Value of a generic data exchange based data marketplace using Federated Learning - Exploratory Data Analysis

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1 Personal Information

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GitHub : https://github.com/ben7pram/ddm-fl-project-2023

2 Data Context

The main focus of the research is to investigate the value of Federated Learning techniques on a Predictive Maintenance use-case using operational data from multiple airline fleets, within a consortium governed Digital Data Marketplace (DDM) ecosystem. In the real world, there will be no direct access to this operational data as the this data is held privately and is confidential. The main idea of Federated Learning is to train a model across multiple decentralized edge nodes holding local data, without exposing or transmitting privately held data. For the actual experiments within a DDM, airline operational dataset(s) related to Boeing aircraft(s) such as 787 Supplemental Cooling Unit(SCU), or 747 Bleed Air Valves will be used. This data is private and is expected to be made available by the participating airline KLM, within the DDM ecosystem, in the month of April 2023.

As an alternative to private and confidential airline operational datasets, publicly available dataset is being explored during the research to make comparisons between centralized and federated learning methods. This simulated dataset is provided by the NASA Ames Prognostics Center of Excellence (PCoE). Engine degradation simulation was carried out using the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). Four different sets (FD001, FD002, FD003, FD004) were simulated under different combinations of operational conditions and fault modes. This records several sensor channels to characterize fault evolution.

References :

1. Data Set Download: https://data.nasa.gov/Aerospace/CMAPSS-Jet-Engine-Simulated-Data/ff5v-kuh6
2. Data Set Citation: A. Saxena, K. Goebel, D. Simon, and N. Eklund, Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation, in the Proceedings of the Ist In-

ternational Conference on Prognostics and Health Management (PHM08), Denver CO, Oct 2008.

3 Data Description

3.0.1 Data Set

All the data sets consist of multiple multivariate time series. Each data set is further divided into training and test subsets. Each time series is from a different engine i.e., the data can be considered to be from a fleet of engines of the same type. Each engine starts with different degrees of initial wear and manufacturing variation which is unknown to the user. This wear and variation is considered normal, i.e., it is not considered a fault condition. There are three operational settings that have a substantial effect on engine performance. These settings are also included in the data. The data is contaminated with sensor noise.The engine is operating normally at the start of each time series, and develops a fault at some point during the series. In the training set, the fault grows in magnitude until system failure. In the test set, the time series ends some time prior to system failure. The objective is to predict the number of remaining operational cycles before failure in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate. The data set also includes a vector of true Remaining Useful Life (RUL) values for the test data.

There are 4 datasets available as part of the CMAPSS download. Data Set FD001 is used as the public dataset for this research project. The dataset includes train data, test data and ground truth Remaining Useful Life (RUL) values for the test data. Further, for Federated Learning experiments, the training data will be split into one subset for initial training (10 engines) and 3 subsets for each of Federated Learning Nodes (30 engines each). The test data will also be split for validation and testing.

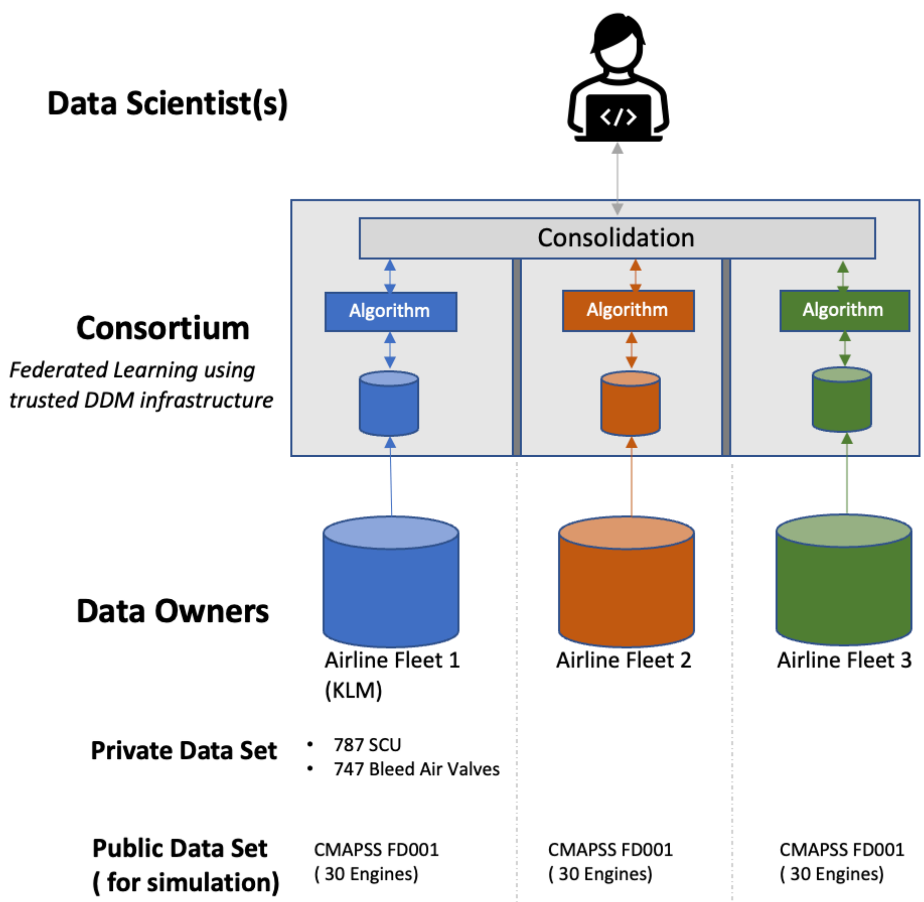
3.0.2 Structure

The data are provided as a zip-compressed text file with 26 columns of numbers, separated by spaces. Each row is a snapshot of data taken during a single operational cycle, each column is a different variable. The columns correspond to: 1) unit number 2) time, in cycles 3) operational setting 1 4) operational setting 2 5) operational setting 3 6) sensor measurement 1 7) sensor measurement 2 ... 26) sensor measurement 26

3.0.3 Analysis

- Data Set FD001 has data from 100 engines and has 20631 entries.
- ‘Operational setting 3’, and Sensor Measurements 1, 5, 6, 10, 16, 18,19 have constant values and hence hold no information related to RUL.
- Correlation : There is high correlation (close to 1 or -1) between the following sensor pairs: (4,11), (4,12), (7,11), (7,12), (8,13), (9,14), (11,12)
- Target Variable: A variable for Remaining User Life (RUL) will be computed. This will also serve as a target variable for supervised learning.As there is no information about RUL in the training data, we assume that the RUL decreases linearly with time and will have a value of 0 at the last time cycle of the engine. The calculated RUL and the histogram show that most engines breakdown around 200 cycles and the distribution is right skewed.

- Trends : The various sensor plots w.r.t RUL show that Sensors 1, 5, 10, 16, 18 and 19 do not indicate a increasing or decreasing trend. They are constant. Sensors 2, 3, 4, 8, 11, 13, 15 and 17 indicate an increasing trend. Sensor 7, 12, 20, 21 indicate an declining trend. Sensor 6 peaks downwards but is not clear. Sensor 9 and Sensor 14 display similar pattern with gradual change for a while and then indicate an abrupt increasing or decreasing trend, at certain point in time.
- Experiments : Regression experiments to predict the RUL value, using supervised learning will be setup and performed in the Federated Learning Environment. The picture below depcits the overall flow including the data that will be used. The results from federated learning will then be compared to (non-federated) centralized learning methods.



[1]:
```python
# Imports
import os
import numpy as np
import pandas as pd
import math
import random
import matplotlib.pyplot as plt
```

```python
import seaborn as sns;
```

3.0.4 Data Loading

[ ]:
```python
# CMAPSS FD001 DataSet
```

[2]:
```python
# define filepath to read data
dir_path = './data/'

# define column names for easy indexing
index_names = ['unit_nr', 'time_cycles']
setting_names = ['setting_1', 'setting_2', 'setting_3']
sensor_names = ['s_{}'.format(i) for i in range(1,22)]
col_names = index_names + setting_names + sensor_names

# read data
train = pd.read_csv((dir_path+'train_FD001.txt'), sep='\s+', header=None,␣
 ↪names=col_names)
test = pd.read_csv((dir_path+'test_FD001.txt'), sep='\s+', header=None,␣
 ↪names=col_names)
y_test = pd.read_csv((dir_path+'RUL_FD001.txt'), sep='\s+', header=None,␣
 ↪names=['RUL'])

train.head()
```

[2]:
```
   unit_nr  time_cycles  setting_1  setting_2  setting_3     s_1     s_2  \
0        1            1    -0.0007    -0.0004      100.0  518.67  641.82
1        1            2     0.0019    -0.0003      100.0  518.67  642.15
2        1            3    -0.0043     0.0003      100.0  518.67  642.35
3        1            4     0.0007     0.0000      100.0  518.67  642.35
4        1            5    -0.0019    -0.0002      100.0  518.67  642.37

       s_3      s_4    s_5  …    s_12     s_13     s_14    s_15  s_16  s_17  \
0  1589.70  1400.60  14.62  …  521.66  2388.02  8138.62  8.4195  0.03   392
1  1591.82  1403.14  14.62  …  522.28  2388.07  8131.49  8.4318  0.03   392
2  1587.99  1404.20  14.62  …  522.42  2388.03  8133.23  8.4178  0.03   390
3  1582.79  1401.87  14.62  …  522.86  2388.08  8133.83  8.3682  0.03   392
4  1582.85  1406.22  14.62  …  522.19  2388.04  8133.80  8.4294  0.03   393

   s_18   s_19   s_20     s_21
0  2388  100.0  39.06  23.4190
1  2388  100.0  39.00  23.4236
2  2388  100.0  38.95  23.3442
3  2388  100.0  38.88  23.3739
4  2388  100.0  38.90  23.4044
```

```
[5 rows x 26 columns]
```

3.0.5 Descriptive Statistics

[3]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20631 entries, 0 to 20630
Data columns (total 26 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   unit_nr      20631 non-null  int64
 1   time_cycles  20631 non-null  int64
 2   setting_1    20631 non-null  float64
 3   setting_2    20631 non-null  float64
 4   setting_3    20631 non-null  float64
 5   s_1          20631 non-null  float64
 6   s_2          20631 non-null  float64
 7   s_3          20631 non-null  float64
 8   s_4          20631 non-null  float64
 9   s_5          20631 non-null  float64
 10  s_6          20631 non-null  float64
 11  s_7          20631 non-null  float64
 12  s_8          20631 non-null  float64
 13  s_9          20631 non-null  float64
 14  s_10         20631 non-null  float64
 15  s_11         20631 non-null  float64
 16  s_12         20631 non-null  float64
 17  s_13         20631 non-null  float64
 18  s_14         20631 non-null  float64
 19  s_15         20631 non-null  float64
 20  s_16         20631 non-null  float64
 21  s_17         20631 non-null  int64
 22  s_18         20631 non-null  int64
 23  s_19         20631 non-null  float64
 24  s_20         20631 non-null  float64
 25  s_21         20631 non-null  float64
dtypes: float64(22), int64(4)
memory usage: 4.1 MB
```

[4]:
```
# Number of  engines
len(train['unit_nr'].unique())
```

[4]: 100

[5]:
```
# inspect unit_nr
train[index_names].describe()
```

[5]:

	unit_nr	time_cycles
count	20631.000000	20631.000000
mean	51.506568	108.807862
std	29.227633	68.880990
min	1.000000	1.000000
25%	26.000000	52.000000
50%	52.000000	104.000000
75%	77.000000	156.000000
max	100.000000	362.000000

[6]:
```
# time cycles
train[index_names].groupby('unit_nr').max().describe()
```

[6]:

	time_cycles
count	100.000000
mean	206.310000
std	46.342749
min	128.000000
25%	177.000000
50%	199.000000
75%	229.250000
max	362.000000

[7]:
```
# settings
train[setting_names].describe()
```

[7]:

	setting_1	setting_2	setting_3
count	20631.000000	20631.000000	20631.0
mean	-0.000009	0.000002	100.0
std	0.002187	0.000293	0.0
min	-0.008700	-0.000600	100.0
25%	-0.001500	-0.000200	100.0
50%	0.000000	0.000000	100.0
75%	0.001500	0.000300	100.0
max	0.008700	0.000600	100.0

[8]:
```
# sensor values
train[sensor_names].describe().transpose()
```

[8]:

	count	mean	std	min	25%	50%	\
s_1	20631.0	518.670000	6.537152e-11	518.6700	518.6700	518.6700	
s_2	20631.0	642.680934	5.000533e-01	641.2100	642.3250	642.6400	
s_3	20631.0	1590.523119	6.131150e+00	1571.0400	1586.2600	1590.1000	
s_4	20631.0	1408.933782	9.000605e+00	1382.2500	1402.3600	1408.0400	
s_5	20631.0	14.620000	3.394700e-12	14.6200	14.6200	14.6200	
s_6	20631.0	21.609803	1.388985e-03	21.6000	21.6100	21.6100	
s_7	20631.0	553.367711	8.850923e-01	549.8500	552.8100	553.4400	

```
s_8   20631.0  2388.096652  7.098548e-02  2387.9000  2388.0500  2388.0900
s_9   20631.0  9065.242941  2.208288e+01  9021.7300  9053.1000  9060.6600
s_10  20631.0     1.300000  4.660829e-13     1.3000     1.3000     1.3000
s_11  20631.0    47.541168  2.670874e-01    46.8500    47.3500    47.5100
s_12  20631.0   521.413470  7.375534e-01   518.6900   520.9600   521.4800
s_13  20631.0  2388.096152  7.191892e-02  2387.8800  2388.0400  2388.0900
s_14  20631.0  8143.752722  1.907618e+01  8099.9400  8133.2450  8140.5400
s_15  20631.0     8.442146  3.750504e-02     8.3249     8.4149     8.4389
s_16  20631.0     0.030000  1.556432e-14     0.0300     0.0300     0.0300
s_17  20631.0   393.210654  1.548763e+00   388.0000   392.0000   393.0000
s_18  20631.0  2388.000000  0.000000e+00  2388.0000  2388.0000  2388.0000
s_19  20631.0   100.000000  0.000000e+00   100.0000   100.0000   100.0000
s_20  20631.0    38.816271  1.807464e-01    38.1400    38.7000    38.8300
s_21  20631.0    23.289705  1.082509e-01    22.8942    23.2218    23.2979

            75%        max
s_1    518.6700   518.6700
s_2    643.0000   644.5300
s_3   1594.3800  1616.9100
s_4   1414.5550  1441.4900
s_5     14.6200    14.6200
s_6     21.6100    21.6100
s_7    554.0100   556.0600
s_8   2388.1400  2388.5600
s_9   9069.4200  9244.5900
s_10     1.3000     1.3000
s_11    47.7000    48.5300
s_12   521.9500   523.3800
s_13  2388.1400  2388.5600
s_14  8148.3100  8293.7200
s_15     8.4656     8.5848
s_16     0.0300     0.0300
s_17   394.0000   400.0000
s_18  2388.0000  2388.0000
s_19   100.0000   100.0000
s_20    38.9500    39.4300
s_21    23.3668    23.6184
```

[9]:

```python
cols_nan = train.columns[train.isna().any()].tolist()
print('Columns without data: \n' + str(cols_nan) + '\n')
```

```
Columns without data:
[]
```

[10]:

```python
train.count()
```

[10]:

```
unit_nr        20631
time_cycles    20631
setting_1      20631
setting_2      20631
setting_3      20631
s_1            20631
s_2            20631
s_3            20631
s_4            20631
s_5            20631
s_6            20631
s_7            20631
s_8            20631
s_9            20631
s_10           20631
s_11           20631
s_12           20631
s_13           20631
s_14           20631
s_15           20631
s_16           20631
s_17           20631
s_18           20631
s_19           20631
s_20           20631
s_21           20631
dtype: int64
```

3.0.6 Target Variable - Remaining Useful Life (RUL)

[11]:

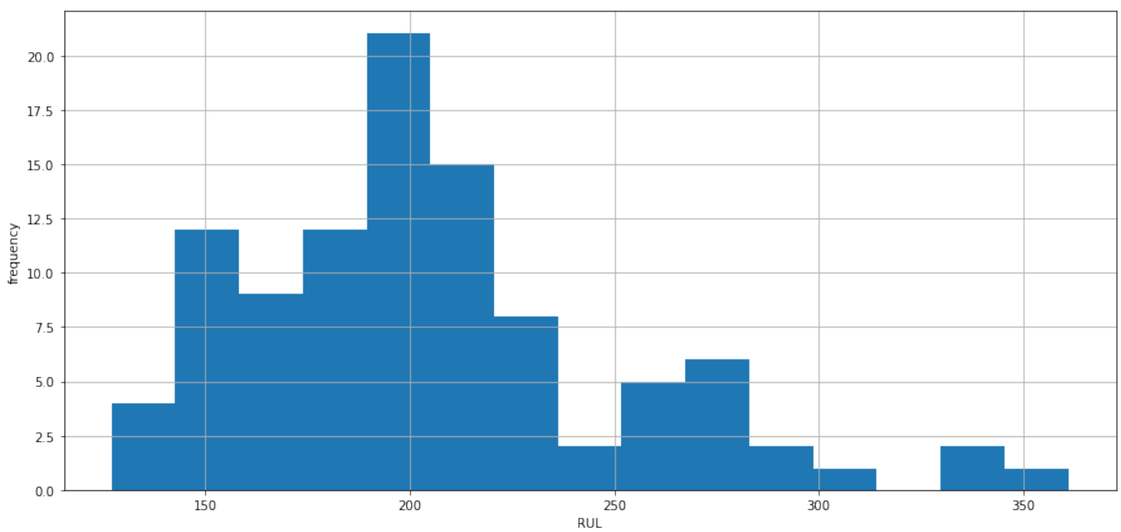
```
#Compute Remaining Useful Life(RUL) of the component
def add_remaining_useful_life(df):
    # Get the total number of cycles for each unit
    grouped_by_unit = df.groupby(by="unit_nr")
    max_cycle = grouped_by_unit["time_cycles"].max()

    # Merge the max cycle back into the original frame
    result_frame = df.merge(max_cycle.to_frame(name='max_cycle'),␣
↪left_on='unit_nr', right_index=True)

    # Calculate remaining useful life for each row
    remaining_useful_life = result_frame["max_cycle"] -␣
↪result_frame["time_cycles"]
    result_frame["RUL"] = remaining_useful_life

    # drop max_cycle as it's no longer needed
    result_frame = result_frame.drop("max_cycle", axis=1)
```

```
    return result_frame

train = add_remaining_useful_life(train)
train[index_names+['RUL']].head()
```

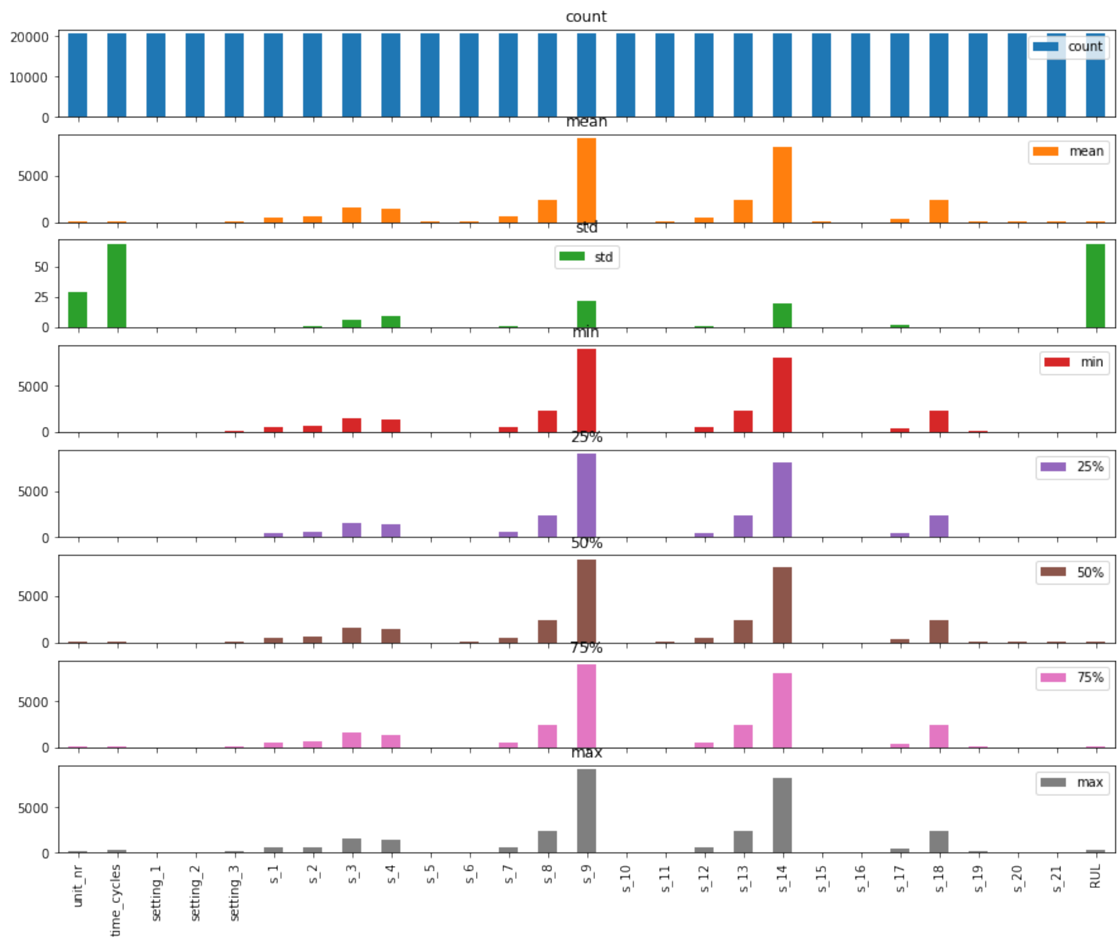
[11]:

	unit_nr	time_cycles	RUL
0	1	1	191
1	1	2	190
2	1	3	189
3	1	4	188
4	1	5	187

[12]:
```
df_max_rul = train[['unit_nr', 'RUL']].groupby('unit_nr').max().reset_index()
df_max_rul['RUL'].hist(bins=15, figsize=(15,7))
plt.xlabel('RUL')
plt.ylabel('frequency')
plt.show()
# Most Engines break down around 200 cycles and the distribution is right skewed
```



[13]:
```
# plot of all columns
axes = train.describe().T.plot.bar(subplots=True, figsize=(15,12))
```



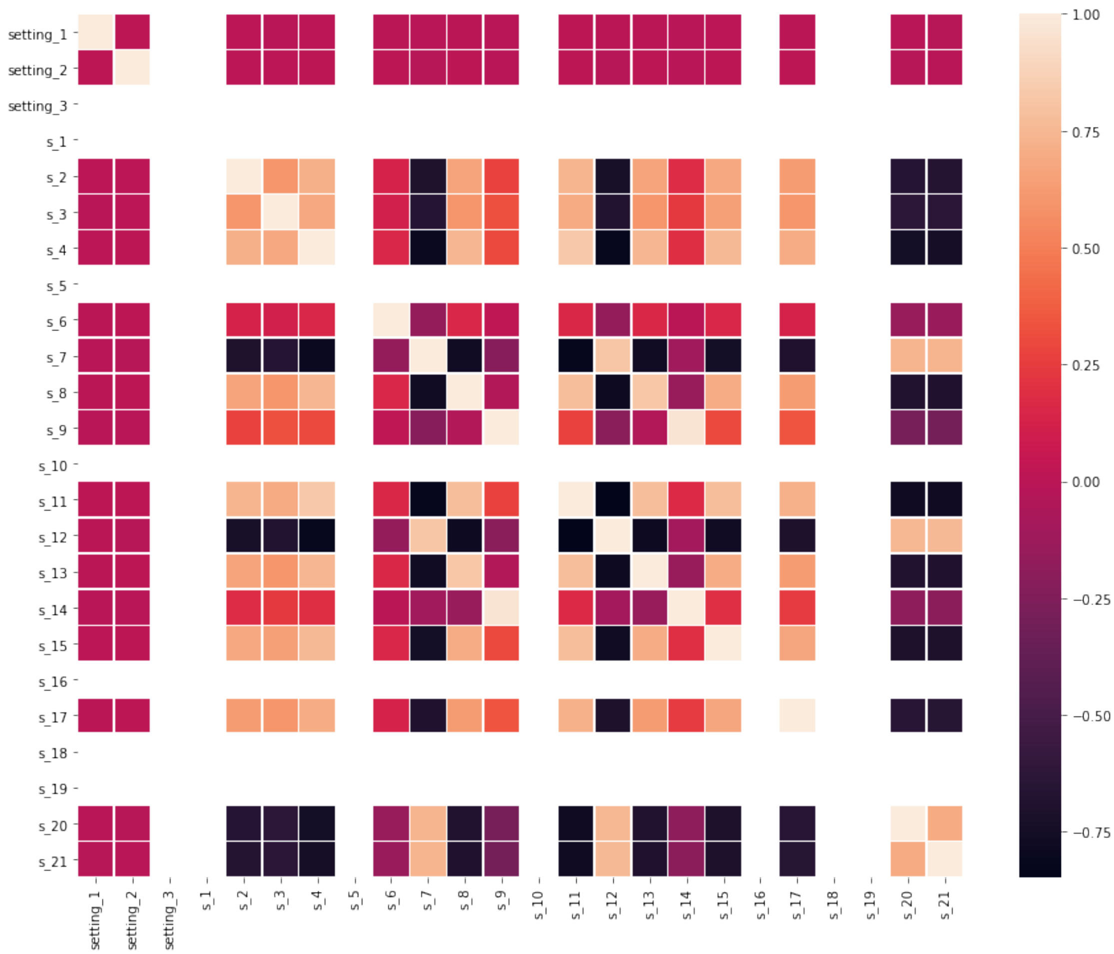
[14]:
```python
#There are a few columns with constant values
cols_const = [ col for col in train.columns if len(train[col].unique()) <= 2 ]
print('Columns with constant values: \n' + str(cols_const) + '\n')
#Columns with constant values:
#['setting_3', 's_1', 's_5', 's_6', 's_10', 's_16', 's_18', 's_19']
```

```
Columns with constant values:
['setting_3', 's_1', 's_5', 's_6', 's_10', 's_16', 's_18', 's_19']
```

3.0.7 Correlations

[15]:
```python
# print correlation heatmap
analysis_corr = train[setting_names + sensor_names].corr(method='pearson')
fig, ax = plt.subplots(figsize=(15,12))
sns.heatmap(analysis_corr, linewidths=.5)
```

[15]: `<AxesSubplot:>`



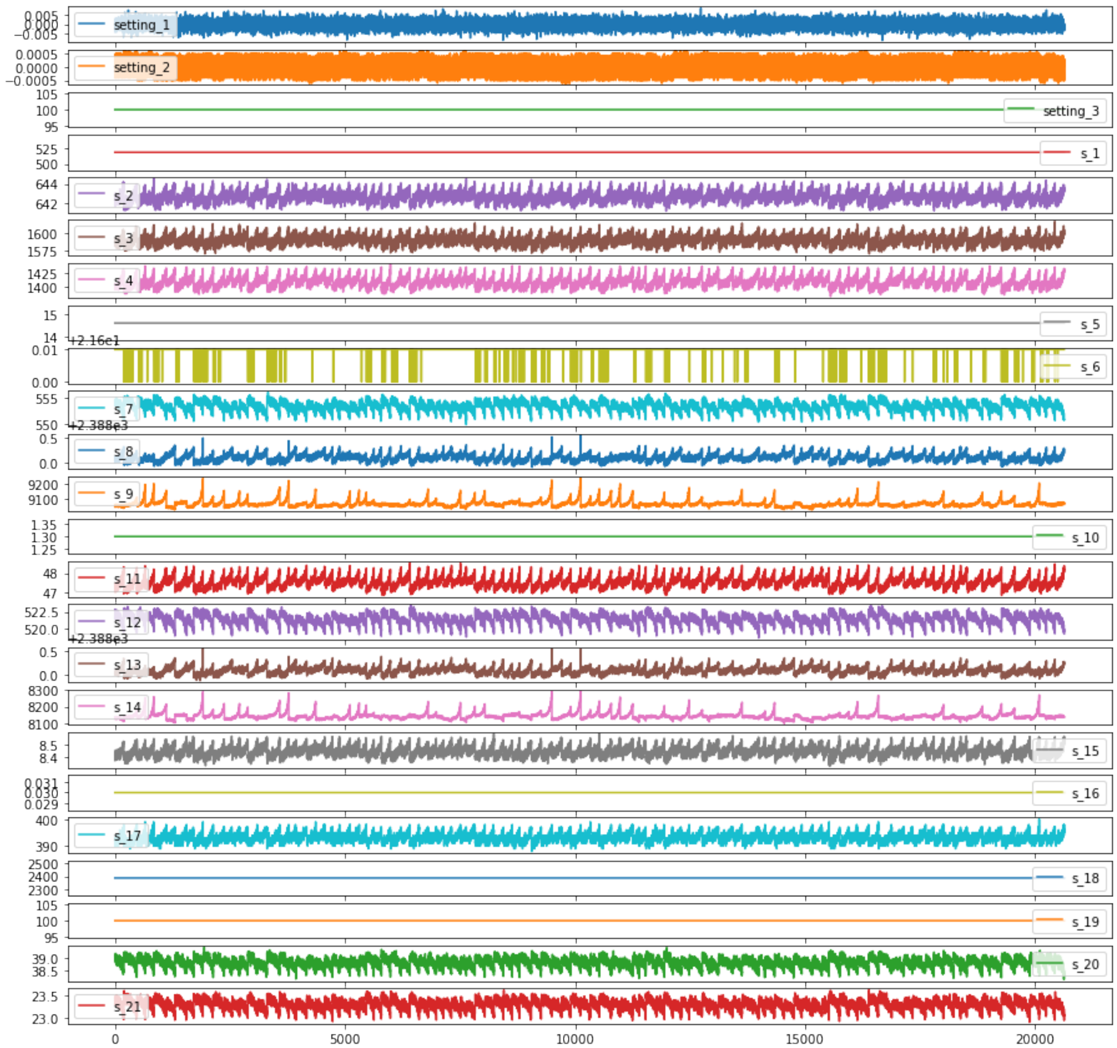
[16]:
```
# print highly correlated values
analysis_corr2 = pd.DataFrame(np.tril(analysis_corr.values),␣
 ↪columns=analysis_corr.columns, index = analysis_corr.index)

correlating = []
for col in analysis_corr2.columns:
    ser = analysis_corr2[col]
    idx = np.logical_or(-0.8 > ser,  ser > 0.8)
    for i, c in zip(ser[idx].index, ser[idx].values):
        if (i, col, c) not in correlating and i != col:
            correlating.append((col, i, c))

print('Highly correlating values:')
for c in correlating:
    print(c)
```

```
Highly correlating values:
('s_4', 's_11', 0.8301356963159815)
```

```
('s_4', 's_12', -0.815590516105214)
('s_7', 's_11', -0.8228050249957691)
('s_7', 's_12', 0.812712601325414)
('s_8', 's_13', 0.8260843322333569)
('s_9', 's_14', 0.9631566003059776)
('s_11', 's_12', -0.8468835930051095)
```

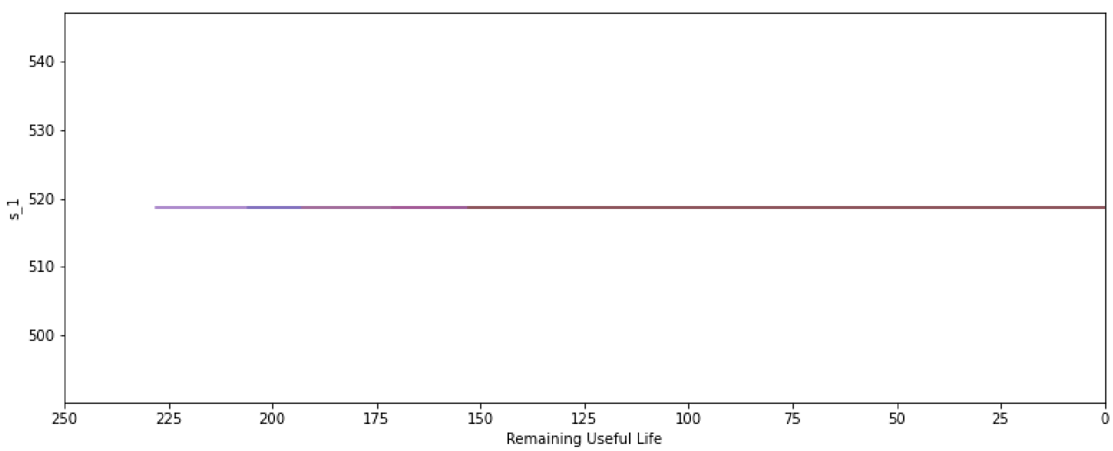
3.0.8 Trends

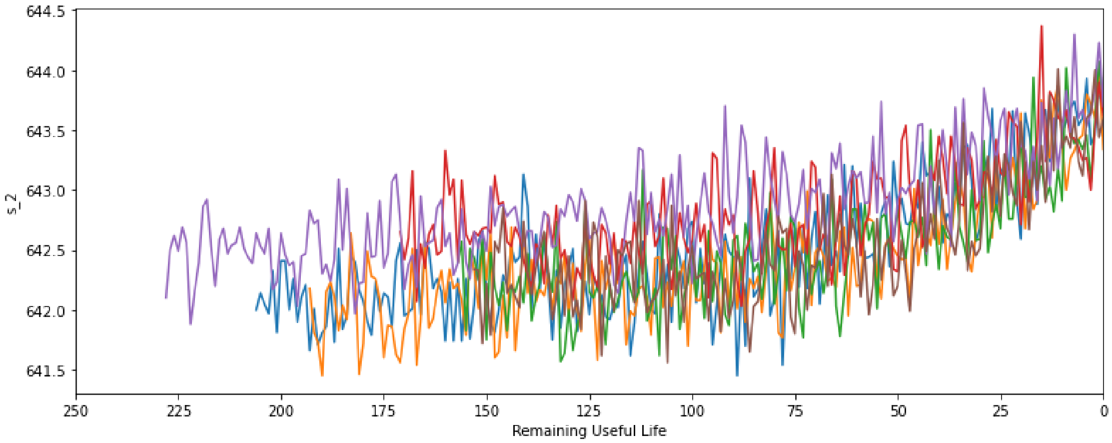
[17]:
```
# plot all train data - settings, sensors
t = train[setting_names + sensor_names].plot(subplots=True, figsize=(15, 15))
```

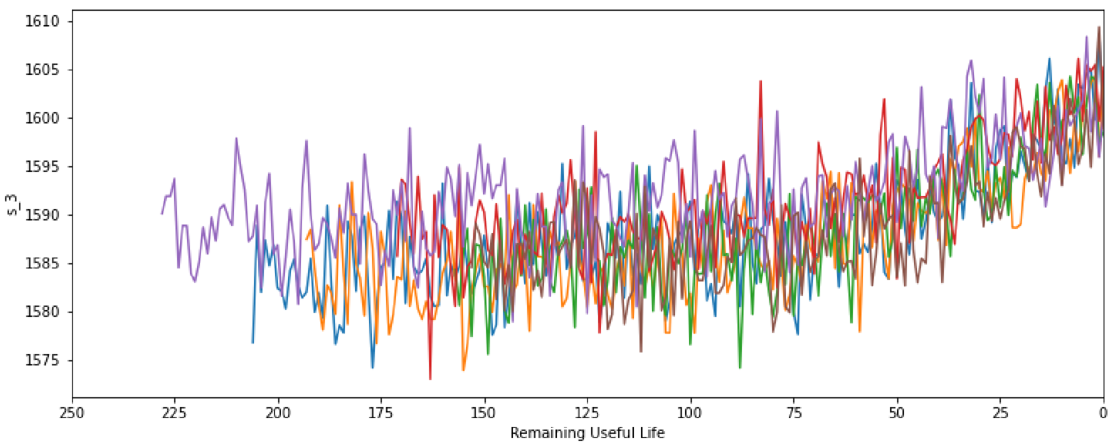


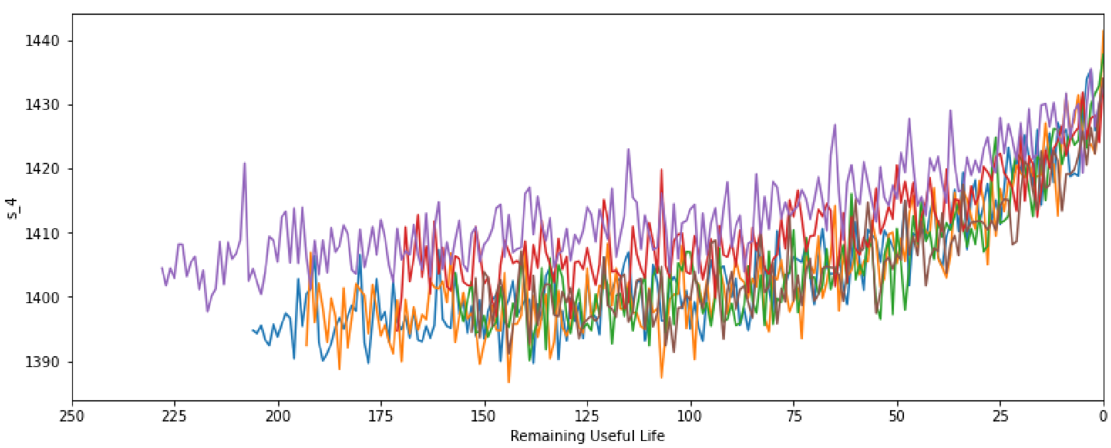
[18]:
```
# Plot each sensor
def plot_sensor(sensor_name):
    plt.figure(figsize=(13,5))
```

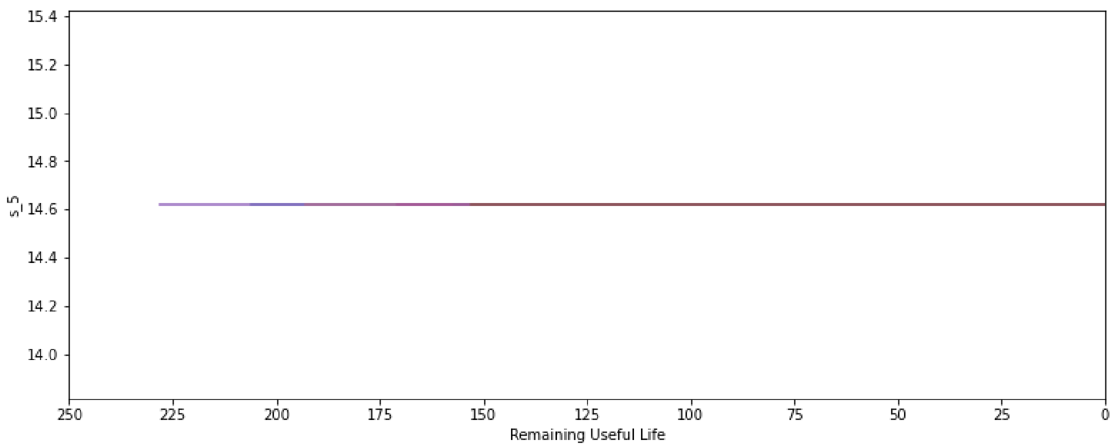
```
    for i in train['unit_nr'].unique():
        if (i % 15 == 0):  # only plot every 10th unit_nr
            plt.plot('RUL', sensor_name,
                     data=train[train['unit_nr']==i])
    plt.xlim(250, 0)  # reverse the x-axis so RUL counts down to zero
    plt.xticks(np.arange(0, 275, 25))
    plt.ylabel(sensor_name)
    plt.xlabel('Remaining Useful Life')
    plt.show()

for sensor_name in sensor_names:
    plot_sensor(sensor_name)

# Plot Sensors w.r.t RUL and observe the trends
# Constant : Sensors 1, 5, 10, 16, 18, 19
# Rising Trend : Sensors 2, 3, 4, 8, 11, 13, 15, 17
# Declining Trend: Sensor 7, 12, 20, 21
# Others:
#        Sensor 6 peaks downwards.
#        Sensors 9, 14 display similar pattern, gradual change for a while and
 ↪then abrupt increase or decrease.
```

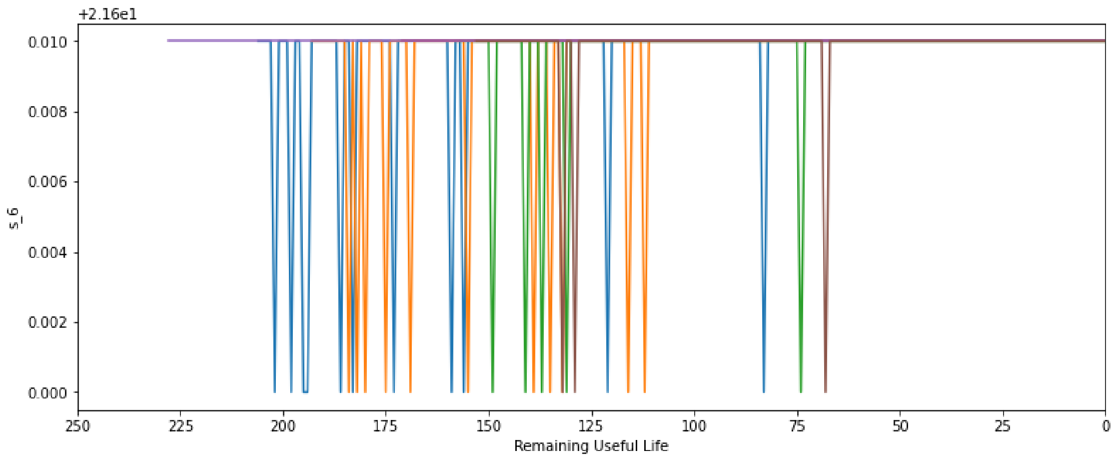


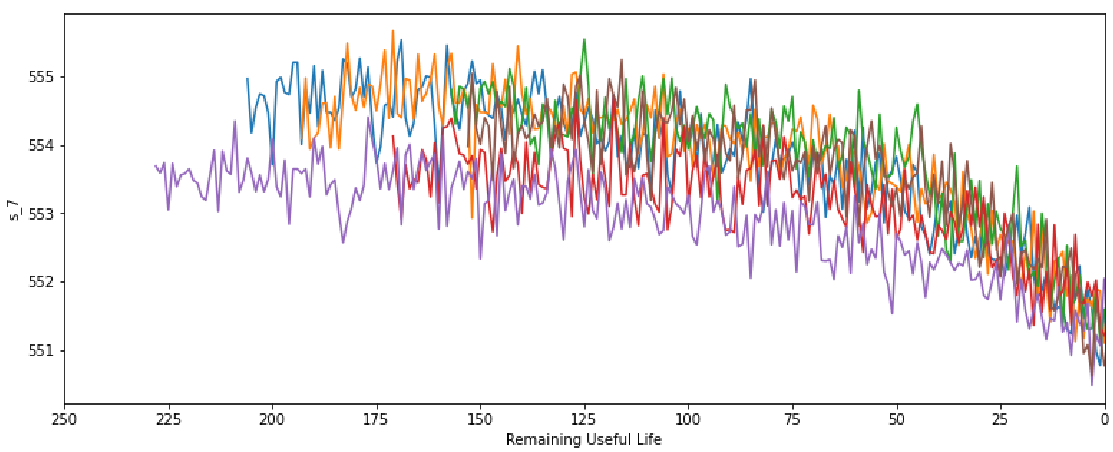

644.5
644.0
643.5
643.0
642.5
642.0
641.5
s_2
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life

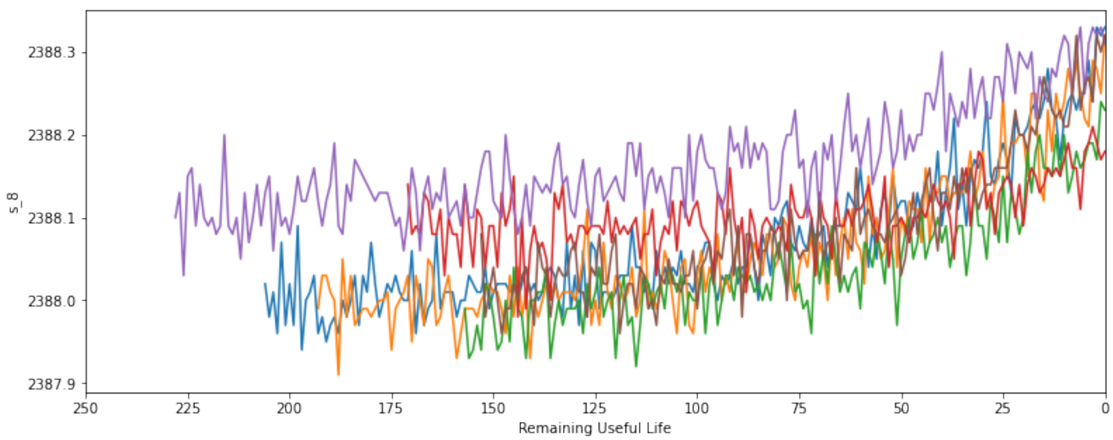

1610
1605
1600
1595
1590
1585
1580
1575
s_3
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life


1440
1430
1420
1410
1400
1390
s_4
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life


15.4
15.2
15.0
14.8
14.6
14.4
14.2
14.0
s_5
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life


+2.16e1
0.010
0.008
0.006
0.004
0.002
0.000
s_6
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life


555
554
553
552
551
s_7
250
225
200
175
150
125
100
75
50
25
0
Remaining Useful Life



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2387.9
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25
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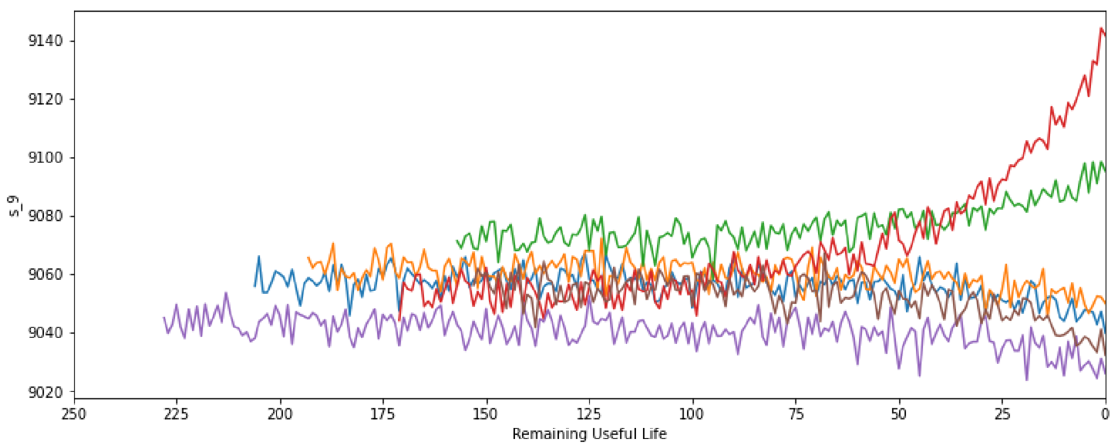
Remaining Useful Life



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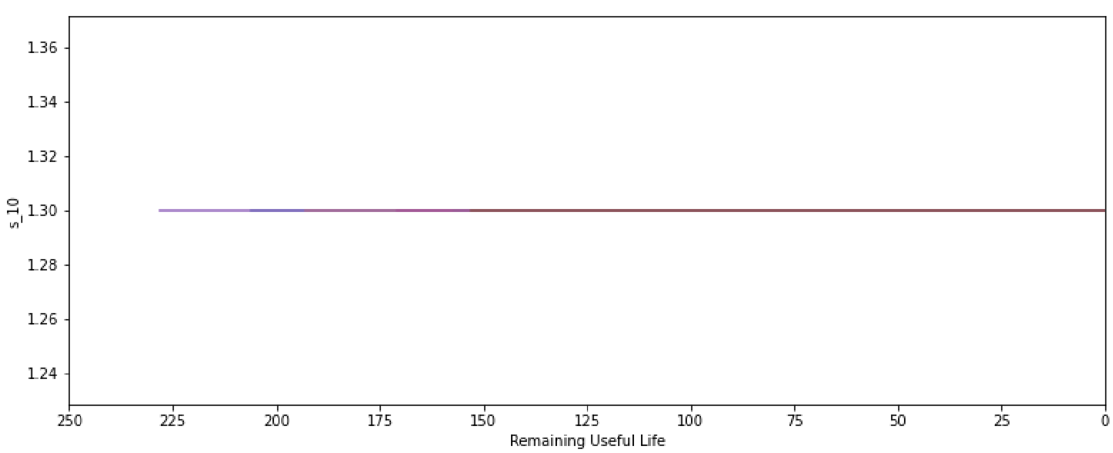

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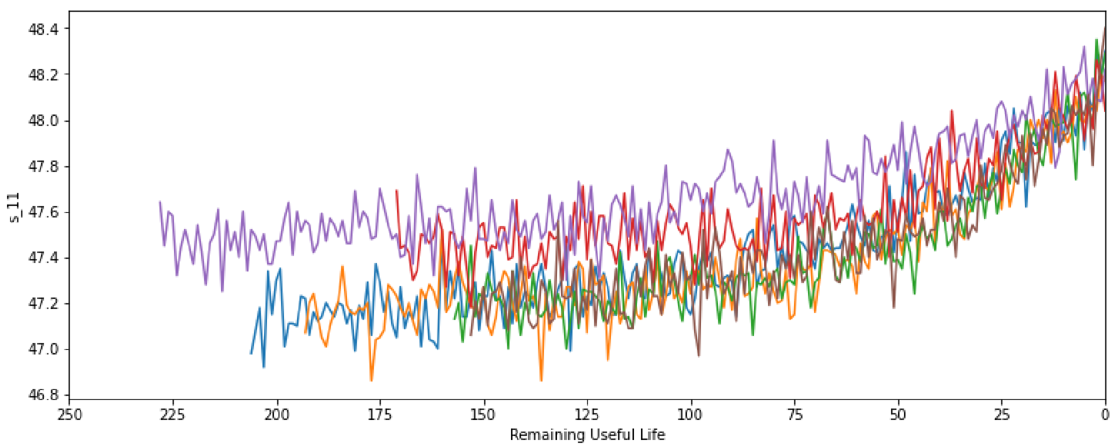
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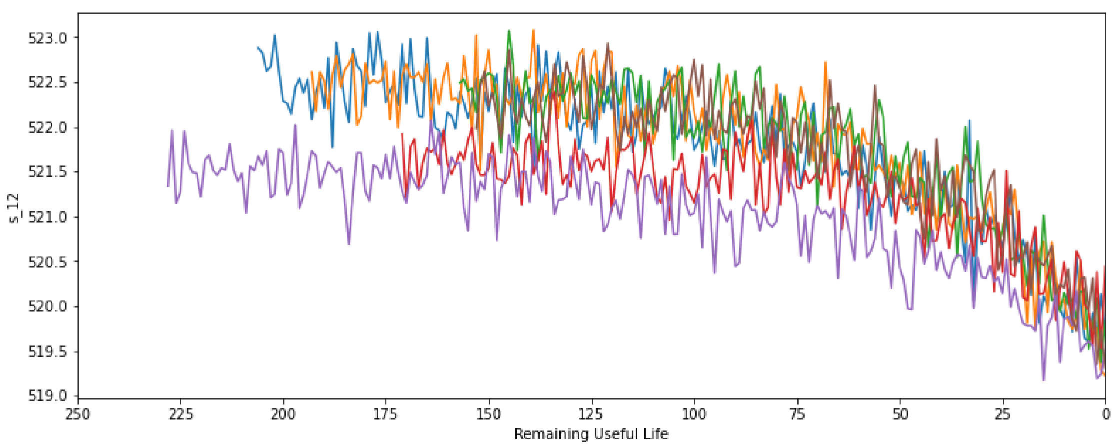
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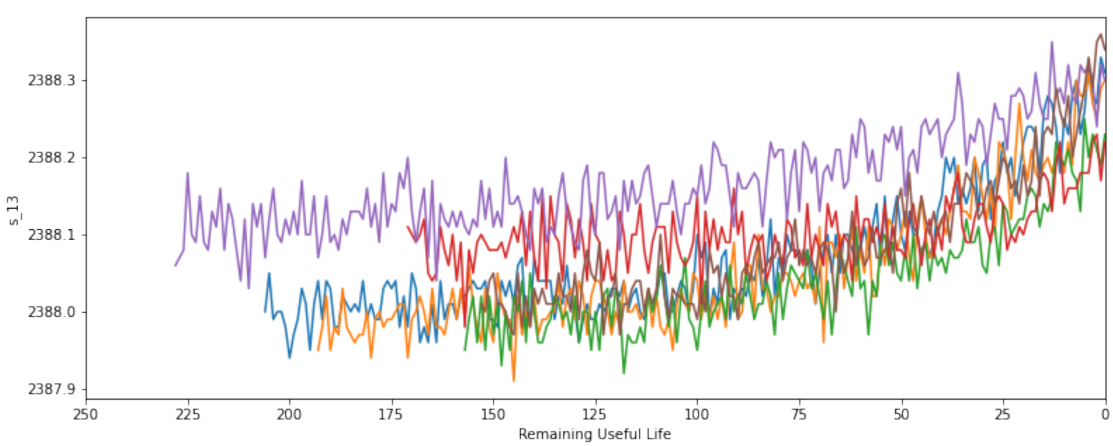
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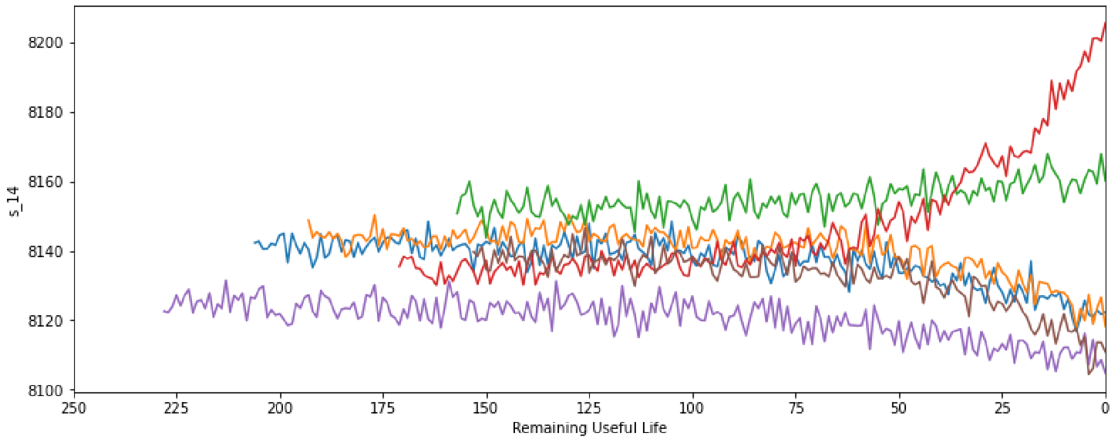
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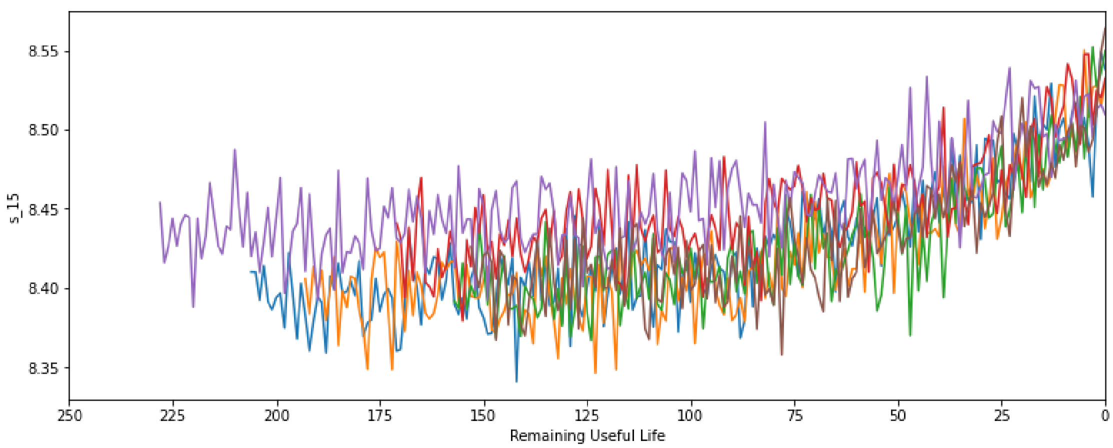
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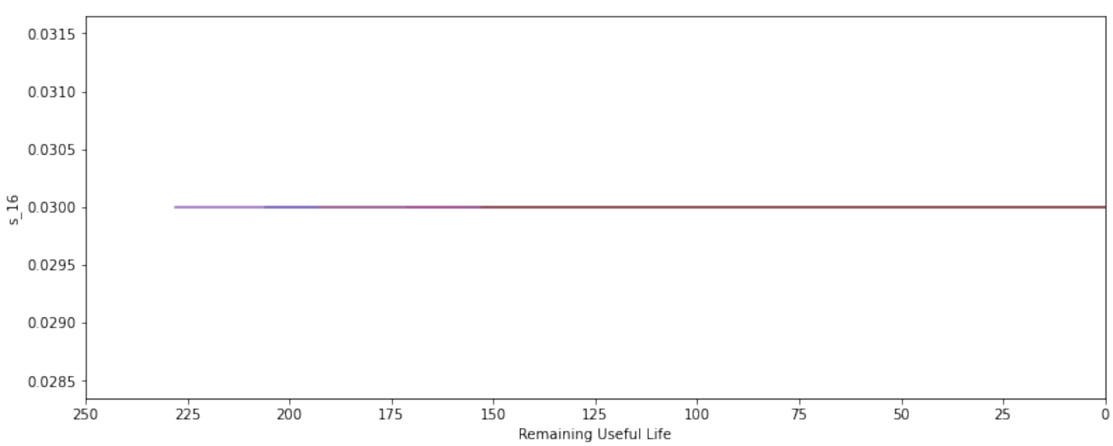
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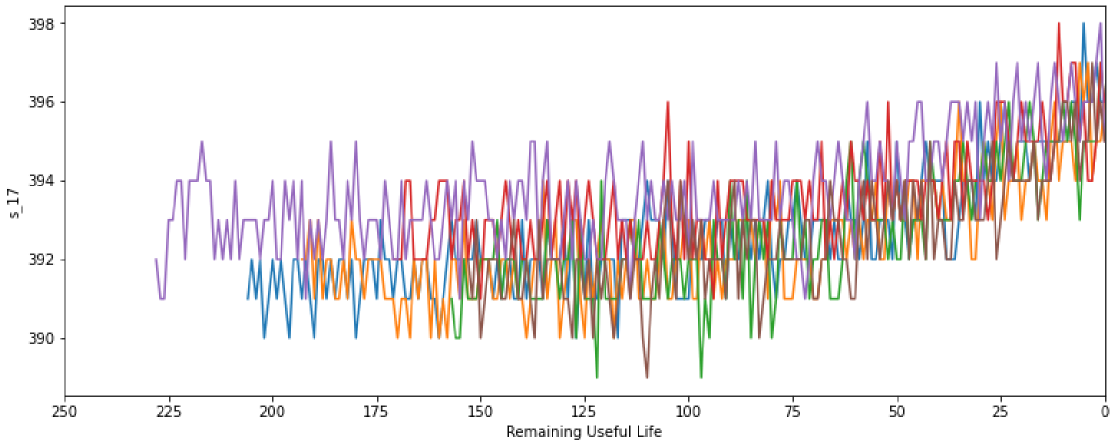
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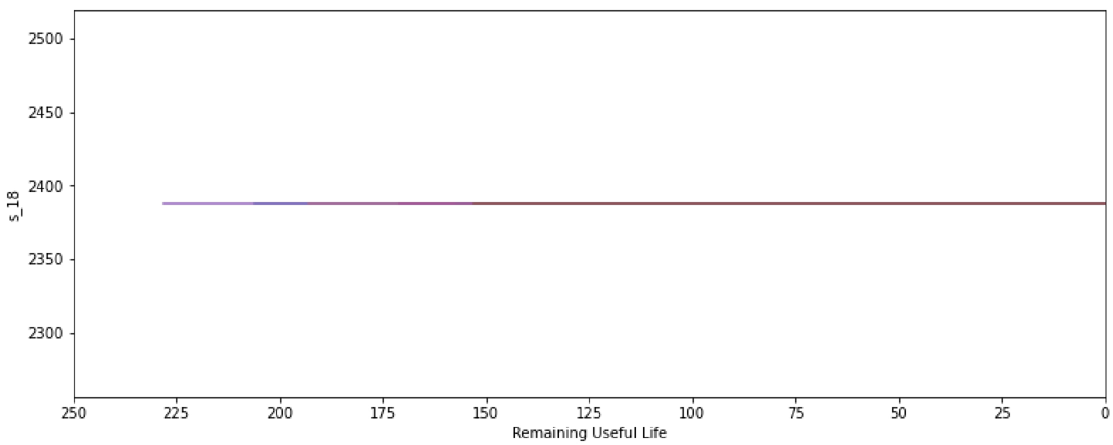
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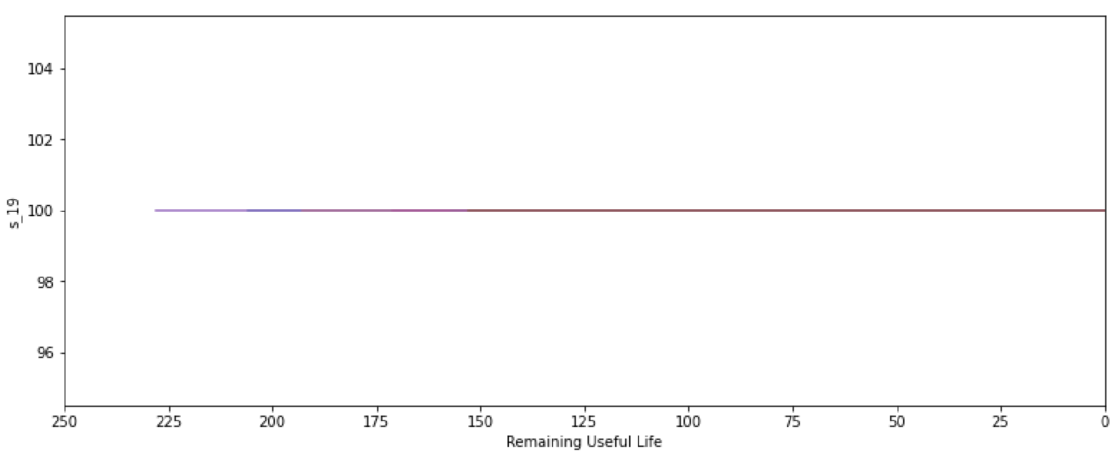
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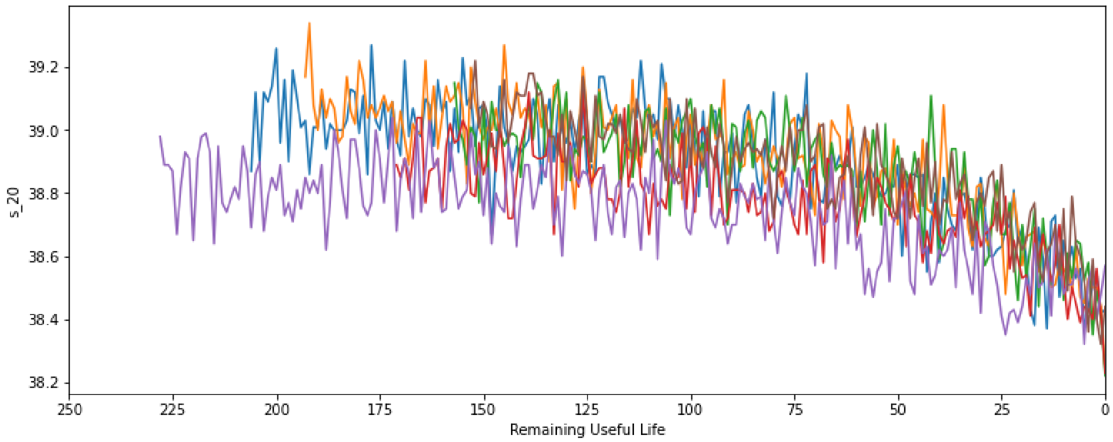
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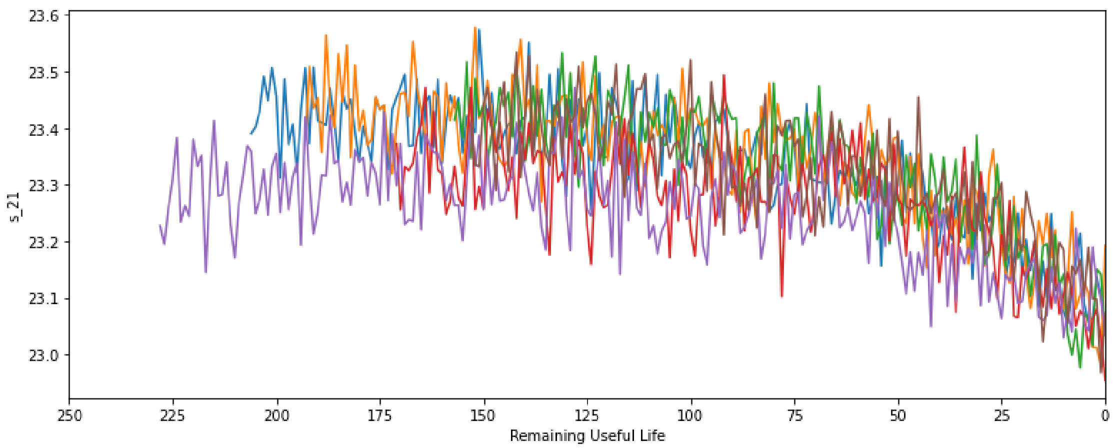
Remaining Useful Life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23.1
23.0
s_21
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100
75
50
25
0
Remaining Useful Life

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