HACKER EARTH - On The Plague Trail

https://www.kaggle.com/shivammittal99/hackerearth-on-the-plague-trail (https://www.kaggle.com/shivammittal99/hackerearth-on-the-plague-trail)

Predict the total number of people infected by the 7 different pathogens.

Plague is an epidemic event caused by Bacteria. A group of senior scientists misplaced a package containing fatal plague bacteria during one of their trips. With no means of tracking where the package is, scientists are now trying to come up with a solution to stop the plague. This plague has 7 different strains that are unique for each continent. This strain is expanding rapidly in each continent.

The dataset contains escalations of the plague for all the seven strains. The dataset is a time series in which the training set contains the number of individuals that are infected by the plague over a defined period of time.

Your mission, should you choose to accept it, is to defend the world against this plague by building an algorithm that can minimize the damage.

No. Column Label Column Description

1.ID - A calculated unique ID for each research.

2.DateTime - Represents the data and time on which the event is recorded

3.TempOut - Outside Temperature

4.HiTemp - Highest Temperature

5.LowTemp - Lowest Temperature

6.OutHum - Outside Humidity

7.DewPt - Dew Point

8.WindSpeed - Wind Speed

9.WindDir - Wind Direction

10.WindRun - Wind Run Flow

11.HiSpeed - Highest Speed of the wind

12.HiDir - Direction of the wind which has highest speed

13.WindChill - Chillness of the wind

14.HeatIndex - Heat Index

15.THWIndex - THW Index

16.Bar - Barometer Reading

17.Rain - Rain

18.RainRate - Frequency of Rain

19.HeatDD - Heat DD

20.CoolDD - Cool DD

21.InTemp - Temperature Inside

22.InHum - Humidity Inside

23.InDew - Dew Inside

24.InHeat - Heat Inside

25.InEMC - EMC Inside

26.InAirDensity - Air Density

27.WindSamp - Wind - Attribute 1

28.WindTx - Wind - Attribute 2

29.ISSRecpt - Reception

30.ArcInt - Attribute

31.PA - Total No of People infected by Pathogen A

32.PB - Total No of People infected by Pathogen B

33.PC - Total No of People infected by Pathogen C

34.PD - Total No of People infected by Pathogen D

35.PE - Total No of People infected by Pathogen E

36.PF - Total No of People infected by Pathogen F

37.PG - Total No of People infected by Pathogen G

What to do

Given is the train data where based on the features, no. of people infected by Pathogen A,B,C,D,E,F,G are given. A model has to be built and trained with the data provided such that for a given set of conditions/features(test) it has to predict the no. of people that will get infected due to Pathogen A,B,C,D,E,F,G accurately.

As we have to predict the number of people infected due to the Pathogens this is a Regression Problem.

Root Mean Squared Error : Used to measure the differences between actual and predicted values.

RMSE = sqrt(mean(actual-predicted)^2)

Evaluation based on Root Mean Squared Error (RMSE).

score = max(0,(100 - rmse))

Importing required libraries

In [1]:

```
import keras
from keras.datasets import cifar10
from keras.models import Model, Sequential
from keras.layers import Dense, Dropout, Flatten, Input, AveragePooling2D, merge, Activation
from keras.layers import Conv2D, MaxPooling2D, BatchNormalization
from keras.layers import Concatenate
from keras.optimizers import Adam
from tensorflow.keras import models, layers
from tensorflow.keras.models import Model
from tensorflow.keras.layers import BatchNormalization, Activation, Flatten
from tensorflow.keras.optimizers import Adam,RMSprop
from keras.preprocessing.image import ImageDataGenerator
from keras import regularizers
from keras.callbacks import LearningRateScheduler
import numpy as np
import pandas as pd
```

```
Using TensorFlow backend.
```

Reading Train Data into a dataframe

In [2]:

```
data_train=pd.read_csv("train.csv")
print(data_train.columns)
```

```
Index(['ID', 'DateTime', 'TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt',
       'WindSpeed', 'WindDir', 'WindRun', 'HiSpeed', 'HiDir', 'WindChill',
       'HeatIndex', 'THWIndex', 'Bar', 'Rain', 'RainRate', 'HeatDD', 'CoolDD',
       'InTemp', 'InHum', 'InDew', 'InHeat', 'InEMC', 'InAirDensity',
       'WindSamp', 'WindTx', 'ISSRecpt', 'ArcInt', 'PA', 'PB', 'PC', 'PD',
       'PE', 'PF', 'PG'],
      dtype='object')
```

In [3]:

```
print(data_train.head(5))
```

```
        ID          DateTime  TempOut  HiTemp  LowTemp  OutHum  DewPt  \
0  PR00001  07/12/2040 0:15     53.5    53.6     53.5      85   49.1
1  PR00002  07/12/2040 0:30     53.5    53.5     53.4      85   49.1
2  PR00003  07/12/2040 0:45     53.3    53.5     53.2      85   48.9
3  PR00004  07/12/2040 1:00     53.1    53.3     53.0      86   49.0
4  PR00005  07/12/2040 1:15     52.9    53.1     52.9      86   48.8

   WindSpeed WindDir  WindRun  ...  WindTx ISSRecpt  ArcInt  PA  PB  PC  PD  \
0          2     SSE      0.5  ...       1    100.0      15   1   1   1   1
1          2     SSE      0.5  ...       1    100.0      15   1   1   1   1
2          2     SSE      0.5  ...       1    100.0      15   1   1   1   1
3          2       S      0.5  ...       1    100.0      15   1   1   1   1
4          2       S      0.5  ...       1    100.0      15   1   1   1   1

   PE  PF  PG
0   1   1   1
1   1   1   1
2   1   1   1
3   1   1   1
4   1   1   1

[5 rows x 37 columns]
```

In [4]:

```
print(data_train.shape)
```

```
(40000, 37)
```

Reading Test data into a dataframe

In [5]:

```
data_test=pd.read_csv("test.csv")
print(data_test.columns)
```

```
Index(['ID', 'DateTime', 'TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt',
       'WindSpeed', 'WindDir', 'WindRun', 'HiSpeed', 'HiDir', 'WindChill',
       'HeatIndex', 'THWIndex', 'Bar', 'Rain', 'RainRate', 'HeatDD', 'CoolDD',
       'InTemp', 'InHum', 'InDew', 'InHeat', 'InEMC', 'InAirDensity',
       'WindSamp', 'WindTx', 'ISSRecpt', 'ArcInt'],
      dtype='object')
```

In [6]:

```
print(data_test.head(5))
```

```
        ID           DateTime  TempOut  HiTemp  LowTemp  OutHum  DewPt  \
0  PR40001  08-04-2041 11:30     82.6    83.6     80.8      38   54.4
1  PR40002  08-04-2041 11:45     82.6    83.2     82.1      36   52.9
2  PR40003  08-04-2041 12:00     83.6    84.5     82.4      38   55.3
3  PR40004  08-04-2041 12:15     85.1    85.5     83.4      37   55.9
4  PR40005  08-04-2041 12:30     86.5    87.3     85.1      37   57.1

   WindSpeed WindDir  WindRun  ...  InTemp InHum  InDew  InHeat  InEMC  \
0          4     SSE      1.0  ...    68.3    29   34.8    64.6   6.08
1          4       S      1.0  ...    69.3    58   53.9    68.5  10.75
2          4       S      1.0  ...    68.4    30   35.7    64.8   6.25
3          4       S      1.0  ...    69.9    56   53.5    68.7  10.35
4          4     SSE      1.0  ...    68.5    67   57.1    68.7  12.38

   InAirDensity  WindSamp  WindTx  ISSRecpt  ArcInt
0        0.0748       351       1     100.0      15
1        0.0741       351       1     100.0      15
2        0.0747       351       1     100.0      15
3        0.0740       352       1     100.0      15
4        0.0740       351       1     100.0      15

[5 rows x 30 columns]
```

In [7]:

```
print(data_test.shape)
```

```
(22446, 30)
```

Converting datatime format, adding Year, Month, Day & sorting train and test data

In [8]:

```
cols = ['Date' if x=='DateTime' else x for x in list(data_train.columns)]

data_train['Date']=pd.to_datetime(data_train['DateTime'])
data_train.drop(['DateTime'],axis=1,inplace=True)
data_train.sort_values(by=['Date'],inplace=True)
```

In [9]:

```
cols = ['Date' if x=='DateTime' else x for x in list(data_test.columns)]

data_test['Date']=pd.to_datetime(data_test['DateTime'])
data_test.drop(['DateTime'],axis=1,inplace=True)
data_test.sort_values(by=['Date'],inplace=True)
```

In [10]:

```
data_train['Year'] = data_train['Date'].dt.year
data_train['Month'] = data_train['Date'].dt.month
data_train['Day'] = data_train['Date'].dt.day
```

In [11]:

```
data_test['Year'] = data_test['Date'].dt.year
data_test['Month'] = data_test['Date'].dt.month
data_test['Day'] = data_test['Date'].dt.day
```

In [12]:

```
print(data_train.columns)
```

```
Index(['ID', 'TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt', 'WindSpeed',
       'WindDir', 'WindRun', 'HiSpeed', 'HiDir', 'WindChill', 'HeatIndex',
       'THWIndex', 'Bar', 'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp',
       'InHum', 'InDew', 'InHeat', 'InEMC', 'InAirDensity', 'WindSamp',
       'WindTx', 'ISSRecpt', 'ArcInt', 'PA', 'PB', 'PC', 'PD', 'PE', 'PF',
       'PG', 'Date', 'Year', 'Month', 'Day'],
      dtype='object')
```

Train data Info

In [13]:

```
print(data_train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40000 entries, 25556 to 29447
Data columns (total 40 columns):
ID              40000 non-null object
TempOut         40000 non-null float64
HiTemp          40000 non-null float64
LowTemp         40000 non-null float64
OutHum          40000 non-null int64
DewPt           40000 non-null float64
WindSpeed       40000 non-null int64
WindDir         40000 non-null object
WindRun         40000 non-null float64
HiSpeed         40000 non-null int64
HiDir           40000 non-null object
WindChill       40000 non-null float64
HeatIndex       40000 non-null float64
THWIndex        40000 non-null float64
Bar             40000 non-null float64
Rain            40000 non-null float64
RainRate        40000 non-null float64
HeatDD          40000 non-null float64
CoolDD          40000 non-null float64
InTemp          40000 non-null float64
InHum           40000 non-null int64
InDew           40000 non-null float64
InHeat          40000 non-null float64
InEMC           40000 non-null float64
InAirDensity    40000 non-null float64
WindSamp        40000 non-null int64
WindTx          40000 non-null int64
ISSRecpt        40000 non-null float64
ArcInt          40000 non-null int64
PA              40000 non-null int64
PB              40000 non-null int64
PC              40000 non-null int64
PD              40000 non-null int64
PE              40000 non-null int64
PF              40000 non-null int64
PG              40000 non-null int64
Date            40000 non-null datetime64[ns]
Year            40000 non-null int64
Month           40000 non-null int64
Day             40000 non-null int64
dtypes: datetime64[ns](1), float64(19), int64(17), object(3)
memory usage: 12.5+ MB
None
```

2 Categorical variables : WindDir, HiDir

Test data Info

In [14]:

```
print(data_test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 22446 entries, 0 to 5218
Data columns (total 33 columns):
ID              22446 non-null object
TempOut         22446 non-null float64
HiTemp          22446 non-null float64
LowTemp         22446 non-null float64
OutHum          22446 non-null int64
DewPt           22446 non-null float64
WindSpeed       22446 non-null int64
WindDir         22446 non-null object
WindRun         22446 non-null float64
HiSpeed         22446 non-null int64
HiDir           22446 non-null object
WindChill       22446 non-null float64
HeatIndex       22446 non-null float64
THWIndex        22446 non-null float64
Bar             22446 non-null float64
Rain            22446 non-null float64
RainRate        22446 non-null float64
HeatDD          22446 non-null float64
CoolDD          22446 non-null float64
InTemp          22446 non-null float64
InHum           22446 non-null int64
InDew           22446 non-null float64
InHeat          22446 non-null float64
InEMC           22446 non-null float64
InAirDensity    22446 non-null float64
WindSamp        22446 non-null int64
WindTx          22446 non-null int64
ISSRecpt        22446 non-null float64
ArcInt          22446 non-null int64
Date            22446 non-null datetime64[ns]
Year            22446 non-null int64
Month           22446 non-null int64
Day             22446 non-null int64
dtypes: datetime64[ns](1), float64(19), int64(10), object(3)
memory usage: 5.8+ MB
None
```

2 Categorical variables : WindDir, HiDir

Checking for missing data in train & test

In [15]:

```
data_train_na = (data_train.isnull().sum() / len(data_train)) * 100
print(data_train_na)
```

```
ID              0.0
TempOut         0.0
HiTemp          0.0
LowTemp         0.0
OutHum          0.0
DewPt           0.0
WindSpeed       0.0
WindDir         0.0
WindRun         0.0
HiSpeed         0.0
HiDir           0.0
WindChill       0.0
HeatIndex       0.0
THWIndex        0.0
Bar             0.0
Rain            0.0
RainRate        0.0
HeatDD          0.0
CoolDD          0.0
InTemp          0.0
InHum           0.0
InDew           0.0
InHeat          0.0
InEMC           0.0
InAirDensity    0.0
WindSamp        0.0
WindTx          0.0
ISSRecpt        0.0
ArcInt          0.0
PA              0.0
PB              0.0
PC              0.0
PD              0.0
PE              0.0
PF              0.0
PG              0.0
Date            0.0
Year            0.0
Month           0.0
Day             0.0
dtype: float64
```

In [16]:

```
data_test_na = (data_test.isnull().sum() / len(data_test)) * 100
print(data_test_na)
```

```
ID              0.0
TempOut         0.0
HiTemp          0.0
LowTemp         0.0
OutHum          0.0
DewPt           0.0
WindSpeed       0.0
WindDir         0.0
WindRun         0.0
HiSpeed         0.0
HiDir           0.0
WindChill       0.0
HeatIndex       0.0
THWIndex        0.0
Bar             0.0
Rain            0.0
RainRate        0.0
HeatDD          0.0
CoolDD          0.0
InTemp          0.0
InHum           0.0
InDew           0.0
InHeat          0.0
InEMC           0.0
InAirDensity    0.0
WindSamp        0.0
WindTx          0.0
ISSRecpt        0.0
ArcInt          0.0
Date            0.0
Year            0.0
Month           0.0
Day             0.0
dtype: float64
```

Observation:

No missing data in train & test

In [15]:

```
import pandas_profiling as pp
pp.ProfileReport(data_train)
```

Overview

Dataset info

Number of variables	41
Number of observations	40000
Missing cells	0 (0.0%)
Duplicate rows	0 (0.0%)
Total size in memory	12.5 MiB
Average record size in memory	328.0 B

Variables types

Numeric	18
Categorical	4
Boolean	0
Date	1
URL	0
Text (Unique)	1
Rejected	17
Unsupported	0

Warnings

`ArcInt` has constant value "15"	Rejected
`CoolDD` has 29824 (74.6%) zeros	Zeros
`HeatDD` has 10258 (25.6%) zeros	Zeros
`HiSpeed` has 6624 (16.6%) zeros	Zeros
`HiTemp` is highly correlated with `HeatIndex` (ρ = 0.9959465518)	Rejected
`InEMC` is highly correlated with `InDew` (ρ = 0.9399179535)	Rejected
`InHum` is highly correlated with `InEMC` (ρ = 0.9928735576)	Rejected
`LowTemp` is highly correlated with `HiTemp` (ρ = 0.9977990261)	Rejected
`PB` is highly correlated with `PA` (ρ = 0.9989997082)	Rejected
`PC` is highly correlated with `PB` (ρ = 0.9991912524)	Rejected
`PD` is highly correlated with `PC` (ρ = 0.9993263306)	Rejected

Out[15]:

Observation:

1. Constants variable : ArcInt,WindTx
2. Highly Correlated variables : HiTemp,InEMC,InHu,LowTemp,TempOut,THWIndex,WindChill,WindRun
3. ISSRecpt & Year can be considered as categorical along with WindDir, HiDir based on the value counts.

In [16]:

```
pp.ProfileReport(data_test)
```

Overview

Dataset info

Number of variables	34
Number of observations	22446
Missing cells	0 (0.0%)
Duplicate rows	0 (0.0%)
Total size in memory	5.8 MiB
Average record size in memory	272.0 B

Variables types

Numeric	17
Categorical	4
Boolean	0
Date	1
URL	0
Text (Unique)	1
Rejected	11
Unsupported	0

Warnings

`ArcInt` has constant value "15"	Rejected
`CoolDD` has 18899 (84.2%) zeros	Zeros
`HeatDD` has 3577 (15.9%) zeros	Zeros
`HiSpeed` has 3854 (17.2%) zeros	Zeros
`HiTemp` is highly correlated with `HeatIndex` (ρ = 0.9951141768)	Rejected
`InHum` is highly correlated with `InEMC` (ρ = 0.9969142021)	Rejected
`InTemp` is highly correlated with `InHeat` (ρ = 0.9726988169)	Rejected
`LowTemp` is highly correlated with `HiTemp` (ρ = 0.9975010306)	Rejected
`Rain` has 21250 (94.7%) zeros	Zeros
`RainRate` is highly skewed (γ1 = 93.76387198)	Skewed
`RainRate` has 21558 (96.0%) zeros	Zeros

Out[16]:

Observation:

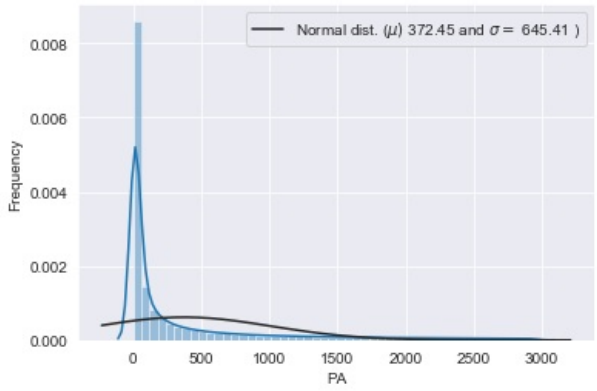
1. Constants variable : ArcInt,WindTx
2. Highly Correlated variables : HiTemp,InEMC,InHu,LowTemp,TempOut,THWIndex,WindChill,WindRun

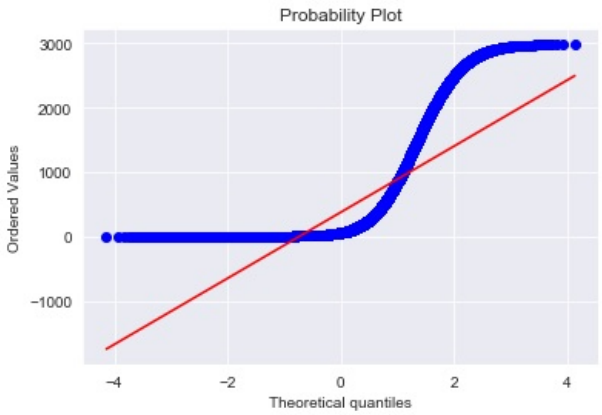
Target Variables Analysis

In [20]:

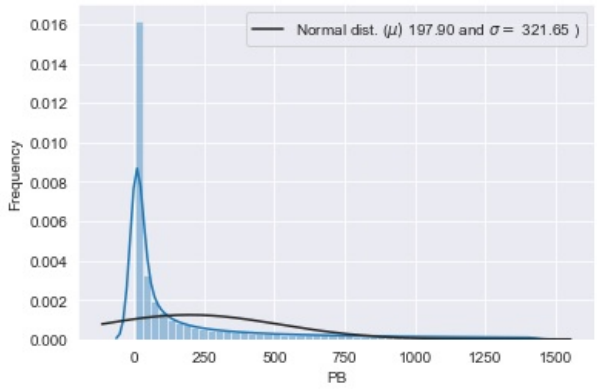
```
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
from scipy import stats
from scipy.stats import norm

cols = ['PA','PB','PC','PD','PE','PF','PG']

for c in cols:
    sns.distplot(data_train[c], fit=norm)

    (mu,sigma) = norm.fit(data_train[c])

    print("Dist Plot & QQ for:",c)
    print("*"*50)
    print('\n mu = {:.2f} and sigma = {:.2f}\n' .format(mu,sigma))

    plt.legend(['Normal dist. ($\mu)$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu,sigma)],loc='best')
    plt.ylabel('Frequency')
    plt.xlabel(c)

    fig=plt.figure()
    res=stats.probplot(data_train[c],plot=plt)
    plt.show()
```

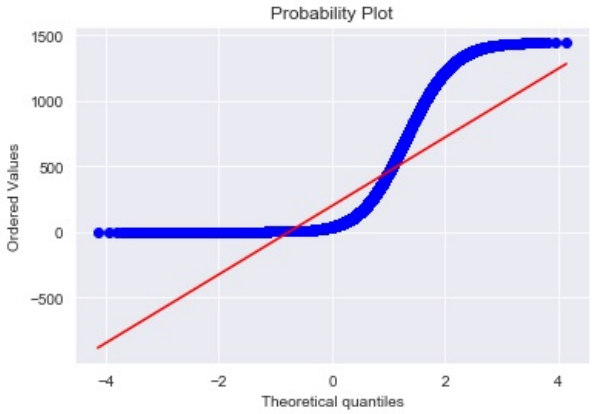
```
C:\Users\srila\AppData\Local\Programs\Python\Python36\Lib\site-packages\scipy\stats\stats.py:1713: F
utureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple
(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.arr
ay(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

Dist Plot & QQ for: PA
**************************************************

 mu = 372.45 and sigma = 645.41
```






```
Dist Plot & QQ for: PB
**************************************************

 mu = 197.90 and sigma = 321.65
```

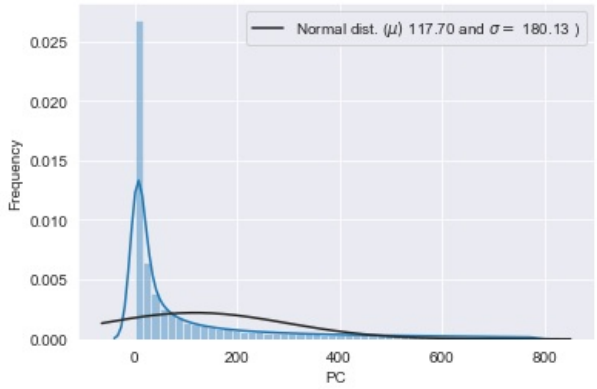


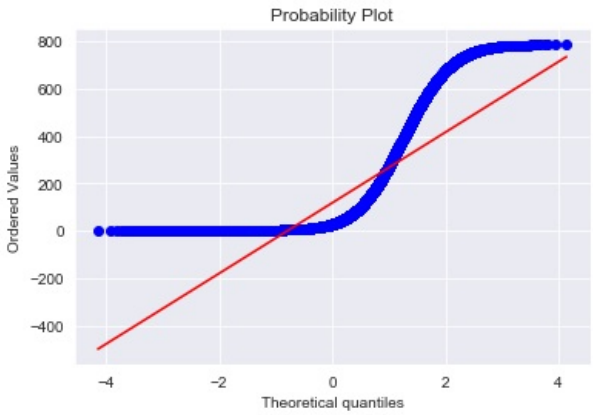


Dist Plot & QQ for: PC

****

mu = 117.70 and sigma = 180.13

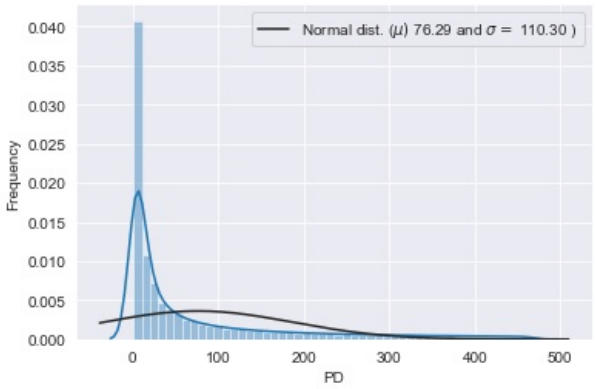


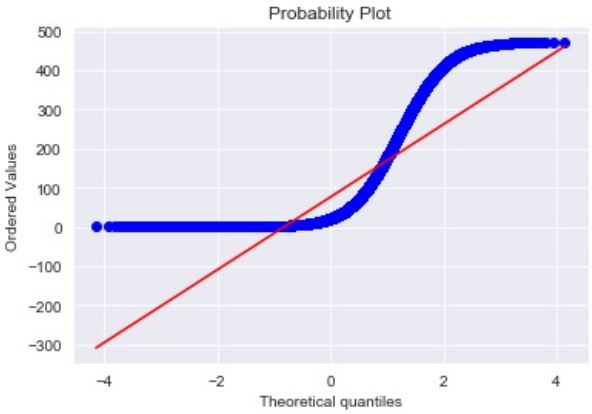


Dist Plot & QQ for: PD

****

mu = 76.29 and sigma = 110.30

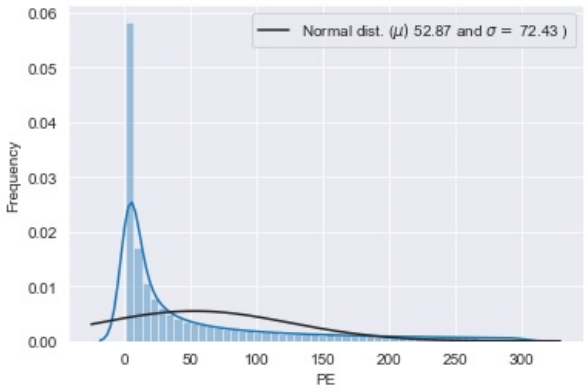


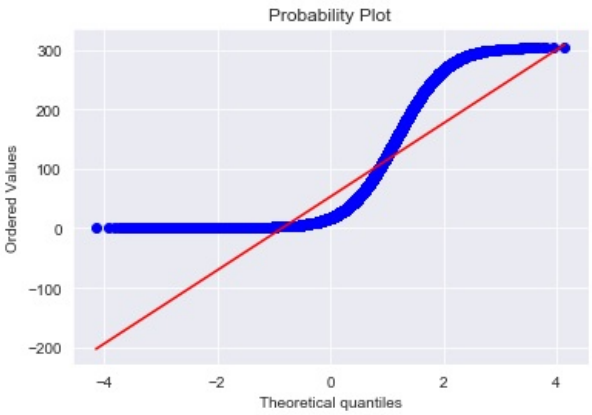


Dist Plot & QQ for: PE

****

mu = 52.87 and sigma = 72.43

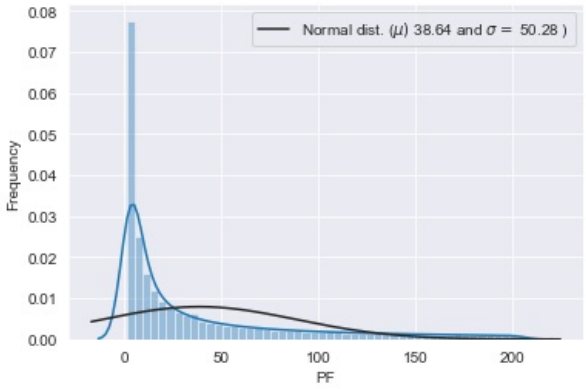


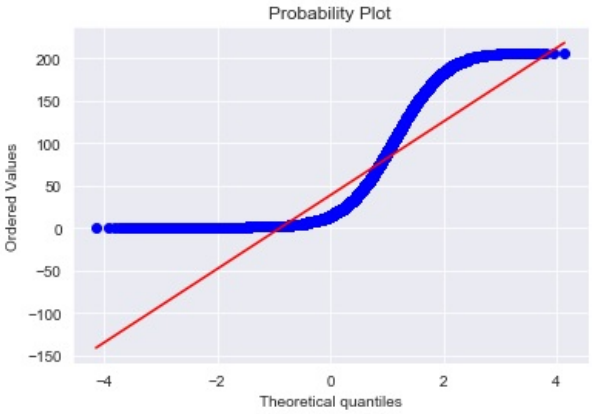


Dist Plot & QQ for: PF

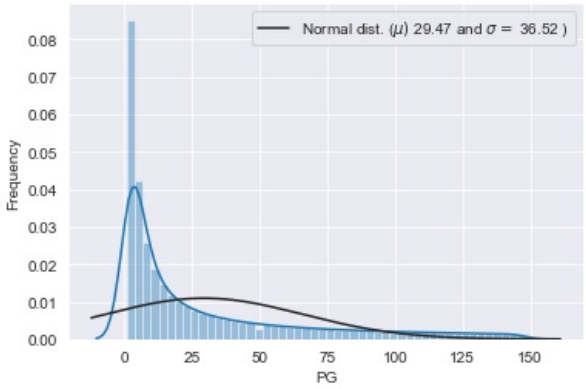
****

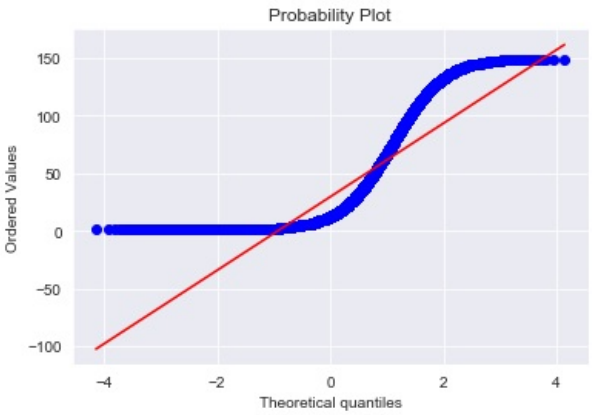
mu = 38.64 and sigma = 50.28






```
Dist Plot & QQ for: PG
**************************************************

 mu = 29.47 and sigma = 36.52
```





Obervation:

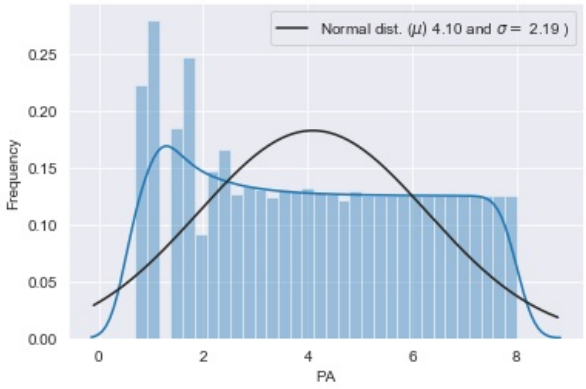
1. All the target variables are right skewed. Applying log transformation on all the target variables to normalise the data

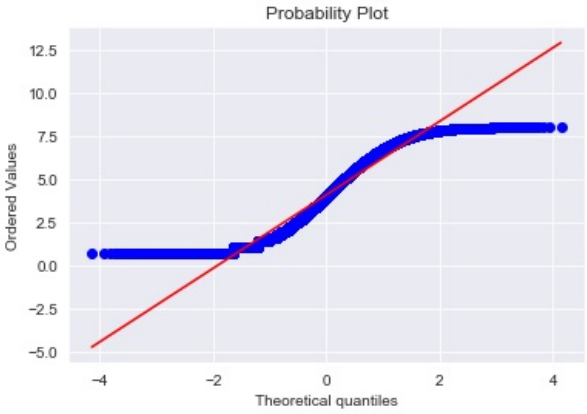
In [21]:

```
cols = ['PA','PB','PC','PD','PE','PF','PG']

for c in cols:

    data_train[c]=np.log1p(data_train[c])

    sns.distplot(data_train[c], fit=norm)

    (mu,sigma) = norm.fit(data_train[c])

    print("Dist Plot & QQ for:",c)
    print("*"*50)
    print('\n mu = {:.2f} and sigma = {:.2f}\n' .format(mu,sigma))

    plt.legend(['Normal dist. ($\mu)$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu,sigma)],loc='best')
    plt.ylabel('Frequency')
    plt.xlabel(c)

    fig=plt.figure()
    res=stats.probplot(data_train[c],plot=plt)
    plt.show()
```

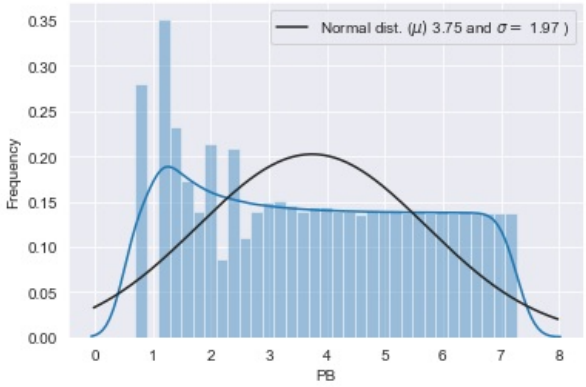
```
C:\Users\srila\AppData\Local\Programs\Python\Python36\Lib\site-packages\scipy\stats\stats.py:1713: F
utureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple
(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.arr
ay(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

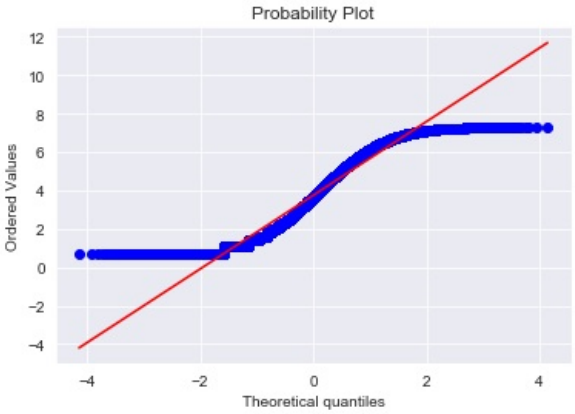
```
Dist Plot & QQ for: PA
**************************************************

 mu = 4.10 and sigma = 2.19
```






```
Dist Plot & QQ for: PB
**************************************************

 mu = 3.75 and sigma = 1.97
```

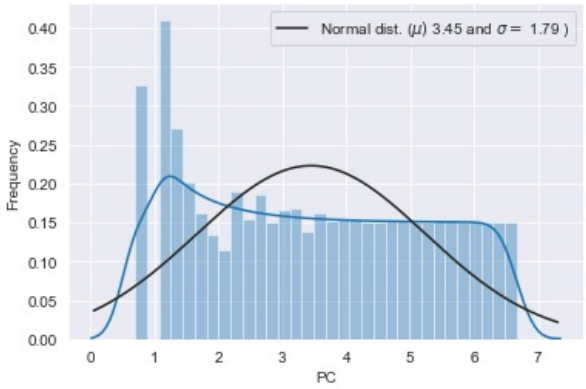


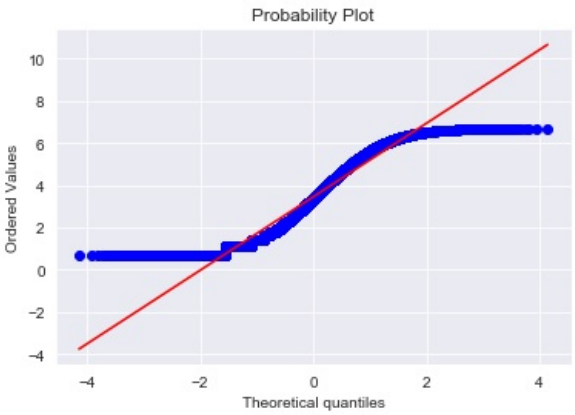


Dist Plot & QQ for: PC

****

mu = 3.45 and sigma = 1.79

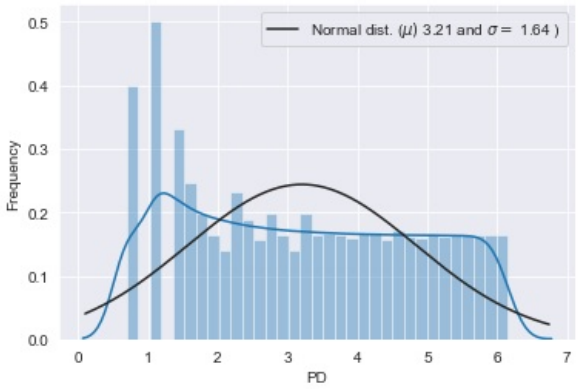


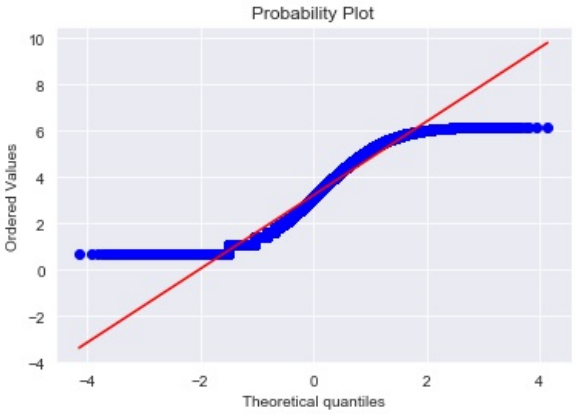


Dist Plot & QQ for: PD

****

mu = 3.21 and sigma = 1.64

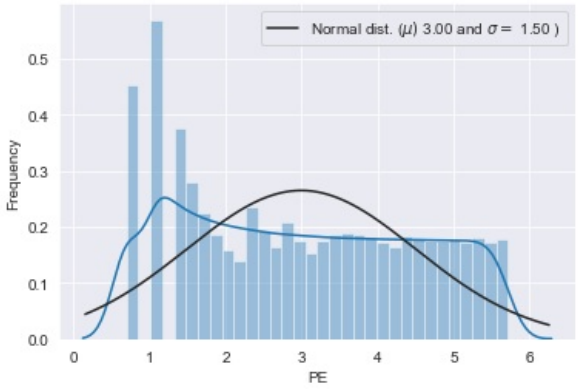


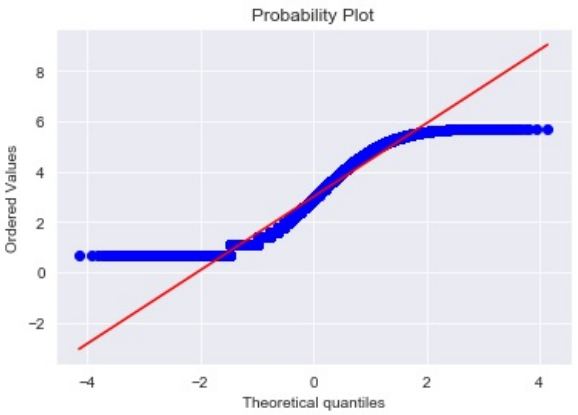


Dist Plot & QQ for: PE

****

mu = 3.00 and sigma = 1.50

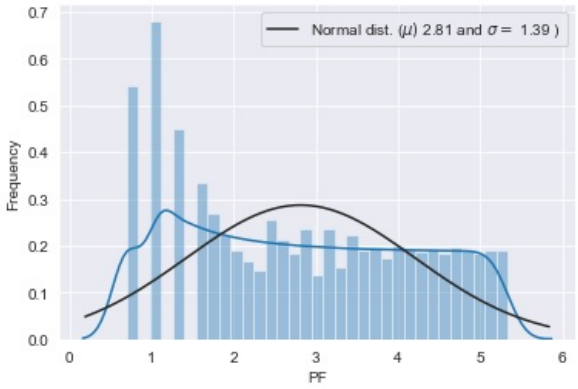


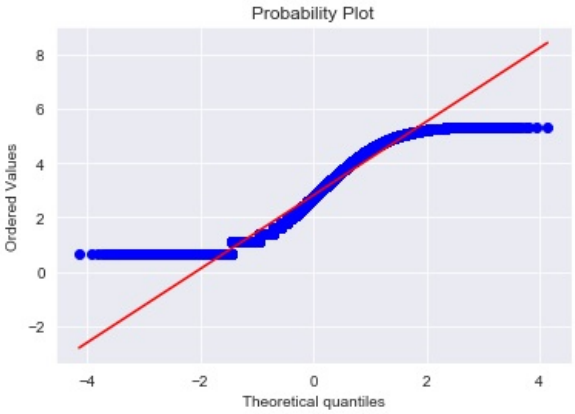


Dist Plot & QQ for: PF

****

mu = 2.81 and sigma = 1.39

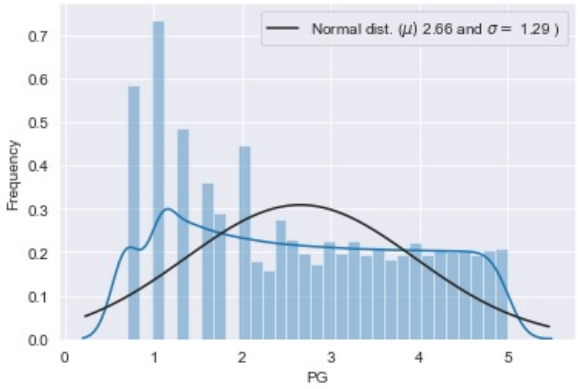


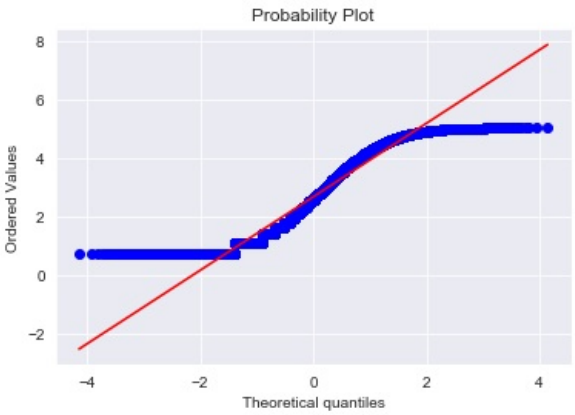


Dist Plot & QQ for: PG

****

mu = 2.66 and sigma = 1.29





In [22]:

```
print(data_train.head(5))
```

```
            ID  TempOut  HiTemp  LowTemp  OutHum  DewPt  WindSpeed WindDir  \
25556  PR25557     54.2    54.4     54.1      85   49.8          3      SE
25557  PR25558     53.7    54.1     53.7      86   49.6          3      SE
25558  PR25559     53.3    53.7     53.3      87   49.5          3     SSE
25559  PR25560     53.0    53.3     53.0      88   49.5          3     SSE
25560  PR25561     52.9    53.0     52.8      88   49.4          3     SSE

       WindRun  HiSpeed  ...       PB        PC        PD        PE        PF  \
25556     0.75        8  ...  4.65396  4.276666  3.951244  3.688879  3.433987
25557     0.75        8  ...  4.65396  4.276666  3.951244  3.688879  3.433987
25558     0.75        9  ...  4.65396  4.276666  3.951244  3.688879  3.433987
25559     0.75        9  ...  4.65396  4.276666  3.951244  3.688879  3.433987
25560     0.75        9  ...  4.65396  4.276666  3.951244  3.688879  3.433987

             PG                Date  Year  Month  Day
25556  3.218876 2040-07-01 00:15:00  2040      7    1
25557  3.218876 2040-07-01 00:30:00  2040      7    1
25558  3.218876 2040-07-01 00:45:00  2040      7    1
25559  3.218876 2040-07-01 01:00:00  2040      7    1
25560  3.218876 2040-07-01 01:15:00  2040      7    1

[5 rows x 40 columns]
```

Categorical variables WindDir, HiDir, ISSRecpt, Year of train & test

In [23]:

```
print(data_train['WindDir'].value_counts())
```

```
SSE    9870
---    6625
S      4513
SW     3842
WSW    2567
SE     2188
SSW    1860
WNW    1609
W      1549
N      1172
NW     1148
ESE     724
NNW     714
ENE     508
E       494
NNE     320
NE      297
Name: WindDir, dtype: int64
```

In [24]:

```
print(data_test['WindDir'].value_counts())
```

```
SSE    4653
---    3854
S      2463
SW     1733
SE     1580
WSW    1276
SSW    1148
W       985
NW      844
WNW     801
ESE     712
N       596
E       566
NNW     466
ENE     462
NNE     171
NE      136
Name: WindDir, dtype: int64
```

In [25]:

```
print(data_train['HiDir'].value_counts())
```

```
SSE    8470
---    6624
S      3862
SW     3313
WSW    2968
SE     2745
SSW    2551
W      2051
N      1444
WNW    1408
NW     1066
ESE    1056
NNW     941
E       534
ENE     419
NNE     321
NE      227
Name: HiDir, dtype: int64
```

In [26]:

```
print(data_test['HiDir'].value_counts())
```

```
SSE    4367
---    3854
S      2241
SE     1704
SW     1468
WSW    1463
SSW    1319
W      1144
ESE     818
WNW     771
N       763
NW      713
NNW     608
E       491
ENE     418
NNE     167
NE      137
Name: HiDir, dtype: int64
```

In [27]:

```
print(data_train['ISSRecpt'].value_counts())
```

```
100.0    39985
94.4        10
94.7         5
Name: ISSRecpt, dtype: int64
```

In [28]:

```
print(data_test['ISSRecpt'].value_counts())
```

```
100.0    22437
94.4         5
94.7         3
95.0         1
Name: ISSRecpt, dtype: int64
```

In [29]:

```
print(data_train['Year'].value_counts())
```

```
2041    20729
2040    17663
2042     1608
Name: Year, dtype: int64
```

In [30]:

```
print(data_test['Year'].value_counts())
```

```
2041    14307
2042     8139
Name: Year, dtype: int64
```

In [31]:

```
cols=('HiDir','WindDir','ISSRecpt','Year')
for c in cols:
    dum = pd.get_dummies(data_train[c],prefix=c)
    data_train = pd.concat([data_train,dum],axis=1)
    data_train.drop([c],axis=1,inplace=True)

print(data_train.columns)
```

```
Index(['ID', 'TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt', 'WindSpeed',
       'WindRun', 'HiSpeed', 'WindChill', 'HeatIndex', 'THWIndex', 'Bar',
       'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp', 'InHum', 'InDew',
       'InHeat', 'InEMC', 'InAirDensity', 'WindSamp', 'WindTx', 'ArcInt', 'PA',
       'PB', 'PC', 'PD', 'PE', 'PF', 'PG', 'Date', 'Month', 'Day', 'HiDir_---',
       'HiDir_E', 'HiDir_ENE', 'HiDir_ESE', 'HiDir_N', 'HiDir_NE', 'HiDir_NNE',
       'HiDir_NNW', 'HiDir_NW', 'HiDir_S', 'HiDir_SE', 'HiDir_SSE',
       'HiDir_SSW', 'HiDir_SW', 'HiDir_W', 'HiDir_WNW', 'HiDir_WSW',
       'WindDir_---', 'WindDir_E', 'WindDir_ENE', 'WindDir_ESE', 'WindDir_N',
       'WindDir_NE', 'WindDir_NNE', 'WindDir_NNW', 'WindDir_NW', 'WindDir_S',
       'WindDir_SE', 'WindDir_SSE', 'WindDir_SSW', 'WindDir_SW', 'WindDir_W',
       'WindDir_WNW', 'WindDir_WSW', 'ISSRecpt_94.4', 'ISSRecpt_94.7',
       'ISSRecpt_100.0', 'Year_2040', 'Year_2041', 'Year_2042'],
      dtype='object')
```

In [32]:

```
cols=('HiDir','WindDir','ISSRecpt','Year')
for c in cols:
    dum = pd.get_dummies(data_test[c],prefix=c)
    data_test = pd.concat([data_test,dum],axis=1)
    data_test.drop([c],axis=1,inplace=True)

print(data_test.columns)
```

```
Index(['ID', 'TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt', 'WindSpeed',
       'WindRun', 'HiSpeed', 'WindChill', 'HeatIndex', 'THWIndex', 'Bar',
       'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp', 'InHum', 'InDew',
       'InHeat', 'InEMC', 'InAirDensity', 'WindSamp', 'WindTx', 'ArcInt',
       'Date', 'Month', 'Day', 'HiDir_---', 'HiDir_E', 'HiDir_ENE',
       'HiDir_ESE', 'HiDir_N', 'HiDir_NE', 'HiDir_NNE', 'HiDir_NNW',
       'HiDir_NW', 'HiDir_S', 'HiDir_SE', 'HiDir_SSE', 'HiDir_SSW', 'HiDir_SW',
       'HiDir_W', 'HiDir_WNW', 'HiDir_WSW', 'WindDir_---', 'WindDir_E',
       'WindDir_ENE', 'WindDir_ESE', 'WindDir_N', 'WindDir_NE', 'WindDir_NNE',
       'WindDir_NNW', 'WindDir_NW', 'WindDir_S', 'WindDir_SE', 'WindDir_SSE',
       'WindDir_SSW', 'WindDir_SW', 'WindDir_W', 'WindDir_WNW', 'WindDir_WSW',
       'ISSRecpt_94.4', 'ISSRecpt_94.7', 'ISSRecpt_95.0', 'ISSRecpt_100.0',
       'Year_2041', 'Year_2042'],
      dtype='object')
```

Removing ID,Date,ArcInt,WindTx,Labels fro Train & test data

In [33]:

```
label=data_train[['PA', 'PB', 'PC', 'PD','PE', 'PF', 'PG']]
train=data_train.drop(['ID','Date','PA', 'PB', 'PC', 'PD','PE', 'PF', 'PG','ArcInt','WindTx'],axis=1)
test=data_test.drop(['ID','Date','ArcInt','WindTx'],axis=1)
print("Train columns",train.columns)
print("Label columns",label.columns)
print("Test columns",test.columns)
```

```
Train columns Index(['TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt', 'WindSpeed',
       'WindRun', 'HiSpeed', 'WindChill', 'HeatIndex', 'THWIndex', 'Bar',
       'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp', 'InHum', 'InDew',
       'InHeat', 'InEMC', 'InAirDensity', 'WindSamp', 'Month', 'Day',
       'HiDir_---', 'HiDir_E', 'HiDir_ENE', 'HiDir_ESE', 'HiDir_N', 'HiDir_NE',
       'HiDir_NNE', 'HiDir_NNW', 'HiDir_NW', 'HiDir_S', 'HiDir_SE',
       'HiDir_SSE', 'HiDir_SSW', 'HiDir_SW', 'HiDir_W', 'HiDir_WNW',
       'HiDir_WSW', 'WindDir_---', 'WindDir_E', 'WindDir_ENE', 'WindDir_ESE',
       'WindDir_N', 'WindDir_NE', 'WindDir_NNE', 'WindDir_NNW', 'WindDir_NW',
       'WindDir_S', 'WindDir_SE', 'WindDir_SSE', 'WindDir_SSW', 'WindDir_SW',
       'WindDir_W', 'WindDir_WNW', 'WindDir_WSW', 'ISSRecpt_94.4',
       'ISSRecpt_94.7', 'ISSRecpt_100.0', 'Year_2040', 'Year_2041',
       'Year_2042'],
      dtype='object')
Label columns Index(['PA', 'PB', 'PC', 'PD', 'PE', 'PF', 'PG'], dtype='object')
Test columns Index(['TempOut', 'HiTemp', 'LowTemp', 'OutHum', 'DewPt', 'WindSpeed',
       'WindRun', 'HiSpeed', 'WindChill', 'HeatIndex', 'THWIndex', 'Bar',
       'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp', 'InHum', 'InDew',
       'InHeat', 'InEMC', 'InAirDensity', 'WindSamp', 'Month', 'Day',
       'HiDir_---', 'HiDir_E', 'HiDir_ENE', 'HiDir_ESE', 'HiDir_N', 'HiDir_NE',
       'HiDir_NNE', 'HiDir_NNW', 'HiDir_NW', 'HiDir_S', 'HiDir_SE',
       'HiDir_SSE', 'HiDir_SSW', 'HiDir_SW', 'HiDir_W', 'HiDir_WNW',
       'HiDir_WSW', 'WindDir_---', 'WindDir_E', 'WindDir_ENE', 'WindDir_ESE',
       'WindDir_N', 'WindDir_NE', 'WindDir_NNE', 'WindDir_NNW', 'WindDir_NW',
       'WindDir_S', 'WindDir_SE', 'WindDir_SSE', 'WindDir_SSW', 'WindDir_SW',
       'WindDir_W', 'WindDir_WNW', 'WindDir_WSW', 'ISSRecpt_94.4',
       'ISSRecpt_94.7', 'ISSRecpt_95.0', 'ISSRecpt_100.0', 'Year_2041',
       'Year_2042'],
      dtype='object')
```

In [34]:

```
x_train,x_test=train,test
y_train=label
print("Data Train, Test shapes:",x_train.shape,x_test.shape)
print("Label Train, Test shapes:",y_train.shape)
```

```
Data Train, Test shapes: (40000, 65) (22446, 65)
Label Train, Test shapes: (40000, 7)
```

In [35]:

```
print(x_train.head(5))
```

```
       TempOut  HiTemp  LowTemp  OutHum  DewPt  WindSpeed  WindRun  HiSpeed  \
25556     54.2    54.4     54.1      85   49.8          3     0.75        8
25557     53.7    54.1     53.7      86   49.6          3     0.75        8
25558     53.3    53.7     53.3      87   49.5          3     0.75        9
25559     53.0    53.3     53.0      88   49.5          3     0.75        9
25560     52.9    53.0     52.8      88   49.4          3     0.75        9

       WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  WindDir_WNW  \
25556       54.2       54.1  ...           0          0            0
25557       53.7       53.6  ...           0          0            0
25558       53.3       53.3  ...           0          0            0
25559       53.0       53.0  ...           0          0            0
25560       52.9       52.9  ...           0          0            0

       WindDir_WSW  ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_100.0  Year_2040  \
25556            0              0              0               1          1
25557            0              0              0               1          1
25558            0              0              0               1          1
25559            0              0              0               1          1
25560            0              0              0               1          1

       Year_2041  Year_2042
25556          0          0
25557          0          0
25558          0          0
25559          0          0
25560          0          0

[5 rows x 65 columns]
```

In [36]:

```
print(x_test.head(5))
```

```
   TempOut  HiTemp  LowTemp  OutHum  DewPt  WindSpeed  WindRun  HiSpeed  \
0     82.6    83.6     80.8      38   54.4          4      1.0        9
1     82.6    83.2     82.1      36   52.9          4      1.0       11
2     83.6    84.5     82.4      38   55.3          4      1.0       11
3     85.1    85.5     83.4      37   55.9          4      1.0       11
4     86.5    87.3     85.1      37   57.1          4      1.0       10

   WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  WindDir_WNW  WindDir_WSW  \
0       82.6       81.8  ...           0          0            0            0
1       82.6       81.5  ...           0          0            0            0
2       83.6       83.3  ...           0          0            0            0
3       85.1       84.7  ...           0          0            0            0
4       86.5       86.2  ...           0          0            0            0

   ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_95.0  ISSRecpt_100.0  Year_2041  \
0              0              0              0               1          1
1              0              0              0               1          1
2              0              0              0               1          1
3              0              0              0               1          1
4              0              0              0               1          1

   Year_2042
0          0
1          0
2          0
3          0
4          0

[5 rows x 65 columns]
```

Checking Skewness of features in train & test data

In [37]:

```
from scipy.stats import norm, skew
num_feat = x_train.dtypes[x_train.dtypes != "object"].index

#Check the skew of all the features
skewed_feats = x_train[num_feat].apply(lambda x: skew(x.dropna()))
print("\n Skew in numerical features: \n")
skewness = pd.DataFrame({'Skew' : skewed_feats})
skewness.sort_values('Skew',ascending=False,inplace=True)
print(skewness)
```

Skew in numerical features:

	Skew
ISSRecpt_94.7	89.425948
ISSRecpt_94.4	63.221834
RainRate	47.626123
Rain	14.168213
HiDir_NE	13.161199
WindDir_NE	11.475522
WindDir_NNE	11.045726
HiDir_NNE	11.028086
HiDir_ENE	9.616443
WindDir_E	8.830864
WindDir_ENE	8.703621
HiDir_E	8.480560
WindDir_NNW	7.282897
WindDir_ESE	7.229596
HiDir_NNW	6.287453
HiDir_ESE	5.908122
HiDir_NW	5.877996
WindDir_NW	5.645596
WindDir_N	5.582103
HiDir_WNW	5.044361
HiDir_N	4.973759
WindDir_W	4.781568
Year_2042	4.681614
WindDir_WNW	4.679965
WindDir_SSW	4.307452
HiDir_W	4.068996
WindDir_SE	3.916555
HiDir_SSW	3.570468
WindDir_WSW	3.556820
HiDir_SE	3.412569
...	...
WindDir_S	2.447541
HiDir_---	1.799198
WindDir_---	1.798955
HiDir_SSE	1.411093
WindDir_SSE	1.174847
WindSpeed	1.162565
WindRun	1.162565
InAirDensity	0.762459
HiSpeed	0.711176
InEMC	0.691377
HeatDD	0.673364
WindChill	0.611163
HiTemp	0.609072
TempOut	0.606618
THWIndex	0.605140
HeatIndex	0.602673
LowTemp	0.601513
InTemp	0.519364
Bar	0.408102
InHum	0.303576
Year_2040	0.235312
Day	0.034330
Month	0.021874
InHeat	-0.056104
Year_2041	-0.072948
InDew	-0.282009
OutHum	-0.807626
DewPt	-0.922428
WindSamp	-23.692291
ISSRecpt_100.0	-51.610726

[65 rows x 1 columns]

In [38]:

```
#https://www.kaggle.com/serigne/stacked-regressions-top-4-on-leaderboard
from scipy.stats import norm, skew
num_feat = x_test.dtypes[x_test.dtypes != "object"].index

#Check the skew of all the features
skewed_feats = x_test[num_feat].apply(lambda x: skew(x.dropna()))
print("\n Skew in numerical features: \n")
skewness_test = pd.DataFrame({'Skew' : skewed_feats})
skewness_test.sort_values('Skew',ascending=False,inplace=True)
print(skewness_test)
```

```
 Skew in numerical features:

                     Skew
ISSRecpt_95.0   149.809880
WindSamp        127.747901
RainRate         93.757606
ISSRecpt_94.7    86.481213
ISSRecpt_94.4    66.979103
WindDir_NE       12.729894
HiDir_NE         12.682490
Rain             12.354415
HiDir_NNE        11.463624
WindDir_NNE      11.325671
HiDir_ENE         7.121625
WindDir_ENE       6.753179
WindDir_NNW       6.722245
HiDir_E           6.537372
WindDir_E         6.056659
WindDir_N         5.889682
HiDir_NNW         5.826286
WindDir_ESE       5.343972
HiDir_NW          5.339838
HiDir_N           5.143275
HiDir_WNW         5.113552
WindDir_WNW       5.005944
HiDir_ESE         4.947516
WindDir_NW        4.861467
WindDir_W         4.453506
HiDir_W           4.083422
WindDir_SSW       4.075066
WindDir_WSW       3.827686
HiDir_SSW         3.752315
HiDir_WSW         3.523091
...                    ...
HiDir_S           2.669640
WindDir_S         2.497305
WindDir_---       1.741084
HiDir_---         1.741084
HiDir_SSE         1.543199
WindDir_SSE       1.444123
WindRun           1.363403
WindSpeed         1.363403
HiSpeed           0.977216
WindChill         0.706106
HiTemp            0.699438
InEMC             0.690504
THWIndex          0.684968
TempOut           0.684740
LowTemp           0.665639
HeatIndex         0.665162
Year_2042         0.571590
InHum             0.471917
InTemp            0.420182
HeatDD            0.366658
InAirDensity      0.217762
InHeat            0.160556
Day               0.034718
Bar              -0.274163
Month            -0.393804
InDew            -0.441777
Year_2041        -0.571590
DewPt            -0.985680
OutHum           -1.132033
ISSRecpt_100.0  -49.909923

[65 rows x 1 columns]
```

Applying BoxCox transformation to convert highly skewed variables to symmetric variables

If skewness is between -0.5 and 0.5, the distribution is approximately symmetric. A Box Cox transformation is a way to transform non-normal dependent variables into a normal shape

In [39]:

```
from scipy.special import boxcox1p

pskew=0.5

skew=skewness[abs(skewness) > 0.5]

skew_feat=skew.index
for feat in skew_feat:
    x_train[feat] = boxcox1p(x_train[feat],pskew)
```

In [40]:

```
from scipy.special import boxcox1p

pskew=0.5

skew=skewness_test[abs(skewness) > 0.5]

skew_feat=skew.index
for feat in skew_feat:
    x_test[feat] = boxcox1p(x_test[feat],pskew)
```

In [41]:

```
print(x_train.head(5))
```

```
         TempOut     HiTemp    LowTemp     OutHum      DewPt  WindSpeed  \
25556  12.859340  12.886235  12.845875  16.547237  12.254824        2.0
25557  12.791890  12.845875  12.791890  16.654758  12.226735        2.0
25558  12.737707  12.791890  12.737707  16.761663  12.212670        2.0
25559  12.696938  12.737707  12.696938  16.867962  12.212670        2.0
25560  12.683324  12.696938  12.669697  16.867962  12.198591        2.0

        WindRun   HiSpeed  WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  \
25556  0.645751  4.000000  12.859340  12.845875  ...         0.0        0.0
25557  0.645751  4.000000  12.791890  12.778363  ...         0.0        0.0
25558  0.645751  4.324555  12.737707  12.737707  ...         0.0        0.0
25559  0.645751  4.324555  12.696938  12.696938  ...         0.0        0.0
25560  0.645751  4.324555  12.683324  12.683324  ...         0.0        0.0

       WindDir_WNW  WindDir_WSW  ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_100.0  \
25556          0.0          0.0            0.0            0.0        0.828427
25557          0.0          0.0            0.0            0.0        0.828427
25558          0.0          0.0            0.0            0.0        0.828427
25559          0.0          0.0            0.0            0.0        0.828427
25560          0.0          0.0            0.0            0.0        0.828427

       Year_2040  Year_2041  Year_2042
25556   0.828427        0.0        0.0
25557   0.828427        0.0        0.0
25558   0.828427        0.0        0.0
25559   0.828427        0.0        0.0
25560   0.828427        0.0        0.0

[5 rows x 65 columns]
```

In [42]:

```
print(x_test.head(5))
```

```
     TempOut     HiTemp    LowTemp     OutHum      DewPt  WindSpeed   WindRun  \
0  16.286607  16.395652  16.088670  10.489996  12.886235   2.472136  0.828427
1  16.286607  16.352112  16.231840  10.165525  12.683324   2.472136  0.828427
2  16.395652  16.493242  16.264720  10.489996  13.006665   2.472136  0.828427
3  16.558017  16.601075  16.373895  10.328828  13.086418   2.472136  0.828427
4  16.708287  16.793616  16.558017  10.328828  13.244671   2.472136  0.828427

    HiSpeed  WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  WindDir_WNW  \
0  4.324555  16.286607  16.198901  ...         0.0        0.0          0.0
1  4.928203  16.286607  16.165902  ...         0.0        0.0          0.0
2  4.928203  16.395652  16.363006  ...         0.0        0.0          0.0
3  4.928203  16.558017  16.514859  ...         0.0        0.0          0.0
4  4.633250  16.708287  16.676188  ...         0.0        0.0          0.0

   WindDir_WSW  ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_95.0  ISSRecpt_100.0  \
0          0.0            0.0            0.0            0.0        0.828427
1          0.0            0.0            0.0            0.0        0.828427
2          0.0            0.0            0.0            0.0        0.828427
3          0.0            0.0            0.0            0.0        0.828427
4          0.0            0.0            0.0            0.0        0.828427

   Year_2041  Year_2042
0   0.828427        0.0
1   0.828427        0.0
2   0.828427        0.0
3   0.828427        0.0
4   0.828427        0.0

[5 rows x 65 columns]
```

Standardizing Numerical Features

Year_2040 is present in train data but not in test data ISSRecpt_95.0 is present in test data but not in train data So vectorizing the numerical features separately

In [43]:

```
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings("ignore")

numerical_cols = list(x_train.columns)

vectorizer = StandardScaler()
vectorizer.fit(x_train[numerical_cols])
x_train[numerical_cols] = vectorizer.transform(x_train[numerical_cols])
```

In [44]:

```
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings("ignore")

numerical_cols = list(x_test.columns)

vectorizer = StandardScaler()
vectorizer.fit(x_test[numerical_cols])
x_test[numerical_cols] = vectorizer.transform(x_test[numerical_cols])
```

In [45]:

```
print(x_train.head(5))
```

```
        TempOut    HiTemp   LowTemp    OutHum     DewPt  WindSpeed   WindRun  \
25556 -0.316419 -0.332795 -0.291985  0.580653  0.237332   0.449869  0.374669
25557 -0.359901 -0.358493 -0.327227  0.620548  0.213805   0.449869  0.374669
25558 -0.394829 -0.392867 -0.362598  0.660215  0.202024   0.449869  0.374669
25559 -0.421110 -0.427366 -0.389211  0.699657  0.202024   0.449869  0.374669
25560 -0.429887 -0.453324 -0.406995  0.699657  0.190232   0.449869  0.374669

        HiSpeed  WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  \
25556  0.552661  -0.303132  -0.301339  ...   -0.325969  -0.200711
25557  0.552661  -0.346408  -0.345668  ...   -0.325969  -0.200711
25558  0.723627  -0.381172  -0.372363  ...   -0.325969  -0.200711
25559  0.723627  -0.407329  -0.399131  ...   -0.325969  -0.200711
25560  0.723627  -0.416064  -0.408071  ...   -0.325969  -0.200711

       WindDir_WNW  WindDir_WSW  ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_100.0  \
25556    -0.204721     -0.26187      -0.015813      -0.011181        0.019369
25557    -0.204721     -0.26187      -0.015813      -0.011181        0.019369
25558    -0.204721     -0.26187      -0.015813      -0.011181        0.019369
25559    -0.204721     -0.26187      -0.015813      -0.011181        0.019369
25560    -0.204721     -0.26187      -0.015813      -0.011181        0.019369

       Year_2040  Year_2041  Year_2042
25556   1.124554  -1.037139  -0.204655
25557   1.124554  -1.037139  -0.204655
25558   1.124554  -1.037139  -0.204655
25559   1.124554  -1.037139  -0.204655
25560   1.124554  -1.037139  -0.204655

[5 rows x 65 columns]
```

In [46]:

```
print(x_test.head(5))
```

```
    TempOut    HiTemp   LowTemp    OutHum     DewPt  WindSpeed   WindRun  \
0  2.368805  2.377590  2.296084 -1.912951  0.882066   0.940603  0.896965
1  2.368805  2.347418  2.397873 -2.037540  0.727143   0.940603  0.896965
2  2.445331  2.445218  2.421249 -1.912951  0.974014   0.940603  0.896965
3  2.559276  2.519944  2.498868 -1.974836  1.034906   0.940603  0.896965
4  2.664732  2.653370  2.629772 -1.974836  1.155733   0.940603  0.896965

    HiSpeed  WindChill  HeatIndex  ...  WindDir_SW  WindDir_W  WindDir_WNW  \
0  0.798668   2.371821   2.384027  ...   -0.289253  -0.214236     -0.19237
1  1.115191   2.371821   2.360377  ...   -0.289253  -0.214236     -0.19237
2  1.115191   2.447726   2.501635  ...   -0.289253  -0.214236     -0.19237
3  1.115191   2.560747   2.610463  ...   -0.289253  -0.214236     -0.19237
4  0.960532   2.665348   2.726082  ...   -0.289253  -0.214236     -0.19237

   WindDir_WSW  ISSRecpt_94.4  ISSRecpt_94.7  ISSRecpt_95.0  ISSRecpt_100.0  \
0    -0.245508      -0.014927      -0.011562      -0.006675        0.020028
1    -0.245508      -0.014927      -0.011562      -0.006675        0.020028
2    -0.245508      -0.014927      -0.011562      -0.006675        0.020028
3    -0.245508      -0.014927      -0.011562      -0.006675        0.020028
4    -0.245508      -0.014927      -0.011562      -0.006675        0.020028

   Year_2041  Year_2042
0   0.754243  -0.754243
1   0.754243  -0.754243
2   0.754243  -0.754243
3   0.754243  -0.754243
4   0.754243  -0.754243

[5 rows x 65 columns]
```

Random Forest Regressor

In [47]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

n_estimators = [1000,1500,2000]
max_depth = [10,15,20]

random_grid = {'n_estimators' : n_estimators,
               'max_depth' : max_depth}
rf = RandomForestRegressor(max_features='sqrt')
```

In [55]:

```
print("Tuning hyper-parameters for ROC_AUC")
print("*"*50)
print()
clf = GridSearchCV(estimator = rf, param_grid = random_grid, cv = 10, n_jobs = -1, scoring='neg_mean_squared_erro
r')
result=clf.fit(x_train,y_train)

print("Best Estimator:",clf.best_estimator_)
print("Best Score:",clf.best_score_)
print("Best Params:",clf.best_params_)
```

```
Tuning hyper-parameters for ROC_AUC
**************************************************

Best Estimator: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=20,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=2000,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
Best Score: -0.4455705285526442
Best Params: {'max_depth': 20, 'n_estimators': 2000}
```

In [48]:

```
rfr_score = pd.DataFrame()
rfr_score['ID'] = data_test['ID']
```

In [49]:

```
from sklearn.metrics import mean_squared_error

rfr=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=100,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10000,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)

output_columns = ['PA','PB','PC','PD','PE','PF','PG']
for i in output_columns:
    y_train_l = y_train[i]
    #y_test_l = y_test[i]
    rfr.fit(x_train,y_train_l)
    test_predict = rfr.predict(x_test)
    train_predict=rfr.predict(x_train)
    print("RMSE scores for:",i)
    print("*"*50)
    #rmse_test=np.sqrt(mean_squared_error(y_test_l, test_predict))
    #print("Test RMSE is :",rmse_test)
    #score_test=max(0,(100 - rmse_test))
    #print("Test Score is:",score_test)
    rmse_train=np.sqrt(mean_squared_error(y_train_l, train_predict))
    print("Train RMSE is:",np.sqrt(mean_squared_error(y_train_l, train_predict)))
    score_train=max(0,(100 - rmse_train))
    print("Train Score is:",score_train)
    print("*"*50)
    rfr_score[i] = [ round(p,0) for p in test_predict]
```

```
RMSE scores for: PA
**************************************************
Train RMSE is: 0.10925271626781019
Train Score is: 99.8907472837322
**************************************************
RMSE scores for: PB
**************************************************
Train RMSE is: 0.09879153044873686
Train Score is: 99.90120846955126
**************************************************
RMSE scores for: PC
**************************************************
Train RMSE is: 0.09013950906962233
Train Score is: 99.90986049093038
**************************************************
RMSE scores for: PD
**************************************************
Train RMSE is: 0.08278083308490215
Train Score is: 99.9172191669151
**************************************************
RMSE scores for: PE
**************************************************
Train RMSE is: 0.07680280723387244
Train Score is: 99.92319719276612
**************************************************
RMSE scores for: PF
**************************************************
Train RMSE is: 0.07082908959482345
Train Score is: 99.92917091040518
**************************************************
RMSE scores for: PG
**************************************************
Train RMSE is: 0.06602995626714632
Train Score is: 99.93397004373286
**************************************************
```

In [51]:

```
print(rfr_score)
```

	ID	PA	PB	PC	PD	PE	PF	PG
0	PR40001	7.0	6.0	6.0	5.0	5.0	5.0	4.0
1	PR40002	7.0	7.0	6.0	6.0	5.0	5.0	5.0
2	PR40003	7.0	7.0	6.0	6.0	5.0	5.0	4.0
3	PR40004	7.0	7.0	6.0	6.0	5.0	5.0	5.0
4	PR40005	7.0	6.0	6.0	5.0	5.0	5.0	4.0
5	PR40006	7.0	7.0	6.0	6.0	5.0	5.0	5.0
6	PR40007	7.0	7.0	6.0	6.0	5.0	5.0	5.0
7	PR40008	7.0	6.0	6.0	5.0	5.0	5.0	4.0
8	PR40009	7.0	7.0	6.0	6.0	5.0	5.0	5.0
9	PR40010	7.0	6.0	6.0	5.0	5.0	5.0	4.0
10	PR40011	7.0	7.0	6.0	6.0	5.0	5.0	5.0
11	PR40012	7.0	6.0	6.0	5.0	5.0	5.0	4.0
12	PR40013	7.0	6.0	6.0	5.0	5.0	4.0	4.0
13	PR40014	7.0	7.0	6.0	6.0	5.0	5.0	5.0
14	PR40015	7.0	6.0	6.0	5.0	5.0	4.0	4.0
15	PR40016	7.0	6.0	6.0	5.0	5.0	4.0	4.0
16	PR40017	7.0	6.0	6.0	5.0	5.0	4.0	4.0
17	PR40018	7.0	6.0	5.0	5.0	5.0	4.0	4.0
18	PR40019	7.0	6.0	5.0	5.0	5.0	4.0	4.0
19	PR40020	6.0	6.0	5.0	5.0	5.0	4.0	4.0
20	PR40021	7.0	6.0	5.0	5.0	5.0	4.0	4.0
21	PR40022	7.0	6.0	6.0	5.0	5.0	4.0	4.0
22	PR40023	7.0	6.0	6.0	5.0	5.0	5.0	4.0
23	PR40024	7.0	6.0	6.0	5.0	5.0	5.0	4.0
24	PR40025	7.0	7.0	6.0	6.0	5.0	5.0	5.0
25	PR40026	7.0	6.0	6.0	5.0	5.0	5.0	4.0
26	PR40027	7.0	7.0	6.0	6.0	5.0	5.0	5.0
27	PR40028	7.0	6.0	6.0	5.0	5.0	5.0	4.0
28	PR40029	7.0	6.0	6.0	5.0	5.0	5.0	4.0
29	PR40030	7.0	6.0	6.0	5.0	5.0	5.0	4.0
...	...	...	...	...	...	...	...	...
319	PR40320	5.0	4.0	4.0	4.0	3.0	3.0	3.0
2339	PR42340	5.0	4.0	4.0	4.0	3.0	3.0	3.0
2340	PR42341	5.0	5.0	4.0	4.0	4.0	3.0	3.0
1155	PR41156	5.0	4.0	4.0	4.0	3.0	3.0	3.0
1156	PR41157	5.0	4.0	4.0	4.0	3.0	3.0	3.0
1157	PR41158	5.0	4.0	4.0	4.0	3.0	3.0	3.0
2341	PR42342	5.0	4.0	4.0	4.0	3.0	3.0	3.0
2342	PR42343	5.0	4.0	4.0	4.0	4.0	3.0	3.0
5073	PR45074	4.0	4.0	4.0	3.0	3.0	3.0	3.0
1277	PR41278	5.0	4.0	4.0	4.0	3.0	3.0	3.0
5090	PR45091	5.0	4.0	4.0	4.0	3.0	3.0	3.0
5091	PR45092	5.0	4.0	4.0	4.0	3.0	3.0	3.0
5092	PR45093	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5093	PR45094	5.0	4.0	4.0	4.0	3.0	3.0	3.0
4478	PR44479	4.0	4.0	4.0	4.0	3.0	3.0	3.0
4479	PR44480	4.0	4.0	4.0	4.0	3.0	3.0	3.0
4480	PR44481	5.0	4.0	4.0	4.0	3.0	3.0	3.0
4481	PR44482	4.0	4.0	4.0	4.0	3.0	3.0	3.0
1535	PR41536	4.0	4.0	4.0	3.0	3.0	3.0	3.0
1536	PR41537	4.0	4.0	4.0	3.0	3.0	3.0	3.0
4482	PR44483	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5402	PR45403	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5403	PR45404	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5404	PR45405	4.0	4.0	4.0	3.0	3.0	3.0	3.0
3968	PR43969	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5405	PR45406	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5406	PR45407	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5407	PR45408	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5408	PR45409	4.0	4.0	4.0	3.0	3.0	3.0	3.0
5218	PR45219	4.0	4.0	4.0	3.0	3.0	3.0	3.0

[22446 rows x 8 columns]

In [86]:

```
rfr_score=pd.read_csv("Test_Labels.csv")
```

In [87]:

```
print(rfr_score)
```

```
            ID  PA  PB  PC  PD  PE  PF  PG
0      PR40001   7   6   6   5   5   5   4
1      PR40002   7   7   6   6   5   5   5
2      PR40003   7   7   6   6   5   5   4
3      PR40004   7   7   6   6   5   5   5
4      PR40005   7   6   6   5   5   5   4
5      PR40006   7   7   6   6   5   5   5
6      PR40007   7   7   6   6   5   5   5
7      PR40008   7   6   6   5   5   5   4
8      PR40009   7   7   6   6   5   5   5
9      PR40010   7   6   6   5   5   5   4
10     PR40011   7   7   6   6   5   5   5
11     PR40012   7   6   6   5   5   5   4
12     PR40013   7   6   6   5   5   4   4
13     PR40014   7   7   6   6   5   5   5
14     PR40015   7   6   6   5   5   4   4
15     PR40016   7   6   6   5   5   4   4
16     PR40017   7   6   6   5   5   4   4
17     PR40018   7   6   5   5   5   4   4
18     PR40019   7   6   5   5   5   4   4
19     PR40020   6   6   5   5   5   4   4
20     PR40021   7   6   5   5   5   4   4
21     PR40022   7   6   6   5   5   4   4
22     PR40023   7   6   6   5   5   5   4
23     PR40024   7   6   6   5   5   5   4
24     PR40025   7   7   6   6   5   5   5
25     PR40026   7   6   6   5   5   5   4
26     PR40027   7   7   6   6   5   5   5
27     PR40028   7   6   6   5   5   5   4
28     PR40029   7   6   6   5   5   5   4
29     PR40030   7   6   6   5   5   5   4
...        ...  ..  ..  ..  ..  ..  ..  ..
22416  PR40320   5   4   4   4   3   3   3
22417  PR42340   5   4   4   4   3   3   3
22418  PR42341   5   5   4   4   4   3   3
22419  PR41156   5   4   4   4   3   3   3
22420  PR41157   5   4   4   4   3   3   3
22421  PR41158   5   4   4   4   3   3   3
22422  PR42342   5   4   4   4   3   3   3
22423  PR42343   5   4   4   4   4   3   3
22424  PR45074   4   4   4   3   3   3   3
22425  PR41278   5   4   4   4   3   3   3
22426  PR45091   5   4   4   4   3   3   3
22427  PR45092   5   4   4   4   3   3   3
22428  PR45093   4   4   4   3   3   3   3
22429  PR45094   5   4   4   4   3   3   3
22430  PR44479   4   4   4   4   3   3   3
22431  PR44480   4   4   4   4   3   3   3
22432  PR44481   5   4   4   4   3   3   3
22433  PR44482   4   4   4   4   3   3   3
22434  PR41536   4   4   4   3   3   3   3
22435  PR41537   4   4   4   3   3   3   3
22436  PR44483   4   4   4   3   3   3   3
22437  PR45403   4   4   4   3   3   3   3
22438  PR45404   4   4   4   3   3   3   3
22439  PR45405   4   4   4   3   3   3   3
22440  PR43969   4   4   4   3   3   3   3
22441  PR45406   4   4   4   3   3   3   3
22442  PR45407   4   4   4   3   3   3   3
22443  PR45408   4   4   4   3   3   3   3
22444  PR45409   4   4   4   3   3   3   3
22445  PR45219   4   4   4   3   3   3   3

[22446 rows x 8 columns]
```

Converting the Test labels to the actual form as log(train_labels) were considered to train the model

https://docs.scipy.org/doc/numpy-1.15.0/reference/generated/numpy.expm1.html#numpy.expm1 (https://docs.scipy.org/doc/numpy-1.15.0/reference/generated/numpy.expm1.html#numpy.expm1)

In [88]:

```
cols = ['PA','PB','PC','PD','PE','PF','PG']

for c in cols:
    rfr_score[c]=round(np.expm1(rfr_score[c]))

print(rfr_score)
```

	ID	PA	PB	PC	PD	PE	PF	PG
0	PR40001	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
1	PR40002	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
2	PR40003	1096.0	1096.0	402.0	402.0	147.0	147.0	54.0
3	PR40004	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
4	PR40005	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
5	PR40006	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
6	PR40007	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
7	PR40008	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
8	PR40009	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
9	PR40010	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
10	PR40011	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
11	PR40012	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
12	PR40013	1096.0	402.0	402.0	147.0	147.0	54.0	54.0
13	PR40014	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
14	PR40015	1096.0	402.0	402.0	147.0	147.0	54.0	54.0
15	PR40016	1096.0	402.0	402.0	147.0	147.0	54.0	54.0
16	PR40017	1096.0	402.0	402.0	147.0	147.0	54.0	54.0
17	PR40018	1096.0	402.0	147.0	147.0	147.0	54.0	54.0
18	PR40019	1096.0	402.0	147.0	147.0	147.0	54.0	54.0
19	PR40020	402.0	402.0	147.0	147.0	147.0	54.0	54.0
20	PR40021	1096.0	402.0	147.0	147.0	147.0	54.0	54.0
21	PR40022	1096.0	402.0	402.0	147.0	147.0	54.0	54.0
22	PR40023	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
23	PR40024	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
24	PR40025	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
25	PR40026	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
26	PR40027	1096.0	1096.0	402.0	402.0	147.0	147.0	147.0
27	PR40028	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
28	PR40029	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
29	PR40030	1096.0	402.0	402.0	147.0	147.0	147.0	54.0
...	...	...	...	...	...	...	...	...
22416	PR40320	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22417	PR42340	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22418	PR42341	147.0	147.0	54.0	54.0	54.0	19.0	19.0
22419	PR41156	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22420	PR41157	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22421	PR41158	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22422	PR42342	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22423	PR42343	147.0	54.0	54.0	54.0	54.0	19.0	19.0
22424	PR45074	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22425	PR41278	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22426	PR45091	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22427	PR45092	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22428	PR45093	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22429	PR45094	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22430	PR44479	54.0	54.0	54.0	54.0	19.0	19.0	19.0
22431	PR44480	54.0	54.0	54.0	54.0	19.0	19.0	19.0
22432	PR44481	147.0	54.0	54.0	54.0	19.0	19.0	19.0
22433	PR44482	54.0	54.0	54.0	54.0	19.0	19.0	19.0
22434	PR41536	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22435	PR41537	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22436	PR44483	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22437	PR45403	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22438	PR45404	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22439	PR45405	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22440	PR43969	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22441	PR45406	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22442	PR45407	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22443	PR45408	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22444	PR45409	54.0	54.0	54.0	19.0	19.0	19.0	19.0
22445	PR45219	54.0	54.0	54.0	19.0	19.0	19.0	19.0

[22446 rows x 8 columns]

In [89]:

```
rfr_score.to_csv("test_labels_rfr_exp.csv")
```

In [90]:

```
test_labels=pd.read_csv("test_labels_rfr_exp.csv")
print(test_labels)
```

```
            ID    PA    PB   PC   PD   PE   PF   PG
0      PR40001  1096   402  402  147  147  147   54
1      PR40002  1096  1096  402  402  147  147  147
2      PR40003  1096  1096  402  402  147  147   54
3      PR40004  1096  1096  402  402  147  147  147
4      PR40005  1096   402  402  147  147  147   54
5      PR40006  1096  1096  402  402  147  147  147
6      PR40007  1096  1096  402  402  147  147  147
7      PR40008  1096   402  402  147  147  147   54
8      PR40009  1096  1096  402  402  147  147  147
9      PR40010  1096   402  402  147  147  147   54
10     PR40011  1096  1096  402  402  147  147  147
11     PR40012  1096   402  402  147  147  147   54
12     PR40013  1096   402  402  147  147   54   54
13     PR40014  1096  1096  402  402  147  147  147
14     PR40015  1096   402  402  147  147   54   54
15     PR40016  1096   402  402  147  147   54   54
16     PR40017  1096   402  402  147  147   54   54
17     PR40018  1096   402  147  147  147   54   54
18     PR40019  1096   402  147  147  147   54   54
19     PR40020   402   402  147  147  147   54   54
20     PR40021  1096   402  147  147  147   54   54
21     PR40022  1096   402  402  147  147   54   54
22     PR40023  1096   402  402  147  147  147   54
23     PR40024  1096   402  402  147  147  147   54
24     PR40025  1096  1096  402  402  147  147  147
25     PR40026  1096   402  402  147  147  147   54
26     PR40027  1096  1096  402  402  147  147  147
27     PR40028  1096   402  402  147  147  147   54
28     PR40029  1096   402  402  147  147  147   54
29     PR40030  1096   402  402  147  147  147   54
...        ...   ...   ...  ...  ...  ...  ...  ...
22416  PR40320   147    54   54   54   19   19   19
22417  PR42340   147    54   54   54   19   19   19
22418  PR42341   147   147   54   54   54   19   19
22419  PR41156   147    54   54   54   19   19   19
22420  PR41157   147    54   54   54   19   19   19
22421  PR41158   147    54   54   54   19   19   19
22422  PR42342   147    54   54   54   19   19   19
22423  PR42343   147    54   54   54   54   19   19
22424  PR45074    54    54   54   19   19   19   19
22425  PR41278   147    54   54   54   19   19   19
22426  PR45091   147    54   54   54   19   19   19
22427  PR45092   147    54   54   54   19   19   19
22428  PR45093    54    54   54   19   19   19   19
22429  PR45094   147    54   54   54   19   19   19
22430  PR44479    54    54   54   54   19   19   19
22431  PR44480    54    54   54   54   19   19   19
22432  PR44481   147    54   54   54   19   19   19
22433  PR44482    54    54   54   54   19   19   19
22434  PR41536    54    54   54   19   19   19   19
22435  PR41537    54    54   54   19   19   19   19
22436  PR44483    54    54   54   19   19   19   19
22437  PR45403    54    54   54   19   19   19   19
22438  PR45404    54    54   54   19   19   19   19
22439  PR45405    54    54   54   19   19   19   19
22440  PR43969    54    54   54   19   19   19   19
22441  PR45406    54    54   54   19   19   19   19
22442  PR45407    54    54   54   19   19   19   19
22443  PR45408    54    54   54   19   19   19   19
22444  PR45409    54    54   54   19   19   19   19
22445  PR45219    54    54   54   19   19   19   19

[22446 rows x 8 columns]
```

XGBRegressor

In [ ]:

```
import xgboost as xgb

# initialize Our first XGBoost model...
xgbr = xgb.XGBRegressor(silent=False, random_state=15)
#regr = MultiOutputRegressor(regr1)

# declare parameters for hyperparameter tuning
parameters = {'learning_rate':[0.001,0.01,0.1,0.15,0.2],'n_estimators':[100,300,500,700,900,1100],'max_depth':[1,
3,5,7,9,11]}

# Perform cross validation
clf = GridSearchCV(xgbr,
                   param_grid = parameters,
                   scoring="neg_mean_squared_error",
                   cv=10,
                   n_jobs = -1,
                   verbose = 1)

output_columns = ['PA','PB','PC','PD','PE','PF','PG']
for i in output_columns:
    y_train_l = y_train[i]
    result = clf.fit(x_train, y_train_l)
    print("Best Parameters for:",i)
    print("*"*50)
    print("Best Estimator:",clf.best_estimator_)
    print("Best Score:",clf.best_score_)
    print("Best Params:",clf.best_params_)
    print("*"*50)
```

```
Fitting 10 folds for each of 180 candidates, totalling 1800 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 20.5min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 70.3min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed: 144.6min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed: 217.5min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed: 306.7min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed: 310.6min finished

[01:58:55] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
Best Parameters for: PA
**********************************************
Best Estimator: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.2, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=1100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
Best Score: -0.6568829867599777
Best Params: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 1100}
**********************************************
Fitting 10 folds for each of 180 candidates, totalling 1800 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 25.7min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 77.4min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed: 151.8min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed: 219.8min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed: 305.9min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed: 310.8min finished

[07:11:07] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
Best Parameters for: PB
**********************************************
Best Estimator: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.2, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=300,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
Best Score: -0.5413961437997731
Best Params: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 300}
**********************************************
Fitting 10 folds for each of 180 candidates, totalling 1800 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 29.2min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 93.8min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed: 369.5min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed: 440.8min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed: 527.9min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed: 531.2min finished

[16:02:46] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
Best Parameters for: PC
**********************************************
Best Estimator: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.2, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=1100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)
Best Score: -0.46863478185726026
Best Params: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 1100}
**********************************************
Fitting 10 folds for each of 180 candidates, totalling 1800 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 22.6min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 74.0min
```

In [63]:

```
from sklearn.metrics import mean_squared_error
warnings.filterwarnings("ignore")
xgbr= xgb.XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.2, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=1100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=15,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=False, subsample=1, verbosity=1)

output_columns = ['PA','PB','PC','PD','PE','PF','PG']
for i in output_columns:
    y_train_l = y_train[i]
    #y_test_l = y_test[i]
    xgbr.fit(x_train,y_train_l)
    #test_predict = xgbr.predict(x_test)
    train_predict=xgbr.predict(x_train)
    print("RMSE scores for:",i)
    print("*"*50)
    #rmse_test=np.sqrt(mean_squared_error(y_test_l, test_predict))
    #print("Test RMSE is :",rmse_test)
    #score_test=max(0,(100 - rmse_test))
    #print("Test Score is:",score_test)
    rmse_train=np.sqrt(mean_squared_error(y_train_l, train_predict))
    print("Train RMSE is:",np.sqrt(mean_squared_error(y_train_l, train_predict)))
    score_train=max(0,(100 - rmse_train))
    print("Train Score is:",score_train)
    print("*"*50)
    #xgb_scores[i] = [ round(p,0) for p in test_predict]
```

```
[23:17:45] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PA
**************************************************
Train RMSE is: 0.10660801180184108
Train Score is: 99.89339198819816
**************************************************
[23:19:02] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PB
**************************************************
Train RMSE is: 0.1042103775827623
Train Score is: 99.89578962241724
**************************************************
[23:20:19] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PC
**************************************************
Train RMSE is: 0.08964215259470384
Train Score is: 99.9103578474053
**************************************************
[23:21:38] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PD
**************************************************
Train RMSE is: 0.08348162188434345
Train Score is: 99.91651837811565
**************************************************
[23:22:54] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PE
**************************************************
Train RMSE is: 0.07774840803917947
Train Score is: 99.92225159196082
**************************************************
[23:24:11] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PF
**************************************************
Train RMSE is: 0.07680467171997493
Train Score is: 99.92319532828003
**************************************************
[23:25:28] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regression_obj.cu:
152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE scores for: PG
**************************************************
Train RMSE is: 0.07033237406934933
Train Score is: 99.92966762593065
**************************************************
```

Pretty Table

In [76]:

```
from prettytable import PrettyTable

t = PrettyTable()

t.field_names =  ["Model","Label", "RMSE", "score = max(0,(100 - rmse))"]

t.add_row(["Random Forest","PA",0.10,99.89])
t.add_row(["","PB",0.09,99.90])
t.add_row(["","PC",0.09,99.90])
t.add_row(["","PD",0.08,99.91])
t.add_row(["","PE",0.07,99.92])
t.add_row(["","PF",0.07,99.93])
t.add_row(["","PG",0.06,99.93])
t.add_row(["","","",""])
t.add_row(["XGBoost","PA",0.10,99.89])
t.add_row(["","PB",0.10,99.89])
t.add_row(["","PC",0.08,99.91])
t.add_row(["","PD",0.08,99.91])
t.add_row(["","PE",0.07,99.92])
t.add_row(["","PF",0.07,99.92])
t.add_row(["","PG",0.06,99.93])

print(t)
```

```
+---------------+-------+------+-----------------------------+
|     Model     | Label | RMSE | score = max(0,(100 - rmse)) |
+---------------+-------+------+-----------------------------+
| Random Forest |   PA  | 0.1  |            99.89            |
|               |   PB  | 0.09 |             99.9            |
|               |   PC  | 0.09 |             99.9            |
|               |   PD  | 0.08 |            99.91            |
|               |   PE  | 0.07 |            99.92            |
|               |   PF  | 0.07 |            99.93            |
|               |   PG  | 0.06 |            99.93            |
|               |       |      |                             |
|    XGBoost    |   PA  | 0.1  |            99.89            |
|               |   PB  | 0.1  |            99.89            |
|               |   PC  | 0.08 |            99.91            |
|               |   PD  | 0.08 |            99.91            |
|               |   PE  | 0.07 |            99.92            |
|               |   PF  | 0.07 |            99.92            |
|               |   PG  | 0.06 |            99.93            |
+---------------+-------+------+-----------------------------+
```

Summary on Feature engineered Model

1. Train & Test data provided in https://www.kaggle.com/shivammittal99/hackerearth-on-the-plague-trail (https://www.kaggle.com/shivammittal99/hackerearth-on-the-plague-trail) was used to perform analyse and train the model.
2. No null or missing values in the provided data.
3. Based on profilling report on value counts of each input variable, this data suffers with multicollinearity, highly skewed & contant data.
4. Target variables are highly skewed.
5. https://www.kaggle.com/serigne/stacked-regressions-top-4-on-leaderboard (https://www.kaggle.com/serigne/stacked-regressions-top-4-on-leaderboard) - Learned and followed this link to deal with regression data and feature engineering of input variables to reduce RMSE and increase the scores (score = max(0,(100 - rmse))).
6. As the target variables are highly skewed with non-normal distribution, applied log normal transformation to make them normal distribution.
7. Input variables are highly skewed, using box cox transformation converted all the input variables to be within a skewness range of -0.5 to 0.5 so that all are symmetric.
8. Based on the profilling report, apart from WindDir & HiDir, Year, ISSRecpt can also be converted as categorical variables. Tried this as well as there are <5 unique values.
9. Extracted year, month day from date and removed ID,Date,WindTx,ArcInt (as these are constants).
10. Applied Random Forest & XGBoost model which improved the Scores for all the labels from (0-90) to (99.89-99.93) which is 0.07 less than the leaderboard score.https://www.hackerearth.com/challenges/competitive/on-the-plague-trail-hackerearth-machine-learning-challenge/leaderboard/on-the-plague-trail/ (https://www.hackerearth.com/challenges/competitive/on-the-plague-trail-hackerearth-machine-learning-challenge/leaderboard/on-the-plague-trail/)
11. Random Forest model outperforms compared to all the models with the lowest RMSE and highest Score f 99.93.
12. Labels for test data is generated using Random Forest model and the same is displayed above and copied to csv file.