regression2

April 29, 2022

1 Linear Regression (logarithmic rate of return)

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
import sklearn.metrics as metrics
```

1.0.2 Uploading data

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

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

[3]:

	symbol	sector	score	date	close	return_rate
0	SU	Energy Minerals	0.953727	2004-02-11	13.285000	0.008314
1	GGG	Producer Manufacturing	0.952753	2004-02-11	9.388889	0.011665
2	CWT	Utilities	0.934181	2004-02-11	14.720000	0.004767
3	BLL	Process Industries	0.922862	2004-02-11	8.095000	0.002783
4	APA	Energy Minerals	0.912117	2004-02-11	39.830002	0.005791

[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]:
```
       symbol                  sector     score        date       close  \
30232     PEP  Consumer Non-Durables  0.701507  2022-02-09  171.940002
30233    SSNC    Technology Services  0.701123  2022-02-09   82.419998
30234     GEF     Process Industries  0.697954  2022-02-09   56.930000
30235     DPZ      Consumer Services  0.697741  2022-02-09  444.760010
30236   LIFZF    Non-Energy Minerals  0.695644  2022-02-09   34.410000

       return_rate
30232    -0.000465
30233     0.020718
30234    -0.016549
30235     0.013651
30236     0.024714
```

1.0.3 Information about dataset

Data types:

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30237 entries, 0 to 30236
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   symbol       30237 non-null  object
 1   sector       30237 non-null  object
 2   score        30237 non-null  float64
 3   date         30237 non-null  object
 4   close        30237 non-null  float64
 5   return_rate  30237 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]:
```
symbol         0
sector         0
score          0
date           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  30237.000000   30237.000000  30237.000000
mean       0.731151     100.004819      0.000359
std        0.117728    2570.896942      0.020784
min        0.413554       0.020000     -0.470004
25%        0.653611      26.097500     -0.008011
50%        0.741462      44.730000      0.000228
75%        0.813387      74.300003      0.009173
max        0.987225  441225.000000      0.470004
```

There are in total 30 237 observations. The mean score for this dataset is 0,73, mean closing price is 100 and mean return rate is 0,0004.

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

```
[11]: SHW     169
GEF     140
ORLY    138
INGR    122
GPC     122
       …
MRVL      1
VCTR      1
YELL      1
HOV       1
VIVO      1
Name: symbol, Length: 1330, dtype: int64
```

There are 1330 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

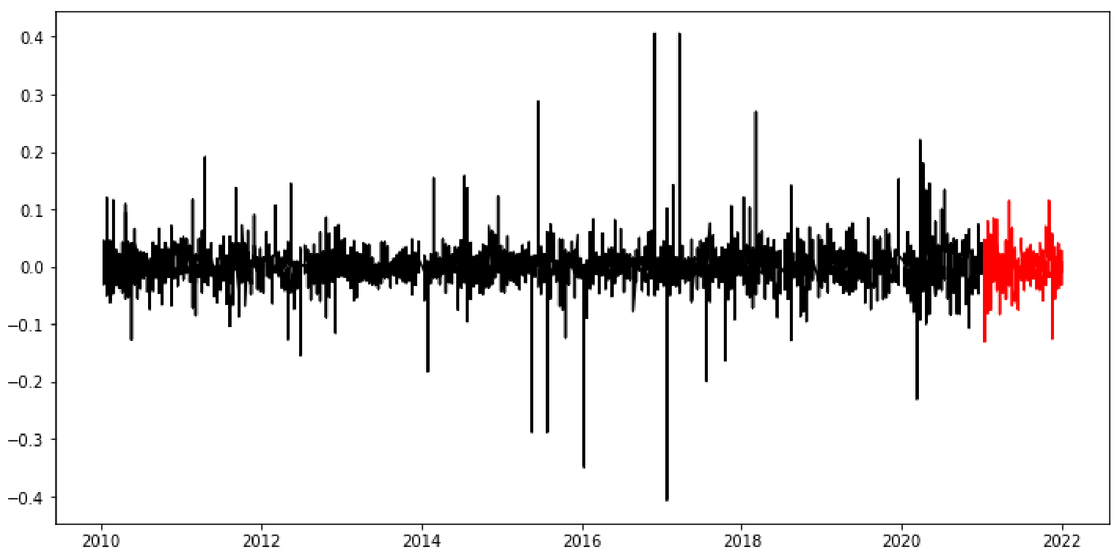
Training set involves data from 2010 to 2020 and testing set includes the year 2021.

```
[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']
```

```
&lt;ipython-input-12-e0a87765a94e&gt;: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 0x29d7485d160>]`



[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:  (19498, 1)
Number transactions y_train dataset:  (19498,)
Number transactions X_test dataset:  (2045, 1)
Number transactions y_test dataset:  (2045,)
```

1.0.5 Dummy regression

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

[16]:
```
# 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.

[17]:
```
# 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): -0.00043
Mean absolute error (MAE): 0.01345
Residual sum of squares (MSE): 0.00038
Root mean squared error (RMSE): 0.01952
```

1.0.6 Linear regression

[18]:
```
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: 0.002063735575619896
Intercept: 0.005969336426938953
Slope: [-0.00769272]
```

f(x) = b x + b

f(x) = - 0.008x + 0.006

^{2} = 0.0021

Model explains only 0.0021 of the variation in the response variable around its mean.

Measure of fit of a model

[19]:
```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:
[-0.00109287 -0.00096759 -0.00092766 …  0.00049922  0.00050799
  0.00051727]
Coefficient of determination (R2): -0.00584
Mean absolute error (MAE): 0.01353
Residual sum of squares (MSE): 0.00038
Root mean squared error (RMSE): 0.01957
```

Adjusted R squared is adjusted for the number of independent variables in the model and equal -0.00584 (adjusted R^2 will always be less than or equal to R^2).

The average of the residuals equal 0.01353

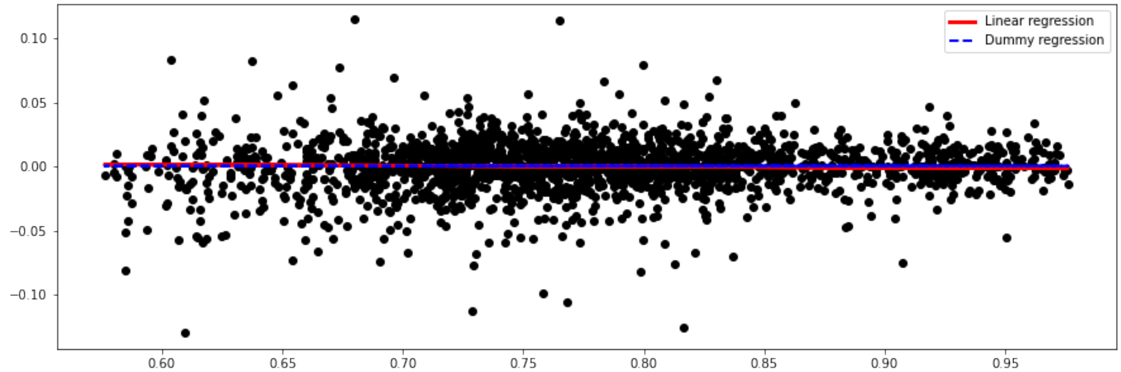
The variance of the residuals equal 0.00038

The standard deviation of residuals equal 0.01957

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

[20]:
```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()
```

[20]:
```
<matplotlib.legend.Legend at 0x29d74a13dc0>
```



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.