which at least one error occurred:

```
# Create a column for each error type
error_count = pd.get_dummies(errors.set_index('datetime')).reset_index()
error_count.columns = ['datetime', 'machineID', 'error1', 'error2', 'error3', 'error4', 'error5']

# Combine errors for a given machine in a given hour
error_count = error_count.groupby(['machineID', 'datetime']).sum().reset_index()
error_count.head()
```

Now, we will add feature 'datetime' and 'machineID' from telemetry data set and add blank entries for all other hourly timepoints (since no errors occurred at those times):

1	1	2015-01-03 20:00:00	0	0	1	0	0

```
error_count = telemetry[['datetime', 'machineID']].merge(error_count, on=['machineID', 'datetime'],
                                                          how='left').fillna(0.0)
```

```
error_count.head()
```

	datetime	machineID	error1	error2	error3	error4	error5
0	2015-01-01 06:00:00	1	0.0	0.0	0.0	0.0	0.0
1	2015-01-01 07:00:00	1	0.0	0.0	0.0	0.0	0.0
2	2015-01-01 08:00:00	1	0.0	0.0	0.0	0.0	0.0
3	2015-01-01 09:00:00	1	0.0	0.0	0.0	0.0	0.0
4	2015-01-01 10:00:00	1	0.0	0.0	0.0	0.0	0.0

```
error_count.describe()
```

	machineID	error1	error2	error3	error4	error5
count	876100.000000	876100.000000	876100.000000	876100.000000	876100.000000	876100.000000
mean	50.500000	0.001153	0.001128	0.000957	0.000830	0.000406
std	28.866087	0.033934	0.033563	0.030913	0.028795	0.020154
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	25.750000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	50.500000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	75.250000	0.000000	0.000000	0.000000	0.000000	0.000000
max	100.000000	1.000000	1.000000	1.000000	1.000000	1.000000

Finally, we can compute the total number of errors of each type over the last 24 hours, for timepoints taken every 3 hours:

```
temp = []
fields = ['error%d' % i for i in range(1,6)]
for col in fields:
    temp.append(pd.pivot_table(error_count,
                                           index='datetime',
                                           columns='machineID',
                                     values=col).rolling(window=24).sum().resample('3H',
                                                closed='left', label='right').first().unstack())


error_count = pd.concat(temp, axis=1)
error_count.columns = [i + 'count' for i in fields]
# error_count.reset_index(inplace=True)#To be activate
error_count = error_count.dropna()
error_count.head()
```

		error1count	error2count	error3count	error4count	error5count
machineID	**datetime**					
1	**2015-01-02 06:00:00**	0.0	0.0	0.0	0.0	0.0
	2015-01-02 09:00:00	0.0	0.0	0.0	0.0	0.0
	2015-01-02 12:00:00	0.0	0.0	0.0	0.0	0.0
	2015-01-02 15:00:00	0.0	0.0	0.0	0.0	0.0
	2015-01-02 18:00:00	0.0	0.0	0.0	0.0	0.0

```
error_count.describe()
```

	error1count	error2count	error3count	error4count	error5count
count	291400.000000	291400.000000	291400.000000	291400.000000	291400.000000
mean	0.027649	0.027069	0.022907	0.019904	0.009753
std	0.166273	0.164429	0.151453	0.140820	0.098797
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	2.000000	2.000000	2.000000	2.000000	2.000000

Count nos of Days Since Last Replacement of component from Maintenance data

A crucial data set in this example is the maintenance records which contain the information of component replacement records. Possible features from this data set can be, for example, the number of replacements of each component in the last 3 months to incorporate the frequency of replacements. However, more relevent information would be to calculate how long it has been since a component is last replaced as that would be expected to correlate better with component failures since the longer a component is used, the more degradation should be expected.

As a side note, creating lagging features from maintenance data is not as straightforward as for telemetry and errors, so the features from this data are generated in a more custom way. This type of ad-hoc feature engineering is very common in predictive maintenance. In the following step, the numbers of days since last component replacement are calculated for each component type as features from the maintenance data.

```
import numpy as np
from tqdm.notebook import tqdm_notebook

# Create a column for each error type
comp_rep = pd.get_dummies(maint.set_index('datetime')).reset_index()
comp_rep.columns = ['datetime', 'machineID', 'comp1', 'comp2', 'comp3', 'comp4']

# Combine repairs for a given machine in a given hour
comp_rep = comp_rep.groupby(['machineID', 'datetime']).sum().reset_index()

# Add timepoints where no components were replaced
comp_rep = telemetry[['datetime', 'machineID']].merge(comp_rep,
                                                      on=['datetime', 'machineID'],
                                     how='outer').fillna(0).sort_values(by=['machineID', 'datetime'])


components = ['comp1', 'comp2', 'comp3', 'comp4']
for comp in tqdm_notebook(components):
    # Convert indicator to most recent date of component change
    comp_rep.loc[comp_rep[comp] < 1, comp] = None
    comp_rep.loc[-comp_rep[comp].isnull(), comp] = comp_rep.loc[-comp_rep[comp].isnull(),'datetime']

    # Forward-fill the most-recent date of component change
    comp_rep[comp] = comp_rep[comp].fillna(method='ffill')

# Remove dates in 2014 (may have NaN or future component change dates)
comp_rep = comp_rep.loc[comp_rep['datetime'] > pd.to_datetime('2015-01-01')]

# Replace dates of most recent component change with days since most recent component change
for comp in tqdm_notebook(components):
    comp_rep[comp] = (comp_rep['datetime'] - comp_rep[comp]) / np.timedelta64(1, 'D')

comp_rep.describe()
```

100% 4/4 [00:02<00:00, 1.60it/s]

100% 4/4 [00:00<00:00, 41.88it/s]

	machineID	comp1	comp2	comp3	comp4
count	876100.000000	876100.000000	876100.000000	876100.000000	876100.000000
mean	50.500000	53.525185	51.540806	52.725962	53.834191
std	28.866087	62.491679	59.269254	58.873114	59.707978
min	1.000000	0.000000	0.000000	0.000000	0.000000
25%	25.750000	13.291667	12.125000	13.125000	13.000000

```
comp_rep.head()
```

	datetime	machineID	comp1	comp2	comp3	comp4
0	2015-01-01 06:00:00	1	19.000000	214.000000	154.000000	169.000000
1	2015-01-01 07:00:00	1	19.041667	214.041667	154.041667	169.041667
2	2015-01-01 08:00:00	1	19.083333	214.083333	154.083333	169.083333
3	2015-01-01 09:00:00	1	19.125000	214.125000	154.125000	169.125000
4	2015-01-01 10:00:00	1	19.166667	214.166667	154.166667	169.166667

Machine Features

The machine features can be used without further modification. These include descriptive information about the type of each machine and its age (number of years in service). If the age information had been recorded as a "first use date" for each machine, a transformation would have been necessary to turn those into a numeric values indicating the years in service.

Lastly, we merge all the feature data sets we created above to get the final feature matrix.

```
final_feat = telemetry_feat.merge(error_count, on=['datetime', 'machineID'], how='left')
final_feat = final_feat.merge(comp_rep, on=['datetime', 'machineID'], how='left')
final_feat = final_feat.merge(machines, on=['machineID'], how='left')

print(final_feat.head())
final_feat.describe()
```

```
   machineID            datetime  volt_min_3h  rotate_min_3h  pressure_min_3h  \
0          1 2015-01-01 09:00:00   162.879223     402.747490        75.237905
1          1 2015-01-01 12:00:00   157.610021     346.149335        95.927042
2          1 2015-01-01 15:00:00   156.556031     398.648781       101.001083
3          1 2015-01-01 18:00:00   160.263954     382.483543        96.480976
4          1 2015-01-01 21:00:00   153.353492     402.461187        86.012440

   vibration_min_3h  volt_max_3h  rotate_max_3h  pressure_max_3h  \
0         34.178847   176.217853     527.349825       113.077935
1         25.990511   172.504839     435.376873       111.886648
2         35.482009   175.324524     499.071623       111.755684
3         38.543681   169.218423     460.850670       104.848230
4         39.739883   182.739113     490.672921        93.484954

   vibration_max_3h  ...  error2count  error3count  error4count  error5count  \
0         45.087686  ...          NaN          NaN          NaN          NaN
1         41.122144  ...          NaN          NaN          NaN          NaN
2         45.482287  ...          NaN          NaN          NaN          NaN
3         42.675800  ...          NaN          NaN          NaN          NaN
```

Label Construction

When using multi-class classification for predicting failure due to a problem, labelling is done by taking a time window prior to the failure of an asset and labelling the feature records that fall into that window as "about to fail due to a problem" while labelling all other records as "normal". This time window should be picked according to the business case: in some situations it may be enough to predict failures hours in advance, while in others days or weeks may be needed to allow e.g. for arrival of replacement parts.

The prediction problem for this example scenario is to predict that a machine will fail in the near future due to a failure of a certain component or not. More specifically, **the goal is to predict that a machine will fail in the next 24 hours due to a certain component failure (component 1, 2, 3, or 4)** or not. Below, a categorical `failure` feature is created to serve as the label. All records within a 24 hour window before a failure of component 1 have `failure=comp1`, and so on for components 2, 3, and 4; all records not within 24 hours of a component failure have `failure=none`.

```
labeled_features = final_feat.merge(failures, on=['datetime', 'machineID'], how='left')
labeled_features = labeled_features.fillna(method='bfill', limit=7) # fill backward up to 24h
labeled_features['failure'] = labeled_features['failure'].astype('str')
labeled_features.replace({'nan': "none"}, inplace= True)
```

```
labeled_features.head(2)
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	ro
0	1	2015-01-01 09:00:00	162.879223	402.747490	75.237905	34.178847	176.217853	
1	1	2015-01-01 12:00:00	157.610021	346.149335	95.927042	25.990511	172.504839	

2 rows × 22 columns

Below is an example of records that are labeled as failure=comp4 in the failure column. Notice that the first 8 records all occur in the 24-hour window before the first recorded failure of component 4. The next 8 records are within the 24 hour window before another failure of component 4.

```
labeled_features.loc[labeled_features['failure'] == 'comp4'][:16]
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h
24	1	2015-01-04 09:00:00	142.666469	433.279499	97.709630	48.238941	191.168936
25	1	2015-01-04 12:00:00	153.143558	438.091311	94.524894	51.647981	215.656488
26	1	2015-01-04 15:00:00	129.016707	421.728389	91.675576	45.951349	173.525320
27	1	2015-01-04 18:00:00	168.503141	365.213804	82.400818	43.917862	184.640476
28	1	2015-01-04 21:00:00	183.684832	414.481164	103.159963	41.674887	199.755983
29	1	2015-01-05 00:00:00	162.368945	447.101400	89.260131	50.240045	180.562703
30	1	2015-01-05 03:00:00	127.163620	376.719605	89.969588	46.845600	161.928938
31	1	2015-01-05 06:00:00	177.317220	387.005318	94.686208	45.202347	202.520488
1344	1	2015-06-18 09:00:00	142.165191	417.834555	96.780895	51.105583	198.380679
1345	1	2015-06-18 12:00:00	184.681384	387.342414	91.050336	40.747029	197.240367
1346	1	2015-06-18 15:00:00	143.320854	402.864601	86.351078	39.927737	178.305492
1347	1	2015-06-18 18:00:00	176.531054	408.749781	107.166360	47.609185	180.957236
1348	1	2015-06-18 21:00:00	142.194697	437.599207	96.911121	39.065462	169.116734
1349	1	2015-06-19 00:00:00	147.914394	432.857174	94.930887	47.202762	171.499274
1350	1	2015-06-19 03:00:00	159.988324	427.759024	97.214002	41.311111	179.542958
1351	1	2015-06-19	155.705646	398.739627	93.204419	51.974600	184.385379

```
# #Save pre-processed data in CSV.
# labeled_features.to_csv('/content/drive/MyDrive/AAIC/Case_study_1/preprocessed_1.csv', encoding='utf-8', index=False)
```

Modeling

After the feature engineering and labeling steps, below, modeling process is being described.

Training, Validation and Testing

When working with time-stamped data as in this example, record partitioning into training, validation, and test sets should be performed carefully to prevent overestimating the performance of the models. In predictive maintenance, the features are usually generated using lagging aggregates: records in the same time window will likely have identical labels and similar feature values.

These correlations can give a model an "unfair advantage" when predicting on a test set record that shares its time window with a training set record. We therefore partition records into training, validation, and test sets in large chunks, to minimize the number of time intervals shared between them.

Predictive models have no advance knowledge of future chronological trends: in practice, such trends are likely to exist and to adversely impact the model's performance. To obtain an accurate assessment of a predictive model's performance, it is recommended to train on older records and validating/testing using newer records.

For both of these reasons, a time-dependent record splitting strategy is an excellent choice for predictive maintenance models. The featured dataset has been splitted into three dataset "Training", "Cross Validation and "Test" dataset with time.

All the featured dataset has been saved in "preprocessed.csv" for ease of analysis.

```
# #Importing the "preprocessed.csv".
import pandas as pd
labeled_features= pd.read_csv("/content/drive/MyDrive/AAIC/Case_study_1/preprocessed_1.csv")
# Format datetime field which comes in as string

labeled_features['datetime'] = pd.to_datetime(labeled_features['datetime'], format="%Y-%m-%d %H:%M:%S")
```

```
labeled_features.head(2)
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	ro
0	1	2015-01-01 09:00:00	162.879223	402.747490	75.237905	34.178847	176.217853	
1	1	2015-01-01 12:00:00	157.610021	346.149335	95.927042	25.990511	172.504839	

2 rows × 22 columns

```
labeled_features.tail(2)
```

	machineID	datetime	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3
292140	100	2016-01-01 06:00:00	165.475310	413.77167	94.132837	35.123072	192.48341
292141	100	2016-01-01 09:00:00	171.336037	496.09687	79.095538	37.845245	171.33603

2 rows × 22 columns

```
labeled_features.describe()
```

	machineID	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	r
count	292142.000000	292142.000000	292142.000000	292142.000000	292142.000000	292142.000000	2
mean	50.499127	158.084403	404.139147	92.386747	36.149700	183.475185	
std	28.866542	11.880281	40.835358	8.786371	4.210870	11.911030	

```
#https://towardsdatascience.com/time-based-cross-validation-d259b13d42b8
#https://machinelearningmastery.com/backtest-machine-learning-models-time-series-forecasting/
import numpy as np
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
```

75%	75.000000	165.847573	432.060311	97.282725	38.668287	190.897064

Split the "preprocessed.csv" with Sklearn "train_test_split" function with "shuffle=False".

```
X = labeled_features.drop(['datetime', 'machineID', 'failure'], 1)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: In a future version of pandas all arg
  """Entry point for launching an IPython kernel.
```

```
X.head(2)
```

	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	rotate_max_3h	pressure_
0	162.879223	402.747490	75.237905	34.178847	176.217853	527.349825	113
1	157.610021	346.149335	95.927042	25.990511	172.504839	435.376873	111

```
X_final = pd.get_dummies(X)
X_final.head(2)
```

	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	rotate_max_3h	pressure_
0	162.879223	402.747490	75.237905	34.178847	176.217853	527.349825	113
1	157.610021	346.149335	95.927042	25.990511	172.504839	435.376873	111

2 rows × 22 columns

```
X_final.describe()
```

	volt_min_3h	rotate_min_3h	pressure_min_3h	vibration_min_3h	volt_max_3h	rotate_max_3h	p
count	292142.000000	292142.000000	292142.000000	292142.000000	292142.000000	292142.000000	
mean	158.084403	404.139147	92.386747	36.149700	183.475185	489.018718	
std	11.880281	40.835358	8.786371	4.210870	11.911030	40.808835	
min	97.333604	138.432075	51.237106	14.877054	134.008631	237.641009	
25%	150.371360	379.495432	86.863417	33.457799	175.270908	463.308453	
50%	158.173045	406.887098	92.119195	36.088670	182.771283	489.156358	
75%	165.847573	432.060311	97.282725	38.668287	190.897064	515.371091	
max	235.726785	565.962115	160.026994	68.001841	255.124717	695.020984	

8 rows × 22 columns

```
X_final_train = X_final.values
X_final_train[1]
```

```
array([157.61002119, 346.14933504,  95.92704169,  25.990511  ,
       172.5048392 , 435.37687302, 111.88664821,  41.12214409,
         0.        ,   0.        ,   0.        ,   0.        ,
         0.        ,  19.25      , 214.25      , 154.25      ,
       169.25      ,  18.        ,   0.        ,   0.        ,
         1.        ,   0.        ])
```

```
y_final=labeled_features['failure']
y_final.head(2)
```

```
0    none
1    none
Name: failure, dtype: object
```

```
y_final_train = y_final.values
y_final_train[1]
```

```
'none'
```

```
X_train, X_test, y_train, y_test = train_test_split(X_final_train, y_final_train,test_size=0.20, shuffle=False)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.20, shuffle=False)
```

```
print('X_train Observations: %d' % (len(X_train)))
print('y_train Observations: %d' % (len(y_train)))

print('X_cv Observations: %d' % (len(X_cv)))
print('y_cv Observations: %d' % (len(y_cv)))

print('X_test Observations: %d' % (len(X_test)))
print('y_test Observations: %d' % (len(y_test)))
```

```
X_train Observations: 186970
y_train Observations: 186970
X_cv Observations: 46743
y_cv Observations: 46743
X_test Observations: 58429
y_test Observations: 58429
```

```
#Reference: AAIC Case_study_2.
# This function plots the confusion matrices given y_i, y_i_hat.
from sklearn.metrics import confusion_matrix, recall_score, accuracy_score, precision_score
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    A =(((C.T)/(C.sum(axis=1))).T)
    B =(C/C.sum(axis=0))

    labels = ['comp1', 'comp2', 'comp3', 'comp4', 'none']
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*20, "Precision matrix (Columm Sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # representing B in heatmap format
    print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
```

```
    plt.ylabel('Original Class')
    plt.show()
```

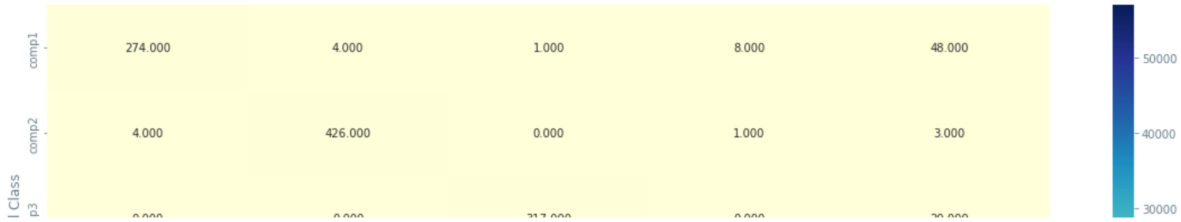
Apply model XGBClassifier

```
from xgboost import XGBClassifier

x_cfl=XGBClassifier()
x_cfl.fit(X_train,y_train)
```

```
XGBClassifier(objective='multi:softprob')
```

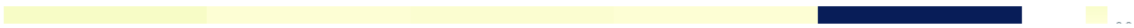
```
plot_confusion_matrix(y_test, x_cfl.predict(X_test))
```

```
-------------------- Confusion matrix --------------------
```




```python
from prettytable import PrettyTable

# Specify the Column Names
myTable = PrettyTable(["Model name (Recall score )", "comp1", "comp2", "comp3", 'comp4', 'none(no fail)'])

# Add rows

myTable.add_row(["Xgboost with available 19 nos of features",
                 "0.206", "0.366", "0.639", "0.556", "1"])

myTable.add_row(["Xgboost with new 22 nos of features",
                 "0.818", "0.982", "0.941", "0.903", "1"])


print(myTable)
```

```
+-------------------------------------------+-------+-------+-------+-------+---------------+
|         Model name (Recall score )        | comp1 | comp2 | comp3 | comp4 | none(no fail) |
+-------------------------------------------+-------+-------+-------+-------+---------------+
| Xgboost with available 19 nos of features | 0.206 | 0.366 | 0.639 | 0.556 |       1       |
|    Xgboost with new 22 nos of features    | 0.818 | 0.982 | 0.941 | 0.903 |       1       |
+-------------------------------------------+-------+-------+-------+-------+---------------+
```



Observation on the above approach:

We are more concerned about the miss-classified data points/even predicted by our predictive model, so we will monitor the 'Recall' metric of the computed model. If recall value of comp1 is 0.80, this means our model identified 80% of comp1 failure correctly. From the above table, it is observed recall value of all the failure components has increased a lot after creating new features (without performing hyper-parameter tuning).

Next step:

1. New lag features will be created and compute rolling aggregate measures of "mean and standard deviation" to represent the short term history of the telemetry over the lag window in the next Part-2 of FE.
2. For capturing a longer term effect, 24 hour lag features of telemetry will be created.
3. All the feature created in FE_Part-1 and FE_Part-2 will be merged to build final feature set from telemetry.

Predicted Class

>>>>>>>> End of "FE_Case_study_1_part_1" <<<<<<<<