Exercise 8: Clustering stocks using KMeans

In this exercise, you'll cluster companies using their daily stock price movements (i.e. the dollar difference between the closing and opening prices for each trading day). You are given a NumPy array movements of daily price movements from 2010 to 2015, where each row corresponds to a company, and each column corresponds to a trading day.

Some stocks are more expensive than others. To account for this, include a Normalizer at the beginning of your pipeline. The Normalizer will separately transform each company's stock price to a relative scale before the clustering begins.

Normalizer vs StandardScaler

Note that Normalizer() is different to StandardScaler(), which you used in the previous exercise. While StandardScaler() standardizes features (such as the features of the fish data from the previous exercise) by removing the mean and scaling to unit variance, Normalizer() rescales each sample - here, each company's stock price - independently of the other.

This dataset was obtained from the Yahoo! Finance API.

From the course *Transition to Data Science*. Buy the entire course for just \$10 for many more exercises and helpful video lectures.

Step 1: Load the data (written for you)

```
In [2]: import pandas as pd

fn = 'datasets/company-stock-movements-2010-2015-incl.csv'
    stocks_df = pd.read_csv(fn, index_col=0)
```

Step 2: Inspect the first few rows of the DataFrame stocks_df by calling its head() function.

```
In [6]: stocks_df.head()
Out[6]:
                          2010-01-04 2010-01-05 2010-01-06 2010-01-07 2010-01-08
                            0.580000 -0.220005
                                                    -3.409998 -1.170000
                                                                              1.680011
        Apple
        AIG
                           -0.640002 -0.650000
                                                    -0.210001
                                                                -0.420000
                                                                              0.710001
                           -2.350006
                                                    -2.350006 -2.009995
        Amazon
                                        1.260009
                                                                              2.960006
                            0.109997
                                         0.000000
                                                    0.260002 0.720002
                                                                              0.190003
        American express
                            0.459999
                                         1.770000
                                                     1.549999
                                                                 2.690003
                                                                              0.059997
        Boeing
                          2010-01-11 \quad 2010-01-12 \quad 2010-01-13 \quad 2010-01-14 \quad 2010-01-15 \quad \backslash
                           -2.689994
                                                                -0.680003
        Apple
                                       -1.469994
                                                     2.779997
                                                                             -4.999995
        AIG
                           -0.200001
                                        -1.130001
                                                     0.069999
                                                                -0.119999
                                                                             -0.500000
                                                                -1.790001
                           -2.309997
                                       -1.640007
                                                     1.209999
                                                                             -2.039994
        Amazon
                           -0.270001
                                         0.750000
                                                     0.300004
                                                                 0.639999
                                                                             -0.130001
        American express
```

Boeing	-1.080002	0.360000	0.549999	0.530002	-0.709999	
		2013-10-16	2013-10-17	2013-10-18	2013-10-21	\
	• • •					\
Apple	• • •	0.320008	4.519997	2.899987	9.590019	
AIG		0.919998	0.709999	0.119999	-0.480000	
Amazon		2.109985	3.699982	9.570008	-3.450013	
American express		0.680001	2.290001	0.409996	-0.069999	
Boeing		1.559997	2.480003	0.019997	-1.220001	
	2013-10-22	2013-10-23	2013-10-24	2013-10-25	2013-10-28	/
Apple	-6.540016	5.959976	6.910011	-5.359962	0.840019	
AIG	0.010002	-0.279998	-0.190003	-0.040001	-0.400002	
Amazon	4.820008	-4.079986	2.579986	4.790009	-1.760009	
American express	0.100006	0.069999	0.130005	1.849999	0.040001	
Boeing	0.480003	3.020004	-0.029999	1.940002	1.130005	
	2012 10 20					
	2013-10-29					
Apple	-19.589981					
AIG	0.660000					
Amazon	3.740021					
American express	0.540001					
Boeing	0.309998					
[5 rows x 963 col	ıımnal					
[O TOMP X 202 COT	uiiii18 j					

Step 3: Extract the NumPy array movements from the DataFrame and the list of company names (*written for you*)

Step 4: Make the necessary imports:

- Normalizer from sklearn.preprocessing.
- KMeans from sklearn.cluster.
- make_pipeline from sklearn.pipeline.

Step 3: Create an instance of Normalizer called normalizer.

```
In [8]: normalizer = Normalizer()
```

Step 4: Create an instance of KMeans called kmeans with 14 clusters.

```
In [15]: kmeans = KMeans(n_clusters=14)
```

Step 5: Using make_pipeline(), create a pipeline called pipeline that chains normalizer and kmeans.

```
In [16]: pipeline = make_pipeline(normalizer, kmeans)
```

Step 6: Fit the pipeline to the movements array.

```
In [17]: pipeline.fit(movements)
Out[17]: Pipeline(steps=[('normalizer', Normalizer(copy=True, norm='12')), ('kmeans', KMean n_clusters=14, n_init=10, n_jobs=1, precompute_distances='auto', random_state=None, tol=0.0001, verbose=0))])
```

In the next exercise: Let's check out your clustering!