initial_modelling

June 5, 2022

1 Linear Regression

1.0.1 Importing libraries

[11]:
```
import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, median_absolute_error
import sklearn.metrics as metrics
```

1.0.2 Uploading data

[2]:
```
url = "https://raw.githubusercontent.com/Agablue-red/Machine-Learning/master/
 ↪data/data_rate.csv"
data = pd.read_csv(url)
```

[3]:
```
data.head()
```

[3]:
```
  symbol     score        Date  log_rate
0      A  0.572765  2008-07-02 -0.063982
1      A  0.576979  2008-07-16  0.016846
2      A  0.579936  2008-07-30  0.019815
3      A  0.569940  2008-08-13 -0.019493
4      A  0.550504  2016-07-13  0.042472
```

1.0.3 Information about dataset

Data types:

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29996 entries, 0 to 29995
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
```

```
 0   symbol    29996 non-null  object
 1   score     29996 non-null  float64
 2   Date      29996 non-null  object
 3   log_rate  29996 non-null  float64
dtypes: float64(2), object(2)
memory usage: 937.5+ KB
```

Changing the type of 'date' variable:

[39]:
```
data["Date"] = pd.to_datetime(data["Date"])
data = data.set_index('Date')
data.sort_index(inplace=True)
```

[40]:
```
data.head()
```

[40]:

Date	symbol	score	log_rate
2004-02-11	FCFS	0.686924	0.049570
2004-02-11	RCI	0.757159	0.003422
2004-02-11	ESE	0.747727	0.005126
2004-02-11	NL	0.709419	0.017833
2004-02-11	KSWS	0.826617	-0.020834

Fundamental statistics on numeric variables

[8]:
```
data.describe()
```

[8]:

	score	log_rate
count	29996.000000	29996.000000
mean	0.731574	0.006215
std	0.117569	0.055155
min	0.413554	-0.527210
25%	0.654207	-0.020007
50%	0.741993	0.007245
75%	0.813804	0.033962
max	0.987225	0.916291

There are in total 29 996 observations. The mean score for this dataset is 0,73 and mean return rate is 0,006.

[9]:
```
data.symbol.value_counts()
```

[9]:
```
SHW     170
GEF     140
ORLY    138
INGR    122
GPC     122
       …
BMI       1
```

```
BOOT       1
POST       1
ULH        1
HLX        1
Name: symbol, Length: 1319, dtype: int64
```

There are 1319 companies in total, some of them occur only once in the time series and some even over 100 times.

1.0.4 Splitting the data into training and test sets

Training set involves data from 2010 to 2020 and test set includes the year 2021.

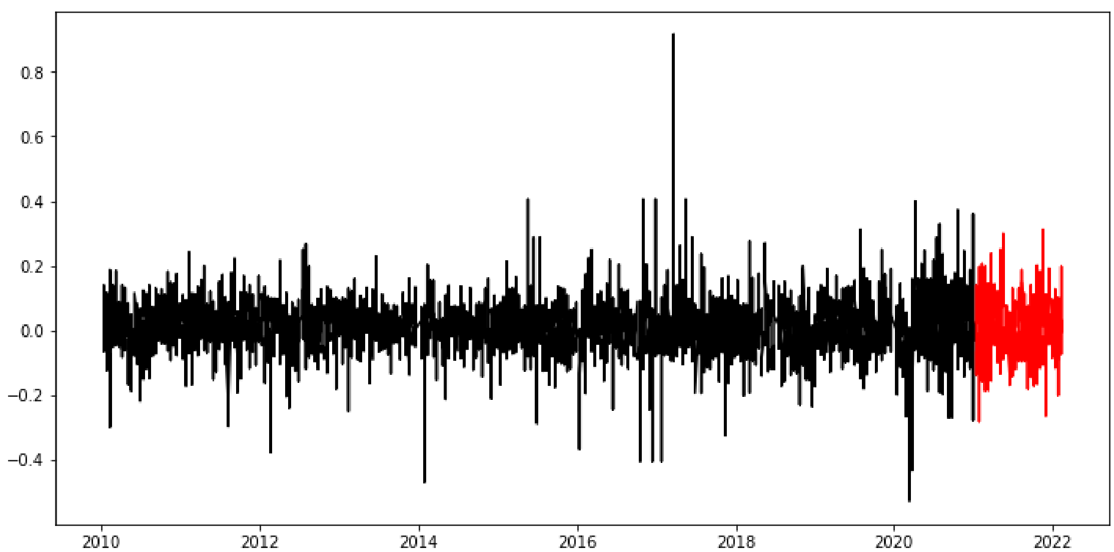
[63]:
```
X_train = data['2010':'2020'].drop(['symbol','log_rate'], axis = 1)
y_train = data.loc['2010':'2020', 'log_rate']

X_test = data['2021':'2022'].drop(['symbol','log_rate'], axis = 1)
y_test = data.loc['2021':'2022', 'log_rate']
```

[64]:
```
fig, ax=plt.subplots(figsize=(12, 6))

plt.plot(y_train, color = "black")
plt.plot(y_test, color = "red")
```

[64]:
```
[<matplotlib.lines.Line2D at 0x19b387269d0>]
```



[65]:
```
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
```

```
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (19328, 1)
Number transactions y_train dataset:  (19328,)
Number transactions X_test dataset:  (2260, 1)
Number transactions y_test dataset:  (2260,)
```

1.0.5 Dummy regression

[66]:
```
from sklearn.dummy import DummyRegressor
```

[67]:
```
# train model
reg_dummy = DummyRegressor(strategy = 'mean').fit(X_train, y_train)

print('Coefficient of determination:', reg_dummy.score(X_train, y_train))
```

```
Coefficient of determination: 0.0
```

0% indicates thet the model does not fit the training data.

[68]:
```
# predict & evaluate
y_pred_dum = reg_dummy.predict(X_test)

print("Coefficient of determination (R2): %.5f" % r2_score(y_test , y_pred_dum)␣
 ↪)
print("Mean absolute error (MAE): %.5f" % np.mean(np.absolute(y_pred_dum -␣
 ↪y_test)))
print("Residual sum of squares (MSE): %.5f" % mean_squared_error(y_test,␣
 ↪y_pred_dum))
print("Root mean squared error (RMSE): %.5f" % np.sqrt(metrics.
 ↪mean_squared_error(y_test, y_pred_dum)))
```

```
Coefficient of determination (R2): -0.00022
Mean absolute error (MAE): 0.04444
Residual sum of squares (MSE): 0.00349
Root mean squared error (RMSE): 0.05905
```

1.0.6 Linear regression

[69]:
```
from sklearn import metrics

# train model
lm = LinearRegression().fit(X_train, y_train)

print('Coefficient of determination:', lm.score(X_train, y_train))
print('Intercept:', lm.intercept_)
print('Slope:', lm.coef_)
```

```
Coefficient of determination: 0.00040496151184277185
Intercept: 0.013150793836373038
Slope: [-0.00907272]
```

f(x) = b x + b

f(x) = -0.009x + 0.013

^{2} = 0.0004

0.0004% indicates thet the model does not fit the training data.

Measure of fit a model

[70]:
```python
# predict & evaluate
y_pred = lm.predict(X_test)

print('predicted response:', y_pred, sep='\n')

print("Coefficient of determination (R2): %.5f" % r2_score(y_test , y_pred) )
print("Mean absolute error (MAE): %.5f" % np.mean(np.absolute(y_pred - y_test)))
print("Residual sum of squares (MSE): %.5f" % mean_squared_error(y_test,␣
↪y_pred))
print("Root mean squared error (RMSE): %.5f" % np.sqrt(metrics.
↪mean_squared_error(y_test, y_pred)))
```

```
predicted response:
[0.00565683 0.0075637  0.0068274  … 0.00566467 0.00608964 0.00454928]
Coefficient of determination (R2): -0.00050
Mean absolute error (MAE): 0.04445
Residual sum of squares (MSE): 0.00349
Root mean squared error (RMSE): 0.05906
```

Adjusted R squared is adjusted for the number of independent variables in the model and equal -0.00050 (adjusted R^2 will always be less than or equal to R^2).

The average of the residuals equal 0.04445.

The variance of the residuals equal 0.00349.

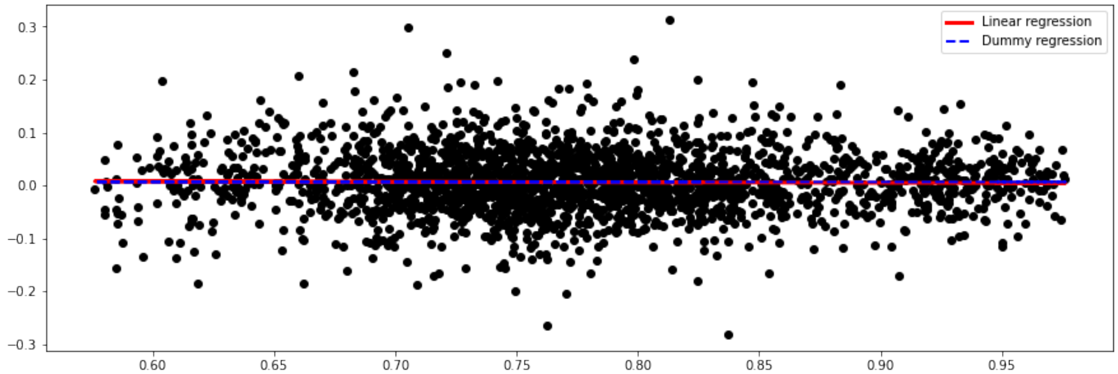
The standard deviation of residuals equal 0.05906.

1.0.7 Comparison between dummy regression and linear regression combinaed with observations from the test set.

[71]:
```python
fig, ax=plt.subplots(figsize=(15, 5))

plt.scatter(X_test, y_test,  color='black')
plt.plot(X_test, y_pred, color='red', linewidth=3, label='Linear regression')
plt.plot(X_test, y_pred_dum, color='blue', linestyle = 'dashed', linewidth=2,␣
↪label = 'Dummy regression')
ax.legend()
```

[71]: <matplotlib.legend.Legend at 0x19b45b79820>



Model does not explain any of the variation in the response variable around its mean.

Linear regression is marginally better than dummy regression.

Both models do not fit the variables.