test_ticks

January 8, 2020

1 One Piece to the Puzzle

1.0.1 Some Time Series Modeling, Exploratory Analysis:

Below code transforms historic nickel data to be used by multivariate regression algorithms to make price forecasts for one-year ahead of time.

A target variable, y (which represents one year ahead of time) is constructed by shifting all other variables back by one year.

[32]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.model_selection import ParameterGrid
from sklearn import linear_model
from sklearn.preprocessing import PolynomialFeatures
from sklearn.ensemble import RandomForestRegressor
from sklearn import neighbors
from sklearn.ensemble import AdaBoostRegressor

from pylab import rcParams
rcParams['figure.figsize'] = 9, 6
import ast
```

[33]:
```
'''

Time Series Modeling/Explorations Portion:

Below code transforms historic nickel data to be used by multivariate␣
↪regression algorithms to make price

forecasts for one-year ahead of time. Features are created by taking lagged␣
↪copies of itself and a target
```

```
variable, y, which represents one year ahead of time, can be built by shifting␣
↪all other X variables

back by one year (261 business days).

'''
```

[33]:

```
'\n\nTime Series Modeling/Explorations Portion: \n\nBelow code transforms
historic nickel data to be used by multivariate regression algorithms to make
price\n\nforecasts for one-year ahead of time. Features are created by taking
lagged copies of itself and a target\n\nvariable, y, which represents one year
ahead of time, can be built by shifting all other X variables \n\nback by one
year (261 business days). \n\n'
```

[34]:

```
def LME_clean():
    '''Reads source file and cleans and reformats data as a time series in␣
↪business days (B) as time units'''

    LME_futures = pd.read_excel('forecasting_raw_data/LME Futures Price.xlsx')
    LME_futures = LME_futures.iloc[3:, 1:]
    LME_futures.columns = ['Date', 'Cash Price ($/MT)', 'Inventory (MT)']
    LME_futures.index = LME_futures['Date']
    LME_futures = LME_futures[LME_futures.index.year>=2018] # For now only use␣
↪years after 2005

    LME_futures = LME_futures.iloc[:, 1:]

    LME = LME_futures.iloc[:, 0]
    LME = LME.astype(float)
    LME = LME.resample('B').mean()
    LME = LME.squeeze()
    return LME

def stationarity_preprocess(series, window_setting):
    '''
    Transforms Series data by taking difference of rolling average method for␣
↪time series stationary. This
    will allow us to build more effective predictive models.'''

    moving_avg = series.rolling(window=window_setting).mean().shift()
    moving_avg_diff = series-moving_avg
    return moving_avg_diff

def reverse_stationarity(series, train_tail, window_setting):
    '''
    Uses moving averages from the tail-end of training data
    before using its own unscaled predictions to perform reverse differencing.
    '''
```

```
    unscaled = []
    for key, item in series.items():
        moving_avg = train_tail.tail(window_setting).mean()
        unscaled_result = item+moving_avg # reverse of differencing
        train_tail = train_tail.append(pd.Series([unscaled_result])) # Appends to tail-end of train_tail series before moving average is taken again
        unscaled.append(unscaled_result)

    unscaled = pd.Series(unscaled)
    unscaled.index = series.index
    return unscaled

def time_series_train_test_split(df):

    X = df[['lag0', 'lag1', 'lag2', 'lag3', 'lag4', 'lag5', 'lag6', 'lag7', 'lag8', 'lag9', 'lag10',
           ]]
    y= df['y']
    X_test = X.loc['2017-10-14':,:]
    y_test = y['2017-10-14':]
    X_train = X.loc[:'2017-10-14', :]
    y_train = y[:'2017-10-14']
    return X_train, X_test, y_train, y_test

def time_series_train_test_split_no_gap(df):

    X = df[['lag1', 'lag2', 'lag3', 'lag4', 'lag5', 'lag6', 'lag7', 'lag8', 'lag9', 'lag10',
           ]]
    y= df['lag0']
    X_test = X.loc['2017-10-14':,:]
    y_test = y['2017-10-14':]
    X_train = X.loc[:'2017-10-14', :]
    y_train = y[:'2017-10-14']
    return X_train, X_test, y_train, y_test

def minimum_mae(mae_results, model_name):

    '''Takes in dictionary of mae_results and parameter settings outputed from grid search
    and 1. calculates the optimal mae and associated parameter settings and 2. prints all mae results.'''

    key_min = min(mae_results.keys(), key=(lambda k: mae_results[k]))
    min_test_mae = mae_results[key_min]
    min_parameters = key_min
```

```
    print()
    print(str(model_name) + ' MAE Results by Parameter Setting:')
    for key, value in mae_results.items():
        print(key, value)

    print()
    print(str(model_name) + ' Minimum Test MAE: ', min_test_mae)
    print(str(model_name) + ' Best Parameters: ', min_parameters)

    return min_test_mae, min_parameters

def fit_predict(model, X_train, X_test, y_train, y_test, train_tail):
    '''
    1) Fits model on training data
    2) Makes predictions on test data
    3) Calls reverse_stationarity function
    '''
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_pred = pd.Series(y_pred)
    y_pred.index = y_test.index
    y_pred_unscaled = reverse_stationarity(y_pred, train_tail, window_setting)
    y_unscaled = reverse_stationarity(y_test, train_tail, window_setting)
    return y_pred_unscaled, y_unscaled


def regression_plot(y_hat, y, model_name):
    # Set the locator
    locator = mdates.MonthLocator()  # every month
    # Specify the format - %b gives us Jan, Feb...
    fmt = mdates.DateFormatter('%m-%y')


    plt.plot(y_hat)
    plt.plot(y)


    X = plt.gca().xaxis
    X.set_major_locator(locator)
    # Specify formatter
    X.set_major_formatter(fmt)


    plt.legend(['y_hat', 'y'])
    plt.grid(linestyle="dashed")
    plt.title(model_name + ' Regression Prediction Results', fontsize=15)
```

```
    plt.show()

def preprocess_time_series(window_setting, lag_length):
    '''Prepares time series data for supervised learning experiments by␣
 ↪creating additional lagged columns of the original
    column and assigning a target y variable by pushing all predictor X␣
 ↪variables back by one year'''
    LME = LME_clean()
    LME_shifted = LME.shift(-261).dropna()

    LME_stationary = stationarity_preprocess(LME, window_setting)
    df = pd.DataFrame(list(zip(list(LME_stationary.index),␣
 ↪list(LME_stationary))), columns = ['ds', 'lag0'])

    for i in range(1, 11):
        lag_string = 'lag'+str(i)
        df[lag_string] = df.lag0.shift(periods=i*lag_length)

    df.index = df['ds']
    df = df.iloc[:, 1:]


    df['y'] = df['lag0'].shift(-261)
    df = df.dropna()

    return df, LME_shifted
```

[45]:
```
import matplotlib.dates as mdates

import matplotlib.backends.backend_pdf

LME = LME_clean()

# Set the locator
locator = mdates.MonthLocator()  # every month
# Specify the format - %b gives us Jan, Feb...
fmt = mdates.DateFormatter('%b-%y')

plt.plot(LME)


X = plt.gca().xaxis
X.set_major_locator(locator)
# Specify formatter
X.set_major_formatter(fmt)
plt.xticks( rotation=45 )
```

```
plt.grid(linestyle="dashed")

pdf = matplotlib.backends.backend_pdf.PdfPages("output.pdf")
plt.show()
pdf.savefig(plt)

##################

plt.plot(LME_shifted)


X = plt.gca().xaxis
X.set_major_locator(locator)
# Specify formatter
X.set_major_formatter(fmt)
plt.xticks( rotation=45 )

plt.grid(linestyle="dashed")
plt.show()
pdf.savefig( plt )


#for fig in xrange(1, figure().number): ## will open an empty extra figure :(
pdf.close()
```

```
␣
↪---------------------------------------------------------------------------

    ValueError                                Traceback (most recent call␣
↪last)

    <ipython-input-45-420dd9861e29> in <module>
     23 pdf = matplotlib.backends.backend_pdf.PdfPages("output.pdf")
     24 plt.show()
---> 25 pdf.savefig(plt)
     26 
     27 ##################


␣
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\backends\backend_pdf.
↪py in savefig(self, figure, **kwargs)
   2437                 manager = Gcf.get_fig_manager(figure)
   2438             if manager is None:
-> 2439                 raise ValueError("No figure {}".format(figure))
   2440             figure = manager.canvas.figure
   2441         # Force use of pdf backend, as PdfPages is tightly coupled␣
↪with it.


    ValueError: No figure <module 'matplotlib.pyplot' from 'C:
↪\\Users\\ckato\\AppData\\Local\\Continuum\\anaconda3\\lib\\site-packages\\matplotlib\\pyplot
↪py'>
```

[42]:

```
import fpdf

data=[1,2,3,4,5,6]

pdf = fpdf.FPDF(format='letter')
pdf.add_page()
pdf.set_font("Arial", size=12)

for i in data:
    pdf.write(5,str(i))
    pdf.ln()
pdf.output("testings.pdf")
```

```
 ␣
↪---------------------------------------------------------------------------

    ModuleNotFoundError                       Traceback (most recent call␣
↪last)

    <ipython-input-42-4031d26bbb28> in <module>
  ----> 1 import fpdf
        2
        3 data=[1,2,3,4,5,6]
        4
        5 pdf = fpdf.FPDF(format='letter')


    ModuleNotFoundError: No module named 'fpdf'
```

[35]:
```
'''
The following functions

    1) Fit models on training data/make predictions on test data
    2) Execute parameter tuning (depending on method used)
    2) Assess mean absolute errors (mae's) of multiple models and identifies/
↪outputs highest performing model/set of parameters

'''


def run_linear_reg(X_train, X_test, y_train, y_test, train_tail):
    '''No parameter tuning for linear reg model'''

    # Model Fitting & Predictions
    regressor = LinearRegression()
    y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
↪y_train, y_test, train_tail)
    mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
    model_name = str(regressor).split('(')[0]
    print('Test Linear Regression MAE: ', mae)

    regression_plot(y_pred_unscaled, y_unscaled, model_name)

    min_test_mae = mae
    min_parameters = 'None'
    return min_test_mae, min_parameters, model_name
```

```
def run_polynomial(X_train, X_test, y_train, y_test, train_tail):
    '''Polynomial regression needs to be fitted manually, since it piggybacks␣
↪off of linear regression model'''

    params1= range(2,5) # Evaluates different degrees of polynomial curve

    mae_results = {}

    for deg in params1:
        # Model Fitting & Predictions
        polynomial_features= PolynomialFeatures(degree=deg)

        X_poly = polynomial_features.fit_transform(X_train)

        regressor = LinearRegression()
        regressor.fit(X_poly, y_train)

        X_poly_test = polynomial_features.fit_transform(X_test)
        y_poly_pred = regressor.predict(X_poly_test)
        y_poly_pred = pd.Series(y_poly_pred)
        y_poly_pred.index = y_test.index

        y_pred_unscaled, y_unscaled = reverse_stationarity(y_poly_pred,␣
↪train_tail, window_setting), reverse_stationarity(y_test, train_tail,␣
↪window_setting)

        mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
        mae_results[str(deg)] = mae

    # To find the best/optimal parameters
    model_name = "Polynomial"
    min_test_mae, min_parameters = minimum_mae(mae_results, model_name)
    min_parameters = ast.literal_eval(min_parameters)

    polynomial_features= PolynomialFeatures(degree=min_parameters)

    X_poly = polynomial_features.fit_transform(X_train)

    regressor = LinearRegression()
    regressor.fit(X_poly, y_train)

    X_poly_test = polynomial_features.fit_transform(X_test)
    y_poly_pred = regressor.predict(X_poly_test)
    y_poly_pred = pd.Series(y_poly_pred)
    y_poly_pred.index = y_test.index
```

```
    y_pred_unscaled, y_unscaled = reverse_stationarity(y_poly_pred, train_tail,␣
↪window_setting), reverse_stationarity(y_test, train_tail, window_setting)

    regression_plot(y_pred_unscaled, y_unscaled, model_name)


    return min_test_mae, min_parameters, model_name


def run_lasso_grid(X_train, X_test, y_train, y_test, train_tail):

    params1= ParameterGrid({'alpha' : [ .00001 ,.0001, .001, .01, .1, 1]
                            })
    mae_results = {}

    for params in params1:
        # Model Fitting & Predictions
        regressor = linear_model.Lasso(**params, random_state=1)
        y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
↪y_train, y_test, train_tail)
        mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
        mae_results[str(params)] = mae

    # To find the best/optimal parameters
    model_name = str(regressor).split('(')[0]
    min_test_mae, min_parameters = minimum_mae(mae_results, model_name)
    min_parameters = ast.literal_eval(min_parameters) # Converts optimal␣
↪parameters string to dict
    regressor = linear_model.Lasso(**min_parameters, random_state=1)

    y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
↪y_train, y_test, train_tail)

    regression_plot(y_pred_unscaled, y_unscaled, model_name)


    return min_test_mae, min_parameters, model_name


def run_adaboost_grid(X_train, X_test, y_train, y_test, train_tail):
    '''Executes parameter tuning using grid search.
    One final set of parameters is chosen and outputted with resulting MAE'''

    params1= ParameterGrid({'n_estimators' : [50, 100, 150, 200, 250],
                        'learning_rate': [ .1, .01, .001, .0001]})

    mae_results = {}
```

```
    for params in params1:
        # Model Fitting & Predictions
        regressor = AdaBoostRegressor(**params, random_state=1)
        y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)

        mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
        mae_results[str(params)] = mae

    # To find the best/optimal parameters
    model_name = str(regressor).split('(')[0]
    min_test_mae, min_parameters = minimum_mae(mae_results, model_name)
    min_parameters = ast.literal_eval(min_parameters) # Converts optimal␣
 ↪parameters string to dict
    regressor = AdaBoostRegressor(**min_parameters, random_state=1)

    y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)
    regression_plot(y_pred_unscaled, y_unscaled, model_name)

    return min_test_mae, min_parameters, model_name

def run_rf_grid(X_train, X_test, y_train, y_test, train_tail):
    '''Random Forest Regression'''

    params1=  ParameterGrid({'n_estimators' : [50, 100, 150, 200, 250, 300],
                            'min_samples_leaf': [ .15,  .25, .35, .45]})
    mae_results = {}

    for params in params1:
        # Model Fitting & Predictions
        regressor = RandomForestRegressor(**params, random_state=1)
        y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)
        mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
        mae_results[str(params)] = mae

    # To find the best/optimal parameters
    model_name = str(regressor).split('(')[0]
    min_test_mae, min_parameters = minimum_mae(mae_results, model_name)
    min_parameters = ast.literal_eval(min_parameters) # Converts optimal␣
 ↪parameters string to dict
    regressor = RandomForestRegressor(**params, random_state=1)

    y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)
```

```
    regression_plot(y_pred_unscaled, y_unscaled, model_name)

    return min_test_mae, min_parameters, model_name


def run_knn(X_train, X_test, y_train, y_test, train_tail):

    params1= range(1,67,3) # Evaluates different values of K number of␣
 ↪observations in a neighborhood

    mae_results = {}

    for K in params1:
        # Model Fitting & Predictions
        regressor = neighbors.KNeighborsRegressor(n_neighbors=K)
        y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)
        mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
        mae_results[str(K)] = mae

    # To find the best/optimal parameters
    model_name = str(regressor).split('(')[0]
    min_test_mae, min_parameters = minimum_mae(mae_results, model_name)
    min_parameters = ast.literal_eval(min_parameters) # Converts optimal␣
 ↪parameters string to dict
    regressor = regressor = neighbors.
 ↪KNeighborsRegressor(n_neighbors=min_parameters)

    y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train, X_test,␣
 ↪y_train, y_test, train_tail)

    regression_plot(y_pred_unscaled, y_unscaled, model_name)
    return min_test_mae, min_parameters, model_name
```

[36]:
```
if __name__ == "__main__":
    window_setting= 5*4 # Rolling Average window setting for␣
 ↪stationarity_preprocess function

    lag_length = 10 # lag length 2 weeks (5 business days)
    df, LME_shifted = preprocess_time_series(window_setting, lag_length)

    model_functions = [run_linear_reg,
             run_polynomial,
             run_lasso_grid,
             run_adaboost_grid,
             run_rf_grid,
             run_knn]
```

```
    # Evaluations for one year ahead of time predictions compared to just one␣
↪day ahead predictions (no gap)
    for j, y_lag_type in enumerate([time_series_train_test_split(df),␣
↪time_series_train_test_split_no_gap(df)]):
        if j == 0:
            print("One Year Ahead of Time Predictions")
            print()
        else:
            print("One Day Ahead Predictions")
            print()
        X_train, X_test, y_train, y_test = y_lag_type
        train_tail = LME_shifted.loc[y_train.index[-window_setting:]]

        mae = []
        parameter_setting = []
        model_name_list = []

        for i in range(5):
            min_test_mae, min_parameters, model_name =␣
↪model_functions[i](X_train, X_test, y_train, y_test, train_tail)
            mae.append(min_test_mae)
            parameter_setting.append(min_parameters)
            model_name_list.append(model_name)

        if j == 0:
            results = pd.DataFrame({'model_name': model_name_list, 'mae': mae,␣
↪'parameters': parameter_setting})
            results.to_csv('results/automodeling_mae.csv', index = False)
```

```
One Year Ahead of Time Predictions



        ␣
↪---------------------------------------------------------------------------

        ValueError                                Traceback (most recent call␣
↪last)

        <ipython-input-36-f9d17e7a27be> in <module>
         28
         29         for i in range(5):
    ---> 30             min_test_mae, min_parameters, model_name =␣
↪model_functions[i](X_train, X_test, y_train, y_test, train_tail)
         31             mae.append(min_test_mae)
         32             parameter_setting.append(min_parameters)
```

```
    <ipython-input-35-60fce3e20cce> in run_linear_reg(X_train, X_test,␣
↪y_train, y_test, train_tail)
     14     # Model Fitting & Predictions
     15     regressor = LinearRegression()
---> 16     y_pred_unscaled, y_unscaled = fit_predict(regressor, X_train,␣
↪X_test, y_train, y_test, train_tail)
     17     mae = metrics.mean_absolute_error(y_unscaled, y_pred_unscaled)
     18     model_name = str(regressor).split('(')[0]


    <ipython-input-34-d4ce5e8cb95d> in fit_predict(model, X_train, X_test,␣
↪y_train, y_test, train_tail)
     89     3) Calls reverse_stationarity function
     90     '''
---> 91     model.fit(X_train, y_train)
     92     y_pred = model.predict(X_test)
     93     y_pred = pd.Series(y_pred)


     ␣
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\linear_model\base.
↪py in fit(self, X, y, sample_weight)
    461         n_jobs_ = self.n_jobs
    462         X, y = check_X_y(X, y, accept_sparse=['csr', 'csc', 'coo'],
--> 463                          y_numeric=True, multi_output=True)
    464
    465         if sample_weight is not None and np.
↪atleast_1d(sample_weight).ndim > 1:


     ␣
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.
↪py in check_X_y(X, y, accept_sparse, accept_large_sparse, dtype, order, copy,␣
↪force_all_finite, ensure_2d, allow_nd, multi_output, ensure_min_samples,␣
↪ensure_min_features, y_numeric, warn_on_dtype, estimator)
    717                     ensure_min_features=ensure_min_features,
    718                     warn_on_dtype=warn_on_dtype,
--> 719                     estimator=estimator)
    720     if multi_output:
    721         y = check_array(y, 'csr', force_all_finite=True,␣
↪ensure_2d=False,
```

```
                ␣
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.
↪py in check_array(array, accept_sparse, accept_large_sparse, dtype, order,␣
↪copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, warn_on_dtype, estimator)
        548                              " minimum of %d is required%s."
        549                              % (n_samples, array.shape,␣
↪ensure_min_samples,
    --> 550                                 context))
        551
        552     if ensure_min_features > 0 and array.ndim == 2:


        ValueError: Found array with 0 sample(s) (shape=(0, 11)) while a minimum␣
↪of 1 is required.
```

1.0.2 New

[37]:
```
X_train
```

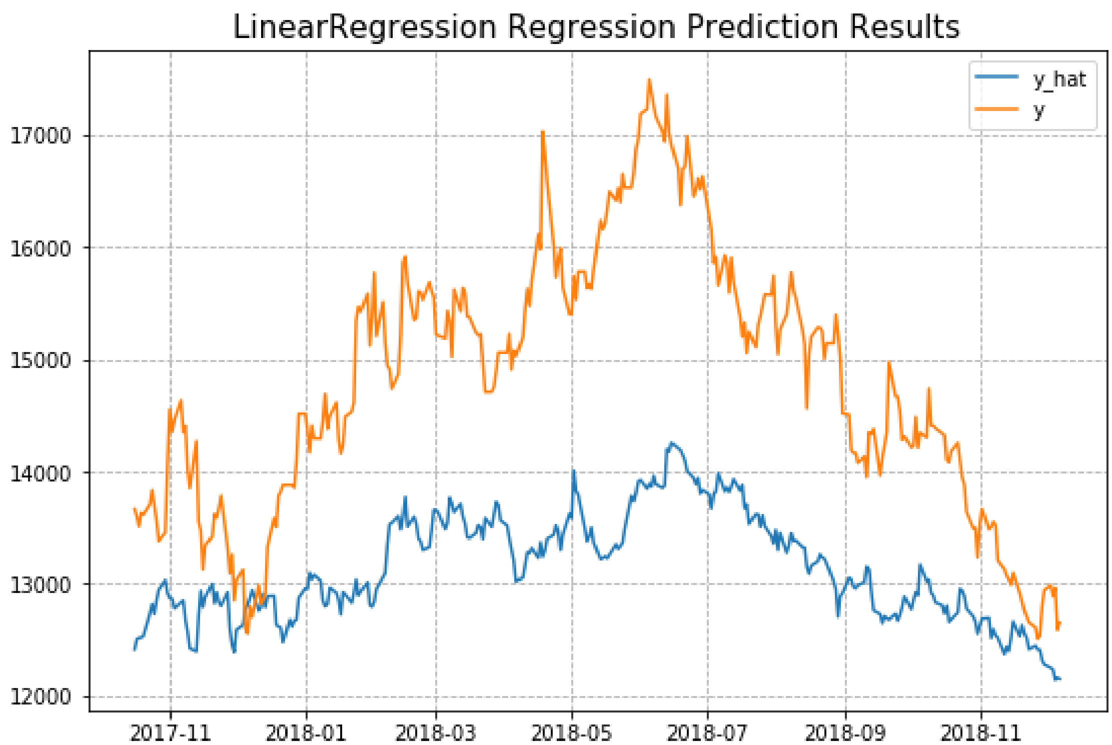
[37]:
```
Empty DataFrame
Columns: [lag0, lag1, lag2, lag3, lag4, lag5, lag6, lag7, lag8, lag9, lag10]
Index: []
```

[ ]:
```

```

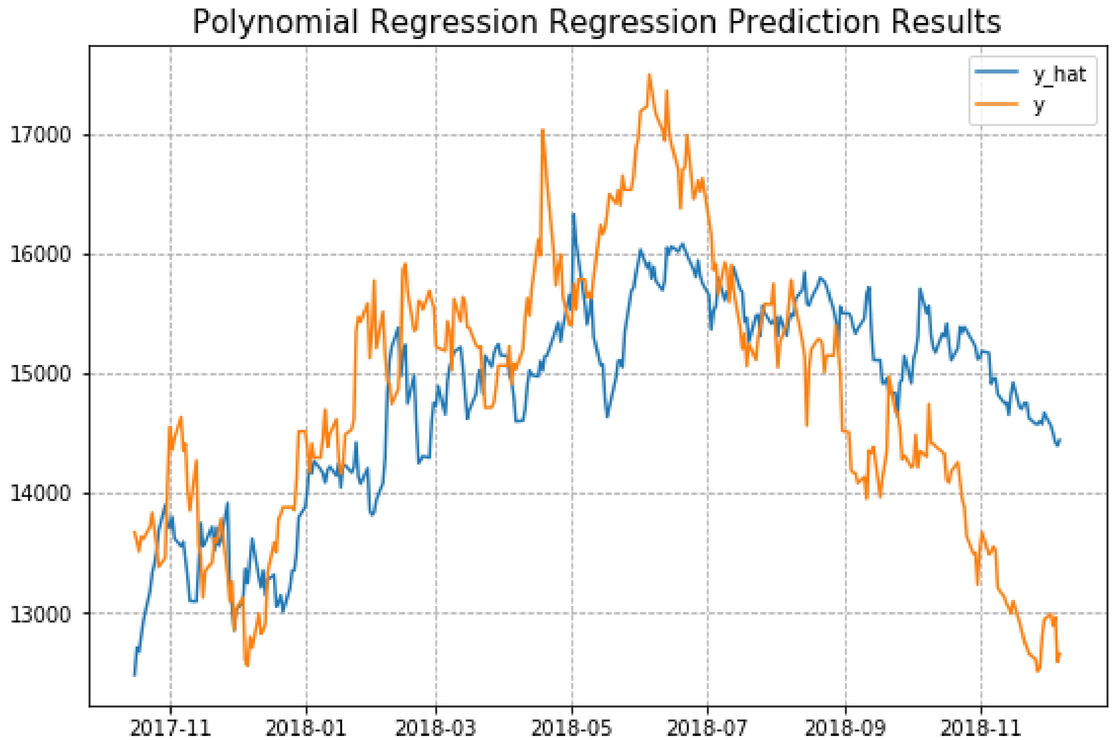
[102]:
```

```

[108]:
```
#min_test_mae, min_parameters, model_name = run_rf_grid(X_train, X_test,␣
 ↪y_train, y_test, train_tail)

'''

functions = [run_linear_reg,
             run_polynomial,
             run_lasso_grid,
             run_adaboost_grid,
             run_rf_grid,
             run_knn]
'''
```

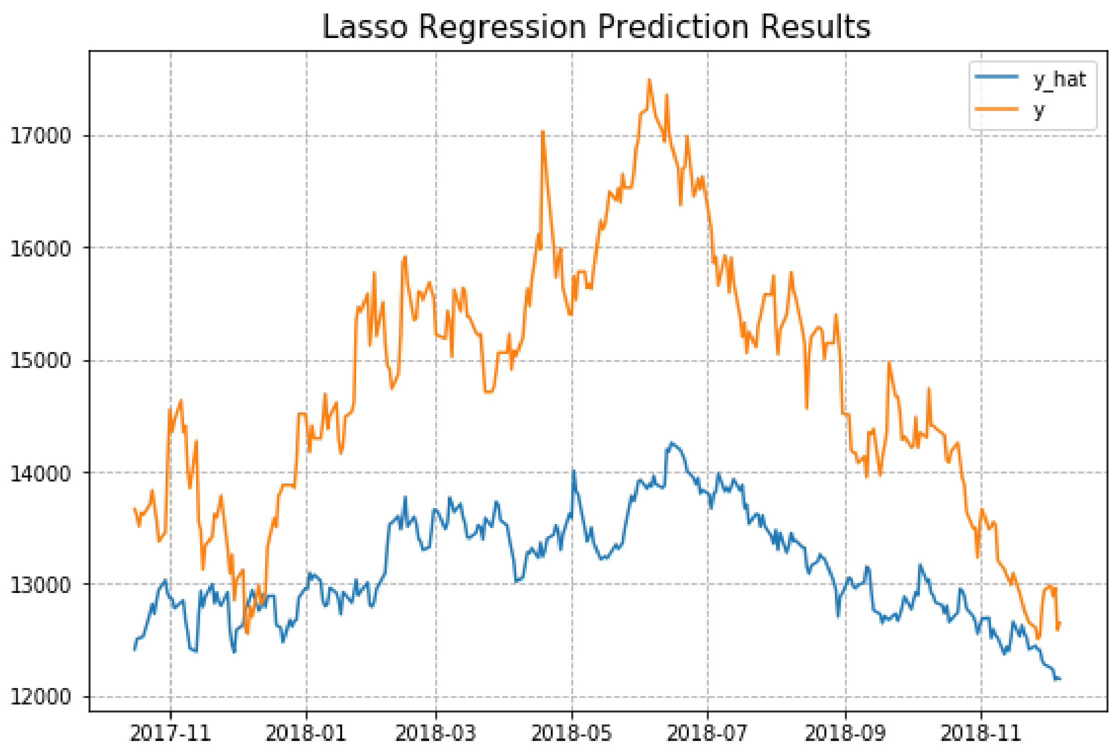
```
Test MAE:  1662.9468654921607
```




```
MAE Results by Parameter Setting:
2 1175.9846292816144
3 761.0707242076479
4 945.2139169212273

Minimum Test MAE:  761.0707242076479
Best Parameters:  3
```

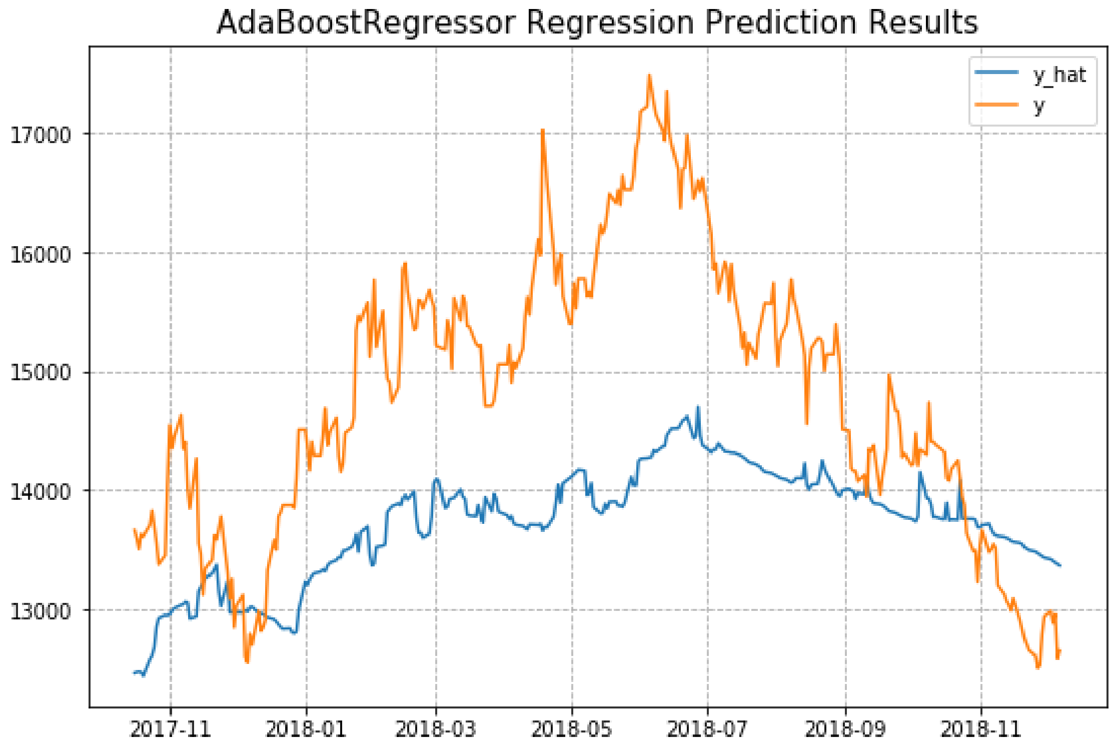



```
MAE Results by Parameter Setting:
{'alpha': 1e-05} 1662.9468655056294
{'alpha': 0.0001} 1662.9468656279964
{'alpha': 0.001} 1662.9468668543952
{'alpha': 0.01} 1662.9468790681908
{'alpha': 0.1} 1662.9469997144618
{'alpha': 1} 1662.94818631197

Minimum Test MAE:  1662.9468655056294
Best Parameters:  {'alpha': 1e-05}
```



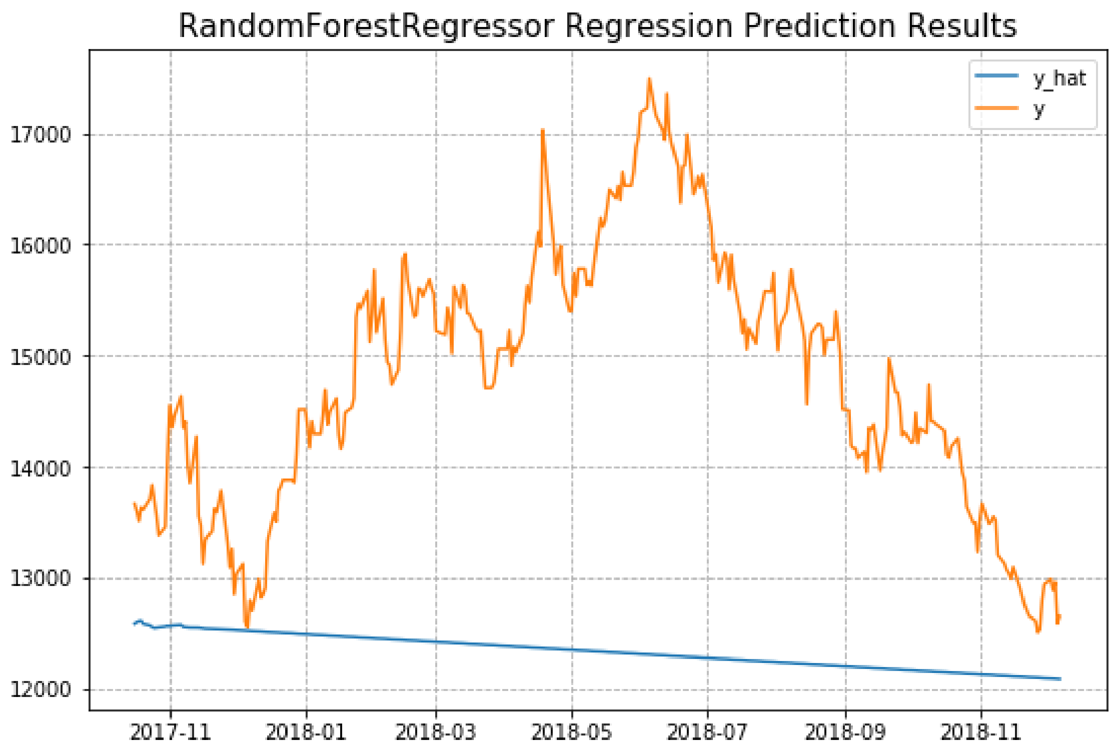

```
MAE Results by Parameter Setting:
{'learning_rate': 0.1, 'n_estimators': 50} 1352.2395280222518
{'learning_rate': 0.1, 'n_estimators': 100} 1267.2395109681402
{'learning_rate': 0.1, 'n_estimators': 150} 1342.5092205739545
{'learning_rate': 0.1, 'n_estimators': 200} 1598.1247219190723
{'learning_rate': 0.1, 'n_estimators': 250} 1817.966706778851
{'learning_rate': 0.01, 'n_estimators': 50} 1291.886505701608
{'learning_rate': 0.01, 'n_estimators': 100} 1198.371683837774
{'learning_rate': 0.01, 'n_estimators': 150} 1323.3915943932866
{'learning_rate': 0.01, 'n_estimators': 200} 1427.9369519750837
{'learning_rate': 0.01, 'n_estimators': 250} 1405.4394411410317
{'learning_rate': 0.001, 'n_estimators': 50} 1453.584367668518
{'learning_rate': 0.001, 'n_estimators': 100} 1381.4804967384441
{'learning_rate': 0.001, 'n_estimators': 150} 1347.4375878686544
{'learning_rate': 0.001, 'n_estimators': 200} 1350.5517972412863
{'learning_rate': 0.001, 'n_estimators': 250} 1365.039941004427
{'learning_rate': 0.0001, 'n_estimators': 50} 1390.460151396599
{'learning_rate': 0.0001, 'n_estimators': 100} 1414.8599180158883
{'learning_rate': 0.0001, 'n_estimators': 150} 1394.6479238686434
{'learning_rate': 0.0001, 'n_estimators': 200} 1437.381352823003
{'learning_rate': 0.0001, 'n_estimators': 250} 1442.0946826628503
```

```
Minimum Test MAE:  1198.371683837774
Best Parameters:  {'learning_rate': 0.01, 'n_estimators': 100}
```



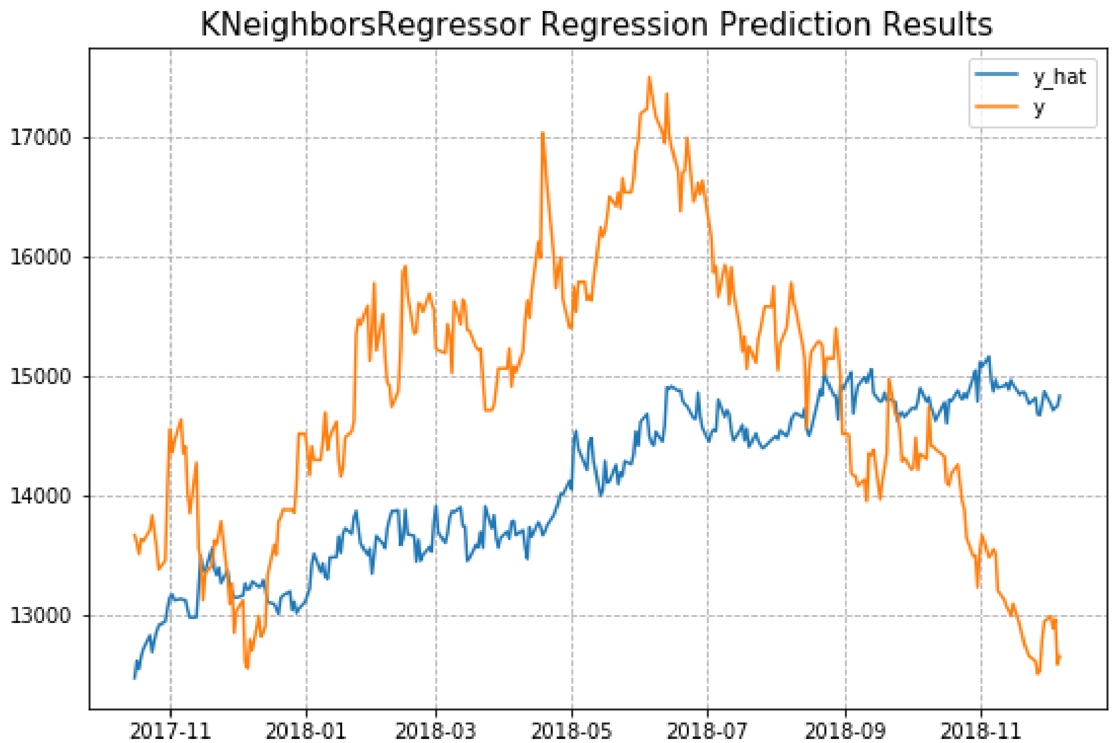

```
MAE Results by Parameter Setting:
{'min_samples_leaf': 0.15, 'n_estimators': 50} 1172.4041814890088
{'min_samples_leaf': 0.15, 'n_estimators': 100} 1115.570915908886
{'min_samples_leaf': 0.15, 'n_estimators': 150} 1078.8567478356538
{'min_samples_leaf': 0.15, 'n_estimators': 200} 1074.2171328611137
{'min_samples_leaf': 0.15, 'n_estimators': 250} 1049.390779431973
{'min_samples_leaf': 0.15, 'n_estimators': 300} 1041.0421796647756
{'min_samples_leaf': 0.25, 'n_estimators': 50} 1174.749577368381
{'min_samples_leaf': 0.25, 'n_estimators': 100} 1150.8416185886508
{'min_samples_leaf': 0.25, 'n_estimators': 150} 1126.7915098626722
{'min_samples_leaf': 0.25, 'n_estimators': 200} 1124.106625490553
{'min_samples_leaf': 0.25, 'n_estimators': 250} 1116.3616023220777
{'min_samples_leaf': 0.25, 'n_estimators': 300} 1113.8710177062442
{'min_samples_leaf': 0.35, 'n_estimators': 50} 2508.2638846153154
{'min_samples_leaf': 0.35, 'n_estimators': 100} 2514.5584700750333
{'min_samples_leaf': 0.35, 'n_estimators': 150} 2480.003625496875
{'min_samples_leaf': 0.35, 'n_estimators': 200} 2484.8618333844747
{'min_samples_leaf': 0.35, 'n_estimators': 250} 2464.16135133132
{'min_samples_leaf': 0.35, 'n_estimators': 300} 2461.818855272004
```

```
{'min_samples_leaf': 0.45, 'n_estimators': 50} 2508.2638846153154
{'min_samples_leaf': 0.45, 'n_estimators': 100} 2514.5584700750333
{'min_samples_leaf': 0.45, 'n_estimators': 150} 2480.003625496875
{'min_samples_leaf': 0.45, 'n_estimators': 200} 2484.8618333844747
{'min_samples_leaf': 0.45, 'n_estimators': 250} 2464.16135133132
{'min_samples_leaf': 0.45, 'n_estimators': 300} 2461.818855272004

Minimum Test MAE:  1041.0421796647756
Best Parameters:  {'min_samples_leaf': 0.15, 'n_estimators': 300}
```

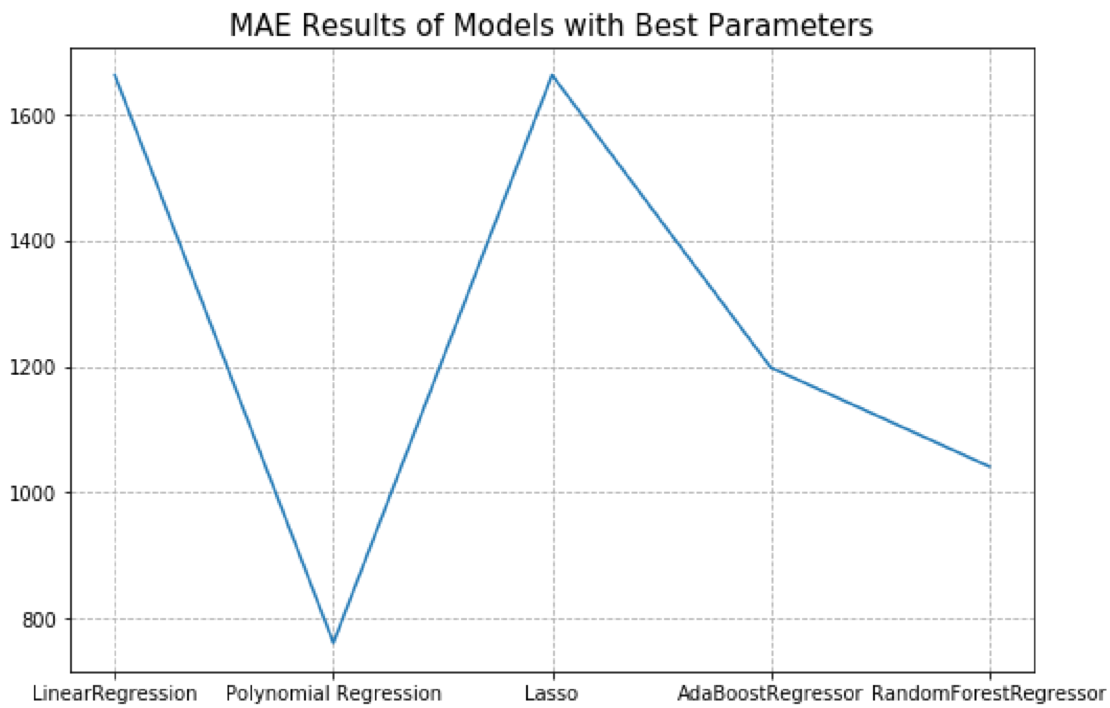



```
MAE Results by Parameter Setting:
1 1406.7157121838295
4 1333.504973199537
7 1327.0977765002895
10 1329.2890163986567
13 1365.3011668322756
16 1349.6967704974159
19 1319.0681497239798
22 1329.8888303995543
25 1322.6103772491128
28 1310.4649889629447
31 1316.9132986772045
```

```
34 1303.8538363621842
37 1290.7240703467362
40 1301.5533081686888
43 1289.6478203903953
46 1279.0859688979383
49 1280.1720297039415
52 1266.6909101915292
55 1257.7255632596948
58 1251.2802598770036
61 1264.2928304309787
64 1257.1503716703585

Minimum Test MAE:  1251.2802598770036
Best Parameters:  58
```



[91]:
```
plt.plot(model_name_list, mae)
plt.grid(linestyle="dashed")
plt.title('MAE Results of Models with Best Parameters', fontsize=15)

plt.show()
```



[ ]:

```

```

[ ]:

```
plt.plot(df_results['results'])
plt.title('MAE Results (full) for 16 years training period testing for one year␣
 ↪test period\n ' + 'MAE: '+ str(df_results['results'].mean()), fontsize=15)
plt.axhline(df_results['results'].mean(), color='r', linestyle='dotted')
plt.grid(linestyle='dashed')
plt.show()
```

[ ]:

```

```

[ ]:

```

```

[ ]:

```
'''
y_pred = regressor.predict(X_test)
y_pred = pd.Series(y_pred)
y_pred.index = y_test.index

y_pred_train  = regressor.predict(X_train)
y_pred_train = pd.Series(y_pred_train)
y_pred_train.index = y_train.index
'''
```

2 Other Kinds of Regression

Grid Search for RIDGE Regression

3 MAIN GOOD ONES

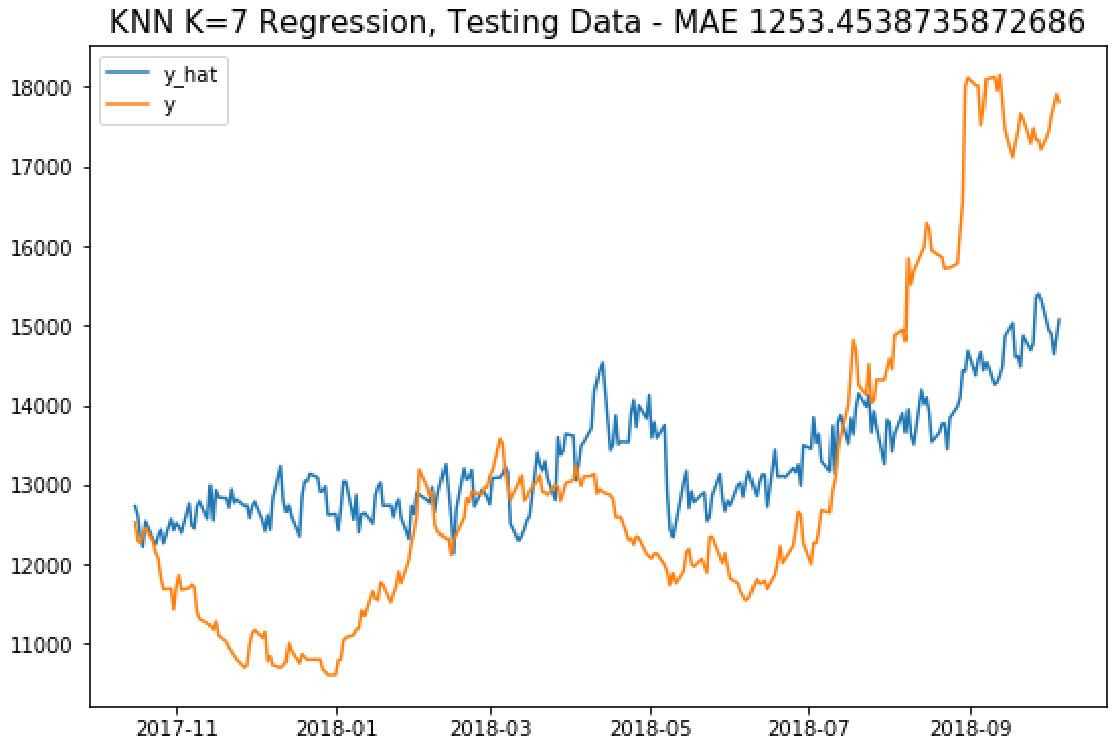
Knn K=6 2 week lags at 3 week rolling average windows
Knn K=7 4 week lags at 4 week rolling average windows
Polynomial 4 month lags 8 week rolling average windows

[183]:
```
K = 7
regressor = neighbors.KNeighborsRegressor(n_neighbors=K)
regressor.fit(X_train, y_train)

y_pred_train  = regressor.predict(X_train)
y_pred_train = pd.Series(y_pred_train)
y_pred_train.index = y_train.index

y_pred = regressor.predict(X_test)
y_pred = pd.Series(y_pred)
y_pred.index = y_test.index

LME_shifted = LME.shift(-261).dropna()

original_tail = LME_shifted.loc[y_train.index[-window_setting:]]
y_pred_unscaled = reverse_stationarity(y_pred, original_tail, window_setting)
y_pred_unscaled.index = y_test.index


y_unscaled = reverse_stationarity(y_test, original_tail, window_setting)
y_unscaled.index = y_test.index
print(y_unscaled.head())

###############

original_tail_train = LME_shifted.loc[y_train.index[:window_setting]]

original_y_train = unscale(y_train.iloc[window_setting:], original_tail_train,␣
 ↪window_setting)
original_y_train.index = y_train[window_setting:].index

y_pred_train_unscaled = unscale(y_pred_train.iloc[window_setting:],␣
 ↪original_tail_train, window_setting)
y_pred_train_unscaled.index = y_train[window_setting:].index

print(original_y_train.head())

###########

plt.plot(unscaled)
plt.plot(original_y)
plt.legend(['y_hat', 'y'])
```

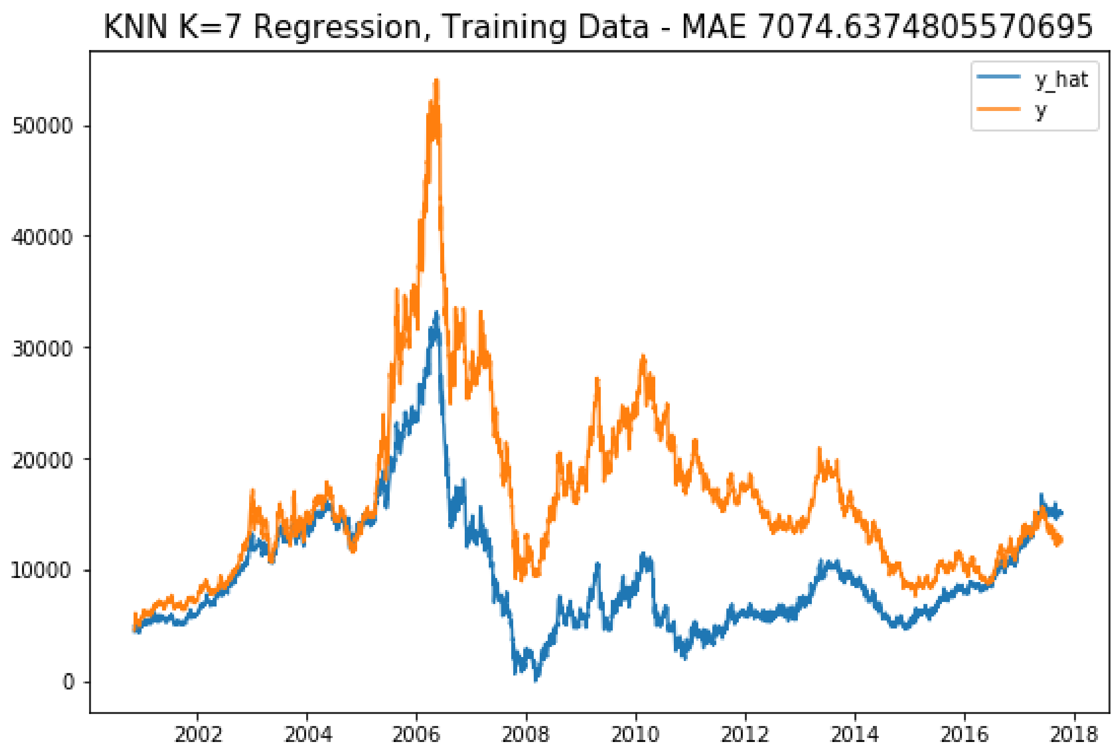
```python
plt.title('KNN K=' +str(K) +' Regression, Testing Data - MAE ' + str(metrics.mean_absolute_error(original_y, unscaled)), fontsize=15)
filename = 'results/KNN_' + 'window_'+ str(window_setting) + 'lag_'+str(lag_length)+'_test.png'
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y, unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y, unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(original_y, unscaled)))

results = pd.DataFrame({'y_test': original_y, 'y_pred_unscaled': unscaled})
results['error'] = results['y_test'] - results['y_pred_unscaled']



plt.plot(y_pred_train_unscaled)
plt.plot(original_y_train)
plt.legend(['y_hat', 'y'])
plt.title('KNN K=' +str(K)+' Regression, Training Data - MAE '+ str(metrics.mean_absolute_error(original_y_train, y_pred_train_unscaled)), fontsize=15)
filename = 'results/KNN_' + 'window_'+ str(window_setting) + 'lag_'+str(lag_length)+'_train.png'

#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y_train, y_pred_train_unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y_train, y_pred_train_unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(original_y_train, y_pred_train_unscaled)))
```

```
ds
2017-10-16    12516.5
2017-10-17    12298.5
2017-10-18    12276.0
2017-10-19    12372.0
2017-10-20    12447.5
dtype: float64
ds
2000-11-06    4521.0
2000-11-07    4532.0
2000-11-08    4614.0
2000-11-09    4891.0
```

```
2000-11-10    5499.5
dtype: float64
```




```
Mean Absolute Error: 1253.4538735872686
Mean Squared Error: 2347471.5514717815
Root Mean Squared Error: 1532.1460607500126
```



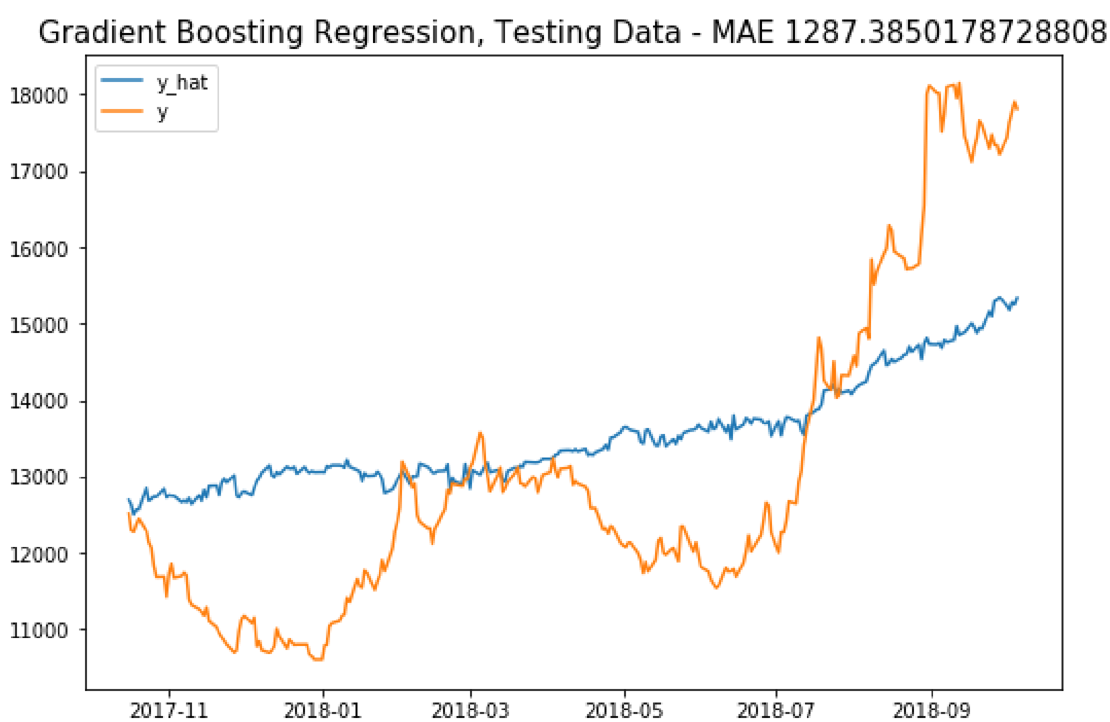

```
Mean Absolute Error: 7074.6374805570695
Mean Squared Error: 84440250.35487752
Root Mean Squared Error: 9189.137628465334
```

[33]:
```
regressor=mid_model

y_pred_train  = regressor.predict(X_train)
y_pred_train = pd.Series(y_pred_train)
y_pred_train.index = y_train.index

y_pred = regressor.predict(X_test)
y_pred = pd.Series(y_pred)
y_pred.index = y_test.index

LME_shifted = LME.shift(-261).dropna()

original_tail = LME_shifted.loc[y_train.index[-window_setting:]]
unscaled = unscale(y_pred, original_tail, window_setting)
unscaled.index = y_test.index


original_y = unscale(y_test, original_tail, window_setting)
original_y.index = y_test.index
```

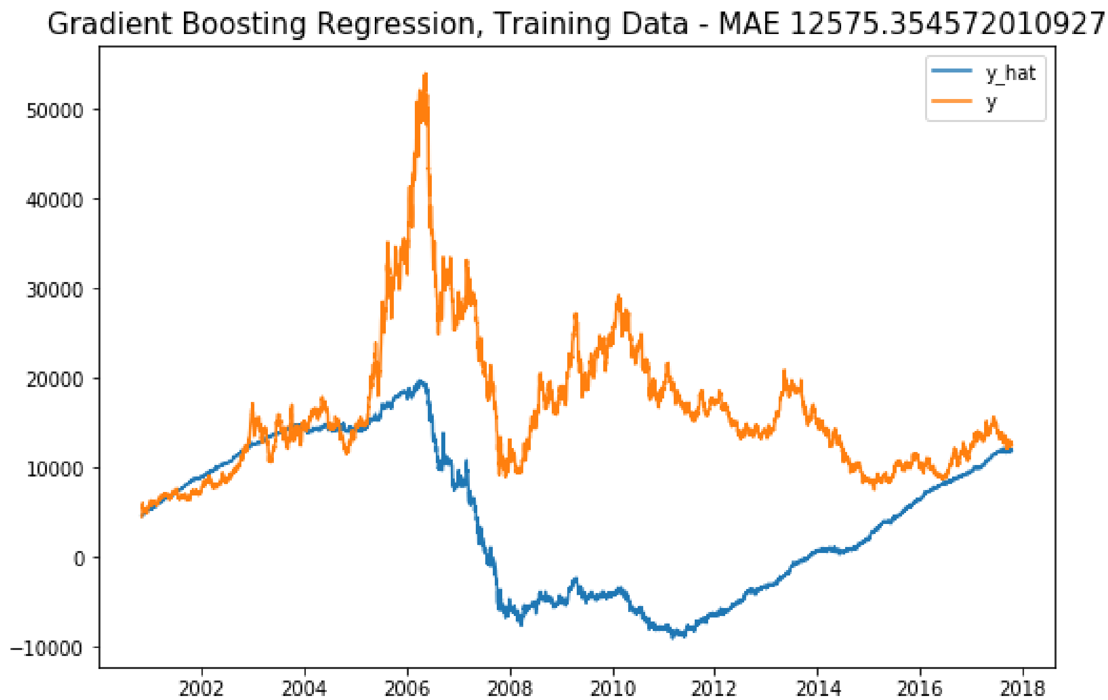
```python
print(original_y.head())

###############

original_tail_train = LME_shifted.loc[y_train.index[:window_setting]]

original_y_train = unscale(y_train.iloc[window_setting:], original_tail_train,␣
 ↪window_setting)
original_y_train.index = y_train[window_setting:].index

y_pred_train_unscaled = unscale(y_pred_train.iloc[window_setting:],␣
 ↪original_tail_train, window_setting)
y_pred_train_unscaled.index = y_train[window_setting:].index

print(original_y_train.head())

###########

plt.plot(unscaled)
plt.plot(original_y)
plt.legend(['y_hat', 'y'])
plt.title('Gradient Boosting Regression, Testing Data - MAE ' + str(metrics.
 ↪mean_absolute_error(original_y, unscaled)), fontsize=15)
filename = 'results/gradient_boost_mid_' + 'window_'+ str(window_setting) +␣
 ↪'lag_'+str(lag_length)+'_test.png'
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y, unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y, unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(original_y, unscaled)))

results = pd.DataFrame({'y_test': original_y, 'y_pred_unscaled': unscaled})
results['error'] = results['y_test'] - results['y_pred_unscaled']



plt.plot(y_pred_train_unscaled)
plt.plot(original_y_train)
plt.legend(['y_hat', 'y'])
plt.title('Gradient Boosting Regression, Training Data - MAE '+ str(metrics.
 ↪mean_absolute_error(original_y_train, y_pred_train_unscaled)), fontsize=15)
filename = 'results/gradient_boost_mid_' + 'window_'+ str(window_setting) +␣
 ↪'lag_'+str(lag_length)+'_train.png'
```

```
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(original_y_train, y_pred_train_unscaled)))
```

```
ds
2017-10-16    12516.5
2017-10-17    12298.5
2017-10-18    12276.0
2017-10-19    12372.0
2017-10-20    12447.5
dtype: float64
ds
2000-11-06    4521.0
2000-11-07    4532.0
2000-11-08    4614.0
2000-11-09    4891.0
2000-11-10    5499.5
dtype: float64
```



```
Mean Absolute Error: 1287.3850178728808
Mean Squared Error: 2380259.539884321
Root Mean Squared Error: 1542.8089771207326
```



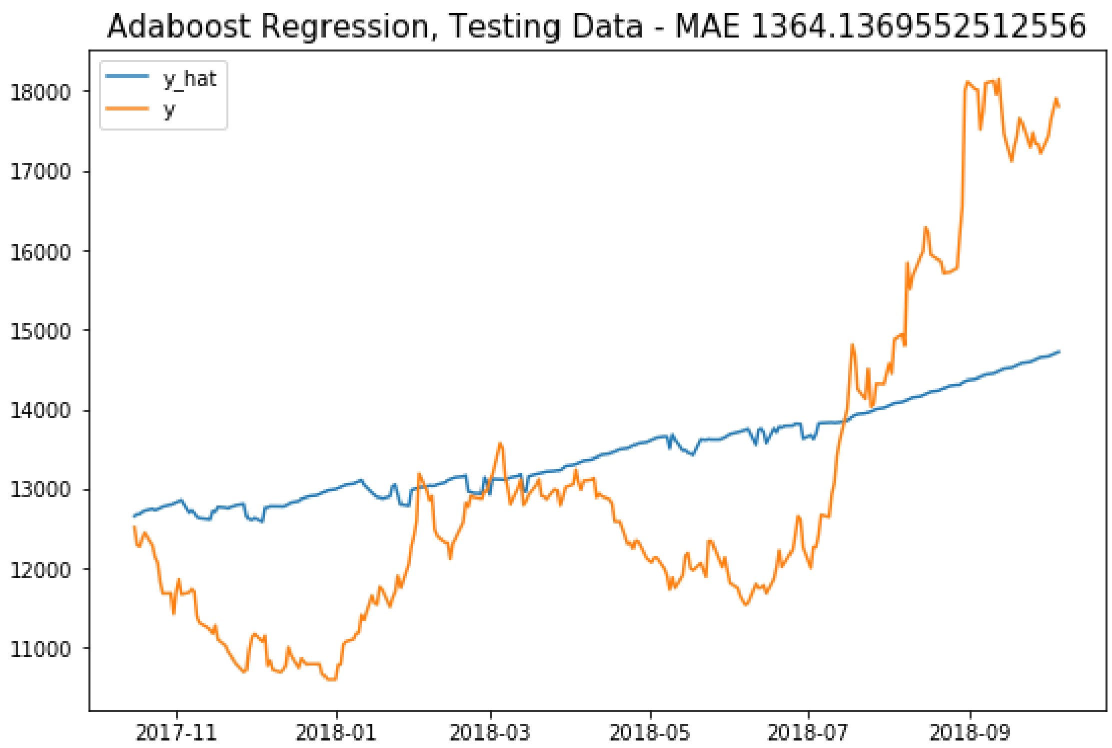

```
Mean Absolute Error: 12575.354572010927
Mean Squared Error: 264481461.72992408
Root Mean Squared Error: 16262.886020935031
```

[184]:

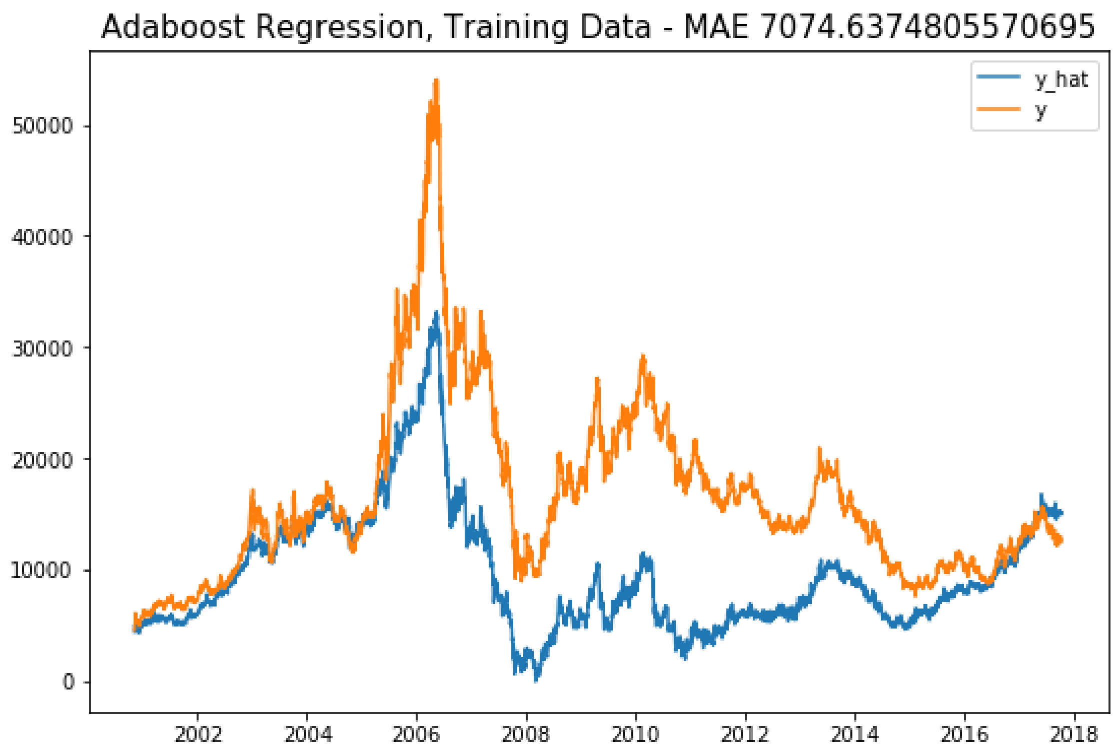
```
regressor = AdaBoostRegressor(learning_rate=.0001, n_estimators=50,␣
 ↪random_state=1)

regressor.fit(X_train, y_train)

y_pred = regressor.predict(X_test)
y_pred = pd.Series(y_pred)
y_pred.index = y_test.index

original_tail = LME_shifted.loc[y_train.index[-window_setting:]]
unscaled = unscale(y_pred, original_tail, window_setting)
unscaled.index = y_test.index


original_y = unscale(y_test, original_tail, window_setting)
original_y.index = y_test.index
```

```
#print(original_y.head())

###############

original_tail_train = LME_shifted.loc[y_train.index[:window_setting]]

original_y_train = unscale(y_train.iloc[window_setting:], original_tail_train,␣
 ↪window_setting)
original_y_train.index = y_train[window_setting:].index

y_pred_train_unscaled = unscale(y_pred_train.iloc[window_setting:],␣
 ↪original_tail_train, window_setting)
y_pred_train_unscaled.index = y_train[window_setting:].index

#print(original_y_train.head())

###########

plt.plot(unscaled)
plt.plot(original_y)
plt.legend(['y_hat', 'y'])
plt.title('Adaboost Regression, Testing Data - MAE ' + str(metrics.
 ↪mean_absolute_error(original_y, unscaled)), fontsize=15)
filename = 'results/adaboost_' + 'window_'+ str(window_setting) +␣
 ↪'lag_'+str(lag_length)+'_test.png'
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y, unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y, unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(original_y, unscaled)))

results = pd.DataFrame({'y_test': original_y, 'y_pred_unscaled': unscaled})
results['error'] = results['y_test'] - results['y_pred_unscaled']



plt.plot(y_pred_train_unscaled)
plt.plot(original_y_train)
plt.legend(['y_hat', 'y'])
plt.title('Adaboost Regression, Training Data - MAE '+ str(metrics.
 ↪mean_absolute_error(original_y_train, y_pred_train_unscaled)), fontsize=15)
filename = 'results/adaboost_' + 'window_'+ str(window_setting) +␣
 ↪'lag_'+str(lag_length)+'_train.png'
```

```python
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(original_y_train, y_pred_train_unscaled)))
```




```
Mean Absolute Error: 1364.1369552512556
Mean Squared Error: 2668909.322509097
Root Mean Squared Error: 1633.6796878547204
```

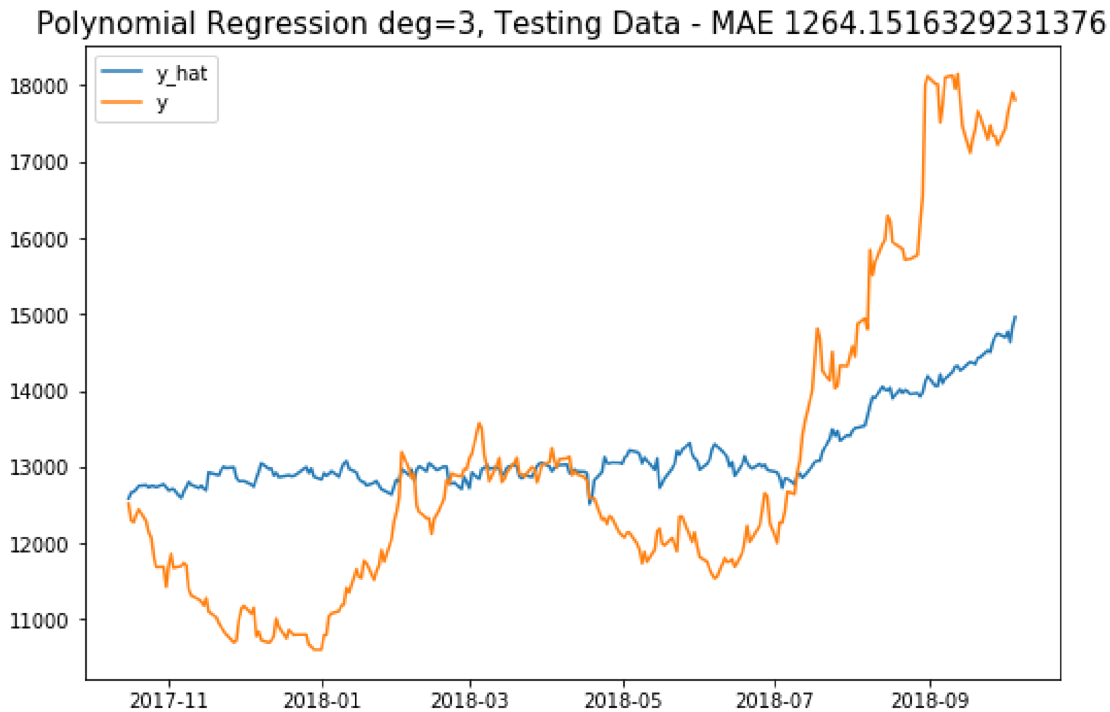



```
Mean Absolute Error: 7074.6374805570695
Mean Squared Error: 84440250.35487752
Root Mean Squared Error: 9189.137628465334
```

[185]:
```
polynomial_features= PolynomialFeatures(degree=3)

X_poly = polynomial_features.fit_transform(X_train)

regressor = LinearRegression()
regressor.fit(X_poly, y_train)

X_poly_test = polynomial_features.fit_transform(X_test)
y_poly_pred = regressor.predict(X_poly_test)
y_poly_pred = pd.Series(y_poly_pred)
y_poly_pred.index = y_test.index

y_pred = y_poly_pred


X_poly_train = polynomial_features.fit_transform(X_train)
y_poly_pred = regressor.predict(X_poly_train)
y_poly_pred = pd.Series(y_poly_pred)
y_poly_pred.index = y_train.index
```

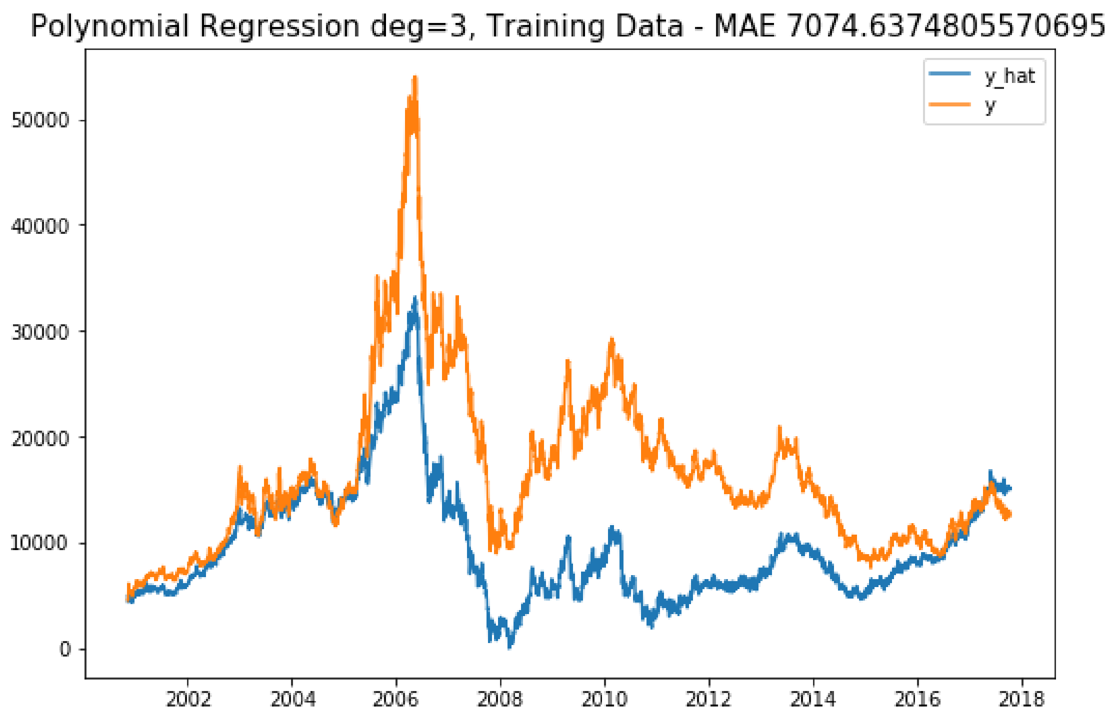
```
y_pred_train_unscaled = y_poly_pred


##############

original_tail = LME_shifted.loc[y_train.index[-window_setting:]]
unscaled = unscale(y_pred, original_tail, window_setting)
unscaled.index = y_test.index


original_y = unscale(y_test, original_tail, window_setting)
original_y.index = y_test.index
#print(original_y.head())

###############

original_tail_train = LME_shifted.loc[y_train.index[:window_setting]]

original_y_train = unscale(y_train.iloc[window_setting:], original_tail_train,␣
↪window_setting)
original_y_train.index = y_train[window_setting:].index

y_pred_train_unscaled = unscale(y_pred_train.iloc[window_setting:],␣
↪original_tail_train, window_setting)
y_pred_train_unscaled.index = y_train[window_setting:].index

#print(original_y_train.head())

###########

plt.plot(unscaled)
plt.plot(original_y)
plt.legend(['y_hat', 'y'])
plt.title('Polynomial Regression deg=3, Testing Data - MAE ' + str(metrics.
↪mean_absolute_error(original_y, unscaled)), fontsize=15)
filename = 'results/polynomial_' + 'window_'+ str(window_setting) +␣
↪'lag_'+str(lag_length)+'_test.png'
#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y, unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y, unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
↪mean_squared_error(original_y, unscaled)))

results = pd.DataFrame({'y_test': original_y, 'y_pred_unscaled': unscaled})
```

```
results['error'] = results['y_test'] - results['y_pred_unscaled']



plt.plot(y_pred_train_unscaled)
plt.plot(original_y_train)
plt.legend(['y_hat', 'y'])
plt.title('Polynomial Regression deg=3, Training Data - MAE '+ str(metrics.
 ↪mean_absolute_error(original_y_train, y_pred_train_unscaled)), fontsize=15)
filename = 'results/polynomial_' + 'window_'+ str(window_setting) +␣
 ↪'lag_'+str(lag_length)+'_train.png'

#plt.savefig(filename)
plt.show()

print('Mean Absolute Error:', metrics.mean_absolute_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Mean Squared Error:', metrics.mean_squared_error(original_y_train,␣
 ↪y_pred_train_unscaled))
print('Root Mean Squared Error:', np.sqrt(metrics.
 ↪mean_squared_error(original_y_train, y_pred_train_unscaled)))
```




```
Mean Absolute Error: 1264.1516329231376
```

```
Mean Squared Error: 2543648.9721006383
Root Mean Squared Error: 1594.882118559437
```




```
Mean Absolute Error: 7074.6374805570695
Mean Squared Error: 84440250.35487752
Root Mean Squared Error: 9189.137628465334
```

[45]:

```
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true))*100

def root_mean_squared_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.sqrt(((y_pred - y_true) **2).mean())
    #return np.mean(np.abs((y_true - y_pred) / y_true))*100
```

[47]:

```
print('mape', mean_absolute_percentage_error(cmp_df['y'], cmp_df['yhat']))

print('rmse', root_mean_squared_error(cmp_df['y'], cmp_df['yhat']))
```

```
mape 219.83967767924054
rmse 0.05529372373011725
```