Davide Modolo - final 'AI for Finance' project

Is AI suitable for forecasting stock prices?

Introduction

The first thing that comes to my mind when I hear 'Artificial Intelligence' and 'Finance' in the same sentence, is the idea of forecasting stock prices using AI (as deep learning algorithms). I wanted to try it myself to predict the **following day average price**.

I decided to use Ordinary Least Squares as baseline econometric method and I built a Neural Network from scratch that could get comparable result in relation to the ones OLS was giving and study their difference.

I also wanted to include some *Sentiment Analysis* value in the forecasting, using a pretrained Natural Language Understanding model.

Forecasting Models

Ordinary Least Squares

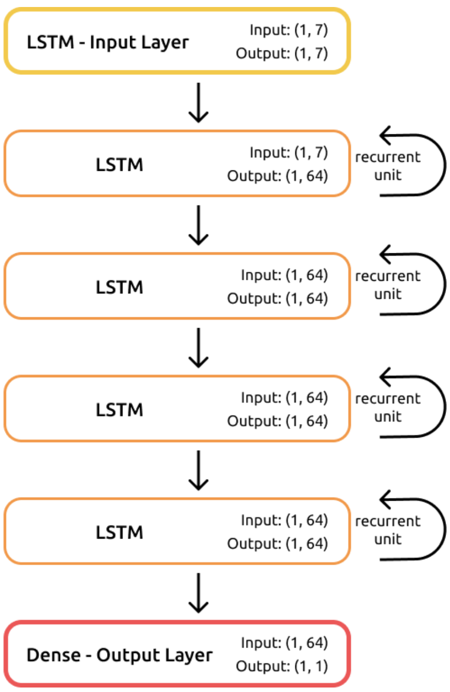
I used the `statsmodels API` implementation of OLS, a common technique to estimate coefficients of a linear regression equation with one or more explanatory variables `x` and one independent variable `y`. It's a mathematic method that, with the same implementation, from the same data gives the same result every time (contrarily to neural networks that have some random/stochastic factor in the training phase).

Neural Network

Using `Tensorflow` and `Keras` I built a Recurrent Neural Network using four *LSTM* (Long Short-Term Memory) layers that can keep a buffer of past information to make a prediction; since we are talking about time series, it happened to be the right use-case.

I tried dozens of architectures, adding and removing *Dense* or *Dropout* layers, but with the final architecture(the picture on the right) I got quite good results.

And even with this, results vary much depending on the stock analyzed. I also tried pre-built models but I wasn't getting any valuable improvement so I decided to stick to my version.



Data

Data taken from Refinitiv Eikon APIs database with Python.

Data retrieval

Due to APIs limitations, the maximum number of news headlines per request is 100.

Since I wanted to get news headlines for each of the n day in order to perform a **Sentiment Analysis** task, I had to make n different requests. Regarding numerical data, fortunately it was possible to make one request for the entire time period.

Regarding the time period, I've been forced to use only the last fifteen months since Eikon APIs didn't allow me to get news headlines before 1st April 2021. This could bring up problems like overfitting, but I'll discuss this in the conclusion part.

Data cleaning

First of all, explanatory variables for the regression are: open price, close price, highest price, lowest price, volume, count and sentiment value. I computed the average price doing $(\text{OPEN} + \text{CLOSE})/2$ and I shifted it by one day getting the dependent variable. My goal was to predict the **following day average price**.

Then, using the news headlines provided by the APIs, I run the **SentimentIntensityAnalyzer** model given by the `NLTK` library. It returns four values: `[negative, neutral, positive, compound]` as percentages, and I used a modified sign function (with a threshold) to get the overall sentiment from every day:

$$\text{sign}(x) = \begin{cases} 0 & \text{if } -t \leq x \geq t \\ 1 & \text{if } x > t \\ -1 & \text{if } x < -t \end{cases} \qquad \text{given a positive small number } t$$

And the entire Sentiment Analysis function, that gives the *sentiment* value for a day n given a set of titles of that day $\text{titles}_{\text{day}_n}$, becomes:

$$\text{sentiment}_{\text{day}_n} = \sum^{\text{titles}_{\text{day}_n}} \text{sign}(\text{compound}(\text{title}))$$

The ending list of independent variables is: open, close, high, low, volume, count, sentiment.

Talking about missing data (for example when market are closed or in any other case that data was not available), I decided to not fill the gaps since Machine Learning is highly sensitive to bad quality input data, and synthetic data is obviously not perfect, and I kept the same dataset for OLS to be able to fairly compare results.

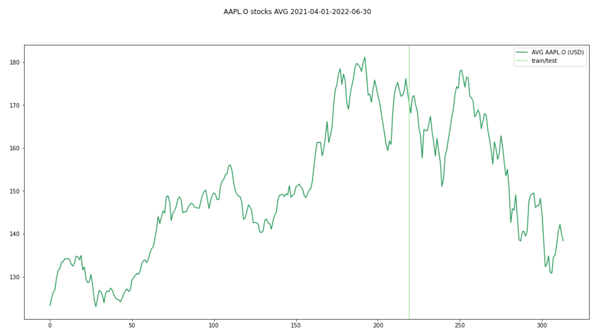
For the training part of my NN, I scaled the data between 0 and 1, and regarding OLS that needs stationary data, I tried scaling the data also for that. I was getting almost the same parameters values (the only noticeable difference was in the constant value), but it would bring some problems in the code. Results in the **Econometric Analysis** paragraph are result of scaled data, but in the *appendix* code, data will be unscaled for OLS.

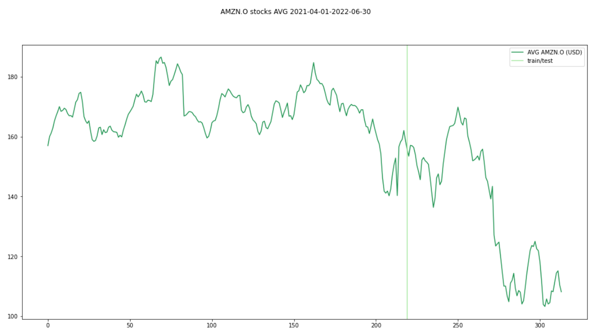
Predictions are then *shifted* in order to better compare them with real values.

Analysis

I'll use as example Apple and Amazon stocks as they have similar R-squared values and a 5-years beta similar too (1.21 and 1.25) (and more can be found in the *appendix*).

First this we can see is that, even if they are quite unstable, we can clearly notice that Apple has more 'seasonality', where Amazon unfortunately has almost a different trend between the part I encoded as train and the part I encoded as test. Maybe addressable changing the memory size of *LSTM* layers but I wasn't able to get important differences in my tries.





Econometric Analysis

```
Apple
                    Results: Ordinary least squares
=====================================================================
Model:              OLS              Adj. R-squared:     0.991
Dependent Variable: AVG_TOMORROW     AIC:                -959.1764
Date:               2022-07-10 18:19 BIC:                -932.0638
No. Observations:   219              Log-Likelihood:     487.59
Df Model:           7                F-statistic:        3291.
Df Residuals:       211              Prob (F-statistic): 1.29e-211
R-squared:          0.991            Scale:              0.00070768
----------------------------------------------------------------------
              Coef.   Std.Err.     t      P>|t|    [0.025    0.975]
----------------------------------------------------------------------
const       -0.0026    0.0065  -0.4096   0.6825  -0.0154   0.0101
HIGH         0.0703    0.1840   0.3822   0.7027  -0.2923   0.4329
LOW          0.3530    0.1740   2.0292   0.0437   0.0101   0.6959
OPEN        -0.2727    0.1455  -1.8745   0.0622  -0.5594   0.0141
CLOSE        0.8412    0.1181   7.1241   0.0000   0.6085   1.0740
COUNT        0.0744    0.0351   2.1213   0.0351   0.0053   0.1435
VOLUME      -0.0523    0.0297  -1.7591   0.0800  -0.1109   0.0063
SENT         0.0204    0.0132   1.5408   0.1249  -0.0057   0.0464
---------------------------------------------------------------------
Omnibus:             25.455       Durbin-Watson:          1.804
Prob(Omnibus):       0.000        Jarque-Bera (JB):       89.092
Skew:                0.354        Prob(JB):               0.000
Kurtosis:            6.043        Condition No.:          191
=====================================================================
```

```
Amazon
                    Results: Ordinary least squares
=====================================================================
Model:              OLS              Adj. R-squared:     0.932
Dependent Variable: AVG_TOMORROW     AIC:                -704.5708
Date:               2022-07-10 18:18 BIC:                -677.4582
No. Observations:   219              Log-Likelihood:     360.29
Df Model:           7                F-statistic:        429.1
Df Residuals:       211              Prob (F-statistic): 4.90e-121
R-squared:          0.934            Scale:              0.0022633
----------------------------------------------------------------------
              Coef.   Std.Err.     t      P>|t|    [0.025    0.975]
----------------------------------------------------------------------
const       -0.0121    0.0213  -0.5701   0.5692  -0.0540   0.0298
HIGH         0.2066    0.1918   1.0769   0.2827  -0.1715   0.5847
LOW          0.5186    0.1888   2.7472   0.0065   0.1465   0.8907
OPEN        -0.4795    0.1754  -2.7347   0.0068  -0.8252  -0.1339
CLOSE        0.7404    0.1547   4.7856   0.0000   0.4354   1.0453
COUNT        0.1333    0.0794   1.6785   0.0947  -0.0233   0.2899
VOLUME      -0.0865    0.0778  -1.1119   0.2675  -0.2399   0.0669
SENT         0.0036    0.0201   0.1791   0.8581  -0.0359   0.0431
---------------------------------------------------------------------
Omnibus:             72.461       Durbin-Watson:          2.063
Prob(Omnibus):       0.000        Jarque-Bera (JB):       2043.977
Skew:                -0.534       Prob(JB):               0.000
Kurtosis:            17.928       Condition No.:          153
=====================================================================
```

If we look at each P-value and we consider < 0.05 as statistically significant threshold, we can see that:

- it depends on the stock; for Apple, its statistically significant results are: `[low, close, count]` (and `open` it's almost there) and for Amazon we got `[low, open, close]`;
- it depends on scaling of data; without scaling (as we can see in the *appendix*) results change, giving more significance to sentiment and removing volume and count due to the fact that are really huge numbers compared to the other explanatory variables.

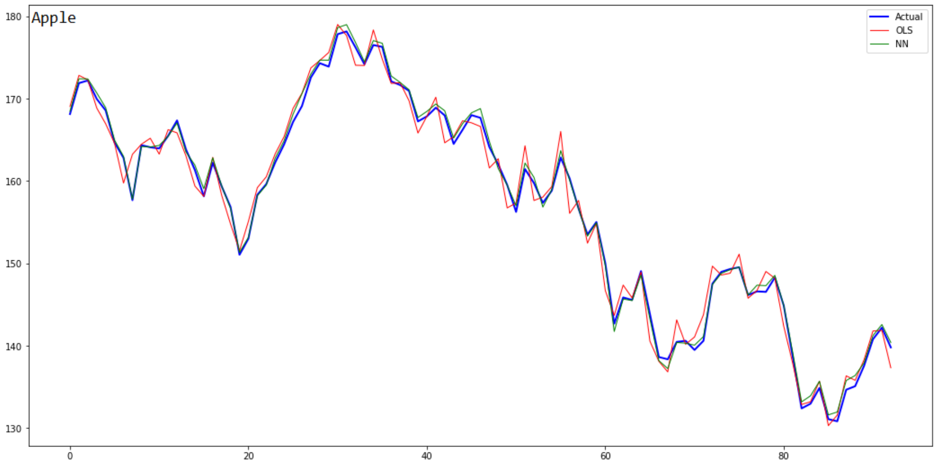
But we can say that, at least for these two firms, the `close` value is very important for the following day average, maybe because the starting value of the following day starts from the closing of the previous day (and then all 'buffered' orders are completed).

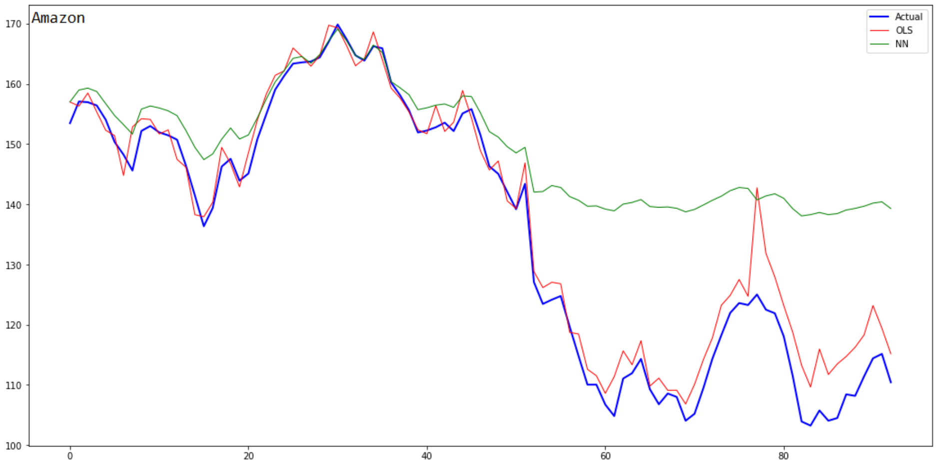
Talking about the Sentiment Analysis factor, we can see that even with two 'big and discussed' companies, there is a huge difference in their *P-values*, and even more in the appended code.

Given this, I think that we cannot write a general 'rule' that comprehends every stock, but overall we can see in the plots in the *Neural Network Analysis* paragraph (and in the *appendix*) that OLS doesn't perform well with quick spikes.

Mean Squared Error of OLS for Apple is 2.709 and for Amazon is 18.039.

Neural Network Analysis





I split the data in train and test with 70%/30%; it's the usual splitting strategy and also the one that gave me better results. Scaled data was also needed to perform the training of the neural network, otherwise units of the layers could get some problems in the process.

The training step is repeated for 40 epochs, hyperparameter chosen on various different runs (with a batch size of 32). Regarding the *LSTM* memory lag, I sticked to the value 1 since I was able to get so few samples and I wanted to have the maximum possible amount of data to train and test.

The first thing that catches the eye is that in the Amazon plot, the NN result is extremely wrong after half of the values; this could be due to some problems I will discuss in the *Conclusion* paragraph (overfitting).

It's also important to underline the limited availability of data. With more available data, the network could have been able to better learn some rare behaviors. But it also depends on the architecture of the network, and in my case, I came to the final architecture because I tried to get interesting results with also the inclusion of the sentiment analysis part.

Mean Squared Error of NN for Apple is 0.256 and for Amazon is 346.394;
for Apple NN is one order of magnitude better, for Amazon is one order of magnitude worse than OLS.

Conclusion

Stock	Market Cap	Beta	R-squared	NN MSE	OLS MSE
AAPL	2.38T	1.21	0.991	0.256	2.709
AMZN	1.18T	1.25	0.932	346.394	18.039
MSFT	2T	0.93	0.991	5.331	5.747
KO	273B	0.58	0.979	0.024	0.149

I wanted to include two more stocks in the last paragraph (and in the appended code even more can be found). The difference between *NN* MSE and *OLS* MSE values highly depends on the stock, but we can see that on average, the NN has a lower error. From the table, we can also deduce that probably the error is not related to *Market Capitalization*, *beta* value or *R-squared* value.

With some stocks my code works pretty fine, but with other it is totally wrong.

This could be due to an *overfitting* problem or to the number of available training samples: since in the training we are not able to have a general representation of all possible behaviors, the NN is not able to understand them and neither to predict them. This is clearly visible in the Amazon stock plot where the training part is quite stable but in the test we immediately have a big drop in average price: the NN predictions continue the past trend. This could be a clue that, since market movements could be unpredictable, there could always be an unexpected behavior that breaks our strategy.

Also, the network didn't learned general parameters, but it has been trained from scratch for each stock.

So, after seeing that I could not get consistent results, is this work useless? In my opinion it's not. First of all, thanks to this project and this course I was able to learn from zero concepts of the entire economic field, better understanding terms and methodologies used, and I think this project helped me merge this new world with what I'm mainly studying.

And secondly, the model could be improved (in the architecture, parameters, hyperparameters, available data and so on) to create an indicator or metric that, if there isn't something unusual 'in the air', would create some reliable forecasts to use as baseline for some choices and strategies.

Appendix: Python Notebook with code and more stocks results

Final Project Davide Modolo

Is AI suitable for forecasting Stock prices?

This is the code I implemented for the AI for Finance course final project. The idea is to predict the average price of the following day starting from open, close, high, low, volume, count, sentiment_value of a day

Libraries

A part from the usual python libraries, for this project there are 3 main types of libs we need to use:

- **Eikon Libraries to exchange information with the Refinitiv database**
- **Statsmodel API to use OLS as the required econometric method**
- **Neural Network libs, divided in Natural Language in order to perform a Sentiment Analysis on news headlines and Neural Network in order to build our NN for forecasting price**

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from math import floor, ceil
from IPython.display import clear_output #to write download progress in console
from os.path import exists


# Importing Eikon libraries for stock data
import eikon as ek
import cufflinks as cf
import configparser as cp
ek.set_app_key("8d0e9a8a1665482792d06cd4a41a00f3517de11b")


### Econometric Methods libraries, for OLS ###
import statsmodels.api as sm

### Neural Network libraries ##
# Natural Language Processing libraries
from nltk.sentiment import SentimentIntensityAnalyzer
# Recurrent Neural Network libraries
import tensorflow as tf
tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR) # remove warnings in the tr
aining
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

In [3]:

```
def sign(num, threshold=0.1):
    '''Takes a number and performs the sign function (with a threshold)'''
    if(num <= threshold and num >= -1*threshold):
        return 0
    if(num < -1 * threshold):
        return -1
    else:
        return 1

def daily_sentiment_value(day, ticker):
    '''
    Takes a day in the form of 'YYYY-MM-DD' and gets the news headlines for that day
    It returns the sum of the sentiment of each headline
    '''
    # some days may return exeptions, so we ignore them assining a 0 sentiment value
```

```
    try:
        titles = ek.get_news_headlines(f'R:{ticker} and LANGUAGE:EN',
                                  date_from=f'{day}T00:00:02',
                                  date_to=f'{day}T23:59:58', count = 100)['text']
    except:
        print(f'exeption at day {day}')
        return 0
    # initialize the sentiment analyzer
    sia = SentimentIntensityAnalyzer()
    # compute the total sentiment value for the day
    total_sent = 0
    for t in titles:
        # we get 4 values for each headline (+, -, neutral, compound)
        total_sent+=sign(sia.polarity_scores(t)["compound"])

    return total_sent
```

Get Stock Data

Since Eikon APIs allow to request a maximum of 100 headlines for each HTTP request, we need to make a request for each day in our dataset, resulting in a very slow data retreving process (~2mins in total). (Un)fortunately, Eikon provides us headlines only from 1st April 2021, so we have a bit more than a year of data for this project

In [4]:

```
def get_data(DAYS=1,
             ticker = 'AAPL.O',
             sentiment = False,
             fromFile = False,
             train_size = 0.7,
             starting_day = "2021-04-01",
             ending_day = "2022-06-30"
            ):
    '''
    DAYS: number of days we want as lag
    ticker: stock ticker
    sentiment: if we want to include the sentiment column in the data
    It returns a dataset with the following columns:
    - date: as index
    - avg: (open+close)/2
    - avg_tomorrow: avg of the next day (for training purposes)
    - close: closing price
    - open: opening price
    - high: highest price
    - low: lowest price
    - volume: volume
    - count: count
    - sentiment: sentiment value for the day
    '''
    if(fromFile and exists(f'stock_data/{ticker}.pkl')):
        # print('data loaded from file')
        dataDF = pd.read_pickle(f'stock_data/{ticker}.pkl')
    else:
        # get the data from Eikon, that provides us headlines only from 1st April 2021
        dataDF = ek.get_timeseries(f'{ticker}',
                                fields='*',  # all fields
                                start_date=starting_day,
                                end_date=ending_day)
        # if the flag sentiment is True, we add the sentiment column to the data (slow proc
ess)
        if sentiment:
            d2 = dataDF
            d2.reset_index(inplace=True)
            # we get the list of dates
            d2['Date'] = d2['Date'].apply(lambda x: str(x)[:10])

            i_total = len(d2['Date'])
            sentiment_values = []
            for i, day in enumerate(d2['Date']):
                clear_output(wait=True)
                print(f'Downloading sentiment data: {i}/{i_total} [{round(i*100/i_total, 2
```

```
)}%]')
                # we get the sentiment value for the day
                sentiment_values.append(daily_sentiment_value(day, ticker))
            clear_output(wait=True)

            dataDF['SENT'] = sentiment_values

        # add the column 'AVG' using (dataDF['close']+dataDF['open'])/2 to the dataDF
        dataDF['AVG'] = (dataDF['CLOSE']+dataDF['OPEN'])/2
        # shift the AVG column by DAYS to get the following day's average (for training)
        dataDF['AVG_TOMORROW'] = dataDF['AVG'].shift(-DAYS)
        # remove last row from dataDf (since we shifted the last row by DAYS)
        dataDF = dataDF[:-DAYS]
        dataDF.to_pickle(f"stock_data/{ticker}.pkl")
    fig, plot = plt.subplots(figsize=(18, 9))
    fig.suptitle(f'{ticker} stocks AVG {starting_day}-{ending_day}')
    plot.plot(dataDF['AVG'], color='#219653', label=f'AVG {ticker} (USD)')
    plot.axvline(int(len(dataDF)*train_size), color = '#A7E9A1', label = 'train/test')
    plt.legend()
    plt.show()

    return dataDF
```

In [5]:

```
def split_data(x, y, train_size=0.7):
    '''
    Split the data into training and testing sets divided according to the train_size param
eter
    returns x_train, y_train, x_test, y_test
    '''
    train_size = int(len(x)*train_size)

    x_train = x[:train_size]
    y_train = y[:train_size]

    x_test = x[train_size:]
    y_test = y[train_size:]

    return x_train, y_train, x_test, y_test
```

Ordinary Least Squares

Chosen Econometric Method.

In [6]:

```
def do_OLS(x, y, x_names=[], y_name=''):
    '''
    x: array of training x values
    y: array of training y values
    x_names: list of features names
    y_name: name of the target variable
    It returns the OLS model parameters
    '''

    X = sm.add_constant(np.array(x, dtype='float32' ))
    model = sm.OLS(np.array(y, dtype='float32' ), X)
    fitted = model.fit()
    # print the results

    if len(x_names) == 0 or len(y_name) == 0:
        print(fitted.summary())
    else:
        print(fitted.summary2(xname=['const']+x_names, yname=y_name))

    return fitted.params
```

Recurrent Neural Network

Manually builded with 4 LSTM (Long Short-Term Memory) layers with 64 units, ending in a Dense layer with 1 unit to get the value.

In [7]:

```
def do_RNN(x_train, x_labels, y_train, x_test, y_test, epochs=10, n_steps=1):
    '''
    Perform a RNN model training on the data, returns the list of predictions on x_test
    '''
    # since we are working with data of different magnitudes, we need to scale and reshape
the data
    scalerX = MinMaxScaler(feature_range=(0, 1))
    scalerY = MinMaxScaler(feature_range=(0, 1))
    x_train = scalerX.fit_transform(x_train)
    x_test = scalerX.transform(x_test)
    y_train = scalerY.fit_transform(y_train.reshape(-1, 1))

    # we need to reshape the data to be compatible with the RNN
    n_records_train = len(x_train)
    n_features = len(x_labels)
    X_train = []
    Y_train = []
    for i in range(n_steps, n_records_train):
        X_train.append(x_train[i-n_steps:i])
        Y_train.append(y_train[i][0])
    X_train, Y_train = np.array(X_train), np.array(Y_train)
    X_train_shaped = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], X_train.shap
e[2]))

    # we start building the model
    model = Sequential()
    # LSTM layers are the one with some 'memory of the past' values (Long Short Term Memory
), they use past values for their predictions
    model.add(LSTM(units = 64, return_sequences = True, input_shape = (n_steps, n_features
)))
    model.add(LSTM(units = 64, return_sequences = True))
    model.add(LSTM(units = 64, return_sequences = True))
    model.add(LSTM(units = 64, return_sequences = True))
    # One 'neuron' for the output since we want a number
    model.add(Dense(units = 1))
    # we use the mean squared error as the loss function and Adam as optimizer since it all
ows to get better results quickly and then it settles
    model.compile(optimizer='adam', loss='mean_squared_error')
    # we train the model
    model.fit(X_train_shaped, Y_train, epochs=epochs, batch_size = 32, verbose = 0)

    # we get the predictions on the test set
    n_records_test = len(x_test)
    X_test = []
    for i in range(n_steps, n_records_test):
        X_test.append(x_test[i-n_steps:i])
    X_test = np.array(X_test)
    y_res = model.predict(X_test)
    predictions_transformed = []
    for val in y_res:
        predictions_transformed.append(val[0])
    predictions_transformed = np.array(predictions_transformed)
    # we need to inverse the scaling of the predictions and we return them
    return scalerY.inverse_transform(predictions_transformed)
```

MAIN Function

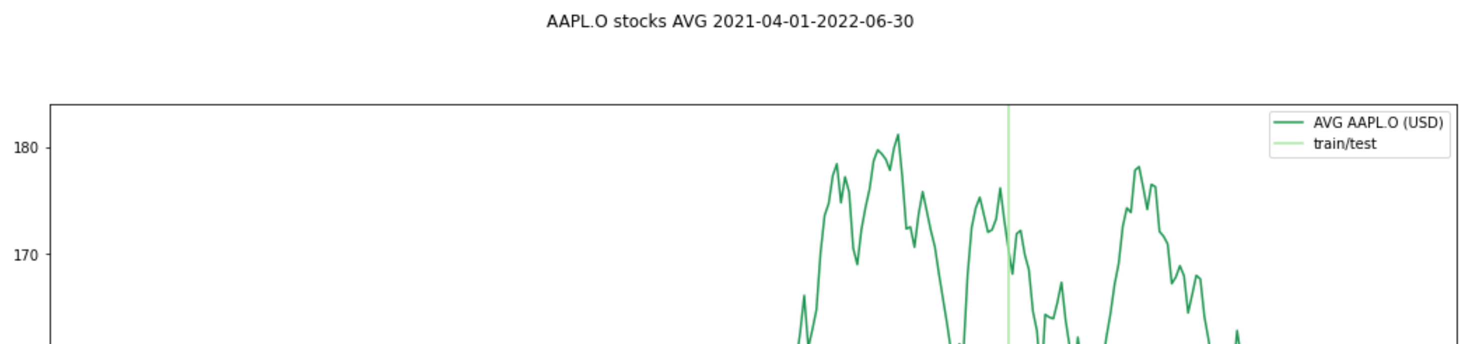
- **Get data from Eikon (or from file if it's available)**
- **Perform Sentiment Analysis on news headline**
- **Compute OLS Regression and RNN regression**
- **Compare results on test**
- **Compute MSE**

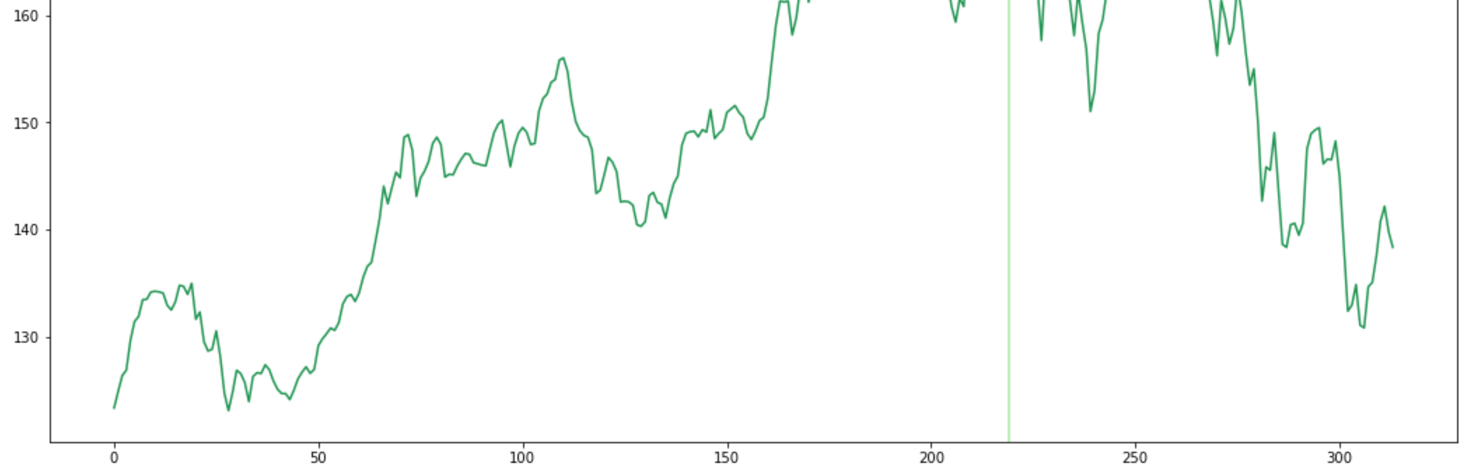
In [8]:

```
def main(
    epochs = 40,
    lag = 1,
    train_size = 0.7,
    sentiment=True,
    ticker = 'AAPL.O',
    fromFile = True
):
    # get data from Eikon database
    data = get_data(sentiment=sentiment, ticker=ticker, fromFile=fromFile, train_size=trai
n_size)
    # if we don't want to download sentiment data, we just set sentiment=False
    if sentiment:
        x_labels = ['HIGH', 'LOW', 'OPEN', 'CLOSE', 'COUNT', 'VOLUME', 'SENT']
    else:
        x_labels = ['HIGH', 'LOW', 'OPEN', 'CLOSE', 'COUNT', 'VOLUME']
    y_label = 'AVG_TOMORROW'

    # divide and prepare data
    x = data[x_labels].values
    y = data[y_label].values
    x_train, y_train, x_test, y_test = split_data(x, y, train_size=train_size)
    # compute the OLS econometric method
    parameters = do_OLS(x_train, y_train, x_names=x_labels, y_name=y_label)
    # compute the results of the OLS model
    OLS_predictions = []
    for entry in x_test:
        tmp = 0
        for i, p in enumerate(parameters):
            if i == 0:
                tmp += p
            else:
                tmp += p*entry[i-1]
        OLS_predictions.append(tmp)
    # get results of x_test from the builded Neural Network
    res = do_RNN(x_train, x_labels, y_train, x_test, y_test, epochs=epochs, n_steps=lag)

    # prepare data to plot
    df_NN = pd.DataFrame(res, columns = ['NN']).shift(-lag)
    df_OLS = pd.DataFrame(OLS_predictions, columns = ['OLS']).shift(-lag)
    train_size = int(len(x)*train_size)
    df_Actual = pd.DataFrame(y_test, columns = ['Actual'])
    dfResults = pd.concat([df_OLS, df_Actual, df_NN], axis=1)
    dfResults = dfResults[:-2*lag]

    fig, plot = plt.subplots(figsize=(18, 9))
    plot.plot(dfResults['Actual'], color='blue', label='Actual', linewidth=2)
    plot.plot(dfResults['OLS'], color='red', label='OLS', linewidth=1)
    plot.plot(dfResults['NN'], color='green', label='NN', linewidth=1)
    plt.legend()
    plt.show()

    # calculate mse for both NN and OLS
    mse_NN = np.mean(np.square(dfResults['NN']-dfResults['Actual']))
    mse_OLS = np.mean(np.square(dfResults['OLS']-dfResults['Actual']))
    print('Mean Squared Error of NN model: ', mse_NN)
    print('Mean Squared Error of OLS: ', mse_OLS)
```

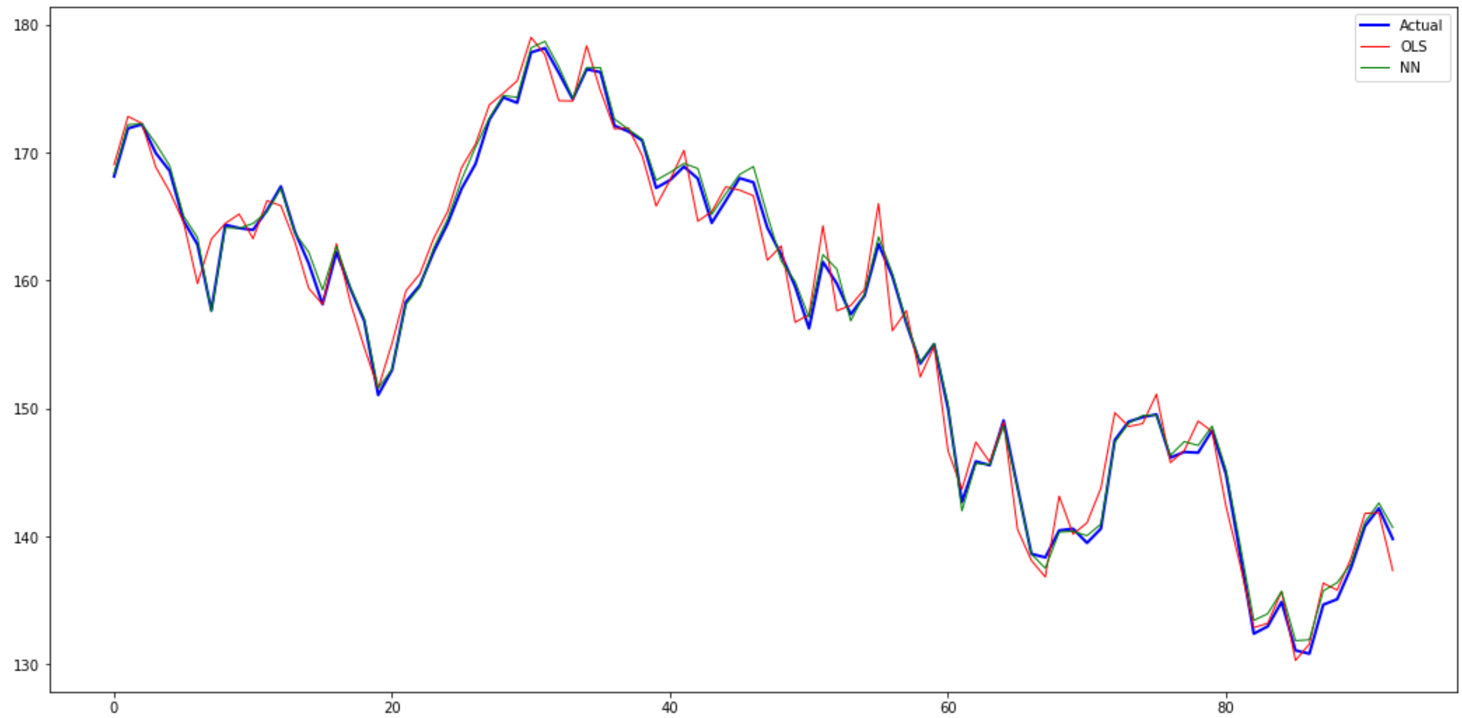
In [9]:

```
main(ticker = 'AAPL.O')
```






```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.991
Dependent Variable: AVG_TOMORROW     AIC:                819.9010
Date:               2022-07-11 17:44 BIC:                847.0136
No. Observations:   219              Log-Likelihood:     -401.95
Df Model:           7                F-statistic:        3291.
Df Residuals:       211              Prob (F-statistic): 1.29e-211
R-squared:          0.991            Scale:              2.3872
--------------------------------------------------------------------
             Coef.    Std.Err.      t      P>|t|     [0.025   0.975]
--------------------------------------------------------------------
const        1.6959    1.1537    1.4699   0.1431   -0.5784   3.9702
HIGH         0.0695    0.1818    0.3822   0.7027   -0.2889   0.4279
LOW          0.3605    0.1777    2.0292   0.0437    0.0103   0.7107
OPEN        -0.2663    0.1421   -1.8745   0.0622   -0.5463   0.0137
CLOSE        0.8248    0.1158    7.1241   0.0000    0.5965   1.0530
COUNT        0.0000    0.0000    2.1213   0.0351    0.0000   0.0000
VOLUME      -0.0000    0.0000   -1.7591   0.0800   -0.0000   0.0000
SENT         0.0211    0.0137    1.5408   0.1249   -0.0059   0.0482
------------------------------------------------------------------
Omnibus:              25.455       Durbin-Watson:          1.804
Prob(Omnibus):        0.000        Jarque-Bera (JB):       89.093
Skew:                 0.354        Prob(JB):               0.000
Kurtosis:             6.043        Condition No.:          997698643
==================================================================
* The condition number is large (1e+09). This might indicate
strong multicollinearity or other numerical problems.
```

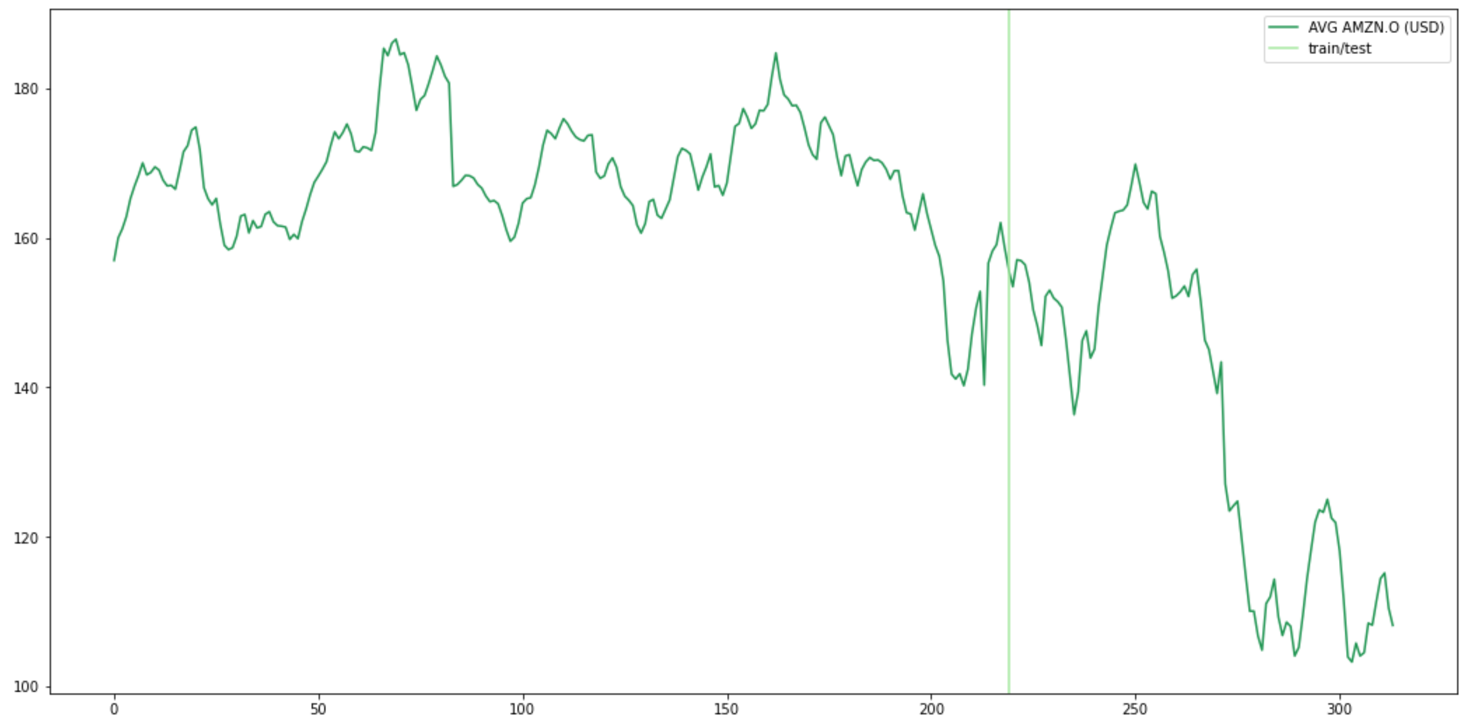



```
Mean Squared Error of NN model:  0.3078726244338866
Mean Squared Error of OLS:  2.709550415781781
```

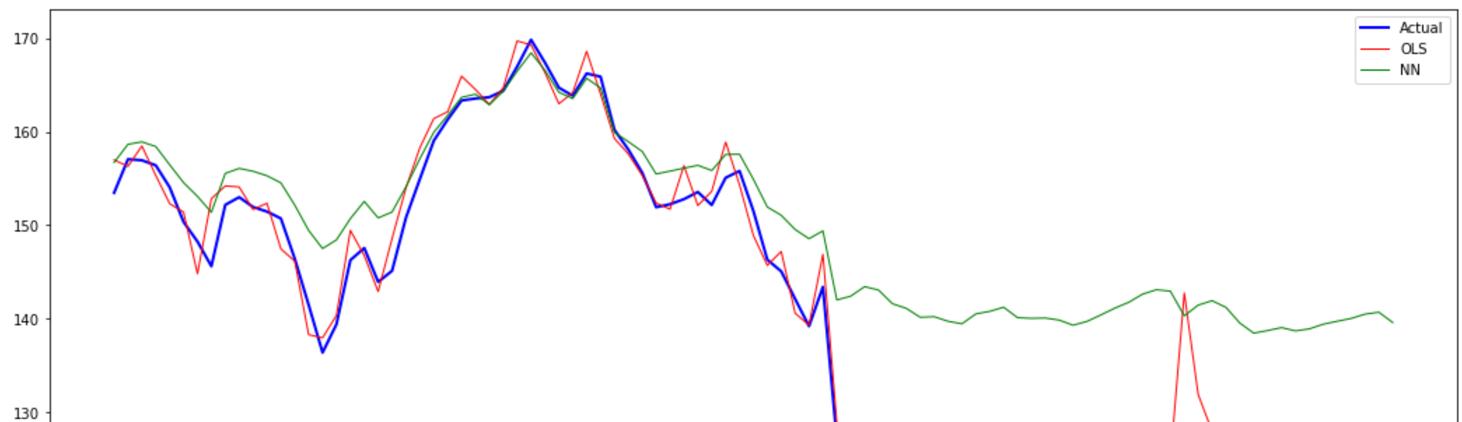
In [10]:

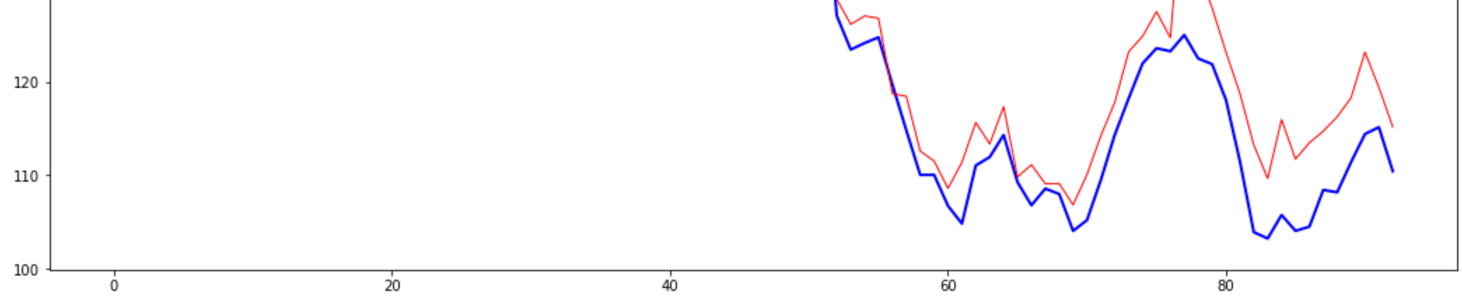
```
main(ticker = 'AMZN.O')
```

AMZN.O stocks AVG 2021-04-01-2022-06-30




```
                    Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.932
Dependent Variable: AVG_TOMORROW     AIC:                975.6470
Date:               2022-07-11 17:44 BIC:                1002.7596
No. Observations:   219              Log-Likelihood:     -479.82
Df Model:           7                F-statistic:        429.1
Df Residuals:       211              Prob (F-statistic): 4.90e-121
R-squared:          0.934            Scale:              4.8612
--------------------------------------------------------------------
            Coef.    Std.Err.     t       P>|t|     [0.025    0.975]
--------------------------------------------------------------------
const       7.1581    3.2873    2.1775    0.0305    0.6780   13.6382
HIGH        0.2125    0.1973    1.0769    0.2828   -0.1765    0.6014
LOW         0.4856    0.1768    2.7472    0.0065    0.1372    0.8341
OPEN       -0.4611    0.1686   -2.7347    0.0068   -0.7934   -0.1287
CLOSE       0.7190    0.1502    4.7856    0.0000    0.4228    1.0151
COUNT       0.0000    0.0000    1.6785    0.0947   -0.0000    0.0000
VOLUME     -0.0000    0.0000   -1.1119    0.2675   -0.0000    0.0000
SENT        0.0020    0.0112    0.1791    0.8581   -0.0201    0.0241
------------------------------------------------------------------
Omnibus:              72.461       Durbin-Watson:          2.063
Prob(Omnibus):        0.000        Jarque-Bera (JB):       2043.975
Skew:                 -0.534       Prob(JB):               0.000
Kurtosis:             17.928       Condition No.:          1655746863
==================================================================
* The condition number is large (2e+09). This might indicate
strong multicollinearity or other numerical problems.
```



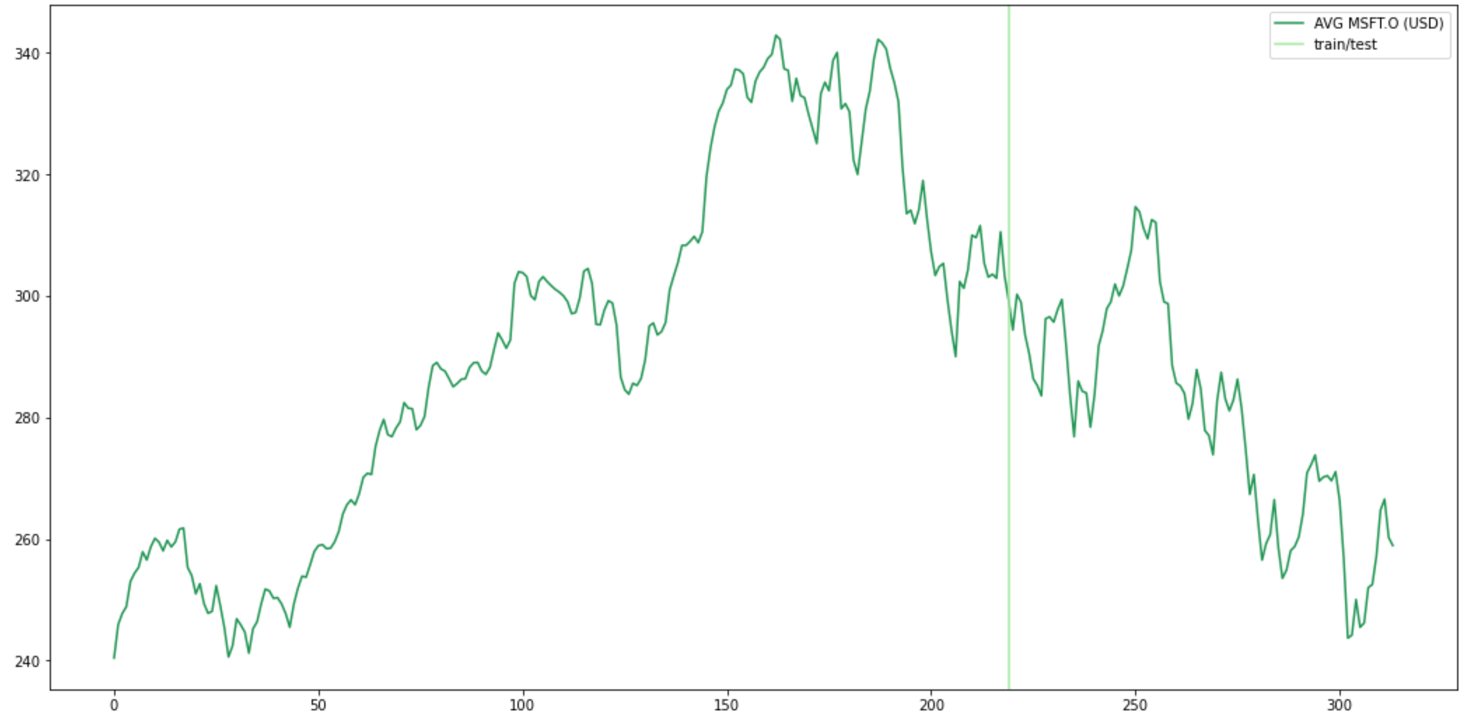



```
Mean Squared Error of NN model:  354.98378447301786
Mean Squared Error of OLS:  18.039098109551034
```

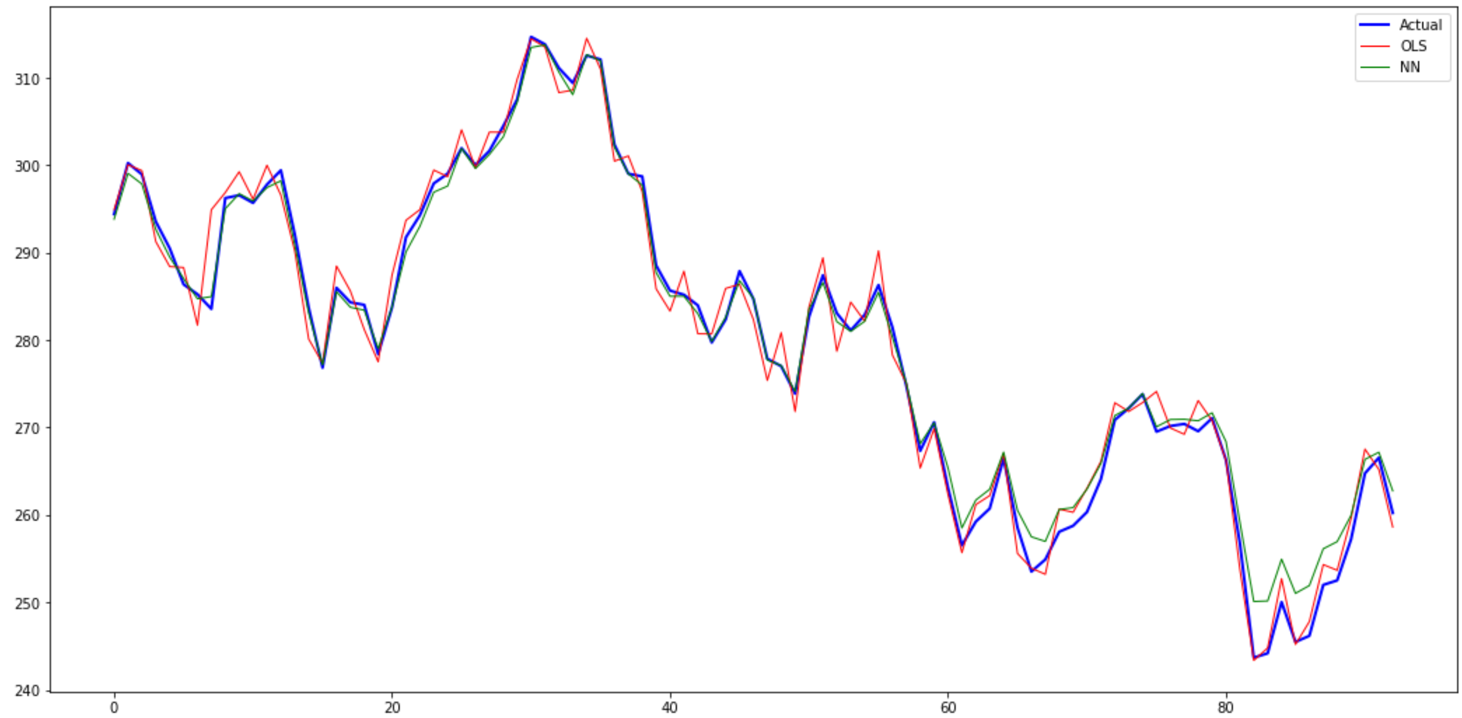
In [11]:

```
main(ticker = 'MSFT.O')
```

MSFT.O stocks AVG 2021-04-01-2022-06-30



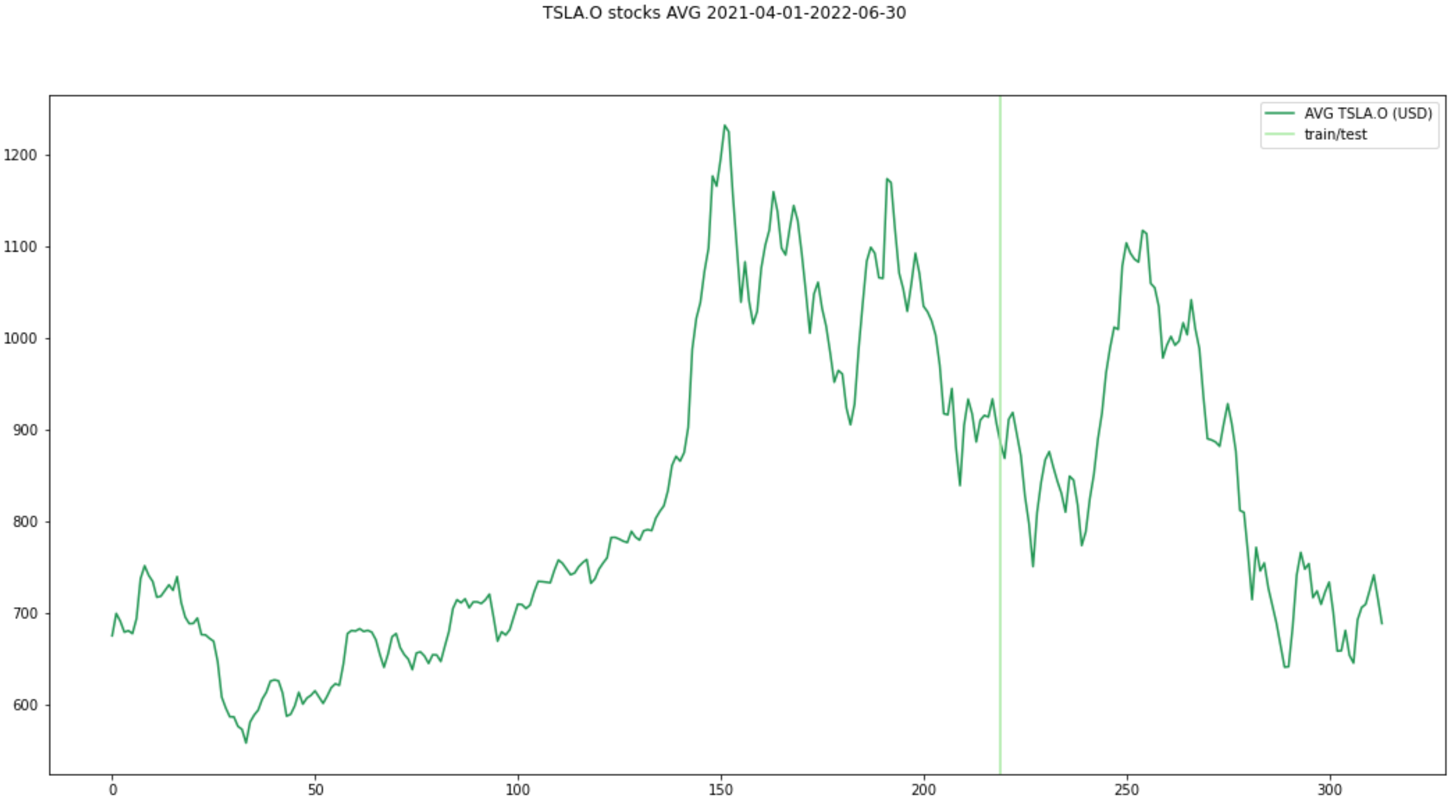

```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.991
Dependent Variable: AVG_TOMORROW     AIC:                1091.2358
Date:               2022-07-11 17:44 BIC:                1118.3484
No. Observations:   219              Log-Likelihood:     -537.62
Df Model:           7                F-statistic:        3284.
Df Residuals:       211              Prob (F-statistic): 1.57e-211
R-squared:          0.991            Scale:              8.2407
--------------------------------------------------------------------
             Coef.    Std.Err.     t      P>|t|     [0.025   0.975]
--------------------------------------------------------------------
const        3.0106    2.2313   1.3492   0.1787   -1.3879   7.4091
HIGH         0.1915    0.1724   1.1106   0.2680   -0.1484   0.5313
LOW          0.0376    0.1609   0.2336   0.8155   -0.2795   0.3547
OPEN        -0.0648    0.1288  -0.5034   0.6152   -0.3187   0.1890
CLOSE        0.8242    0.1110   7.4224   0.0000    0.6053   1.0431
COUNT        0.0000    0.0000   0.5179   0.6051   -0.0000   0.0000
VOLUME      -0.0000    0.0000  -0.6747   0.5006   -0.0000   0.0000
SENT         0.0510    0.0244   2.0870   0.0381    0.0028   0.0991
------------------------------------------------------------------
Omnibus:               14.292       Durbin-Watson:          1.918
Prob(Omnibus):         0.001        Jarque-Bera (JB):       38.100
Skew:                  -0.108       Prob(JB):               0.000
Kurtosis:              5.032        Condition No.:          335860040
==================================================================
* The condition number is large (3e+08). This might indicate
strong multicollinearity or other numerical problems.
```




```
Mean Squared Error of NN model:  3.5941229033255193
Mean Squared Error of OLS:  5.746718169131486
```

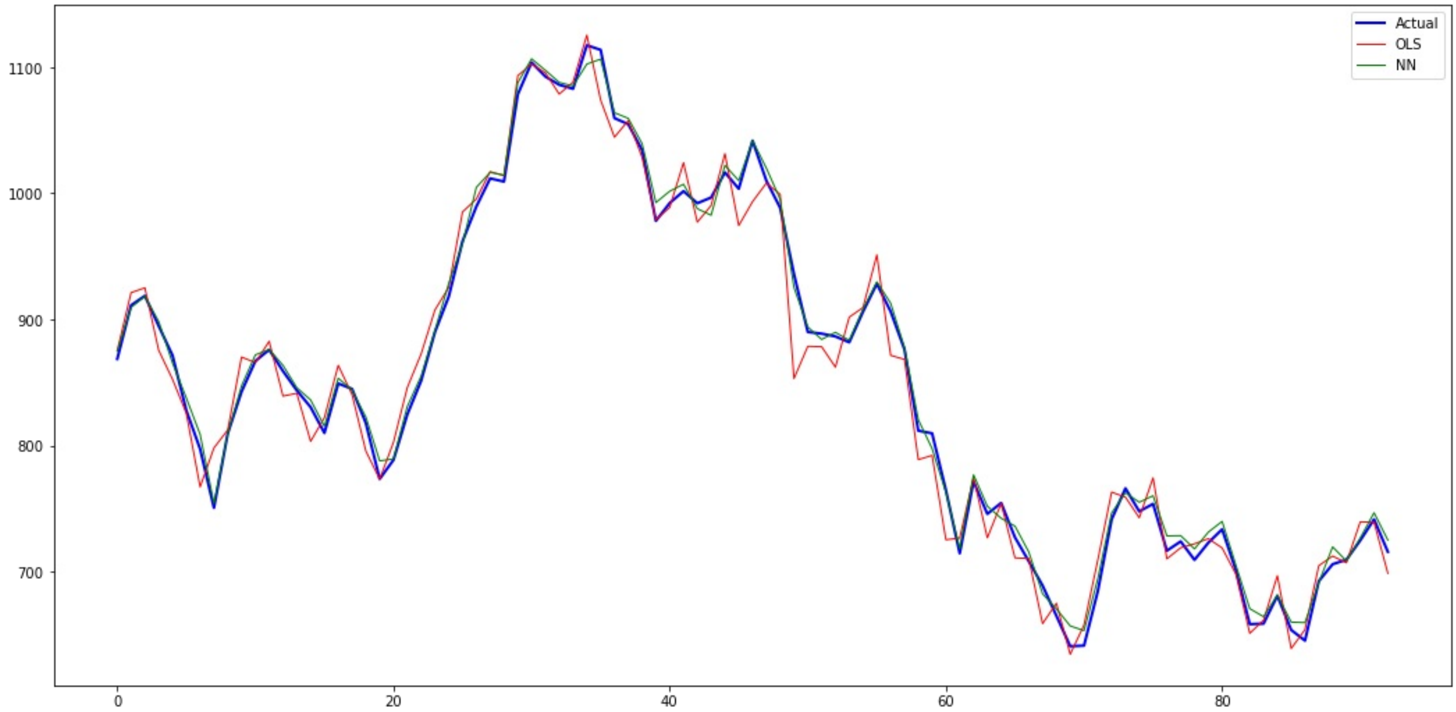
In [12]:

```
main(ticker = 'TSLA.O')
```




```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.988
Dependent Variable: AVG_TOMORROW     AIC:                1938.2710
Date:               2022-07-11 17:44 BIC:                1965.3836
No. Observations:   219              Log-Likelihood:     -961.14
Df Model:           7                F-statistic:        2542.
Df Residuals:       211              Prob (F-statistic): 6.58e-200
R-squared:          0.988            Scale:              394.19
--------------------------------------------------------------------
           Coef.    Std.Err.     t      P>|t|     [0.025     0.975]
--------------------------------------------------------------------
const      0.6783   10.2520   0.0662   0.9473   -19.5312   20.8877
HIGH      -0.1348    0.1760  -0.7658   0.4446    -0.4819    0.2122
```

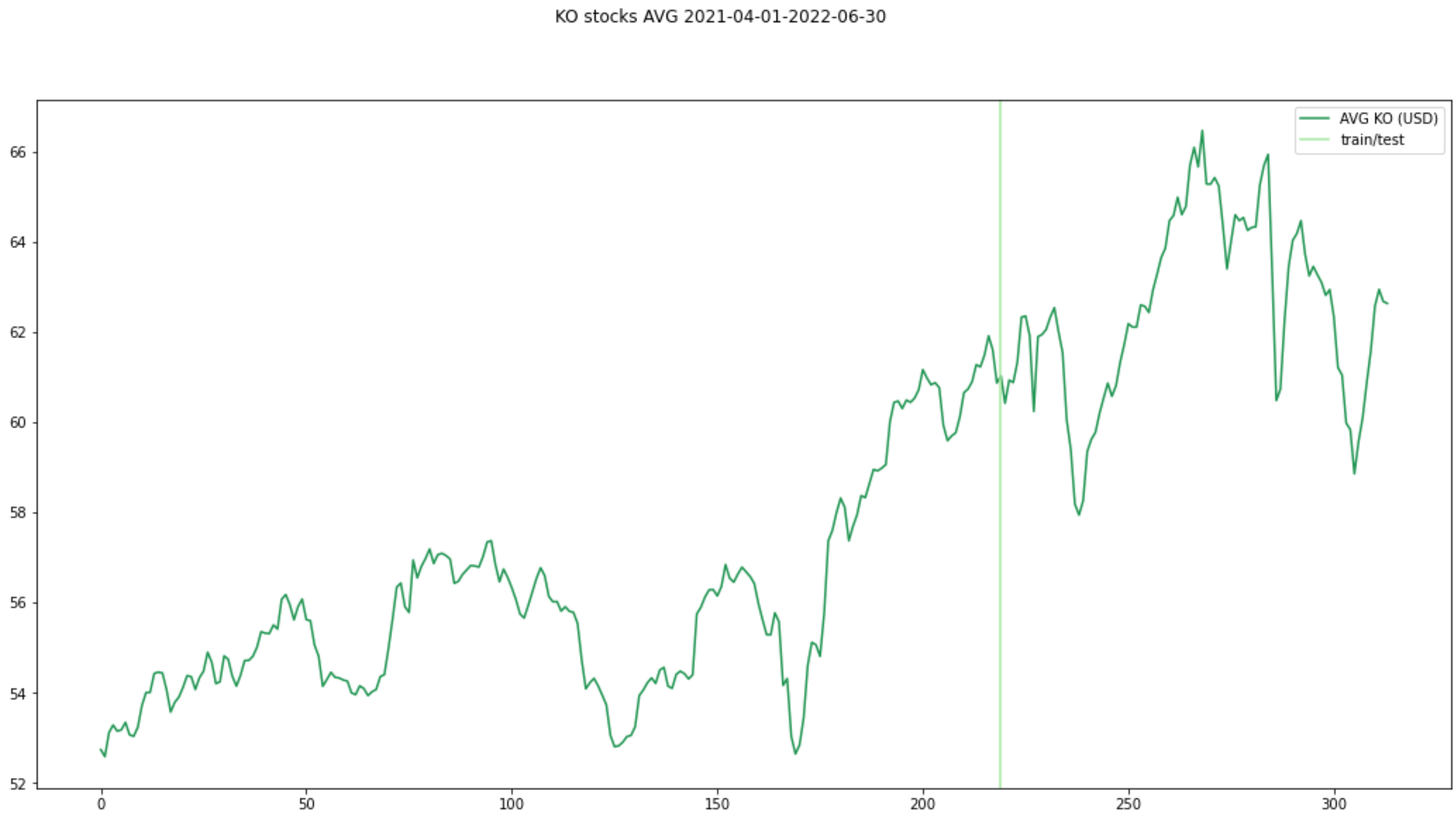
```
LOW         0.1427      0.1619     0.8812    0.3792     -0.1765     0.4618
OPEN       -0.0057      0.1321    -0.0433    0.9655     -0.2662     0.2547
CLOSE       1.0025      0.1209     8.2913    0.0000      0.7642     1.2409
COUNT       0.0000      0.0000     0.6922    0.4896     -0.0000     0.0000
VOLUME     -0.0000      0.0000    -0.3347    0.7382     -0.0000     0.0000
SENT       -0.4144      0.1614    -2.5677    0.0109     -0.7325    -0.0962
==================================================================
Omnibus:                  64.807      Durbin-Watson:          1.898
Prob(Omnibus):            0.000       Jarque-Bera (JB):       352.122
Skew:                     1.014       Prob(JB):               0.000
Kurtosis:                 8.872       Condition No.:          206721043
==================================================================
* The condition number is large (2e+08). This might indicate
strong multicollinearity or other numerical problems.
```



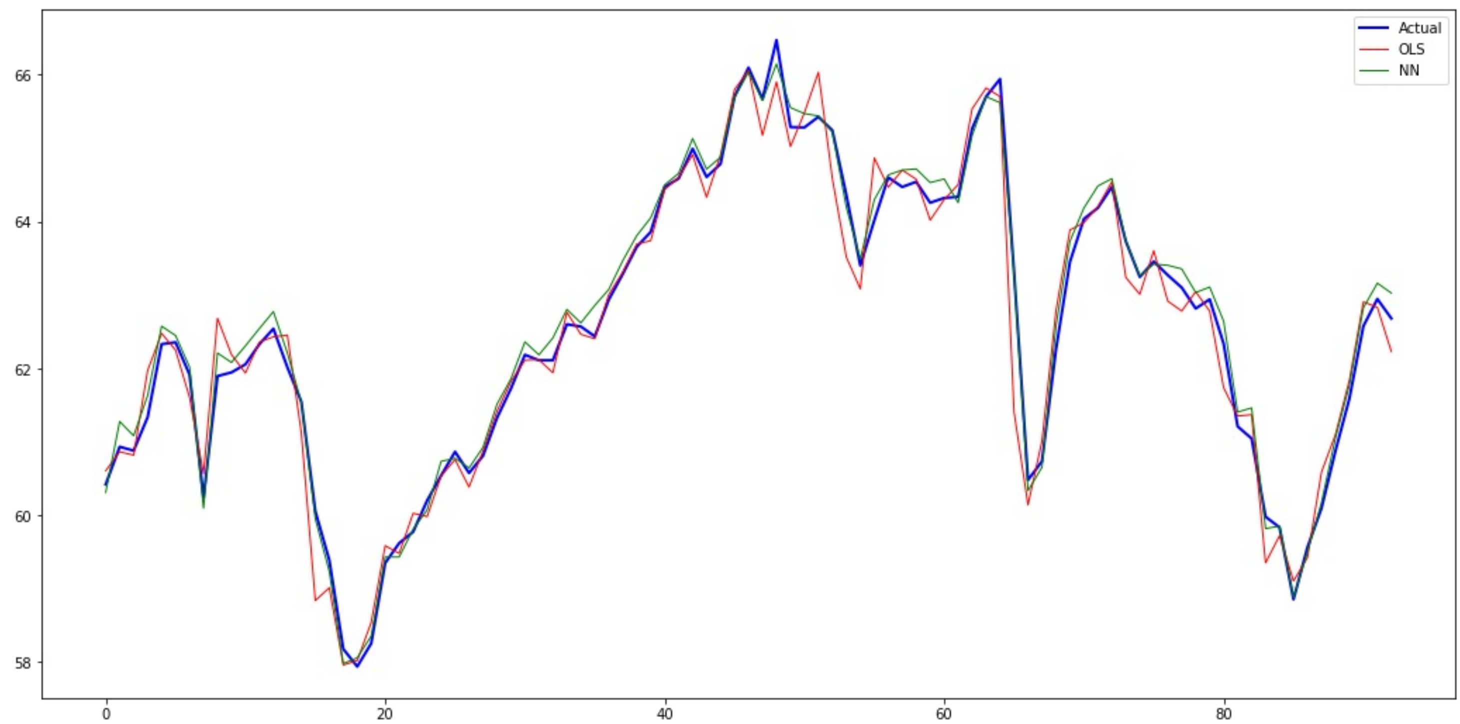

```
Mean Squared Error of NN model:  53.66423920956459
Mean Squared Error of OLS:  357.66524529296174
```

In [13]:

```
main(ticker = 'KO')
```



```
                    Results: Ordinary least squares
==================================================================
Model:                  OLS              Adj. R-squared:     0.979
Dependent Variable: AVG_TOMORROW         AIC:                145.6368
Date:                   2022-07-11 17:45 BIC:                172.7494
No. Observations:       219              Log-Likelihood:     -64.818
Df Model:               7                F-statistic:        1430.
Df Residuals:           211              Prob (F-statistic): 5.62e-174
R-squared:              0.979            Scale:              0.10984
--------------------------------------------------------------------
             Coef.    Std.Err.     t      P>|t|    [0.025   0.975]
--------------------------------------------------------------------
const        1.1257    0.5780   1.9475   0.0528   -0.0137   2.2652
HIGH        -0.0246    0.1480  -0.1661   0.8682   -0.3162   0.2671
LOW          0.0577    0.1528   0.3774   0.7062   -0.2435   0.3589
OPEN         0.0250    0.1106   0.2262   0.8213   -0.1930   0.2430
CLOSE        0.9209    0.1127   8.1698   0.0000    0.6987   1.1432
COUNT        0.0000    0.0000   1.3523   0.1777   -0.0000   0.0000
VOLUME      -0.0000    0.0000  -1.2127   0.2266   -0.0000   0.0000
SENT         0.0001    0.0077   0.0150   0.9880   -0.0150   0.0152
------------------------------------------------------------------
Omnibus:              31.886       Durbin-Watson:          1.923
Prob(Omnibus):        0.000        Jarque-Bera (JB):       205.973
Skew:                 -0.186       Prob(JB):               0.000
Kurtosis:             7.736        Condition No.:          428713390
==================================================================
* The condition number is large (4e+08). This might indicate
strong multicollinearity or other numerical problems.
```

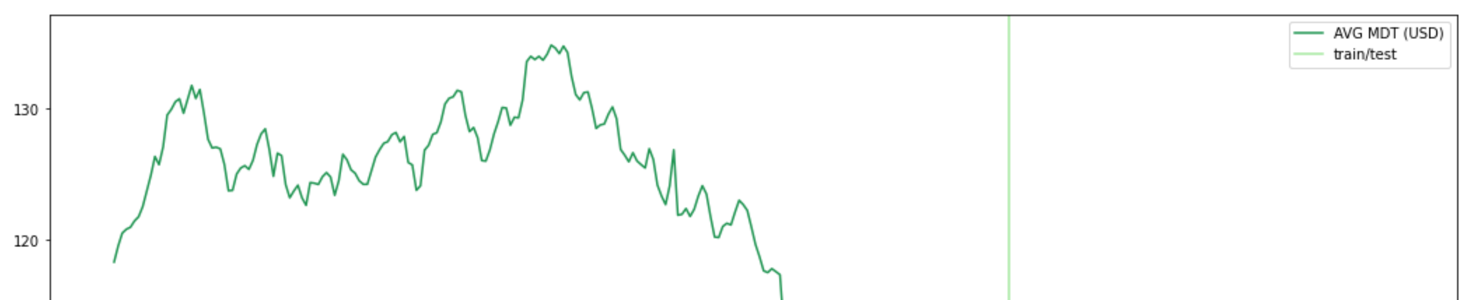



```
Mean Squared Error of NN model:  0.03518033576646622
Mean Squared Error of OLS:  0.14887357320834885
```

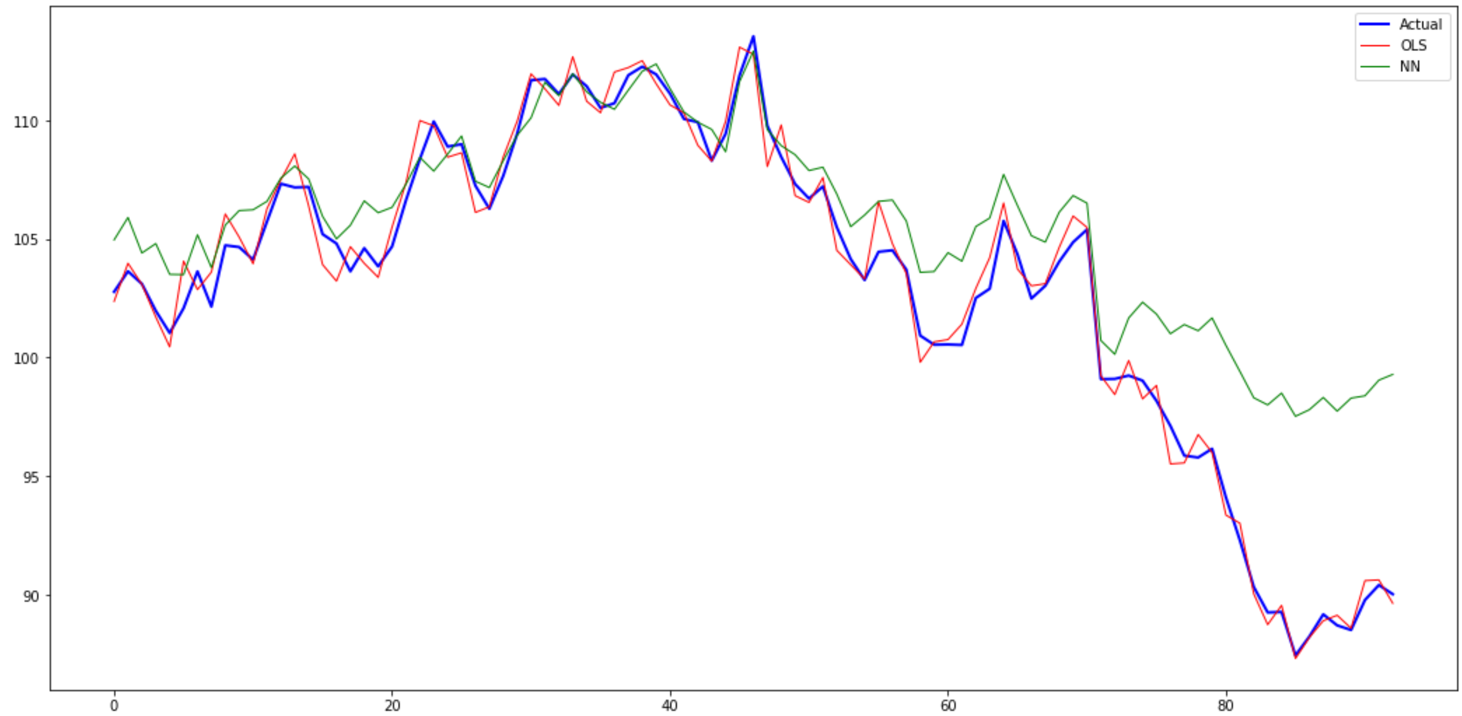
In [14]:

```
main(ticker = 'MDT')
```

MDT stocks AVG 2021-04-01-2022-06-30



```
                  Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.988
Dependent Variable: AVG_TOMORROW     AIC:                653.1308
Date:               2022-07-11 17:45 BIC:                680.2433
No. Observations:   219              Log-Likelihood:     -318.57
Df Model:           7                F-statistic:        2576.
Df Residuals:       211              Prob (F-statistic): 1.60e-200
R-squared:          0.988            Scale:              1.1147
--------------------------------------------------------------------
            Coef.    Std.Err.     t      P>|t|     [0.025    0.975]
--------------------------------------------------------------------
const       1.8628     1.3473   1.3826   0.1682   -0.7931    4.5188
HIGH        0.0915     0.1373   0.6664   0.5059   -0.1791    0.3621
LOW        -0.3642     0.1725  -2.1114   0.0359   -0.7043   -0.0242
OPEN        0.0964     0.1154   0.8353   0.4045   -0.1311    0.3239
CLOSE       1.1627     0.1289   9.0172   0.0000    0.9085    1.4168
COUNT      -0.0000     0.0000  -0.8876   0.3758   -0.0000    0.0000
VOLUME     -0.0000     0.0000  -0.5657   0.5722   -0.0000    0.0000
SENT        0.0218     0.0250   0.8704   0.3851   -0.0275    0.0711
------------------------------------------------------------------
Omnibus:             117.048      Durbin-Watson:         2.076
Prob(Omnibus):       0.000        Jarque-Bera (JB):      930.070
Skew:                -1.920       Prob(JB):              0.000
Kurtosis:            12.337       Condition No.:         110772817
==================================================================
* The condition number is large (1e+08). This might indicate
strong multicollinearity or other numerical problems.
```

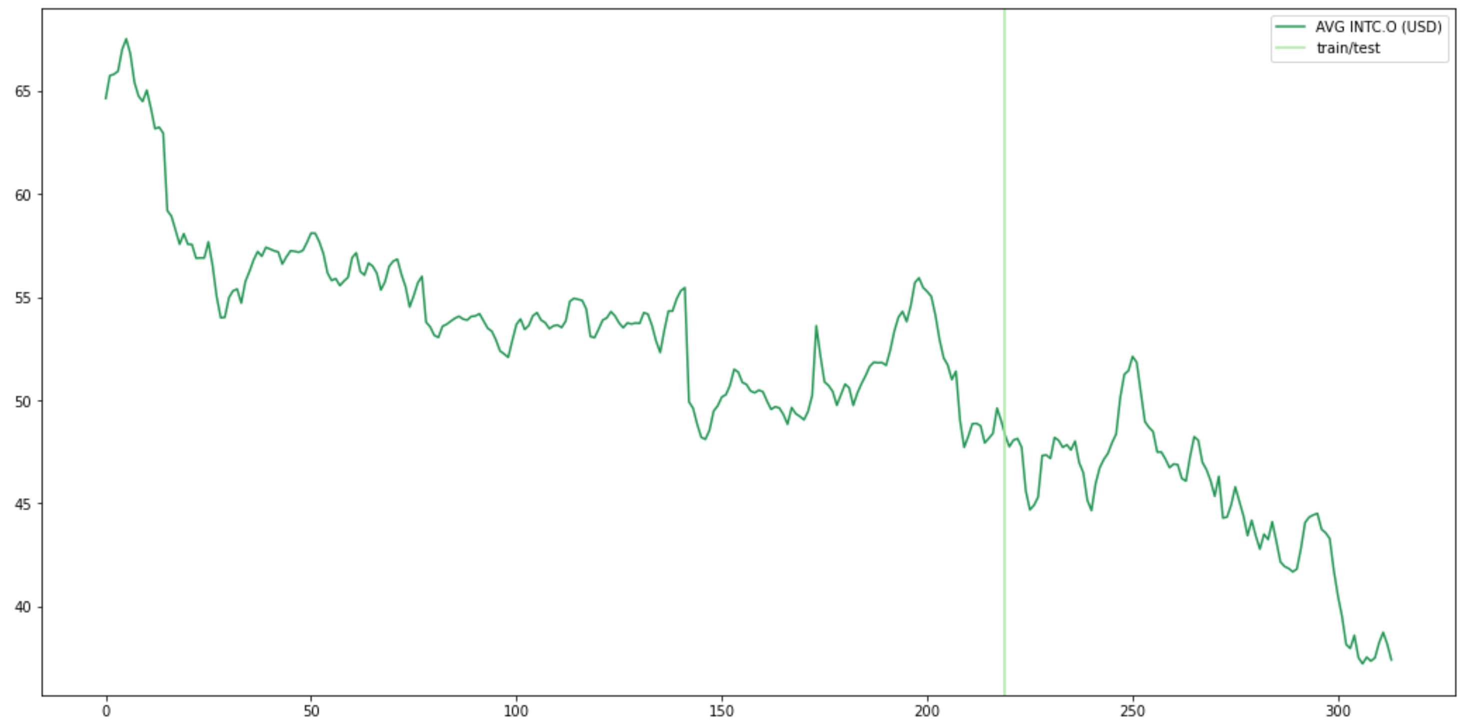



```
Mean Squared Error of NN model:  14.32723729168111
Mean Squared Error of OLS:  0.6154328313213744
```

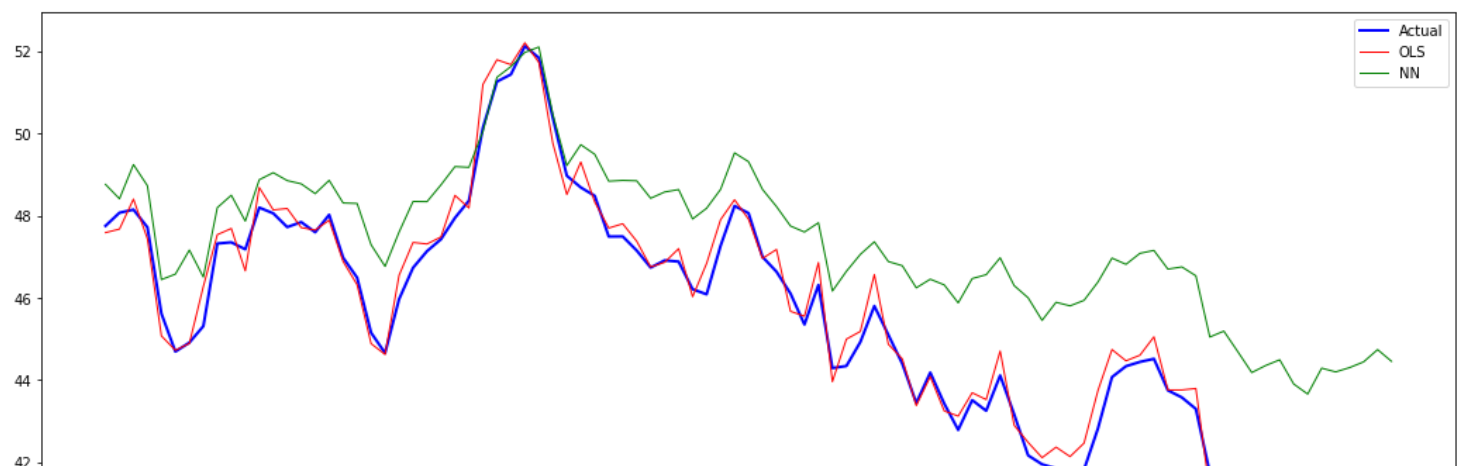
In [15]:

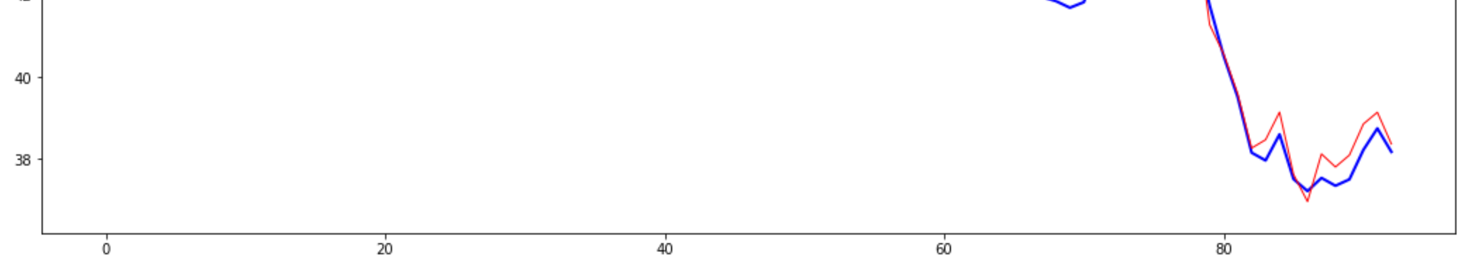
```
main(ticker = 'INTC.O')
```

INTC.O stocks AVG 2021-04-01-2022-06-30




```
                   Results: Ordinary least squares
==================================================================
Model:               OLS              Adj. R-squared:     0.968
Dependent Variable: AVG_TOMORROW     AIC:                475.7126
Date:                2022-07-11 17:45 BIC:                502.8251
No. Observations:    219              Log-Likelihood:     -229.86
Df Model:            7                F-statistic:        951.7
Df Residuals:        211              Prob (F-statistic): 8.25e-156
R-squared:           0.969            Scale:              0.49583
--------------------------------------------------------------------
            Coef.    Std.Err.     t      P>|t|     [0.025    0.975]
--------------------------------------------------------------------
const       2.2691     0.7483   3.0324   0.0027    0.7941    3.7442
HIGH        0.0143     0.1918   0.0748   0.9405   -0.3638    0.3925
LOW        -0.1066     0.2020  -0.5277   0.5983   -0.5047    0.2916
OPEN        0.1743     0.1504   1.1590   0.2477   -0.1222    0.4709
CLOSE       0.8812     0.1454   6.0618   0.0000    0.5946    1.1677
COUNT       0.0000     0.0000   0.6925   0.4894   -0.0000    0.0000
VOLUME     -0.0000     0.0000  -1.6250   0.1057   -0.0000    0.0000
SENT       -0.0284     0.0116  -2.4468   0.0152   -0.0512   -0.0055
------------------------------------------------------------------
Omnibus:              173.845      Durbin-Watson:         1.860
Prob(Omnibus):        0.000        Jarque-Bera (JB):      4687.876
Skew:                 -2.708       Prob(JB):              0.000
Kurtosis:             25.009       Condition No.:         495588717
==================================================================
* The condition number is large (5e+08). This might indicate
strong multicollinearity or other numerical problems.
```



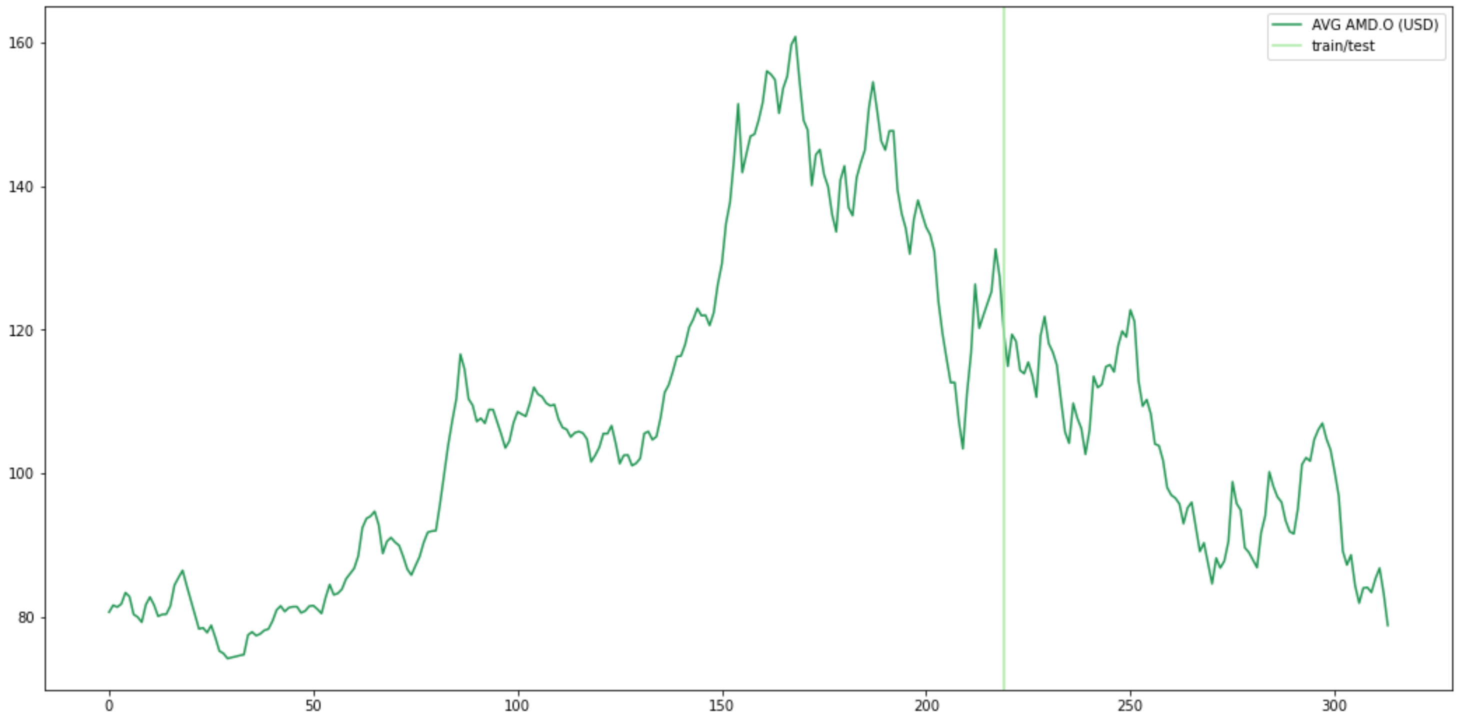


```
Mean Squared Error of NN model:  9.014551307937955
Mean Squared Error of OLS:  0.16681711345034678
```

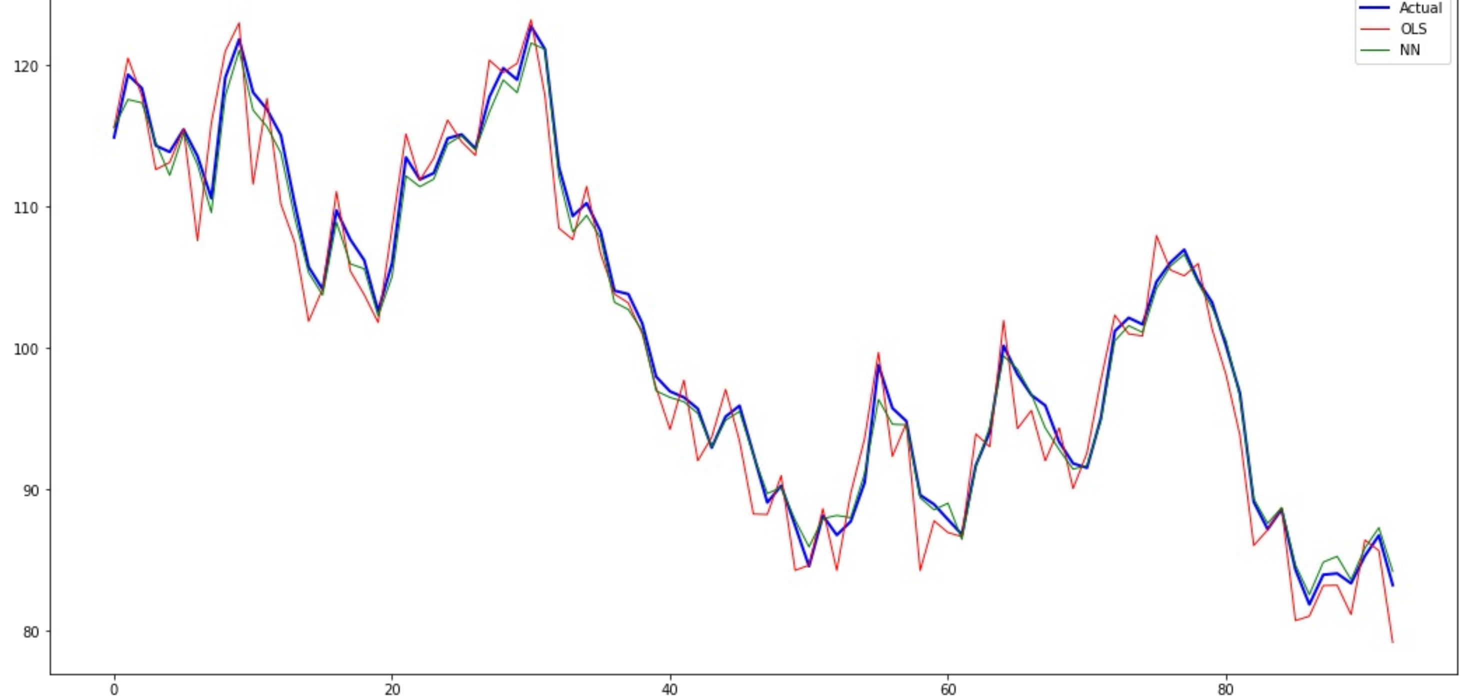
In [16]:

```python
main(ticker = 'AMD.O')
```

AMD.O stocks AVG 2021-04-01-2022-06-30



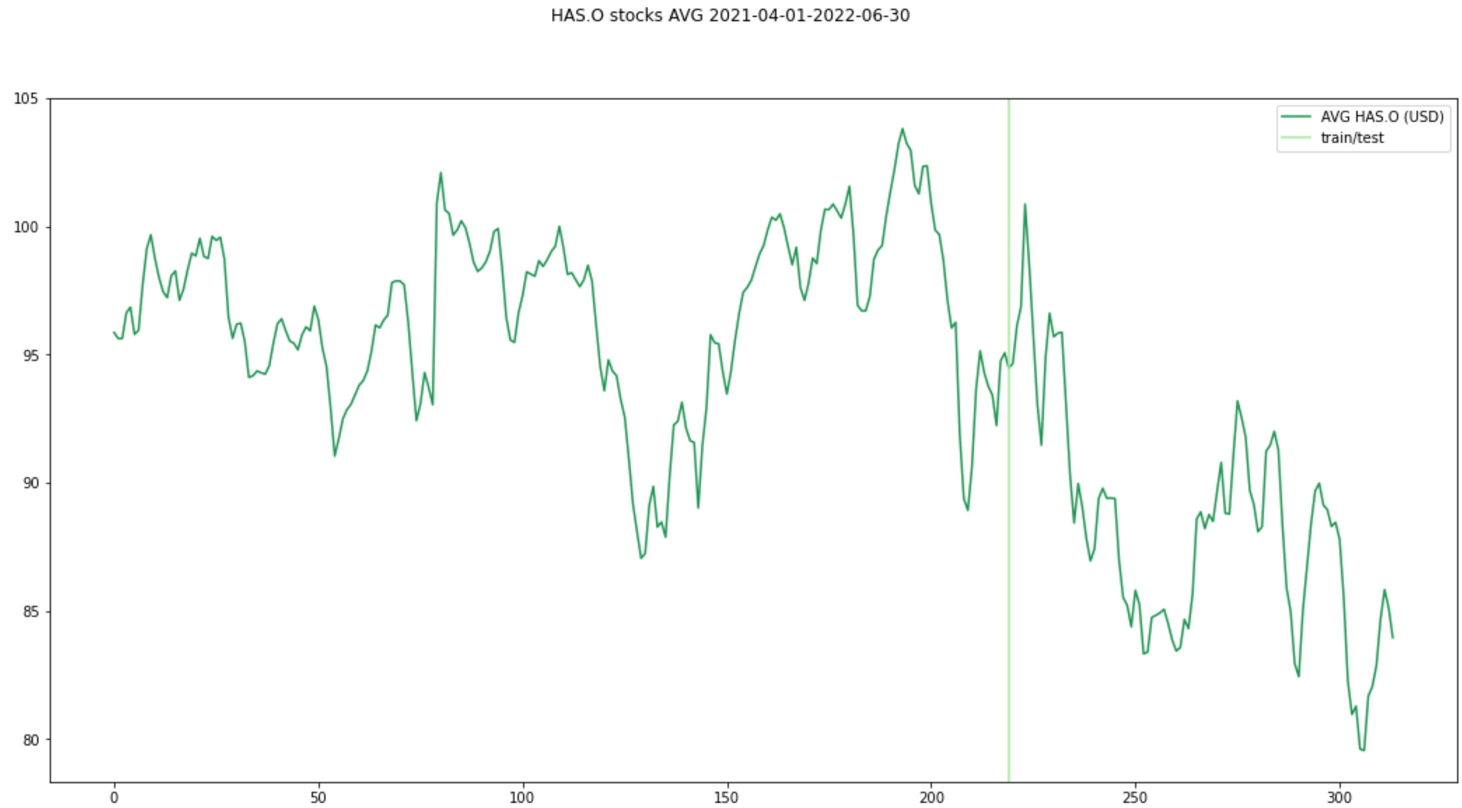

```
                 Results: Ordinary least squares
==================================================================
Model:               OLS              Adj. R-squared:     0.993
Dependent Variable:  AVG_TOMORROW     AIC:                956.7436
Date:                2022-07-11 17:45 BIC:                983.8562
No. Observations:    219              Log-Likelihood:     -470.37
Df Model:            7                F-statistic:        4139.
Df Residuals:        211              Prob (F-statistic): 4.85e-222
R-squared:           0.993            Scale:              4.4592
--------------------------------------------------------------------
             Coef.    Std.Err.      t      P>|t|     [0.025   0.975]
--------------------------------------------------------------------
const       -0.4790    0.8195   -0.5845   0.5595   -2.0945   1.1365
HIGH        -0.2950    0.1510   -1.9534   0.0521   -0.5927   0.0027
LOW          0.2781    0.1511    1.8396   0.0672   -0.0199   0.5760
OPEN        -0.0742    0.1113   -0.6668   0.5057   -0.2937   0.1452
CLOSE        1.1045    0.1058   10.4403   0.0000    0.8959   1.3130
COUNT        0.0000    0.0000    1.1296   0.2599   -0.0000   0.0000
VOLUME      -0.0000    0.0000   -1.2376   0.2172   -0.0000   0.0000
SENT         0.1301    0.0356    3.6507   0.0003    0.0598   0.2003
------------------------------------------------------------------
Omnibus:              16.219       Durbin-Watson:          2.164
Prob(Omnibus):        0.000        Jarque-Bera (JB):       26.148
Skew:                 0.434        Prob(JB):               0.000
Kurtosis:             4.453        Condition No.:          377766364
==================================================================
* The condition number is large (4e+08). This might indicate
strong multicollinearity or other numerical problems.
```




```
Mean Squared Error of NN model:  0.6372774357276006
Mean Squared Error of OLS:  5.339673521376355
```

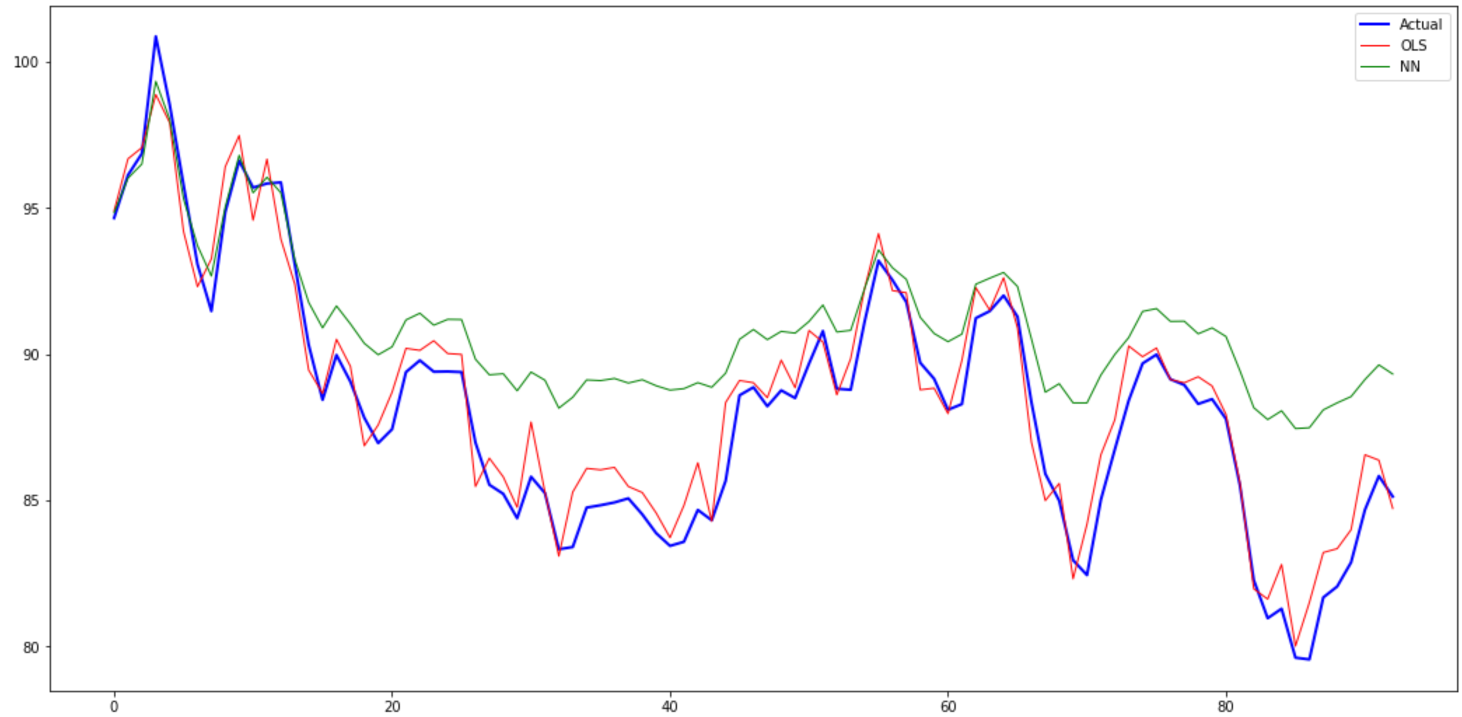
In [17]:

```
main(ticker = 'HAS.O')
```




```
                  Results: Ordinary least squares
====================================================================
Model:              OLS              Adj. R-squared:     0.923
Dependent Variable: AVG_TOMORROW     AIC:                603.2424
Date:               2022-07-11 17:45 BIC:                630.3550
No. Observations:   219              Log-Likelihood:     -293.62
Df Model:           7                F-statistic:        371.9
Df Residuals:       211              Prob (F-statistic): 5.86e-115
R-squared:          0.925            Scale:              0.88764
----------------------------------------------------------------------
             Coef.    Std.Err.     t       P>|t|     [0.025    0.975]
----------------------------------------------------------------------
const        6.8315     1.9166   3.5645   0.0005    3.0535   10.6096
HIGH        -0.0293     0.1301  -0.2253   0.8220   -0.2858    0.2272
LOW          0.2150     0.1386   1.5519   0.1222   -0.0581    0.4882
```

```
OPEN        -0.1111      0.1083    -1.0255    0.3063    -0.3247     0.1025
CLOSE        0.8585      0.1073     7.9993    0.0000     0.6469     1.0701
COUNT       -0.0000      0.0000    -1.2890    0.1988    -0.0001     0.0000
VOLUME       0.0000      0.0000     1.7511    0.0814    -0.0000     0.0000
SENT        -0.0032      0.0227    -0.1405    0.8884    -0.0480     0.0416
------------------------------------------------------------------
Omnibus:                183.302       Durbin-Watson:           1.955
Prob(Omnibus):          0.000         Jarque-Bera (JB):        7180.044
Skew:                   2.785         Prob(JB):                0.000
Kurtosis:               30.492        Condition No.:           27345181
==================================================================
* The condition number is large (3e+07). This might indicate
strong multicollinearity or other numerical problems.
```

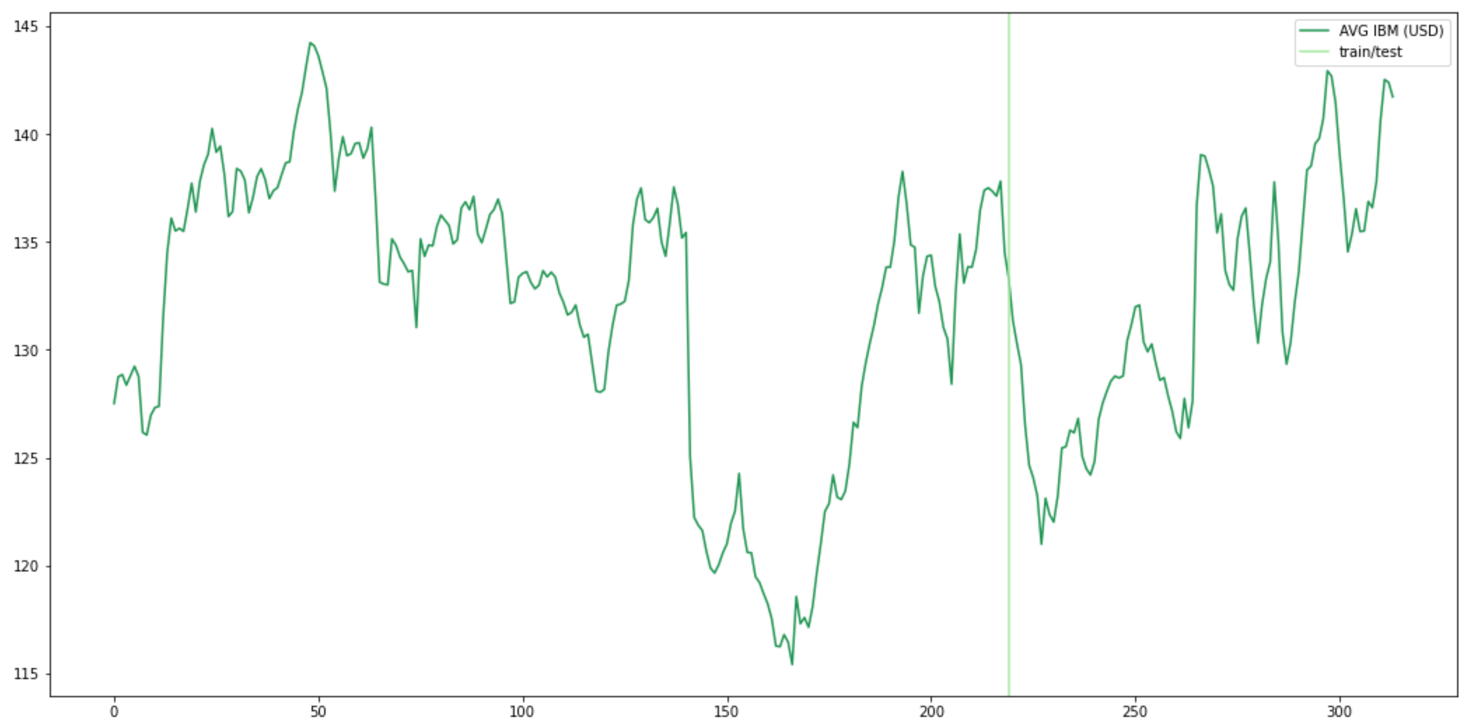



```
Mean Squared Error of NN model:  11.46175095076568
Mean Squared Error of OLS:  1.0464642363408918
```

In [18]:

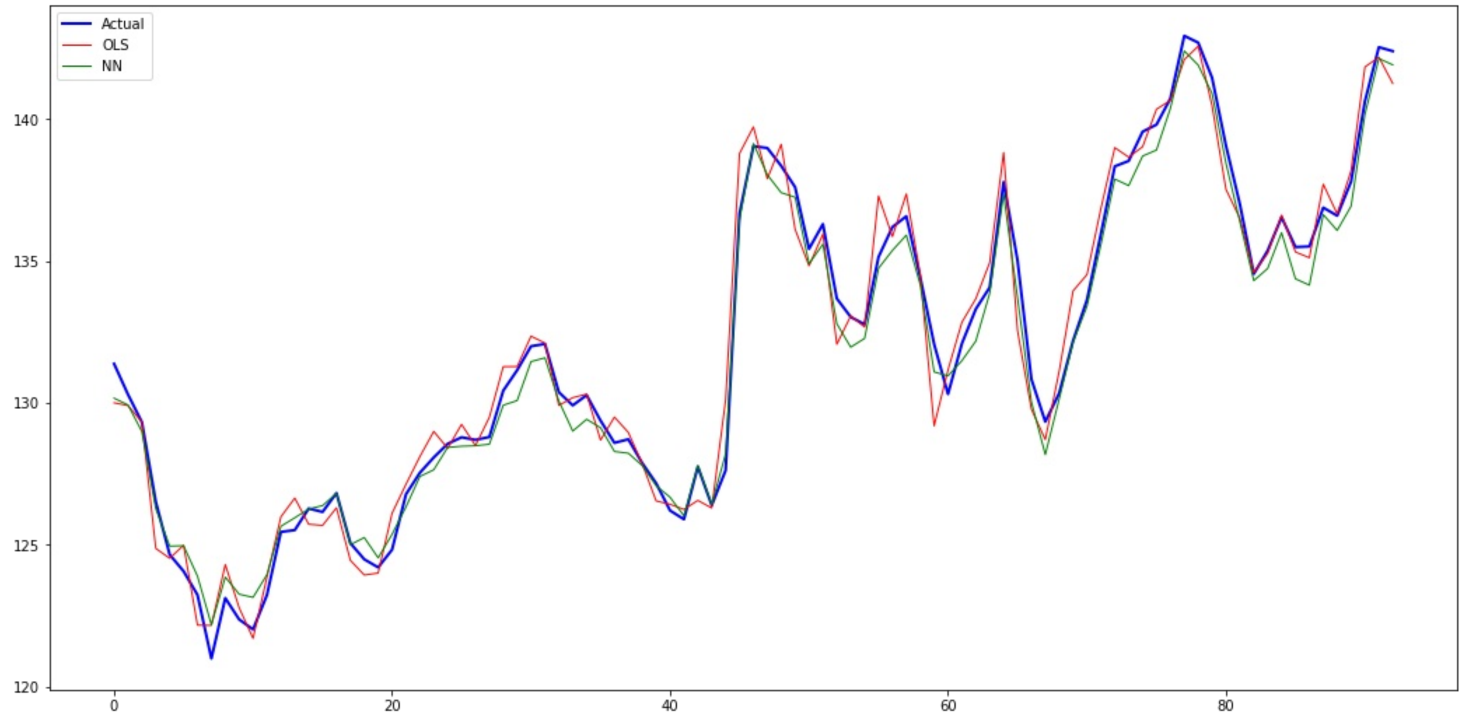
```
main(ticker='IBM')
```

IBM stocks AVG 2021-04-01-2022-06-30




```
Results: Ordinary least squares
```

```
====================================================================
Model:               OLS              Adj. R-squared:     0.964
Dependent Variable:  AVG_TOMORROW     AIC:                730.6087
Date:                2022-07-11 17:45 BIC:                757.7213
No. Observations:    219              Log-Likelihood:     -357.30
Df Model:            7                F-statistic:        841.5
Df Residuals:        211              Prob (F-statistic): 2.31e-150
R-squared:           0.965            Scale:              1.5879
----------------------------------------------------------------------
             Coef.    Std.Err.     t       P>|t|     [0.025   0.975]
----------------------------------------------------------------------
const        4.0754    1.8123    2.2487   0.0256    0.5028   7.6480
HIGH        -0.1246    0.1595   -0.7815   0.4354   -0.4391   0.1898
LOW         -0.1064    0.1742   -0.6108   0.5420   -0.4499   0.2370
OPEN         0.1086    0.1267    0.8577   0.3921   -0.1411   0.3584
CLOSE        1.0905    0.1325    8.2329   0.0000    0.8294   1.3516
COUNT       -0.0000    0.0000   -0.3495   0.7270   -0.0000   0.0000
VOLUME       0.0000    0.0000    0.3212   0.7484   -0.0000   0.0000
SENT         0.0626    0.0218    2.8703   0.0045    0.0196   0.1056
--------------------------------------------------------------------
Omnibus:              163.619      Durbin-Watson:         1.979
Prob(Omnibus):        0.000        Jarque-Bera (JB):      3815.977
Skew:                 -2.522       Prob(JB):              0.000
Kurtosis:             22.818       Condition No.:         127697156
====================================================================
* The condition number is large (1e+08). This might indicate
strong multicollinearity or other numerical problems.
```

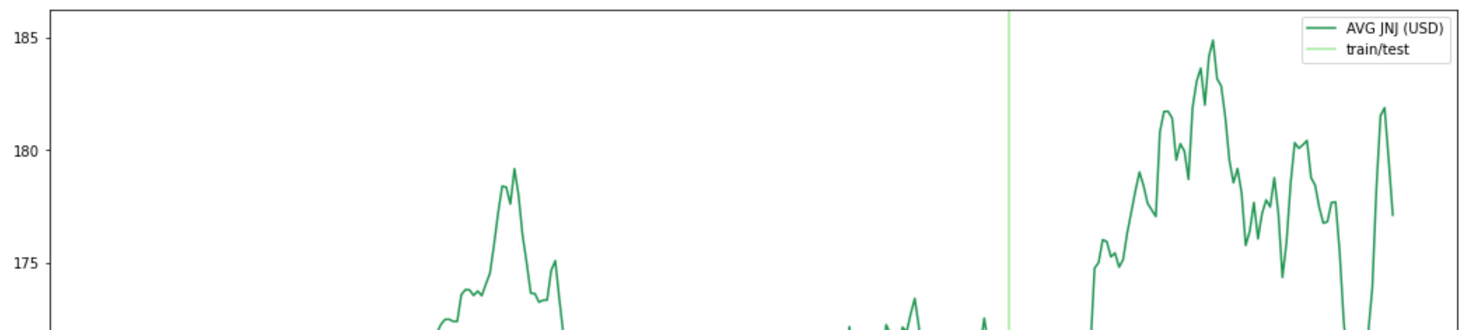


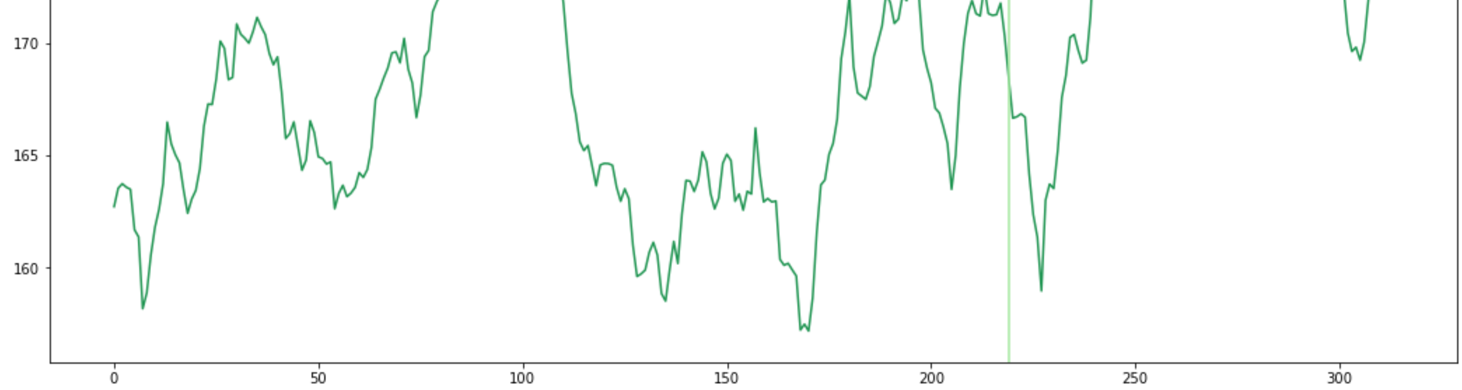

```
Mean Squared Error of NN model:  0.405187505919918
Mean Squared Error of OLS:  0.846706029230757
```

In [19]:

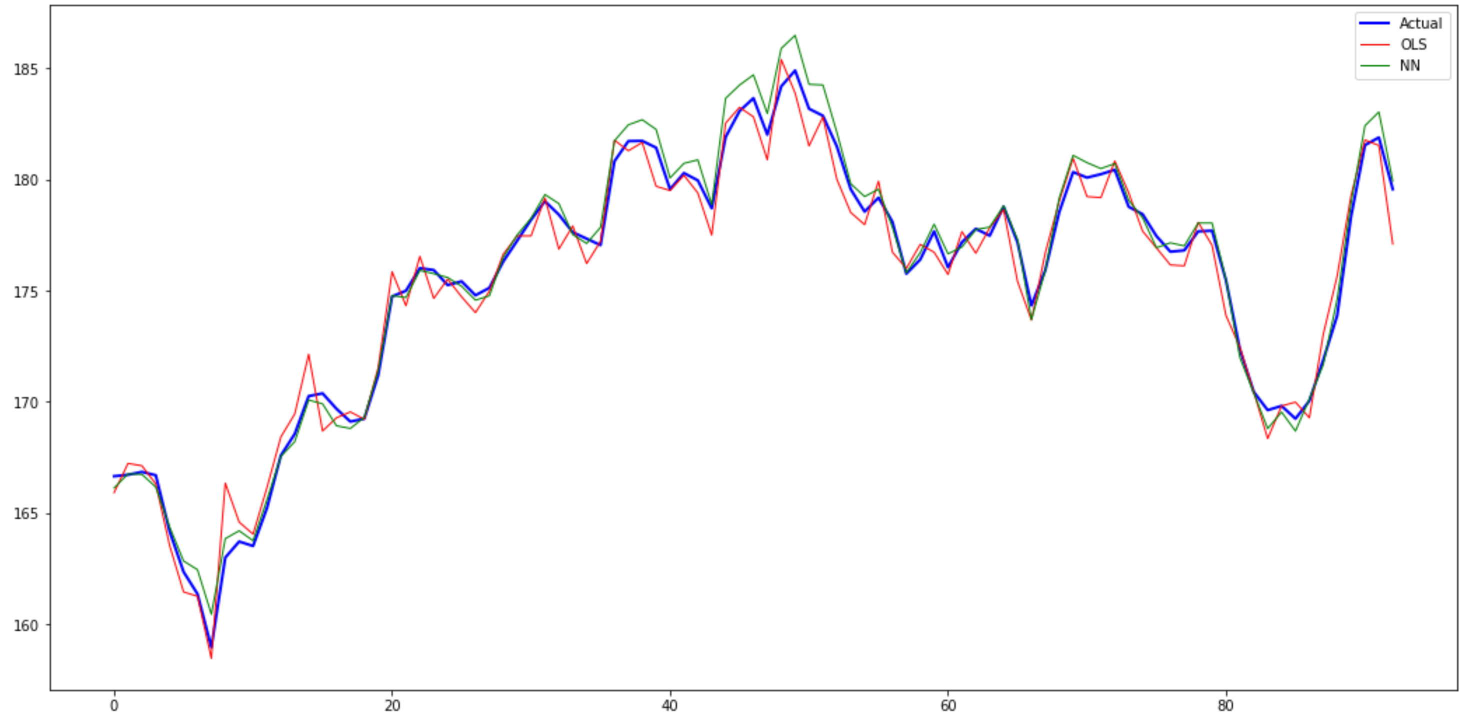
```
main(ticker='JNJ')
```

JNJ stocks AVG 2021-04-01-2022-06-30






```
                  Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.960
Dependent Variable: AVG_TOMORROW     AIC:                603.9600
Date:               2022-07-11 17:45 BIC:                631.0726
No. Observations:   219              Log-Likelihood:     -293.98
Df Model:           7                F-statistic:        751.1
Df Residuals:       211              Prob (F-statistic): 2.40e-145
R-squared:          0.961            Scale:              0.89055
--------------------------------------------------------------------
            Coef.    Std.Err.     t      P>|t|     [0.025    0.975]
--------------------------------------------------------------------
const       5.4194     2.5201   2.1505   0.0327    0.4517   10.3872
HIGH        0.0771     0.1321   0.5835   0.5602   -0.1833    0.3375
LOW        -0.1795     0.1267  -1.4167   0.1581   -0.4294    0.0703
OPEN        0.0621     0.0919   0.6757   0.5000   -0.1191    0.2433
CLOSE       1.0082     0.1006  10.0227   0.0000    0.8099    1.2065
COUNT      -0.0000     0.0000  -0.5560   0.5788   -0.0000    0.0000
VOLUME     -0.0000     0.0000  -0.1876   0.8513   -0.0000    0.0000
SENT        0.0018     0.0074   0.2408   0.8099   -0.0128    0.0164
------------------------------------------------------------------
Omnibus:              27.566       Durbin-Watson:          2.079
Prob(Omnibus):        0.000        Jarque-Bera (JB):       58.301
Skew:                 -0.606       Prob(JB):               0.000
Kurtosis:             5.219        Condition No.:          289643708
==================================================================
* The condition number is large (3e+08). This might indicate
strong multicollinearity or other numerical problems.
```




```
Mean Squared Error of NN model:  0.39148453583006615
Mean Squared Error of OLS:  0.8841508974201747
```