regression

April 24, 2022

1 Linear Regression

1.0.1 Importing libraries

[1]:
```
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
```

1.0.2 Uploading data

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

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

[3]:

	Date	symbol	sector	score	close	return_rate
0	2004-02-11	SU	Energy Minerals	0.953727	12.830000	NaN
1	2004-02-11	GGG	Producer Manufacturing	0.952753	9.322222	NaN
2	2004-02-11	CWT	Utilities	0.934181	14.245000	NaN
3	2004-02-11	BLL	Process Industries	0.922862	8.012500	NaN
4	2004-02-11	APA	Energy Minerals	0.912117	39.509998	NaN

[4]:
```
nan_rows = data[data['return_rate'].isnull()]
if nan_rows.symbol.nunique() == len(nan_rows):
    print("NaN for first period")
```

```
NaN for first period
```

Replacing NaNs with 0 value:

[5]:
```
data['return_rate'] = data['return_rate'].fillna(0)
```

Looking at the tail of the data, meaning the newest observations:

[6]:
```
data.tail()
```

[6]:
```
             Date symbol                 sector     score       close  \
30546  2022-02-09    PEP  Consumer Non-Durables  0.701507  171.940002
30547  2022-02-09   SSNC    Technology Services  0.701123   82.419998
30548  2022-02-09    GEF     Process Industries  0.697954   56.930000
30549  2022-02-09    DPZ      Consumer Services  0.697741  444.760010
30550  2022-02-09  LIFZF    Non-Energy Minerals  0.695644   34.410000

       return_rate
30546    -0.003189
30547     0.025890
30548    -0.001753
30549     0.015272
30550     0.069630
```

1.0.3 Information about dataset

Data types:

[7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30551 entries, 0 to 30550
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         30551 non-null  object
 1   symbol       30551 non-null  object
 2   sector       30551 non-null  object
 3   score        30551 non-null  float64
 4   close        30551 non-null  float64
 5   return_rate  30551 non-null  float64
dtypes: float64(3), object(3)
memory usage: 1.4+ MB
```

Checking if there is any lack of data:

[8]:
```
data.isnull().sum()
```

[8]:
```
Date           0
symbol         0
sector         0
score          0
close          0
return_rate    0
dtype: int64
```

Changing the type of 'date' variable:

```
[9]: data['Date'] = pd.to_datetime(data['Date'], format = '%Y-%m-%d')
     data = data.set_index('Date')
```

Fundamental statistics on numeric variables

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

```
[10]:              score          close   return_rate
      count  30551.000000   30551.000000  30551.000000
      mean       0.731206     101.353658      0.003849
      std        0.117692    2627.016498      0.044643
      min        0.413554       0.020000     -0.951550
      25%        0.653428      26.072500     -0.016298
      50%        0.741474      44.770000      0.002865
      75%        0.813471      73.910004      0.023672
      max        0.987225  453000.000000      0.632911
```

There are in total 30 551 observations. The mean score for this dataset is 0,73, mean closing price is 101,3 and mean return rate is 0,004.

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

```
[11]: SHW      170
      GEF      140
      ORLY     138
      INGR     122
      GPC      122
              …
      TREVF      1
      HRNNF      1
      REGI       1
      PRMW       1
      DWSN       1
      Name: symbol, Length: 1338, dtype: int64
```

There are 1338 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 testing sets

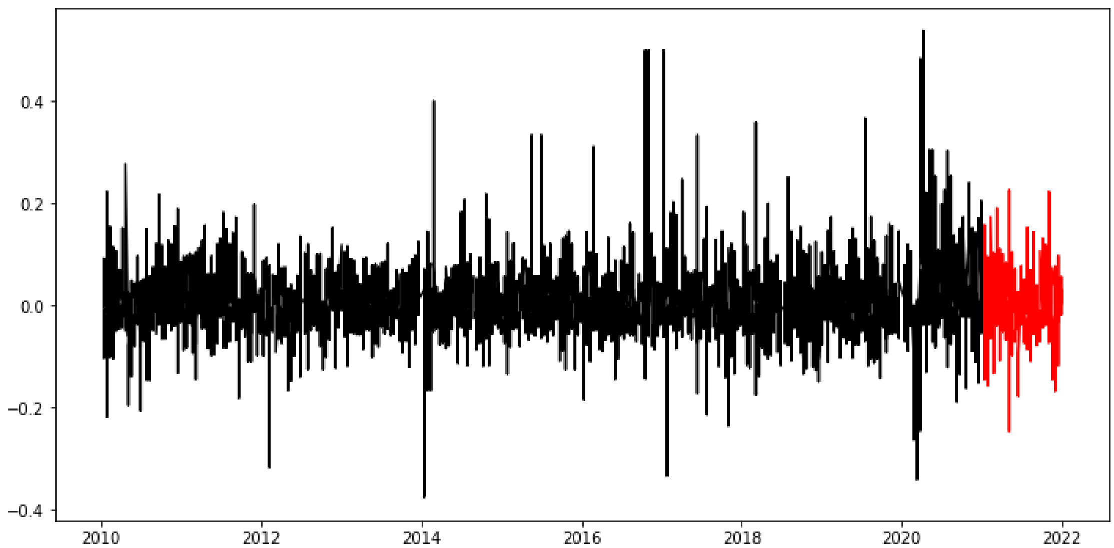
Training set involves data from 2010 to 2020 and testing set includes the year 2021.

```
[12]: X_train = data['2010':'2020'].drop(['symbol','sector','return_rate', 'close'],␣
       ↪axis = 1)
      y_train = data.loc['2010':'2020', 'return_rate']

      X_test = data['2021'].drop(['symbol','sector','return_rate', 'close'], axis = 1)
      y_test = data.loc['2021', 'return_rate']
```

```
<ipython-input-12-e0a87765a94e>:4: FutureWarning: Indexing a DataFrame with a
datetimelike index using a single string to slice the rows, like
`frame[string]`, is deprecated and will be removed in a future version. Use
`frame.loc[string]` instead.
  X_test = data['2021'].drop(['symbol','sector','return_rate', 'close'], axis =
1)
```

[13]:
```
fig, ax=plt.subplots(figsize=(12, 6))

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

[13]:
```
[<matplotlib.lines.Line2D at 0x24b4770d580>]
```



[14]:
```
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:  (19797, 1)
Number transactions y_train dataset:  (19797,)
Number transactions X_test dataset:  (2021, 1)
Number transactions y_test dataset:  (2021,)
```

1.0.5 Dummy regression

[15]:
```
from sklearn.dummy import DummyRegressor
```

```
[32]: # 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% represents a model that does not explain any of the variation in the response variable around its mean.

```
[34]: # 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 -␣
 ↪y_pred_dum)))
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): -0.00140
Mean absolute error (MAE): 0.00214
Residual sum of squares (MSE): 0.00178
Root mean squared error (RMSE): 0.04214
```

1.0.6 Linear regression

```
[24]: 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: 0.005437296983874185
Intercept: 0.02420106384509441
Slope: [-0.02744261]
```

f(x) = b x + b

f(x) = - 0.027x + 0.024

^{2} = 0.0054

Model explains only 0.0054 of the variation in the response variable around its mean.

Measure of fit of a model

[30]:
```
# 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:
[-0.00099228 -0.00054537 -0.00040295 …  0.00468725  0.00471852
  0.00475165]
Coefficient of determination (R2): -0.00431
Mean absolute error (MAE): 0.03100
Residual sum of squares (MSE): 0.00178
Root mean squared error (RMSE): 0.04220
```

Adjusted R squared is adjusted for the number of independent variables in the model and equal -0.00431 (adjusted R^2 will always be less than or equal to R^2).

The average of the residuals equal 0.031.

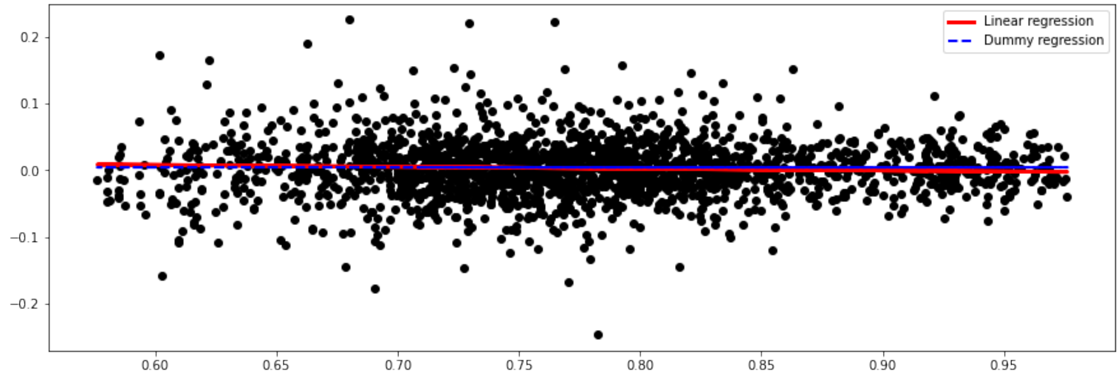
The variance of the residuals equal 0.00178.

The standard deviation of residuals equal 0.0422.

1.0.7 Comparison between dummy regression and linear regression in combination with observations from test set.

[19]:
```
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()
```

[19]:
```
<matplotlib.legend.Legend at 0x24b49a5c880>
```



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 are not well fit.