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

Data Given:

1. Train Data - 30 input variables, 7 target variables.
2. Test Data - 30 input variables.
3. sample.csv - Need to predict 7 target variables of test data and create a csv file.

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))

Reading train and test data into a dataframe

In [46]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
```

In [2]:

```
data=pd.read_csv('train.csv')
#label=data[['PA','PB','PC','PD','PE','PF','PG']]
#data.drop(['PA','PB','PC','PD','PE','PF','PG'],axis=1,inplace=True)
print("Columns in data are:",data.columns)
#print("Columns in label are:",label.columns)
```

```
Columns in data are: 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.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 [47]:

```
test=pd.read_csv("test.csv")
print(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 [48]:

```
print(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]
```

Exploratory Data Analysis on Train & Test Data

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40000 entries, 0 to 39999
Data columns (total 37 columns):
ID              40000 non-null object
DateTime        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
dtypes: float64(19), int64(14), object(4)
memory usage: 11.3+ MB
```

In [49]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22446 entries, 0 to 22445
Data columns (total 30 columns):
ID              22446 non-null object
DateTime        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
dtypes: float64(19), int64(7), object(4)
memory usage: 5.1+ MB
```

Obervations

1. Wind Direction(WindDir) and HiDir (Direction of the wind which has highest speed) are Categorical features and the all other features are numerical(int & float).

WindDir & HiDir categorical unique counts

In [5]:

```
# Wind Direction Categories
data['WindDir'].value_counts()
```

Out[5]:

```
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 [6]:

```
# HiDir Categories
data['HiDir'].value_counts()
```

Out[6]:

```
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
```

Removing WindDir, HiDir (Categories), PA, PB, PC, PD, PE, PF, PG(labels) to describe the other fields and see the mean,std,percentiles

In [7]:

```
data_mod1=data.drop(['WindDir','HiDir','PA','PB','PC','PD','PE','PF','PG'],axis=1)
data_mod1.describe()
```

Out[7]:

	TempOut	HiTemp	LowTemp	OutHum	DewPt	WindSpeed	WindRun	HiSpeed	WindCl
count	40000.000000	40000.000000	40000.000000	40000.000000	40000.000000	40000.000000	40000.000000	40000.000000	40000.0000
mean	58.508625	58.975230	58.056785	72.915750	48.156873	2.348650	0.587163	6.028675	58.3733
std	12.119640	12.323427	11.916335	20.873482	7.895771	2.346365	0.586591	4.808251	12.1670
min	29.300000	29.500000	29.300000	4.000000	1.200000	0.000000	0.000000	0.000000	29.0000
25%	51.100000	51.300000	50.800000	58.000000	43.600000	0.000000	0.000000	2.000000	50.8000
50%	56.400000	56.800000	56.100000	79.000000	49.700000	2.000000	0.500000	5.000000	56.3000
75%	65.300000	66.000000	64.700000	91.000000	53.900000	4.000000	1.000000	9.000000	65.2000
max	110.300000	111.000000	108.600000	98.000000	66.900000	16.000000	4.000000	33.000000	110.3000

8 rows × 26 columns

In [51]:

```
test_mod1=test.drop(['WindDir','HiDir'],axis=1)
test_mod1.describe()
```

Out[51]:

	TempOut	HiTemp	LowTemp	OutHum	DewPt	WindSpeed	WindRun	HiSpeed	Winc
count	22446.000000	22446.000000	22446.000000	22446.000000	22446.000000	22446.000000	22446.000000	22446.000000	22446.00
mean	55.093451	55.505908	54.692956	77.012964	46.563579	2.150138	0.537535	5.672637	54.86
std	10.841577	11.030381	10.651194	20.310674	8.407785	2.292685	0.573171	4.876028	10.92
min	30.200000	30.400000	30.100000	7.000000	6.700000	0.000000	0.000000	0.000000	30.20
25%	48.700000	49.000000	48.400000	65.000000	41.300000	0.000000	0.000000	2.000000	48.30
50%	53.700000	54.000000	53.500000	85.000000	48.500000	2.000000	0.500000	4.000000	53.50
75%	60.000000	60.500000	59.500000	93.000000	52.600000	3.000000	0.750000	9.000000	59.90
max	93.600000	93.700000	93.000000	98.000000	66.300000	15.000000	3.750000	32.000000	93.60

8 rows × 26 columns

Observations:

1. Test data min and max range are within the train data min and max range. Performing further analysis on train data only.

Profile Report of Train data

In [52]:

```python
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

Out[52]:

Observation:

1. Constants variable : ArcInt,WindTx
2. Highly Correlated variables : HiTemp,InEMC,InHu,LowTemp,TempOut,THWIndex,WindChill,WindRun, PA,PB,PC,PD,PE,PF,PG

Correlation Matrix

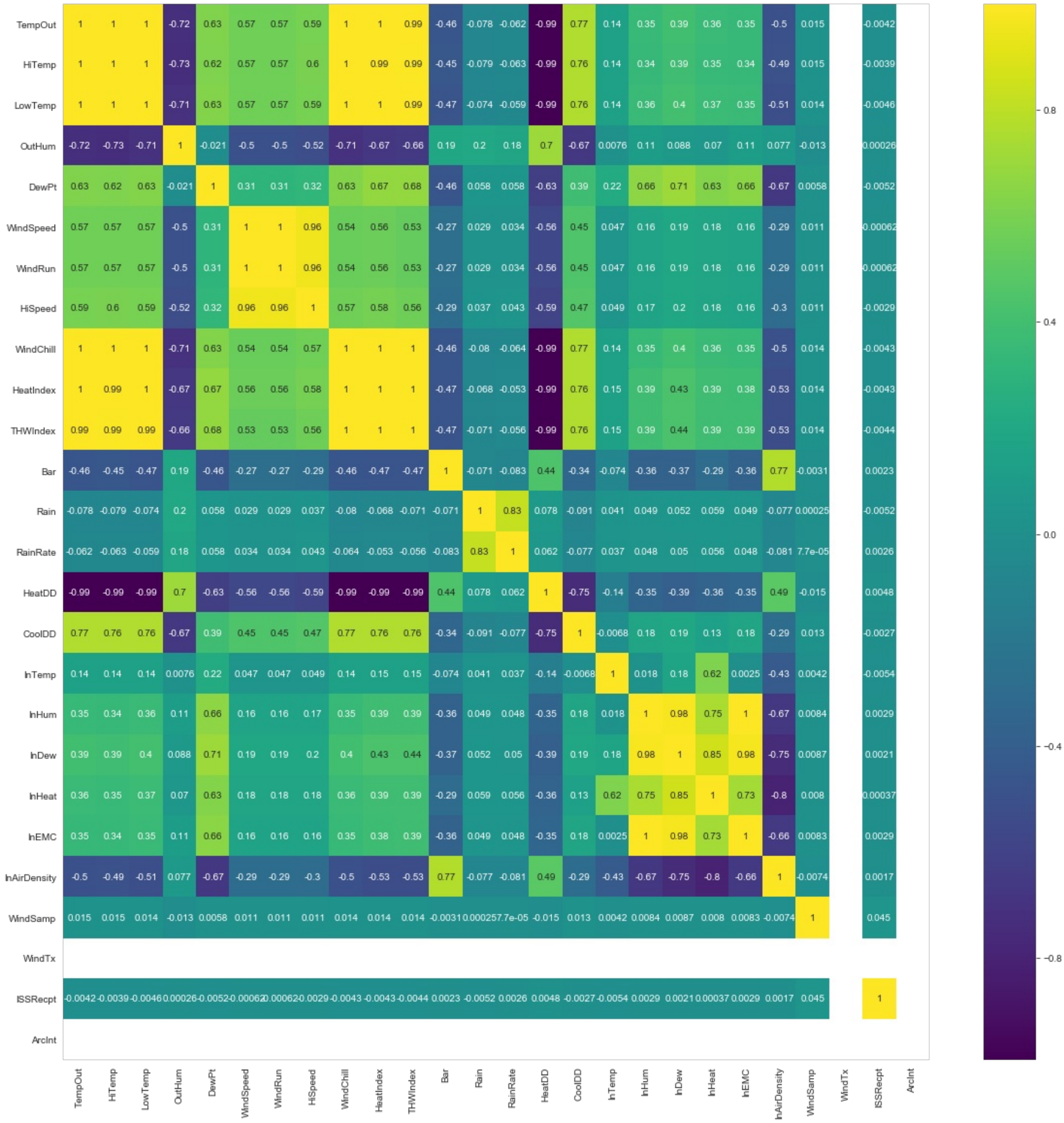
1. As this is regression data, constructing a correlation matrix will help us understand the correlations between input variables.
2. With below correlation we can find positively, negatively and zero correlated features.

In [9]:

```python
from scipy.stats import spearmanr
corr_matrix=data_mod1.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corr_matrix,annot=True,cmap = 'viridis')
```

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1274fc499e8>
```



Observations:

1. WindTx,ArcInt has 0 correlation so need to drop this feature as this does not any value to the data.
2. WindSamp and ISSRecpt has almost 0 correlation with all the other input variables. We can see for any ways to convert these and use these features to construct a model

In [10]:

```python
data_mod1.drop(['ID','DateTime'],axis=1,inplace=True)
```

Variable Inflation Factor for checking multicollinearity

The Variance Inflation Factor (VIF) is a measure of colinearity among input variables within a multiple regression

In [12]:

```
#https://stats.stackexchange.com/questions/155028/how-to-systematically-remove-collinear-variables-in-python
#https://etav.github.io/python/vif_factor_python.html
from statsmodels.stats.outliers_influence import variance_inflation_factor
var=list(range(data_mod1.shape[1]))
vif = pd.DataFrame()

vif['VIF values'] = [variance_inflation_factor(data_mod1.iloc[:, var].values, ix)
               for ix in range(data_mod1.iloc[:, var].shape[1])]
vif['Features']=data_mod1.columns
print("Variance Inflation Factor values")
print("*"*50)
print(vif)
```

```
C:\Users\srila\AppData\Local\Continuum\anaconda3\lib\site-packages\statsmodels\stats\outliers_influe
nce.py:185: RuntimeWarning: divide by zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)

Variance Inflation Factor values
**************************************************
      VIF values      Features
0   2.246645e+07       TempOut
1   6.609406e+02        HiTemp
2   3.191581e+02       LowTemp
3   2.664789e+01        OutHum
4   2.985874e+01         DewPt
5            inf     WindSpeed
6            inf       WindRun
7   1.122731e+01       HiSpeed
8   2.246853e+07     WindChill
9   2.131593e+07     HeatIndex
10  2.153310e+07      THWIndex
11  1.455541e+02           Bar
12  2.137997e+00          Rain
13  2.076243e+00      RainRate
14  8.543694e+04        HeatDD
15  4.474921e+04        CoolDD
16  2.244822e+02        InTemp
17  5.969054e+02         InHum
18  1.368182e+02         InDew
19  1.152392e+02        InHeat
20  1.782872e+02         InEMC
21  4.512283e+02  InAirDensity
22  2.493382e+00      WindSamp
23  0.000000e+00        WindTx
24  2.492902e+00      ISSRecpt
25  0.000000e+00        ArcInt

C:\Users\srila\AppData\Local\Continuum\anaconda3\lib\site-packages\statsmodels\regression\linear_mod
el.py:1636: RuntimeWarning: divide by zero encountered in double_scalars
  return 1 - self.ssr/self.centered_tss
```

Observations

1. Windspeed, WindRun has infinity as Variation Inflation factor. Need to remove either Windspeed or Windrun as they explain the same variance within the dataset for further analysis.
2. WindTx & ArcInt has 0 Variance Inflation factor so both can be removed from the data set.
3. WindSamp & ISSRecpt has 2.493 as Variation Inflation factor. Need to remove either WindSamp or ISSRecpt as they explain the same variance within the dataset.

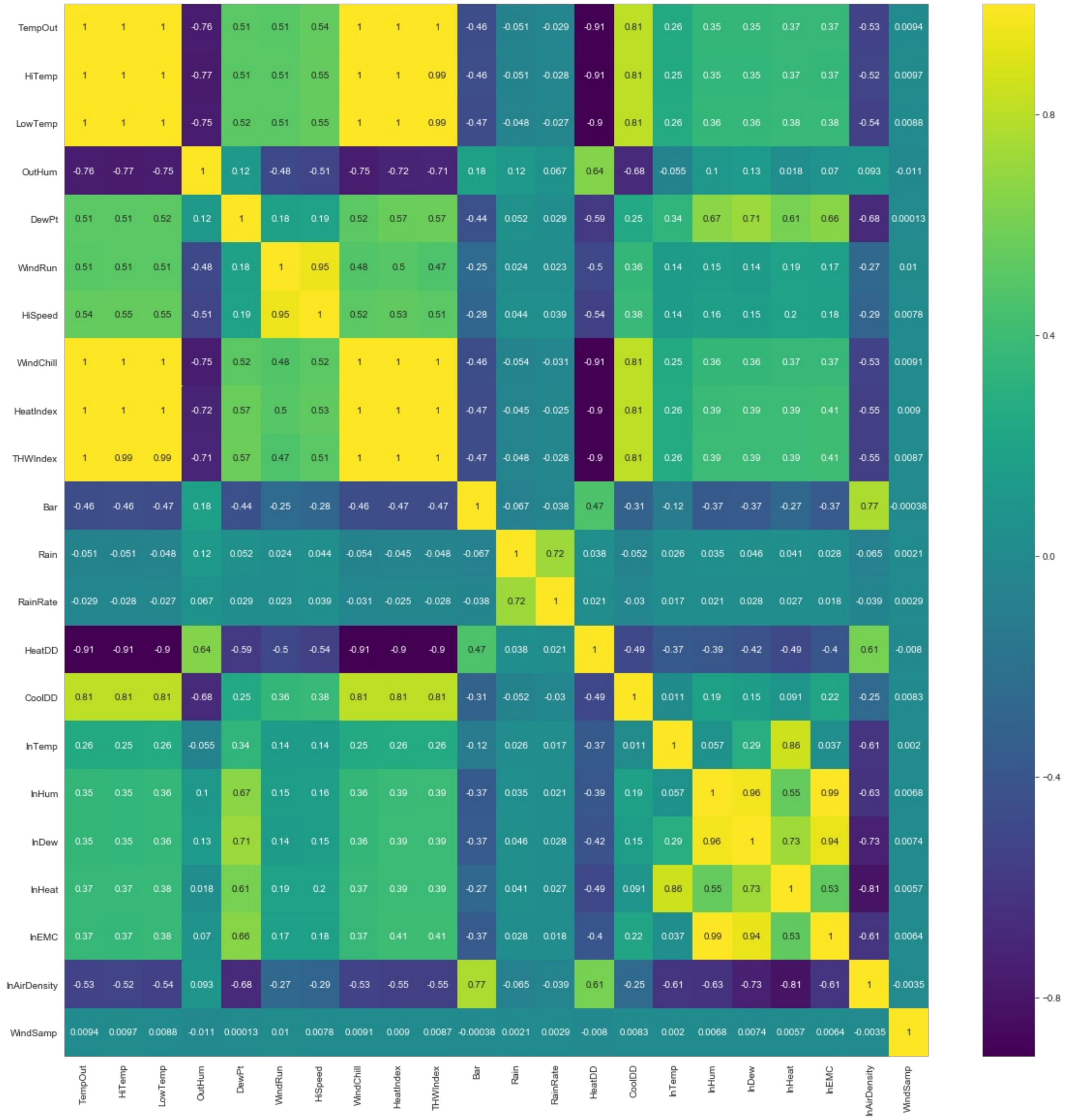
Removing WindSpeed, WindTx, ISSRecpt,ArcInt as per above observations

In [16]:

```
data_mod1.drop(['WindSpeed','WindTx','ISSRecpt','ArcInt'],axis=1,inplace=True)
corr_matrix=data_mod1.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corr_matrix,annot=True,cmap = 'viridis')
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1274b3c0438>
```



Observations:

1. TempOut,HiTemp,LowTemp and WindChill,HeatIndex,THWIndex are highly correlated as their values are 1.0.
2. HeatDD has negative correlation with many input variables.
3. This data has suffers with multicollinearity as 1 input variable can be linearly predicted using other input variables.
4. This data has input variables with both positive and negative correlations.

Variable Inflation Factor for checking multicollinearity after removing the features.

In [17]:

```
#data=pd.read_csv('train.csv')
#data_mod2=data.drop(['ID','DateTime','WindDir','HiDir','WindSpeed','WindTx','ISSRecpt','ArcInt','PA','PB','PC','
PD','PE','PF','PG'],axis=1)
from statsmodels.stats.outliers_influence import variance_inflation_factor
var=list(range(data_mod1.shape[1]))
vif = pd.DataFrame()

vif['VIF values'] = [variance_inflation_factor(data_mod1.iloc[:, var].values, ix)
               for ix in range(data_mod1.iloc[:, var].shape[1])]
vif['Features']=data_mod1.columns
print("Variance Inflation Factor values")
print("*"*50)
print(vif)
```

```
Variance Inflation Factor values
**************************************************
      VIF values      Features
0   5.417530e+08       TempOut
1   1.579306e+04        HiTemp
2   7.888574e+03       LowTemp
3   3.516639e+02        OutHum
4   1.140542e+03         DewPt
5   2.515497e+01       WindRun
6   2.887488e+01       HiSpeed
7   5.396512e+08     WindChill
8   5.336829e+08     HeatIndex
9   5.320822e+08      THWIndex
10  6.087825e+06           Bar
11  2.168366e+00          Rain
12  2.085821e+00      RainRate
13  1.533457e+04        HeatDD
14  4.264942e+03        CoolDD
15  2.538391e+05        InTemp
16  7.464862e+03         InHum
17  4.489725e+03         InDew
18  7.265917e+04        InHeat
19  2.677534e+03         InEMC
20  5.893110e+06  InAirDensity
21  2.424477e+05      WindSamp
```

In [49]:

```
print(data_mod1.columns)
```

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

Checking for Outliers in INT Fields - OutHum,HiSpeed,InHum

In [19]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod1["OutHum"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 4
10 percentile value is 42
20 percentile value is 53
30 percentile value is 63
40 percentile value is 71
50 percentile value is 79
60 percentile value is 85
70 percentile value is 89
80 percentile value is 92
90 percentile value is 95
100 percentile value is  98
```

In [21]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod1["HiSpeed"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 0
10 percentile value is 0
20 percentile value is 2
30 percentile value is 3
40 percentile value is 4
50 percentile value is 5
60 percentile value is 7
70 percentile value is 8
80 percentile value is 10
90 percentile value is 13
100 percentile value is  33
```

In [22]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod1["InHum"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 16
10 percentile value is 30
20 percentile value is 34
30 percentile value is 38
40 percentile value is 42
50 percentile value is 46
60 percentile value is 51
70 percentile value is 55
80 percentile value is 60
90 percentile value is 67
100 percentile value is  88
```

Observations :

1. No Outliers found in the above INT features

Removing OutHum,HiSpeed,InHum(as these are INT) to plot Boxplots,distplots & ProbPlots.

In [23]:

```
data_mod3=data_mod1.drop(['OutHum','HiSpeed','InHum'],axis=1)
print(data_mod3.columns)
print(len(data_mod3.columns))
```

```
Index(['TempOut', 'HiTemp', 'LowTemp', 'DewPt', 'WindRun', 'WindChill',
       'HeatIndex', 'THWIndex', 'Bar', 'Rain', 'RainRate', 'HeatDD', 'CoolDD',
       'InTemp', 'InDew', 'InHeat', 'InEMC', 'InAirDensity', 'WindSamp'],
      dtype='object')
19
```

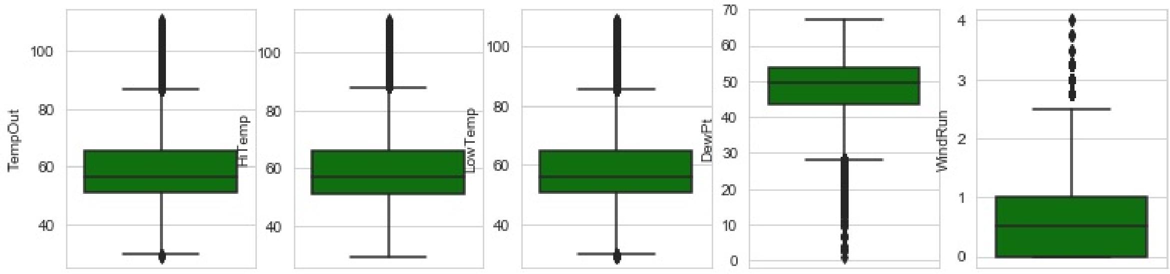
[https://nbviewer.jupyter.org/github/PBPatil/Exploratory_Data_Analysis-Wine_Quality_Dataset/blob/master/winequality_white.ipynb (https://nbviewer.jupyter.org/github/PBPatil/Exploratory_Data_Analysis-Wine_Quality_Dataset/blob/master/winequality_white.ipynb)](https://nbviewer.jupyter.org/github/PBPatil/Exploratory_Data_Analysis-Wine_Quality_Dataset/blob/master/winequality_white.ipynb)

Plotted BoxPlots, DistPlots, ProbPlots for few features at a time to see if there are any outliers and the how the distribution of the data is

BoxPlots, DistPlots, ProbPlots for TempOut, HiTemp,LowTemp,DewPt,WindRun

In [27]:

```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(0,5):
    plt.subplot(rows + 1,cols,i+1)
    sns.set_style('whitegrid')
    sns.boxplot(data_mod3[val[i]],color='green',orient='v')
    #plt.tight_layout()
```



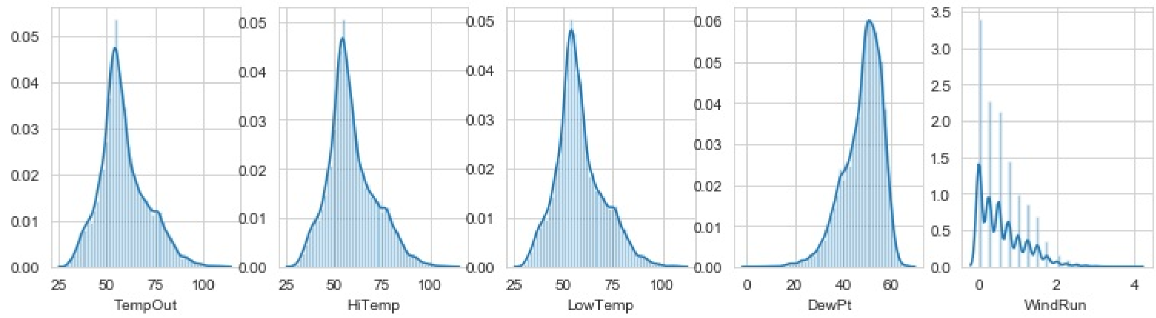
Observations

1. Looking at the box plots, DewPt & WindRun might have some outliers. Other features look good.

In [28]:

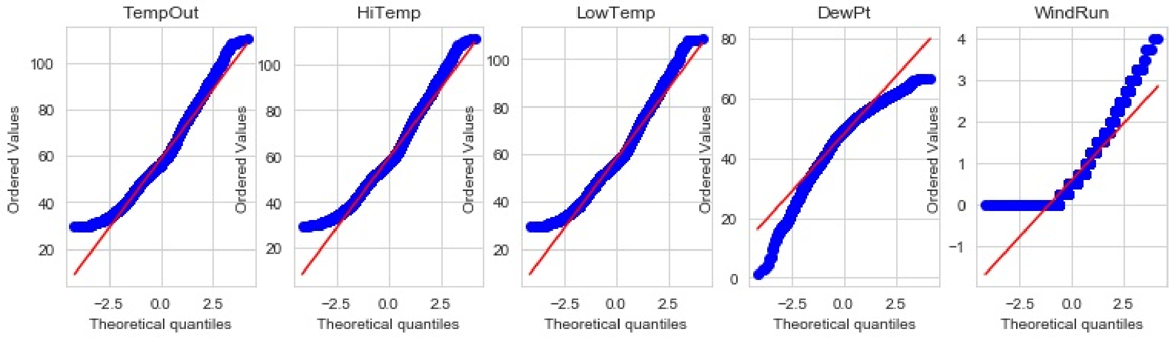
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(0,5):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```

```
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
```



In [30]:

```
import scipy
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(0,5):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    scipy.stats.probplot(data_mod3[val[i]].values, plot=plt)
    plt.title(val[i])
    #sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```



Checking for Outliers in DewPt,WindRun

In [67]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["TempOut"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 76.1
91 percentile value is 76.9
92 percentile value is 77.7
93 percentile value is 78.7
94 percentile value is 79.9
95 percentile value is 81.1
96 percentile value is 82.6
97 percentile value is 84.4
98 percentile value is 86.9
99 percentile value is 91.6
100 percentile value is  110.3
```

In [68]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["HiTemp"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 76.9
91 percentile value is 77.7
92 percentile value is 78.5
93 percentile value is 79.6
94 percentile value is 80.7
95 percentile value is 82.0
96 percentile value is 83.4
97 percentile value is 85.3
98 percentile value is 87.7
99 percentile value is 92.3
100 percentile value is  111.0
```

In [69]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["LowTemp"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 75.3
91 percentile value is 76.1
92 percentile value is 76.9
93 percentile value is 77.8
94 percentile value is 79.0
95 percentile value is 80.4
96 percentile value is 81.7
97 percentile value is 83.6
98 percentile value is 86.0
99 percentile value is 90.8
100 percentile value is  108.6
```

In [31]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["DewPt"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 56.9
91 percentile value is 57.1
92 percentile value is 57.4
93 percentile value is 57.8
94 percentile value is 58.1
95 percentile value is 58.5
96 percentile value is 59.0
97 percentile value is 59.5
98 percentile value is 60.1
99 percentile value is 61.2
100 percentile value is  66.9
```

In [32]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["WindRun"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 1.5
91 percentile value is 1.5
92 percentile value is 1.5
93 percentile value is 1.5
94 percentile value is 1.5
95 percentile value is 1.75
96 percentile value is 1.75
97 percentile value is 2.0
98 percentile value is 2.0
99 percentile value is 2.5
100 percentile value is  4.0
```

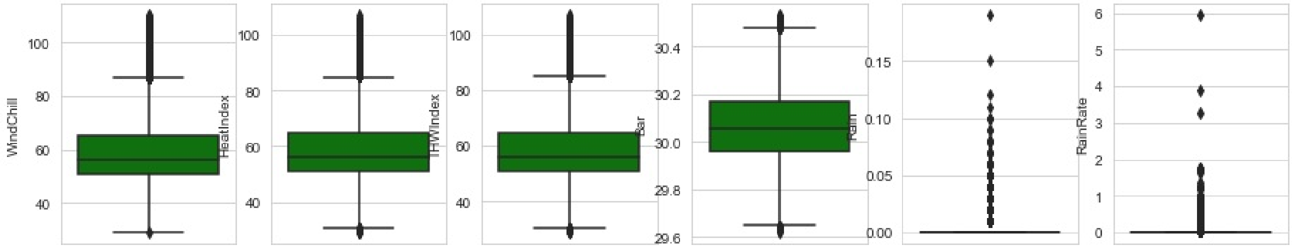
Observations:

1. No notable Outliers found in DewPt,WindRun

Boxplots,Distplots,Probplots for WindChill,HeatIndex,THWIndex,Bar,Rain,RainRate

In [35]:

```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(5,11):
    plt.subplot(rows + 1,cols,i+1)
    sns.set_style('whitegrid')
    sns.boxplot(data_mod3[val[i]],color='green',orient='v')
    #plt.tight_layout()
```



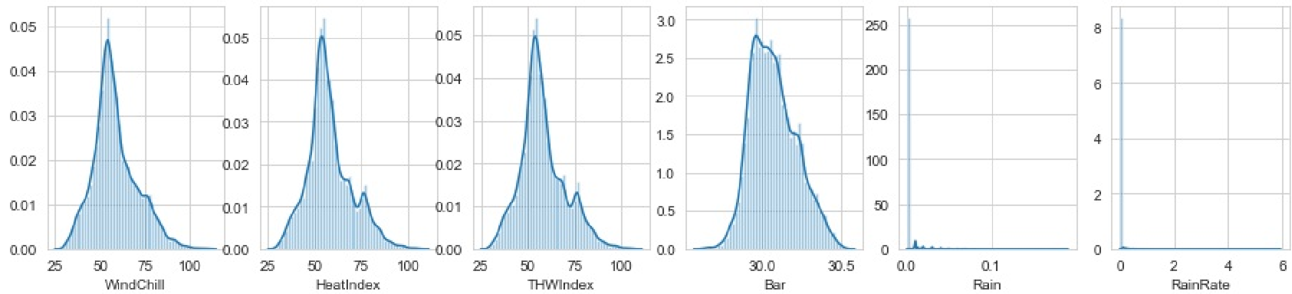
Observaions

1. Rain & RainRate may have outliers. Other features look good.

In [36]:

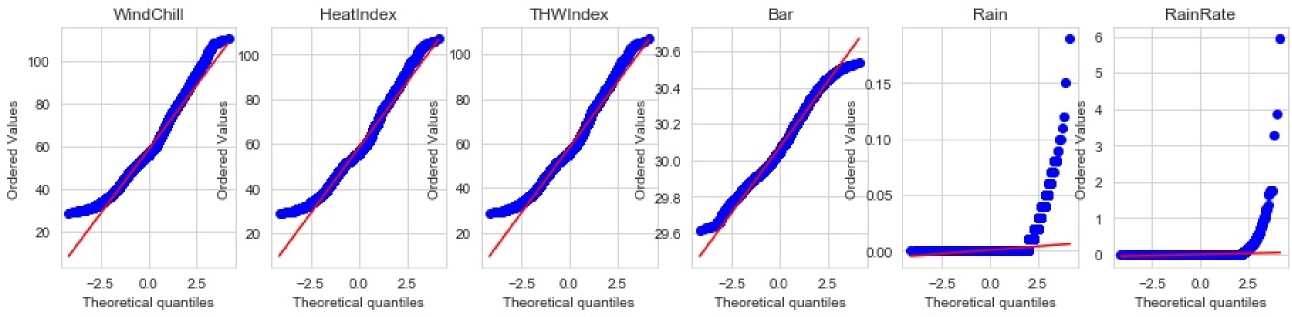
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(5,11):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```

```
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
```



In [37]:

```
import scipy
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(5,11):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    scipy.stats.probplot(data_mod3[val[i]].values, plot=plt)
    plt.title(val[i])
    #sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```



Checking for Outliers in Rain & RainRate

In [61]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["WindChill"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 76.0
91 percentile value is 76.8
92 percentile value is 77.6
93 percentile value is 78.7
94 percentile value is 79.8
95 percentile value is 81.1
96 percentile value is 82.6
97 percentile value is 84.4
98 percentile value is 86.9
99 percentile value is 91.6
100 percentile value is  110.3
```

In [63]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["HeatIndex"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 75.9
91 percentile value is 76.5
92 percentile value is 77.2
93 percentile value is 78.1
94 percentile value is 79.1
95 percentile value is 80.3
96 percentile value is 81.9
97 percentile value is 83.8
98 percentile value is 85.8
99 percentile value is 90.0
100 percentile value is  107.1
```

In [65]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["THWIndex"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 75.8
91 percentile value is 76.4
92 percentile value is 77.2
93 percentile value is 78.0
94 percentile value is 79.1
95 percentile value is 80.3
96 percentile value is 81.9
97 percentile value is 83.7
98 percentile value is 85.8
99 percentile value is 90.0
100 percentile value is  107.1
```

In [66]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["Bar"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 29.619
10 percentile value is 29.904
20 percentile value is 29.945
30 percentile value is 29.98
40 percentile value is 30.017
50 percentile value is 30.055
60 percentile value is 30.094
70 percentile value is 30.141
80 percentile value is 30.201999999999998
90 percentile value is 30.276
100 percentile value is  30.534000000000002
```

In [57]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["Rain"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 0.0
10 percentile value is 0.0
20 percentile value is 0.0
30 percentile value is 0.0
40 percentile value is 0.0
50 percentile value is 0.0
60 percentile value is 0.0
70 percentile value is 0.0
80 percentile value is 0.0
90 percentile value is 0.0
100 percentile value is  0.19
```

In [59]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["RainRate"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

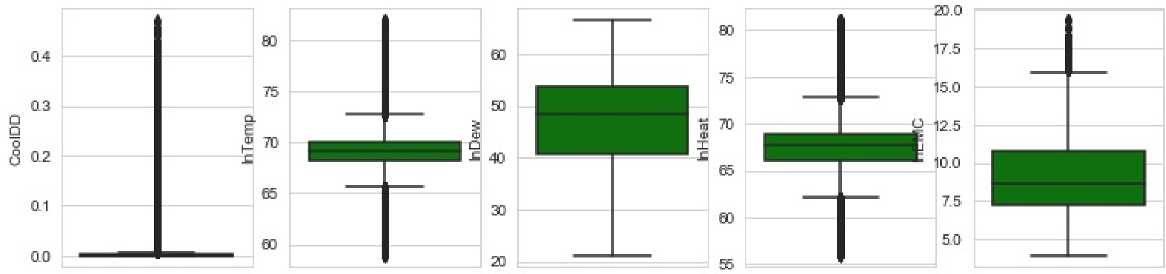
```
90 percentile value is 0.0
91 percentile value is 0.0
92 percentile value is 0.0
93 percentile value is 0.0
94 percentile value is 0.0
95 percentile value is 0.0
96 percentile value is 0.0
97 percentile value is 0.0
98 percentile value is 0.0
99 percentile value is 0.11
100 percentile value is  5.94
```

No notable outlier found for Rain & RainRate

BoxPlots,DistPlots,ProbPlots fro CoolDD,InTemp,InDew,InHeat,inEMC

In [40]:

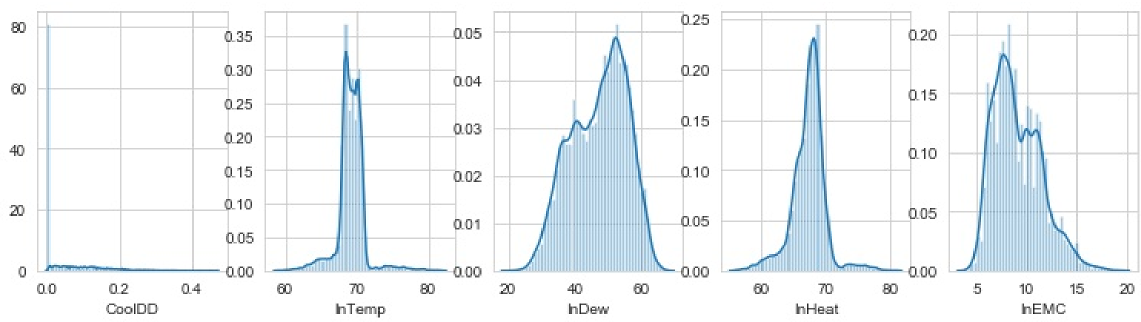
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(12,17):
    plt.subplot(rows + 1,cols,i+1)
    sns.set_style('whitegrid')
    sns.boxplot(data_mod3[val[i]],color='green',orient='v')
    #plt.tight_layout()
```



In [41]:

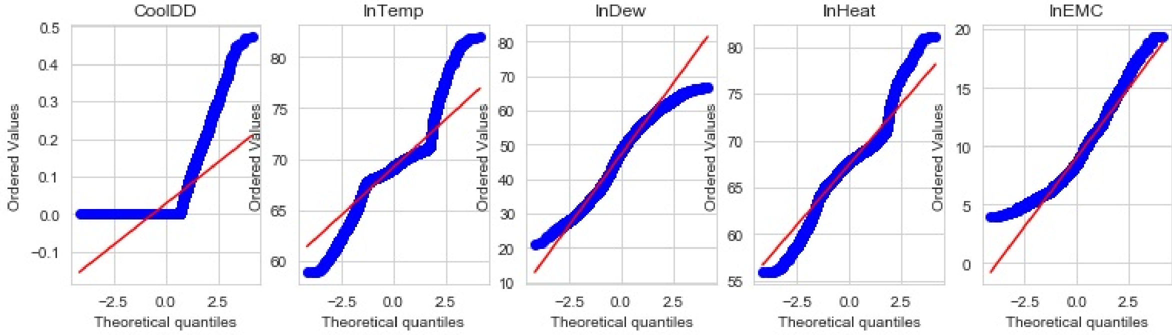
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(12,17):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```

```
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
```



In [42]:

```
import scipy
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(12,17):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    scipy.stats.probplot(data_mod3[val[i]].values, plot=plt)
    plt.title(val[i])
    #sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```



Checking for Outliers in CoolDD

In [43]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(90,100):
    var =data_mod3["CoolDD"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
90 percentile value is 0.11599999999999999
91 percentile value is 0.124
92 percentile value is 0.132
93 percentile value is 0.14300000000000002
94 percentile value is 0.155
95 percentile value is 0.168
96 percentile value is 0.183
97 percentile value is 0.20199999999999999
98 percentile value is 0.228
99 percentile value is 0.27699999999999997
100 percentile value is  0.47200000000000003
```

In [51]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["lnTemp"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 58.9
10 percentile value is 67.7
20 percentile value is 68.2
30 percentile value is 68.5
40 percentile value is 68.8
50 percentile value is 69.2
60 percentile value is 69.6
70 percentile value is 69.9
80 percentile value is 70.3
90 percentile value is 70.7
100 percentile value is  82.0
```

In [53]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["InDew"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 21.1
10 percentile value is 35.3
20 percentile value is 39.0
30 percentile value is 42.2
40 percentile value is 45.5
50 percentile value is 48.3
60 percentile value is 50.7
70 percentile value is 52.7
80 percentile value is 54.9
90 percentile value is 57.4
100 percentile value is  66.6
```

In [55]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["InHeat"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 55.9
10 percentile value is 64.5
20 percentile value is 65.7
30 percentile value is 66.5
40 percentile value is 67.2
50 percentile value is 67.7
60 percentile value is 68.1
70 percentile value is 68.5
80 percentile value is 69.0
90 percentile value is 69.8
100 percentile value is  81.1
```

In [56]:

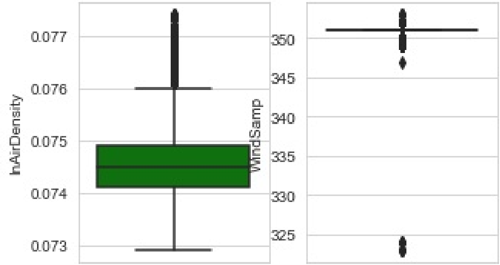
```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["InEMC"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 3.94
10 percentile value is 6.25
20 percentile value is 6.85
30 percentile value is 7.53
40 percentile value is 8.03
50 percentile value is 8.64
60 percentile value is 9.44
70 percentile value is 10.19
80 percentile value is 11.05
90 percentile value is 12.35
100 percentile value is  19.36
```

BoxPlots,DistPlots,ProbPlots for InAirDensity, WindSamp

In [45]:

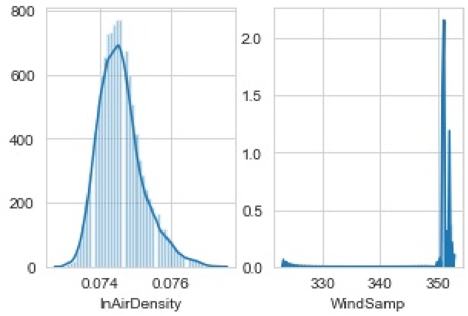
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(17,19):
    plt.subplot(rows + 1,cols,i+1)
    sns.set_style('whitegrid')
    sns.boxplot(data_mod3[val[i]],color='green',orient='v')
    #plt.tight_layout()
```



In [46]:

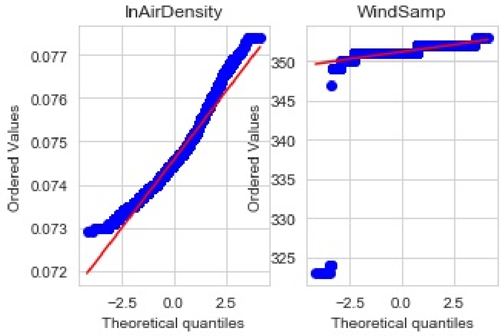
```
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(17,19):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```

```
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
```



In [47]:

```
import scipy
val = data_mod3.columns.values
cols=19
rows = len(val)-1/cols
plt.figure(figsize=(50,70))
for i in range(17,19):
    plt.subplot(rows + 1,cols,i+1)
    #sns.set_style('whitegrid')
    scipy.stats.probplot(data_mod3[val[i]].values, plot=plt)
    plt.title(val[i])
    #sns.distplot(data_mod3[val[i]],kde=True)
    #plt.tight_layout()
```



Checking for Outliers

In [50]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["InAirDensity"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 0.0729
10 percentile value is 0.0738
20 percentile value is 0.07400000000000001
30 percentile value is 0.0742
40 percentile value is 0.0743
50 percentile value is 0.0745
60 percentile value is 0.0746
70 percentile value is 0.0748
80 percentile value is 0.075
90 percentile value is 0.0754
100 percentile value is  0.0774
```

In [48]:

```
#calculating 99-100th percentile to find a the correct percentile value for removal of outliers
for i in range(0,100,10):
    var =data_mod3["WindSamp"].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is 323
10 percentile value is 351
20 percentile value is 351
30 percentile value is 351
40 percentile value is 351
50 percentile value is 351
60 percentile value is 351
70 percentile value is 351
80 percentile value is 352
90 percentile value is 352
100 percentile value is  353
```

EDA Summary

1. As per the EDA on train data, there are 2 categorical variables - WindDir & HiDir & all others are numerical variables(Int & Float).
2. There are 7 labels PA,PB,PC,PD,PE,PF,PG in the train data and using the train data need to predict 7 labels for the given test data.
3. Data description looks good with no outliers as the min,max,percententiles, mean & std are within a range for both train and test data.
4. TempOut is highly correlated with HiTemp,LowTemp,WindChill,HeatIndex,THWIndex and many other variables are highly correlated with each other.
5. HeatDD is negatively correlated with TempOut,HiTemp,LowTemp,WindChill,HeatIndex,THWIndex and many other variables are negatively correlated with each other.
6. This data suffers with multicollinearity problem as this data has postive and negative correaltions.
7. Using Variable inflation factor, measure of collinearity between input variables can be found and avoided for further analysis.
8. Based on VIF- Windspeed, WindRun has infinity as Variation Inflation factor. Need to remove either Windspeed or Windrun as they explain the same variance within the dataset.
9. WindTx & ArcInt has 0 Variance Inflation factor so both can be removed from the data set.
10. WindSamp & ISSRecpt has 2.493 as Variation Inflation factor. Need to remove either WindSamp or ISSRecpt as they explain the same variance within the dataset. 11.. Almost all the input variables are skewed and target labels are highly correlated.
11. Random Forest & XGBoost are immune to multicollinearity by nature as the tree splits based on the perfectly correlated features. (https://towardsdatascience.com/why-feature-correlation-matters-a-lot-847e8ba439c4 (https://towardsdatascience.com/why-feature-correlation-matters-a-lot-847e8ba439c4))

Training a model based on the features without any feature engineering.

In [2]:

```
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.
```

In [27]:

```
data_train=pd.read_csv("train.csv")
data_test=pd.read_csv("test.csv")
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)
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)

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

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

print(data_train.columns)
print(data_test.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')
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', 'Date', 'Year', 'Month', 'Day'],
      dtype='object')
```

In [28]:

```
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',
       'WindDir', 'WindRun', 'HiSpeed', 'HiDir', 'WindChill', 'HeatIndex',
       'THWIndex', 'Bar', 'Rain', 'RainRate', 'HeatDD', 'CoolDD', 'InTemp',
       'InHum', 'InDew', 'InHeat', 'InEMC', 'InAirDensity', 'WindSamp',
       'ISSRecpt', 'Year', 'Month', 'Day'],
      dtype='object')
Label columns Index(['PA', 'PB', 'PC', 'PD', 'PE', 'PF', 'PG'], dtype='object')
Test columns Index(['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',
       'ISSRecpt', 'Year', 'Month', 'Day'],
      dtype='object')
```

In [29]:

```
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, 29) (22446, 29)
Label Train, Test shapes: (40000, 7)
```

Vectorizing WindDir, HiDir

In [30]:

```
from sklearn.preprocessing import LabelEncoder
cols = ('WindDir','HiDir')

for c in cols:
    lbl=LabelEncoder()
    lbl.fit(list(x_train[c].values))
    x_train[c]=lbl.transform(list(x_train[c].values))
    x_test[c]=lbl.transform(list(x_test[c].values))

print("Shape of train,test data",x_train.shape,x_test.shape)
```

```
Shape of train,test data (40000, 29) (22446, 29)
```

Vectorizing Numerical features

In [31]:

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

Models

Random Forest

In [32]:

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

n_estimators = [100,300,500,700,900]
max_depth = [1,3,5,7,9]

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

In [33]:

```
print("Tuning hyper-parameters for ROC_AUC")
print("*"*50)
print()
clf = GridSearchCV(estimator = rf, param_grid = random_grid, cv = 5, n_jobs = -1, scoring='neg_mean_squared_error
')
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=9,
                      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=100,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
Best Score: -97274.2143382412
Best Params: {'max_depth': 9, 'n_estimators': 100}
```

In [35]:

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

In [36]:

```
from sklearn.metrics import mean_squared_error

rfr=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=9,
                      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=100,
                      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: 212.3624664652438
Train Score is: 0
**************************************************
RMSE scores for: PB
**************************************************
Train RMSE is: 102.34676106224074
Train Score is: 0
**************************************************
RMSE scores for: PC
**************************************************
Train RMSE is: 57.54735702024344
Train Score is: 42.45264297975656
**************************************************
RMSE scores for: PD
**************************************************
Train RMSE is: 31.64813397108407
Train Score is: 68.35186602891594
**************************************************
RMSE scores for: PE
**************************************************
Train RMSE is: 21.91043609727262
Train Score is: 78.08956390272738
**************************************************
RMSE scores for: PF
**************************************************
Train RMSE is: 16.006419847106592
Train Score is: 83.9935801528934
**************************************************
RMSE scores for: PG
**************************************************
Train RMSE is: 10.302806853865476
Train Score is: 89.69719314613452
**************************************************
```

In [37]:

```
print(rfr_score)
```

```
           ID      PA      PB     PC     PD     PE     PF     PG
0     PR40001  1883.0   911.0  527.0  338.0  223.0  139.0  115.0
1     PR40002  2095.0  1032.0  562.0  351.0  213.0  149.0  112.0
2     PR40003  1999.0   959.0  541.0  343.0  233.0  140.0  114.0
3     PR40004  2037.0  1035.0  565.0  364.0  216.0  152.0  112.0
4     PR40005  2146.0  1052.0  583.0  375.0  237.0  154.0  117.0
5     PR40006  2076.0   981.0  581.0  367.0  246.0  146.0  121.0
6     PR40007  2152.0   982.0  590.0  363.0  222.0  156.0  115.0
7     PR40008  2203.0  1048.0  597.0  370.0  236.0  158.0  117.0
8     PR40009  1976.0   961.0  567.0  347.0  234.0  140.0  119.0
9     PR40010  2263.0  1058.0  595.0  373.0  234.0  158.0  117.0
10    PR40011  1957.0   958.0  575.0  353.0  238.0  140.0  120.0
11    PR40012  2306.0  1079.0  597.0  376.0  233.0  161.0  120.0
12    PR40013  2344.0  1080.0  608.0  377.0  243.0  157.0  119.0
13    PR40014  2012.0   981.0  559.0  351.0  233.0  141.0  117.0
14    PR40015  2288.0  1081.0  590.0  373.0  235.0  156.0  120.0
15    PR40016  2183.0  1057.0  562.0  361.0  231.0  157.0  113.0
16    PR40017  1910.0   908.0  521.0  320.0  202.0  136.0  109.0
17    PR40018  2150.0  1067.0  575.0  362.0  222.0  153.0  117.0
18    PR40019  2143.0  1053.0  558.0  370.0  228.0  154.0  110.0
19    PR40020  1885.0   858.0  492.0  322.0  200.0  137.0  110.0
20    PR40021  1887.0   894.0  531.0  362.0  225.0  140.0  112.0
21    PR40022  2085.0  1005.0  551.0  370.0  223.0  154.0  110.0
22    PR40023  1831.0   899.0  532.0  326.0  215.0  136.0  113.0
23    PR40024  2144.0  1001.0  573.0  363.0  219.0  155.0  113.0
24    PR40025  1941.0   907.0  517.0  348.0  214.0  135.0  112.0
25    PR40026  2042.0  1036.0  550.0  353.0  206.0  144.0  111.0
26    PR40027  1893.0   818.0  486.0  307.0  210.0  124.0  111.0
27    PR40028  2068.0   967.0  544.0  349.0  213.0  152.0  109.0
28    PR40029  1803.0   807.0  505.0  296.0  213.0  125.0  106.0
29    PR40030  1982.0   975.0  528.0  339.0  212.0  150.0  108.0
...       ...     ...     ...    ...    ...    ...    ...    ...
319   PR40320   313.0   205.0  110.0   75.0   55.0   44.0   34.0
2339  PR42340   518.0   276.0  154.0   98.0   62.0   55.0   42.0
2340  PR42341   652.0   300.0  212.0  137.0   84.0   61.0   48.0
1155  PR41156   368.0   215.0  112.0   74.0   57.0   44.0   31.0
1156  PR41157   369.0   200.0  123.0   76.0   59.0   42.0   31.0
1157  PR41158   360.0   204.0  106.0   72.0   56.0   41.0   30.0
2341  PR42342   395.0   213.0  143.0   99.0   58.0   48.0   38.0
2342  PR42343   485.0   221.0  146.0  103.0   67.0   52.0   38.0
5073  PR45074   338.0   198.0  115.0   79.0   57.0   44.0   35.0
1277  PR41278   336.0   192.0  120.0   77.0   58.0   43.0   35.0
5090  PR45091   335.0   195.0  123.0   72.0   58.0   40.0   36.0
5091  PR45092   334.0   211.0  130.0   85.0   64.0   47.0   37.0
5092  PR45093   320.0   185.0  125.0   83.0   64.0   47.0   33.0
5093  PR45094   345.0   189.0  130.0   79.0   59.0   48.0   35.0
4478  PR44479   326.0   187.0  110.0   78.0   67.0   45.0   35.0
4479  PR44480   286.0   193.0  103.0   67.0   53.0   41.0   32.0
4480  PR44481   319.0   172.0  105.0   70.0   52.0   40.0   34.0
4481  PR44482   309.0   176.0  113.0   75.0   55.0   42.0   35.0
1535  PR41536   327.0   192.0  118.0   74.0   53.0   45.0   36.0
1536  PR41537   306.0   179.0  106.0   72.0   52.0   44.0   33.0
4482  PR44483   277.0   179.0  101.0   68.0   51.0   44.0   32.0
5402  PR45403   285.0   177.0  105.0   72.0   52.0   44.0   32.0
5403  PR45404   269.0   172.0  110.0   71.0   53.0   43.0   31.0
5404  PR45405   272.0   160.0  105.0   71.0   53.0   43.0   31.0
3968  PR43969   270.0   168.0  106.0   70.0   55.0   44.0   31.0
5405  PR45406   267.0   166.0  104.0   71.0   56.0   42.0   34.0
5406  PR45407   314.0   168.0  102.0   72.0   55.0   45.0   33.0
5407  PR45408   310.0   169.0   96.0   75.0   52.0   43.0   32.0
5408  PR45409   335.0   175.0  107.0   79.0   54.0   42.0   34.0
5218  PR45219   297.0   169.0   96.0   74.0   49.0   41.0   33.0

[22446 rows x 8 columns]
```

XGBoost

In [38]:

```
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:   46.2s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 13.2min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 51.9min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed: 103.9min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed: 162.5min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed: 250.1min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed: 258.7min finished

[03:54:58] 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=0.01, max_delta_step=0,
             max_depth=5, 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: -122913.64456468185
Best Params: {'learning_rate': 0.01, 'max_depth': 5, '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:   43.5s
[Parallel(n_jobs=-1)]: Done 176 tasks      | elapsed: 13.5min
[Parallel(n_jobs=-1)]: Done 426 tasks      | elapsed: 51.8min
[Parallel(n_jobs=-1)]: Done 776 tasks      | elapsed: 103.7min
[Parallel(n_jobs=-1)]: Done 1226 tasks      | elapsed: 162.3min
[Parallel(n_jobs=-1)]: Done 1776 tasks      | elapsed: 250.5min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed: 258.6min finished

[08:13:53] 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=0.01, max_delta_step=0,
             max_depth=5, 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: -27790.391450822855
Best Params: {'learning_rate': 0.01, 'max_depth': 5, '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:   42.2s

---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-38-3f4a29780c06> in <module>()
     19 for i in output_columns:
     20     y_train_l = y_train[i]
---> 21     result = clf.fit(x_train, y_train_l)
     22     print("Best Parameters for:",i)
     23     print("*"*50)

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\sklearn\model_selection\_search.py in fit
(self, X, y, groups, **fit_params)
    685                 return results
    686 
--> 687             self._run_search(evaluate_candidates)
    688 
    689         # For multi-metric evaluation, store the best_index_, best_params_ and

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\sklearn\model_selection\_search.py in _ru
n_search(self, evaluate_candidates)
   1146     def _run_search(self, evaluate_candidates):
   1147         """Search all candidates in param_grid"""
-> 1148         evaluate_candidates(ParameterGrid(self.param_grid))
   1149 
   1150 

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\sklearn\model_selection\_search.py in eva
luate_candidates(candidate_params)
    664                                for parameters, (train, test)
    665                                in product(candidate_params,
--> 666                                           cv.split(X, y, groups)))
    667 
    668                 if len(out) < 1:

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\joblib\parallel.py in __call__(self, iter
able)
    932 
    933             with self._backend.retrieval_context():
--> 934                 self.retrieve()
    935             # Make sure that we get a last message telling us we are done
    936             elapsed_time = time.time() - self._start_time

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\joblib\parallel.py in retrieve(self)
    831             try:
    832                 if getattr(self._backend, 'supports_timeout', False):
--> 833                     self._output.extend(job.get(timeout=self.timeout))
    834                 else:
    835                     self._output.extend(job.get())

~\AppData\Local\Programs\Python\Python36\Lib\site-packages\joblib\_parallel_backends.py in wrap_futu
re_result(future, timeout)
    519         AsyncResults.get from multiprocessing."""
    520         try:
--> 521             return future.result(timeout=timeout)
    522         except LokyTimeoutError:
    523             raise TimeoutError()

~\AppData\Local\Continuum\anaconda3\lib\concurrent\futures\_base.py in result(self, timeout)
    425                 return self.__get_result()
    426 
--> 427             self._condition.wait(timeout)
    428 
    429             if self._state in [CANCELLED, CANCELLED_AND_NOTIFIED]:

~\AppData\Local\Continuum\anaconda3\lib\threading.py in wait(self, timeout)
    293         try:    # restore state no matter what (e.g., KeyboardInterrupt)
    294             if timeout is None:
--> 295                 waiter.acquire()
    296                 gotit = True
    297             else:

KeyboardInterrupt: 
```

In [39]:

```
import xgboost as xgb
xgb_scores = pd.DataFrame()
xgb_scores['ID'] = data_test['ID']
```

In [41]:

```
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=0.01, max_delta_step=0,
             max_depth=5, 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)

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]
```

```
[08:26:29] 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: 108.3126842605122
Train Score is: 0
**************************************************
[08:26:49] 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: 53.89643721591441
Train Score is: 46.10356278408559
**************************************************
[08:27:08] 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: 30.043703321318393
Train Score is: 69.95629667868161
**************************************************
[08:27:26] 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: 18.253331619400576
Train Score is: 81.74666838059943
**************************************************
[08:27:44] 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: 11.916117330255442
Train Score is: 88.08388266974455
**************************************************
[08:28:02] 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: PF
**************************************************
Train RMSE is: 8.286591693501665
Train Score is: 91.71340830649834
**************************************************
[08:28:20] 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: 6.025240895455415
Train Score is: 93.97475910454459
**************************************************
```

In [42]:

```
print(xgb_scores)
```

```
          ID      PA      PB     PC     PD     PE     PF     PG
0     PR40001  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
1     PR40002  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
2     PR40003  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
3     PR40004  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
4     PR40005  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
5     PR40006  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
6     PR40007  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
7     PR40008  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
8     PR40009  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
9     PR40010  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
10    PR40011  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
11    PR40012  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
12    PR40013  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
13    PR40014  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
14    PR40015  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
15    PR40016  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
16    PR40017  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
17    PR40018  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
18    PR40019  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
19    PR40020  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
20    PR40021  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
21    PR40022  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
22    PR40023  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
23    PR40024  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
24    PR40025  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
25    PR40026  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
26    PR40027  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
27    PR40028  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
28    PR40029  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
29    PR40030  2731.0  1323.0  724.0  434.0  280.0  192.0  138.0
...       ...     ...     ...    ...    ...    ...    ...    ...
319   PR40320   455.0   241.0  139.0   88.0   62.0   46.0   35.0
2339  PR42340   661.0   313.0  174.0  106.0   68.0   50.0   40.0
2340  PR42341   692.0   353.0  213.0  139.0   94.0   64.0   48.0
1155  PR41156   499.0   266.0  153.0   97.0   64.0   47.0   37.0
1156  PR41157   499.0   266.0  153.0   97.0   64.0   47.0   37.0
1157  PR41158   499.0   266.0  153.0   97.0   64.0   47.0   37.0
2341  PR42342   562.0   296.0  171.0  111.0   75.0   53.0   41.0
2342  PR42343   610.0   313.0  192.0  127.0   85.0   57.0   42.0
5073  PR45074   393.0   208.0  123.0   80.0   56.0   42.0   33.0
1277  PR41278   393.0   208.0  123.0   80.0   56.0   42.0   33.0
5090  PR45091   393.0   208.0  123.0   80.0   57.0   43.0   33.0
5091  PR45092   393.0   208.0  123.0   80.0   57.0   43.0   34.0
5092  PR45093   393.0   208.0  123.0   80.0   57.0   43.0   34.0
5093  PR45094   393.0   208.0  123.0   80.0   57.0   43.0   34.0
4478  PR44479   393.0   208.0  123.0   80.0   56.0   43.0   34.0
4479  PR44480   393.0   208.0  123.0   79.0   56.0   43.0   34.0
4480  PR44481   393.0   208.0  123.0   79.0   56.0   43.0   34.0
4481  PR44482   393.0   208.0  123.0   79.0   56.0   43.0   34.0
1535  PR41536   393.0   208.0  123.0   79.0   56.0   43.0   34.0
1536  PR41537   393.0   208.0  123.0   79.0   56.0   43.0   34.0
4482  PR44483   393.0   208.0  123.0   79.0   56.0   43.0   34.0
5402  PR45403   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5403  PR45404   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5404  PR45405   391.0   206.0  121.0   79.0   56.0   43.0   34.0
3968  PR43969   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5405  PR45406   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5406  PR45407   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5407  PR45408   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5408  PR45409   391.0   206.0  121.0   79.0   56.0   43.0   34.0
5218  PR45219   384.0   206.0  121.0   79.0   56.0   43.0   34.0

[22446 rows x 8 columns]
```

Pretty Table

In [45]:

```
from prettytable import PrettyTable

t = PrettyTable()

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

t.add_row(["Random Forest","PA",212.36,0])
t.add_row(["","PB",102.35,0])
t.add_row(["","PC",57.55,42.45])
t.add_row(["","PD",31.65,68.35])
t.add_row(["","PE",21.91,78.08])
t.add_row(["","PF",16.01,83.99])
t.add_row(["","PA",10.30,89.69])
t.add_row(["","","",""])
t.add_row(["XGBoost","PA",108.31,0])
t.add_row(["","PB",53.89,46.10])
t.add_row(["","PC",30.04,69.95])
t.add_row(["","PD",18.25,81.74])
t.add_row(["","PE",11.91,88.08])
t.add_row(["","PF",8.28,91.71])
t.add_row(["","PA",6.02,93.97])

print(t)
```

```
+---------------+-------+--------+-----------------------------+
|     Model     | Label |  RMSE  | score = max(0,(100 - rmse)) |
+---------------+-------+--------+-----------------------------+
| Random Forest |   PA  | 212.36 |              0              |
|               |   PB  | 102.35 |              0              |
|               |   PC  | 57.55  |            42.45            |
|               |   PD  | 31.65  |            68.35            |
|               |   PE  | 21.91  |            78.08            |
|               |   PF  | 16.01  |            83.99            |
|               |   PA  |  10.3  |            89.69            |
|               |       |        |                             |
|    XGBoost    |   PA  | 108.31 |              0              |
|               |   PB  | 53.89  |             46.1            |
|               |   PC  | 30.04  |            69.95            |
|               |   PD  | 18.25  |            81.74            |
|               |   PE  | 11.91  |            88.08            |
|               |   PF  |  8.28  |            91.71            |
|               |   PA  |  6.02  |            93.97            |
+---------------+-------+--------+-----------------------------+
```

EDA Summary

1. As per the EDA on train data, there are 2 categorical variables - WindDir & HiDir & all others are numerical variables(Int & Float).
2. There are 7 labels PA,PB,PC,PD,PE,PF,PG in the train data and using the train data need to predict 7 labels for the given test data.
3. Data description looks good with no outliers as the min,max,percententiles, mean & std are within a range for both train and test data.
4. TempOut is highly correlated with HiTemp,LowTemp,WindChill,HeatIndex,THWIndex and many other variables are highly correlated with each other.
5. HeatDD is negatively correlated with TempOut,HiTemp,LowTemp,WindChill,HeatIndex,THWIndex and many other variables are negatively correlated with each other.
6. This data suffers with multicollinearity problem as this data has postive and negative correaltions.
7. Using Variable inflation factor, measure of collinearity between input variables can be found and avoided for further analysis.
8. Based on VIF- Windspeed, WindRun has infinity as Variation Inflation factor. Need to remove either Windspeed or Windrun as they explain the same variance within the dataset.
9. WindTx & ArcInt has 0 Variance Inflation factor so both can be removed from the data set.
10. WindSamp & ISSRecpt has 2.493 as Variation Inflation factor. Need to remove either WindSamp or ISSRecpt as they explain the same variance within the dataset. 11.. Almost all the input variables are skewed and target labels are highly correlated.
11. Random Forest & XGBoost are immune to multicollinearity by nature as the tree splits based on the perfectly correlated features. (https://towardsdatascience.com/why-feature-correlation-matters-a-lot-847e8ba439c4 (https://towardsdatascience.com/why-feature-correlation-matters-a-lot-847e8ba439c4))

Basic Model Summary:

1. As per the EDA there are 2 categorical featureas and rest are numerical features.
2. Used label encoding on categorical features & standardised all the data.
3. Trained a Random Forest model & recorded RMSE for 7 labels.
4. RMSE's & scores are not as expected and this data needs some feature engineering to get lower RMSE and higher scores.
5. srilaxmik15@gmail.com_27_model_train_test - In this notebook, I have used some feature engineering to lower the RMSE and increase the scores.

In [ ]:

```

```