Energy Forecasting - Time Series

April 5, 2019

1 Energy forecasting: aggregated to a jurisdiction area

Purpose: The purpose of this work is to predict energy consumption for a residential area.
In the recent past, I have been curious to analyze patterns in energy consumption and eventually develop models to perform short term energy/load forecasting. Electric demand or energy consumption forecasting have had been existed for number of years, and almost every energy company uses some kind of forecasting model. Predicting the demand is essential for electric utility operations and planning in order to provide reliable electric power to customers. With the integration of Distribution Energy Resources (DERs) and emphasis on demand response management programs, the complexity in forecasting has grown many folds. This is my first attempt at it in understanding time series analysis as while building a model with low test error.

About data: Electric consumption (watt-hour) data for years between 2013 - 2018 is analyzed. Here, I have 15 minute interval meter readings for a small area with their geographical information. I will use Mean Absolute Percentage Error (MAPE) for comparing accuracies.

What else I can infer from the data: 1. The first and foremost to understand is that it is a time series data. The dependency of time requires special attention. Energy consumption patterns vary with time of day, day of week, weather patterns, holiday, size of customer, customer behavior, etc. 2. A jurisdiction area will have different types of customers - industrial, residential, commercial, farms, etc. 2. Missing data and recording errors.

For privacy and other legal concerns that might arise, I cannot provide data files.

```
In [1]: #Imports
        from pymongo import MongoClient
        import pandas as pd
        import numpy as np

        import glob
        import datetime
        import time
        %matplotlib inline
        import matplotlib.pyplot as plt
        import seaborn as sns
        from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
        from statsmodels.tsa.stattools import adfuller
        from numpy import log
        from statsmodels.tsa.seasonal import seasonal_decompose
        from sklearn.preprocessing import StandardScaler
```

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.pipeline import Pipeline
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import FeatureUnion
from sklearn_pandas import DataFrameMapper
```

```
/home/sravan/anaconda3/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarnin
  from pandas.core import datetools
```

Here I will be connecting to my mongoDB to read the required meter data using MongoClient.
Note: Considering residential meters only. This information is provided in meter profile.

```
In [2]: GroupId = "FDR_14442"
        DBModelName = "AGADEMO-model"
        DBMeasurementsName = "AGADEMO-measurements"
```

```
In [3]: #Create mongo client
        client = MongoClient('localhost', 27019)
        #Read meter profile
        #Set database and collection
        db=client[DBModelName]
        coll=db['model.e.meter.profile']
        #Query residential meters.
        docsProf = coll.find({"rateCode":"PMRS_R","groupId":GroupId})
        listMeterId = []
        d = {'meterId':listMeterId}
        for dc in docsProf:
            listMeterId.append(dc['meterId'])
        dfMeters = pd.DataFrame(d)
        dfMeters.head(), dfMeters.shape
```

```
Out[3]: (                              meterId
         0  776428360310_21351300_NXA112132261
         1  776428700240_21351220_1ND350444587
         2  776428700240_21351230_NXA112132238
         3  776428700240_21351250_1ND351364785
         4  776428700240_21351255_NYA111197195, (425, 1))
```

We got list of residential meters. Now let us run the query on meter usage database.

```
In [4]: #Read meter interval data
        #Set database and collection
        db=client[DBMeasurementsName]
        coll=db['measurements.meter.daily.bag']
```

```
#Query consumption data
docsReads = coll.find({"groupId":GroupId})
#Transform json documents into dataframe with consumption and timestamp.
readDate = []
meterUsage = []
meterId = []
d = {'meterId':meterId, 'DataDate':readDate, 'Usage':meterUsage}
for doc in docsReads:
    intvlData = doc['intervalData']
    for data in intvlData:
        meterId.append(doc['meterId'])
        readDate.append(data[9])
        meterUsage.append(data[0])
df = pd.DataFrame(d)
```

```
In [5]: df.head() , df.shape
```

```
Out[5]: (        DataDate        Usage                                meterId
         0  1357088400000  1431.294069  777428010690_20136117_KZD353381298
         1  1357092000000  1456.469362  777428010690_20136117_KZD353381298
         2  1357095600000  1466.303461  777428010690_20136117_KZD353381298
         3  1357099200000  1493.996283  777428010690_20136117_KZD353381298
         4  1357102800000  1523.734597  777428010690_20136117_KZD353381298,
         (8532024, 3))
```

Here we have 21 million readings. But this is for all meters in the area. Lets extract data only for meters in dfMeters dataframe.

```
In [6]: dfUsage = pd.merge(df, dfMeters, on='meterId', how='inner')
```

```
In [7]: dfUsage.head()
```

```
Out[7]:         DataDate        Usage                                meterId
        0  1357088400000  1185.945002  777429430560_21300410_1ND350452599
        1  1357092000000  1141.532082  777429430560_21300410_1ND350452599
        2  1357095600000  1145.133130  777429430560_21300410_1ND350452599
        3  1357099200000  1188.345701  777429430560_21300410_1ND350452599
        4  1357102800000  1189.546050  777429430560_21300410_1ND350452599
```

We have raw readings which need to be preprocessed. Timestamp can be extracted to individual time components.

```
In [8]: #convert timestamp in milliseconds to datetime
        def tsmsToDate(ts):
            return datetime.datetime.fromtimestamp(ts/1000)
```

```
In [9]: #Extract time and date features from consumption data
        dfUsage['Date'] = dfUsage['DataDate'].apply(tsmsToDate)
        dtcol = dfUsage['Date'].dt
```

```
dfUsage['year'] = dtcol.year
dfUsage['month'] = dtcol.month
dfUsage['daymonth'] = dtcol.day
dfUsage['hour'] = dtcol.hour
dfUsage['dayinweek'] = dtcol.weekday
```

In [10]:
```
dfUsage.head()
```

Out[10]:
```
        DataDate        Usage                               meterId  \
0  1357088400000  1185.945002  777429430560_21300410_1ND350452599
1  1357092000000  1141.532082  777429430560_21300410_1ND350452599
2  1357095600000  1145.133130  777429430560_21300410_1ND350452599
3  1357099200000  1188.345701  777429430560_21300410_1ND350452599
4  1357102800000  1189.546050  777429430560_21300410_1ND350452599

                 Date  year  month  daymonth  hour  dayinweek
0 2013-01-01 20:00:00  2013      1         1    20          1
1 2013-01-01 21:00:00  2013      1         1    21          1
2 2013-01-01 22:00:00  2013      1         1    22          1
3 2013-01-01 23:00:00  2013      1         1    23          1
4 2013-01-02 00:00:00  2013      1         2     0          2
```

Aggregate user consumption to a day. The dataframe dfUsageDaily holds aggregated daily user consumption readings for all meters under consideration.

In [11]:
```
dfUsageDaily = dfUsage.groupby(['year','month','daymonth'])['Usage'].sum().reset_index(
```

In [12]:
```
dfUsageDaily.shape
```

Out[12]:
```
(827, 4)
```

In [13]:
```
#Filter outliers around mean
def rejectOutliers(data, s =2.):
    flags = []
    stdev = np.std(data)
    mean = np.mean(data)
    slow = mean - s * stdev
    sup = mean + s * stdev
    for d in data:
        if d < slow or d > sup:
            flags.append(False)
        else:
            flags.append(True)
    return flags
```

In [14]:
```
#Converting watthour to kwh
dfUsageDaily['Usage'] = dfUsageDaily['Usage']/1000
#dfUsageDaily = dfUsageDaily[rejectOutliers(dfUsageDaily['Usage'])]
```

In [15]:
```
dfUsageDaily.head()
```

Out[15]:
```
   year  month  daymonth      Usage
0  2013      1         1   4.660956
1  2013      1         2  41.910111
2  2013      1         3  79.960422
3  2013      1         4  76.447949
4  2013      1         5  77.976908
```

In [16]:
```
dfUsageDaily.year.unique(), dfUsageDaily.month.unique(), dfUsageDaily.daymonth.unique()
```

Out[16]:
```
(array([2013, 2014, 2015, 2018]),
 array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12]),
 array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
        18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31]))
```

1.1 Visualization

Considering 2013 and 2014 data.

In [17]:
```
dfUsageDailyY = pd.DataFrame()
#dfUsageDaily2013 = dfUsageDaily[dfUsageDaily['year']==2013]
#dfUsageDailyY = dfUsageDaily2013[dfUsageDaily2013['month']>=6]  ##Bad data for Jan-May
dfUsageDailyY = dfUsageDailyY.append(dfUsageDaily[dfUsageDaily['year']==2014])
#dfUsageDailyY = dfUsageDailyY[dfUsageDailyY['month']==8]

dfUsageDailyY = dfUsageDailyY.append(dfUsageDaily[dfUsageDaily['year']==2015])
```

In [18]:
```
dfUsageDailyY.count()
```

Out[18]:
```
year        457
month       457
daymonth    457
Usage       457
dtype: int64
```

In [19]:
```
#convert timestamp in milliseconds to datetime
def paramToDate(y,m,d):
    dt= datetime.datetime(year=y, month=m, day=d)
    return dt
```

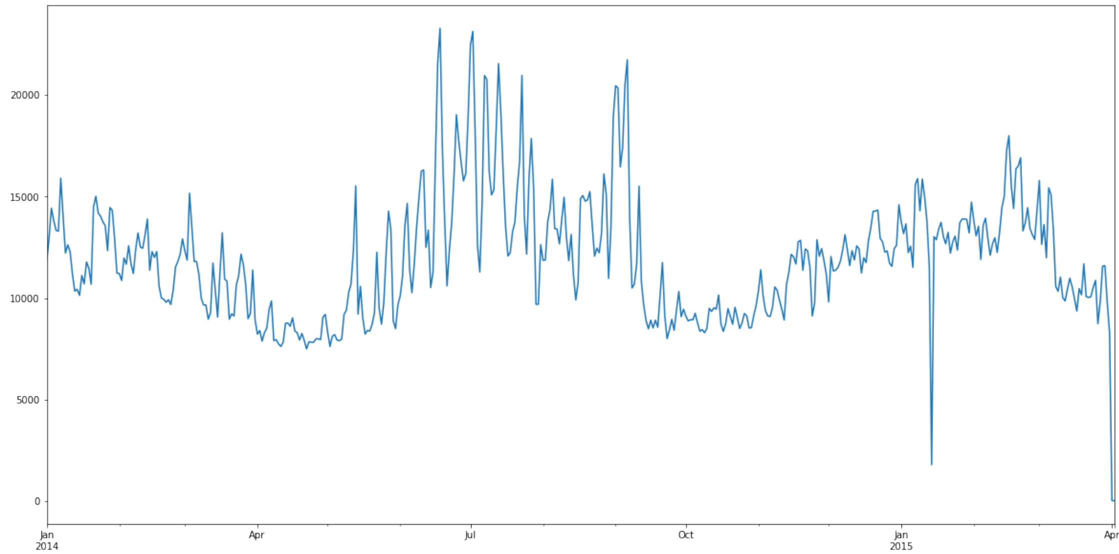
To visualize as time series, I moved the data into panda series.

In [20]:
```
y = pd.Series()
y = list(map(lambda x : paramToDate(x.year,x.month,x.daymonth), dfUsageDailyY.itertuple
series = pd.Series( dfUsageDailyY['Usage'].values, y)
series[0:5]
```

Out[20]:
```
2014-01-01    11822.307025
2014-01-02    12942.309043
2014-01-03    14432.091790
2014-01-04    13826.123779
2014-01-05    13338.632715
dtype: float64
```

```
In [21]: plt.figure(figsize=(20,10))
         series.plot()
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f1e0fa9b0>
```

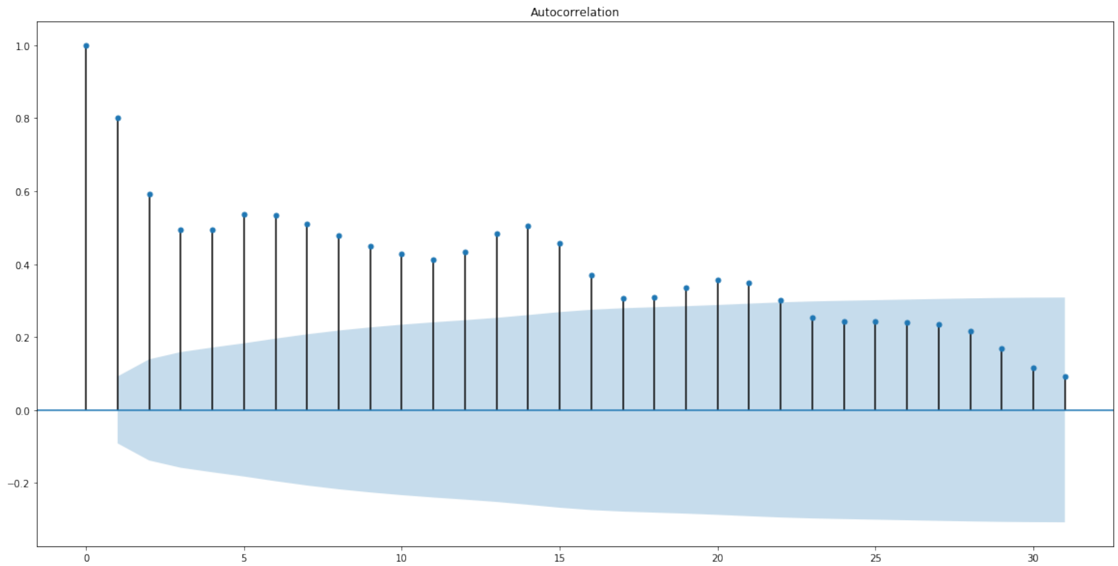


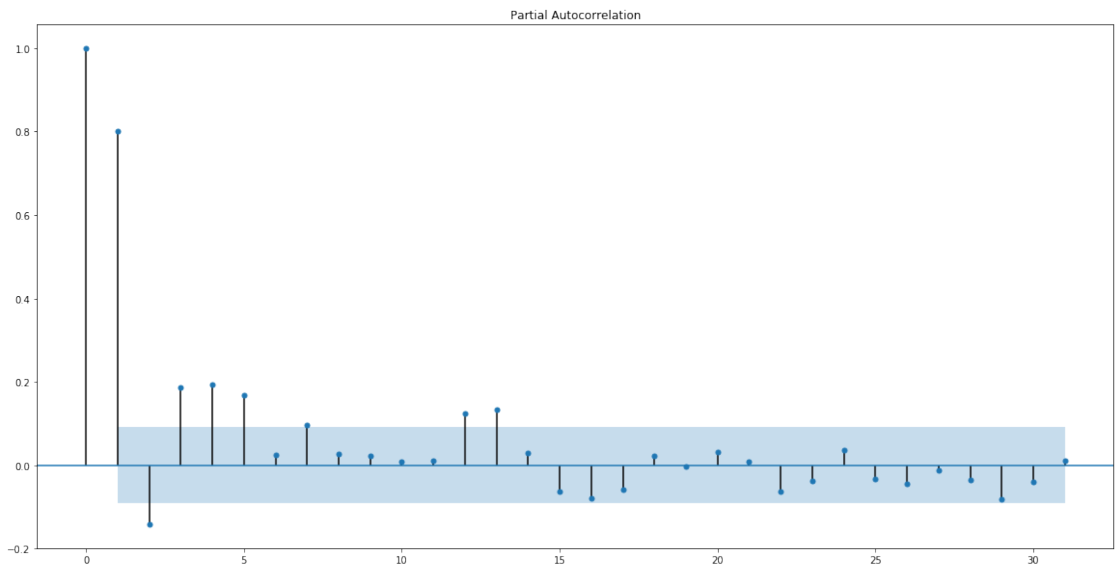
Observations: 1. Cyclical patterns across the year - probably seasonal variations. 2. Small cycles within month - probably daily/weekly variations. 3. Can be a lot of other things including white noise.

1.1.1 Is the series stationary ?

Lets plot auto-correlation and partial correlation plots.

```
In [22]: plt.rc("figure", figsize=(20,10))
         fig = plot_acf(dfUsageDailyY['Usage'], lags=31)
         fig1=plot_pacf(dfUsageDailyY['Usage'], lags=31)
```





Does not look stationary. Lot of points outside the critical boundary.

Augmented Dickey-Fuller test

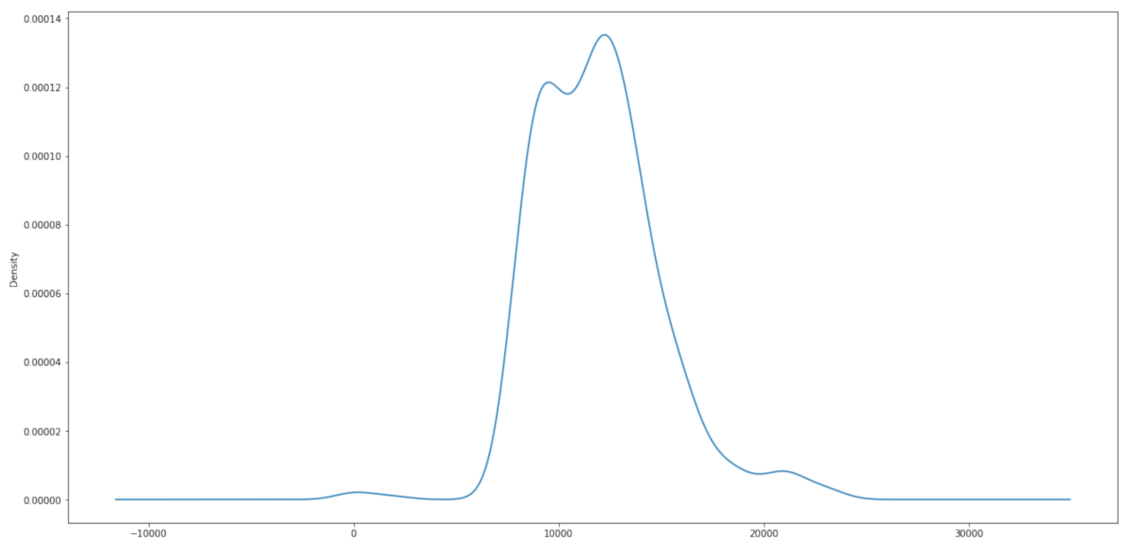
```
In [23]: result = adfuller(dfUsageDailyY.Usage)
         print('ADF Statistic: %f' % result[0])
         print('p-value: %f' % result[1])
         print('Critical Values:')
         for key, value in result[4].items():
             print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -1.638200
p-value: 0.463201
Critical Values:
	1%: -3.445
	5%: -2.868
	10%: -2.570
```

ADF statistic value is greater than 1%. This indicates of non-stationarity. Lets make the series stationary. Here I will experiment with different things such as differencing, applying log or both.

```
In [24]: dfUsageDailyY.Usage.plot(kind='kde')
```

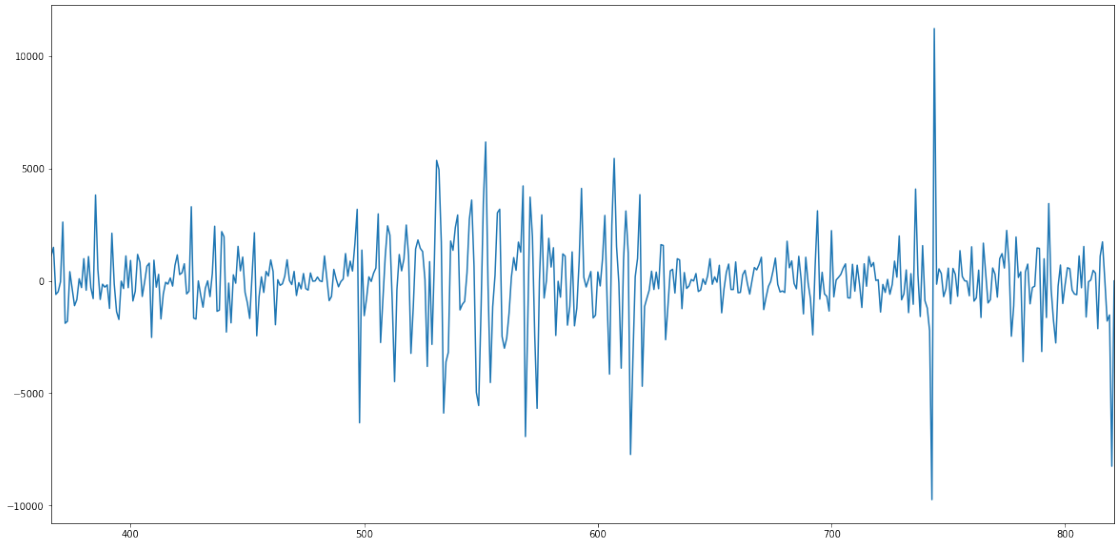
```
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f21f79240>
```



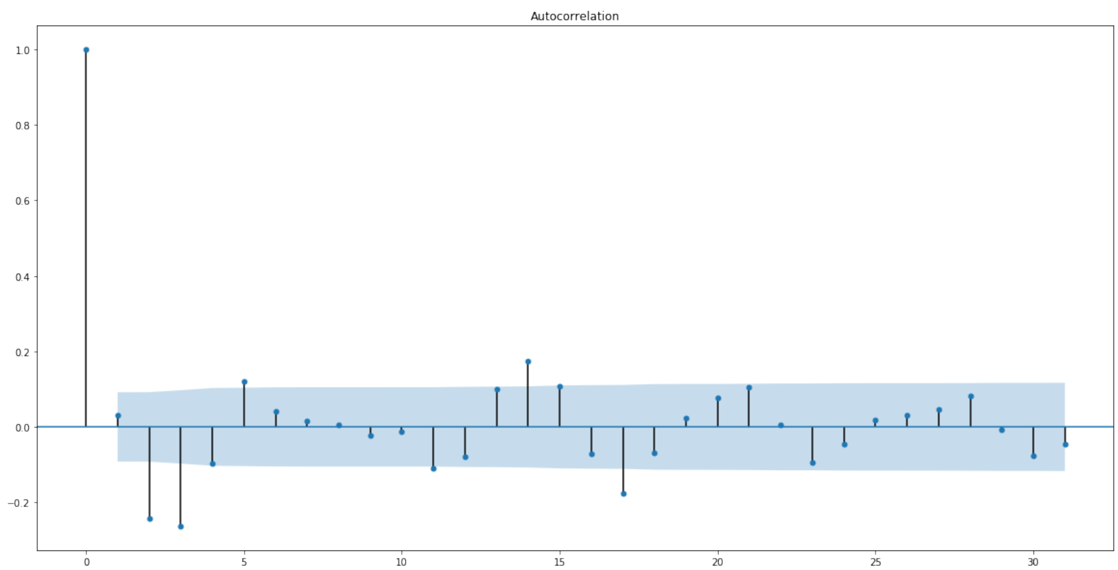
Perform difference of series

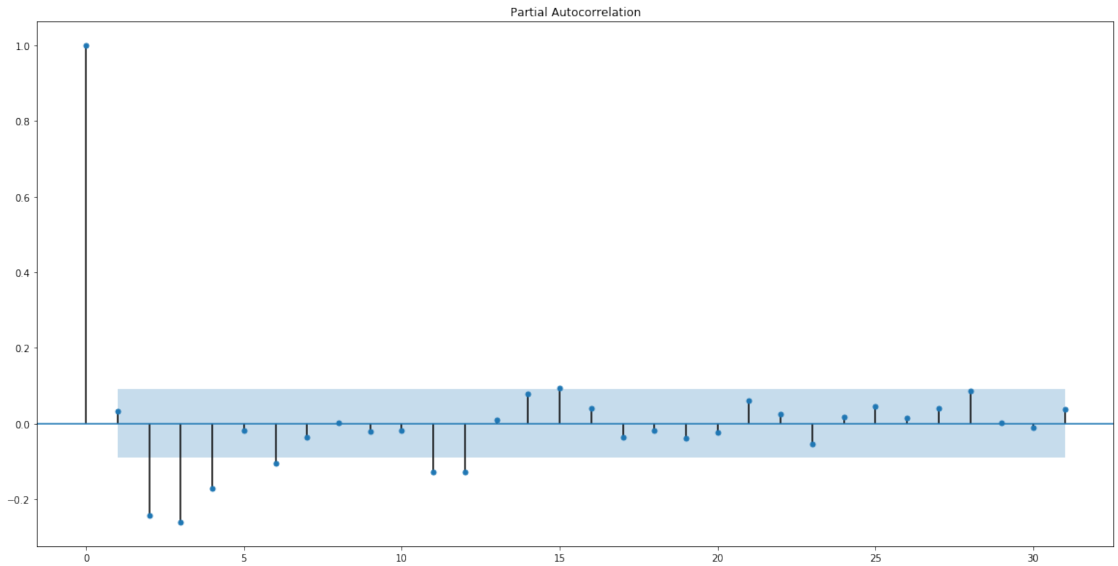
```
In [25]: diff1Usage = dfUsageDailyY['Usage'].diff()
         diff1Usage = diff1Usage.dropna()
         plt.figure(figsize=(20,10))

         diff1Usage.plot()
```

```
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f2dbba518>
```




```
In [26]: fig=plot_acf(diff1Usage, lags=31)
         fig1=plot_pacf(diff1Usage, lags=31)
```



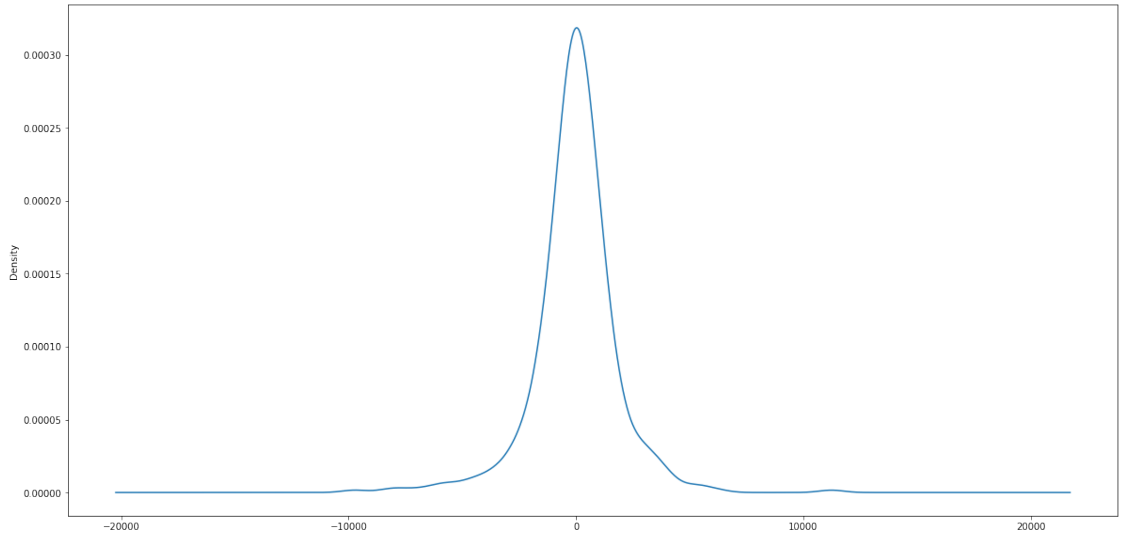



```
In [27]: result = adfuller(diff1Usage)
         print('ADF Statistic: %f' % result[0])
         print('p-value: %f' % result[1])
         print('Critical Values:')
         for key, value in result[4].items():
             print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -9.739731
p-value: 0.000000
Critical Values:
	1%: -3.445
	5%: -2.868
	10%: -2.570
```

```
In [28]: diff1Usage.plot(kind='kde')
```

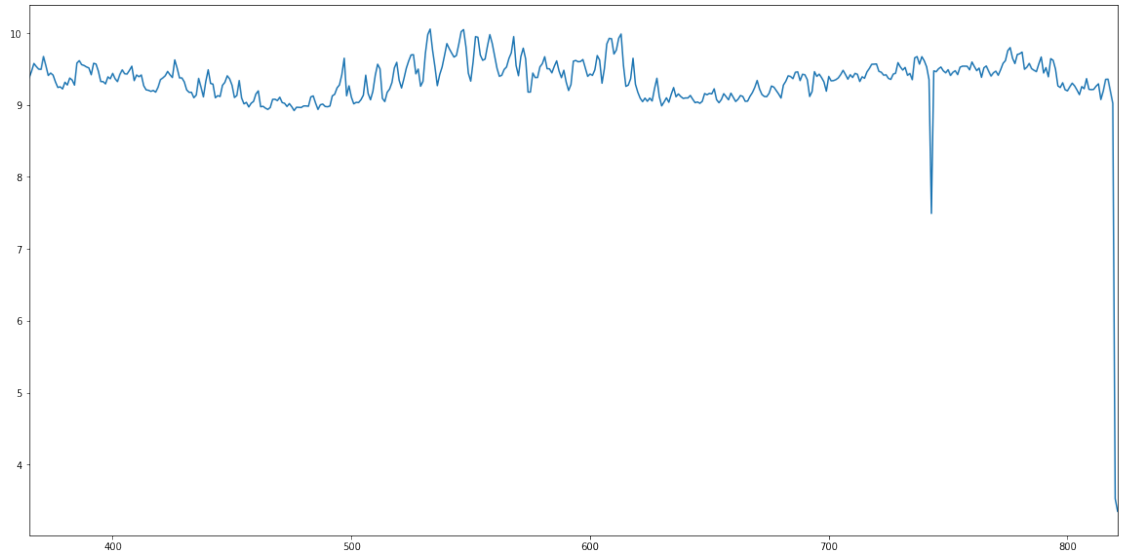
```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f32cc02b0>
```



Looks lot better. Will try some more things.

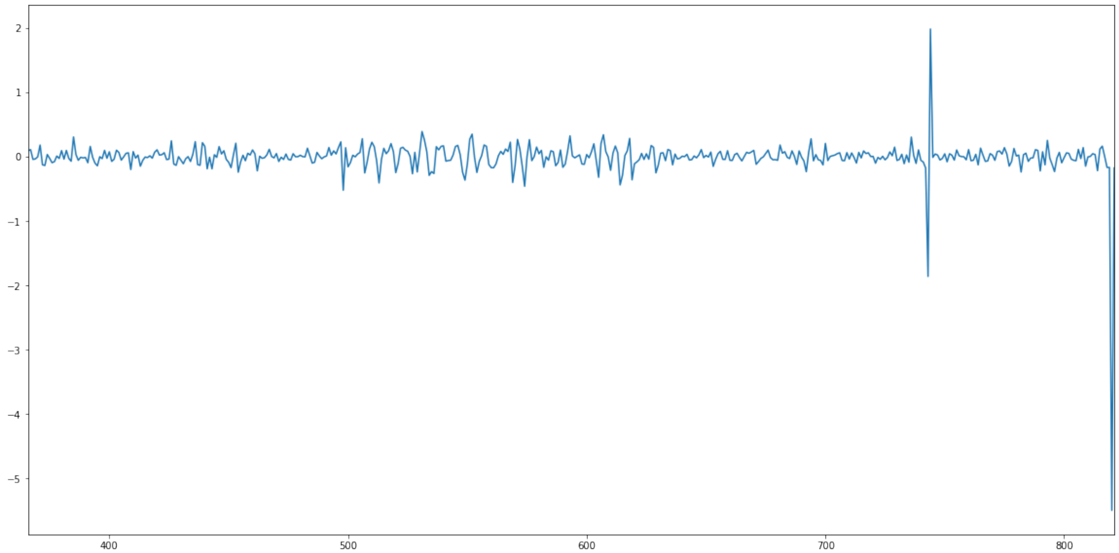
```
In [29]: diffLUsage = log(dfUsageDailyY.Usage)
         diffLUsage = diffLUsage.dropna()
         plt.figure(figsize=(20,10))
         diffLUsage.plot()

         from statsmodels.tsa.stattools import adfuller
         result = adfuller(diffLUsage)
         print('ADF Statistic: %f' % result[0])
         print('p-value: %f' % result[1])
         print('Critical Values:')
         for key, value in result[4].items():
             print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -1.756394
p-value: 0.402316
Critical Values:
        1%: -3.445
        5%: -2.868
        10%: -2.570
```

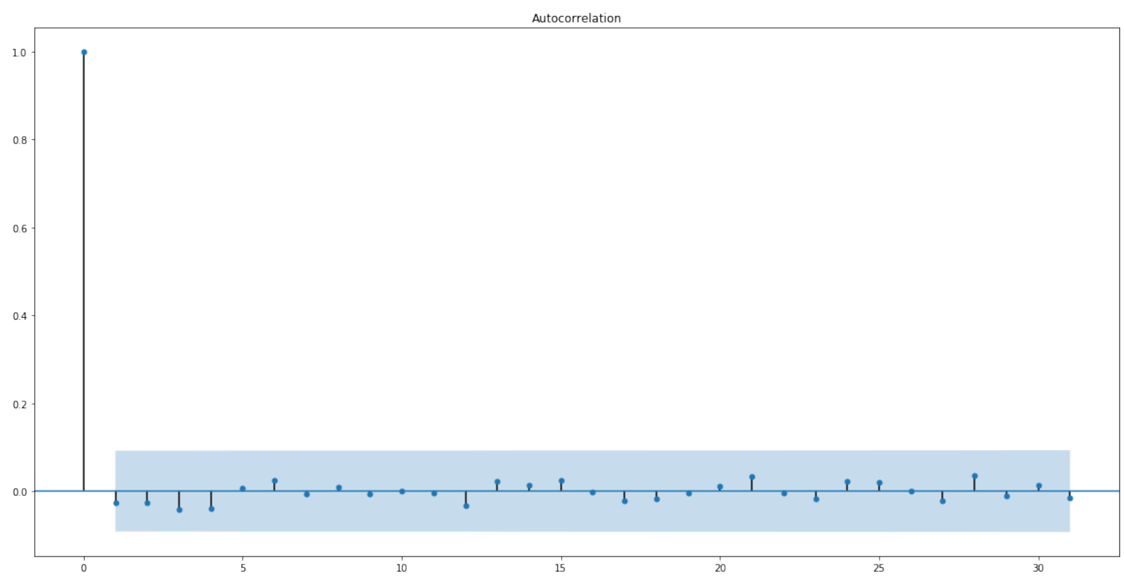


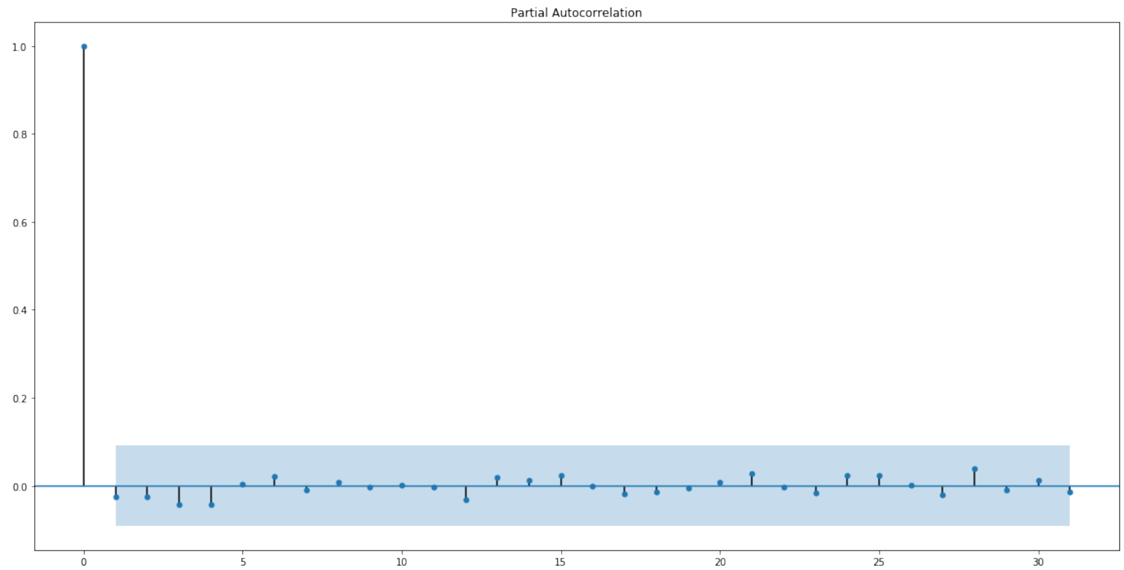

```
In [30]: diffLUsage = log(dfUsageDailyY.Usage)
         diffLDUsage = diffLUsage.diff()
         diffLDUsage = diffLDUsage.dropna()

         plt.figure(figsize=(20,10))
         diffLDUsage.plot()

         result = adfuller(diffLDUsage)
         print('ADF Statistic: %f' % result[0])
         print('p-value: %f' % result[1])
         print('Critical Values:')
         for key, value in result[4].items():
             print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -8.214302
p-value: 0.000000
Critical Values:
        1%: -3.445
        5%: -2.868
        10%: -2.570
```




```
In [31]: fig = plot_acf(diffLDUsage, lags=31)
         fig1=plot_pacf(diffLDUsage, lags=31)
```

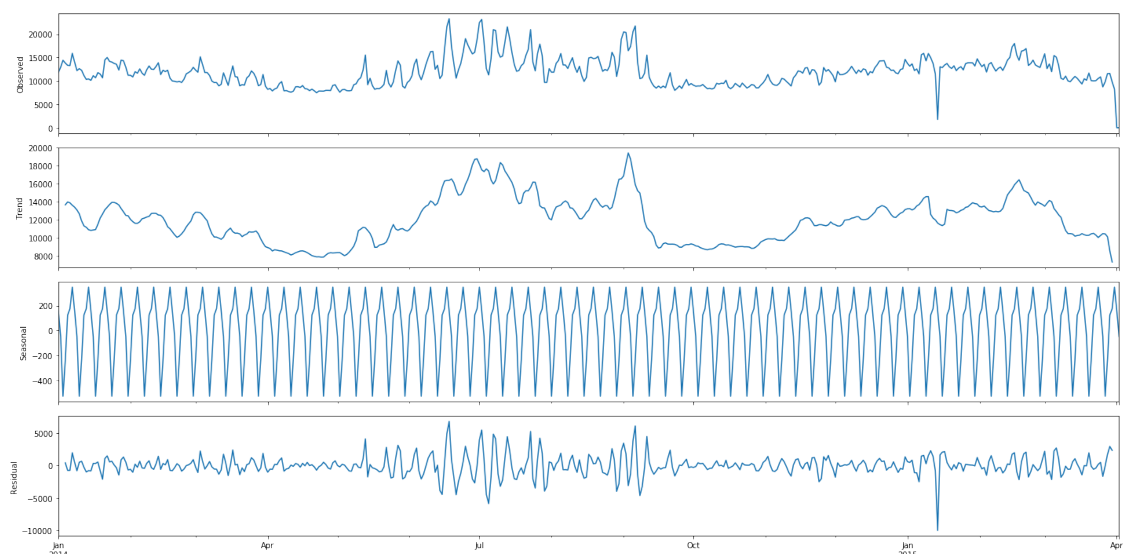




Difference of log values looks great. ACF and PCF shows no signs of dependence on past values.

1.1.2 Time series decomposition

```
In [32]: decomposition = seasonal_decompose(series, model='additive')
         fig = decomposition.plot()
```



Here we see that the series exhibits cyclic trend. Also, we see high frequency seasonal variations and residual. We need to train a model that accounts for seasonal variations. I am interested in building regression based models. I will be experimenting with different independent variables that might have an affect on system load. Some of the obvious variables will be weather parameters and time. There can be many other variables such as customers house sqft, customer behaviour, renewebles, demand response plan, etc. For my analysis, I am dealing with weather and time parameters.

1.1.3 Weather data

In [33]:
```
#Courtesy: https://www.noaa.gov/
#Read weather data
#read weather hourly data from csv
path="/home/sravan/Dolphin/STLF/V1/"
dfWeather = pd.read_csv(path+"weather_washington_reagan_airport.csv")
```

In [34]:
```
#Sample data:
#Date         Temperature                DAILYHeatingDegreeDays        DAILYCoolingDegre
#2013-01-11 01:00        44                 17         0                    51         0
#2013-01-11 01:52        43                                               56         0         1
#2013-01-11 02:52        41                                               62         0         1
#2013-01-11 03:52        40                                               70         0         1
```

In [35]:
```
dfWeather.describe()
```

Out[35]:
```
       Unnamed: 2  DAILYHeatingDegreeDays  DAILYCoolingDegreeDays  \
count         0.0             2909.000000             2909.000000
mean          NaN               12.146442                4.308697
std           NaN               13.664652                6.257287
min           NaN                0.000000                0.000000
25%           NaN                0.000000                0.000000
50%           NaN                7.000000                0.000000
75%           NaN               23.000000                9.000000
max           NaN               53.000000               23.000000

       DAILYAverageRelativeHumidity  HourlyRelativeHumidity  HourlyWindSpeed  \
count                    678.000000             30760.000000      30747.00000
mean                      59.132743                63.343466          8.40882
std                       13.512402                18.769669          5.18879
min                       25.000000                12.000000          0.00000
25%                       49.000000                48.000000          5.00000
50%                       59.000000                65.000000          8.00000
75%                       69.000000                81.000000         11.00000
max                       95.000000               100.000000         46.00000

       DailySunrise   DailySunset
count  31545.000000  31545.000000
mean     593.055603   1797.811222
std       98.110778     96.911128
min      442.000000   1646.000000
25%      513.000000   1719.000000
```

```
50%      611.000000   1807.000000
75%      702.000000   1905.000000
max      727.000000   1937.000000
```

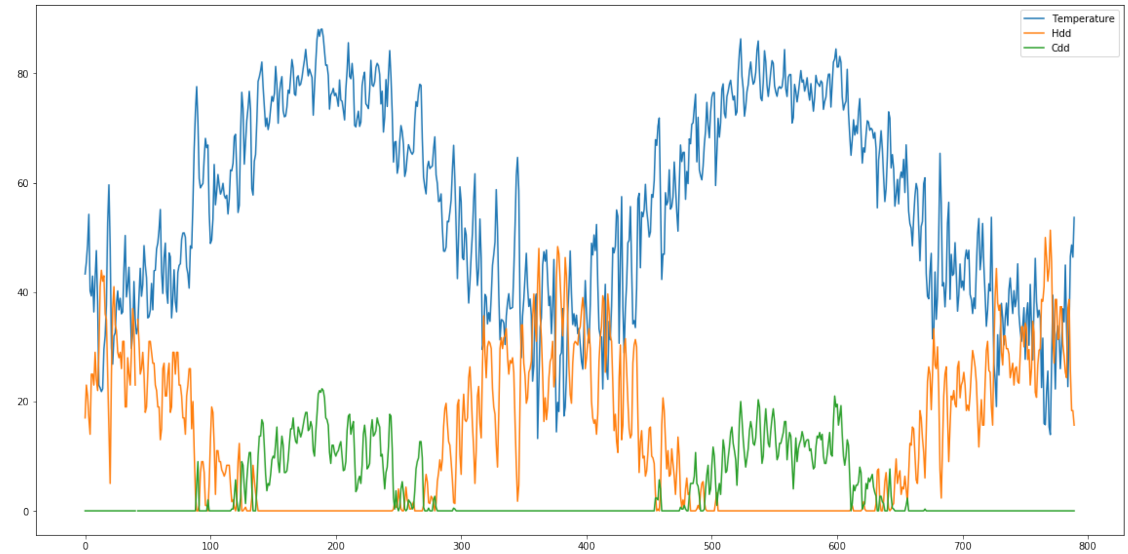
It looks like it needs lot of cleaning and aggregation.

In [36]:
```
#set date format and convert string to datetime
fmt="%Y-%m-%d %H:%M"
def strToDate(str):
    return datetime.datetime.strptime(str,fmt)
```

In [37]:
```
#Extract time and date features from weather data
#The weather data doesnt align to a time grid. Also HDD and CDD are provided for the en
#HDD and CDD can be computed from temperature. So, these can be dependent values that u
dfw = pd.DataFrame()
dfw2 = pd.DataFrame()
dfw['Date'] = dfWeather['Date'].apply(strToDate)
dfw['Temperature'] = pd.to_numeric(dfWeather['Temperature'],errors='coerce')
dfw2['Hdd'] = pd.to_numeric(dfWeather['DAILYHeatingDegreeDays'],errors='coerce')
dfw2['Cdd'] = pd.to_numeric(dfWeather['DAILYCoolingDegreeDays'],errors='coerce')
dfw = dfw.dropna()
dtcol = dfw['Date'].dt
dfw['year'] = dtcol.year
dfw['month'] = dtcol.month
dfw['daymonth'] = dtcol.day
dfw['hour'] = dtcol.hour
dfw['dayinweek'] = dtcol.weekday
dfw2['year'] = dtcol.year
dfw2['month'] = dtcol.month
dfw2['daymonth'] = dtcol.day
dfw2['hour'] = dtcol.hour
dfw2grpHdd = dfw2.groupby(['year','month','daymonth'])['Hdd'].mean().reset_index()
dfw2grpCdd = dfw2.groupby(['year','month','daymonth'])['Cdd'].mean().reset_index()
dfw2daily = pd.merge(dfw2grpHdd, dfw2grpCdd,  how='left', on=['year','month','daymonth'
dfwdaily = dfw.groupby(['year','month','daymonth','dayinweek'])['Temperature'].mean().r
dfwdaily = pd.merge(dfwdaily, dfw2daily,  how='left', on=['year','month','daymonth'])
dfwDaily = dfwdaily.dropna()
```

In [38]:
```
plt.figure(figsize=(20,10))
plt.plot(dfwdaily['Temperature'])
plt.plot(dfwdaily['Hdd'])
plt.plot(dfwdaily['Cdd'])
plt.legend()
```

Out[38]: `<matplotlib.legend.Legend at 0x7f9f33c73b70>`



Data looks reasonable for daily temperatures for period January 2013 - March 2015.

In [39]:
```
#Merge usage and weather data so that we have data for same day.
df_full = pd.merge(dfUsageDailyY, dfwDaily,  how='inner', on=['year','month','daymonth'
df_full.head()
```

Out[39]:

	year	month	daymonth	Usage	dayinweek	Temperature	Hdd	Cdd
0	2014	1	1	11822.307025	2	38.750000	26.000000	0.0
1	2014	1	2	12942.309043	3	35.688525	27.333333	0.0
2	2014	1	3	14432.091790	4	23.707317	35.000000	0.0
3	2014	1	4	13826.123779	5	26.575758	39.666667	0.0
4	2014	1	5	13338.632715	6	37.813559	34.000000	0.0

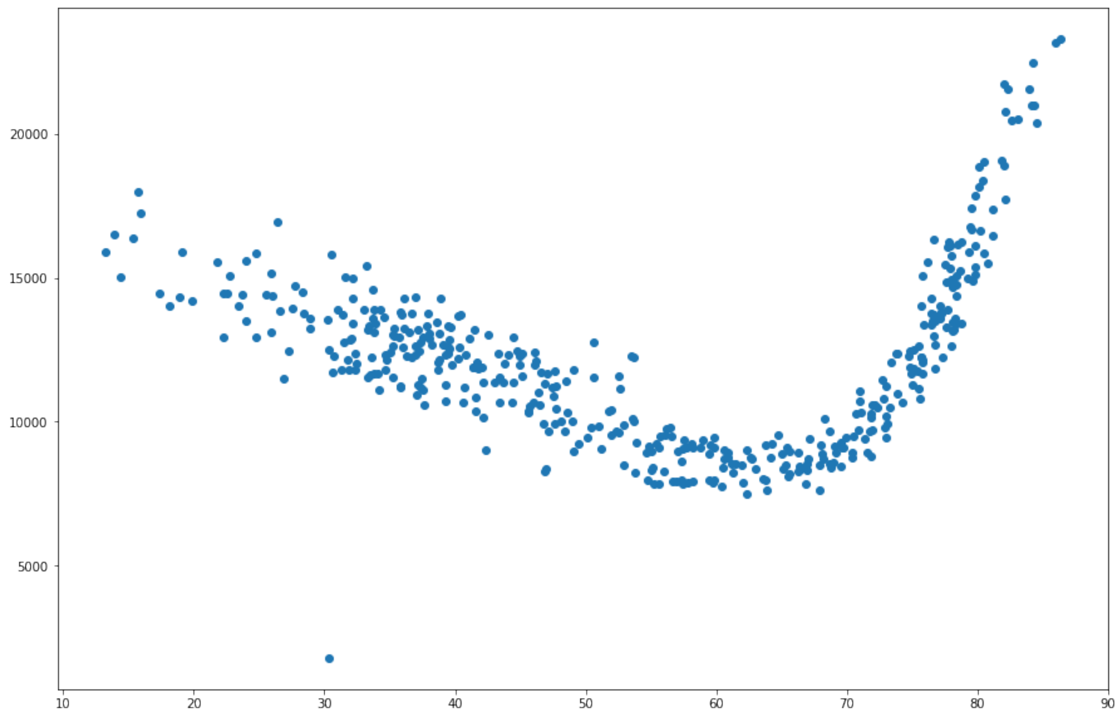
In [40]:
```
df_full.describe(), df_full.tail()
```

Out[40]:
```
(                 Usage   dayinweek  Temperature         Hdd         Cdd
 count      435.000000  435.000000   435.000000  435.000000  435.000000
 mean     12062.440695    2.997701    54.267470   14.469540    3.568966
 std       3010.500168    2.000575    18.679471   14.286785    5.592219
 min       1794.711893    0.000000    13.218750    0.000000    0.000000
 25%       9589.219620    1.000000    37.885653    0.000000    0.000000
 50%      11908.010252    3.000000    54.738095   11.666667    0.000000
 75%      13643.373022    5.000000    72.078235   26.500000    6.666667
 max      23291.055200    6.000000    86.324324   51.333333   21.000000,
      year  month  daymonth         Usage  dayinweek  Temperature        Hdd  Cdd
 430  2015      3         7  13343.798136          5    33.375000  38.666667  0.0
 431  2015      3         8  10577.047283          6    46.531250  25.666667  0.0
 432  2015      3         9  10336.432475          0    48.625000  18.333333  0.0
 433  2015      3        10  11039.225510          1    46.394366  18.333333  0.0
 434  2015      3        11  10028.328429          2    53.666667  15.666667  0.0)
```

In [41]:
```
#Create more features
#create another feature that says if it is a weekend or not.
df_full['weekend'] = np.array(df_full['dayinweek']>=5,dtype=int)
df['prevWkUsage'] = df['Usage'].shift(7*24)
#df['prevDayUsage'] = df['Usage'].shift(24)
#Diffs for 1 lag
df['diffL1Usage'] = df['Usage'].shift(1) - df['Usage'].shift(2)
print("Columns:", df_full.columns)
```

```
Columns: Index(['year', 'month', 'daymonth', 'Usage', 'dayinweek', 'Temperature', 'Hdd',
       'Cdd', 'weekend'],
      dtype='object')
```

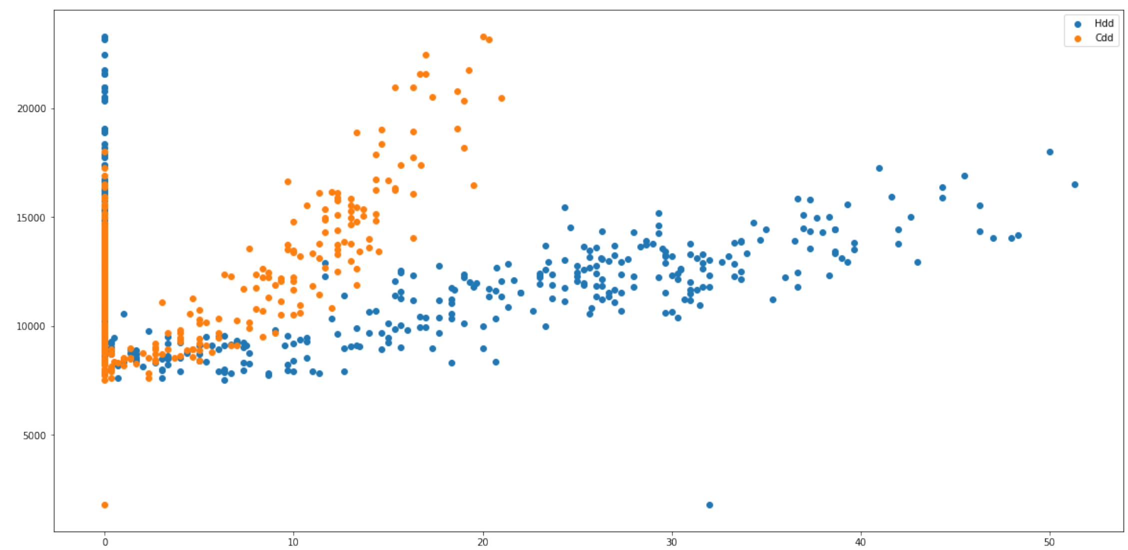
In [42]:
```
plt.figure(figsize=(15,10))
plt.scatter(df_full['Temperature'], df_full['Usage']);
```



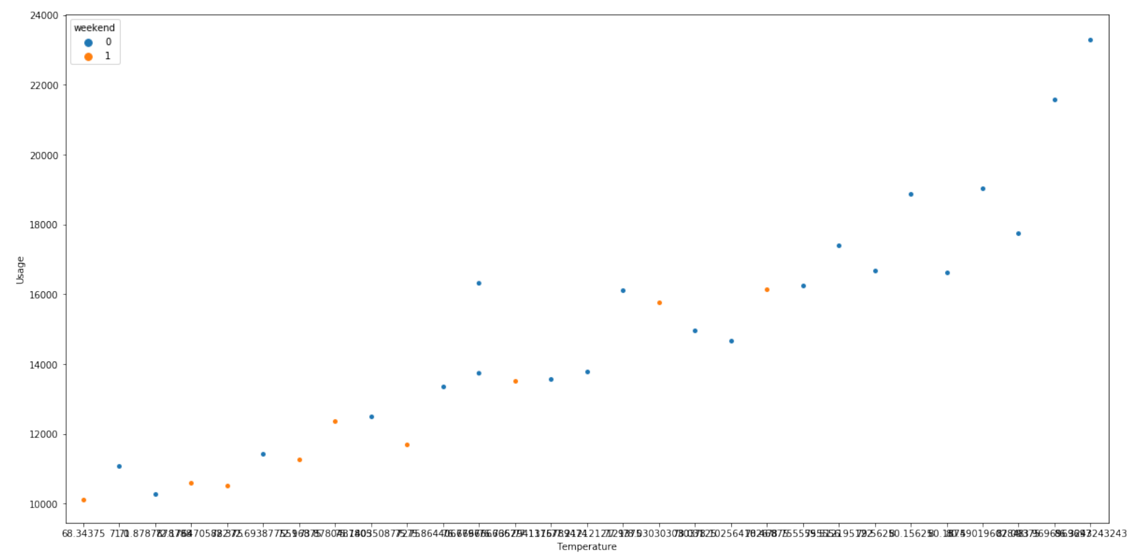
The plot above is Energy consumption vs Temperature. The energy usage is at its lowest when the temperature is around 65F, but it is linear with high slope when the temperature gets hotter.

In [43]:
```
plt.scatter(df_full['Hdd'],df_full['Usage']);
plt.scatter(df_full['Cdd'], df_full['Usage']);
plt.legend(('Hdd', 'Cdd'))
```

Out[43]: <matplotlib.legend.Legend at 0x7f9f2c979f60>




```
In [44]: dfTemp = df_full[df_full['year']==2014]
         dfTemp = dfTemp[dfTemp['month']==6]
         sns.swarmplot(x=dfTemp['Temperature'], y=df_full['Usage'], hue=dfTemp['weekend']);
```



I want to see if there is any pattern between weekend and weekdays. Above plot is usage vs temperature for a month. Some weekends, the consumption is high and some weekends it is low. We would need customers' schedule for better correlation.

```
In [45]: #separate input and target
         y = df_full['Usage']
         #drop the features that might not be useful
```

```
df = df_full.drop(['year','Usage','daymonth','Temperature'],axis=1)
df.columns
```

Out[45]: Index(['month', 'dayinweek', 'Hdd', 'Cdd', 'weekend'], dtype='object')

In [46]:
```
def setupFeatures(df, y, splitN):
    #test-train split
    #splitN = 24
    xtrain, xtest, ytrain, ytest = df.head(-splitN), df.tail(splitN), y.head(-splitN),
    print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)

    #fft of signal
    print("FFT")
    xsig = fftSignal(ytrain,splitN)
    xtrain['sig'] = xsig[:-splitN]
    xtest['sig'] = xsig[-splitN:]

    xtest = xtest.reset_index(drop=True);
    ytest = ytest.reset_index(drop=True);
    return xtrain, xtest, ytrain, ytest
    #scale prediction data
    #df_full = scaleFeatures(df_full, False)
```

In [47]:
```
#Here I want to try out adding a cosine signal with high frequencies filtered out.
#Following FFT signal generation code copied from google.com.
def fftSignal(y, npredict):
    from numpy import fft
    n=len(y)
    print("len:",n)
    indexes = list(range(n))
    n_harm = 3                  # number of harmonics in model
    x_freqdom = []
    f = []
    t = np.arange(0, n)


    print("training fft")
    p = np.polyfit(t, y, 1)         # find linear trend in x
    x_notrend = y - p[0] * t        # detrended x
    x_freqdom = fft.fft(x_notrend)  # detrended x in frequency domain
    f = fft.fftfreq(n)              # frequencies
    print("Frequencies:")
    indexes.sort(key = lambda i: np.absolute(f[i]))
    print(len(x_freqdom))
    print(len(f))
    t = np.arange(0, n+npredict)
    restored_sig = np.zeros(t.size)
```

```
            for i in indexes[:1 + n_harm ]:
                ampli = np.absolute(x_freqdom[i]) / n   # amplitude
                phase = np.angle(x_freqdom[i])          # phase
                restored_sig += ampli * np.cos(2 * np.pi * f[i] * t + phase)
            restored_sig = restored_sig + p[0] * t
            return restored_sig
```

```
In [48]: print(df.shape)
         split = 30 #(30 days of testing data)
         xtrain, xtest, ytrain, ytest = setupFeatures(df, y, split)
         print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)
```

```
(435, 5)
(405, 5) (30, 5) (405,) (30,)
FFT
len: 405
training fft
Frequencies:
405
405
(405, 6) (30, 6) (405,) (30,)


/home/sravan/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:10: SettingWithCopyWarn
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  # Remove the CWD from sys.path while we load stuff.
/home/sravan/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:11: SettingWithCopyWarn
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  # This is added back by InteractiveShellApp.init_path()
```

I will create data pipelines and will train Linear regression, MLP Neural Nets and Gradient boosting. I will compare MAPE for each of these on test data set and plot the actual vs predicted energy usage plots.

```
In [49]: def createPipelines():
             scalCols = ['Hdd','Cdd', 'sig','diffL1Usage', 'prevWkUsage']
             #scalCols = ['Hdd','Cdd']
             encodCols = ['weekend']
             mapper = DataFrameMapper([(d, LabelEncoder()) for d in encodCols])
             funion = FeatureUnion([('categorical',Pipeline([('mapper', mapper), ('onehot', OneH
                                  ('scaler',StandardScaler(scalCols))])
             pipe_lr = Pipeline([('funion', funion),('regressor',LinearRegression())])
```

```
        pipe_mlpr = Pipeline([('funion', funion),('regressor',MLPRegressor())])
        pipe_mlpr.set_params(regressor__hidden_layer_sizes=(10),regressor__solver='lbfgs')
        pipe_gbr = Pipeline([('funion', funion),('regressor',GradientBoostingRegressor())])
        pipes = {"Linear":pipe_lr,"MLP":pipe_mlpr, "GradientBoosting":pipe_gbr}
        return pipes
```

```
In [50]: models = {}
         pipes = createPipelines()
         #print(pipes)
         for pipe, est in enumerate(pipes):
             print(est)
             model = pipes[est].fit(xtrain, ytrain)
             print(model)
             models[est] = model
```

```
Linear
Pipeline(memory=None,
     steps=[('funion', FeatureUnion(n_jobs=1,
       transformer_list=[('categorical', Pipeline(memory=None,
     steps=[('mapper', DataFrameMapper(default=False, df_out=False,
        features=[('weekend', LabelEncoder())], input_df=False,
        sparse=False)), ('onehot', OneHotEncoder(categorical_fea...None)), ('regressor', LinearR
MLP
Pipeline(memory=None,
     steps=[('funion', FeatureUnion(n_jobs=1,
       transformer_list=[('categorical', Pipeline(memory=None,
     steps=[('mapper', DataFrameMapper(default=False, df_out=False,
        features=[('weekend', LabelEncoder())], input_df=False,
        sparse=False)), ('onehot', OneHotEncoder(categorical_fea...True, solver='lbfgs', tol=0.0
       verbose=False, warm_start=False))])
GradientBoosting
Pipeline(memory=None,
     steps=[('funion', FeatureUnion(n_jobs=1,
       transformer_list=[('categorical', Pipeline(memory=None,
     steps=[('mapper', DataFrameMapper(default=False, df_out=False,
        features=[('weekend', LabelEncoder())], input_df=False,
        sparse=False)), ('onehot', OneHotEncoder(categorical_fea...s=100, presort='auto', random
             subsample=1.0, verbose=0, warm_start=False))])
```

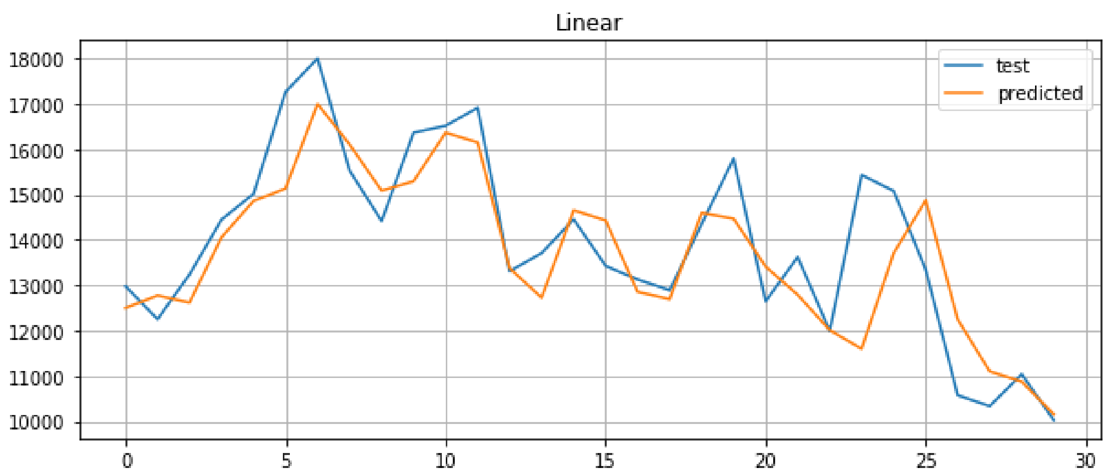
```
In [51]: #Calculate MAPE
         def mean_absolute_percentage_error(y_true, y_pred):
             return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

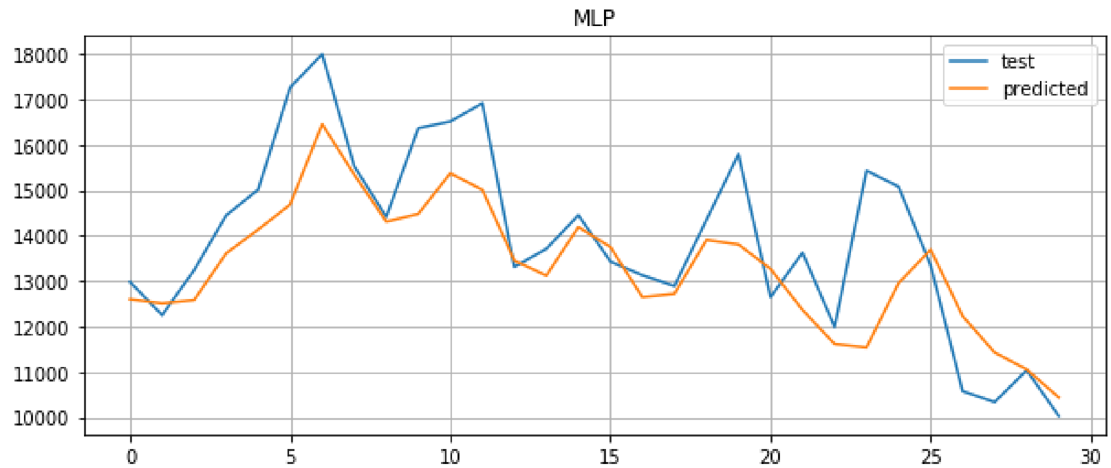
```
In [52]: ypredicts = {}
         def forecast(df, models):
             for model in models:
                 print(model)
                 ypredict = models[model].predict(df)
```

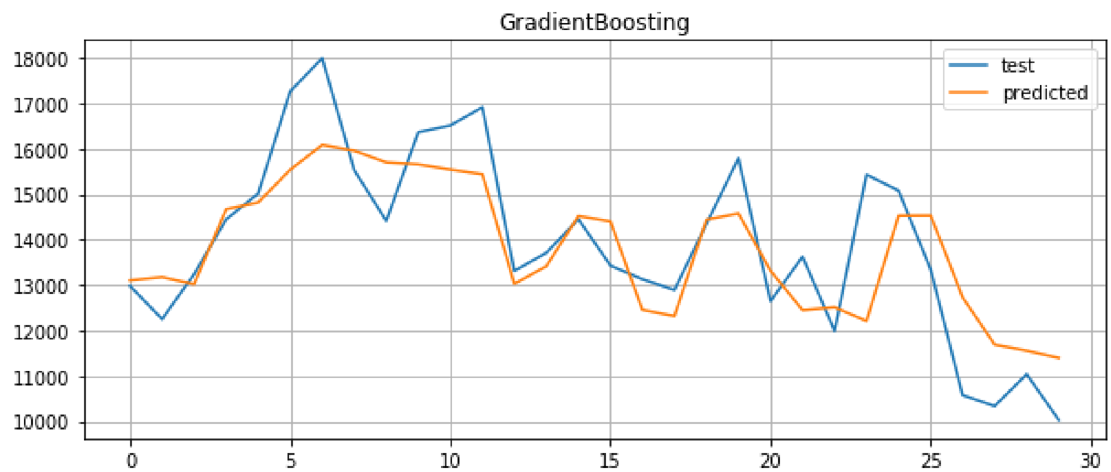
```
        mape = mean_absolute_percentage_error(ytest, ypredict)
        ypredicts[model] = ypredict
        print("MAPE for %s "%model, ":%f" %mape)
        #Test data against predicted data
        plt.figure(figsize=(10,4))
        plt.title(model)
        plt.plot(ytest, label = 'test')
        plt.plot(ypredict, label = 'predicted')
        ax =plt.gca()
        handles, labels = ax.get_legend_handles_labels()
        ax.legend(handles, labels)
        plt.grid('on')
```

```
In [53]: yForecast = forecast(xtest, models)
```

```
Linear
MAPE for Linear  :5.618996
MLP
MAPE for MLP  :6.557275
GradientBoosting
MAPE for GradientBoosting  :6.589504
```







The predictions look decent enough. Here are couple of key observations: 1. Data anomalies in usage patterns can be detected by comparing MAPE values. 2. Ensemble methods performing better than simple linear regression. Lasso regression does a good job as well. Often simpler models will get the job done. 3. With more training data, neural nets perform better. 4. Always scale continuous values and encode categorical values. If not, the distance based algorithms will quantify them based on the magnitude and may give rise to spurious regression. 5. Consumer usage patterns over the weekends are not strongly correlated with weather. This is due to the fact that we do not have their weekend schedules. It is observed that certain weekends, the load usage is high where as for other weekends it is very low keeping all other variables constant. 6. Not all kinds of loads correlate with weather. Take for example industrial loading will have dependency on economic parameters rather than weather. 7. I have explored classical models ARIMAX/SARIMAX. I feel with regression based, I have great flexibility to experiment with different input features. 8. Harmonic filtering 3-7 gave good accuracy for hourly models. Using higher order harmonics will introduce more variance to the model.