```
In [45]: #Homework1
         #AMS559: Smart Enegry in the Information Age
         #Author: Shivasagar Boraiah, Nikhil Siddhartha
         #Prediction of Absolute Mean Error for Home Data by training the model
         #I concentrated on one Home data and generated all posible plots such a
         s (Weekly variation, Monthly Variation,
         # Daily Variation and other intresting plots according to dataset give
         n.)
         #Trained with Linear Regression, RandomForestRegressor, SARIMA Model.
         #Acheived an RMSE of 1.37, 1.36 and 1.74 respectively
         #I have discussed this problem with Sravani Panakanti and reffered GitHu
         b
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.linear model import LinearRegression
         from datetime import datetime
         %matplotlib inline
         from sklearn.metrics import mean squared error
         from sklearn.metrics import mean absolute error
         from sklearn.pipeline import make pipeline
         from sklearn import linear model
         from sklearn.linear model import Ridge
         from sklearn.ensemble import RandomForestRegressor
In [46]: #Adding the calender to the dataset to get more features to train
         time = datetime.strptime('2014-12-01 00:00:00', '%Y-%m-%d %H:%M:%S')
         time
Out[46]: datetime.datetime(2014, 12, 1, 0, 0)
In [48]: #Interval the data with the frequency of 15Mins
         range = pd.date range('2014-12-01',periods=35039 ,freq="15min")
         print (len(range ))
         35039
In [49]: data1 = pd.read csv('Home1 yr1.csv')
In [50]: data1['userId'] = 1
In [51]: date range=range(0, 35040)
In [52]: len(data1)
         data1['dateval']=range(0, 35039)
```

```
In [53]: data1.head()
```

Out[53]:

	0.65018	userld	dateval
0	1.45400	1	0
1	0.72971	1	1
2	3.10750	1	2
3	0.63572	1	3
4	0.69720	1	4

```
In [54]: data1['month'] = range_.month
```

```
In [55]: data1['dayofweek'] = range_.dayofweek
```

In [56]: data1['weekday'] = range_.weekday

In [57]: data1['hour'] = range_.hour

In [58]: data1.head()

Out[58]:

	0.65018	userld	dateval	month	dayofweek	weekday	hour
0	1.45400	1	0	12	0	0	0
1	0.72971	1	1	12	0	0	0
2	3.10750	1	2	12	0	0	0
3	0.63572	1	3	12	0	0	0
4	0.69720	1	4	12	0	0	1

In [59]: data1 = data1.rename(columns={'0.65018': 'demand'})
 data1.describe()

Out[59]:

	demand	userld	dateval	month	dayofweek	weekday
count	35039.000000	35039.0	35039.000000	35039.000000	35039.000000	35039.000000
mean	1.327227	1.0	17519.000000	6.525900	2.991866	2.991866
std	1.399034	0.0	10115.032378	3.447867	2.003398	2.003398
min	0.015124	1.0	0.000000	1.000000	0.000000	0.000000
25%	0.315675	1.0	8759.500000	4.000000	1.000000	1.000000
50%	0.722890	1.0	17519.000000	7.000000	3.000000	3.000000
75%	1.988550	1.0	26278.500000	10.000000	5.000000	5.000000
max	15.500000	1.0	35038.000000	12.000000	6.000000	6.000000

In [60]: data1.head()

Out[60]:

	demand	userld	dateval	month	dayofweek	weekday	hour
0	1.45400	1	0	12	0	0	0
1	0.72971	1	1	12	0	0	0
2	3.10750	1	2	12	0	0	0
3	0.63572	1	3	12	0	0	0
4	0.69720	1	4	12	0	0	1

```
In [61]: rf = RandomForestRegressor()
len(data1)
```

Out[61]: 35039

```
In [62]: import pandas as pd
         import numpy as np
         import seaborn as sns
         import sklearn as sk
         import scipy.stats as scp
         import matplotlib.pyplot as plt
         from sklearn.model selection import train test split
         from sklearn.metrics import mean squared error
         from math import sqrt
         from statsmodels.tsa.stattools import adfuller
         import statsmodels.api as sm
         from statsmodels.tsa.stattools import acf
         from statsmodels.tsa.stattools import pacf
         from statsmodels.tsa.seasonal import seasonal decompose
         import itertools as it
         import warnings
```

In [63]: X = data1.drop('demand',axis=1)

```
y = y = data1[['demand']]
In [64]: from sklearn.model selection import train test split
In [65]: X train, X test, y train, y test = train test split(X, y, test size=0.3,
          random state=42)
In [66]: #Thanks to Abhishek Reddy Y N for helping me with this API
         from sklearn.metrics import mean squared error
         from sklearn.pipeline import Pipeline
         from sklearn.linear model import LinearRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import mean_squared_error
         standard scaler = StandardScaler().fit(X train)
         rescaled X train = standard scaler.transform(X train)
         lin_model = LinearRegression()
         lin model.fit(rescaled X train, y train)
         pred = lin_model.predict(X_test)
         error = np.sqrt(mean_squared_error(y_test,pred))
         print(error)
         9647.228373844928
In [67]: print(pred)
         [[-12142.88964776]
          [-424.00229051]
          [-13970.30428738]
          [-13321.28148451]
          [ -1600.57611836]
          [-15315.29040964]]
In [68]: | def getUserData(id, frame):
             currentdata = data1[data1.userId==id]
             currentdata = currentdata.sample(frac=1).reset index(drop=True)
                      np.split(currentdata, [int(.6*len(currentdata)), int(.8*len
             return
         (currentdata))])
In [69]: train, validate, test = getUserData(1,data1)
In [70]: y train = train[['demand']]
In [71]: x train = train.drop(['demand', 'userId', 'month', 'weekday', 'dateval'], axi
         s=1)
In [72]: x test = test.drop(['demand', 'userId', 'month', 'weekday', 'dateval'], axis=
         1)
In [73]: y test = test[['demand']]
```

```
In [74]: rf.fit(x_train, y_train)
         /anaconda3/lib/python3.6/site-packages/ipykernel launcher.py:1: DataCon
         versionWarning: A column-vector y was passed when a 1d array was expect
         ed. Please change the shape of y to (n samples,), for example using rav
         el().
           """Entry point for launching an IPython kernel.
Out[74]: RandomForestRegressor(bootstrap=True, criterion='mse', max depth=None,
                    max features='auto', 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=10, n jobs=1,
                    oob score=False, random state=None, verbose=0, warm start=Fa
         lse)
In [78]: ypredRf = rf.predict(x test)
         error = np.sqrt(mean_squared_error(y_test,ypredRf))
         print(error)
         1.3868311874833565
In [79]: print(ypredRf)
         [1.06838918 1.30402286 1.39387371 ... 1.25520045 1.26780932 1.26780932]
In [80]: ypredRf
Out[80]: array([1.06838918, 1.30402286, 1.39387371, ..., 1.25520045, 1.26780932,
                1.267809321)
In [81]: def getUserData(id, frame):
             currentdata = data1[data1.userId==id]
             currentdata = currentdata.sample(frac=1).reset index(drop=True)
                       np.split(currentdata, [int(.6*len(currentdata)), int(.3*len
             return
         (currentdata))])
         y train = train[['demand']]
In [82]:
         x train = train.drop(['demand', 'userId', 'month', 'weekday', 'dateval'],axi
         s=1)
         x test = test.drop(['demand', 'userId', 'month', 'weekday', 'dateval'], axis=
         1)
         y_test = test[['demand']]
         lin model = LinearRegression()
         lin model.fit(x train, y train)
         pred = lin model.predict(x test)
         error = np.sqrt(mean squared error(y test,pred))
         print(error)
```

1.4074206220659675

```
In [83]:
         print(pred)
          [[1.14837053]
           [1.78300474]
           [1.40545103]
           [1.41310572]
           [1.49247904]
           [1.49247904]]
In [84]: week_split = seasonal_decompose(data1.iloc[:672*2].demand, freq=96)
          fig = plt.figure()
          fig = week_split.plot()
          fig.set_size_inches(15, 8)
          <Figure size 432x288 with 0 Axes>
           7.5
          5.0
2.5
           2.5
          Pi 2.0
           1.5
                          200
                                                                 1000
                                                                           1200
                                                                                     1400
In [85]: #Electricity Consumption according to the daily time(96 rows)
          df=list(data1.demand)
          daily=[]
          for i in range(0,34943,96):
              sum=0
              for j in range(i,i+96):
                   sum = sum + df[j]
```

daily.append(sum)

```
In [43]: plt.plot(daily)
           plt.ylabel('Electricity demand')
Out[43]: Text(0,0.5, 'Electricity demand')
             350
             300
           Electricity demand
             250
             200
             150
             100
              50
                   ò
                        50
                             100
                                   150
                                         200
                                                     300
          np.corrcoef(data1[0:-1], data1[1:])
 In [ ]:
In [86]:
           #sum of consumptions of each month
           monthly=[]
           for i in range(0,335,30):
               sum=0
               for j in range(i,i+30):
                    sum = sum + daily[j]
               monthly.append(sum)
           print(len(monthly))
          12
In [87]: plt.plot(monthly)
           plt.ylabel('Electricity demand')
Out[87]: Text(0,0.5,'Electricity demand')
             7000
             6000
           Electricity demand
             5000
             4000
             3000
             2000
```

10

1000

ó

```
In [92]:
          # Naive approach
          meanSquaredError=mean squared error(data1[1344:1440], data1[1248:1344])
          rootMeanSquaredError = sqrt(meanSquaredError)
          print("RMSE:", rootMeanSquaredError)
          RMSE: 36.43542520500079
In [95]:
          # create training and testing variables
          X train, X test = train test split(data1, test size=0.0027398)
          print (X train.shape)
          print (X_test.shape)
          (34943, 7)
          (96, 7)
In [96]:
         fig = plt.figure(figsize=(12,8))
          ax1 = fig.add_subplot(211)
          fig = sm.graphics.tsa.plot acf(X train.demand[97:], lags=40, ax=ax1)
          ax2 = fig.add subplot(212)
          fig = sm.graphics.tsa.plot_pacf(X_train.demand[97:], lags=40, ax=ax2)
                                            Autocorrelation
          1.0
          0.8
          0.6
          0.4
          0.2
          0.0
                                10
                                          Partial Autocorrelation
          1.0
          0.8
          0.6
          0.4
          0.2
          0.0
```

In [98]: seasonal_decompose(data1, freq=96)

15

Out[98]: <statsmodels.tsa.seasonal.DecomposeResult at 0x1c21c51908>

10

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```
In [100]: X_train=data1[:1344]
X_train = X_train.rename(columns={'0.65018': 'demand'})
X_train.describe()
```

Out[100]:

	demand	userld	dateval	month	dayofweek	weekday	hour
count	1344.000000	1344.0	1344.000000	1344.0	1344.000000	1344.000000	1344.000000
mean	1.948154	1.0	671.500000	12.0	3.000000	3.000000	11.500000
std	1.606076	0.0	388.123692	0.0	2.000744	2.000744	6.924763
min	0.318900	1.0	0.000000	12.0	0.000000	0.000000	0.000000
25%	0.670080	1.0	335.750000	12.0	1.000000	1.000000	5.750000
50%	1.437700	1.0	671.500000	12.0	3.000000	3.000000	11.500000
75%	2.632600	1.0	1007.250000	12.0	5.000000	5.000000	17.250000
max	8.570700	1.0	1343.000000	12.0	6.000000	6.000000	23.000000

```
In [103]: print(data1.corrwith(data1['demand']))
```

demand 1.000000
userId NaN
dateval -0.372315
month -0.244674
dayofweek -0.008742
weekday -0.008742
hour 0.203713
dtype: float64

```
In [105]: def test_stationarity(timeseries):
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value',
    '#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)
```

```
In [107]: test_stationarity(X_train.demand)
          Results of Dickey-Fuller Test:
          Test Statistic
                                         -8.598752e+00
          p-value
                                          6.961221e-14
          #Lags Used
                                          5.000000e+00
          Number of Observations Used
                                          1.338000e+03
          Critical Value (1%)
                                         -3.435247e+00
          Critical Value (5%)
                                         -2.863703e+00
          Critical Value (10%)
                                         -2.567921e+00
          dtype: float64
In [108]: p = range(0, 2)
          d = range(0, 2)
          q = range(0, 2)
          params = list(it.product(p, d, q))
          seasonal_params = [(x[0], x[1], x[2], 96) for x in list(it.product(p, d,
           q))]
```

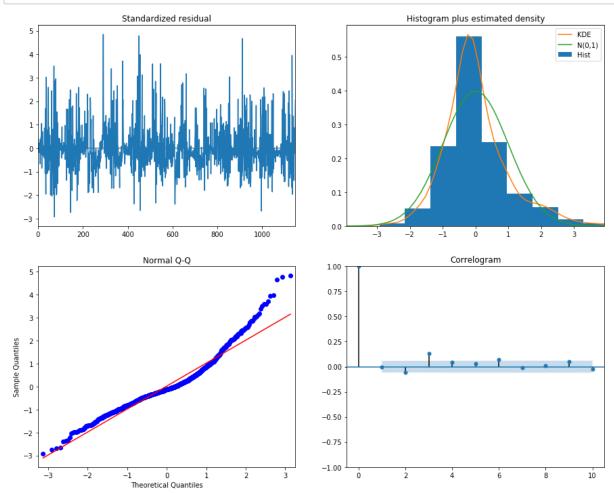
```
SARIMAX(0, 0, 0)x(0, 0, 0, 96) - AIC:6301.24
SARIMAX(0, 0, 0)x(0, 0, 1, 96) - AIC:5443.55
SARIMAX(0, 0, 0)x(0, 1, 0, 96) - AIC:5207.97
SARIMAX(0, 0, 0)x(0, 1, 1, 96) - AIC:4241.75
SARIMAX(0, 0, 0)x(1, 0, 0, 96) - AIC:5012.58
SARIMAX(0, 0, 0)x(1, 0, 1, 96) - AIC:4657.78
SARIMAX(0, 0, 0)x(1, 1, 0, 96) - AIC:4509.88
SARIMAX(0, 0, 0)x(1, 1, 1, 96) - AIC:4243.2
SARIMAX(0, 0, 1)\times(0, 0, 0, 96) - AIC:5532.7
SARIMAX(0, 0, 1)x(0, 0, 1, 96) - AIC:4956.34
SARIMAX(0, 0, 1)x(0, 1, 0, 96) - AIC:5075.23
SARIMAX(0, 0, 1)x(0, 1, 1, 96) - AIC:4063.45
SARIMAX(0, 0, 1)x(1, 0, 0, 96) - AIC:4783.16
SARIMAX(0, 0, 1)x(1, 0, 1, 96) - AIC:4474.6
SARIMAX(0, 0, 1)x(1, 1, 0, 96) - AIC:4347.16
SARIMAX(0, 0, 1)x(1, 1, 1, 96) - AIC:4117.11
SARIMAX(0, 1, 0)x(0, 0, 0, 96) - AIC:5038.38
SARIMAX(0, 1, 0)x(0, 0, 1, 96) - AIC:4649.74
SARIMAX(0, 1, 0)x(0, 1, 0, 96) - AIC:5573.91
SARIMAX(0, 1, 0)x(0, 1, 1, 96) - AIC:4465.14
SARIMAX(0, 1, 0)x(1, 0, 0, 96) - AIC:4654.01
SARIMAX(0, 1, 0)x(1, 0, 1, 96) - AIC:4651.73
SARIMAX(0, 1, 0)x(1, 1, 0, 96) - AIC:4769.49
SARIMAX(0, 1, 0)x(1, 1, 1, 96) - AIC:4505.45
SARIMAX(0, 1, 1)x(0, 0, 0, 96) - AIC:4693.65
SARIMAX(0, 1, 1)x(0, 0, 1, 96) - AIC:4330.99
SARIMAX(0, 1, 1)x(0, 1, 0, 96) - AIC:5158.21
SARIMAX(0, 1, 1)x(0, 1, 1, 96) - AIC:4130.53
SARIMAX(0, 1, 1)x(1, 0, 0, 96) - AIC:4338.09
SARIMAX(0, 1, 1)x(1, 0, 1, 96) - AIC:4332.89
SARIMAX(0, 1, 1)x(1, 1, 0, 96) - AIC:4427.55
SARIMAX(0, 1, 1)x(1, 1, 1, 96) - AIC:4181.39
SARIMAX(1, 0, 0)x(0, 0, 0, 96) - AIC:4906.44
SARIMAX(1, 0, 0)x(0, 0, 1, 96) - AIC:4530.67
SARIMAX(1, 0, 0)x(0, 1, 0, 96) - AIC:5069.47
SARIMAX(1, 0, 0)x(0, 1, 1, 96) - AIC:4054.26
SARIMAX(1, 0, 0)x(1, 0, 0, 96) - AIC:4529.62
SARIMAX(1, 0, 0)x(1, 0, 1, 96) - AIC:4462.69
SARIMAX(1, 0, 0)x(1, 1, 0, 96) - AIC:4339.79
SARIMAX(1, 0, 0)x(1, 1, 1, 96) - AIC:4103.68
SARIMAX(1, 0, 1)x(0, 0, 0, 96) - AIC:4687.89
SARIMAX(1, 0, 1)x(0, 0, 1, 96) - AIC:4323.2
SARIMAX(1, 0, 1)x(0, 1, 0, 96) - AIC:5066.75
SARIMAX(1, 0, 1)x(0, 1, 1, 96) - AIC:4051.88
SARIMAX(1, 0, 1)x(1, 0, 0, 96) - AIC:4327.32
SARIMAX(1, 0, 1)x(1, 0, 1, 96) - AIC:4325.15
SARIMAX(1, 0, 1)x(1, 1, 0, 96) - AIC:4341.66
SARIMAX(1, 0, 1)x(1, 1, 1, 96) - AIC:4100.01
SARIMAX(1, 1, 0)x(0, 0, 0, 96) - AIC:4899.99
SARIMAX(1, 1, 0)x(0, 0, 1, 96) - AIC: 4516.33
SARIMAX(1, 1, 0)x(0, 1, 0, 96) - AIC:5413.61
SARIMAX(1, 1, 0)x(0, 1, 1, 96) - AIC:4346.17
SARIMAX(1, 1, 0)x(1, 0, 0, 96) - AIC:4516.28
SARIMAX(1, 1, 0)x(1, 0, 1, 96) - AIC:4518.27
SARIMAX(1, 1, 0)x(1, 1, 0, 96) - AIC:4647.38
SARIMAX(1, 1, 0)x(1, 1, 1, 96) - AIC:4388.42
SARIMAX(1, 1, 1)x(0, 0, 0, 96) - AIC:4642.88
```

```
SARIMAX(1, 1, 1)x(0, 0, 1, 96) - AIC:4290.45
SARIMAX(1, 1, 1)x(0, 1, 0, 96) - AIC:5069.43
SARIMAX(1, 1, 1)x(0, 1, 1, 96) - AIC:4050.39
SARIMAX(1, 1, 1)x(1, 0, 0, 96) - AIC:4293.35
SARIMAX(1, 1, 1)x(1, 0, 1, 96) - AIC:4292.43
SARIMAX(1, 1, 1)x(1, 1, 0, 96) - AIC:4341.71
SARIMAX(1, 1, 1)x(1, 1, 1, 96) - AIC:4099.75
```

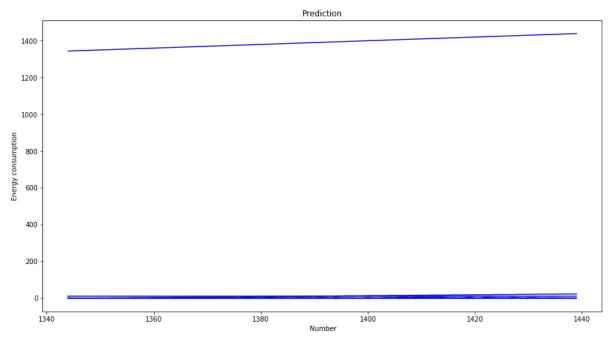
```
In [110]: SARIMA model = sm.tsa.statespace.SARIMAX(X_train.demand,
                                           order=(1, 1, 1),
                                           seasonal_order=(0, 1, 1, 96),
                                           enforce_stationarity=False,
                                           enforce invertibility=False)
          results = SARIMA_model.fit()
          print(results.summary().tables[1])
```

=========	========	========	:=======	========	=========	=
0.975]	coef	std err	z	P> z	[0.025	
						_
ar.L1 0.413	0.3702	0.022	17.106	0.000	0.328	
ma.L1 -0.976	-0.9859	0.005	-187.622	0.000	-0.996	
ma.S.L96 451.756	-1.0000	231.002	-0.004	0.997	-453.756	
sigma2 761.319	1.6777	387.579	0.004	0.997	-757.964	

In [111]: results.plot_diagnostics(figsize=(15, 12))
 plt.show()



```
In [118]: pred_uc = results.get_forecast(steps=96)
    plt.rcParams['figure.figsize'] = [15, 8]
    plt.plot(pred_uc.predicted_mean)
    plt.plot(data1[1344:1440], color='blue')
    plt.xlabel(' Number')
    plt.ylabel('Energy consumption')
    plt.title('Prediction')
    plt.show()
```



```
In [114]: pred_uc.predicted_mean = pred_uc.predicted_mean.astype(int)
```

RMSE: 1.7452254974474286

```
In [ ]: import seaborn as sns
   import matplotlib.pyplot as plt
   spearman_correlation = data1.corr(method='spearman')
   pick_columns=spearman_correlation.nlargest(10, 'demand').index
   correlationmap = np.corrcoef(data1[pick_columns].values.T)
   sns.set(font_scale=1.0)
   heatmap = sns.heatmap(correlationmap, cbar=True, annot=True, square=True
   , fmt='.2f', yticklabels=data1.values, xticklabels=data1.values)
   plt.show()
```