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Weeks	Coursera 4번째 강의

## Lab session: Introduction to the Uber Dataset

## 2주차 중간~

## Lab session: Company Distances and Industry Distances

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Company Distances and Industry Distances

In [58]: #We can use euclidean distance to see how far away two companies are in terms of words
def findDist(company1, company2):
    return sum((company1-company2)**2)**.5
print(findDist(word_frequency['The_Bank_of_New_York_Mellon'], word_frequency['JPMorgan_Chase_%26_Co.']))
print(findDist(word_frequency['Facebook'], word_frequency['The_Bank_of_New_York_Mellon']))

0.069269383058396
0.09419186927592427

In [59]: #We can use itertools to find the combinations
from itertools import combinations
combinations = list(combinations(word_frequency.columns, 2))
print(combinations)

[('3M', 'AT%26T'), ('3M', 'AbbVie_Inc.'), ('3M', 'Abbott_Laboratories'), ('3M', 'Accenture'), ('3M', 'Adobe_Inc.'), ('3M', 'Allerga
n'), ('3M', 'Allstate'), ('3M', 'Alphabet_Inc.'), ('3M', 'Altria'), ('3M', 'Amazon.com'), ('3M', 'American_Express'), ('3M', 'Americ
an_International_Group'), ('3M', 'Amgen'), ('3M', 'Apple_Inc.'), ('3M', 'Bank_of_America'), ('3M', 'Berkshire_Hathaway'), ('3M', 'Bi
ogen'), ('3M', 'BlackRock'), ('3M', 'Boeing'), ('3M', 'Booking_Holdings'), ('3M', 'Bristol-Myers_Squibb'), ('3M', 'CVS_Health'), ('3
M', 'Capital_One'), ('3M', 'Caterpillar_Inc.'), ('3M', 'Celgene'), ('3M', 'Charter_Communications'), ('3M', 'Chevron_Corporation'),
('3M', 'Cisco_Systems'), ('3M', 'Citigroup'), ('3M', 'Colgate-Palmolive'), ('3M', 'Comcast'), ('3M', 'ConocoPhillips'), ('3M', 'Cost
co_Wholesale_Corp.'), ('3M', 'Danaher_Corporation'), ('3M', 'DowDuPont'), ('3M', 'Dow_Inc.'), ('3M', 'Duke_Energy'), ('3M', 'Eli_Lil
ly_and_Company'), ('3M', 'Emerson_Electric'), ('3M', 'Exelon'), ('3M', 'ExxonMobil'), ('3M', 'Facebook'), ('3M', 'FedEx'), ('3M', 'F
ord_Motor_Company'), ('3M', 'General_Dynamics'), ('3M', 'General_Electric'), ('3M', 'General_Motors'), ('3M', 'Gilead_Sciences'),
('3M', 'Goldman_Sachs'), ('3M', 'Home_Depot'), ('3M', 'Honeywell'), ('3M', 'IBM'), ('3M', 'Intel'), ('3M', 'JPMorgan_Chase_%26_C
o.'), ('3M', 'Johnson_%26_Johnson'), ('3M', 'Kinder_Morgan'), ('3M', 'Kraft_Heinz'), ('3M', 'Lockheed_Martin'), ('3M', 'Lowe%27s'),
('3M', 'MasterCard'), ('3M', 'McDonald%27s'), ('3M', 'Medtronic'), ('3M', 'Merck_%26_Co.'), ('3M', 'MetLife'), ('3M', 'Microsoft'),
('3M', 'Mondelez_International'), ('3M', 'Morgan_Stanley'), ('3M', 'Netflix'), ('3M', 'NextEra_Energy'), ('3M', 'Nike_Inc.'),
('3M', 'Nvidia'), ('3M', 'Occidental_Petroleum'), ('3M', 'Oracle_Corporation'), ('3M', 'PayPal'), ('3M', 'PepsiCo'), ('3M', 'Pfizer_
Inc'), ('3M', 'Philip_Morris_International'), ('3M', 'Procter_%26_Gamble'), ('3M', 'Qualcomm'), ('3M', 'Raytheon'), ('3M', 'Schlumb
erger'), ('3M', 'Simon_Property_Group'), ('3M', 'Southern_Company'), ('3M', 'Starbucks'), ('3M', 'Target_Corporation'), ('3M', 'Texas
_Instruments'), ('3M', 'The_Bank_of_New_York_Mellon'), ('3M', 'The_Coca-Cola_Company'), ('3M', 'The_Walt_Disney_Company'), ('3M',
'U.S._Bancorp'), ('3M', 'Union_Pacific_Corporation'), ('3M', 'United_Health_Group'), ('3M', 'United_Parcel_Service'), ('3M', 'United
_Technologies'), ('3M', 'Verizon_Communications'), ('3M', 'Visa_Inc.'), ('3M', 'Walgreens_Boots_Alliance'), ('3M', 'Walmart'), ('3M',
'Walt_Disney'), ('AT%26T', 'AbbVie_Inc.'), ('AT%26T', 'Abbott_Laboratories'), ('AT%26T', 'Accenture'), ('AT%26T', 'Adobe_Inc.'), ('A

```

similarity 구하는 방법 : 거리를 구해서 비교해본다.

BNY Mellon과 JPMorgan 간 거리가 BNY Mellon 과 Facebook 거리보다 가깝다.

(비슷한 업계니까)

ex) 3M 과 다른 기업 간 text에서 찾을 수 있는 combination 개수를 찾는다.

```
In [60]: #Create the distance dataframe
distance = pd.DataFrame(combinations)
distance.columns = ["Company 1", "Company 2"]
#Create the distance for each combination
distance["Distance"] = distance.apply(lambda x: findDist(word_frequency[x["Company 1"]], word_frequency[x["Company 2"]]), axis=1)
print(distance)
```

	Company 1	Company 2	Distance
0	3M	AT&T	0.067785
1	3M	AbbVie_Inc.	0.066907
2	3M	Abbott_Laboratories	0.082096
3	3M	Accenture	0.099816
4	3M	Adobe_Inc.	0.098538
5	3M	Allergan	0.091710
6	3M	Allstate	0.089795
7	3M	Alphabet_Inc.	0.099336
8	3M	Altria	0.095903
9	3M	Amazon.com	0.084428
10	3M	American_Express	0.098040
11	3M	American_International_Group	0.087494
12	3M	Amgen	0.106996
13	3M	Apple_Inc.	0.084011
14	3M	Bank_of_America	0.093553
15	3M	Berkshire_Hathaway	0.079356
16	3M	Biogen	0.086669
17	3M	BlackRock	0.099466
18	3M	Boeing	0.091513
19	3M	Booking_Holdings	0.107829
20	3M	Bristol-Myers_Squibb	0.077146
21	3M	CVS_Health	0.086509
22	3M	Capital_One	0.093070
23	3M	Caterpillar_Inc.	0.075362
24	3M	Celgene	0.087456
25	3M	Charter_Communications	0.087377
26	3M	Chevron_Corporation	0.079814
27	3M	Cisco_Systems	0.089222

big data → sorting 필요하다

```
#Turn it into a function
def get_company_industries(urls):
    industries_data = []
    for url in urls:
        r = requests.get(url)
        soup = BeautifulSoup(r.content, 'html.parser')
        infobox = soup.find("table", {"class": "infobox"})
        industries = [x.text for x in infobox.find("th", text = "Industry").parent()[1].find_all('a')]
        industries_data.append(industries)
    return industries_data
print(get_company_industries(links_unique[:5]))

#Instead of an array, let's modify to get a dataframe of dummy variables representing what industries each company is tagged with
def get_company_industries(urls):
    industries_data = []
    for url in urls:
        r = requests.get(url)
        soup = BeautifulSoup(r.content, 'html.parser')
        infobox = soup.find("table", {"class": "infobox"})
        industries = [x.text for x in infobox.find("th", text = "Industry").parent()[1].find_all('a')]
        industries = pd.Series(1, index=industries)
        industries_data.append(industries)
    industries_data = pd.concat(industries_data,axis=1,sort=False).fillna(0) ## 행방향
    return industries_data
print(get_company_industries(links_unique[:5]))

#And clean up with transposing and putting in the index of tickers
def get_company_industries(urls):
    industries_data = []
    for url in urls:
        r = requests.get(url)
        soup = BeautifulSoup(r.content, 'html.parser')
        infobox = soup.find("table", {"class": "infobox"})
        industries = [x.text for x in infobox.find("th", text = "Industry").parent()[1].find_all('a')]
        industries = pd.Series(1, index=industries)
        industries_data.append(industries)
    industries_data = pd.concat(industries_data,axis=1,sort=False).fillna(0)
    return industries_data
industries = get_company_industries(links_unique)
industries = industries.transpose()
```

```
industries.index = index
print(industries)
```

	Conglomerate	Telecommunications	Technology	#
3M	1.0	0.0	0.0	
AT&T	0.0	1.0	1.0	
AbbVie_Inc.	0.0	0.0	0.0	
Abbott_Laboratories	0.0	0.0	0.0	
Accenture	0.0	0.0	0.0	
Adobe_Inc.	0.0	0.0	0.0	
Allergan	0.0	0.0	0.0	
Allstate	0.0	0.0	0.0	
Alphabet_Inc.	1.0	0.0	0.0	
Altria	0.0	0.0	0.0	
Amazon.com	0.0	0.0	0.0	
American_Express	0.0	0.0	0.0	
American_International_Group	0.0	0.0	0.0	
Amgen	0.0	0.0	0.0	
Apple_Inc.	0.0	0.0	0.0	
Bank_of_America	0.0	0.0	0.0	
Berkshire_Hathaway	1.0	0.0	0.0	
Biogen	0.0	0.0	0.0	
BlackRock	0.0	0.0	0.0	

```
#Let's see which companies are in financial services
fin_services = industries[industries['financial services'] == 1].index
print(fin_services)
```

```
Index(['American_Express', 'American_International_Group', 'Bank_of_America',
      'Capital_One', 'Caterpillar_Inc.', 'Citigroup', 'Goldman_Sachs',
      'JPMorgan_Chase_%26_Co.', 'MasterCard', 'MetLife', 'Morgan_Stanley',
      'PayPal', 'The_Bank_of_New_York_Mellon', 'U.S._Bancorp', 'Visa_Inc.',
      'Wells_Fargo'],
      dtype='object')
```

```
In [78]: #Let's check how similar companies are within and outside of the financials industry
print(distance.loc[fin_services_index]['Distance'].mean())
print(distance.loc[fin_services_index2]['Distance'].mean())

0.08921896425997317
0.099163444188783
```

```
In [79]: #And check how different industries line up
#First create the base of the dataframe, each combination of industry
from itertools import combinations
industry_distances = pd.DataFrame(list(combinations(industries.columns,2)))
industry_distances.columns = ["Industry 1", "Industry 2"]
print(industry_distances)
```

	Industry 1	Industry 2
0	conglomerate	telecommunications
1	conglomerate	technology
2	conglomerate	mass media
3	conglomerate	entertainment
4	conglomerate	health care
5	conglomerate	computer software
6	conglomerate	insurance
7	conglomerate	tobacco
8	conglomerate	cloud computing
9	conglomerate	artificial intelligence
10	conglomerate	consumer electronics
11	conglomerate	digital distribution
12	conglomerate	banking
13	conglomerate	financial services
14	conglomerate	biotechnology
15	conglomerate	computer hardware
16	conglomerate	semiconductors

```
In [86]: #What about the most similar to financial technology?
print(industry_distances[industry_distances["Industry 1"] == 'financial services'].sort_values(by='Distance').dropna())
```

	Industry 1	Industry 2	Distance
123	financial services	entertainment	0.087768
312	financial services	banking	0.089098
258	financial services	artificial intelligence	0.089152
42	financial services	telecommunications	0.089627
337	financial services	consumer goods	0.090286
342	financial services	pharmaceutical	0.090317
336	financial services	oil and gas	0.090589
295	financial services	digital distribution	0.091025
97	financial services	mass media	0.091230
334	financial services	pharmaceuticals	0.091732
332	financial services	aerospace	0.092209
333	financial services	defense	0.092209
238	financial services	cloud computing	0.092336
172	financial services	computer software	0.092457
148	financial services	health care	0.092548
277	financial services	consumer electronics	0.092594
195	financial services	insurance	0.092609
340	financial services	automotive	0.092721
341	financial services	medical equipment	0.093429
331	financial services	semiconductors	0.093476
335	financial services	retail	0.093893
330	financial services	computer hardware	0.094054
344	financial services	video games	0.094163

```
In [90]: import seaborn as sns
import matplotlib.pyplot as plt
#Plot the heatmap
sns.heatmap(pivot_data)
plt.show()
```



## Application: applying similarity analysis on corporate filings to predict returns

텍스트 분석으로 주식 수익률 계산?

Q. 분기별/연도별 보고서에서 텍스트가 바뀌는 것이 실제로 회사의 변화를 의미하는가

A.

1. 보고서들의 유사성을 확인 (유클리디안 대신 cosine similarity 이용한다.)

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

where  $A_i$  and  $B_i$  are components of vector  $A$  and  $B$  respectively.

**DISTANCE = 1- SIMILARITY**  
 VECTOR DIMENSIONS: [RISK, FINANCE, LEGAL]  
 DOCUMENT A → (7,3,2)    DOCUMENT B → (2,3,0)  
 DISTANCE = (1- COSINE SIMILARITY) IS AS FOLLOWS

$$d_{\text{Cosine}}(A,B) = 1 - \frac{(7,3,2) \cdot (2,3,0)}{\|(7,3,2)\|_2 \cdot \|(2,3,0)\|_2}$$

$$= 1 - \frac{(7 \cdot 2 + 3 \cdot 3 + 2 \cdot 0)}{\sqrt{49 + 9 + 4} \cdot \sqrt{4 + 9}}$$

$$= 1 - \frac{23}{28.4} = 0.19$$

2. 결론 (a paper by Cohen, Malloy, and Nguyen 참조)

- 올해와 전분기 사이에 전혀 변동이 없는 포트폴리오를 사서 작년과 가장 큰 변동폭을 보인 1분기에 주식을 팔면 실제로 상당한 수익률을 보인다.
- 보고서의 법적인 부분의 변화가 제일 큰 영향을 끼친다.

## Lab session: Working with 10-K Data