New_York_Stock_Exchange

June 27, 2022

1 Summary

The dataset for this project was collected from kaggle and originates from from Nasdaq Financials. fundamentals.csv contains New York Stock Exchange historical metrics extracted from annual SEC 10K fillings (2012-2016), should be enough to derive most of popular fundamental indicators.

In this project, we will focus on **clustering** and apply unsupervised learning techniques to find the best candidate algorithm that accurately predicts wether a company has net profit or net loss. To do that, we will transform **Net Income** column into a binary representation of whether or not a company made profit, where **0** represents **loss** and **1** represents **profit**.

Why do we use net income?

Net income indicates a company's profit after all of its expenses have been deducted from revenues. This number appears on a company's income statement and is also an indicator of a company's profitability.

2 Exploratory Data Analysis

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import KMeans
from scipy.cluster import hierarchy

# Mute the sklearn and IPython warnings
import warnings
warnings.filterwarnings('ignore', module='sklearn')
pd.options.display.float_format = '{:.2f}'.format
```

[2]:
```
data = pd.DataFrame(pd.read_csv('./fundamentals.csv', sep=','))
data.head()
```

[2]:
```
   Unnamed: 0 Ticker Symbol Period Ending  Accounts Payable  \
0           0           AAL    2012-12-31     3068000000.00
```

```
1           1           AAL    2013-12-31     4975000000.00
2           2           AAL    2014-12-31     4668000000.00
3           3           AAL    2015-12-31     5102000000.00
4           4           AAP    2012-12-29     2409453000.00

   Accounts Receivable  Add'l income/expense items  After Tax ROE  \
0        -222000000.00              -1961000000.00          23.00
1         -93000000.00              -2723000000.00          67.00
2        -160000000.00               -150000000.00         143.00
3         352000000.00               -708000000.00         135.00
4         -89482000.00                   600000.00          32.00

   Capital Expenditures  Capital Surplus  Cash Ratio  …  \
0        -1888000000.00    4695000000.00       53.00  …
1        -3114000000.00   10592000000.00       75.00  …
2        -5311000000.00   15135000000.00       60.00  …
3        -6151000000.00   11591000000.00       51.00  …
4         -271182000.00     520215000.00       23.00  …

   Total Current Assets  Total Current Liabilities   Total Equity  \
0         7072000000.00              9011000000.00 -7987000000.00
1        14323000000.00             13806000000.00 -2731000000.00
2        11750000000.00             13404000000.00  2021000000.00
3         9985000000.00             13605000000.00  5635000000.00
4         3184200000.00              2559638000.00  1210694000.00

   Total Liabilities  Total Liabilities & Equity  Total Revenue  \
0     24891000000.00              16904000000.00 24855000000.00
1     45009000000.00              42278000000.00 26743000000.00
2     41204000000.00              43225000000.00 42650000000.00
3     42780000000.00              48415000000.00 40990000000.00
4      3403120000.00               4613814000.00  6205003000.00

   Treasury Stock  For Year  Earnings Per Share  Estimated Shares Outstanding
0   -367000000.00   2012.00               -5.60                  335000000.00
1            0.00   2013.00              -11.25                  163022222.22
2            0.00   2014.00                4.02                  716915422.89
3            0.00   2015.00               11.39                  668129938.54
4    -27095000.00   2012.00                5.29                   73283553.88

[5 rows x 79 columns]
```

[3]:
```
data.isnull().sum()
```

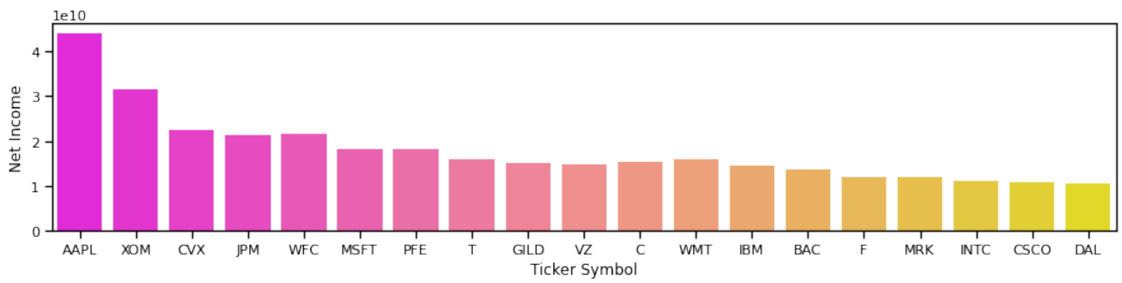
[3]:
```
Unnamed: 0                    0
Ticker Symbol                 0
Period Ending                 0
```

```
Accounts Payable                  0
Accounts Receivable               0
                              …
Total Revenue                     0
Treasury Stock                    0
For Year                        173
Earnings Per Share              219
Estimated Shares Outstanding    219
Length: 79, dtype: int64
```

[4]:
```
plt.figure(figsize = (15, 3))
dt = data.sort_values(by = 'Net Income', ascending=False).head(50)
sns.set_context("notebook")

sns.barplot(x = dt['Ticker Symbol'], y =data['Net Income'], palette=("spring"),␣
 ↪ci=None)
```

[4]:
```
<AxesSubplot:xlabel='Ticker Symbol', ylabel='Net Income'>
```



3 Feature Transformation

- Drop **Unnamed: 0**, **Ticker Symbol** and **Period Ending** column as they don't carry any information.
- Drop columns with missing values.
- Make sure all the columns are continuous which is what we need for K-means clustering.
- Transform **Net Income** into a binary column
- Ensure the data is scaled and normally distributed

[5]:
```
data.drop(['Unnamed: 0', 'Ticker Symbol', 'Period Ending'],axis = 1,␣
 ↪inplace=True)
data.dropna(axis=1,inplace=True)
```

[6]:
```
data.isnull().sum().all() == 0
```

[6]:
```
True
```

[7]:
```python
data.dtypes.all() == 'float64' # all floats except Ticker Symbol
```

[7]:
```
True
```

[8]:
```python
data['Net Income'] = data['Net Income'].apply(lambda x : 1 if x > 0 else 0)
```

[9]:
```python
data['Net Income'].value_counts()
```

[9]:
```
1    1679
0     102
Name: Net Income, dtype: int64
```

[10]:
```python
log_columns = data.skew().sort_values(ascending=False)
log_columns = log_columns.loc[log_columns > 0.75]

log_columns
```

[10]:
```
Pre-Tax ROE                                          18.00
After Tax ROE                                        15.98
Other Operating Activities                           15.83
Minority Interest                                    15.77
Equity Earnings/Loss Unconsolidated Subsidiary       14.91
Accounts Receivable                                  14.46
Common Stocks                                        12.15
Short-Term Debt / Current Portion of Long-Term Debt  11.88
Non-Recurring Items                                  11.80
Long-Term Debt                                       11.36
Interest Expense                                     11.28
Other Liabilities                                    11.07
Short-Term Investments                               10.87
Cash and Cash Equivalents                            10.11
Intangible Assets                                    10.03
Add'l income/expense items                            9.98
Other Current Liabilities                             9.89
Operating Margin                                      9.52
Other Current Assets                                  9.46
Retained Earnings                                     9.44
Long-Term Investments                                 9.25
Pre-Tax Margin                                        9.24
Total Liabilities                                     9.01
Other Assets                                          8.94
Deferred Asset Charges                                8.86
Total Assets                                          8.82
Total Liabilities & Equity                            8.82
Profit Margin                                         8.79
Other Operating Items                                 8.78
Accounts Payable                                      8.73
```

```
Misc. Stocks                                        8.56
Inventory                                           7.91
Income Tax                                          7.41
Other Financing Activities                          6.97
Fixed Assets                                        6.83
Net Cash Flow-Operating                             6.82
Deferred Liability Charges                          6.44
Cost of Revenue                                     6.25
Net Income-Cont. Operations                         6.20
Earnings Before Tax                                 6.15
Total Revenue                                       6.14
Research and Development                            5.93
Depreciation                                        5.83
Total Equity                                        5.82
Sales, General and Admin.                           5.75
Net Receivables                                     5.75
Operating Income                                    5.66
Earnings Before Interest and Tax                    5.66
Capital Surplus                                     5.57
Net Income Applicable to Common Shareholders        5.53
Gross Profit                                        5.17
Goodwill                                            5.11
Total Current Assets                                4.90
Total Current Liabilities                           4.67
Net Cash Flow                                       2.80
Liabilities                                         1.35
dtype: float64
```

[11]:

```
# The log transformations
for col in log_columns.index:
    data[col] = np.log1p(data[col])
```

```
c:\Users\lefte\AppData\Local\Programs\Python\Python39\lib\site-
packages\pandas\core\arraylike.py:358: RuntimeWarning: invalid value encountered
in log1p
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

[12]:

```
data.dropna(axis=1,inplace=True)
```

[13]:

```
sc = StandardScaler()
feature_columns = [x for x in data.columns if x not in 'Net Income']
for col in feature_columns:
    data[col] = sc.fit_transform(data[[col]])

data.head(4)
```

[13]:
```
   Accounts Payable  After Tax ROE  Capital Expenditures  \
0              0.35           0.30                 -0.21
1              0.48           1.39                 -0.63
2              0.47           2.17                 -1.36
3              0.49           2.11                 -1.64

   Cash and Cash Equivalents  Changes in Inventories  Common Stocks  \
0                       0.24                    0.17           0.53
1                       0.51                    0.17          -0.11
2                       0.40                    0.17          -0.04
3                       0.13                    0.17          -0.07

   Cost of Revenue  Deferred Asset Charges  Deferred Liability Charges  \
0             0.42                   -0.84                        0.58
1             0.43                   -0.84                        0.73
2             0.49                   -0.84                        0.71
3             0.43                    1.41                        0.69

   Effect of Exchange Rate  …  Sale and Purchase of Stock  \
0                     0.24  …                        0.28
1                     0.24  …                        0.28
2                     0.24  …                       -0.10
3                     0.24  …                       -1.12

   Short-Term Debt / Current Portion of Long-Term Debt  \
0                                               0.68
1                                               0.68
2                                               0.70
3                                               0.74

   Short-Term Investments  Total Assets  Total Current Assets  \
0                    1.48          0.26                  0.52
1                    1.57          0.70                  0.60
2                    1.54          0.71                  0.58
3                    1.54          0.80                  0.56

   Total Current Liabilities  Total Liabilities  Total Liabilities & Equity  \
0                       0.60               0.61                        0.01
1                       0.65               1.00                        0.70
2                       0.65               0.94                        0.71
3                       0.65               0.97                        0.80

   Total Revenue  Treasury Stock
0           0.84            0.25
1           0.90            0.28
2           1.28            0.28
3           1.25            0.28
```

```
[4 rows x 46 columns]
```

4 Train models

- Fit a **K-means clustering** model with two clusters and
- Fit 2 **Agglomerative clustering** models with two clusters (ward-link and complete-link clustering)
- Compare the results to those obtained by K-means with regards to wine color by reporting the number of red and white observations in each cluster for both K-means and agglomerative clustering.
- Visualize the **dendrogram** produced by agglomerative clustering

4.1 K-means

[14]:
```python
km = KMeans(n_clusters=2, random_state=42)
km = km.fit(data[feature_columns])

data['kmeans'] = km.predict(data[feature_columns])
(data[['Net Income','kmeans']]
 .groupby(['kmeans','Net Income'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

[14]:
```
                   number
kmeans Net Income
0      0                8
       1              295
1      0               94
       1             1384
```

4.2 Agglomerative Clustering

[15]:
```python
for linkage in ['complete', 'ward']:
    ag = AgglomerativeClustering(n_clusters=2, linkage=linkage,␣
 ↪compute_full_tree=True)
    ag = ag.fit(data[feature_columns])
    data[str('agglom_'+linkage)] = ag.fit_predict(data[feature_columns])
```

[16]:
```python
(data[['Net Income','agglom_ward']]
 .groupby(['Net Income','agglom_ward'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

[16]:
```
                          number
Net Income agglom_ward
0          0                  13
           1                  89
1          0                 323
           1                1356
```

[17]:
```
(data[['Net Income','agglom_complete']]
     .groupby(['Net Income','agglom_complete'])
     .size()
     .to_frame()
     .rename(columns={0:'number'}))
```

[17]:
```
                              number
Net Income agglom_complete
0          0                     102
1          0                    1671
           1                       8
```

[18]:
```
# Comparing AgglomerativeClustering with KMeans
(data[['Net Income','agglom_complete', 'agglom_ward','kmeans']]
 .groupby(['Net Income', 'agglom_complete', 'agglom_ward', 'kmeans'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

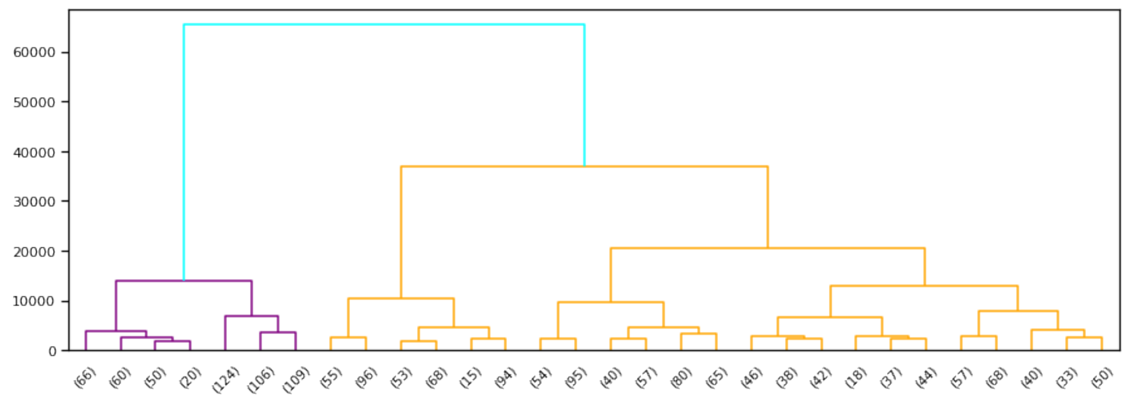
[18]:
```
                                                  number
Net Income agglom_complete agglom_ward kmeans
0          0               0           0             8
                                       1             5
                           1           1            89
1          0               0           0           287
                                       1            28
                           1           1          1356
           1               0           0             8
```

[19]:
```
Z = hierarchy.linkage(ag.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))


hierarchy.set_link_color_palette(['purple', 'orange'])

den = hierarchy.dendrogram(Z, orientation='top',
                           p=30, truncate_mode='lastp',
                           show_leaf_counts=True, ax=ax,
                           above_threshold_color='cyan')
```



5 Results

Comparing the results shows that I am able to predict profit better than loss which is what I expected given that we have more data for companies with profit(1: 1679 vs 0: 102). The best algorithm for predicting loss is the **Complete-link Agglomerative Clustering** model and for predicting profit **KMeans Clustering** seems to be the best candidate althought **Ward-link Agglomerative Clustering** achieved nearly the same result.

Better result could be achieved by performing PCA or hyperparameter tuning.