Tesla Stock Price Prediction using kNN and Random Forest

October 10, 2020

1 Preparation

[82]:
```
import math

from time import time
import datetime

import pandas as pd
import numpy as np
import quandl

#to plot within notebook
import matplotlib.pyplot as plt
%matplotlib inline

#setting figure size
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 20,10
```

1.1 Data Cleaning

[14]:
```
df = pd.read_csv('tesla.csv')
df.index = df['Date']
df = df.sort_index(ascending = True, axis = 0)
```

[34]:
```
df.head()
```

[34]:
```
                  Date      Date.1   Open   High    Low  Close     Volume  \
Date
2012-01-03  2012-01-03  2012-01-03  28.94  29.50  27.65  28.08   928100.0
2012-01-04  2012-01-04  2012-01-04  28.21  28.67  27.50  27.71   630100.0
2012-01-05  2012-01-05  2012-01-05  27.76  27.93  26.85  27.12  1005500.0
2012-01-06  2012-01-06  2012-01-06  27.20  27.79  26.41  26.91   986300.0
2012-01-09  2012-01-09  2012-01-09  27.00  27.49  26.12  27.25   897000.0

            Ex-Dividend  Split Ratio  Adj. Open  …  Adj. Volume          ds  \
Date                                             …
```

```
2012-01-03          0.0          1.0       28.94   …      928100.0   2012-01-03
2012-01-04          0.0          1.0       28.21   …      630100.0   2012-01-04
2012-01-05          0.0          1.0       27.76   …     1005500.0   2012-01-05
2012-01-06          0.0          1.0       27.20   …      986300.0   2012-01-06
2012-01-09          0.0          1.0       27.00   …      897000.0   2012-01-09

                y  Daily Change  Year  Month  Week  Day  Dayofweek  Dayofyear
Date
2012-01-03  28.08         -0.86  2012      1     1    3          1          3
2012-01-04  27.71         -0.50  2012      1     1    4          2          4
2012-01-05  27.12         -0.64  2012      1     1    5          3          5
2012-01-06  26.91         -0.29  2012      1     1    6          4          6
2012-01-09  27.25          0.25  2012      1     2    9          0          9

[5 rows x 23 columns]
```

1.2 Define function

[29]:
```python
def rmse(x,y):
    return math.sqrt(((x-y)**2).mean())

def print_score(m):
    res = [rmse(m.predict(X_train), t_train), rmse(m.predict(X_val), t_val),
            m.score(X_train, t_train), m.score(X_val, t_val)]
    print(f"rmse train {res[0]}, rmse val {res[1]}, r^2 train {res[2]}, r^2 val␣
 ↪{res[3]}")
```

2 Random Forest

2.1 Try to predict using a Single Decision Tree

[30]:
```python
df.columns
```

[30]:
```
Index(['Date', 'Date.1', 'Open', 'High', 'Low', 'Close', 'Volume',
       'Ex-Dividend', 'Split Ratio', 'Adj. Open', 'Adj. High', 'Adj. Low',
       'Adj. Close', 'Adj. Volume', 'ds', 'y', 'Daily Change', 'Year', 'Month',
       'Week', 'Day', 'Dayofweek', 'Dayofyear'],
      dtype='object')
```

[31]:
```python
n_total = df.count()[0]
n_valid = 180 # Six months
n_train = n_total - n_valid

# In this case, I would like to predict the stock price by using OLHC Data
features = ['Adj. Open', 'Adj. Low', 'Adj. High', 'Adj. Close']
df_small = df
```

```
X_df = df_small[features]
t_df = df_small['y']

X_train, X_val = X_df[:n_train].to_numpy(), X_df[n_train:].to_numpy()
t_train, t_val = t_df[:n_train].to_numpy(), t_df[n_train:].to_numpy()
```

[32]:
```
from sklearn import metrics
from sklearn.ensemble import RandomForestRegressor

model = RandomForestRegressor(n_estimators = 1, bootstrap = True,␣
 ↪min_samples_leaf = 25)
model.fit(X_train, t_train)
```

[32]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=25,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=1, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[33]:
```
print_score(model)
```

```
rmse train 5.150626113476439, rmse val 4.382942883692601, r^2 train
0.9965165047631718, r^2 val 0.9729952809567858
```

[37]:
```
model.estimators_[0].get_depth()
```

[37]: 6

The result is not bad, $RMSE$ is pretty low and R^2 is close to 1.

This random forest is a single decision tree with depth of 6 and at least 25 samples in each leaf node. We enabled bootstrapping to avoid overfitting.

I believe the model could be optimized using Random Forest, as it it constructed by some decision trees using bagging.

2.2 Try Random Forest

[39]:
```
model = RandomForestRegressor(n_estimators=40, bootstrap=True,␣
 ↪min_samples_leaf=25)
model.fit(X_train, t_train)

print_score(model)
```

```
rmse train 3.9034098186634734, rmse val 2.4245026785986763, r^2 train
0.9979992930963252, r^2 val 0.9917367027160658
```

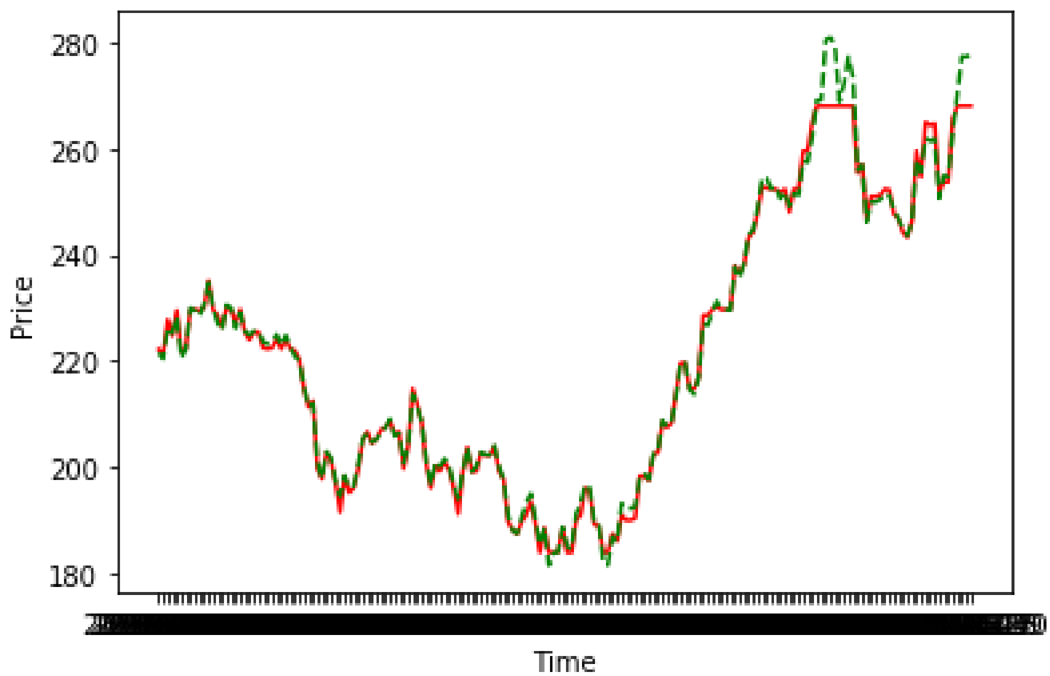
We see a slight improvement in $RMSE$ and R^2 for both training and validation data. It is a better model!

Now let's try to plot out our prediction.

[54]:
```python
np.mean(model.predict(X_val)), np.mean(t_val)
```

[54]: (221.6080401416136, 222.1485555555556)

[52]:
```python
plt.plot(df_small['Date'][n_train:], model.predict(X_val), 'r-')
plt.plot(df_small['Date'][n_train:], t_val, 'g--')
plt.xlabel('Time')
plt.ylabel('Price')
plt.show()
```



2.3 Try to use GridSearch for model selection

[59]:
```python
from sklearn.model_selection import GridSearchCV

parameters = {
    'n_estimators': [30, 40, 50, 60],
    'min_samples_leaf': [20, 25, 30, 40]
}

rf = RandomForestRegressor(bootstrap = True)
```

```
clf = GridSearchCV(rf, parameters)
clf.fit(X_train, t_train)
```

[59]:
```
GridSearchCV(cv=None, error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,
                                             criterion='mse', max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators=100, n_jobs=None,
                                             oob_score=False, random_state=None,
                                             verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'min_samples_leaf': [20, 25, 30, 40],
                         'n_estimators': [30, 40, 50, 60]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

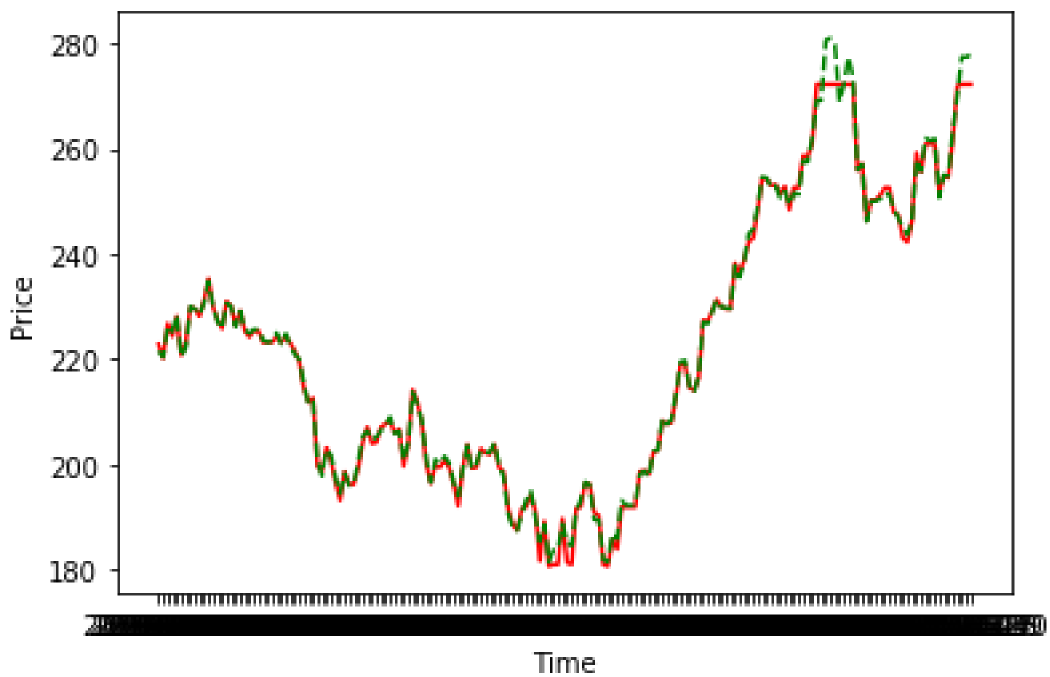
[61]:
```
clf.best_params_
```

[61]:
```
{'min_samples_leaf': 20, 'n_estimators': 40}
```

[77]:
```
best_model = RandomForestRegressor(n_estimators = 40, bootstrap = True,␣
 ↪min_samples_leaf = 20)
best_model.fit(X_train, t_train)
print_score(best_model)
```

```
rmse train 154.7236114644389, rmse val 196.61044864752793
```

[78]:
```
plt.plot(df_small['Date'][n_train:], best_model.predict(X_val), 'r-')
plt.plot(df_small['Date'][n_train:], t_val, 'g--')
plt.xlabel('Time')
plt.ylabel('Price')
plt.show()
```



This model is another great improvement. This tells us the importance of trying different parameters in order to get a better model.

3 KNN

Lastly, we will try K-nearest neighbors to predict the stock price.

[67]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import MinMaxScaler

# It is important to scale the data for kNN
scaler = MinMaxScaler(feature_range = (0, 1))

X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.fit_transform(X_val)
```

[68]:
```
params = {'n_neighbors': [2, 3, 4, 5, 6, 7, 8, 9]}
knn = KNeighborsRegressor()
clf = GridSearchCV(knn, params, cv = 5)

clf.fit(X_train_scaled, t_train)
clf.best_params_
```

[68]:
```
{'n_neighbors': 2}
```

[79]:
```
best_model = KNeighborsRegressor(n_neighbors = 2)
best_model.fit(X_train_scaled, t_train)

def print_score(m):
    res = [rmse(m.predict(X_train_scaled), t_train), rmse(m.
↪predict(X_val_scaled), t_val)]
    print(f"rmse train {res[0]}, rmse val {res[1]}")
```

[80]:
```
print_score(best_model)
```

```
rmse train 0.596753984777006, rmse val 100.14868004648451
```

It seems that K-nearest neighbors is not a good algorithm for predicting this dataset. It is a highly overfitting model. Random Forest is a better choice.

[ ]:
```
```