PHM Data Challenge 2008 : Remaining Useful Lifetime Estimation from Sensor Data

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Introduction:

Amidst many potential uses for machine learning algorithms, data scientists are often interested in the ability to make **predictions** about when events will happen. These predictions can range from weather to hardware failures, as can be found in multiple online data challenges for community members to undertake. One of these challenges, from 2008, was posted by NASA and GE and focuses on the use of sensor data from jet propulsion engines to predict the remaining useful life of the engine itself.

In this challenge, NASA and GE put out a set of training and test data containing unit identifiers, three parameters defining the operational mode of the engine, and sensor data for 21 embedded sensors over multiple operating cycles. In this walkthrough, we will explore the construction of a model for predicting the remaining useful life of the engines with this data.

Some of what we'll go through is based upon my personal approach to modelling systems, which tends to stay on the conservative side. Often, my approach is to chose the simplest possible model to start from. You can always make the model more complex as needed, but simpler models are often better to start and can give you more direct insights into system behavior. So with that, let's dive in.

Loading Packages and Data

Let's start by loading in our data and packages for use. We'll load the data in as if it were a csv file. Since there are no textual delimiters other than spaces, we'll let Pandas know that, as well as defining useful header names.

In [1]:
```python
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from mpl_toolkits import mplot3d
from sklearn.cluster import KMeans
import seaborn as sns
from mlxtend.plotting import scatterplotmatrix as spm
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import pickle
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score
import scipy
import statsmodels.api as sm
from statsmodels.formula.api import ols
import itertools

os.chdir(r'C:\Users\jacob\Desktop\Challenge_Data')
```

In [2]:

```
df_train = pd.read_csv('train.txt', header=None, delimiter=r"\s+")
df_train.columns = [
    'Unit Number',
    'Time in Cycles',
    'OS1',
    'OS2',
    'OS3',
    'SM1',
    'SM2',
    'SM3',
    'SM4',
    'SM5',
    'SM6',
    'SM7',
    'SM8',
    'SM9',
    'SM10',
    'SM11',
    'SM12',
    'SM13',
    'SM14',
    'SM15',
    'SM16',
    'SM17',
    'SM18',
    'SM19',
    'SM20',
    'SM21'
]
df_train.head()
```

Out[2]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM12	
0	1	1	10.0047	0.2501	20.0	489.05	604.13	1499.45	1309.95	10.52	...	372.15	23
1	1	2	0.0015	0.0003	100.0	518.67	642.13	1584.55	1403.96	14.62	...	521.81	23
2	1	3	34.9986	0.8401	60.0	449.44	555.42	1368.17	1122.49	5.48	...	183.26	23
3	1	4	20.0031	0.7005	0.0	491.19	607.03	1488.44	1249.18	9.35	...	314.84	23
4	1	5	42.0041	0.8405	40.0	445.00	549.52	1354.48	1124.32	3.91	...	130.44	23

5 rows × 26 columns

In [3]:
```
df_test = pd.read_csv('test.txt', header=None, delimiter=r"\s+")
df_test.columns = [
    'Unit Number',
    'Time in Cycles',
    'OS1',
    'OS2',
    'OS3',
    'SM1',
    'SM2',
    'SM3',
    'SM4',
    'SM5',
    'SM6',
    'SM7',
    'SM8',
    'SM9',
    'SM10',
    'SM11',
    'SM12',
    'SM13',
    'SM14',
    'SM15',
    'SM16',
    'SM17',
    'SM18',
    'SM19',
    'SM20',
    'SM21'
]
df_test.head()
```

Out[3]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM12	
0	1	1	0.0016	0.0002	100.0	518.67	642.88	1587.21	1412.44	14.62	...	521.44	23
1	1	2	24.9993	0.6215	80.0	462.54	536.45	1262.64	1055.44	7.05	...	164.32	20
2	1	3	0.0004	0.0000	100.0	518.67	642.65	1589.75	1409.54	14.62	...	521.15	23
3	1	4	10.0034	0.2500	20.0	489.05	604.44	1499.93	1315.34	10.52	...	371.42	23
4	1	5	0.0024	0.0011	100.0	518.67	642.74	1585.47	1408.12	14.62	...	520.86	23

5 rows × 26 columns

Quality Checking Training Data

Next, we'll check the data for any missing data, as well as outputting the maximum number of cycles associated with each engine. This will give us some idea what we are dealing with.

In [4]:

```python
unique_units = df_train['Unit Number'].unique()

output_df = []

for uu in unique_units:
    sub_df = df_train[df_train['Unit Number']==uu]
    max_cycles = sub_df['Time in Cycles'].max()
    cols = list(sub_df.columns)
    nan_flag = False
    for col in cols:
        if len(sub_df[sub_df[col].isna()]) > 0:
            missing_data += len(sub_df[sub_df[col]].isna())
            nan_flag = True
    if nan_flag == False:
        sub_list = [uu, 0, max_cycles]
    else:
        sub_list = [uu, missing_data, max_cycles]
    output_df.append(sub_list)

output_df
```

Out[4]:

```
[[1, 0, 223],
 [2, 0, 164],
 [3, 0, 150],
 [4, 0, 159],
 [5, 0, 357],
 [6, 0, 225],
 [7, 0, 168],
 [8, 0, 276],
 [9, 0, 181],
 [10, 0, 228],
 [11, 0, 210],
 [12, 0, 242],
 [13, 0, 210],
 [14, 0, 147],
 [15, 0, 178],
 [16, 0, 172],
 [17, 0, 228],
 [18, 0, 196],
 [19, 0, 167],
```

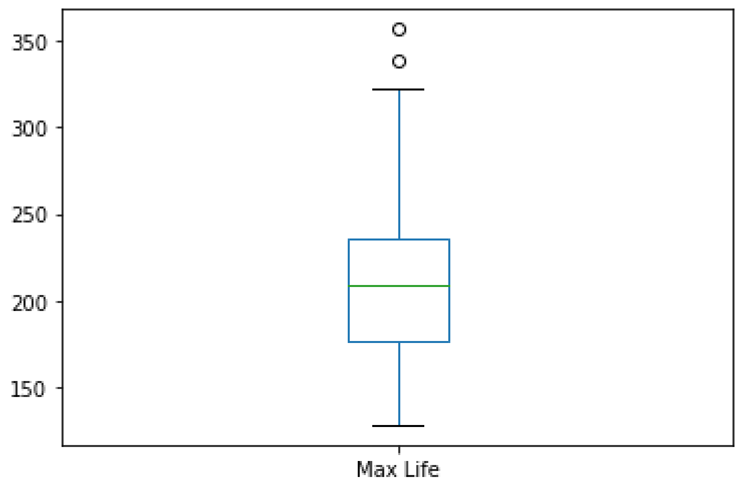
This is good! We don't have any missing (NA or NAN) data for any of the engines. However, we have a high degree of variation in the number of cycles of data that we have available. This may cause an issue for our modelling later, because the variation can introduce noise that will make model building more difficult or introduce error.

To better see this variation, let's look at a box plot of the maximum number of cycles.

In [5]:
```
cycles_total = []
for unit in unique_units:
    cycles_total.append(df_train[df_train['Unit Number']==unit]['Time in Cyc

plot_df = pd.DataFrame(cycles_total, columns=['Max Life'])
plot_df.plot(kind='box',y='Max Life')
```

Out[5]: <AxesSubplot:>



Now it's more clear that we have a large spread with a few statistical outliers in the data. We'll have to keep this in mind for later on.

Converting Cycles to account for variable "starting condition"

For now, since we know that the maximum cycle number should correspond to failure of that unit, we'll convert the cycles to start from negative numbers, which will make 0 our failure point.

In [6]:
```
max_cycles_train = {x:df_train[df_train['Unit Number']==x]['Time in Cycles']
max_cycles_test = {x:df_test[df_test['Unit Number']==x]['Time in Cycles'].ma

df_train['MaxCycles'] = df_train['Unit Number'].apply(lambda x: max_cycles_t
df_test['MaxCycles'] = df_train['Unit Number'].apply(lambda x: max_cycles_tr
df_train['RevCycles'] = df_train['Time in Cycles'] - df_train['MaxCycles']
df_test['RevCycles'] = df_test['Time in Cycles'] - df_test['MaxCycles']

df_train.head()
```

Out[6]:

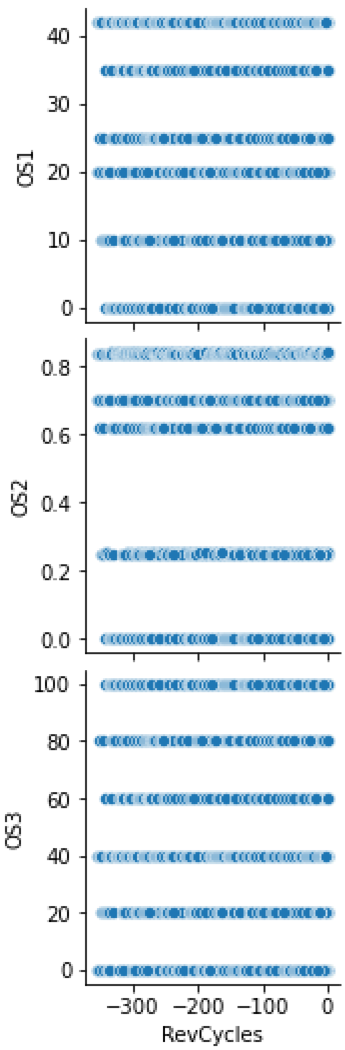
	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM14	
0	1	1	10.0047	0.2501	20.0	489.05	604.13	1499.45	1309.95	10.52	...	8120.83	8
1	1	2	0.0015	0.0003	100.0	518.67	642.13	1584.55	1403.96	14.62	...	8132.87	8
2	1	3	34.9986	0.8401	60.0	449.44	555.42	1368.17	1122.49	5.48	...	8063.84	9
3	1	4	20.0031	0.7005	0.0	491.19	607.03	1488.44	1249.18	9.35	...	8052.30	9
4	1	5	42.0041	0.8405	40.0	445.00	549.52	1354.48	1124.32	3.91	...	8083.67	9

5 rows × 28 columns

Exploring Sensor and Operations Data

Now that we've taken (at least temporarily) of the cycles issue, let's look at our operations mode and sensor data. Starting with the Operations Mode data, we can look at the variation with cycles.

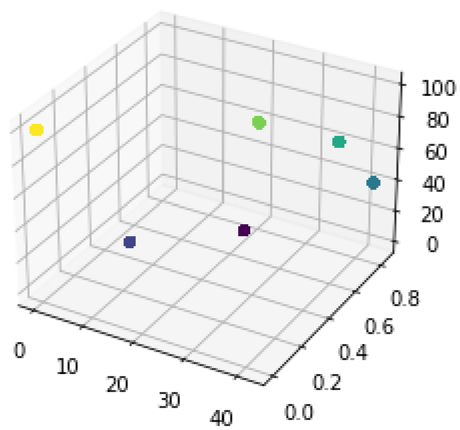
In [7]:
```
pp = sns.pairplot(
    data=df_train,
    x_vars = ['RevCycles'],
    y_vars = [x for x in df_train.columns if ('OS' in x)],
    diag_kind = None
)
```



This is interesting. OS1 shows no variation at all with the cycle, whereas OS2 and OS3 look very clustered and well separated from each other. Let's 3D plot this to see if our clustering holds more broadly.

In [8]:
```
fig = plt.figure()
ax = plt.axes(projection='3d')
xdata = df_train['OS1']
ydata = df_train['OS2']
zdata = df_train['OS3']
ax.scatter3D(xdata,ydata,zdata,c=zdata, cmap='viridis')
```

Out[8]: <mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x1cbd36734c0>



Now we've confirmed our suspicion. We have six (the last one is yellow in the top left) clusters of operations modes that are well separated from each other. That means that we should be able to apply a K-Means technique so that we can reduce the operations modes into a single variable indicating which cluster the data is associated with.

In [9]:

```
km = KMeans(
    n_clusters=6, init='random',
    n_init=10, max_iter=300,
    tol=1e-04, random_state=0
)

X = df_train[['OS1','OS2','OS3']]

y_km = km.fit_predict(X)

df_train['cluster'] = y_km

df_train.head()
```

Out[9]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM15	SI
0	1	1	10.0047	0.2501	20.0	489.05	604.13	1499.45	1309.95	10.52	...	8.6216	(
1	1	2	0.0015	0.0003	100.0	518.67	642.13	1584.55	1403.96	14.62	...	8.3907	(
2	1	3	34.9986	0.8401	60.0	449.44	555.42	1368.17	1122.49	5.48	...	9.3557	(
3	1	4	20.0031	0.7005	0.0	491.19	607.03	1488.44	1249.18	9.35	...	9.2231	(
4	1	5	42.0041	0.8405	40.0	445.00	549.52	1354.48	1124.32	3.91	...	9.2986	(

5 rows × 29 columns

Exploring Training Sensor Data - with Clustering

Our data is now clustered using the K-Means classifier that we trained in above. Now, let's look to see if this resulted in any trends we can take advantage of.

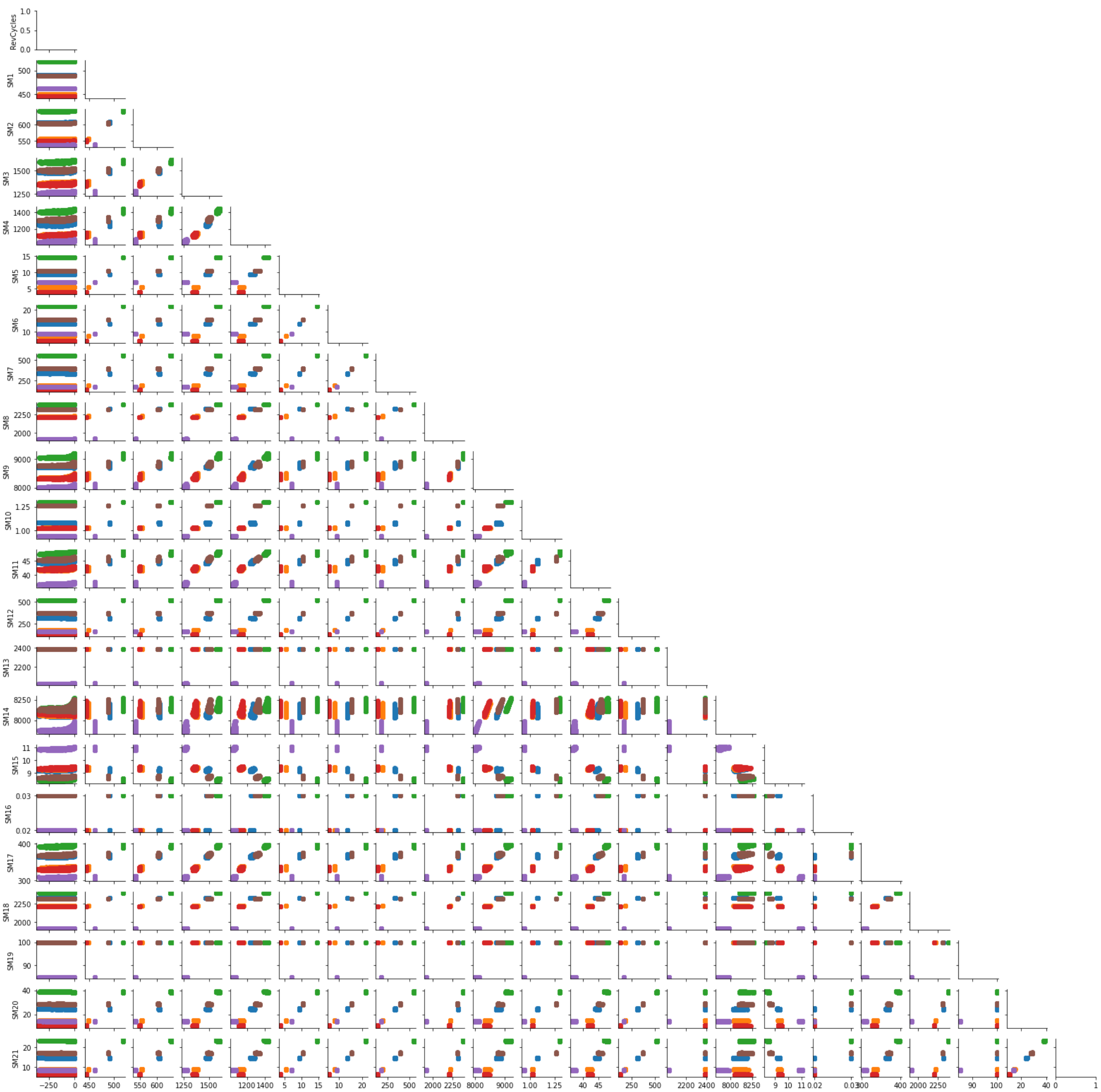
In [10]:

```
features = ['RevCycles','cluster','SM1','SM2','SM3','SM4','SM5','SM6','SM7',
sub_df = df_train[features]

def hide_axis(*args, **kwds):
    plt.gca().set_visible(False)

g = sns.PairGrid(sub_df, hue='cluster', vars=[x for x in features if x != 'c
g.map_lower(plt.scatter)
g.map_upper(hide_axis)
g.map_diag(hide_axis)
g
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x1cbd3379ee0>



With our handy color-coded plot, we can easily see that the clusters we formed in the previous step, we have separated out grouping of units that were subject to similar operating conditions. So, since the clusters help us to identify those, let's see if we can normalize out the clustering. This will allow us to develop a more robust model.

In addition to this cluster, we can see that several of the measurements correlate strongly with each other. For example, SM21 correlates well with SM6, SM7, SM12, and SM20. This broadly indicates that principal components can help us in this situation, but first we want to make sure that we have confidence our sensor measurements are continuous variables as opposed to some discrete variable, such as an open or closed vent. We'll play with this further in a little bit.

In [11]:

```
red_sensors = ['cluster','SM1','SM2','SM3','SM4','SM5','SM6','SM7','SM8','SM

means = df_train[red_sensors].groupby('cluster').mean()
stds = df_train[red_sensors].groupby('cluster').std()

norm_train_df = df_train.copy()


for sensor in [x for x in red_sensors if x != 'cluster']:
    mn = sensor+'_mean'
    sn = sensor+'_std'
    norm_train_df[mn] = norm_train_df['cluster'].apply(lambda x: means[senso
    norm_train_df[sn] = norm_train_df['cluster'].apply(lambda x: stds[sensor
    norm_train_df[sensor] = (norm_train_df[sensor]-norm_train_df[mn])/norm_t

norm_train_df.head()
```

Out[11]:

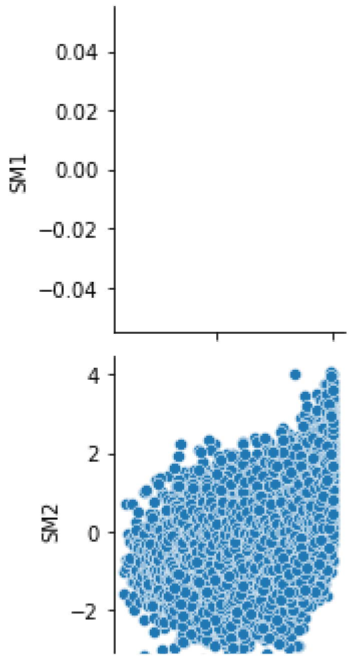
	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM17_
0	1	1	10.0047	0.2501	20.0	inf	-1.665632	-0.460749	-0.168926	inf	...	369.72
1	1	2	0.0015	0.0003	100.0	inf	-1.201429	-1.040821	-0.626306	inf	...	393.26
2	1	3	34.9986	0.8401	60.0	inf	-0.920577	0.218738	-1.283192	-inf	...	334.28
3	1	4	20.0031	0.7005	0.0	inf	-1.212605	0.422369	-0.577304	inf	...	365.44
4	1	5	42.0041	0.8405	40.0	NaN	-0.456453	-0.034709	-0.513961	-inf	...	331.11

5 rows × 71 columns

After performing the normalization, we can see immediately that several of our sensor measurements "normalized" out, meaning that the values exploded (due to a non-existent standard deviation). This means there was no predictive value in those sensors anyway, so it's not a huge loss and it simplifies our modelling going forward. Let's have another look at the normalized data to see what we've got left.

In [12]:

```
pp = sns.pairplot(
    data=norm_train_df,
    x_vars = 'RevCycles',
    y_vars = [x for x in norm_train_df.columns if ('SM' in x) and ('_mean' n
    diag_kind=None
)
```



With our closer look, it is easy to see that SM1, SM5, SM18, and SM19 have been effectively normalized out as factors, so we can drop those features. In addition, since we are going to attempt PCA as a step for developing our model, we do not want to maintain categorical or discrete features. As a result, we will also need to drop SM6, SM10, and SM16, as those are clearly not continuous features.

In [13]:

```
cols_to_drop = ['OS1','OS2','OS3','SM1','SM5','SM6','SM10','SM16','SM18','SM
cols_to_drop2 = [x for x in norm_train_df.columns if ('_mean' in x) or ('_st
red_norm_train_df = norm_train_df.drop(columns=cols_to_drop)
red_norm_train_df = red_norm_train_df.drop(columns=cols_to_drop2)

red_norm_train_df.head()
```

Out[13]:

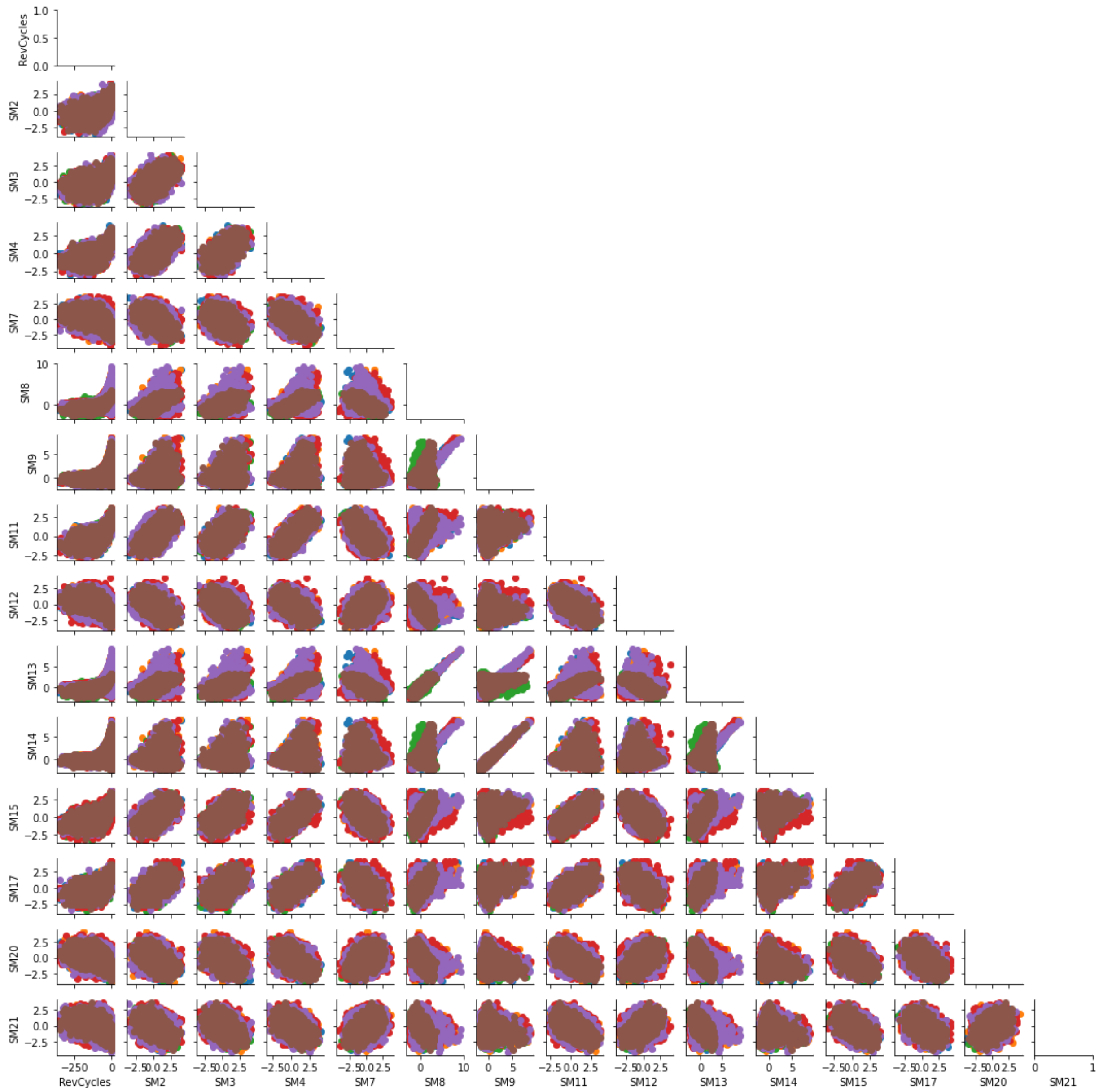
	Unit Number	SM2	SM3	SM4	SM7	SM8	SM9	SM11	SM12
0	1	-1.665632	-0.460749	-0.168926	0.854709	-0.979729	-0.778572	-0.381652	1.356057
1	1	-1.201429	-1.040821	-0.626306	0.423932	-1.379841	-0.837832	-1.033286	0.637697
2	1	-0.920577	0.218738	-1.283192	1.060663	-0.561667	-0.646282	-0.335412	0.668876
3	1	-1.212605	0.422369	-0.577304	0.608356	-1.335711	-0.431113	-0.877818	-0.016306
4	1	-0.456453	-0.034709	-0.513961	-0.856394	-0.500056	-0.689555	-1.595426	-0.271838

At this point, let's take one last look over the remaining features for correlations and to see if the normalization we did actually removed the clustering.

In [14]:
```
sub_df = red_norm_train_df[['SM2','SM3','SM4','SM7','SM8','SM9','SM11','SM12
def hide_axis(*args, **kwds):
    plt.gca().set_visible(False)

g2 = sns.PairGrid(sub_df, hue='cluster', vars=['RevCycles','SM2','SM3','SM4'
g2.map_lower(plt.scatter)
g2.map_upper(hide_axis)
g2.map_diag(hide_axis)
g2
```

Out[14]: <seaborn.axisgrid.PairGrid at 0x1cbd349f970>



Now, we can see that this process did remove the operating mode as a separating factor, since all the clusters have collapsed. We can see in this correlation plot that a few of the modes did show a clear difference based upon operating mode, which hasn't been removed from our data. However, for the time being, we will move past that and proceed with our modelling.

Our next step will be to drop features that do not appear to help us, beyond the non-continuous or non-variant ones we already attacked. In the plot above, we can see that sensors SM8-SM13 and SM9-SM14 correlate well, meaning that they are effectively measuring the same thing. For this process, we'll drop 8 and 9, since we don't need redundant information, as that will bias our predictor later.

In [15]:
```
red_norm_train_df = red_norm_train_df.drop(['SM8','SM9'], axis=1)
red_norm_train_df.head()
```

Out[15]:

	Unit Number	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14
0	1	-1.665632	-0.460749	-0.168926	0.854709	-0.381652	1.356057	-0.360213	-0.822667
1	1	-1.201429	-1.040821	-0.626306	0.423932	-1.033286	0.637697	0.652737	-0.472019
2	1	-0.920577	0.218738	-1.283192	1.060663	-0.335412	0.668876	-0.544988	-0.461147
3	1	-1.212605	0.422369	-0.577304	0.608356	-0.877818	-0.016306	-0.651533	-0.817049
4	1	-0.456453	-0.034709	-0.513961	-0.856394	-1.595426	-0.271838	-0.429268	-0.286493

There are many approaches that we could take at this point, but our goal is to make a linear or polynomial model, so we'd like to reduce the sensor data down to a "health index" or something of the sort that will enable us to make predictions. We can do this via a polynomial fit to the combination of sensors that we have retained, if we assume that (within the training data) the health index starts a 1 (full health) and ends at 0 (no health). We have to do some mathematical gymnatstics to make this work.

In [16]:

```python
ntrain_df = red_norm_train_df.copy()

cycles = {}

for i in ntrain_df['Unit Number'].unique():
    cycles[i] = min(ntrain_df[ntrain_df['Unit Number']==i]['RevCycles'])

ntrain_df['MC'] = ntrain_df['Unit Number'].apply(lambda x: cycles[x])
ntrain_df['Marker'] = ntrain_df['MC'].apply(lambda x: int(abs(x))) - ntrain_
ntrain_df['Marker2'] = ntrain_df['Marker'] + ntrain_df['MC'] +20
ntrain_df['H1'] = np.nan
ntrain_df['H1'] = ntrain_df['Marker'].apply(lambda x: 1.5 if x <= 0 else 1.0
ntrain_df['H2'] = np.nan
ntrain_df['H2'] = ntrain_df['Marker2'].apply(lambda x: 0.5 if x >= 0 else 1.
ntrain_df['Health'] = ntrain_df['H1'] + ntrain_df['H2'] - 1.5
ntrain_df['Health'] = ntrain_df['Health'].apply(lambda x: np.nan if x==0.5 e
ntrain_df.head(20)
```

Out[16]:

	Unit Number	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14
0	1	-1.665632	-0.460749	-0.168926	0.854709	-0.381652	1.356057	-0.360213	-0.822667
1	1	-1.201429	-1.040821	-0.626306	0.423932	-1.033286	0.637697	0.652737	-0.472019
2	1	-0.920577	0.218738	-1.283192	1.060663	-0.335412	0.668876	-0.544988	-0.461147
3	1	-1.212605	0.422369	-0.577304	0.608356	-0.877818	-0.016306	-0.651533	-0.817049
4	1	-0.456453	-0.034709	-0.513961	-0.856394	-1.595426	-0.271838	-0.429268	-0.286493
5	1	-0.486520	-0.966456	0.668783	0.091537	-0.283821	1.047487	-0.803946	-0.761349
6	1	-0.342574	-0.043535	0.428604	1.108920	-0.315426	-1.088904	-0.459980	-0.386247
7	1	-1.304856	-0.192467	-0.210731	0.201810	-0.215623	0.539062	-1.091965	-0.447119
8	1	-0.022372	-0.764258	-1.193000	0.692816	-0.994350	0.510881	-0.365006	-0.480912
9	1	0.249594	-0.262440	-0.412026	-0.562727	-1.083426	-0.622009	-0.367845	-0.150083
10	1	1.527464	-0.438970	0.146589	1.038239	-0.693545	2.837130	-0.209030	-0.872313
11	1	0.058195	-1.130501	-0.171901	1.313273	-0.553111	1.065126	-0.544988	-0.464357
12	1	0.431799	-0.666706	-0.618543	1.063740	-0.102092	0.195056	-0.459980	-0.400669
13	1	0.988765	-0.000609	0.067263	-0.100448	0.332612	0.200784	-0.569443	-0.577081
14	1	-0.608196	-0.732594	-1.065369	0.931431	-0.421704	0.765058	-0.465179	-0.596457
15	1	-0.650494	-0.285254	0.004579	0.179555	0.098972	1.432315	-0.885043	-0.423924
16	1	-0.849781	-1.037428	0.077767	0.809722	-0.449241	1.144960	-0.074222	-0.441783
17	1	-1.454145	0.076058	-0.818365	-0.019922	-1.583211	1.127284	-1.094975	-0.914685
18	1	-0.598981	-1.447201	0.453795	-1.015863	-1.719703	2.075519	-0.605485	-0.691044
19	1	-0.829095	-1.587161	-1.143772	0.119976	-0.682859	0.369974	-0.655789	-0.508776

20 rows × 21 columns

Let's check, for a random engine, to ensure that our mathematical double bar exercise did the trick. For engine #4, we get:

In [17]:
```
ntrain_df[ntrain_df['Unit Number']==4].head(20)
```

Out[17]:

	Unit Number	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14
537	4	-1.284771	-0.336519	-0.634036	0.534392	-0.509571	0.431125	-0.544988	-0.302576
538	4	-1.221509	0.148321	-0.208688	1.038841	-1.302848	0.326575	-0.990009	-0.560673
539	4	-0.375560	-0.646567	-1.118384	0.716609	-0.581912	1.203541	-1.304907	-0.567702
540	4	0.149243	-0.363044	-0.131244	-0.265540	-1.336825	1.540627	-0.512014	-0.436109
541	4	-1.010022	-1.697815	-1.275020	0.931431	-0.501808	0.955703	-0.780077	-0.846949
542	4	-1.676381	-0.646715	-0.893297	1.998308	-0.926763	-0.092144	-0.461319	-0.544193
543	4	-0.925427	-0.108039	-1.284660	0.593854	-1.222744	1.470444	-0.780077	-0.283981
544	4	1.640875	-1.187996	-0.995699	0.145151	-0.506971	1.255322	-0.569443	-0.364453
545	4	-1.967636	-1.017327	-1.059579	-0.223438	-1.206206	0.959459	-0.446067	-0.307712
546	4	-1.477912	-0.391322	-0.948104	1.462455	-1.253268	-0.238607	-0.425278	-0.770588
547	4	0.153158	-0.452146	-0.755710	-0.234743	-1.022484	0.707865	-0.675111	-0.563229
548	4	-0.849563	-0.594014	-1.063176	1.475277	-0.495963	0.679251	-0.956360	-0.710772
549	4	-0.819683	-0.102877	-0.061691	0.563165	-0.501808	0.860381	-0.045314	-0.219441
550	4	0.109834	0.910420	-1.212041	0.011188	-0.600258	0.610882	-0.317154	-0.078399
551	4	-0.661434	-2.710989	-1.048787	0.002019	-1.467426	0.953760	-0.429268	-0.136261
552	4	-1.665632	-0.149332	-0.971387	1.069530	-0.221444	0.059673	-0.570145	-0.362579
553	4	-0.740744	0.521613	-0.789452	0.926603	-0.973407	1.020980	-0.497361	-0.674982
554	4	-1.707929	-0.780769	-0.308694	0.685920	-0.341600	-0.359746	-0.570145	-0.715313
555	4	-0.401098	0.067331	-0.881134	0.324939	-0.326249	1.252062	-0.651533	-0.420751
556	4	0.251597	-0.273155	-1.121178	0.055842	-0.460328	0.581589	-0.533402	-0.273436

20 rows × 21 columns

In [18]:
```python
ntrain_df[ntrain_df['Unit Number']==4].tail(20)
```

Out[18]:

	Unit Number	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14	
676	4	0.851065	0.655879	1.123927	-1.262818	1.861259	-0.988874	1.004346	0.873907	1
677	4	1.433930	0.960953	2.238277	-0.607906	1.903241	0.340961	0.768488	0.644945	0
678	4	0.081481	1.890062	0.817251	-1.574043	1.172196	-1.263853	0.764085	0.674978	2
679	4	0.773451	-0.188505	1.573863	-1.508933	0.946602	-0.098136	1.101221	1.072888	1
680	4	2.087521	1.519513	0.283838	-0.499627	1.108214	-1.954985	0.943520	0.789575	0
681	4	1.320052	0.978606	1.197748	-3.296095	1.519241	-1.263989	0.891335	0.726070	0
682	4	1.971947	0.167247	1.995066	-1.984004	1.981415	-0.359746	1.424211	0.808728	1
683	4	1.782638	1.148660	1.682620	0.658676	2.105066	-0.385071	0.800127	1.307508	1
684	4	1.612419	0.334139	2.130015	-1.707805	2.462039	-2.247129	1.004346	0.920555	1
685	4	0.376865	1.426509	1.126413	-0.581303	1.754492	-1.180295	1.103701	0.919122	1
686	4	1.673816	2.157475	1.843103	-2.697462	2.509923	-1.954985	0.798128	0.873168	2
687	4	0.932865	2.106669	2.414346	-0.924164	1.732575	-1.760065	0.860623	1.028937	1
688	4	2.236280	1.585115	2.054729	-0.859572	2.058423	-2.289099	1.232622	1.036751	2
689	4	1.901928	0.931376	1.432695	-0.076083	2.102810	-0.546293	1.532361	1.517453	2
690	4	1.316337	2.873652	1.787824	-1.186096	2.061519	-2.037420	1.844075	1.862457	0
691	4	2.046150	2.052279	2.950159	-1.914191	3.171841	-1.616809	1.234304	1.352194	3
692	4	1.691735	0.935782	1.950767	-1.575620	1.752741	-3.228142	2.396735	1.523604	1
693	4	2.311646	-0.437314	1.416432	-0.749709	2.712365	0.431125	1.796151	1.857063	2
694	4	1.093783	2.780587	2.363565	-3.426164	1.710312	-1.898401	2.930181	1.547932	1
695	4	2.236280	2.231222	3.260478	-1.283789	2.011779	-1.937586	1.773242	1.965279	2

20 rows × 21 columns

Great! That did it. So, now we can drop all of the excess columns that we don't need anymore.

In [19]:
```
red_train_df = ntrain_df.copy().drop(['Unit Number','cluster','RevCycles','M
red_train_df.head()
```

Out[19]:

	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14	SM15
0	-1.665632	-0.460749	-0.168926	0.854709	-0.381652	1.356057	-0.360213	-0.822667	-1.170261
1	-1.201429	-1.040821	-0.626306	0.423932	-1.033286	0.637697	0.652737	-0.472019	-1.468330
2	-0.920577	0.218738	-1.283192	1.060663	-0.335412	0.668876	-0.544988	-0.461147	0.550747
3	-1.212605	0.422369	-0.577304	0.608356	-0.877818	-0.016306	-0.651533	-0.817049	-0.314185
4	-0.456453	-0.034709	-0.513961	-0.856394	-1.595426	-0.271838	-0.429268	-0.286493	-2.132310

Just to verify that this worked, let's check the correlation between the various sensors and the health index we've made. Ideally, this should show a strong correlation (either positive or negative and close to 1) between each of the sensors and the 'Health' column.

In [20]:
```
df_corr_ = red_train_df.corr()
df_corr_[['Health']]
```

Out[20]:

	Health
SM2	-0.826437
SM3	-0.816026
SM4	-0.898198
SM7	0.702196
SM11	-0.924286
SM12	0.719411
SM13	-0.519472
SM14	-0.365408
SM15	-0.888004
SM17	-0.838119
SM20	0.673348
SM21	0.674502
Health	1.000000

With this table, we can see that most of the sensors show a strong correlation. The few standouts here are SM13 and SM14. We could also argue that SM20 and SM21 are not strongly correlated. For now, we'll continue as if they are correlated. At this point, we are ready to do a linear regression model for each of these sensors against the health index.

In [21]:

```
fit_m = ols('Health ~ SM2+SM3+SM4+SM7+SM11+SM12+SM13+SM14+SM15+SM17+SM20+SM2
print(fit_m.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Health   R-squared:                       0.914
Model:                            OLS   Adj. R-squared:                  0.914
Method:                 Least Squares   F-statistic:                     4242.
Date:                Tue, 18 May 2021   Prob (F-statistic):               0.00
Time:                        12:17:38   Log-Likelihood:                 2405.2
No. Observations:                4796   AIC:                            -4784.
Df Residuals:                    4783   BIC:                            -4700.
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.7164      0.002    307.786      0.000       0.712       0.721
SM2           -0.0271      0.003     -9.191      0.000      -0.033      -0.021
SM3           -0.0238      0.003     -8.376      0.000      -0.029      -0.018
SM4           -0.0620      0.004    -17.632      0.000      -0.069      -0.055
SM7            0.0129      0.003      4.966      0.000       0.008       0.018
SM11          -0.1123      0.004    -26.981      0.000      -0.120      -0.104
SM12           0.0080      0.003      2.970      0.003       0.003       0.013
SM13           0.0042      0.002      2.012      0.044       0.000       0.008
SM14          -0.0308      0.002    -16.143      0.000      -0.034      -0.027
SM15          -0.0647      0.003    -18.700      0.000      -0.071      -0.058
SM17          -0.0282      0.003     -9.426      0.000      -0.034      -0.022
SM20           0.0068      0.002      2.773      0.006       0.002       0.012
SM21           0.0059      0.002      2.373      0.018       0.001       0.011
==============================================================================
Omnibus:                       84.710   Durbin-Watson:                   0.748
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               84.561
Skew:                           0.302   Prob(JB):                     4.34e-19
Kurtosis:                       2.761   Cond. No.                         9.44
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
```

Based upon the P value listed for these fits, we can see that SM13 and SM21 appear to be the least correlated, but are still significant (P < 0.5). So, now we need to revisit our test data and follow the same process of (1) normalizing out the operating modes and (2) dropping sensors that we chose not to use.

In [22]:
```
1 df_test
```

Out[22]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM1
0	1	1	0.0016	0.0002	100.0	518.67	642.88	1587.21	1412.44	14.62	...	8124.(
1	1	2	24.9993	0.6215	80.0	462.54	536.45	1262.64	1055.44	7.05	...	7865.2
2	1	3	0.0004	0.0000	100.0	518.67	642.65	1589.75	1409.54	14.62	...	8121.1
3	1	4	10.0034	0.2500	20.0	489.05	604.44	1499.93	1315.34	10.52	...	8123.5
4	1	5	0.0024	0.0011	100.0	518.67	642.74	1585.47	1408.12	14.62	...	8118.3
...	...	...	...	...	...	...	...	...	...	...	...	
29815	218	86	35.0013	0.8404	60.0	449.44	556.14	1367.80	1129.58	5.48	...	8065.6
29816	218	87	25.0041	0.6200	80.0	462.54	536.97	1262.93	1051.83	7.05	...	7871.9
29817	218	88	20.0043	0.7000	0.0	491.19	607.93	1492.15	1252.99	9.35	...	8059.6
29818	218	89	20.0037	0.7000	0.0	491.19	607.85	1490.80	1254.70	9.35	...	8062.1
29819	218	90	19.9987	0.7009	0.0	491.19	607.75	1485.63	1256.00	9.35	...	8059.1

29820 rows × 28 columns

First, we'll use our cluster predictor from earlier to determine our clusters in the same manner. Then, we'll normalize them out, so the operating mode becomes irrelevant to further analysis.

In [23]:

```
X = df_test[['OS1','OS2','OS3']]

y_km = km.predict(X)

df_test['cluster'] = y_km

df_test.head()
```

Out[23]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM15
0	1	1	0.0016	0.0002	100.0	518.67	642.88	1587.21	1412.44	14.62	...	8.4363
1	1	2	24.9993	0.6215	80.0	462.54	536.45	1262.64	1055.44	7.05	...	10.8935
2	1	3	0.0004	0.0000	100.0	518.67	642.65	1589.75	1409.54	14.62	...	8.4620
3	1	4	10.0034	0.2500	20.0	489.05	604.44	1499.93	1315.34	10.52	...	8.6815
4	1	5	0.0024	0.0011	100.0	518.67	642.74	1585.47	1408.12	14.62	...	8.4617

5 rows × 29 columns

In [24]:

```
red_sensors = ['cluster','SM2','SM3','SM4','SM7','SM11','SM12','SM13','SM14'

means = df_test[red_sensors].groupby('cluster').mean()
stds = df_test[red_sensors].groupby('cluster').std()

norm_test_df = df_test.copy()


for sensor in [x for x in red_sensors if x != 'cluster']:
    mn = sensor+'_mean'
    sn = sensor+'_std'
    norm_test_df[mn] = norm_test_df['cluster'].apply(lambda x: means[sensor]
    norm_test_df[sn] = norm_test_df['cluster'].apply(lambda x: stds[sensor][
    norm_test_df[sensor] = (norm_test_df[sensor]-norm_test_df[mn])/norm_test

norm_test_df.head()
```

Out[24]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM1
0	1	1	0.0016	0.0002	100.0	518.67	0.892997	-0.261926	1.032688	14.62	...	8138
1	1	2	24.9993	0.6215	80.0	462.54	-1.044447	0.364410	1.389960	7.05	...	7875
2	1	3	0.0004	0.0000	100.0	518.67	0.314783	0.247527	0.602306	14.62	...	8138
3	1	4	10.0034	0.2500	20.0	489.05	-0.743742	-0.035385	1.151085	10.52	...	8132
4	1	5	0.0024	0.0011	100.0	518.67	0.541041	-0.610922	0.391568	14.62	...	8138

5 rows × 53 columns

Now, we extract just the sensors of interest and predict our Health index.

In [25]:

```
df_test_red = norm_test_df.drop(['cluster','Unit Number','Time in Cycles','O
cols_to_drop2 = [x for x in df_test_red if ('_std' in x) or ('_mean') in x]
df_test_red = df_test_red.drop(cols_to_drop2, axis=1)
df_test_red.head()
```

Out[25]:

	SM2	SM3	SM4	SM7	SM11	SM12	SM13	SM14	SM15
0	0.892997	-0.261926	1.032688	-0.527303	0.657835	-0.436072	0.405768	-1.314416	0.269937
1	-1.044447	0.364410	1.389960	-1.102306	0.549642	-0.981839	-1.709345	-1.202889	-0.067083
2	0.314783	0.247527	0.602306	0.893031	0.254289	-0.953378	1.965571	-1.574130	1.154604
3	-0.743742	-0.035385	1.151085	-1.291081	0.135661	-0.521275	1.228810	-0.791137	1.077101
4	0.541041	-0.610922	0.391568	-0.237439	1.111824	-1.470683	0.925702	-1.824950	1.144277

In [26]:
```
df_test['Health'] = fit_m.predict(df_test_red)
df_test.head()
```

Out[26]:

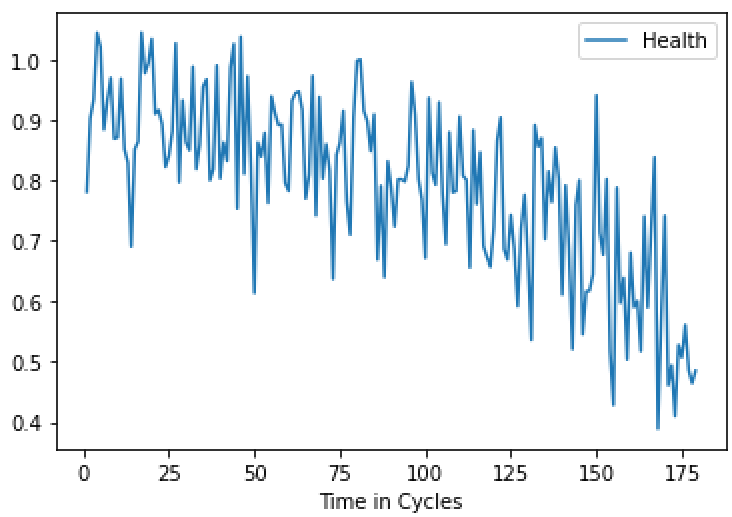
	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM16	SM
0	1	1	0.0016	0.0002	100.0	518.67	642.88	1587.21	1412.44	14.62	...	0.03	3
1	1	2	24.9993	0.6215	80.0	462.54	536.45	1262.64	1055.44	7.05	...	0.02	3
2	1	3	0.0004	0.0000	100.0	518.67	642.65	1589.75	1409.54	14.62	...	0.03	3
3	1	4	10.0034	0.2500	20.0	489.05	604.44	1499.93	1315.34	10.52	...	0.03	3
4	1	5	0.0024	0.0011	100.0	518.67	642.74	1585.47	1408.12	14.62	...	0.03	3

5 rows × 30 columns

With our shiny new Health Index, we can take a look and see what that index looks like against our operating cycles.

In [27]:
```
sub_df = df_test[df_test['Unit Number']==50]
sub_df.plot(x='Time in Cycles',y='Health')
```

Out[27]: <AxesSubplot:xlabel='Time in Cycles'>



We do have a clear trend in our health index. However, it is **very** noisy. We could just continue with the health index as is, but in order to give a more precise predition, we will average out the noise. To do this, we'll use the rolling function chained with the mean function. Following this, we'll use itertools to merge the data in. We alos have to drop empty rows, given that the rolling average will reduce the overall data we have available.

In [28]:

```
def move_avg(df,un):
    tdf = df[df['Unit Number']==un]
    rolling=tdf['Health'].rolling(10).mean()
    return rolling
```

In [29]:

```
rolling_means = [move_avg(df_test,i) for i in df_test['Unit Number'].unique(
df_test = df_test.assign(Health1=list(itertools.chain.from_iterable(rolling_
df_test.dropna(inplace=True)
df_test.head()
```

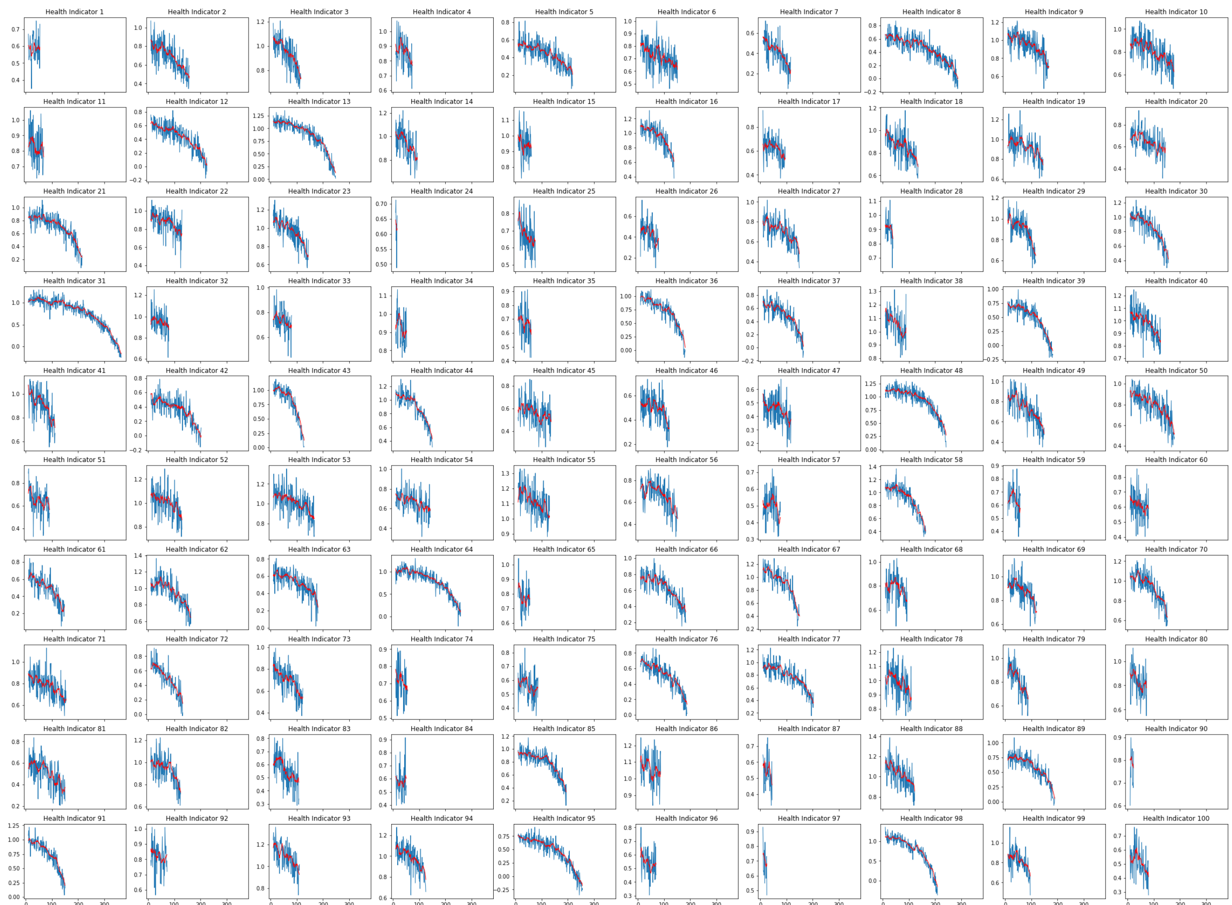
Out[29]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM17	SI
9	1	10	25.0039	0.6200	80.0	462.54	536.93	1263.95	1048.91	7.05	...	306	1
10	1	11	20.0011	0.7000	0.0	491.19	607.69	1480.73	1249.17	9.35	...	365	2
11	1	12	0.0016	0.0009	100.0	518.67	642.10	1593.31	1409.46	14.62	...	393	2
12	1	13	42.0029	0.8400	40.0	445.00	549.53	1360.67	1122.25	3.91	...	332	2
13	1	14	35.0034	0.8400	60.0	449.44	555.98	1358.08	1132.48	5.48	...	334	2

5 rows × 31 columns

Now we can check the health index to see if it looks smoother than the chart above.

In [30]:
```
fig,ax=plt.subplots(10,10,figsize=(40,30),sharex=True)
c=1
for i in range(0,10):
    for j in range(0,10):
        df_un = df_test[df_test['Unit Number']==c]
        ax[i,j].plot(df_un['Time in Cycles'],df_un['Health'],linewidth=1)
        ax[i,j].plot(df_un['Time in Cycles'],df_un['Health1'],linewidth=1,co
        ax[i,j].set_title('Health Indicator '+str(c))
        c+=1
```



From this, we can see that the smoothed health index does appear to be a cleaner approach and will lead to better extrapolations down the road. One other thing to note here is that several of the engines only have a few cycles of test data available for us to fit. These will most certainly be poor fits later, primarily because our approach requires more data than in avaialble.

Now we'll move into the prediction phase, for which we'll need to obtain the actual cycles that each of the above engines ran for. For ease of use in a bit, let's define our scoring function, in accordance with the competition guidance.

In [31]:
```
def scoring_function(error):
    if error >= 0:
        s = np.exp(error/10)-1
        return s
    else:
        s = np.exp(-error/13)-1
        return s
```

Before moving on, we need to import the actual test data, relabel our columns and assemble the actual remaining usable life for each engine, since this is what we'll be predicting against later.

In [32]:
```
df_test_results = pd.read_csv('final_test.txt', header=None, delimiter=r"\s+
df_test_results.head()
```

Out[32]:

	0	1	2	3	4	5	6	7	8	9	...	16	17	
0	1	1	10.0047	0.2501	20.0	489.05	605.02	1498.72	1304.90	10.52	...	371.83	2388.12	8128
1	1	2	0.0015	0.0003	100.0	518.67	642.69	1592.90	1405.35	14.62	...	521.88	2388.09	8128
2	1	3	34.9986	0.8401	60.0	449.44	555.49	1357.71	1127.52	5.48	...	182.97	2387.92	8060
3	1	4	20.0031	0.7005	0.0	491.19	607.62	1479.86	1257.25	9.35	...	315.29	2388.09	8060
4	1	5	42.0041	0.8405	40.0	445.00	549.69	1354.17	1124.17	3.91	...	130.50	2387.84	8080

5 rows × 26 columns

In [33]:

```
df_test_results.columns = [
    'Unit Number',
    'Time in Cycles',
    'OS1',
    'OS2',
    'OS3',
    'SM1',
    'SM2',
    'SM3',
    'SM4',
    'SM5',
    'SM6',
    'SM7',
    'SM8',
    'SM9',
    'SM10',
    'SM11',
    'SM12',
    'SM13',
    'SM14',
    'SM15',
    'SM16',
    'SM17',
    'SM18',
    'SM19',
    'SM20',
    'SM21'
]

df_test_results.head()
```

Out[33]:

	Unit Number	Time in Cycles	OS1	OS2	OS3	SM1	SM2	SM3	SM4	SM5	...	SM12	
0	1	1	10.0047	0.2501	20.0	489.05	605.02	1498.72	1304.90	10.52	...	371.83	23
1	1	2	0.0015	0.0003	100.0	518.67	642.69	1592.90	1405.35	14.62	...	521.88	23
2	1	3	34.9986	0.8401	60.0	449.44	555.49	1357.71	1127.52	5.48	...	182.97	23
3	1	4	20.0031	0.7005	0.0	491.19	607.62	1479.86	1257.25	9.35	...	315.29	23
4	1	5	42.0041	0.8405	40.0	445.00	549.69	1354.17	1124.17	3.91	...	130.50	23

5 rows × 26 columns

With our imported actual lifespans for the test engines, we'll extract the maximum number of cycles that each engine ran for. This will be the number we compare our predictions against, to score this approach. We'll also check that the number of entries we get equates to the number of untis we are expecting.

In [34]:
```
RUL_list = [df_test_results[df_test_results['Unit Number']==x]['Time in Cycl
print(len(RUL_list), len(list(df_test_results['Unit Number'].unique())))
```

```
435 435
```

Now that we've got our actual test data loaded, let's make predictions on the partial test data and see what we get. After that, we'll rework some of the data to make our job easier later on.

In [35]:

```
degrees     = range(6)
degree_fit = []
final_score=[]
estimated_rul_dict={}
roots_dict={}

for i in df_test['Unit Number'].unique():

    uniti = df_test[df_test['Unit Number']==i]

    score = np.empty(len(degrees))

    estimated_rul_dict[i] = {}
    roots_dict[i] = {}

    for d in degrees:
        poly_params = np.polyfit(uniti['Time in Cycles'],uniti['Health1'],d)
        poly_       = np.poly1d(poly_params)
        roots = poly_.r
        roots = roots[np.isreal(roots)].real
        roots = roots[roots>0]

        if roots.shape[0]==1:
            pred_rul = roots - max(uniti['Time in Cycles'])
            errors = pred_rul - RUL_list[i-1]
            score[d]=scoring_function(errors)

            estimated_rul_dict[i][scoring_function(errors).item()] = pred_ru
            roots_dict[i][scoring_function(errors).item()] = roots.item()

        elif roots.shape[0]>1:
            pred_rul = roots[0] - max(uniti['Time in Cycles'])
            errors = pred_rul - RUL_list[i-1]
            score[d]=scoring_function(errors)

            estimated_rul_dict[i][scoring_function(errors).item()] = pred_ru
            roots_dict[i][scoring_function(errors).item()] = roots[0].item()

        else:
            score[d]=scoring_function(7000)


    degree_fit.append(np.argmin(score))
    final_score.append(np.min(score))
```

```
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in ex
p
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in ex
p
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in ex
p
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in ex
p
```

```
  s = np.exp(error/10)-1
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p
  s = np.exp(error/10)-1
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p
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in ex
p
  s = np.exp(error/10)-1
```

Now, we can extract the the best fit value, so that we can create a scoring dataframe in a bit. We'll do the same for the roots of the polynomial fit made.

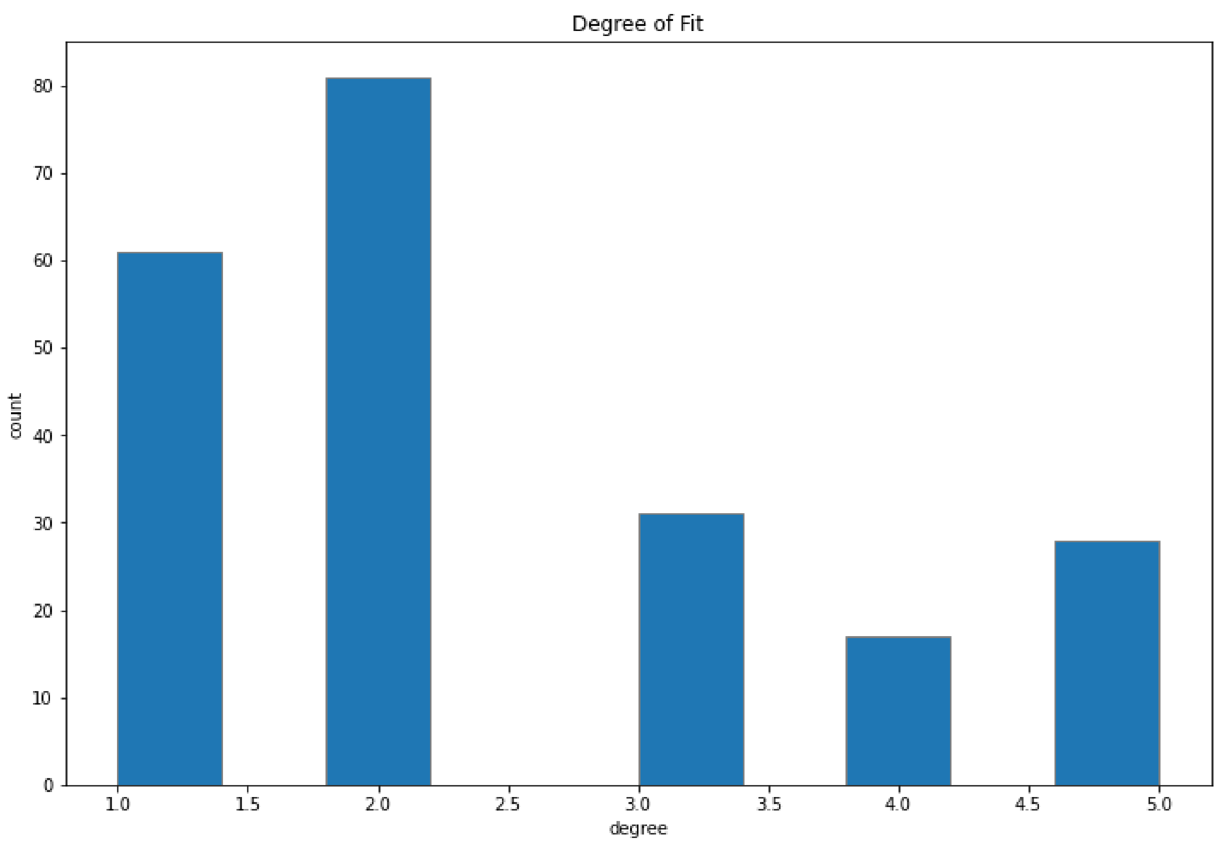
In [37]:

```python
predicted_rul=[]
for i in estimated_rul_dict.keys():
    predicted_rul.append(estimated_rul_dict[i][min(estimated_rul_dict[i].key

roots_list = []
for i in roots_dict.keys():
    roots_list.append(roots_dict[i][min(roots_dict[i].keys())])
```

Let's see what our fit degrees look like, in historgram form.

In [39]:

```python
fig,ax = plt.subplots(1,1,figsize=(12,8))
ax.hist(degree_fit, edgecolor='grey')
ax.set(xlabel='degree',ylabel='count',title='Degree of Fit')
plt.show()
```



One interesting thing to note is that we have several fits that were only linear in nature. As we mentioned earlier, engines without sufficient data are going to be difficult to fit, because at the beginning of an engines lifespan, the data will appear linear.

Next, we can merge the metric data into a single dataframe for plotting and analysis purposes.

In [40]:
```
red_data = zip(list(df_test['Unit Number'].unique()), degree_fit, final_scor
metric_df = pd.DataFrame(red_data, columns=['Unit Number','Degree','Score','

metric_df
```

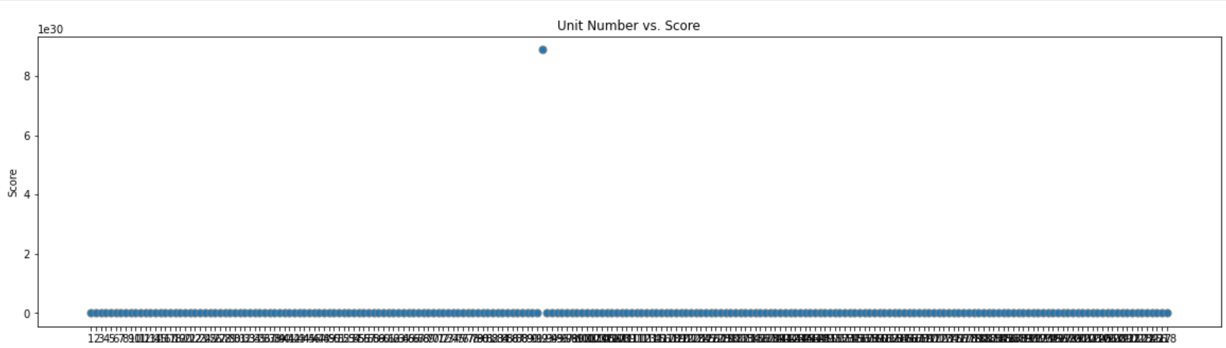
Out[40]:

	Unit Number	Degree	Score	Predicted RUL	Actual RUL	Polynomial Root
0	1	3	4645.803348	32.228847	142	86.228847
1	2	5	6.640220	25.565457	52	182.565457
2	3	4	0.336886	33.903430	31	149.903430
3	4	2	640.314265	66.974245	151	140.974245
4	5	1	65.187418	199.497625	254	417.497625
...	...	...	...	...	...	...
213	214	1	4.957311	134.799950	158	309.799950
214	215	5	7.994297	11.444321	40	79.444321
215	216	5	311933.192012	8.542882	173	41.542882
216	217	5	103.415119	32.571132	93	124.571132
217	218	3	1650.434361	22.677807	119	112.677807

218 rows × 6 columns

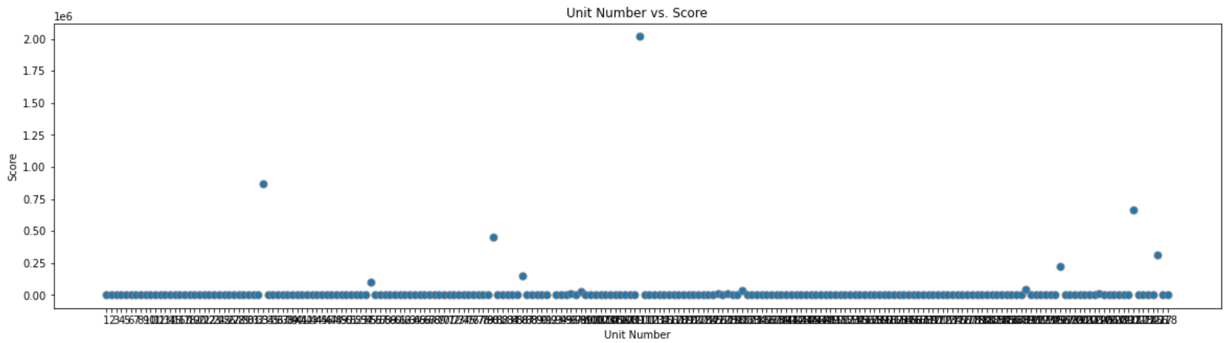
Now that we have our metrics dataframe done, let's see what the score looks like for each of the engines.

In [41]:
```
fig,ax=plt.subplots(1,1,figsize=(20,5))
ax.scatter(metric_df['Unit Number'], metric_df['Score'], edgecolor='gray', s
ax.set_xticks(metric_df['Unit Number'])
ax.set(xlabel='Unit Number',ylabel='Score',title='Unit Number vs. Score')
plt.show()
```



OK, so one prediction did quite bad. Let's exclude that engine and see if things get better.

In [42]:
```
fig,ax=plt.subplots(1,1,figsize=(20,5))
ax.scatter(metric_df[metric_df['Unit Number']!=92]['Unit Number'], metric_df
ax.set_xticks(metric_df['Unit Number'])
ax.set(xlabel='Unit Number',ylabel='Score',title='Unit Number vs. Score')
plt.show()
```

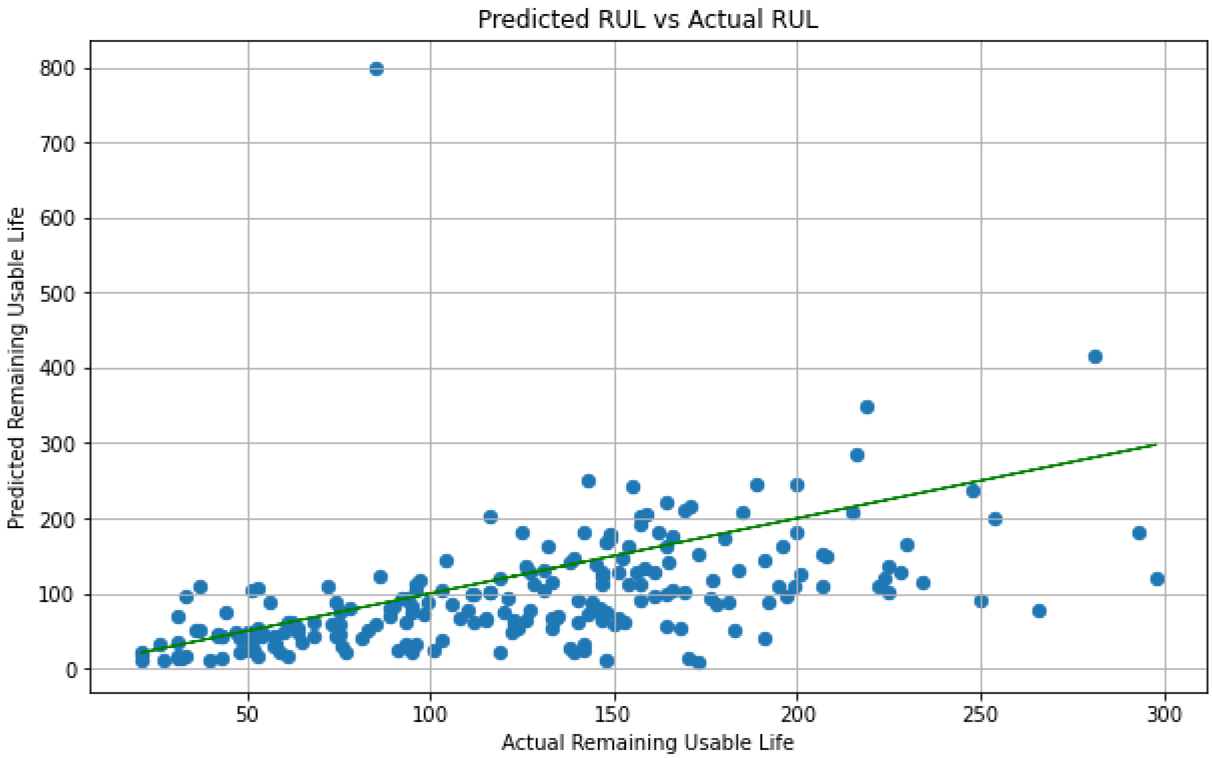


Sadly, it doesn't appear that removing that one engine is going to make things better for us with this model. The variation that is visible in the dots at the bottom indicate that we are just outside of the range needed to see some rather large deviations. This goes back to our linear fits, as those are certainly going to be poor fits no matter what we do.

Let's compare the predicted life with the actual life of the engines, as that might give us a better insight into what happened.

In [43]:

```
fig,ax = plt.subplots(1,1,figsize=(10,6))
ax.scatter(metric_df['Actual RUL'],metric_df['Predicted RUL'], s=40)
ax.grid()
ax.plot(metric_df['Actual RUL'],metric_df['Actual RUL'], c='green',linewidth
ax.set(xlabel='Actual Remaining Usable Life', ylabel='Predicted Remaining Us
plt.show()
```

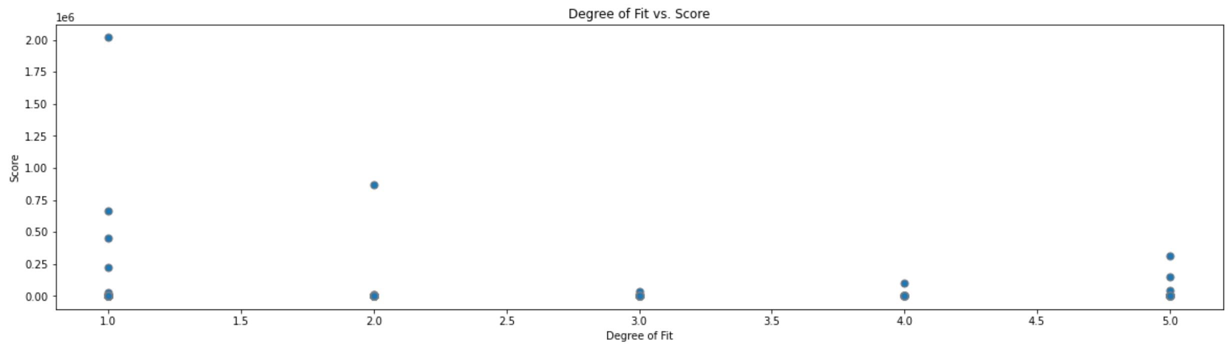


So with that, we have made some predictions for the remaining usable life of some jet engines. Overall, it's not terrible, but not very good. While there are multiple approaches that we could have taken for this, linear or polynomial models, like the one used, are fairly straight-forward and could always be made better.

One of the problems with a model like this is that we are **extrapolating** a significant amount for some of the engines. If we have insufficient data to extrapolate, then we end up with poor predictions. Going back to our degree of fit plot earlier, we allowed for linear fits, which will most certainly end poorly. We could go back and adjust that to ensure we had, at minimum, a cubic fit, which might reduce this problem and make better predictions. However, it would still be extrapolating a lot. Really, we just need to find a way to identify where engines appear to start failing and predict from there.

In [45]:

```
fig,ax=plt.subplots(1,1,figsize=(20,5))
ax.scatter(metric_df[metric_df['Unit Number']!=92]['Degree'], metric_df[metr
ax.set(xlabel='Degree of Fit',ylabel='Score',title='Degree of Fit vs. Score'
plt.show()
```



Type *Markdown* and LaTeX: α^2

In [51]:

```
del score
del degrees
del degree_fit
del final_score
del estimated_rul_dict
del roots_dict

degrees = [2,3,4,5,6]
degree_fit = []
final_score=[]
estimated_rul_dict={}
roots_dict={}

for i in df_test['Unit Number'].unique():

    uniti = df_test[df_test['Unit Number']==i]

    score = np.empty(len(degrees))

    estimated_rul_dict[i] = {}
    roots_dict[i] = {}

    for d in degrees:
        poly_params = np.polyfit(uniti['Time in Cycles'],uniti['Health1'],d)
        poly_ = np.poly1d(poly_params)
        roots = poly_.r
        roots = roots[np.isreal(roots)].real
        roots = roots[roots>0]

        if roots.shape[0]==1:
            pred_rul = roots - max(uniti['Time in Cycles'])
            errors = pred_rul - RUL_list[i-1]
            score[d-2]=scoring_function(errors)

            estimated_rul_dict[i][scoring_function(errors).item()] = pred_ru
            roots_dict[i][scoring_function(errors).item()] = roots.item()

        elif roots.shape[0]>1:
            pred_rul = roots[0] - max(uniti['Time in Cycles'])
            errors = pred_rul - RUL_list[i-1]
            score[d-2]=scoring_function(errors)

            estimated_rul_dict[i][scoring_function(errors).item()] = pred_ru
            roots_dict[i][scoring_function(errors).item()] = roots[0].item()

        else:
            score[d-2]=scoring_function(7000)


    degree_fit.append(np.argmin(score))
    final_score.append(np.min(score)+2)

predicted_rul=[]
for i in estimated_rul_dict.keys():
    predicted_rul.append(estimated_rul_dict[i][min(estimated_rul_dict[i].key
```

```
roots_list = []
for i in roots_dict.keys():
    roots_list.append(roots_dict[i][min(roots_dict[i].keys())])
```

```
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in exp
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in exp
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in exp
  s = np.exp(error/10)-1
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in exp
  s = np.exp(error/10)-1
C:\Users\jacob\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:341
8: RankWarning: Polyfit may be poorly conditioned
  exec(code_obj, self.user_global_ns, self.user_ns)
<ipython-input-31-e322460d87ca>:3: RuntimeWarning: overflow encountered in exp
  s = np.exp(error/10)-1

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-51-0e0e76001106> in <module>
     53 predicted_rul=[]
     54 for i in estimated_rul_dict.keys():
---> 55     predicted_rul.append(estimated_rul_dict[i][min(estimated_rul_dict[i
].keys())])
     56 
     57 roots_list = []

ValueError: min() arg is an empty sequence
```

In [ ]:

```
fig,ax = plt.subplots(1,1,figsize=(12,8))
ax.hist(degree_fit, edgecolor='grey')
ax.set(xlabel='degree',ylabel='count',title='Degree of Fit')
plt.show()
```

In [ ]:

```
red_data = zip(list(df_test['Unit Number'].unique()), degree_fit, final_scor
metric_df = pd.DataFrame(red_data, columns=['Unit Number','Degree','Score','

metric_df
```

In [ ]:

```
fig,ax = plt.subplots(1,1,figsize=(10,6))
ax.scatter(metric_df['Actual RUL'],metric_df['Predicted RUL'], s=40)
ax.grid()
ax.plot(metric_df['Actual RUL'],metric_df['Actual RUL'], c='green',linewidth
ax.set(xlabel='Actual Remaining Usable Life', ylabel='Predicted Remaining Us
plt.show()
```

Poor Models - Principal components

In contrast, there are model choices that *seem* like a good idea, but end up being poor models for this type of problem. One example, in this case, is Principal Components. As was mentioned earlier, several of these sensors seem to be measuring the same "thing". Further, it makes sense that there might be principal components that would indicate the health of a jet engine, given that there are only so many inputs and outputs. So.... why do I say this is a poor model in this case? Well, let's take a look.

We can start here by going back to our large grouping of sensors that were (1) not discrete variables and (2) actually seemed useful. At this point, this still includes sensor 8, 9, 13, and 14. As you'll recall, these seemed highly correlated and, therefore, we only kept one pair of them.

In [16]:

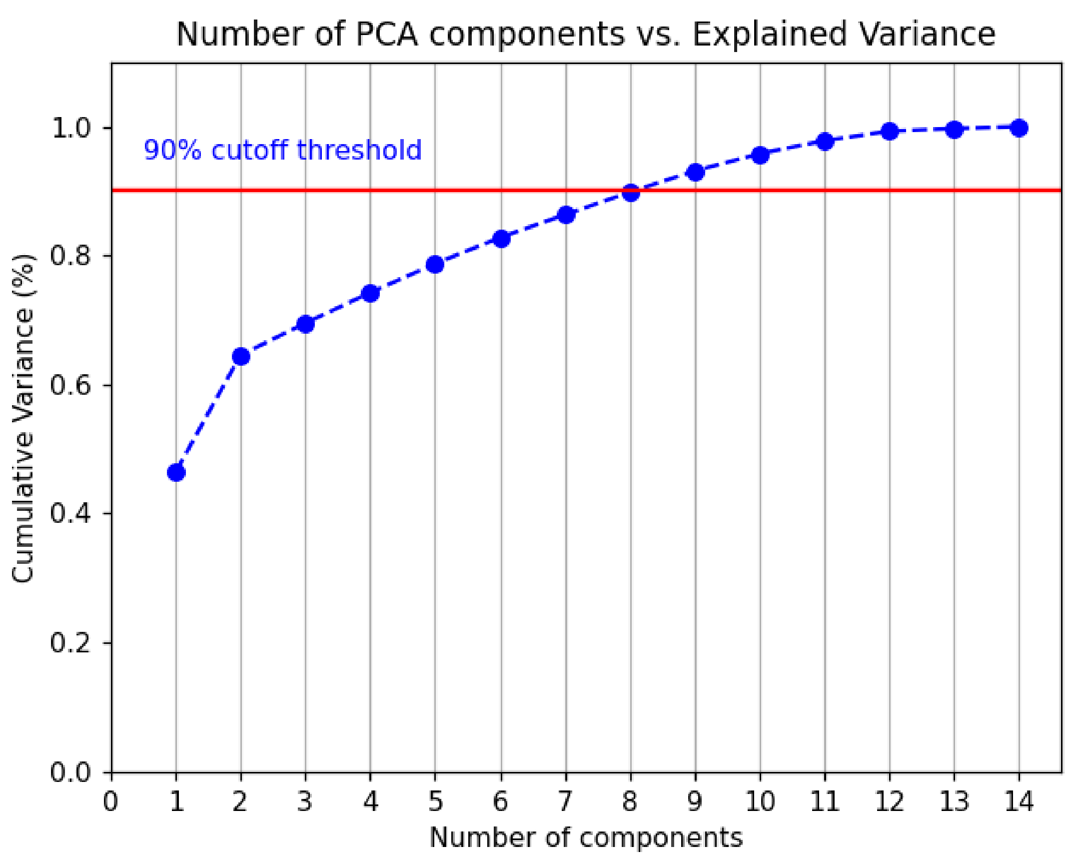
```
x_pca_in = red_norm_train_df[['SM2','SM3','SM4','SM7','SM8','SM9','SM11','SM
x_pca_in.describe()
```

Out[16]:

	SM2	SM3	SM4	SM7	SM8	SM9
count	4.591800e+04	4.591800e+04	4.591800e+04	4.591800e+04	4.591800e+04	4.591800e+04
mean	-1.201851e-12	2.032937e-13	-1.206282e-13	3.468986e-13	-1.986665e-11	1.765637e-13
std	9.999456e-01	9.999456e-01	9.999456e-01	9.999456e-01	9.999456e-01	9.999456e-01
min	-3.462595e+00	-3.350048e+00	-3.036529e+00	-4.222277e+00	-2.699726e+00	-2.044901e+00
25%	-7.000744e-01	-6.895970e-01	-7.087195e-01	-6.586278e-01	-6.114623e-01	-5.803541e-01
50%	-5.832952e-02	-5.623612e-02	-9.571446e-02	2.917163e-02	-1.687069e-01	-1.890300e-01
75%	6.395553e-01	6.381764e-01	6.263048e-01	7.023030e-01	3.932286e-01	2.674522e-01
max	4.075911e+00	4.235689e+00	4.062193e+00	3.797108e+00	9.398807e+00	8.830641e+00

When we run PCA on this to determine an appropriate number of components, here's what we get.

In [19]:
```python
pca = PCA().fit(x_pca_in)

fig, ax = plt.subplots()
xi = np.arange(1,15, step=1)
y = np.cumsum(pca.explained_variance_ratio_)

plt.ylim(0.0,1.1)
plt.plot(xi,y,marker='o', linestyle='--',color='b')
plt.xlabel('Number of components')
plt.xticks(np.arange(0,15,step=1))
plt.ylabel('Cumulative Variance (%)')
plt.title('Number of PCA components vs. Explained Variance')

plt.axhline(y=0.90, color='r', linestyle='-')
plt.text(0.5, 0.95, '90% cutoff threshold', color='blue')

ax.grid(axis='x')
plt.show()
```



If we stick with a 90% threshold, it looks like we need about 8 principal components to explain the variance. However, following our intuition that there should be only a limited set of "things" that matter for this, we will look at 2 components. While not explored here, I have gone through the work for 8 components and we end up with very noisy results for components 3-8, so they don't provide a significant amount of benefit other than better modelling noise.

In [20]:

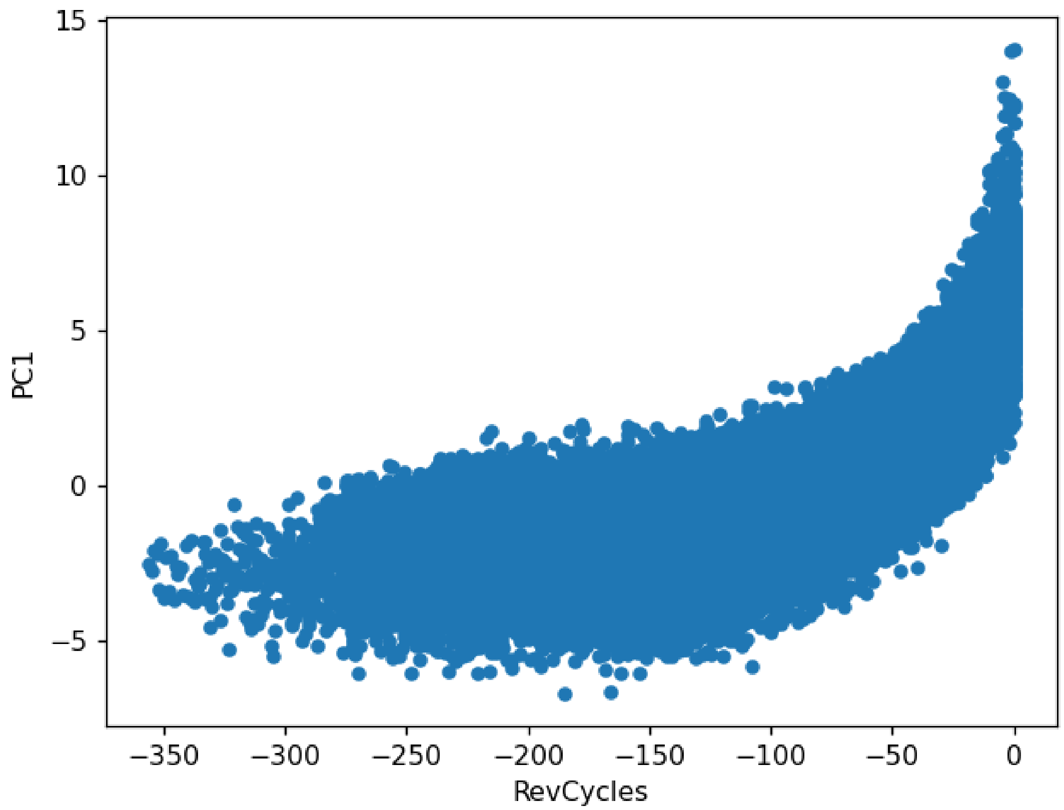
```
x_pca_in = red_norm_train_df[['SM2','SM3','SM4','SM7','SM8','SM9','SM11','SM

pca = PCA(n_components=2).fit(x_pca_in)

principal_components = pca.fit_transform(x_pca_in)

principal_train_df = pd.DataFrame(data = principal_components, columns = ['P
fp_train_df = pd.concat([principal_train_df,red_norm_train_df[['RevCycles','
fp_train_df.head()
```

Out[20]:

	PC1	PC2	RevCycles	Unit Number
0	-2.943715	-0.180131	-222	1
1	-3.213017	0.319781	-221	1
2	-1.403975	-0.486647	-220	1
3	-2.267658	-0.691777	-219	1
4	-2.964554	0.313793	-218	1

So, what does this look like for the first principal component...

In [21]:
```
sensor = 'PC1'
fp_train_df.plot(kind = 'scatter', x='RevCycles', y=sensor)
```



Out[21]: <AxesSubplot:xlabel='RevCycles', ylabel='PC1'>

OK, we are going to stop here. If we compare this graph with the ones we saw earlier for sensors 13 and 14, this looks *very* similar. So, Principal Components did it's job, but it extracted those sensors that seemed to have the largest change. This should make sense intuitively, but if we were going to continue with this approach, we would effectively be doing the same as the linear model, but with only one sensor. Obviously, this would be a poor choice.