stlf_api-meter-hourly-tsAnalysis

March 5, 2019

1 Hourly energy forecasting

1.1 Time Series Analysis - hourly load forecasting

In [1]:
```
### Key points in analyzing time series
#Check for stationary series.
#constant mean, constant variance, autocorrelation that doesnt depend on time.
#Dickey Fuller test # tstaticstic is less than critical - reject null hypothesis.
#Make non-stationary to stationary - detrending, differencing.
#ARMA wont work with non-stationary series -> stationarize first.
#AR -> based on previous. Any sudden change is accounted immedialtely and slowly fades a
#MA --> all sudden change is accounted immedialty and quickly subsides. so the correlati
#I --> determines order of differenceing.
#Augmented dickey fueller test.
#ACF, PACF plots
#Can perform gridsearch for ARIMA parameters such that we get low AIC and BIC.
```

In [2]:
```
#Here I have derived Hdd and Cdd from temperature.
```

1.1.1 Imports

In [3]:
```
#Imports
from pymongo import MongoClient
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import datetime
import time
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

In [5]: #convert timestamp in milliseconds to datetime
        def tsmsToDate(ts):
            return datetime.datetime.fromtimestamp(ts/1000)

In [6]: #set date format and convert string to datetime
        fmt="%Y-%m-%d %H:%M"
        def strToDate(str):
            return datetime.datetime.strptime(str,fmt)

In [7]: #convert timestamp in milliseconds to datetime
        def paramtoDate(y,m,d):
            dt= datetime.datetime(year=y, month=m, day=d)
            return time.mktime(dt.timetuple())

In [8]: #Filter outliers around mean
        def rejectOutliers(data, s =1.):
            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 [9]: #Calculate MAPE
        def mean_absolute_percentage_error(y_true, y_pred):
            return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

1.1.2 Read Consumption and Weather data

```
In [10]: def readData(db):
             ## Read list of meters
             coll=db['model.e.meter.profile']
             docsProf = coll.find({"rateCode":"PMRS_R","groupId":GroupId})
             #Get meter ids for the desired group.
             listmid = []
             d = {'meterId':listmid}
             y = list(map(lambda dc : listmid.append(dc['meterId']), docsProf))
             dfMeters = pd.DataFrame(d)
             print(dfMeters.head())
             #Read meter interval data
             #Set database and collection
```

```
        #Contains data only for feeder FDR_14442
        dfUsage = pd.DataFrame()
        db=client[DBMeasurementsName]
        coll=db['measurements.meter.daily.bag']
        #Query consumption data
        docsReads = coll.find({"meterId":{"$in":dfMeters['meterId'].values.tolist()}})
        print("Documents read:", docsReads.count())
        #Transform json documents into dataframe with consumption and timestamp.
        listDate = []
        listUsage = []
        meterId = []
        d = {'meterId':meterId, 'DataDate':listDate, 'Usage':listUsage}
        for doc in docsReads:
            intdata = doc['intervalData']
            for data in intdata:
                listDate.append(data[9])
                listUsage.append(data[0])
                meterId.append(doc['meterId'])
        dfUsage = pd.DataFrame(d)
        dfUsage.dropna()

        #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")
        return dfUsage, dfWeather

In [11]: def processWeather(dfWeather):
        #Extract time and date features from weather data
        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
        dfwHourly = dfw.groupby(['year','month','daymonth','hour','dayinweek'])['Temperatur
        dfwHourly = dfwHourly.dropna()
```

```
            print(dfwHourly.head(), dfwHourly.shape)
            return dfwHourly

In [12]: def processUsage(dfUsage):
            print(dfUsage.head())
            #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
            #Calculate daily total consumption for daily forecast
            dfUsageDaily = dfUsage.groupby(['year','month','daymonth','hour'])['Usage'].sum().r
            dfUsageDaily['Usage'] = dfUsageDaily['Usage']/1000
            #Filter outliers using standard deviation (on entire dataset)
            dfUsageDaily = dfUsageDaily[rejectOutliers(dfUsageDaily['Usage'])]

            print(dfUsageDaily.head(), dfUsageDaily.shape)
            return dfUsageDaily
```

1.1.3 Create additional features

```
In [13]: def createFeatures(df):

            #Encode weekday/weekend
            dff=pd.DataFrame()
            dff = df[df['year']==2013]
            dff = dff.append(df[df['year']==2014])
            df = dff.append(df[df['year']==2015])

            #df = df[df['month']==5]
            #df = df[df['daymonth']==11]
            df['Hdd'] = 65 - df['Temperature']
            df['Cdd'] = df['Temperature'] - 65
            df['Hdd'] = df['Hdd'].where(df['Hdd'] >= 0, 0)
            df['Cdd'] = df['Cdd'].where(df['Cdd'] >= 0, 0)
            #df['Cdd2'] = pow(df['Cdd'].values,2)
            #df['Cdd3'] = pow(df['Cdd'].values,3)

            df['weekend'] = np.array(df['dayinweek']>=5,dtype=int)
            #Previous day load
            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)
        #    df['diffL1Temp'] = df['Temperature'].shift(1) - df['Temperature'].shift(2)
```

```
#     df['diffL1Hdd'] = df['Hdd'].shift(1) - df['Hdd'].shift(2)
#     df['diffL1Cdd'] = df['Cdd'].shift(1) - df['Cdd'].shift(2)
    #print(df[50:125])
    #Remove columns with NAN
    df = df.dropna()
    #separate input and target
    y = df['Usage']
    df = df.drop(['year','month','Usage','daymonth','dayinweek','Temperature'],axis=1)
    print("Columns:", df.columns)
    return df, y
```

```
In [14]: def setupData(db):
    dfUsage, dfWeather = readData(db)
    print("setupData:Transforming data")
    #Put together consumption and weather data for same timestamps.
    dfUsage = processUsage(dfUsage)
    print("Usage:")
    print(dfUsage.head())

    dfW = processWeather(dfWeather)
    print("Weather:")
    print(dfW.head())
    df_full = pd.merge(dfUsage, dfW,  how='inner', on=['year','month','daymonth','hour'
    return df_full
```

```
In [15]: def setupFeatures(df, y):
    #test-train split
    splitN = 24*7
    xtrain, xtest, ytrain, ytest = df.head(-splitN), df.tail(splitN), y.head(-splitN),
    print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)

    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)
```

1.2 Main methods

1.2.1 Read and setup data

```
In [16]: #Create mongo client
    client = MongoClient('localhost', 27017)
    #Read meter profile
    #Set database and collection
    db=client[DBModelName]
    df = setupData(db)
    df, y = createFeatures(df)
```

```
        print("creating features")
        xtrain, xtest, ytrain, ytest = setupFeatures(df, y)
        print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)
```

```
                            meterId
0  779433740600_21322002_4ED351147198
1  779433740600_21322018_4ED351147170
2  778432020130_21323010_NXA112087970
3  778432560950_21323100_1ND352779332
4  779432250030_21322270_NXA111192397
Documents read: 262526
setupData:Transforming data
        DataDate   Usage                              meterId
0  1420765200000  1047.6  776428360310_21351300_NXA112132261
1  1420768800000   639.6  776428360310_21351300_NXA112132261
2  1420772400000   635.4  776428360310_21351300_NXA112132261
3  1420776000000   712.2  776428360310_21351300_NXA112132261
4  1420779600000   609.6  776428360310_21351300_NXA112132261
      year  month  daymonth  hour       Usage
3312  2013      5        20    21  397.999271
3313  2013      5        20    22  323.167905
3314  2013      5        20    23  284.737692
3315  2013      5        21     0  271.688837
3316  2013      5        21     1  256.874591 (13635, 5)
Usage:
      year  month  daymonth  hour       Usage
3312  2013      5        20    21  397.999271
3313  2013      5        20    22  323.167905
3314  2013      5        20    23  284.737692
3315  2013      5        21     0  271.688837
3316  2013      5        21     1  256.874591
   year  month  daymonth  hour  dayinweek  Temperature
0  2013      1        11     1          4         43.5
1  2013      1        11     2          4         41.0
2  2013      1        11     3          4         40.0
3  2013      1        11     4          4         39.5
4  2013      1        11     5          4         39.0 (18959, 6)
Weather:
   year  month  daymonth  hour  dayinweek  Temperature
0  2013      1        11     1          4         43.5
1  2013      1        11     2          4         41.0
2  2013      1        11     3          4         40.0
3  2013      1        11     4          4         39.5
4  2013      1        11     5          4         39.0
Columns: Index(['hour', 'Hdd', 'Cdd', 'weekend', 'prevWkUsage', 'diffL1Usage'], dtype='object')
creating features
(12822, 6) (168, 6) (12822,) (168,)
(12822, 6) (168, 6) (12822,) (168,)
```

1.2.2 Create pipelines

```
In [17]: def createPipelines():
             scalCols = ['Hdd','Cdd', 'diffL1Usage', 'prevWkUsage']
             encodCols = ['hour','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
```

1.2.3 Fit training data

```
In [18]: 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=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
        input_df=False, sparse=False)), ('onehot', One...None)), ('regressor', LinearRegression(
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=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
        input_df=False, sparse=False)), ('onehot', One...True, solver='lbfgs', tol=0.0001, valid
       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=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
   input_df=False, sparse=False)), ('onehot', One...s=100, presort='auto', random_state=Non
        subsample=1.0, verbose=0, warm_start=False))])
```

1.3 Predict

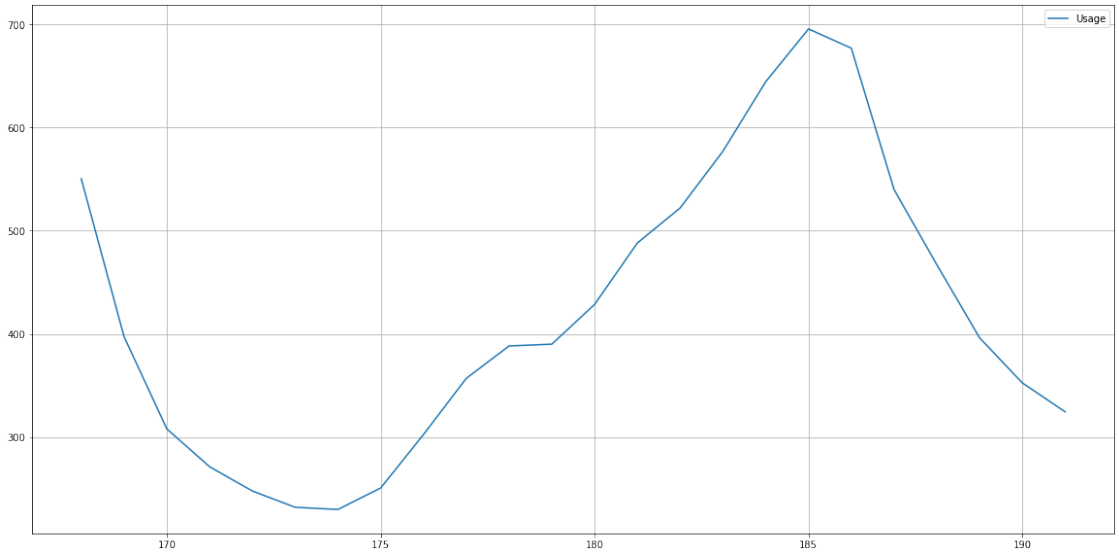
1.3.1 API for predict

In [19]:
```
ypredicts = {}
def forecast(df):
    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 [20]:
```
plt.figure(figsize=(20,10))
#plt.plot(xtrain['sig'],color='g', label = 'fftSignal')
#plt.plot(xtrain['Hdd'],color='r', label = 'Hdd')
#plt.plot(xtrain['Cdd'],color='b', label = 'Cdd')
#plt.plot(xtrain['Temperature']/10,color='y', label = 'Temperature')
plt.plot(ytrain[0:24], label = 'Usage')
ax =plt.gca()
handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, labels)
plt.grid('on')
xtrain.head()
```

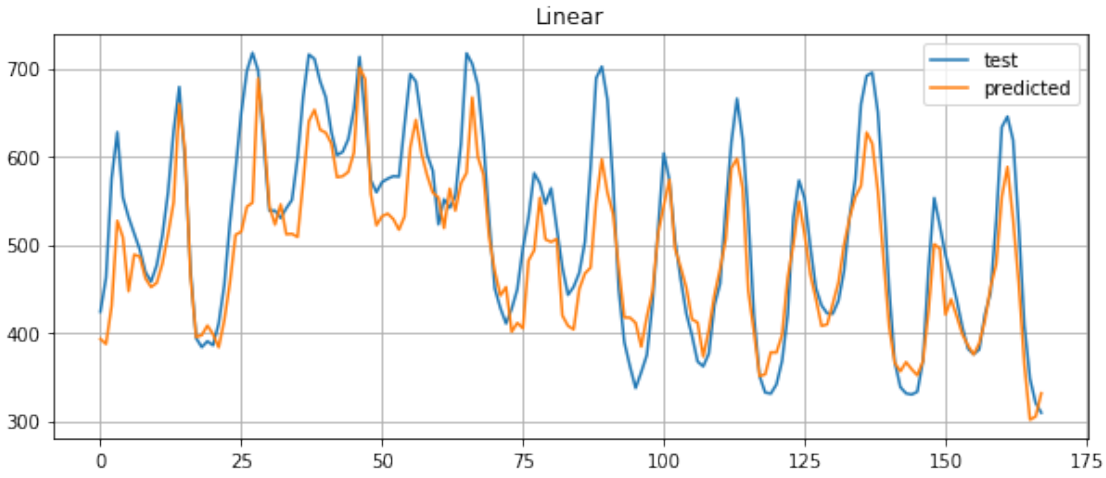
Out[20]:

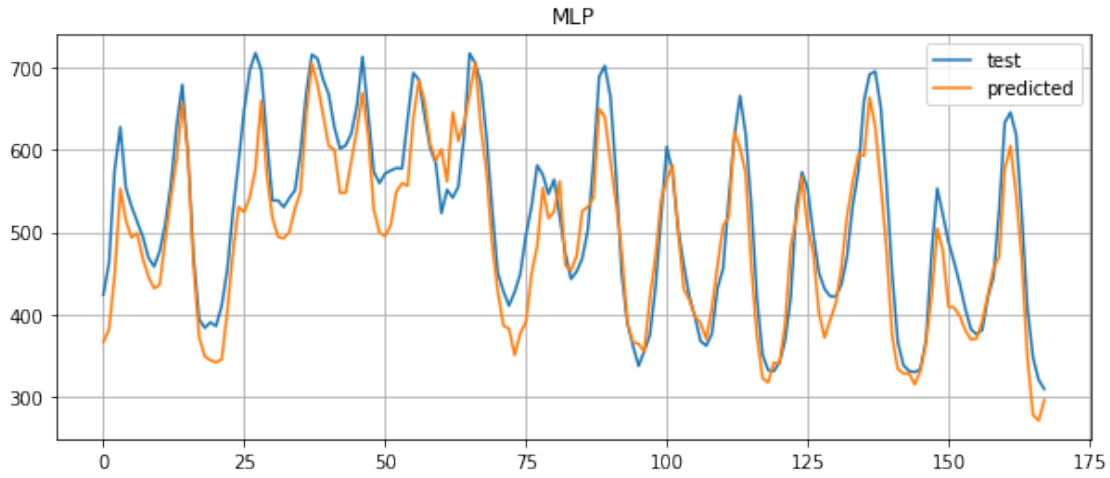
	hour	Hdd	Cdd	weekend	prevWkUsage	diffL1Usage
168	19	0.0	6.0	0	397.999271	19.477958
169	20	0.0	5.0	0	323.167905	-63.978416
170	21	0.0	5.0	0	284.737692	-153.023419
171	22	0.0	5.0	0	271.688837	-89.466474
172	23	0.0	5.0	0	256.874591	-36.690067

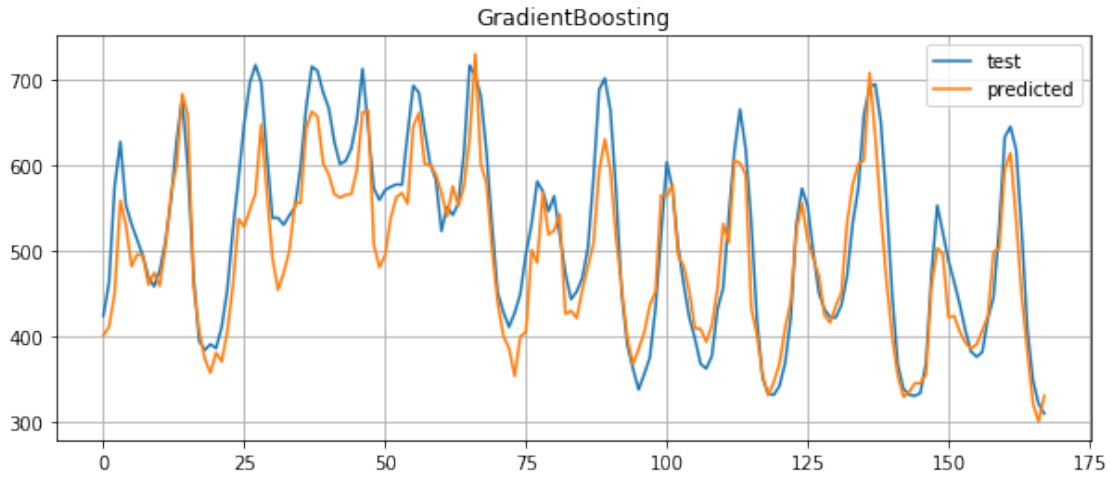



```
In [21]: forecast(xtest)

Linear
MAPE for Linear  :7.641023
MLP
MAPE for MLP  :7.535393
GradientBoosting
MAPE for GradientBoosting  :7.107856
```







from flask import Flask, jsonify, request app = Flask(**name**) @app.route('/predict', methods=['POST']) def apicall(): try: print("Getting json") test_json = request.get_json() test = pd.read_json(test_json, orient='records') except Exception as e: raise e if test.empty: return(bad_request()) else: print("Predicting") predictions = forecast(test) predictions = pd.DataFrame(predictions) responses = jsonify(predictions=predictions.to_json(orient="records")) responses.status_code = 200 return(responses)

1.3.2 API for fit

```
In [22]: def createModels(predictorsDf, targetY):
             xtrain, xtest, ytrain, ytest = setupFeatures(predictorsDf, targetY)
             pipes = createPipelines()
             models = {}
```

```
            #print(pipes)
            for pipe, est in enumerate(pipes):
                print(est)
                model = pipes[est].fit(xtrain, ytrain)
                print(model)
                models[est] = model
            return models
```

```
In [23]: models = createModels(df, y)
```

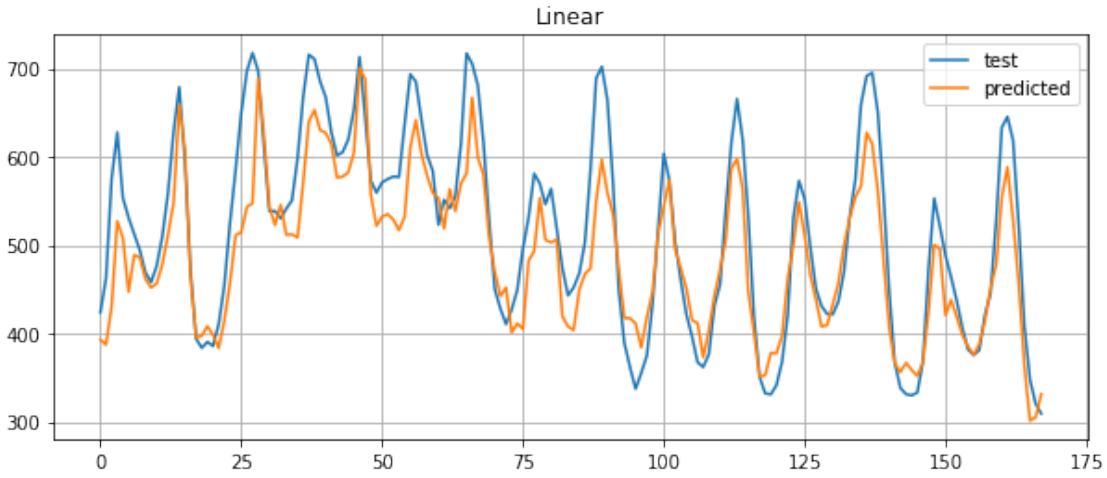
```
(12822, 6) (168, 6) (12822,) (168,)
Linear
Pipeline(memory=None,
     steps=[('funion', FeatureUnion(n_jobs=1,
       transformer_list=[('categorical', Pipeline(memory=None,
     steps=[('mapper', DataFrameMapper(default=False, df_out=False,
        features=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
        input_df=False, sparse=False)), ('onehot', One...None)), ('regressor', LinearRegression(
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=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
        input_df=False, sparse=False)), ('onehot', One...True, solver='lbfgs', tol=0.0001, valid
       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=[('hour', LabelEncoder()), ('weekend', LabelEncoder())],
        input_df=False, sparse=False)), ('onehot', One...s=100, presort='auto', random_state=Non
             subsample=1.0, verbose=0, warm_start=False))])
```

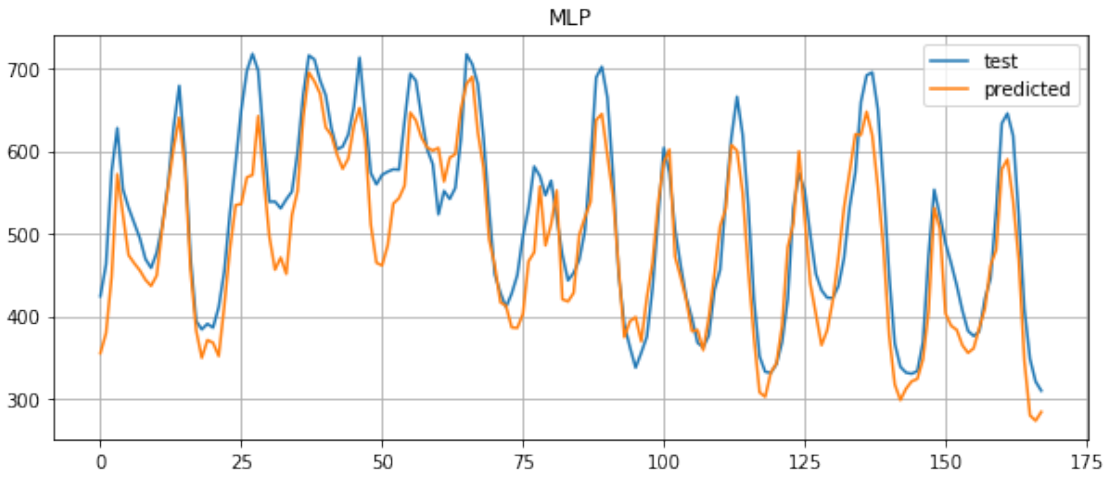
```
In [24]: ypredicts = {}
         def forecast(df, models):
             for model in models:
                 print(model)
                 ypredict = models[model].predict(df)
                 mape = mean_absolute_percentage_error(ytest, ypredict)
                 ypredicts[model] = ypredict
                 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')
```

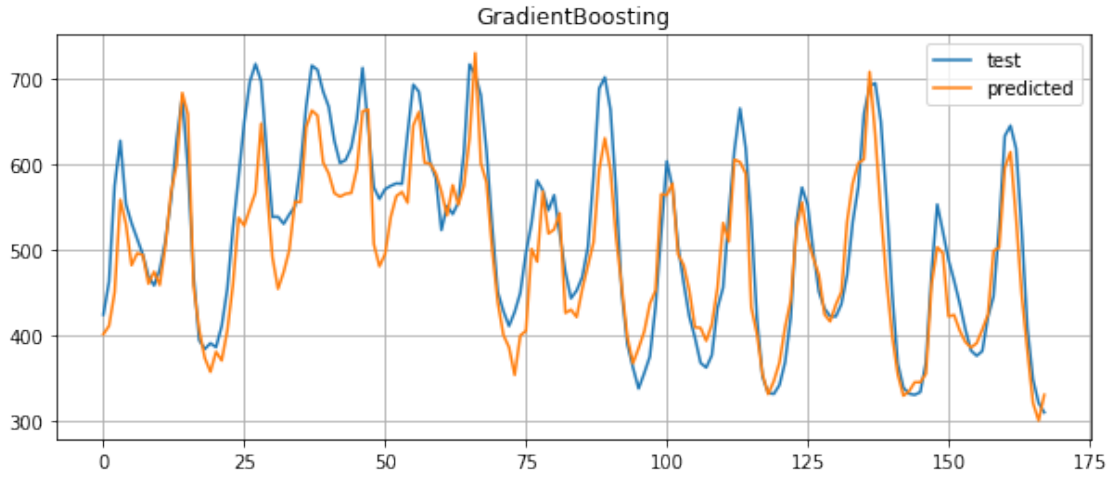
```
                plt.plot(ypredict, label = 'predicted')
                ax =plt.gca()
                handles, labels = ax.get_legend_handles_labels()
                ax.legend(handles, labels)
                plt.grid('on')
```

```
In [25]: yForecast = forecast(xtest, models)
```

```
Linear
MAPE for Linear  :7.641023
MLP
MAPE for MLP  :8.019434
GradientBoosting
MAPE for GradientBoosting  :7.107856
```






GradientBoosting
test
predicted
700
600
500
400
300
0
25
50
75
100
125
150
175