CaixaBank Tech Hackathon

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Date: *28/05/22*

Using: *Anaconda3*

In [ ]:
```
# Requirements (Using anaconda3)
%pip install -q mplfinance
```

```
Note: you may need to restart the kernel to use updated packages.
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import mplfinance as mplf

%matplotlib inline
```

Dataset

In [ ]:
```
df_train = pd.read_csv('train.csv', index_col=0, parse_dates=True)

# Headers
DATE       = 'Date'
OPEN       = 'Open'
HIGH       = 'High'
LOW        = 'Low'
CLOSE      = 'Close'
ADJ_CLOSE  = 'Adj Close'
VOLUME     = 'Volume'
TARGET     = 'Target'
TEST_INDEX = 'test_index'

print(f'Shape: {df_train.shape}')
print(df_train.dtypes)
df_train
```

```
Shape: (6554, 7)
Open          float64
High          float64
Low           float64
Close         float64
Adj Close     float64
Volume        float64
Target          int64
dtype: object
```

Out[ ]:

	Open	High	Low	Close	Adj Close	Volume
Date						
1994-01-03	3615.199951	3654.699951	3581.000000	3654.500000	3654.496338	0.0
1994-01-04	3654.500000	3675.500000	3625.100098	3630.300049	3630.296387	0.0
1994-01-05	3625.199951	3625.199951	3583.399902	3621.199951	3621.196289	0.0
1994-01-06	NaN	NaN	NaN	NaN	NaN	NaN
1994-01-07	3621.199951	3644.399902	3598.699951	3636.399902	3636.396240	0.0
...	...	...	...	...	...	...
2019-05-24	9150.299805	9211.099609	9141.400391	9174.599609	9174.599609	121673100.0
2019-05-27	9225.900391	9294.599609	9204.700195	9216.400391	9216.400391	60178000.0
2019-05-28	9220.400391	9224.900391	9132.900391	9191.799805	9191.799805	218900800.0
2019-05-29	9113.200195	9116.700195	9035.099609	9080.500000	9080.500000	148987100.0
2019-05-30	9120.799805	9175.200195	9114.099609	9157.799805	9157.799805	101389200.0

6554 rows × 7 columns

Data formatting

We could either replace all rows with empty fields (aka NaN) with 0.0 or drop them from the data set

In [ ]:
```
df_train = df_train.dropna(axis=0, how='any')
df_train
```

Out[ ]:

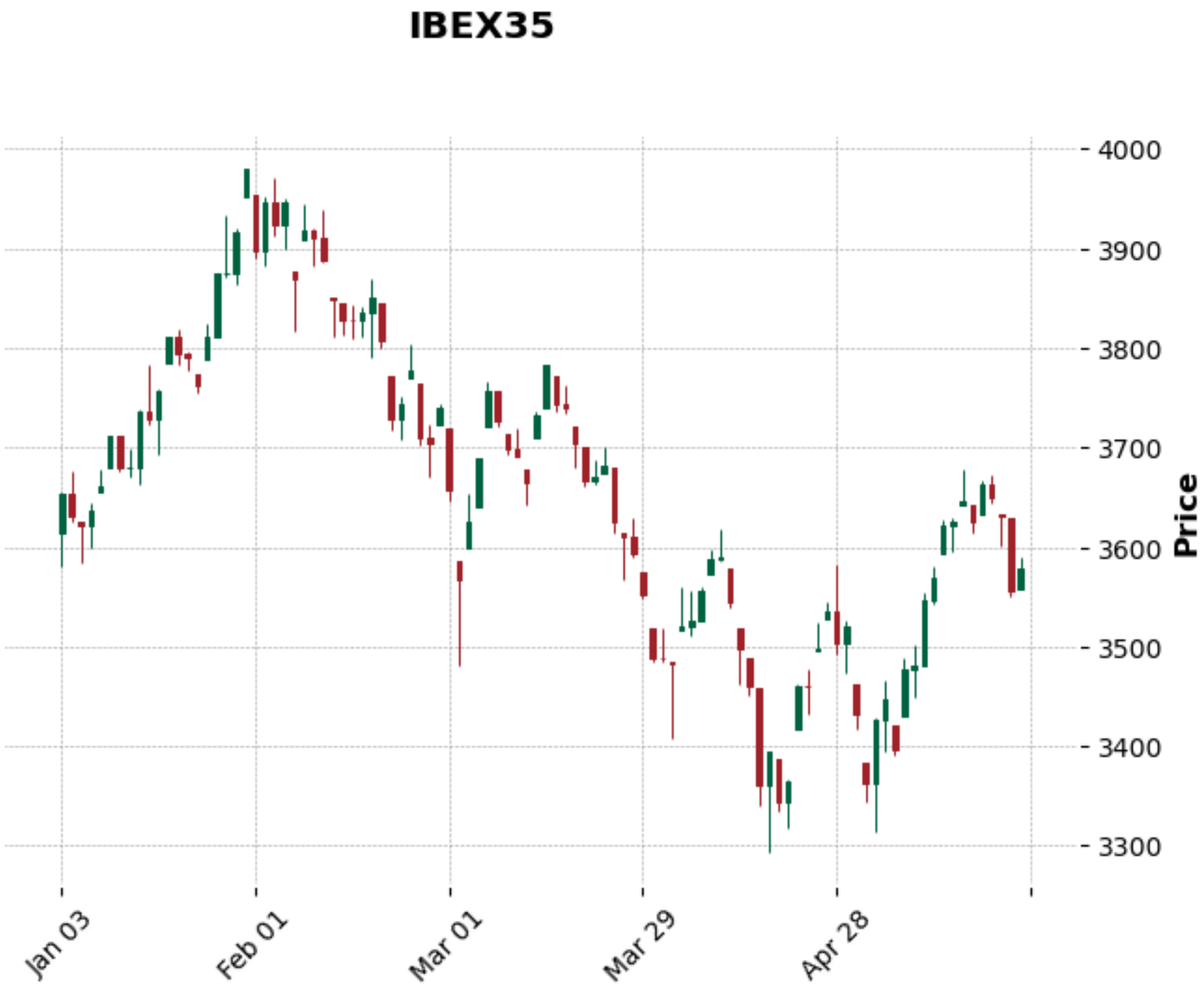
	Open	High	Low	Close	Adj Close	Volume
Date						
1994-01-03	3615.199951	3654.699951	3581.000000	3654.500000	3654.496338	0.0
1994-01-04	3654.500000	3675.500000	3625.100098	3630.300049	3630.296387	0.0
1994-01-05	3625.199951	3625.199951	3583.399902	3621.199951	3621.196289	0.0
1994-01-07	3621.199951	3644.399902	3598.699951	3636.399902	3636.396240	0.0
1994-01-10	3655.199951	3678.199951	3655.199951	3660.600098	3660.596436	0.0
...	...	...	...	...	...	...
2019-05-24	9150.299805	9211.099609	9141.400391	9174.599609	9174.599609	121673100.0
2019-05-27	9225.900391	9294.599609	9204.700195	9216.400391	9216.400391	60178000.0
2019-05-28	9220.400391	9224.900391	9132.900391	9191.799805	9191.799805	218900800.0
2019-05-29	9113.200195	9116.700195	9035.099609	9080.500000	9080.500000	148987100.0
2019-05-30	9120.799805	9175.200195	9114.099609	9157.799805	9157.799805	101389200.0

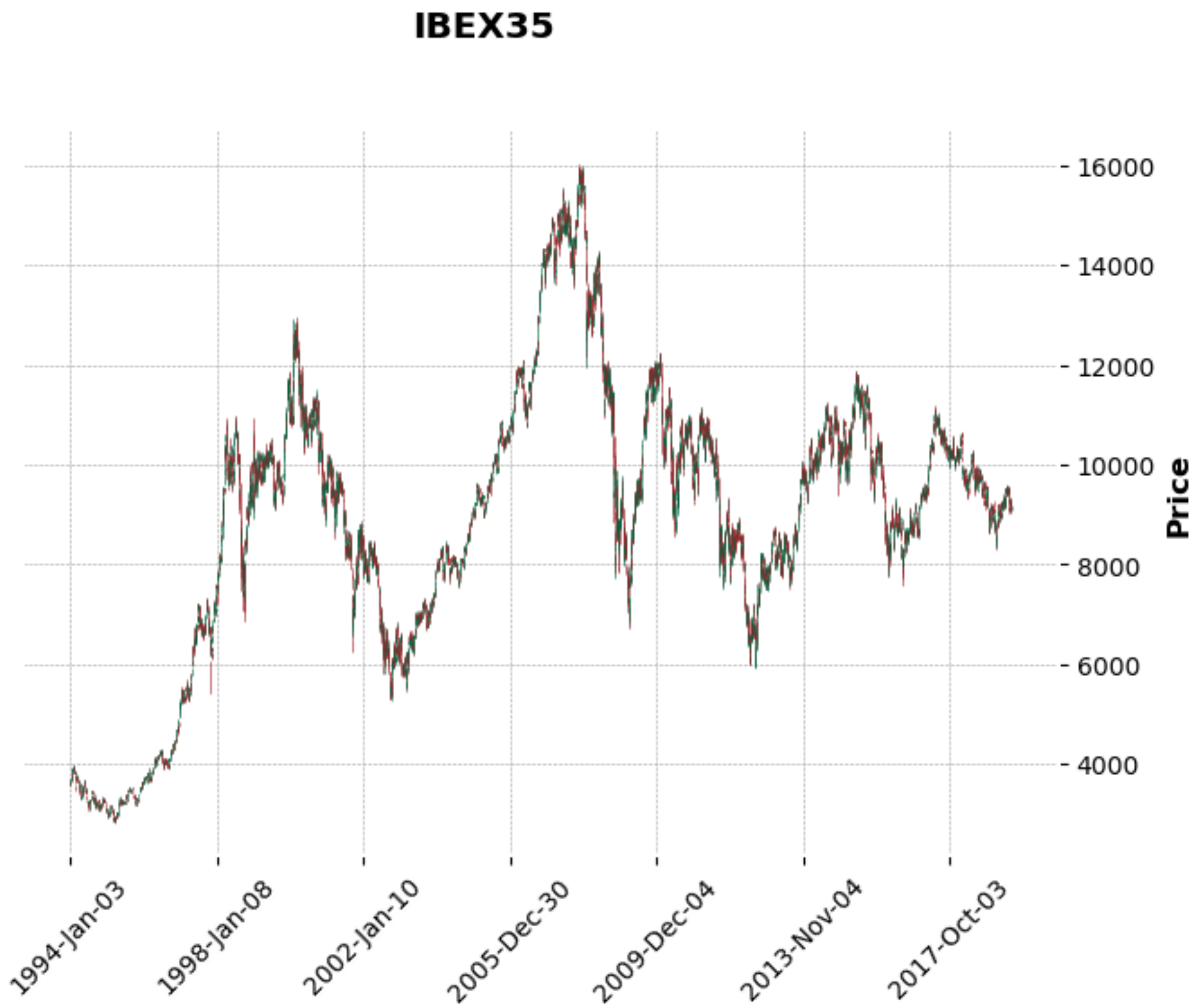
6421 rows × 7 columns

Simple analysis of the problem

In [ ]:

```
# df_train.index = pd.DatetimeIndex(df_train['Date'])

mplf.plot(
    df_train.iloc[:100,:],
    type='candle',
    title='IBEX35',
    style='charles',
    ylabel='Price',
)

mplf.plot(
    df_train,
    type='candle',
    title='IBEX35',
    style='charles',
    ylabel='Price',
    warn_too_much_data=len(df_train)
)

plt.plot(df_train.index, df_train[CLOSE])
```





Out[ ]:
```
[<matplotlib.lines.Line2D at 0x7fe7f2c032b0>]
```


16000
14000
12000
10000
8000
6000
4000
1996
2000
2004
2008
2012
2016
2020

For now, we know that the stock market (aka IBEX35) tends to be very volatile.

But, that does not mean that the prediction is impossible. So, we want to predict a $target$ that defines:

$$target(boolean) = close_{day+3} > close_{day} \tag{1}$$

The strategy of working of ML/AI it's very experimental, so, we could think about different aproaches:

1) *Classification*. We want a target/vector *[y] (1 x 1)* defining a boolean for each vector *[X] (N x 1)*, this boolean just tells us if the closing price 3 days ahead will be greater than the actual day. Thats why we could think about a classification model, classifying for each vectory *[X]* the target (True/False or 1/0).

2) *Regression*. It's a good idea to test a regression in base of the closing price. Predict the closing price 3 days ahead. So, cheking thr actual price and the price 3 days later we could determinate the *target* value.

3) *Time Series*. Analysing and forecasting the

Just for fun we'll try the first approoach because it is very simple to generate the model, the second approcach we could get more important results and surely using the third strategy we'll obtain better results (more difficult and with a more complex analysis) using moving average... thecniques from events happened on the past for being able to predict the stock price 3 days ahead.

Testing Data

Before continuing, the file **test_x.csv** does not contain the *target* column that we need for evaluating our model predictions performance

In [ ]:

```
df_test = pd.read_csv('test_x.csv', index_col=0)
df_test
```

Out[ ]:

test_index	Date	Open	High	Low	Close	Adj Close	
6557	2019-06-05	9136.799805	9173.400391	9095.000000	9150.500000	9150.500000	15
6558	2019-06-06	9169.200195	9246.200195	9136.700195	9169.200195	9169.200195	2
6559	2019-06-07	9186.700195	9261.400391	9185.700195	9236.099609	9236.099609	15
6560	2019-06-10	9284.200195	9302.200195	9248.099609	9294.099609	9294.099609	10
6561	2019-06-11	9288.599609	9332.500000	9273.400391	9282.099609	9282.099609	1
...	...	...	...	...	...	...	
7278	2022-03-25	8314.099609	8363.200195	8286.500000	8330.599609	8330.599609	15
7279	2022-03-28	8354.400391	8485.700195	8354.400391	8365.599609	8365.599609	10
7280	2022-03-29	8451.000000	8621.000000	8419.700195	8614.599609	8614.599609	2
7281	2022-03-30	8583.299805	8597.400391	8508.900391	8550.599609	8550.599609	18
7282	2022-03-31	8562.599609	8588.299805	8445.099609	8445.099609	8445.099609	2

726 rows × 7 columns

In [ ]:

```
test_target_size = len(df_test)
target = np.zeros(test_target_size).astype(int)
for test_index in range(test_target_size-3):
    target[test_index] = df_test.iloc[test_index+3][CLOSE] > df_test.iloc[t

df_test[TARGET] = target
df_test

# NOTE: We should have to drop the last 3 rows because we have no further c
# df_test = df_test.iloc[:-3,:]
```

Out[ ]:

test_index	Date	Open	High	Low	Close	Adj Close	
6557	2019-06-05	9136.799805	9173.400391	9095.000000	9150.500000	9150.500000	1ŧ
6558	2019-06-06	9169.200195	9246.200195	9136.700195	9169.200195	9169.200195	2'
6559	2019-06-07	9186.700195	9261.400391	9185.700195	9236.099609	9236.099609	1ŧ
6560	2019-06-10	9284.200195	9302.200195	9248.099609	9294.099609	9294.099609	1(
6561	2019-06-11	9288.599609	9332.500000	9273.400391	9282.099609	9282.099609	1.
...	...	...	...	...	...	...	
7278	2022-03-25	8314.099609	8363.200195	8286.500000	8330.599609	8330.599609	1ŧ
7279	2022-03-28	8354.400391	8485.700195	8354.400391	8365.599609	8365.599609	1(
7280	2022-03-29	8451.000000	8621.000000	8419.700195	8614.599609	8614.599609	2
7281	2022-03-30	8583.299805	8597.400391	8508.900391	8550.599609	8550.599609	1ε
7282	2022-03-31	8562.599609	8588.299805	8445.099609	8445.099609	8445.099609	2

726 rows × 8 columns

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import f1_score, max_error, mean_squared_error, mean_a

X_train = df_train.iloc[:, :-1]
y_train = df_train[TARGET]
```

Model-1: Decision Tree Classifier

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier(
    max_depth=20
)
```

In [ ]:
```
clf.fit(X_train, y_train)
```

Out[ ]:
```
DecisionTreeClassifier(max_depth=20)
```

In [ ]:
```
# Testing dataset
X_test = df_test.iloc[:, 1:-1]
y_test = df_test[TARGET]

# Predictions
y_pred = clf.predict(X_test)
```

In [ ]:
```
f1_score(
    average='macro',
    y_true=y_test,
    y_pred=y_pred
)
```

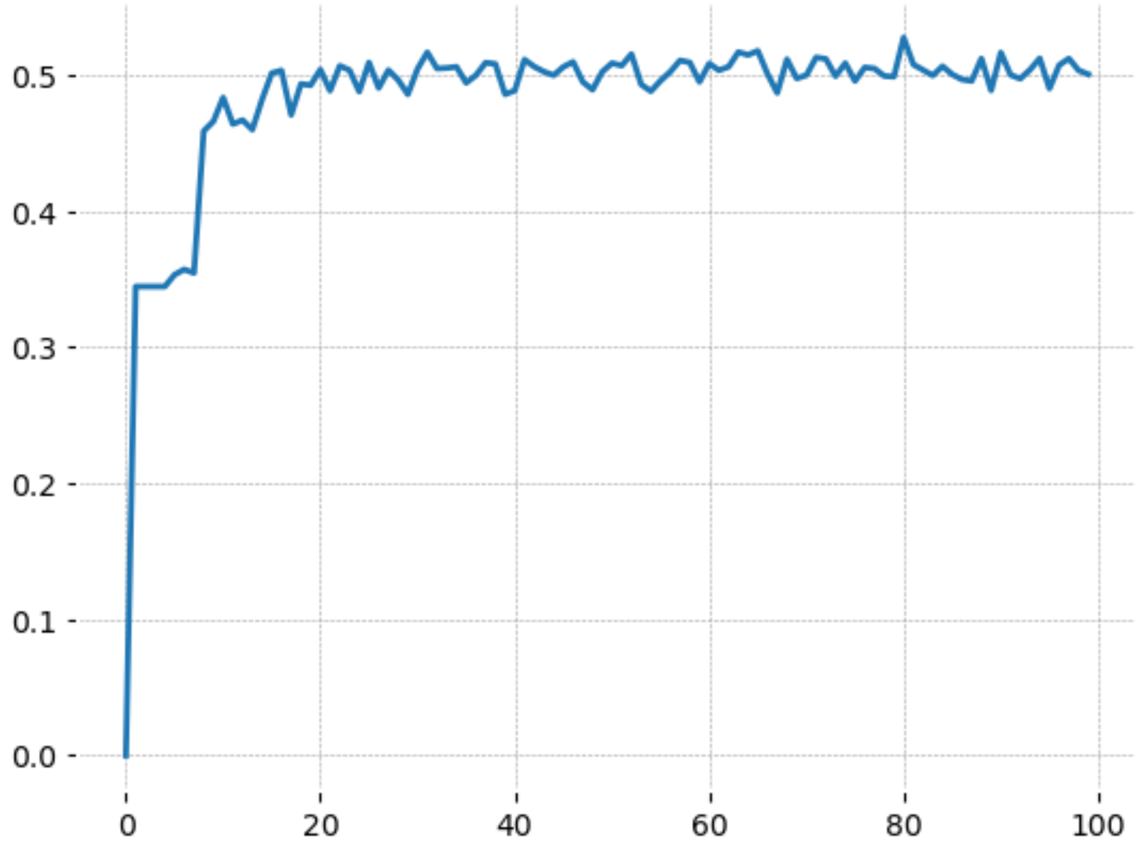
Out[ ]:
```
0.5133824610859175
```

We can see that the score is around 50%, that is to say that the score always will have a random factor of 50% chance. Normalizing the data on Trees does not affect that much, but we could iterate and visualize for each depth that we append how te score varies

In [ ]:
```
depths = np.array(range(100))
scores = np.zeros(100)

for depth in depths[1:]:
    clf = DecisionTreeClassifier(max_depth=depth)
    clf.fit(X_train, y_train)

    scores[depth] = f1_score(average='macro',
        y_true=y_test,
        y_pred=clf.predict(X_test)
    )

print(max(scores), np.where(scores == max(scores)))
plt.plot(depths, scores)
```

```
0.5277644642245807 (array([80]),)
```

Out[ ]:
```
[<matplotlib.lines.Line2D at 0x7fe7f88f3d30>]
```



> NOTE: Finally we can see that using decission trees (as we could've expected) the prediction chance is around 50%. Obvioulsy incrementing the number of the depth we are overfitting the model putting **too much noise** and the model would perform even worse.

Model-2: Random Forest Classifier

In [ ]:
```
clf = RandomForestClassifier(n_estimators=25)
clf.fit(X_train, y_train)

f1_score(
    average='macro',
    y_true=y_test,
    y_pred=clf.predict(X_test)
)
```

Out[ ]:
```
0.5040404755571799
```

> NOTE: Finally, we've seen that using decision trees the score is low around 50% as we could've have expected.

Model-3: Linear Regression || Random Forest Regressor

In [ ]:

```
from sklearn.linear_model import LinearRegression

pd.options.mode.chained_assignment = None # For ignoring the warnings of co
close_3_days = np.zeros(len(X_train))

for date in range(len(X_train) - 3):
    # NOTE: This is an approximation, because on the dataset there are miss
    # dates between rows. For know i've ignored this fact (we could fill a
    # on a certain period of time, ...)
    close_3_days[date] = df_train.iloc[date+3][CLOSE]

# Adding the closing price "3" days ahead from the actual day
df_train[f'{CLOSE}-3'] = close_3_days

# We add also a row for checking the given TARGET vector prediction vs my a
# TARGET.
df_train[f'{TARGET}-check'] = df_train[f'{CLOSE}-3'] > df_train[CLOSE]
df_train[f'{TARGET}-check'] = df_train[f'{TARGET}-check'].astype(int)

print(f1_score(df_train[f'{TARGET}-check'],df_train[TARGET]))
# 0.9822209268434859 (OK! the missing rows does not affect the TARGET vecto

df_train.head(20)
```

```
0.9822209268434859
```

Out[ ]:

	Open	High	Low	Close	Adj Close	Volume	Targ
Date							
1994-01-03	3615.199951	3654.699951	3581.000000	3654.500000	3654.496338	0.0	
1994-01-04	3654.500000	3675.500000	3625.100098	3630.300049	3630.296387	0.0	
1994-01-05	3625.199951	3625.199951	3583.399902	3621.199951	3621.196289	0.0	
1994-01-07	3621.199951	3644.399902	3598.699951	3636.399902	3636.396240	0.0	
1994-01-10	3655.199951	3678.199951	3655.199951	3660.600098	3660.596436	0.0	
1994-01-11	3679.699951	3712.500000	3679.699951	3712.399902	3712.396240	0.0	
1994-01-12	3712.300049	3712.300049	3675.899902	3680.100098	3680.096436	0.0	
1994-	3680.100098	3698.199951	3670.399902	3680.800049	3680.796387	0.0	

01-13						
1994-01-14	3680.800049	3737.399902	3662.899902	3736.399902	3736.395996	0.0
1994-01-17	3736.399902	3783.300049	3723.899902	3729.100098	3729.096436	0.0
1994-01-18	3729.100098	3758.899902	3693.699951	3757.000000	3756.996094	0.0
1994-01-19	3784.300049	3812.100098	3784.300049	3811.300049	3811.296143	0.0
1994-01-20	3811.300049	3819.000000	3783.800049	3794.399902	3794.395996	0.0
1994-01-21	3794.399902	3796.300049	3777.699951	3790.500000	3790.496094	0.0
1994-01-24	3773.399902	3773.399902	3754.399902	3762.600098	3762.596191	0.0
1994-01-25	3788.300049	3823.600098	3788.300049	3811.500000	3811.496094	0.0
1994-01-26	3811.500000	3875.100098	3811.399902	3874.600098	3874.596191	0.0
1994-01-27	3874.600098	3933.100098	3872.100098	3875.899902	3875.895996	0.0
1994-01-28	3875.899902	3920.699951	3863.500000	3915.699951	3915.696045	0.0
1994-01-31	3951.500000	3980.500000	3951.500000	3980.500000	3980.495850	0.0

In [ ]:

```
X_train = df_train.drop([f'{CLOSE}-3', TARGET, f'{TARGET}-check'], axis=1)
y_train = df_train[f'{CLOSE}-3']

reg = LinearRegression()
# reg = RandomForestRegressor()

reg.fit(X_train, y_train)
```

Out[ ]:

```
LinearRegression()
```

In [ ]:

```
df_test = pd.read_csv('test_x.csv', index_col=1, parse_dates=True)
close_3_days = np.zeros(len(X_test))

for date in range(len(X_test) - 3):
    # NOTE: This is an approximation, because on the dataset there are miss
    # dates between rows. For know i've ignored this fact (we could fill a
    # on a certain period of time, ...)
    close_3_days[date] = df_test.iloc[date+3][CLOSE]

# Adding the closing price "3" days ahead from the actual day
df_test[f'{CLOSE}-3'] = close_3_days

# Adding a TARGET testing vector
df_test[TARGET] = df_test[f'{CLOSE}-3'] > df_test[CLOSE]
df_test[TARGET] = df_test[TARGET].astype(int)

df_test
```

Out[ ]:

Date	test_index	Open	High	Low	Close	Adj Close	
2019-06-05	6557	9136.799805	9173.400391	9095.000000	9150.500000	9150.500000	1
2019-06-06	6558	9169.200195	9246.200195	9136.700195	9169.200195	9169.200195	2
2019-06-07	6559	9186.700195	9261.400391	9185.700195	9236.099609	9236.099609	1
2019-06-10	6560	9284.200195	9302.200195	9248.099609	9294.099609	9294.099609	1
2019-06-11	6561	9288.599609	9332.500000	9273.400391	9282.099609	9282.099609	1
...	...	...	...	...	...	...	
2022-03-25	7278	8314.099609	8363.200195	8286.500000	8330.599609	8330.599609	1
2022-03-28	7279	8354.400391	8485.700195	8354.400391	8365.599609	8365.599609	1
2022-03-29	7280	8451.000000	8621.000000	8419.700195	8614.599609	8614.599609	2
2022-03-30	7281	8583.299805	8597.400391	8508.900391	8550.599609	8550.599609	1
2022-03-31	7282	8562.599609	8588.299805	8445.099609	8445.099609	8445.099609	2

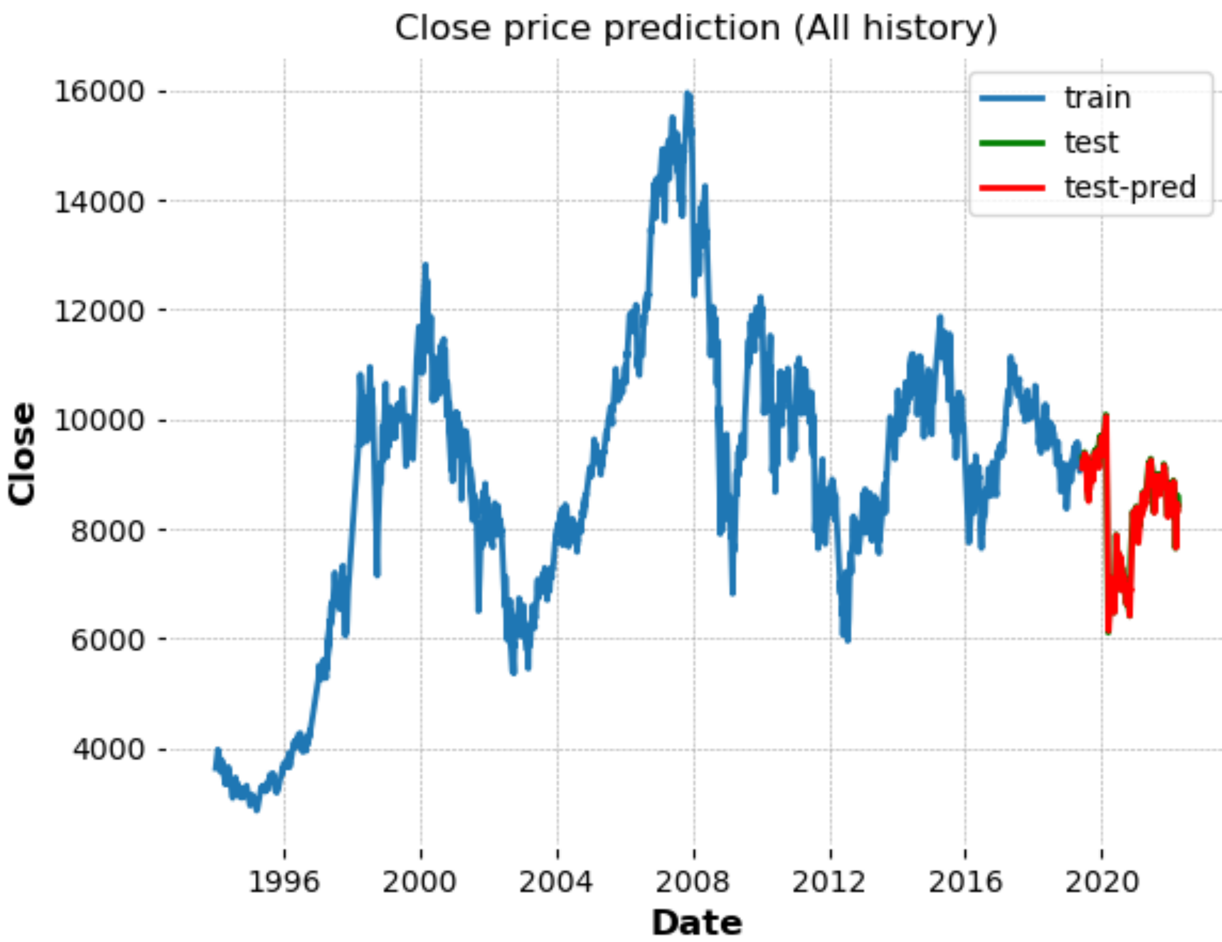
726 rows × 9 columns

In [ ]:

```
X_test = df_test.drop([TEST_INDEX, f'{CLOSE}-3', TARGET], axis=1)
y_test = df_test[f'{CLOSE}-3']
```

In [ ]:

```
y_pred = reg.predict(X_test)
y_pred = pd.DataFrame(data=y_pred, columns=[CLOSE], index=X_test.index)

plt.title('Close price prediction')
plt.ylabel(CLOSE)
plt.xlabel(DATE)
plt.xticks(rotation=45)
plt.plot(y_test[:-3], label='test')
plt.plot(y_pred[:-3], color='red', label='test-pred')
plt.legend()
plt.show()

plt.title('Close price prediction (All history)')
plt.ylabel(CLOSE)
plt.xlabel(DATE)
plt.plot(y_train[:-3], label='train')
plt.plot(y_test[:-3], color ='green', label='test')
plt.plot(y_pred[:-3], color='red', label='test-pred')
plt.legend()
plt.show()
```



In [ ]:
```
print('> MAX:', max_error(y_true=y_test, y_pred=y_pred))
print('> MSE:', mean_squared_error(y_true=y_test, y_pred=y_pred))
print('> MAE:', mean_absolute_error(y_true=y_test, y_pred=y_pred))
```

```
> MAX: 8593.97900466053
> MSE: 343045.88510269934
> MAE: 175.49642862881439
```

Clearly we can see that the mean absolute error is around 175, if the MAE mantains it's value we could say approx. that:

$$close_{day+3} = close_{day+3} \pm 180 \tag{2}$$

In [ ]:
```
df_test[f'{CLOSE}-3-pred'] = y_pred
df_test[f'{TARGET}-pred'] = df_test[f'{CLOSE}-3-pred'] + 30 > df_test[CLOSE
df_test[f'{TARGET}-pred'] = df_test[f'{TARGET}-pred'].astype(int)

df_test

f1_score(
    average='macro',
    y_true=df_test[TARGET],
    y_pred=df_test[f'{TARGET}-pred']
)
```

Out[ ]: 0.32149532710280376

Not a very good result

Neural Network

In [ ]:
```
from sklearn.neural_network import MLPClassifier, MLPRegressor
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

X_train = df_train.iloc[:, :-3]
y_train = df_train[TARGET]

X_train
```

Out[ ]:

Date	Open	High	Low	Close	Adj Close	Volume
1994-01-03	3615.199951	3654.699951	3581.000000	3654.500000	3654.496338	0.0
1994-01-04	3654.500000	3675.500000	3625.100098	3630.300049	3630.296387	0.0
1994-01-05	3625.199951	3625.199951	3583.399902	3621.199951	3621.196289	0.0
1994-01-07	3621.199951	3644.399902	3598.699951	3636.399902	3636.396240	0.0
1994-01-10	3655.199951	3678.199951	3655.199951	3660.600098	3660.596436	0.0
...	...	...	...	...	...	...
2019-05-24	9150.299805	9211.099609	9141.400391	9174.599609	9174.599609	121673100.0
2019-05-27	9225.900391	9294.599609	9204.700195	9216.400391	9216.400391	60178000.0
2019-05-28	9220.400391	9224.900391	9132.900391	9191.799805	9191.799805	218900800.0
2019-05-29	9113.200195	9116.700195	9035.099609	9080.500000	9080.500000	148987100.0
2019-05-30	9120.799805	9175.200195	9114.099609	9157.799805	9157.799805	101389200.0

6421 rows × 6 columns

In [ ]:

```
# NOTE: Very important to scale the data!
X_train = scaler.fit_transform(X_train)
```

In [ ]:

```python
mlp = MLPRegressor(
    solver='lbfgs',
    alpha=0.005,
    hidden_layer_sizes=(200, 1)
)

mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)

f1_score(
    average='macro',
    y_true=
    y_pred=y_pred
)
```

Out[ ]:

```
array([0.52764371, 0.52764371, 0.52764371, 0.52764371, 0.52764371,
       0.52764371, 0.52764371, 0.52764371, 0.52764371, 0.52764371,
       0.52764371, 0.52764371, 0.52764371, 0.52764371, 0.52764371,
       0.52764371, 0.52764371, 0.52764371, 0.52764371, 0.52764371,
       0.52764371, 0.52764371, 0.52764371, 0.52764371, 0.52764371,
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       0.52764371])
```

In [ ]:

```
# y_pred = mlp.predict(scaler.fit_transform(X_test))
# y_pred
# y_test

# f1_score(average='macro', y_pred=y_pred, y_true=df_test[TARGET])
```

Out[ ]:
```
0.34476534296028877
```

In [ ]:
```
X_train
```

Out[ ]:
```
array([[0.05711087, 0.05905903, 0.05733793, 0.06034891, 0.06034891,
        0.        ],
       [0.06010308, 0.06063921, 0.06072114, 0.05849884, 0.05849885,
        0.        ],
       [0.05787224, 0.05681791, 0.05752204, 0.05780315, 0.05780315,
        0.        ],
       ...,
       [0.48387786, 0.48222684, 0.48326049, 0.48367045, 0.48367118,
        0.27726855],
       [0.47571589, 0.47400688, 0.47575756, 0.47516168, 0.4751624 ,
        0.18871305],
       [0.47629451, 0.47845112, 0.48181816, 0.48107118, 0.48107191,
        0.12842363]])
```