Machine Learning approach for Predictive Maintenance Aircraft Engine using IBM Watson Studio

1. INTRODUCTION

1.1 Overview

Aircraft engines are the most expensive parts of an aircraft, and it is in airlines' interest to keep their power plants in tip-top condition. Apart from the fact that they are rather crucial to actual flight and safety, unscheduled service interruptions due to engine problems can quickly become costly affairs.Engine failure is highly risky and needs a lot of time for repair. Unexpected failure leads to loss of money and time. Predicting the failure prior, will save time, effort, money and sometimes even lives. The failure can be detected by installing the sensors and keeping a track of the values. The failure detection and predictive maintenance can be for any device, out of which we will be dealing with the engine failure for a threshold number of days.

1.2 Purpose

The project aims to predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity.

2. LITERATURE SURVEY

2.1 Existing problem

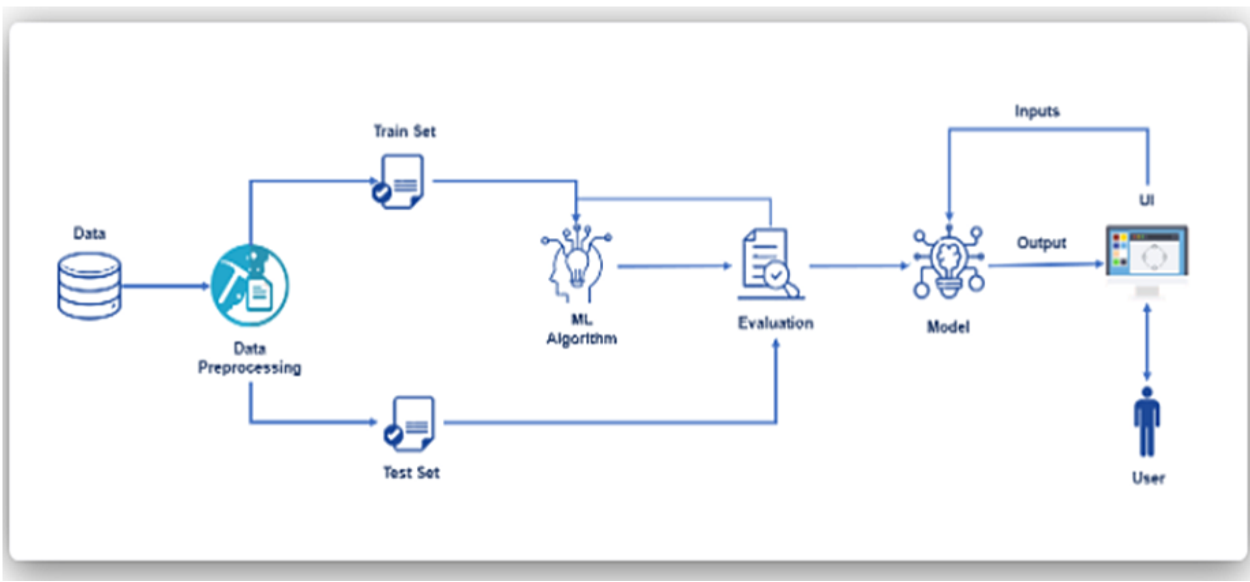
Ideally, pilots and mechanics should work together to make sure the aircraft is operated and maintained properly. As a pilot, you are encouraged to take an active role in maintenance by reviewing inspection results and discussing Airworthiness Directives and Service Bulletins with your mechanic. The existing system is highly risky and needs a lot of time for repair and heavy risk for human lives. we cannot ensure the result from existing system. Maintenance delays are major inconvenience for passengers, and they are serious issue for airlines as well.

2.2 Proposed solution

The project aims to predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity .today's engines have hundreds of sensors and signals that transmit gigabytes of data for each flight. Planes generate a lot of data that can be used to make such predictions we have access to data like this, we can generate predictions using those data. This is a perfect opportunity to use predictive analytics: modern aircraft generate a wealth of data -- a 787 generates as much as a terabyte of sensor data per flight -- and airlines have extensive records of flight delays and their causes. So it makes sense to look the sensor manual data from flights that had unexpected maintenance issues, and see if you can find patterns in the data that indicate a likelihood of a maintenance problem, so you can fix any such issues before they become a delay

3. THEORITICAL ANALYSIS

3.1 Block diagram



3.2 Hardware / Software designing

Hardware Requirements:

Processor : Intel Core I3
RAM : 4.00 GB
Operating system : Windows/Linux/MAC

Software Requirements:

Anaconda
Jupyter Notebook
Spyder
IBM Watson Studio
IBM Machine Learning
IBM Cloud Object Storage

4. EXPERIMENTAL INVESTIGATIONS

- Download the dataset.

Import required libraries such as pandas, numpy, sklearn and Datasets are collected.

- Preprocess or clean the data.

After collecting the datasets we preprocess the data, preprocess involves treating the dataset , preprocessing the dataset , splitting the dataset. we split the data for training , testing purposes and analyze the pre-processed data.

Handling the null values

Handling the categorical values if any

Normalize the data if required.

Identify the dependent and independent variables.

Split the dataset into train and test sets.

- Train the machine with pre-processed data using an appropriate machine learning algorithm.

In this project ,We will be initially considering the Logistic Regression model and fit the data.Here we will be evaluating the model built. We will be using the test set for evaluation. The test set is given to the model for prediction and prediction values are stored in another variable called y_predlog. The actual and predicted values are compared to know the accuracy of the model using the accuracy_score function from sklearn.metrics package. Follow the below steps to find the accuracy of the model. The accuracy for logistic regression in this is .998 . Confusion matrix can be generated to know the true positives.

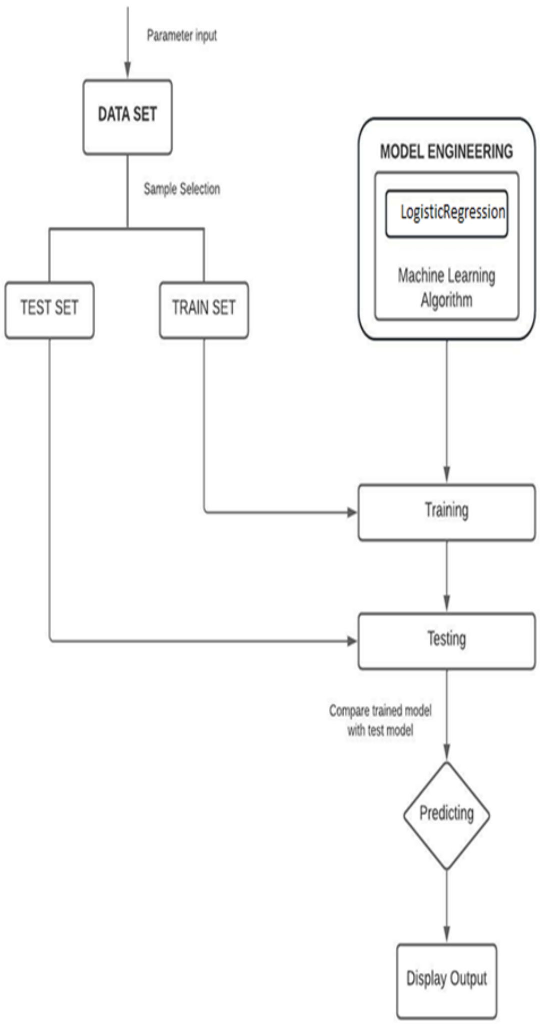
- Save the model and its dependencies.

The finalised model is now to be saved. We will be saving the model as a sav file.

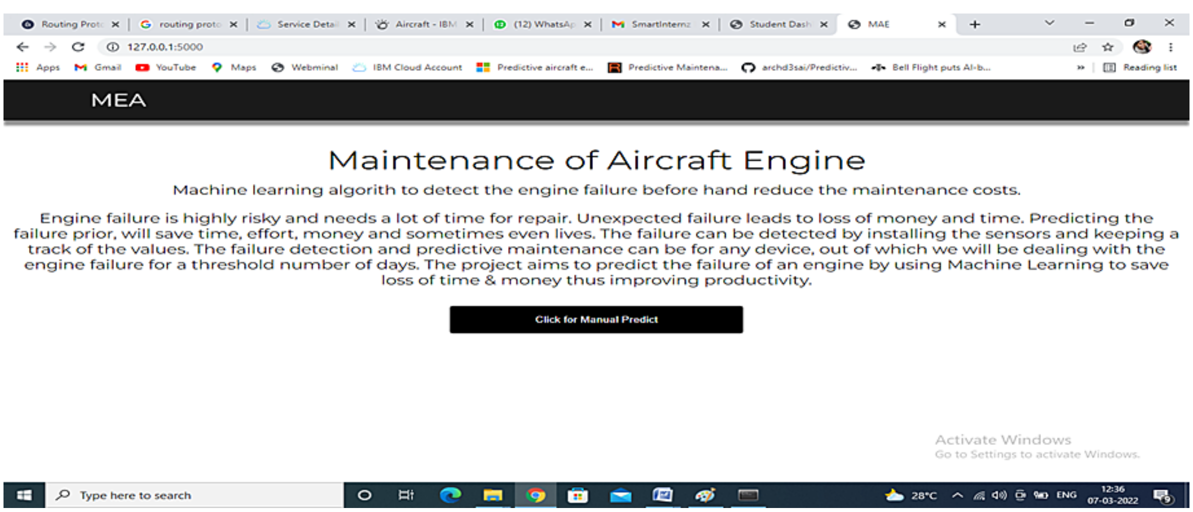
- Build a Web application using flask that integrates with the model built.

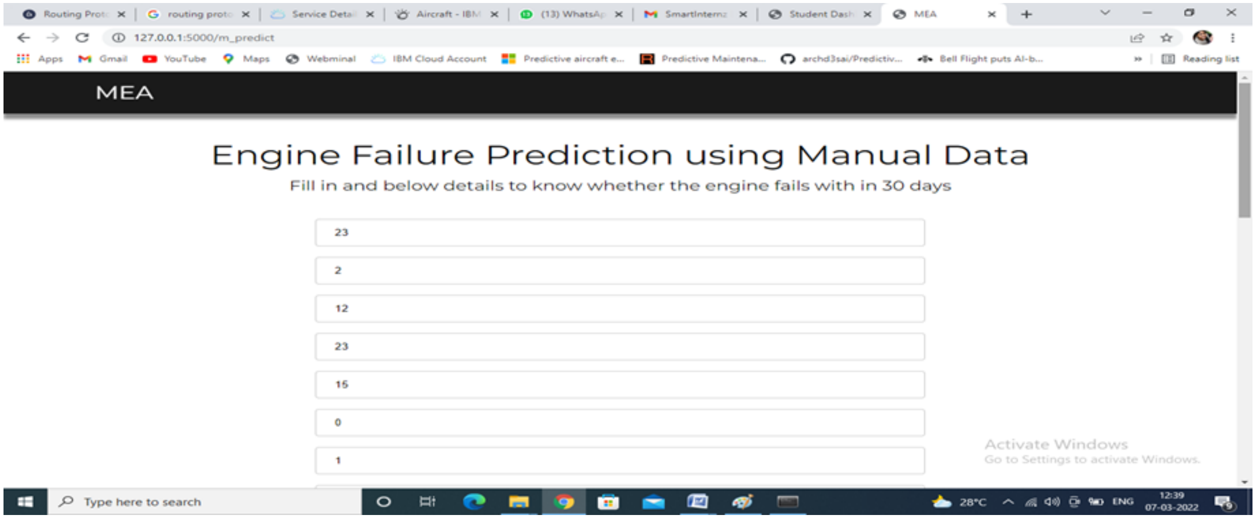
After the model is built, we will be integrating it to a web application where a user can give the sensor data and get to know if the engine fails in the next 30 days or we can even generate the random values and know the prediction for those random data.

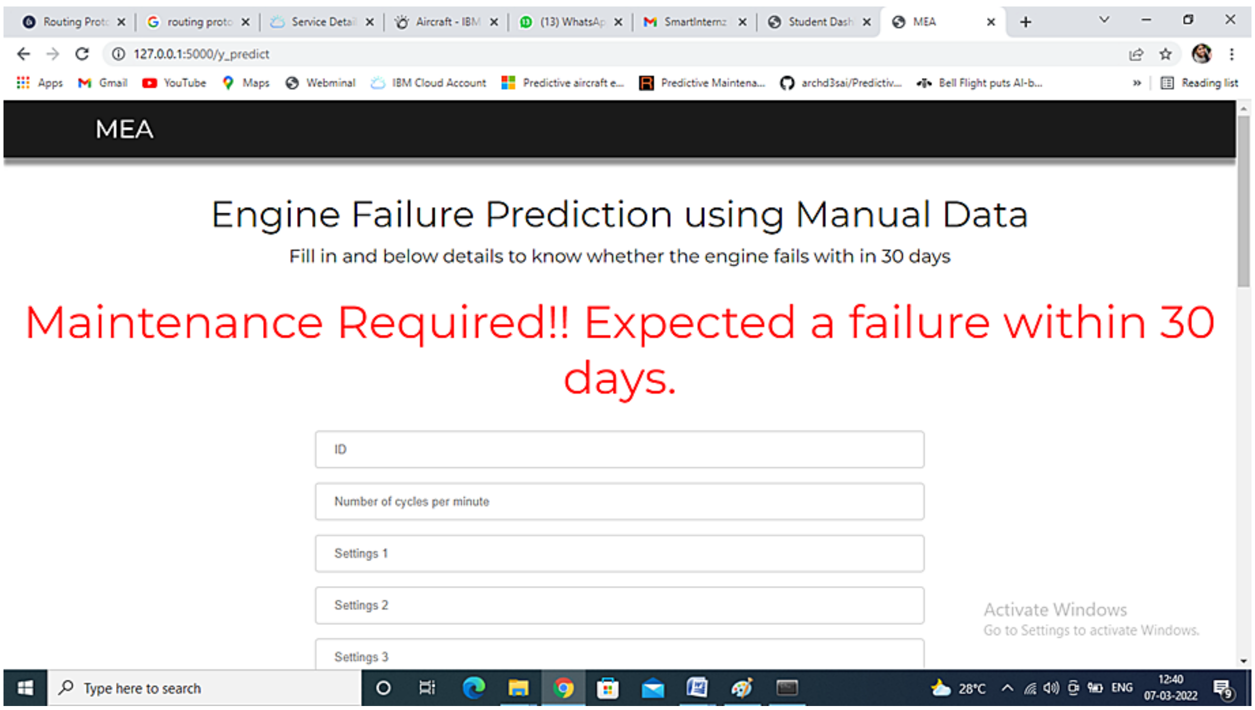
5. FLOWCHART


Parameter input
DATA SET
Sample Selection
TEST SET
TRAIN SET
MODEL ENGINEERING
LogisticRegression
Machine Learning Algorithm
Training
Testing
Compare trained model with test model
Predicting
Display Output

6. RESULT


127.0.0.1:5000
MEA
Maintenance of Aircraft Engine
Machine learning algorith to detect the engine failure before hand reduce the maintenance costs.
Engine failure is highly risky and needs a lot of time for repair. Unexpected failure leads to loss of money and time. Predicting the failure prior, will save time, effort, money and sometimes even lives. The failure can be detected by installing the sensors and keeping a track of the values. The failure detection and predictive maintenance can be for any device, out of which we will be dealing with the engine failure for a threshold number of days. The project aims to predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity.
Click for Manual Predict
Activate Windows
Go to Settings to activate Windows.
Type here to search
28°C
ENG
12:36
07-03-2022





7. ADVANTAGES & DISADVANTAGES

ADVANTAGES

Save time ,effort and money:unexpected failure leads to loss of money and time. Predict the failure of an engine by using machine learning to save loss of time and money thus improving productivity
3-5% increased machine useful life: Since predictive maintenance reduces machine breakdowns and ensures operation in optimum settings

Reduced environmental impact: As machines remain useful for longer periods and as their efficiency increase with advanced analytics, companies will waste less natural resources. Predictive maintenance is one of the few initiatives that both help companies bottom line and their corporate social responsibility goals.

Advanced analytics: Setting up predictive maintenance involves collecting sensor data from diverse machinery. Once that data starts to be automatically collected, analysts have a trove of information ready for analysis. This data can be used to identify parameter and process optimization opportunities.

DISADVANTAGES

Data security: In terms of predictive maintenance, it is critical to guarantee that equipment performance data is not subject to access by outside parties, and that outside parties are not able to control predictive maintenance systems. At a more baseline level, it also remains important to protect information such as customer data.

Additional Cost:Given the complex nature of predictive maintenance, plant personnel needs to be trained on using the equipment and interpreting the analytics. It also involves investment in maintenance tools and systems. Tersely, condition monitoring has a high upfront cost.

8. APPLICATIONS

Aircraft engine maintenance is a step-by-step process similar to a person's health check-up. It consists of washing and drying jet engine parts, exterior and interior visual inspections, a dismantling of the engine, the repair and replacement of any parts, and then the re-assembling and testing of the engine.

Machine Learning play a key part in security as they typically use predictive analysis to improve services and performance, but also to detect anomalies, fraud, understand consumer behavior and enhance data security. 4. ML Algorithms are also known for it's recommendation algorithms like in Facebook or YouTube where similar content will be suggested to engage the user

9. CONCLUSION

In this work, Predictive Maintenance aircraft engine using machine learning, Logistic Regression are considered for determining the status of maintenance of aircraft engine applications. In Logistics Regression has done quite a good performance than expected with 0.99832accuracy . This leads to conclusion that how much important is feature selection and feature transformation is. Our results showed that the most predictive features are EMPLOYER SUCCESS RATE and PREVAILING WAGE.

10. FUTURESCOPE

By adopting a predictive-maintenance (PDM) strategy, you can mine your critical asset data and identify anomalies or deviations from their standard performance. In this paper we are just predicting whether engine fail or not within 30 days. Such insights can help you discover and proactively fix issues days, weeks, or even months before they lead to failures. This can help you avoid unplanned downtime, reduce industrial f maintenance overspend, and mitigate safety and environmental risk.

11. BIBLIOGRAPHY

- Hermawan, A. P., Kim, D-S., and Lee, M-J. (2020). Predictive Maintenance of Aircraft Engine using Deep Learning Technique. In 2020 International Conference on Information and Communication Technology Convergence (ICTC), pp. 1296-1298.
- Amruthnath, N., and Gupta, T. (2018). A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. In 2018 5th International Conference on Industrial Engineering and Applications (ICIEA). pp. 355-361.
- GE Aviation. https://www.geaviation.com/commercial

12. APPENDIX

A. Source Code

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import confusion_matrix,accuracy_score

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, LSTM, Activation
from tensorflow.keras.callbacks import EarlyStopping

import matplotlib.pyplot as plt
plt.style.use('ggplot')
%matplotlib inline
```

In [2]:
```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
client_f50763f7c1f14adfb97b4fbbbc23830b = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='NsjyYpsqxATF6q6gOdgbG0yVNK3RiMUYtyUJDzEyFrIG',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')
```



```
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

streaming_body_1 = client_f50763f7c1f14adfb97b4fbbbc23830b.get_object(Bucket='machinelearningapproachforpredict-donotdelete-pr-d
9duqt0m66f6dx', Key='PM_train.txt')['Body']

# Your data file was loaded into a botocore.response.StreamingBody object.
# Please read the documentation of ibm_boto3 and pandas to learn more about the possibilities to load the data.
# ibm_boto3 documentation: https://ibm.github.io/ibm-cos-sdk-python/
# pandas documentation: http://pandas.pydata.org/
dataset_train=pd.read_csv(streaming_body_1,sep=' ',header=None).drop([26,27],axis=1)
col_names = ['id','cycle','setting1','setting2','setting3','s1','s2','s3','s4','s5','s6','s7','s8','s9','s10','s11','s12','s1
3','s14','s15','s16','s17','s18','s19','s20','s21']
dataset_train.columns=col_names
print('Shape of Train dataset: ',dataset_train.shape)
dataset_train.head()
```

```
Shape of Train dataset:  (20631, 26)
```

Out[2]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s12	s13	s14	s15	s16	s17	s18	s19	s20	
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	521.66	2388.02	8138.62	8.4195	0.03	392	2388	100.0	39.06	2
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	522.28	2388.07	8131.49	8.4318	0.03	392	2388	100.0	39.00	2
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	522.42	2388.03	8133.23	8.4178	0.03	390	2388	100.0	38.95	2
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	522.86	2388.08	8133.83	8.3682	0.03	392	2388	100.0	38.88	2
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	522.19	2388.04	8133.80	8.4294	0.03	393	2388	100.0	38.90	2

5 rows × 26 columns

In [3]:
```
streaming_body_3 = client_f50763f7c1f14adfb97b4fbbbc23830b.get_object(Bucket='machinelearningapproachforpredict-donotdelete-pr-d
9duqt0m66f6dx', Key='PM_test.txt')['Body']

# Your data file was loaded into a botocore.response.StreamingBody object.
# Please read the documentation of ibm_boto3 and pandas to learn more about the possibilities to load the data.
# ibm_boto3 documentation: https://ibm.github.io/ibm-cos-sdk-python/
# pandas documentation: http://pandas.pydata.org/
dataset_test=pd.read_csv(streaming_body_3,sep=' ',header=None).drop([26,27],axis=1)
dataset_test.columns=col_names
#dataset_test.head()
print('Shape of Test dataset: ',dataset_train.shape)
dataset_train.head()
```

```
Shape of Test dataset:  (20631, 26)
```

Out[3]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s12	s13	s14	s15	s16	s17	s18	s19	s20	
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	521.66	2388.02	8138.62	8.4195	0.03	392	2388	100.0	39.06	2
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	522.28	2388.07	8131.49	8.4318	0.03	392	2388	100.0	39.00	2
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	522.42	2388.03	8133.23	8.4178	0.03	390	2388	100.0	38.95	2
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	522.86	2388.08	8133.83	8.3682	0.03	392	2388	100.0	38.88	2
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	522.19	2388.04	8133.80	8.4294	0.03	393	2388	100.0	38.90	2

5 rows × 26 columns

In [4]:
```
streaming_body_5 = client_f50763f7c1f14adfb97b4fbbbc23830b.get_object(Bucket='machinelearningapproachforpredict-donotdelete-pr-d
9duqt0m66f6dx', Key='PM_truth.txt')['Body']

# Your data file was loaded into a botocore.response.StreamingBody object.
# Please read the documentation of ibm_boto3 and pandas to learn more about the possibilities to load the data.
# ibm_boto3 documentation: https://ibm.github.io/ibm-cos-sdk-python/
# pandas documentation: http://pandas.pydata.org/
pm_truth=pd.read_csv(streaming_body_5,sep=' ',header=None).drop([1],axis=1)
pm_truth.columns=['more']
pm_truth['id']=pm_truth.index+1
pm_truth.head()
```

Out[4]:

	more	id
0	112	1
1	98	2
2	69	3
3	82	4
4	91	5

In [5]:
```
pm_truth.shape
```

Out[5]: (100, 2)

In [6]:
```
rul = pd.DataFrame(dataset_test.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
```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In [5]: pm_truth.shape
Out[5]: (100, 2)

In [6]:
```
rul = pd.DataFrame(dataset_test.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
rul.head()
```

Out[6]:

	id	max
0	1	31
1	2	49
2	3	126
3	4	106
4	5	98

In [7]:
```
rul.shape
```

Out[7]: (100, 2)

In [8]:
```
pm_truth['rtf']=pm_truth['more']+rul['max']
pm_truth.head()
```


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Out[8]:

	more	id	rtf
0	112	1	143
1	98	2	147
2	69	3	195
3	82	4	188
4	91	5	189

In [9]:
```
pm_truth.shape
```

Out[9]: (100, 3)

In [10]:
```
pm_truth.drop('more', axis=1, inplace=True)
dataset_test=dataset_test.merge(pm_truth,on=['id'],how='left')
dataset_test['ttf']=dataset_test['rtf'] - dataset_test['cycle']
dataset_test.drop('rtf', axis=1, inplace=True)
dataset_test.head()
```

Out[10]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s13	s14	s15	s16	s17	s18	s19	s20	s21
0	1	1	0.0023	0.0003	100.0	518.67	643.02	1585.29	1398.21	14.62	...	2388.03	8125.55	8.4052	0.03	392	2388	100.0	38.86	23.3735
1	1	2	-0.0027	-0.0003	100.0	518.67	641.71	1588.45	1395.42	14.62	...	2388.06	8139.62	8.3803	0.03	393	2388	100.0	39.02	23.3916
2	1	3	0.0003	0.0001	100.0	518.67	642.46	1586.94	1401.34	14.62	...	2388.03	8130.10	8.4441	0.03	393	2388	100.0	39.08	23.4166
3	1	4	0.0042	0.0000	100.0	518.67	642.44	1584.12	1406.42	14.62	...	2388.05	8132.90	8.3917	0.03	391	2388	100.0	39.00	23.3737

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In [11]:
```
dataset_test.shape
```
Out[11]:
```
(13096, 27)
```

In [12]:
```
dataset_train['ttf'] = dataset_train.groupby(['id'])['cycle'].transform(max)-dataset_train['cycle']
dataset_train.head()
```
Out[12]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s13	s14	s15	s16	s17	s18	s19	s20	s21
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	2388.02	8138.62	8.4195	0.03	392	2388	100.0	39.06	23.4190
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	2388.07	8131.49	8.4318	0.03	392	2388	100.0	39.00	23.4236
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	2388.03	8133.23	8.4178	0.03	390	2388	100.0	38.95	23.3442
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	2388.08	8133.83	8.3682	0.03	392	2388	100.0	38.88	23.3739
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	2388.04	8133.80	8.4294	0.03	393	2388	100.0	38.90	23.4044

5 rows × 27 columns

In [13]:
```
dataset_train.shape
```
Out[13]:
```
(20631, 27)
```

In [14]:
```
dataset_train['ttf'].value_counts()
```
Out[14]:
```
0      100
87     100
118    100
```


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```
346      1
347      1
348      1
351      1
Name: ttf, Length: 362, dtype: int64
```

In [15]:
```
df_train=dataset_train.copy()
df_test=dataset_test.copy()
period=30
df_train['label_bc'] = df_train['ttf'].apply(lambda x: 1 if x <= period else 0)
df_test['label_bc'] = df_test['ttf'].apply(lambda x: 1 if x <= period else 0)
df_train.head()
```
Out[15]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s14	s15	s16	s17	s18	s19	s20	s21	ttf	labe
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	8138.62	8.4195	0.03	392	2388	100.0	39.06	23.4190	191	0
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	8131.49	8.4318	0.03	392	2388	100.0	39.00	23.4236	190	0
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	8133.23	8.4178	0.03	390	2388	100.0	38.95	23.3442	189	0
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	8133.83	8.3682	0.03	392	2388	100.0	38.88	23.3739	188	0
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	8133.80	8.4294	0.03	393	2388	100.0	38.90	23.4044	187	0

5 rows × 28 columns

In [16]:
```
df_train['label_bc'].value_counts()
```


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In [16]: df_train['label_bc'].value_counts()

Out[16]:
```
0    17531
1     3100
Name: label_bc, dtype: int64
```

In [17]:
```
features_col_name=['setting1', 'setting2', 'setting3', 's1', 's2', 's3', 's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11',
                   's12', 's13', 's14', 's15', 's16', 's17', 's18', 's19', 's20', 's21']
target_col_name='label_bc'
```

In [18]:
```
sc=MinMaxScaler()
df_train[features_col_name]=sc.fit_transform(df_train[features_col_name])
df_test[features_col_name]=sc.transform(df_test[features_col_name])
```

In [19]:
```
df_train.head()
```
Out[19]:

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s14	s15	s16	s17	s18	s19	s20	s21
0	1	1	0.459770	0.166667	0.0	0.0	0.183735	0.406802	0.309757	0.0	...	0.199608	0.363986	0.0	0.333333	0.0	0.0	0.713178	0.724662
1	1	2	0.609195	0.250000	0.0	0.0	0.283133	0.453019	0.352633	0.0	...	0.162813	0.411312	0.0	0.333333	0.0	0.0	0.666667	0.731014
2	1	3	0.252874	0.750000	0.0	0.0	0.343373	0.369523	0.370527	0.0	...	0.171793	0.357445	0.0	0.166667	0.0	0.0	0.627907	0.621375
3	1	4	0.540230	0.500000	0.0	0.0	0.343373	0.256159	0.331195	0.0	...	0.174889	0.166603	0.0	0.333333	0.0	0.0	0.573643	0.662386
4	1	5	0.390805	0.333333	0.0	0.0	0.349398	0.257467	0.404625	0.0	...	0.174734	0.402078	0.0	0.416667	0.0	0.0	0.589147	0.704502

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In [20]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20631 entries, 0 to 20630
Data columns (total 28 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   id        20631 non-null  int64
 1   cycle     20631 non-null  int64
 2   setting1  20631 non-null  float64
 3   setting2  20631 non-null  float64
 4   setting3  20631 non-null  float64
 5   s1        20631 non-null  float64
 6   s2        20631 non-null  float64
 7   s3        20631 non-null  float64
 8   s4        20631 non-null  float64
 9   s5        20631 non-null  float64
 10  s6        20631 non-null  float64
 11  s7        20631 non-null  float64
 12  s8        20631 non-null  float64
 13  s9        20631 non-null  float64
 14  s10       20631 non-null  float64
 15  s11       20631 non-null  float64
 16  s12       20631 non-null  float64
 17  s13       20631 non-null  float64
 18  s14       20631 non-null  float64
 19  s15       20631 non-null  float64
 20  s16       20631 non-null  float64
 21  s17       20631 non-null  float64
```


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```
 24  s20       20631 non-null  float64
 25  s21       20631 non-null  float64
 26  ttf       20631 non-null  int64
 27  label_bc  20631 non-null  int64
dtypes: float64(24), int64(4)
memory usage: 4.4 MB
```

In [21]:
```
df_train['ttf'].min()
```

Out[21]: 0

In [22]:
```
df_train['ttf'].max()
```

Out[22]: 361

In [23]:
```
df_train.iloc[0,:]
```

Out[23]:
```
id          1.000000
cycle       1.000000
setting1    0.459770
setting2    0.166667
setting3    0.000000
s1          0.000000
s2          0.183735
s3          0.406802
s4          0.309757
s5          0.000000
s6          1.000000
s7          0.726248
s8          0.242424
```


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In [24]:
```
import seaborn as sns
sns.pairplot(df_train)
```

Out[24]: <seaborn.axisgrid.PairGrid at 0x7f7438048cd0>

```
In [25]: x_train = df_train.iloc[:,:-1].values
         y_train = df_train.iloc[:,-1:].values

In [26]: from sklearn.linear_model import LogisticRegression
         model_log = LogisticRegression()
         model_log.fit(x_train,y_train)

/opt/conda/envs/Python-3.8-main/lib/python3.8/site-packages/sklearn/utils/validation.py:72: DataConversionWarning: A column-vec
tor y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
/opt/conda/envs/Python-3.8-main/lib/python3.8/site-packages/sklearn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs fa
iled to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(

Out[26]: LogisticRegression()

In [27]: import joblib

In [28]: joblib.dump(model_log, "engine_model.sav")

Out[28]: ['engine_model.sav']
```



```
Out[28]: ['engine_model.sav']

In [29]: x_test = df_test.iloc[:,:-1].values
         y_test = df_test.iloc[:,-1:].values

In [30]: y_predlog = model_log.predict(x_test)

In [31]: from sklearn.metrics import accuracy_score
         accuracy_score(y_predlog,y_test)

Out[31]: 0.9993127672571778

In [52]: df_test['label_bc'].value_counts()

Out[52]: 0    12764
         1      332
         Name: label_bc, dtype: int64

In [53]: from sklearn.metrics import confusion_matrix
         cm1 = confusion_matrix(y_test,y_predlog)
         cm1

Out[53]: array([[12763,     1],
                [    8,   324]])

In [54]: import numpy as np
         from sklearn.linear_model import LogisticRegression
         import joblib
```



```
In [55]: inp =[1,1,0.45977,0.166667,0,0,0.183735,0.406802,0.309757,0,1,0.726248,0.242424,0.109755,0,0.369048,0.633262,0.205882,0.199608,
         0.363986,0,0.333333,0,0,0.713178,0.724662,191]

In [56]: out=0

In [57]: model = joblib.load("engine_model.sav")

In [58]: model.predict([inp])

Out[58]: array([0])

In [59]: model.predict([inp])

Out[59]: array([0])

In [60]: import random

In [61]: inp1=[]
         inp1.append(random.randint(0,100)) #id
         inp1.append(random.randint(0,365)) #cycle
         for i in range(0,24):
             inp1.append(random.uniform(0,1))
         inp1.append(random.randint(0,365)) #ttf

In [63]: len(inp1)

Out[63]: 27
```

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```
In [64]: model.predict([inp1])
Out[64]: array([0])

In [65]: !pip install ibm_watson_machine_learning
Requirement already satisfied: ibm_watson_machine_learning in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (1.0.189)
Requirement already satisfied: pandas<1.4.0,>=0.24.2 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson
_machine_learning) (1.3.4)
Requirement already satisfied: tabulate in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_lear
ning) (0.8.9)
Requirement already satisfied: requests in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_lear
ning) (2.26.0)
Requirement already satisfied: ibm-cos-sdk==2.11.* in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_m
achine_learning) (2.11.0)
Requirement already satisfied: lomond in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_learni
ng) (0.3.3)
Requirement already satisfied: packaging in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_lea
rning) (21.3)
Requirement already satisfied: urllib3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_learn
ing) (1.26.7)
Requirement already satisfied: importlib-metadata in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_ma
chine_learning) (4.8.2)
Requirement already satisfied: certifi in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm_watson_machine_learn
ing) (2021.10.8)
Requirement already satisfied: ibm-cos-sdk-s3transfer==2.11.0 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from i
bm-cos-sdk==2.11.*->ibm_watson_machine_learning) (2.11.0)
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from ibm-cos-s
dk==2.11.*->ibm_watson_machine_learning) (0.10.0)
```


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```
In [66]: from ibm_watson_machine_learning import APIClient
         wml_credentials = {
                 "url":"https://us-south.ml.cloud.ibm.com",
                 "apikey":"jqja7xuBXX5cTYoUhTtd_g3PTUQppwhOF0IzQSeixeBl"
         }
         client = APIClient(wml_credentials)

In [ ]:

In [78]: wml_client = APIClient(wml_credentials)
         wml_client.spaces.list()

Note: 'limit' is not provided. Only first 50 records will be displayed if the number of records exceed 50
------------------------------------  --------------  ------------------------
ID                                    NAME            CREATED
1682ef0d-1b09-40e5-9f18-474561193aae  Aircraft_space  2022-03-05T10:27:35.561Z
------------------------------------  --------------  ------------------------

In [84]: SPACE_ID = "1682ef0d-1b09-40e5-9f18-474561193aae"

In [86]: wml_client.set.default_space(SPACE_ID)
Out[86]: 'SUCCESS'

In [87]: wml_client.software_specifications.list()

-----------------------------  ------------------------------------  ----
NAME                           ASSET_ID                              TYPE
```


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```
In [95]: MODEL_NAME="engine_model"
         DEPLOYMENT_NAME="Arcraft_deployment"

In [88]: software_spec_uid = client.software_specifications.get_uid_by_name("default_py3.8")
         software_spec_uid
Out[88]: 'ab9e1b80-f2ce-592c-a7d2-4f2344f77194'

In [89]: model_details = wml_client.repository.store_model(model = model_log, meta_props = {
             wml_client.repository.ModelMetaNames.NAME:"engine_model",
             wml_client.repository.ModelMetaNames.TYPE:"scikit-learn_0.23",
             wml_client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:software_spec_uid }
                                                         )

         model_id = wml_client.repository.get_model_uid(model_details)

This method is deprecated, please use get_model_id()
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm_watson_machine_learning/repository.py:1458: UserWarning: This method
is deprecated, please use get_model_id()
  warn("This method is deprecated, please use get_model_id()")

In [90]: model_id
Out[90]: 'cac0e569-bb5e-490a-a96d-5d5e548f2058'

In [91]: x_train[0]
Out[91]: array([1.00000000e+00, 1.00000000e+00, 4.59770115e-01, 1.66666667e-01,
```

```
model_id = wml_client.repository.get_model_uid(model_details)
```

```
This method is deprecated, please use get_model_id()
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm_watson_machine_learning/repository.py:1458: UserWarning: This method
is deprecated, please use get_model_id()
  warn("This method is deprecated, please use get_model_id()")
```

In [90]:
```
model_id
```

Out[90]:
```
'cac0e569-bb5e-490a-a96d-5d5e548f2058'
```

In [91]:
```
x_train[0]
```

Out[91]:
```
array([1.00000000e+00, 1.00000000e+00, 4.59770115e-01, 1.66666667e-01,
       0.00000000e+00, 0.00000000e+00, 1.83734940e-01, 4.06801831e-01,
       3.09756921e-01, 0.00000000e+00, 1.00000000e+00, 7.26247987e-01,
       2.42424242e-01, 1.09755003e-01, 0.00000000e+00, 3.69047619e-01,
       6.33262260e-01, 2.05882353e-01, 1.99607803e-01, 3.63986149e-01,
       0.00000000e+00, 3.33333333e-01, 0.00000000e+00, 0.00000000e+00,
       7.13178295e-01, 7.24661696e-01, 1.91000000e+02])
```

In [92]:
```
model_log.predict([[1.00000000e+00, 1.00000000e+00, 4.59770115e-01, 1.66666667e-01,
       0.00000000e+00, 0.00000000e+00, 1.83734940e-01, 4.06801831e-01,
       3.09756921e-01, 0.00000000e+00, 1.00000000e+00, 7.26247987e-01,
       2.42424242e-01, 1.09755003e-01, 0.00000000e+00, 3.69047619e-01,
       6.33262260e-01, 2.05882353e-01, 1.99607803e-01, 3.63986149e-01,
       0.00000000e+00, 3.33333333e-01, 0.00000000e+00, 0.00000000e+00,
       7.13178295e-01, 7.24661696e-01, 1.91000000e+02]])
```


Out[92]:
```
array([0])
```