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 are we analysing 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.

Exploratory Data Analysis

In [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
```

In [2]:

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

Out[2]:

	Unnamed: 0	Ticker Symbol	Period Ending	Accounts Payable	Accounts Receivable	Add'l income/expense items	After Tax ROE	Capital Expenditures	Capital Surplus	Cash Ratio
0	0	AAL	2012-12-31	3068000000.00	-222000000.00	-1961000000.00	23.00	-1888000000.00	4695000000.00	53.00
1	1	AAL	2013-12-31	4975000000.00	-93000000.00	-2723000000.00	67.00	-3114000000.00	10592000000.00	75.00
2	2	AAL	2014-12-31	4668000000.00	-160000000.00	-150000000.00	143.00	-5311000000.00	15135000000.00	60.00
3	3	AAL	2015-12-31	5102000000.00	352000000.00	-708000000.00	135.00	-6151000000.00	11591000000.00	51.00
4	4	AAP	2012-12-29	2409453000.00	-89482000.00	600000.00	32.00	-271182000.00	520215000.00	23.00

5 rows × 79 columns

In [3]:

```
data.isnull().sum()
```

Out[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
```

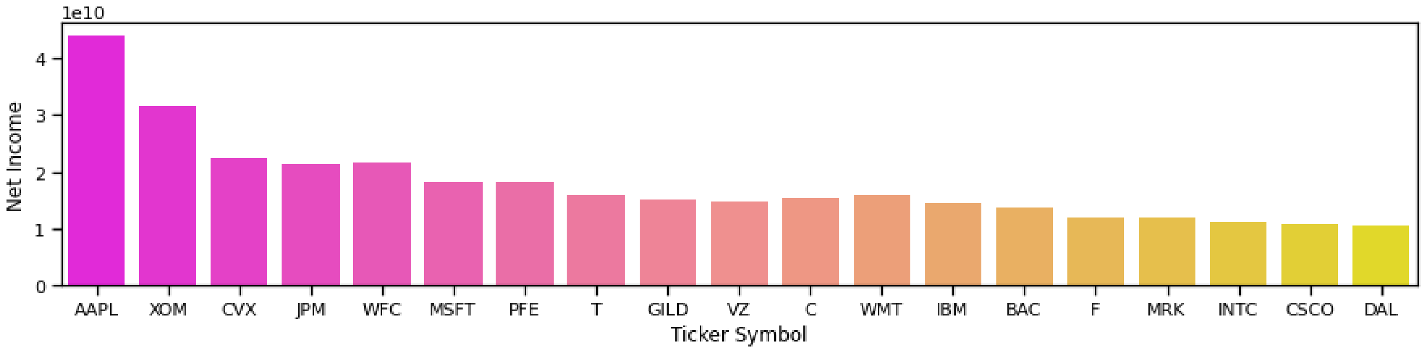
In [4]:

```
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)
```

Out[4]:

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



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**

In [5]:

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

In [6]:

```
data.isnull().sum().all() == 0
```

Out[6]:

```
True
```

In [7]:

```
data.dtypes.all() == 'float64' # all floats except Ticker Symbol
```

Out[7]:

```
True
```

In [8]:

In [8]:

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

In [9]:

```
data['Net Income'].value_counts()
```

Out[9]:

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

In [10]:

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

log_columns
```

Out[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
```

```
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
```

In [11]:

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

```
C:\Users\veres01.CRWIN\Anaconda3\lib\site-packages\pandas\core\series.py:726: RuntimeWarn
ing: invalid value encountered in log1p
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [12]:

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

In [13]:

```python
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)
```

Out[13]:

	Accounts Payable	After Tax ROE	Capital Expenditures	Cash and Cash Equivalents	Changes in Inventories	Common Stocks	Cost of Revenue	Deferred Asset Charges	Deferred Liability Charges	Effect of Exchange Rate	...	Sale and Purchase of Stock
0	0.35	0.30	-0.21	0.24	0.17	0.53	0.42	-0.84	0.58	0.24	...	0.28
1	0.48	1.39	-0.63	0.51	0.17	-0.11	0.43	-0.84	0.73	0.24	...	0.28
2	0.47	2.17	-1.36	0.40	0.17	-0.04	0.49	-0.84	0.71	0.24	...	-0.10
3	0.49	2.11	-1.64	0.13	0.17	-0.07	0.43	1.41	0.69	0.24	...	-1.12

4 rows × 46 columns

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

K-means

In [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'}))
```

Out[14]:

kmeans	Net Income	number
0	0	8
	1	295
1	0	94
	1	1384

Agglomerative Clustering

In [15]:

```
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])
```

In [16]:

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

Out[16]:

Net Income	agglom_ward	number
0	0	13
	1	89
1	0	323
	1	1356

In [17]:

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

Out[17]:

Net Income	agglom_complete	number
0	0	102
1	0	1671
	1	8

In [18]:

```python
# 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'}))
```

Out[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

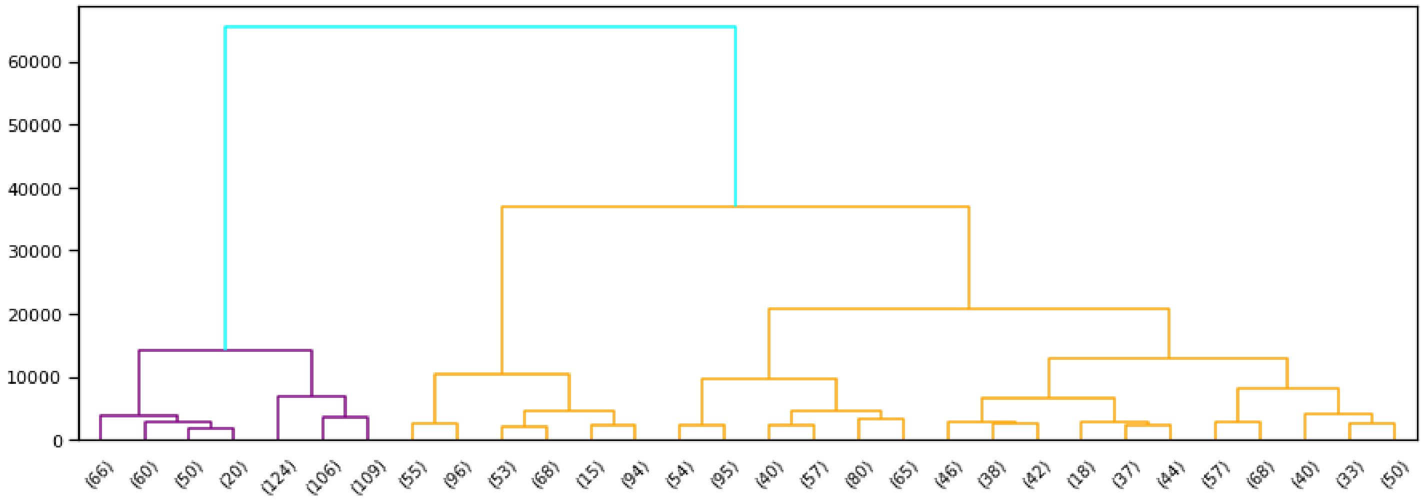
In [19]:

```python
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')
```



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.