Exploring s&p500 stocks

Angelo Menezes

Saulo Mastellini

Overview

Statistical and Machine Learning approaches

Let's import some useful libraries and a script with simple functions to be used ¶

In [1]:

```
import sys
sys.path.append('../')
from utils import *
```

Reading data from a csv and getting some statistics

In [2]:

```
dataset_1yr = pd.read_csv("../../Data/all_stocks_5yr.csv")
dataset_1yr.head()

# Changing the date column to the datetime format (best format to work with time serie
s)
dataset_1yr['Date'] = [dt.datetime.strptime(d,'%Y-%m-%d').date() for d in dataset_1yr[
'Date']]

dataset_1yr.head()
```

Out[2]:

	Date	Open	High	Low	Close	Volume	Name
0	2012-08-13	92.29	92.59	91.74	92.40	2075391.0	MMM
1	2012-08-14	92.36	92.50	92.01	92.30	1843476.0	MMM
2	2012-08-15	92.00	92.74	91.94	92.54	1983395.0	MMM
3	2012-08-16	92.75	93.87	92.21	93.74	3395145.0	MMM
4	2012-08-17	93.93	94.30	93.59	94.24	3069513.0	MMM

In [3]:

```
dataset_1yr.describe()
```

Out[3]:

	Open	High	Low	Close	Volume
count	606417.000000	606593.000000	606574.000000	606801.000000	6.063950e+05
mean	79.529041	80.257435	78.799338	79.557920	4.500925e+06
std	93.383162	94.187977	92.535300	93.382168	9.336171e+06
min	1.620000	1.690000	1.500000	1.590000	0.000000e+00
25%	38.070000	38.460000	37.700000	38.090000	1.077091e+06
50%	59.240000	59.790000	58.690000	59.270000	2.131913e+06
75%	89.390000	90.150000	88.620000	89.430000	4.442768e+06
max	2044.000000	2067.990000	2035.110000	2049.000000	6.182376e+08

In [4]:

```
stocknames = dataset_1yr.Name.unique()
stocknames = np.sort(stocknames, kind='quicksort')
print(stocknames[:20])
```

```
['A' 'AAL' 'AAP' 'AAPL' 'ABBV' 'ABC' 'ABT' 'ACN' 'ADBE' 'ADI' 'ADM' 'ADP'
 'ADS' 'ADSK' 'AEE' 'AEP' 'AES' 'AET' 'AFL' 'AGN']
```

Getting rid of null rows

In [4]:

```
missing_data = pd.DataFrame(dataset_1yr.isnull().sum()).T
print(missing_data)

for index, column in enumerate(missing_data.columns):
    if missing_data.loc[0][index] != 0:
        dataset_1yr = dataset_1yr.drop(dataset_1yr.loc[dataset_1yr[column].isnull()].in
dex)

missing_data = pd.DataFrame(dataset_1yr.isnull().sum()).T
print(missing_data)
```

```
   Date  Open  High  Low  Close  Volume  Name
0     0   384   208  227      0     406     0
   Date  Open  High  Low  Close  Volume  Name
0     0     0     0    0      0       0     0
```

Assigning a mid price column with the mean of the Highest and Lowest values

In [5]:

```
dataset_1yr['Mid'] = (dataset_1yr['High'] + dataset_1yr['Low'])/2
dataset_1yr.head()
```

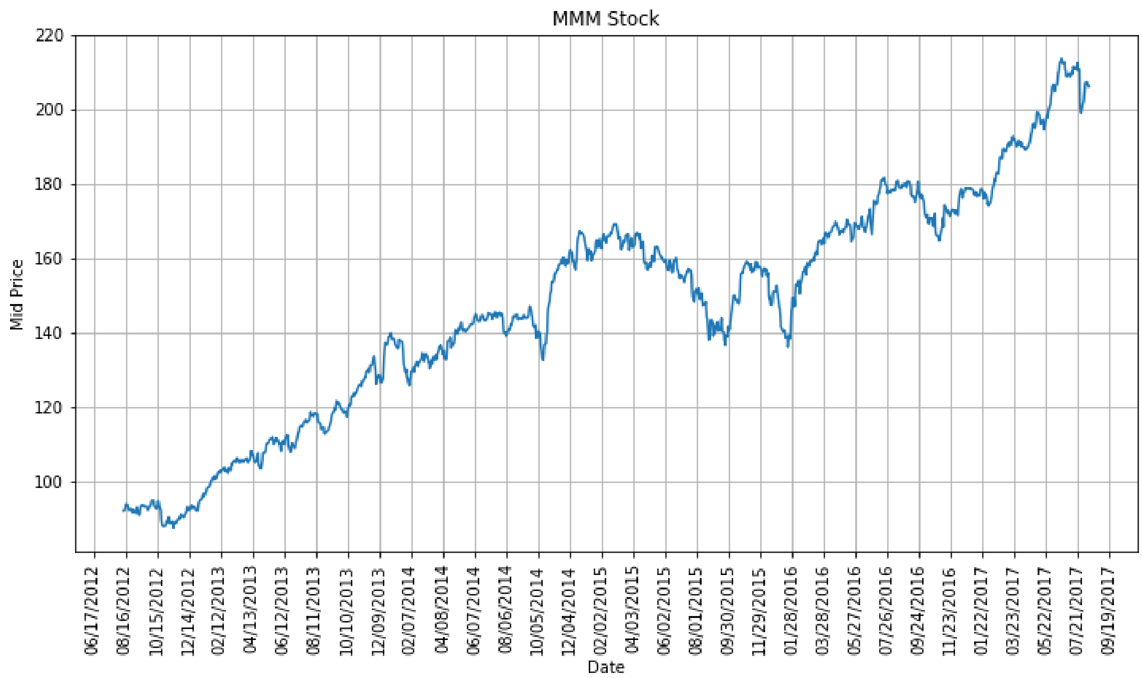
Out[5]:

	Date	Open	High	Low	Close	Volume	Name	Mid
0	2012-08-13	92.29	92.59	91.74	92.40	2075391.0	MMM	92.165
1	2012-08-14	92.36	92.50	92.01	92.30	1843476.0	MMM	92.255
2	2012-08-15	92.00	92.74	91.94	92.54	1983395.0	MMM	92.340
3	2012-08-16	92.75	93.87	92.21	93.74	3395145.0	MMM	93.040
4	2012-08-17	93.93	94.30	93.59	94.24	3069513.0	MMM	93.945

Let's see the behaviour of a popular stock "3M"

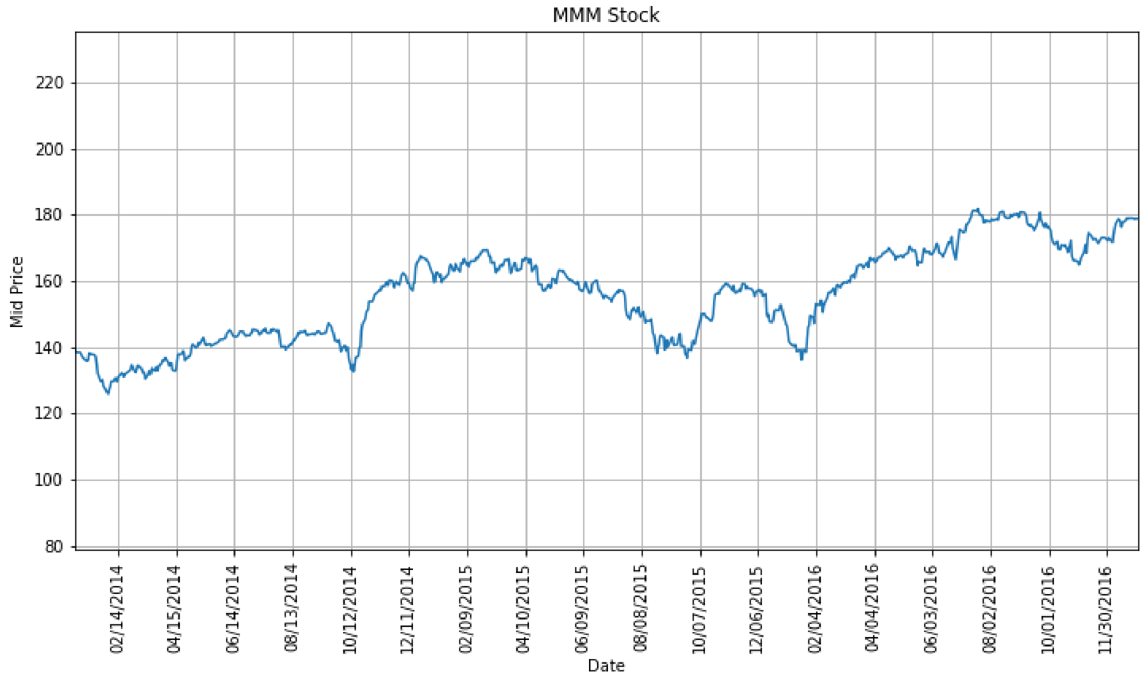
In [6]:

```
fig1 = simple_plot(dataset_1yr, 'MMM', 'Mid')
#plt.savefig('stock.pdf')
```



In [7]:

```
simple_plot_by_date(dataset_1yr, 'MMM', 'Mid', '2014-01-01', '2017-01-01')
#plt.savefig('stock.pdf')
```



Now let's analyze 3M stocks a bit deeper

In [8]:

```
MMM_stocks = dataset_1yr[dataset_1yr['Name'] == 'MMM']

MMM_stocks.head()
```

Out[8]:

	Date	Open	High	Low	Close	Volume	Name	Mid
0	2012-08-13	92.29	92.59	91.74	92.40	2075391.0	MMM	92.165
1	2012-08-14	92.36	92.50	92.01	92.30	1843476.0	MMM	92.255
2	2012-08-15	92.00	92.74	91.94	92.54	1983395.0	MMM	92.340
3	2012-08-16	92.75	93.87	92.21	93.74	3395145.0	MMM	93.040
4	2012-08-17	93.93	94.30	93.59	94.24	3069513.0	MMM	93.945

Creating a percent change column related to the closing price

In [9]:

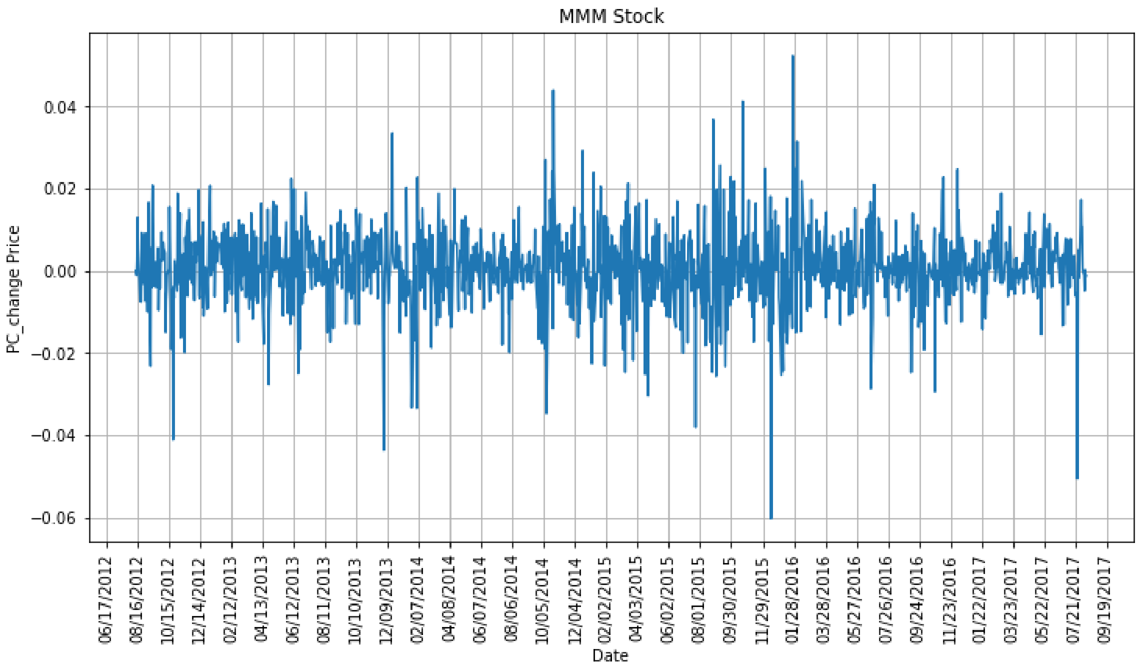
```
percent_change_closing_price = MMM_stocks['Close'].pct_change()
percent_change_closing_price.fillna(0, inplace=True)

MMM_stocks['PC_change'] = pd.DataFrame(percent_change_closing_price)
MMM_stocks.head()
```

Out[9]:

	Date	Open	High	Low	Close	Volume	Name	Mid	PC_change
0	2012-08-13	92.29	92.59	91.74	92.40	2075391.0	MMM	92.165	0.000000
1	2012-08-14	92.36	92.50	92.01	92.30	1843476.0	MMM	92.255	-0.001082
2	2012-08-15	92.00	92.74	91.94	92.54	1983395.0	MMM	92.340	0.002600
3	2012-08-16	92.75	93.87	92.21	93.74	3395145.0	MMM	93.040	0.012967
4	2012-08-17	93.93	94.30	93.59	94.24	3069513.0	MMM	93.945	0.005334

In [10]:

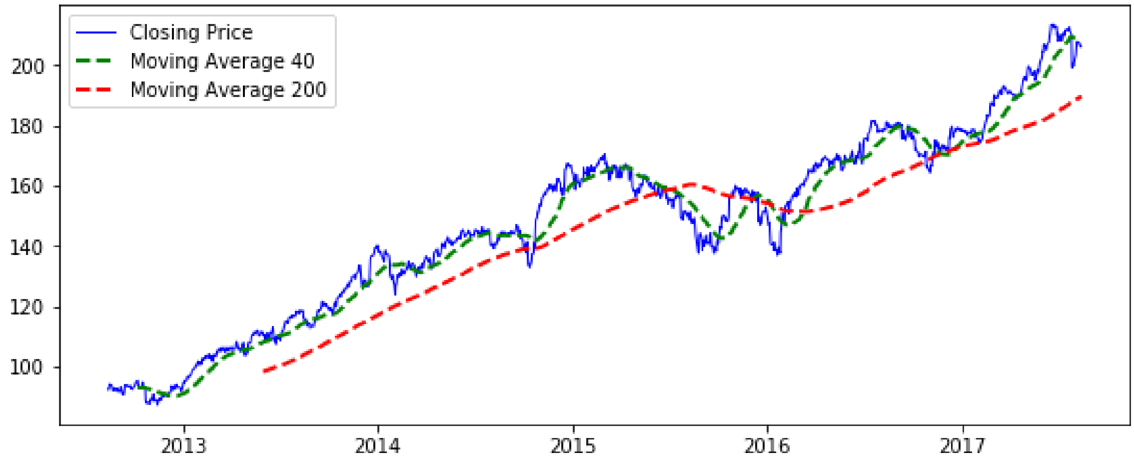
```
simple_plot(MMM_stocks, 'MMM', 'PC_change')
```



Since we will attempt to predict the closing price, let's take a look at how a rolling average window behaves in its data

In [14]:

```
closing_price = MMM_stocks['Close']
moving_avg_40 = closing_price.rolling(window=40).mean()
moving_avg_200 = closing_price.rolling(window=200).mean()
plt.figure(figsize=(10,4))
df = pd.DataFrame({'x': MMM_stocks['Date'] , 'y0': MMM_stocks['Close'], 'y1': moving_av
g_40, 'y2': moving_avg_200})
plt.plot( 'x', 'y0', data=df, marker='', color='blue', linewidth=1, label = "Closing Pr
ice")
plt.plot( 'x', 'y1', data=df, marker='', color='green', linewidth=2, linestyle='dashed'
, label = "Moving Average 40")
plt.plot( 'x', 'y2', data=df, marker='', color='red', linewidth=2, linestyle='dashed',
label="Moving Average 200")
plt.legend()
plt.show()
```



Experiments related to a more statistical approach for predicting the next closing price:

Methods:

- Moving Average

- Single Exponential Smoothing Average

- ARIMA

Experiments:

- Experiment 1: Horizon = 1

- Experiment 2: Horizon = 5

- Experiment 3: Horizon = 5 using predictions as baseline

Metrics used for evaluation:

- MSE

- MAE

- RMSE

- Hit Count

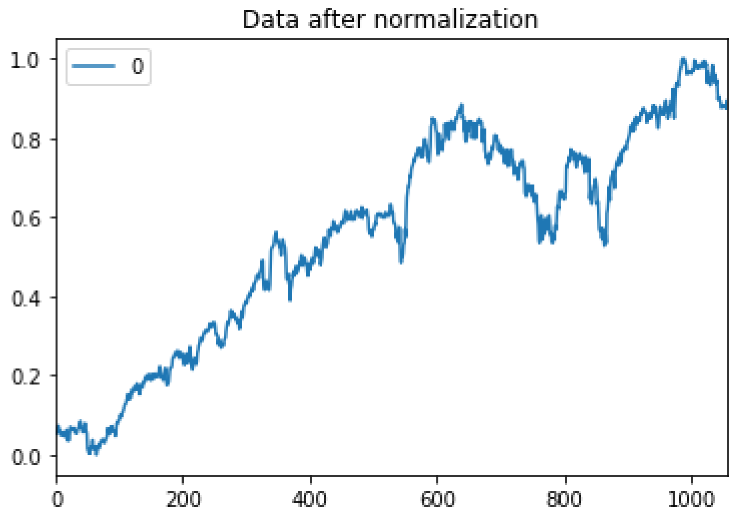
In [15]:

```
from sklearn.preprocessing import MinMaxScaler # It scales the data between 0 and 1

# Let's apply some models to predict closing prices
# Total of samples = 1257

#training_size = int(closing_price.shape[0]*0.9)
training_size = 1057

train_data = np.array(closing_price[:training_size])
test_data = np.array(closing_price[training_size:])

print(train_data.shape)
print(test_data.shape)
```

```
(1057,)
(200,)
```

In [16]:

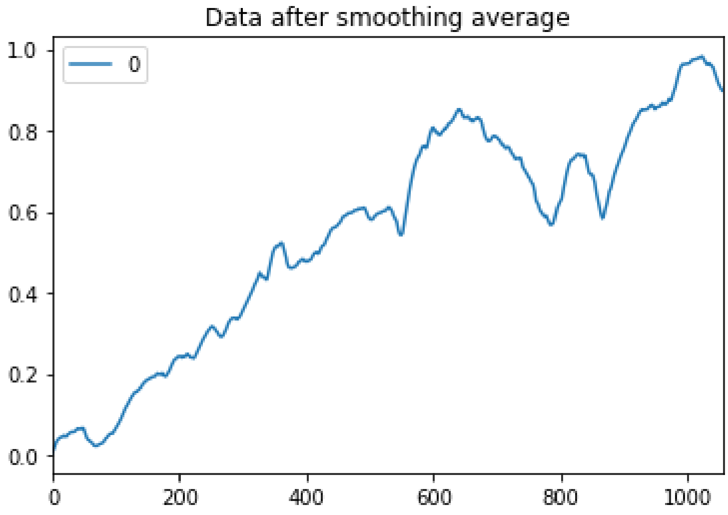
```
train_data = train_data.reshape(-1,1)
test_data = test_data.reshape(-1,1)
scaler = MinMaxScaler()
scaler.fit(train_data)
train_data = scaler.transform(train_data)
test_data = scaler.transform(test_data)
# Reshape both train and test data
train_data = train_data.reshape(-1)
test_data = test_data.reshape(-1)
pd.DataFrame(train_data).plot()
plt.title("Data after normalization")
plt.show()
```



Performing exponential moving average smoothing, so the data will have a smoother curve than the original ragged data

In [17]:

```
EMA = 0.0
gamma = 0.1
for ti in range(len(train_data)):
    EMA = gamma*train_data[ti] + (1-gamma)*EMA
    train_data[ti] = EMA

pd.DataFrame(train_data).plot()
plt.title("Data after smoothing average")
plt.show()

# Used for visualization and test purposes
all_mid_data = scaler.inverse_transform(np.concatenate([train_data,test_data],axis=0).r
eshape(-1,1))
```



Experiment 1 (a): Moving Average applied to training data for window length evaluation

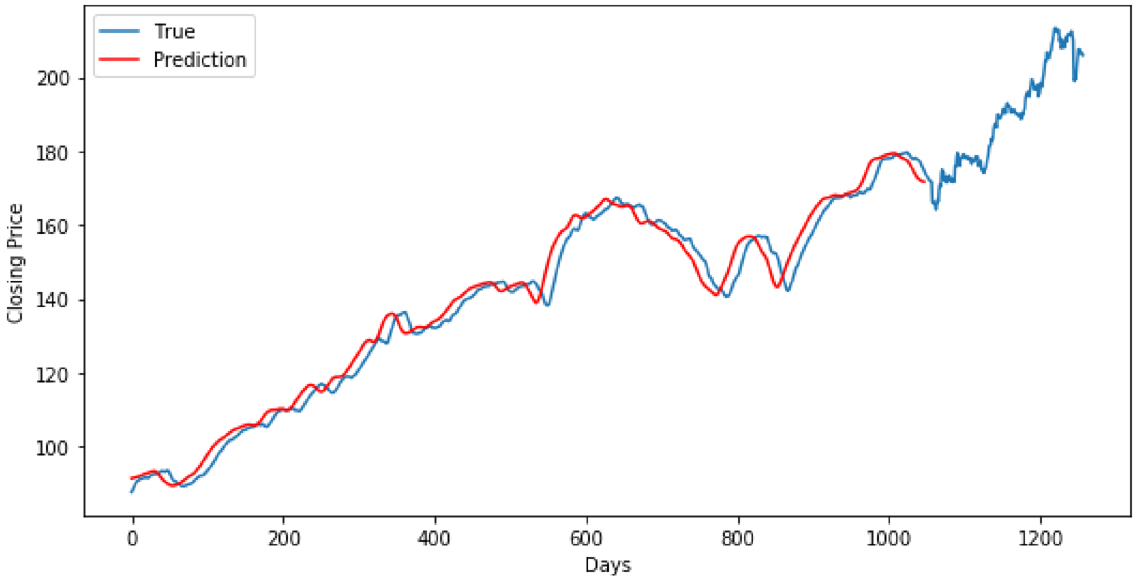
In [23]:

```
from sklearn.metrics import mean_squared_error, mean_absolute_error

window_size = 10
predictions = list()

def moving_window_average(data, window_len):
    mov_avg_prediction = np.mean(data[-window_len:])
    return mov_avg_prediction

for timepoint in range(window_size, train_data.size):
    ActualValue = train_data[timepoint]
    forecast = moving_window_average(train_data[timepoint:window_size+timepoint], windo
w_size)
    predictions.append(forecast)

horizon_predicted = np.array(predictions).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = train_data[window_size:].reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [24]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
plt.figure(figsize = (10,5))
plt.plot(range(MMM_stocks.shape[0]),all_mid_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 1.583224
Mean Absolute Error (Testing Data): 0.971164
Root Mean Squared Error (Testing Data): 1.258262
```



Experiment 1 (b): Moving Average - Prediction of the "Future" with testing points (Horizon = 1)

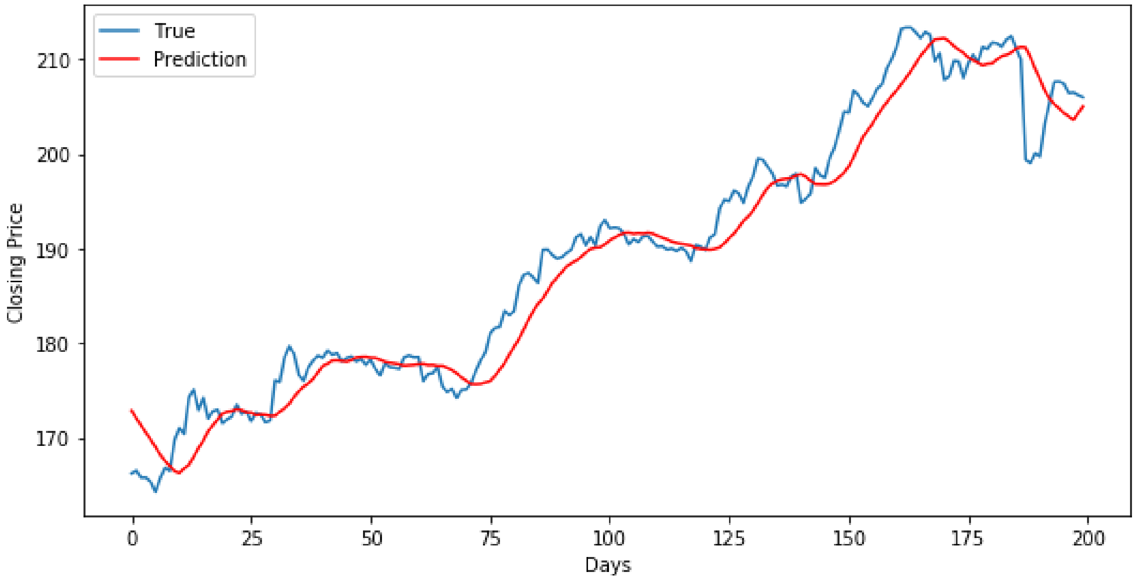
In [25]:

```
window_size = 10
Actual = [x for x in train_data]
predictions = list()

for timepoint in range(len(test_data)):
    ActualValue =  test_data[timepoint]
    forecast = moving_window_average(Actual, window_size)
    #print('Actual=%f, Predicted=%f' % (ActualValue, Prediction))
    predictions.append(forecast)
    Actual.append(ActualValue)

horizon_predicted = np.array(predictions).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = test_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [26]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 10.082745
Mean Absolute Error (Testing Data): 2.389065
Root Mean Squared Error (Testing Data): 3.175334
Number of Hits 104 out of 199
```



Experiment 2: Moving Average - Prediction of the "Future" with testing points (Horizon = 5)

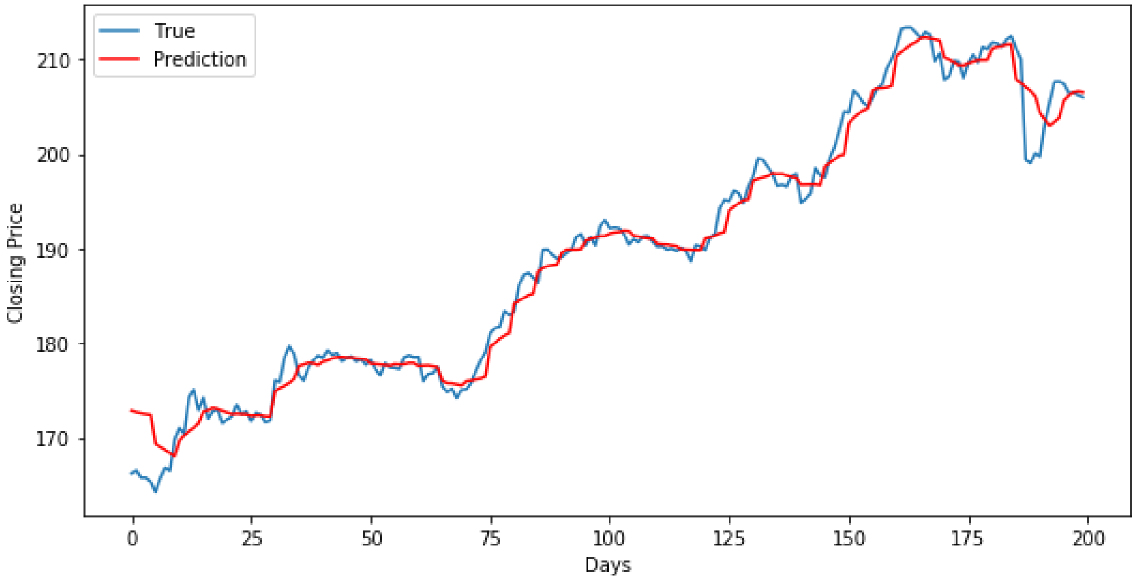
In [29]:

```
window_size = 10
Horizon = 5
Actual = [x for x in train_data]
horizon_predicted = list()
counter = 0

for _ in range(int(len(test_data)/Horizon)):
    for i in range(Horizon):
        forecast = moving_window_average(Actual, window_size)
        Actual.append(forecast)
        horizon_predicted.append(forecast)
        counter = counter + 1

    Actual = Actual[Horizon:-Horizon]
    [Actual.append(term) for term in test_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = test_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [30]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 4.100142
Mean Absolute Error (Testing Data): 1.355498
Root Mean Squared Error (Testing Data): 2.024881
Number of Hits 116 out of 199
```



Experiment 3: Moving Average - Prediction of the "Future" for the last 1030 points (Horizon = 5)

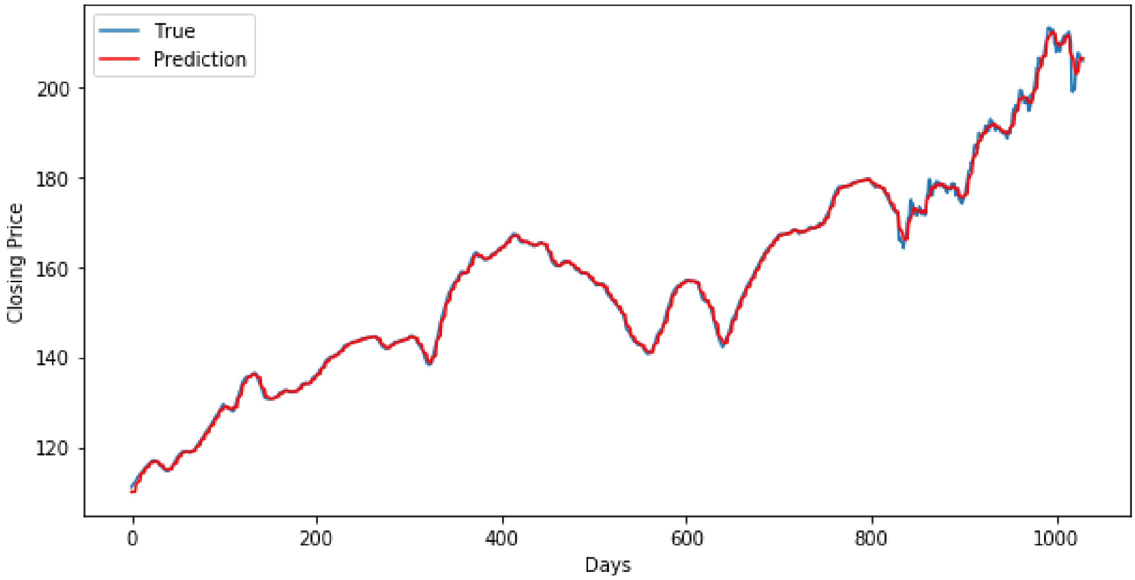
In [31]:

```
window_size = 10
Horizon = 5
Actual = [x for x in train_data[:227]]
horizon_predicted = list()
counter = 0
evaluation_data = np.concatenate([train_data[227:], test_data], axis=0)

for _ in range(int(len(evaluation_data)/Horizon)):
    for i in range(Horizon):
        forecast = moving_window_average(Actual, window_size)
        Actual.append(forecast)
        horizon_predicted.append(forecast)
        counter = counter + 1

    Actual = Actual[Horizon:-Horizon]
    [Actual.append(term) for term in evaluation_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = evaluation_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [32]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 0.911870
Mean Absolute Error (Testing Data): 0.611875
Root Mean Squared Error (Testing Data): 0.954919
Number of Hits 822 out of 1029
```



Experiment 1 (a): Exponential Smoothing Average applied to training data for smoothig constant evaluation

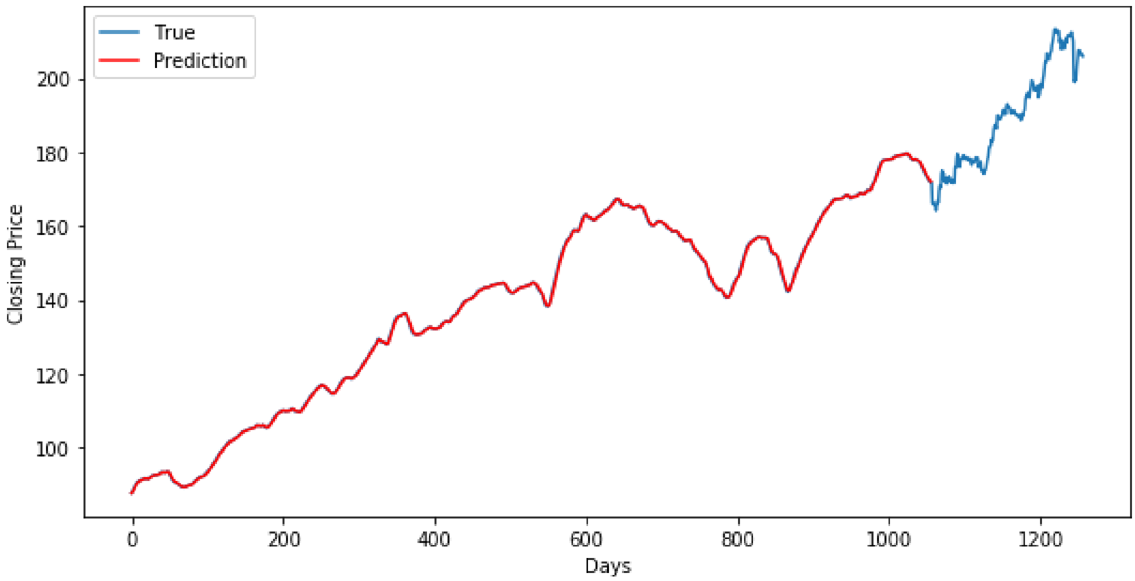
In [33]:

```
smoothing_constant = 0.5

predictions = list()
last_prediction = train_data[0]

for timepoint in range(1, train_data.size):
    last_prediction = last_prediction * smoothing_constant + (1.0 - smoothing_constant)
* train_data[timepoint-1]
    predictions.append(last_prediction)

horizon_predicted = np.array(predictions).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = train_data[1:].reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [34]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)

plt.figure(figsize = (10,5))
plt.plot(range(MMM_stocks.shape[0]),all_mid_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 0.350709
Mean Absolute Error (Testing Data): 0.459215
Root Mean Squared Error (Testing Data): 0.592207
```



Experiment 1 (b): Exponential Smoothing Average - Prediction of the "Future" with testing points (Horizon = 1)

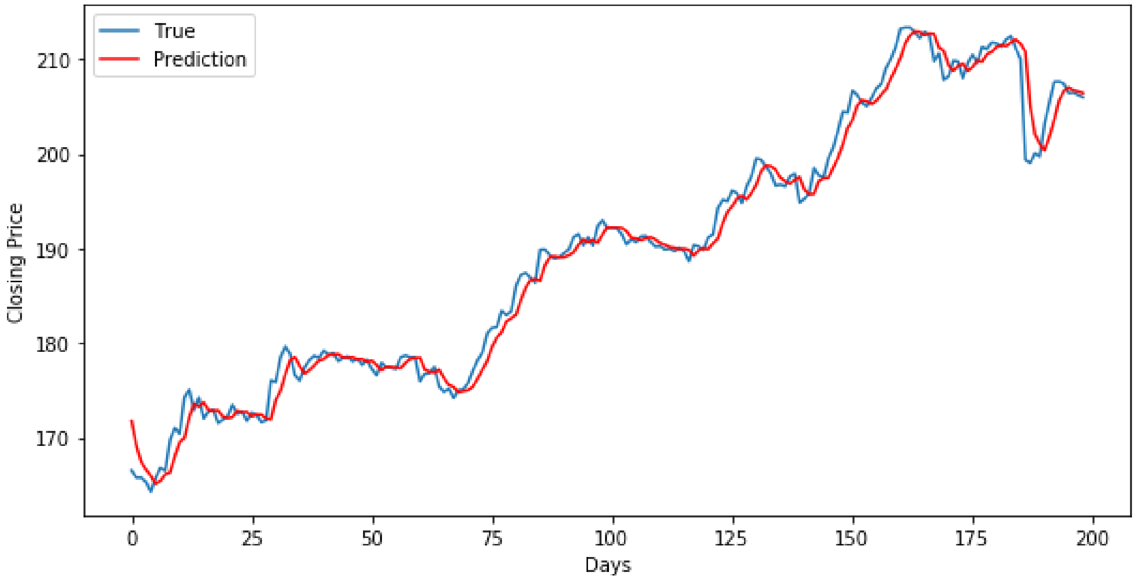
In [35]:

```
smoothing_constant = 0.5

Actual = [train_data[-1:]]
predictions = list()
last_prediction = train_data[-1]

for timepoint in range(1, len(test_data)):
    ActualValue =  test_data[timepoint]
    last_prediction = last_prediction * smoothing_constant + (1.0 - smoothing_constant)
* Actual[timepoint-1]
    predictions.append(last_prediction)
    Actual.append(ActualValue)

horizon_predicted = np.array(predictions).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = test_data[1:].reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [36]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 3.246290
Mean Absolute Error (Testing Data): 1.241121
Root Mean Squared Error (Testing Data): 1.801746
Number of Hits 89 out of 198
```



Experiment 2: Exponential Smoothing Average - Prediction of the "Future" with testing points (Horizon = 5)

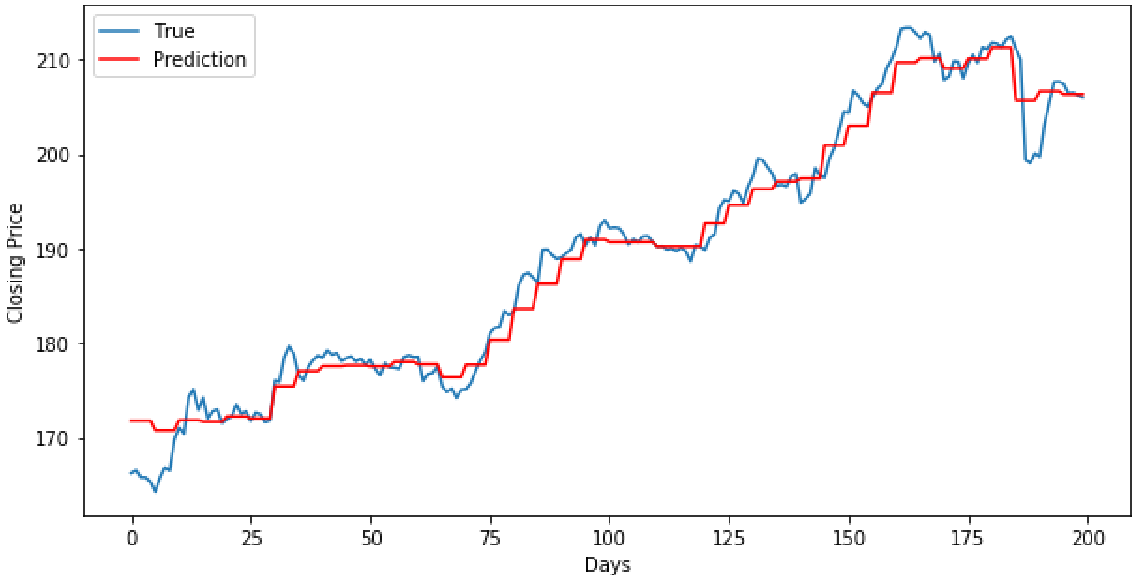
In [37]:

```
smoothing_constant = 0.5
Horizon = 5
Actual = [train_data[-1:]]
horizon_predicted = list()
counter = 0
last_prediction = float(train_data[-1:])

for _ in range(int(len(test_data)/Horizon)):
    for i in range(Horizon):
        last_prediction = last_prediction * smoothing_constant + (1.0 - smoothing_const
ant) * Actual[-1]
        Actual.append(last_prediction)
        horizon_predicted.append(last_prediction)
        counter = counter + 1

    Actual = Actual[:-Horizon]
    [Actual.append(term) for term in test_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = test_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [38]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 5.019785
Mean Absolute Error (Testing Data): 1.612379
Root Mean Squared Error (Testing Data): 2.240488
Number of Hits 23 out of 199
```



Experiment 3: Exponential Smoothing Average - Prediction of the "Future" for the last 1030 points (Horizon = 5)

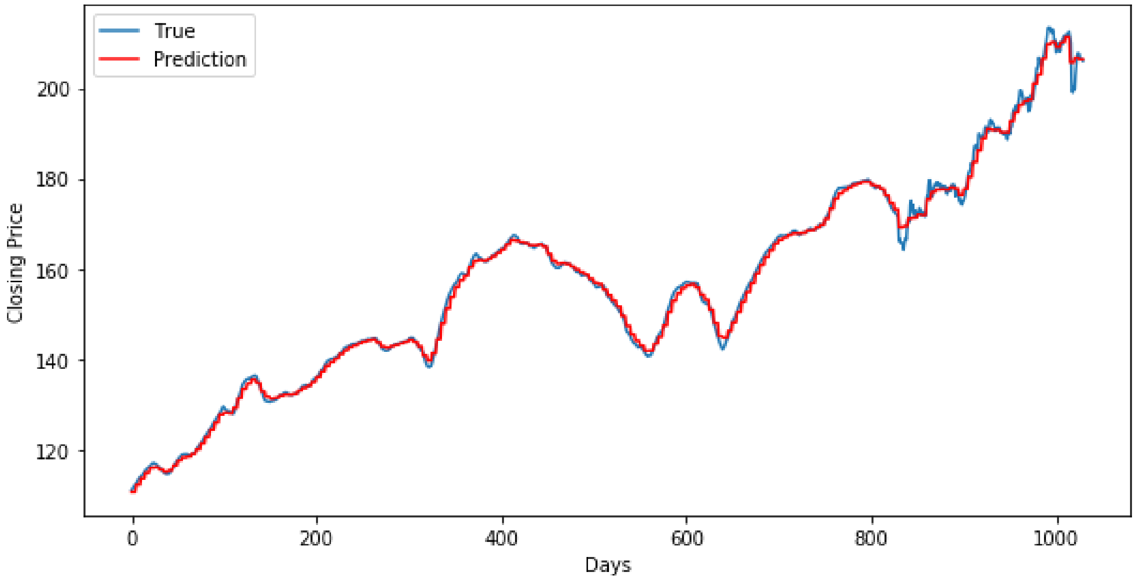
In [39]:

```
smoothing_constant = 0.5
Horizon = 5
Actual = [x for x in train_data[226:227]]
horizon_predicted = list()
counter = 0
evaluation_data = np.concatenate([train_data[227:], test_data], axis=0)
last_prediction = float(train_data[226:227])

for _ in range(int(len(evaluation_data)/Horizon)):
    for i in range(Horizon):
        last_prediction = last_prediction * smoothing_constant + (1.0 - smoothing_const
ant) * Actual[-1]
        Actual.append(last_prediction)
        horizon_predicted.append(last_prediction)
        counter = counter + 1

    Actual = Actual[:-Horizon]
    [Actual.append(term) for term in evaluation_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = evaluation_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

In [40]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 1.520639
Mean Absolute Error (Testing Data): 0.868128
Root Mean Squared Error (Testing Data): 1.233142
Number of Hits 168 out of 1029
```



Experiment 1: ARIMA - Prediction of the "Future" with testing points (Horizon = 1)

In [47]:

```
# Parameters
# p: The number of lag observations included in the model, also called the lag order.
# d: The number of times that the raw observations are differenced, also called the deg
ree of differencing.
# q: The size of the moving average window, also called the order of moving average.
# -> Follow the Box-Jenkins Methodology to find optimal parameters.


#pd.plotting.autocorrelation_plot(pd.DataFrame(train_data))
#plt.show()
```

In [48]:

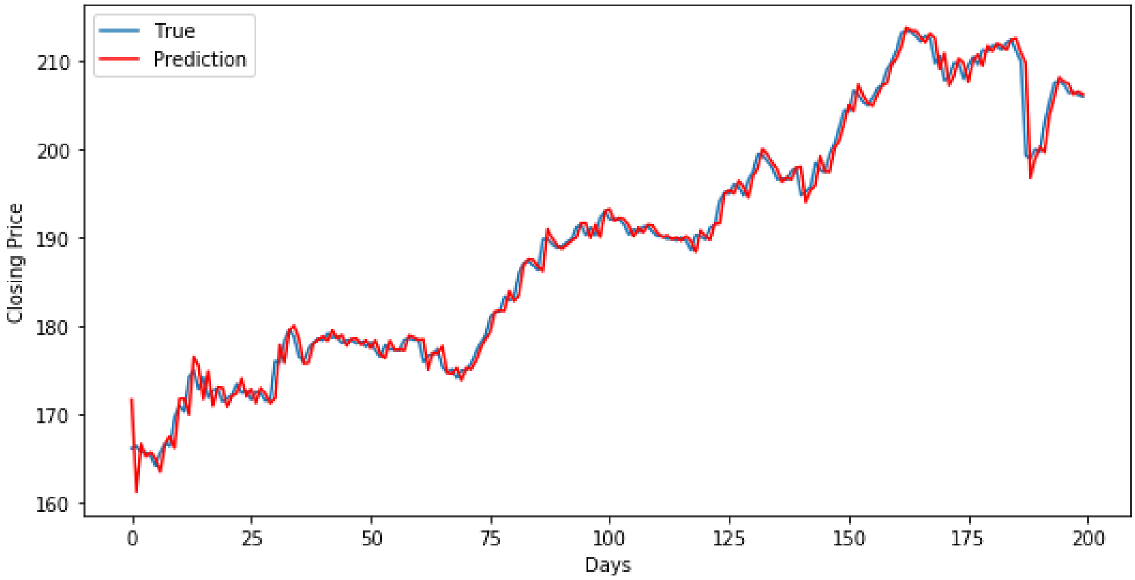
```
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error

def StartARIMAForecasting(Actual, P, D, Q):
    model = ARIMA(Actual, order=(P, D, Q))
    model_fit = model.fit(disp=0)
    prediction = model_fit.forecast()[0]
    return prediction

Actual = [x for x in train_data]
predictions = list()

for timepoint in range(len(test_data)):
    ActualValue =  test_data[timepoint]
    Prediction = StartARIMAForecasting(Actual, 1,1,0)
    predictions.append(Prediction)
    Actual.append(ActualValue)

horizon_predicted = np.array(predictions).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)
inverse_test_data = test_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

```
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

In [49]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 2.482735
Mean Absolute Error (Testing Data): 1.077683
Root Mean Squared Error (Testing Data): 1.575670
Number of Hits 94 out of 199
```



Experiment 2: ARIMA - Prediction of the "Future" with testing points (Horizon = 1)

In [43]:

```
# ARIMA (Horizon = 5)

Horizon = 5
Actual = [x for x in train_data]
horizon_predicted = list()
counter = 0

for _ in range(int(len(test_data)/Horizon)):
    for i in range(Horizon):
        forecast = StartARIMAForecasting(Actual, 1,1,0)
        Actual.append(forecast)
        horizon_predicted.append(forecast)
        counter = counter + 1

    Actual = Actual[Horizon:-Horizon]
    [Actual.append(term) for term in test_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = test_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

```
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
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  "Check mle_retvals", ConvergenceWarning)
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```
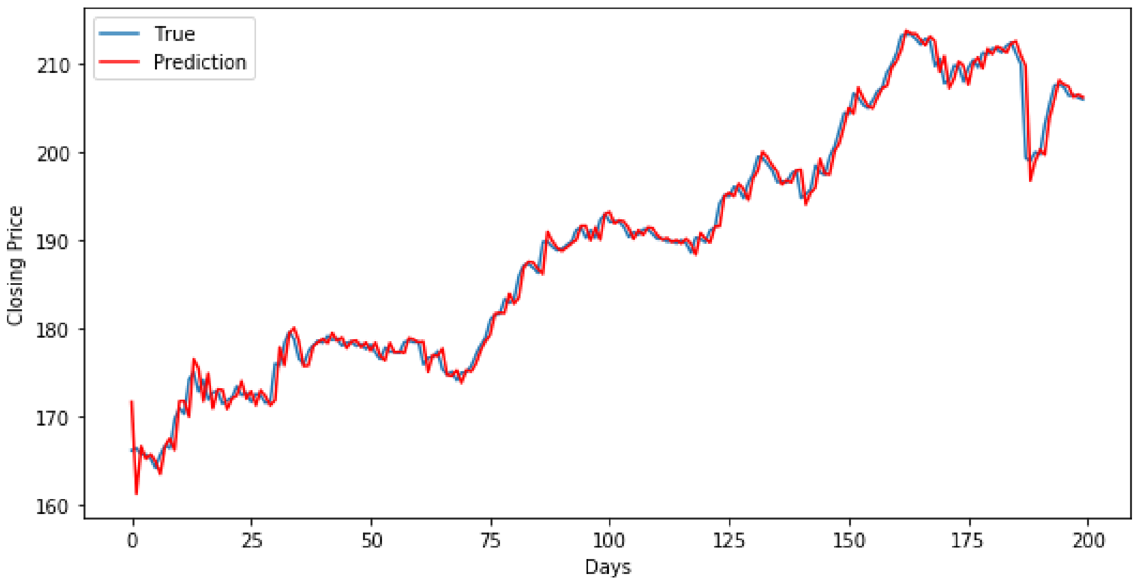

In [50]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 2.482735
Mean Absolute Error (Testing Data): 1.077683
Root Mean Squared Error (Testing Data): 1.575670
Number of Hits 94 out of 199
```



Experiment 3: ARIMA - Prediction of the "Future" for the last 1030 points (Horizon = 5)

In [45]:

```
Horizon = 5
Actual = [x for x in train_data[:227]]
horizon_predicted = list()
counter = 0
evaluation_data = np.concatenate([train_data[227:], test_data], axis=0)

for _ in range(int(len(evaluation_data)/Horizon)):
    for i in range(Horizon):
        forecast = StartARIMAForecasting(Actual, 1,1,0)
        Actual.append(forecast)
        horizon_predicted.append(forecast)
        counter = counter + 1

    Actual = Actual[Horizon:-Horizon]
    [Actual.append(term) for term in evaluation_data[counter:counter+Horizon]]

horizon_predicted = np.array(horizon_predicted).reshape(-1,1)
horizon_predicted = scaler.inverse_transform(horizon_predicted)

inverse_test_data = evaluation_data.reshape(-1,1)
inverse_test_data = scaler.inverse_transform(inverse_test_data)

MSE = mean_squared_error(inverse_test_data, horizon_predicted)
MAE = mean_absolute_error(inverse_test_data, horizon_predicted)
RMSE = np.sqrt(MSE)
```

```
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
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C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
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C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
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  "Check mle_retvals", ConvergenceWarning)
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  "Check mle_retvals", ConvergenceWarning)
C:\Users\IBK1000\Anaconda3\envs\finance_class\lib\site-packages\statsmodel
s\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```
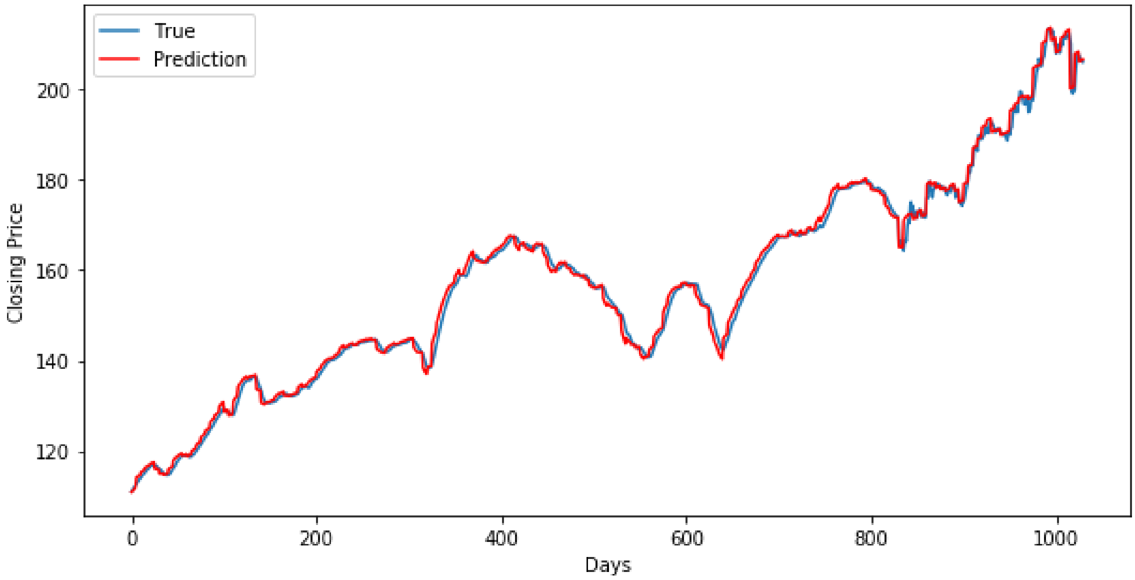

In [46]:

```
print('Mean Squared Error (Testing Data): %.6f' % MSE)
print('Mean Absolute Error (Testing Data): %.6f' % MAE)
print('Root Mean Squared Error (Testing Data): %.6f' % RMSE)
print("Number of Hits %d out of %d" % (hit_count(inverse_test_data, horizon_predicted),
len(horizon_predicted)-1))
plt.figure(figsize = (10,5))
plt.plot(inverse_test_data, label='True')
plt.plot(horizon_predicted, color='red', label='Prediction')
plt.xlabel('Days')
plt.ylabel('Closing Price')
plt.legend(fontsize=10)
plt.show()
```

```
Mean Squared Error (Testing Data): 2.508663
Mean Absolute Error (Testing Data): 1.147877
Root Mean Squared Error (Testing Data): 1.583876
Number of Hits 791 out of 1029
```



Future Work:

- Generalized regression neural networks - "Convergent time-varying regression models for data streams"

- Long-short term memory networks (LSTM)

- Echo-state networks (ESN)

- Adapted WaveNet