Requirements

Calling tensorflow, matplotlib, pandas, numpy and other libraries for prediction and visualization aid.

```
%tensorflow_version 2.x
%matplotlib inline
!pip show tensorflow
```

```
Name: tensorflow
Version: 2.4.0
Summary: TensorFlow is an open source machine learning framework for everyone.
Home-page: https://www.tensorflow.org/
Author: Google Inc.
Author-email: packages@tensorflow.org
License: Apache 2.0
Location: /usr/local/lib/python3.6/dist-packages
Requires: astunparse, flatbuffers, protobuf, tensorflow-estimator, absl-py, google-p
Required-by: fancyimpute
```

```
import datetime
import numpy as np
import pandas as pd
from scipy.io import loadmat
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
```

Function for making MAT data usable for prediction

The data that we used here is a part of NASA's Prognostics Center of Excellence Repository. It can be accessed at the following link: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#battery The data files are in .mat format. We required a function that can convert these highly branched .mat data to simpler dataframe that can be used for learning the patterns from.

```
def load_data(battery):
  mat = loadmat(battery + '.mat')
  print('Total data in dataset: ', len(mat[battery][0, 0]['cycle'][0]))
  counter = 0
  dataset = []
  capacity_data = []
```

```
  for i in range(len(mat[battery][0, 0]['cycle'][0])):
    row = mat[battery][0, 0]['cycle'][0, i]
    if row['type'][0] == 'discharge':
      ambient_temperature = row['ambient_temperature'][0][0]
      date_time = datetime.datetime(int(row['time'][0][0]),
                                   int(row['time'][0][1]),
                                   int(row['time'][0][2]),
                                   int(row['time'][0][3]),
                                   int(row['time'][0][4])) + datetime.timedelta(seconds=int(ro
      data = row['data']
      capacity = data[0][0]['Capacity'][0][0]
      for j in range(len(data[0][0]['Voltage_measured'][0])):
        voltage_measured = data[0][0]['Voltage_measured'][0][j]
        current_measured = data[0][0]['Current_measured'][0][j]
        temperature_measured = data[0][0]['Temperature_measured'][0][j]
        current_load = data[0][0]['Current_load'][0][j]
        voltage_load = data[0][0]['Voltage_load'][0][j]
        time = data[0][0]['Time'][0][j]
        dataset.append([counter + 1, ambient_temperature, date_time, capacity,
                        voltage_measured, current_measured,
                        temperature_measured, current_load,
                        voltage_load, time])
      capacity_data.append([counter + 1, ambient_temperature, date_time, capacity])
      counter = counter + 1
  print(dataset[0])
  return [pd.DataFrame(data=dataset,
                       columns=['cycle', 'ambient_temperature', 'datetime',
                                'capacity', 'voltage_measured',
                                'current_measured', 'temperature_measured',
                                'current_load', 'voltage_load', 'time']),
          pd.DataFrame(data=capacity_data,
                       columns=['cycle', 'ambient_temperature', 'datetime',
                                'capacity'])]
```

Now we used this simpler dataframe in order to prepare training and testing sets for validation of the model in further steps. Here we shall split the loaded data in main data and capacity data. In this specific case, the battery capacity data is used to predict the capacity in the following cycles using the first data of the first 50 cycles in such a way that we can know when the battery threshold is reached and estimate the missing cycles to reach the end of the battery life.

50 of the all data rows are implemented for training.

```
dataset_val, capacity_val = load_data('B0005')
attrib=['cycle', 'datetime', 'capacity']
dis_ele = capacity_val[attrib]
rows=['cycle','capacity']
dataset=dis_ele[rows]
```

```
data_train=dataset[(dataset['cycle']<50)]
data_set_train=data_train.iloc[:,1:2].values
data_test=dataset[(dataset['cycle']>=50)]
data_set_test=data_test.iloc[:,1:2].values

sc=MinMaxScaler(feature_range=(0,1))
data_set_train=sc.fit_transform(data_set_train)
data_set_test=sc.transform(data_set_test)

X_train=[]
y_train=[]
#take the last 10t to predict 10t+1
for i in range(10,49):
    X_train.append(data_set_train[i-10:i,0])
    y_train.append(data_set_train[i,0])
X_train,y_train=np.array(X_train),np.array(y_train)

X_train=np.reshape(X_train,(X_train.shape[0],X_train.shape[1],1))
```

```
Total data in dataset:  616
[1, 24, datetime.datetime(2008, 4, 2, 15, 25, 41), 1.8564874208181574, 4.19149180750
```

For each of the capacity value in training target(y_train) we use 10 previous capacity values as features(X_train) for training.

Neural Network building

Calling the necessary tensorflow models, layers and optimizers.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import LSTM
from tensorflow.keras.optimizers import Adam
```

Here we used LSTM(long short term memory) artificial recurrent neural network architecture. Its difference from the standard neural networks is that it has feedback capabilities unlike their feedforward connections. Most of the RNN's are capable of using feedback or memory advantage to optimize their learning but a standard RNN may find it difficult to utilize a very distant learning in the network. This is called **Long Term Dependency issue**.

A Long Short Term Memory (**LSTM**) RNN is capable of dealing with long term dependencies as it is innate nature of its layer architecture. It has a bit more complex layer structure than a standard RNN which helps it become more slective at decision making and learning from data.

```
regress = Sequential()
regress.add(LSTM(units=200, return_sequences=True, input_shape=(X_train.shape[1],1)))
regress.add(Dropout(0.3))
regress.add(LSTM(units=200, return_sequences=True))
regress.add(Dropout(0.3))
regress.add(LSTM(units=200, return_sequences=True))
regress.add(Dropout(0.3))
regress.add(LSTM(units=200))
regress.add(Dropout(0.3))
regress.add(Dense(units=1))
regress.compile(optimizer='adam',loss='mean_squared_error')
regress.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 10, 200)           161600
_________________________________________________________________
dropout (Dropout)            (None, 10, 200)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_2 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_3 (LSTM)                (None, 200)               320800
_________________________________________________________________
dropout_3 (Dropout)          (None, 200)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 201
=================================================================
Total params: 1,124,201
Trainable params: 1,124,201
Non-trainable params: 0
_________________________________________________________________
```

Train

```
regress.fit(X_train,y_train,epochs=220,batch_size=25)
```

```
Epoch 1/220
```

```
2/2 [==============================] - 6s 89ms/step - loss: 0.3375
Epoch 2/220
2/2 [==============================] - 0s 89ms/step - loss: 0.1295
Epoch 3/220
2/2 [==============================] - 0s 87ms/step - loss: 0.1465
Epoch 4/220
2/2 [==============================] - 0s 87ms/step - loss: 0.0560
Epoch 5/220
2/2 [==============================] - 0s 86ms/step - loss: 0.1045
Epoch 6/220
2/2 [==============================] - 0s 81ms/step - loss: 0.0987
Epoch 7/220
2/2 [==============================] - 0s 83ms/step - loss: 0.0674
Epoch 8/220
2/2 [==============================] - 0s 85ms/step - loss: 0.0487
Epoch 9/220
2/2 [==============================] - 0s 85ms/step - loss: 0.0577
Epoch 10/220
2/2 [==============================] - 0s 86ms/step - loss: 0.0470
Epoch 11/220
2/2 [==============================] - 0s 85ms/step - loss: 0.0451
Epoch 12/220
2/2 [==============================] - 0s 83ms/step - loss: 0.0458
Epoch 13/220
2/2 [==============================] - 0s 84ms/step - loss: 0.0482
Epoch 14/220
2/2 [==============================] - 0s 92ms/step - loss: 0.0460
Epoch 15/220
2/2 [==============================] - 0s 83ms/step - loss: 0.0454
Epoch 16/220
2/2 [==============================] - 0s 86ms/step - loss: 0.0467
Epoch 17/220
2/2 [==============================] - 0s 92ms/step - loss: 0.0455
Epoch 18/220
2/2 [==============================] - 0s 81ms/step - loss: 0.0452
Epoch 19/220
2/2 [==============================] - 0s 90ms/step - loss: 0.0468
Epoch 20/220
2/2 [==============================] - 0s 92ms/step - loss: 0.0446
Epoch 21/220
2/2 [==============================] - 0s 81ms/step - loss: 0.0422
Epoch 22/220
2/2 [==============================] - 0s 83ms/step - loss: 0.0437
Epoch 23/220
2/2 [==============================] - 0s 88ms/step - loss: 0.0427
Epoch 24/220
2/2 [==============================] - 0s 82ms/step - loss: 0.0427
Epoch 25/220
2/2 [==============================] - 0s 83ms/step - loss: 0.0382
Epoch 26/220
2/2 [==============================] - 0s 82ms/step - loss: 0.0388
Epoch 27/220
2/2 [==============================] - 0s 85ms/step - loss: 0.0350
Epoch 28/220
2/2 [==============================] - 0s 82ms/step - loss: 0.0412
Epoch 29/220
2/2 [==============================] - 0s 82ms/step - loss: 0.0392
```

Test prep

Preparing the test data.

```
print(len(data_test))
data_total=pd.concat((data_train['capacity'], data_test['capacity']),axis=0)
inputs=data_total[len(data_total)-len(data_test)-10:].values
inputs=inputs.reshape(-1,1)
inputs=sc.transform(inputs)
```

```
119
```

Testing

```
X_test=[]
for i in range(10,129):
    X_test.append(inputs[i-10:i,0])
X_test=np.array(X_test)
X_test=np.reshape(X_test,(X_test.shape[0],X_test.shape[1],1))
pred=regress.predict(X_test)
print(pred.shape)
pred=sc.inverse_transform(pred)
pred=pred[:,0]
tests=data_test.iloc[:,1:2]
rmse = np.sqrt(mean_squared_error(tests, pred))
print('Test RMSE: %.3f' % rmse)
metrics.r2_score(tests,pred)
```

```
(119, 1)
Test RMSE: 0.064
0.7757345080685858
```

The model was able to predict the remaining useful life for battery test dataset with a root mean square error of 0.064 cycles and the R2 score is attained is reasonably well 77.5%.

Visual rep of results

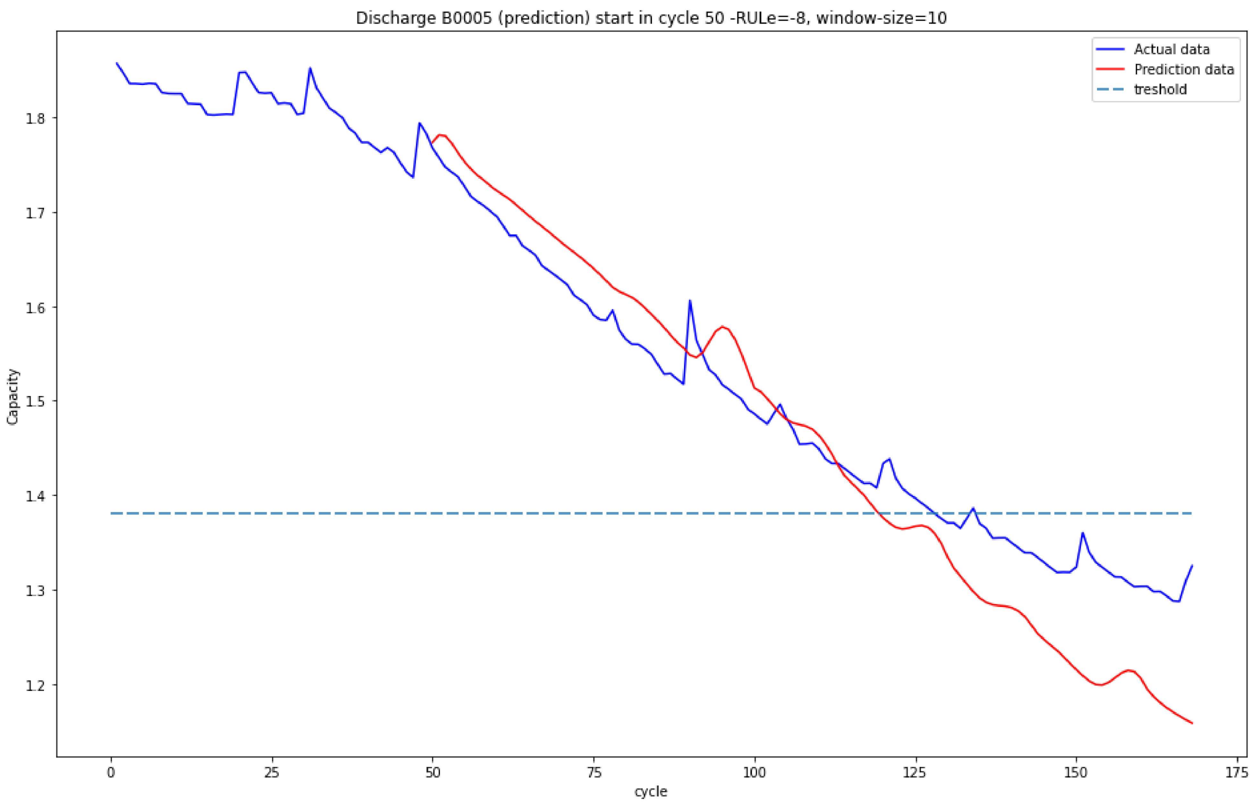
```
ln = len(data_train)
data_test['pre']=pred
plot_df = dataset.loc[(dataset['cycle']>=1),['cycle','capacity']]
plot_per = data_test.loc[(data_test['cycle']>=ln),['cycle','pre']]
```

```
plt.figure(figsize=(16, 10))
plt.plot(plot_df['cycle'], plot_df['capacity'], label="Actual data", color='blue')
plt.plot(plot_per['cycle'],plot_per['pre'],label="Prediction data", color='red')
#Draw threshold
plt.plot([0.,168], [1.38, 1.38],dashes=[6, 2], label="treshold")
plt.ylabel('Capacity')
# make x-axis ticks legible
adf = plt.gca().get_xaxis().get_major_formatter()
plt.xlabel('cycle')
plt.legend()
plt.title('Discharge B0005 (prediction) start in cycle 50 -RULe=-8, window-size=10')
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopy
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta

Text(0.5, 1.0, 'Discharge B0005 (prediction) start in cycle 50 -RULe=-8, window
```



Prediction on the Test set and error calculation

```
pred=0
Afil=0
Pfil=0
a=data_test['capacity'].values
b=data_test['pre'].values
j=0
k=0
for i in range(len(a)):
    actual=a[i]

    if actual<=1.38:
        j=i
        Afil=j
        break
for i in range(len(a)):
    pred=b[i]
    if pred< 1.38:
        k=i
        Pfil=k
        break
print("The Actual fail at cycle number: "+ str(Afil+ln))
print("The prediction fail at cycle number: "+ str(Pfil+ln))
RULerror=Pfil-Afil
print("The error of RUL= "+ str(RULerror)+ " Cycle(s)")
```

```
The Actual fail at cycle number: 128
The prediction fail at cycle number: 119
The error of RUL= -9 Cycle(s)
```

On the test data battery, this model was able to predict the failure(State of charge hitting 20%) with an error of 9 cycles. The fact to be observed is that the model was capable to pre-predict the failure(End of Life) for battery which is very important to avoid complications and improve the quality of Predictive Maintenace feature for this (RUL)Remaining Useful Life Prediction Task.