Stock Recommendation System Based on Social Network Analysis

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Abstract

This project is to develop a trustworthy stock recommender to lead novice investor to get wisdom decision. The recommender utilizes a methodology based on the transactions of highly-rated mutual funds and their corresponding stock holding portfolio to do social network analysis. The measure of effectiveness of this recommender system is scaled by 15 mutual funds recommended by Morningstar rating and it shows effectiveness to year-based investment and display long term trustiness.

1. Introduction

Stock market is an area that has attracted millions of investors who hope to gain profits better than the profits that commercial banks can offer. Thus, thousands of methods of financial analysis have come one after another. However, it is difficult and challenged to judge a wise investment decision on the plenty of available stocks in the market. Uncertainty about the nature of future and difficulty of assuring certain return accompanies the selection of stocks. We have to consider the balance between the expected return which we want to maximize and the associated risk which we want to minimize. The methodologies employed for decision making in stock exchanges can be broadly split into two groups: technical analysis via data and fundamental analysis via financial report. For example, Preeti Paranjape-Voditel[1] and Umesh Deshpande[1] have proposed a stock recommender system based on association rule. The principle is to find the stocks that usually increase together, and they also want to select the stocks that daily return is high. In this way, after finding some satisfied stocks, they found their investment is higher than the stock market index. They also proposed methods how to evaluate and rebalance the portfolio. However, due to my implementation, sometimes the portfolio can surpass the stock market index but during the second year, the performance is not as well as the market. I think the reason is that, we only select highly-returned stocks in the first year but we ignore the fact that the price of stocks will be fluctuated due to the principle of true value. Therefore, the price stocks will decrease to rebalance themselves.

Fundamentally, no matter which recommender system has been proposed, it was developed for novice investors to aid in making subjective judgements based on their need. The vital marks of credibility in a recommendation are based on the majority of trustworthy researchers and expertise so that the system can counter the uncertainty. Researchers and expertise usually will keep in touch of each other to discuss, trade, learn and share knowledge across the network. Therefore, analyzing the network among the investors can provide clear-sightedness to crowds who need wisdom suggestions. However, there is a loophole in this strategy. In such networks the trust between individuals cannot be completely measured and faked relationship can be built. For example, if one knows that his talking is followed then he can put fake conversation and misleading information to influence our investment decision. It is important for us to discover trust in relationships among entities of a social network as premise. However, due to the various skills and hard-to-measure knowledge and experience over time that various expertise have, it is hard to find the professions we satisfy. Thus, since the government ordered, managers of mutual fund have to propose their investment portfolio. Due to the property of mutual fund, they pursue a wise decision to gain more profits in order not to disappoint their investors. Thus, it is trustworthy for us to analyze their network so that we can get some pattern of portfolio and we can reduce the overall risk and increase the expected return.

2. Methodology

By relying on the trust of mutual fund portfolio network, we could gain some knowledge on the social investment relationships among stocks which will be hidden otherwise. We could calculate the centrality among stocks in the entire portfolio network via discovering the position of individual stocks.

Finally, a trust recommendation of stocks is offered in getting the most popular stock in the network. Our novice investors or first-time investors can form a portfolio of relevant stocks in sync with their matched priorities.

What we do is to form a bipartite graph between mutual funds and stock. Following Figure1[2], sets of U represents the mutual funds and set of nodes V represents stock invested by the mutual funds. From the graph, we can have an enlightenment about the total number of stocks and find which ones that mutual funds are most interested in. Hereby, we can derive the 1-mode network, with stocks as nodes, using folding methods which operate directly on the matrix corresponding to the bipartite graph. Two stocks, in the 1-mode network of stocks, are connected if a mutual fund has invested in both the stocks. Then we can derive the 2-mode network of stocks by matrix product of the 1-mode network and the transpose of the 1-mode network. Table 1[2] is the process of 1-mode and 2-mode.

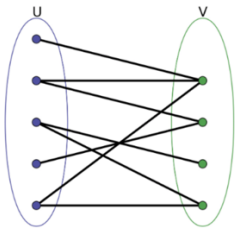


Fig. 1. Bi-Partite Graph representation mutual fund portfolio network

After getting the 2-mode matrix, we need a certain criterion to measure the popularity and influences among stocks. According to Wikipedia[3], degree centrality, especially the indegree centrality is a measure of the number of ties that a node has. In other words, degree centrality is a measure of popularity. Eigenvector centrality is a measure of the influence of a node in a network. Therefore, the preferred stock is selected based on popularity as well as influences.

Hereby, the entire process is that based on user preference of each sector (large, middle and small cap) and industry (finance, IT, pharmaceuticals etc.), we can figure out some high-rating mutual funds by an external agency. Then, as for different mutual funds, we extract associated investment portfolio to form a matrix to get 1-mode and 2-mode network. Then by calculating the degree centrality or eigenvector centrality, we can select from the ranked stocks to form a portfolio.

Table 1. (a) The matrix showing Stock-Mutual Fund (SMF) Investment Matrix where S_i is the i^{th} stock, MF_j the j_{th} mutual fund and $SMF_{i,j}$ assumes values 0 or 1 depending on whether the j^{th} mutual fund invested in i^{th} stock. (b) The matrix showing Stock- Stock (SS) Investment similarity Matrix

(a)

	MF_1	MF_2	$\cdots$	MF_n
S_1	$SMF_{1,1}$	$SMF_{1,2}$	$\cdots$	$SMF_{1,n}$
S_1	$SMF_{2,1}$	$SMF_{2,2}$	$\cdots$	$SMF_{2,n}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_m	$SMF_{m,1}$	$SMF_{m,2}$	$\cdots$	$SMF_{m,n}$

(b)

	S_1	S_2	$\cdots$	S_m
S_1	$SS_{1,1}$	$SS_{1,2}$	$\cdots$	$SS_{1,m}$
S_1	$SS_{2,1}$	$SS_{2,2}$	$\cdots$	$SS_{2,m}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_m	$SS_{m,1}$	$SS_{m,2}$	$\cdots$	$SS_{m,m}$

3. Experiment

I have finished two experiments. One is for testing whether this method is time-witnessed. The other is how the performance of the sector-split portfolio based on the upper criterion. All my selection of mutual funds is based on the Morningstar, which is a global financial services firm and is well known for its rating. From the Appendix, Figure 1 is the result of filter based on the best Morningstar rating and got gold medal. From this graph, you can see that four mutual funds will be dropped: NEFRX, NERYX, TPLGX, and PMEGX. The reason is that two are bond-based and two are low-return. From this selection, we have gathered mutual fund of various sizes: small, median and large. Thus, our filter is fitted.

As for the first test, my operation is that I will choose the last quarterly report of the last year from all mutual funds and take their stocks together instead of industrial filtering. After that, I will derive 2-mode network and get the best 10 stocks based on degree centrality and eigenvector centrality separately. Then, by taking duration of 1 year, I will test the return from five to ten stock-combination partly. In the following, I have attached my results for 4 portfolios. Each one is for a year from 2016 to 2019 and their foundation year is from 2015 to 2018.

Table 1: 2016-2015

2016 strategy based on 2015's analysis	
Eigenvector: ABBV,MSFT,CCL,BA,LLY,MMC,WFC	Year Profit
Combine 4	0.07982588370163686
Combine 5	0.03764179654106046
Combine 6	0.06244949408926017
Combine 7	0.059852843174753596
Degree: CCL,ABBV,MSFT,BA,KMX,TXN,RCL	Year Profit
Combine 4	0.20131510165855396
Combine 5	0.2386941479643695
Combine 6	0.26065840502032217
Combine 7	0.21478251951753516
Nasdaq index's 2016 profit	0.09912309465228011
DOW30 index's 2016 profit	0.13542396286370828
2015'analysis	
Eigenvector: ABBV,MSFT,CCL,BA,LLY,MMC,WFC	Year Profit
Combine 4	0.0885027536010768
Combine 5	0.0705993629530915
Combine 6	0.09093420178510701
Combine 7	0.084023654093595
Degree: CCL,ABBV,MSFT,BA,KMX,TXN,RCL	Year Profit
Combine 4	0.19265107431654677
Combine 5	0.19710951543735913
Combine 6	0.1643181905877602
Combine 7	0.17847234551984625
Nasdaq index's 2015 profit	0.05192383361035399
DOW30 index's 2015 profit	-0.022332909462060454

Table 2: 2017-2016

2017 strategy based on 2016's analysis	
Eigenvector: CCL,MSFT,JPM,MRK,BA,MMC,LLY,TXN,WFC,INTC	Year Profit
Combine 5	0.46006559971827793
Combine 6	0.4236709011042129
Combine 7	0.3864903601216676
Combine 8	0.39042536233282504
Combine 9	0.3661295156070491
Combine 10	0.3608166545304277
Degree: AYI,TDG,COG,CBT,PWR,CCL,JCI,MSFT,JPM	Year Profit
Combine 5	0.08440863415587706
Combine 6	0.0694716283444699
Combine 7	0.09332507863882042
Combine 8	0.11080848414332052
Combine 9	0.09357507414332048
Combine 10	0.23106330132334774
Nasdaq index's 2017 profit	0.27236886984584674
DOW30 index's 2017 profit	0.24386834509691688
2016's analysis	
Eigenvector: CCL,MSFT,JPM,MRK,BA,MMC,LLY,TXN,WFC,INTC	Year Profit
Combine 5	0.13454701575751923
Combine 6	0.1482988011413124
Combine 7	0.10418897681398699
Combine 8	0.1290264505869722
Combine 9	0.12111280607376503
Combine 10	0.11845330684042624
Degree: AYI,TDG,COG,CBT,PWR,CCL,JCI,MSFT,JPM	Year Profit
Combine 5	0.17188997046921142
Combine 6	0.16406225577192876
Combine 7	0.16323540632591194
Combine 8	0.17928760469540632
Combine 9	0.16058594421599562
Combine 10	0.18576477037444833
Nasdaq index's 2016 profit	0.09912309465228011
DOW30 index's 2016 profit	0.13542396286370828

Table 3: 2018-2017

2018 strategy based on 2017's analysis	
Eigenvector: COG,WFC,PM,JPM,CSX,MRK,BMY,UTX,DE,CAT	Year Profit
Combine 5	-0.17713358401409932
Combine 6	-0.1052238130147568
Combine 7	-0.11143526447251219
Combine 8	-0.12329558293602821
Combine 9	-0.10776749615909201
Combine 10	-0.12318200990617484
Degree: PWR,COG,CBOE,ALGN,WFC,JPM,PM,CSX,TROW,UAL	Year Profit
Combine 5	-0.2278755857516303
Combine 6	-0.2148939687014092
Combine 7	-0.2391951386516923
Combine 8	-0.2161019729216894
Combine 9	-0.21157258103394586
Combine 10	-0.18084535778997982
Nasdaq index's 2018 profit	-0.04358394001480965
DOW30 index's 2018 profit	-0.059731056847819236
2017's analysis	
Eigenvector: CCL,MSFT,JPM,MRK,BA,MMC,LLY,TXN,WFC,INTC	Year Profit
Combine 5	0.2141326339613444
Combine 6	0.17010310303065426
Combine 7	0.1518962845806047
Combine 8	0.15268550343372791
Combine 9	0.211796843945459
Combine 10	0.2724570452331812
Degree: AYI,TDG,COG,CBT,PWR,CCL,JCI,MSFT,JPM	Year Profit
Combine 5	0.6715094704854792
Combine 6	0.5737962042405856
Combine 7	0.4759217189213528
Combine 8	0.4480163741575846
Combine 9	0.460049260771408
Combine 10	0.40271625543510453
Nasdaq index's 2017 profit	0.27236886984584674
DOW30 index's 2017 profit	0.24386834509691688

Table 4: 2019-2018

2019 strategy based on 2018's analysis	
Eigenvector: AAL,MSFT,TXN,JPM,MMC,PM,UNP,NSC,HON,DAL	Year Profit
Combine 5	0.23264567876633957
Combine 6	0.2416539261026486
Combine 7	0.2595961652504715
Combine 8	0.2862954917200954
Combine 9	0.29322192133856756
Combine 10	0.2868643494738259
Degree: AAL,COG,BAC,NEP,ULTA,NCLH,SCHW,MSFT,TXN,CCL	Year Profit
Combine 5	0.328200393044419
0.2930215208853487 Combine 6	0.3347252900760515
Combine 7	0.3164785214378319
Combine 8	0.3125057136085235
Combine 9	0.3057719434945179
Combine 10	0.2930215208853487
Nasdaq index's 2019-till-now profit	0.14946000375402083
DOW30 index's 2019-till-now profit	0.2546661631954971
2018's analysis	
Eigenvector: CCL,MSFT,JPM,MRK,BA,MMC,LLY,TXN,WFC,INTC	Year Profit
Combine 5	-0.06348141201870675
Combine 6	-0.12350144501323293
Combine 7	-0.09357601853980137
Combine 8	-0.0725415930376369
Combine 9	-0.07731321353125507
Combine 10	-0.07930494690359512
Degree: AYI,TDG,COG,CBT,PWR,CCL,JCI,MSFT,JPM	Year Profit
Combine 5	0.17188997046921142
-0.06351387484821229, -0.07696918879725856, -0.09894662097520908 Combine 6	-0.04120077790083599
Combine 7	-0.0753907538084142
Combine 8	-0.09127370019035201
Combine 9	-0.06351387484821229
Combine 10	-0.06351387484821229
Nasdaq index's 2018 profit	-0.04358394001480965
DOW30 index's 2018 profit	-0.059731056847819236

From these four tables, we can see that the result of selection and expected return of portfolio based on degree centrality and eigenvector centrality is different. Stocks in every list appear in decreasing order of measure. In other words, the first one in the list is most preferred among Mutual Fund's managers. From the pattern of returns in every year, no matter which centrality we have chosen, we can see that the trend of increasing and decreasing of the portfolio in one year is similar for the pattern happened in the portfolio-foundation year. Therefore, we can say that, when we wonder which centrality we should choose for our portfolio, we should check what the behavior of the portfolio is in the last year and what the degree centrality and eigenvector centrality are separately. If degree centrality is much better than eigenvector centrality, we should choose the portfolio based on degree centrality and vice versa. However, if you check carefully, you can see that there is one outlier, the 2018-2017 portfolio. In 2017, the stock portfolio based on degree centrality is much better than eigenvector centrality's. However, the performance in 2018 is opposite. I think this can be explained from fundamental analysis. From the return in 2017, you can see that the profit is much higher than 30 percent. As what I have said before, stock's price should reveal its true value. Therefore, in 2018, those stocks decrease more to rebalance themselves. As a result, for the selection between degree centrality and eigenvector centrality, we should check how much they have profited partly. If it is higher than 30 percent, we should choose the smaller one. If it is

not, we should choose which one is much better than the other one. If they are similar, we could choose the smaller one since it has more opportunity to reach true value (in other words, increasing).

Table 5: 2019-2018

2019 strategy based on 2018's analysis		
Eigenvector: AAL,MSFT,TXN,JPM,MMC,PM,UNP,NSC,HON,DAL		Year Profit
Combine 5		0.23264567876633957
Combine 6		0.2416539261026486
Combine 7		0.2595961652504715
Combine 8		0.2862954917200954
Combine 9		0.29322192133856756
Combine 10		0.2868643494738259
Degree: AAL,COG,BAC,NEP,ULTA,NCLH,SCHW,MSFT,TXN,CCL		Year Profit
Combine 5		0.328200393044419
0.2930215208853487 Combine 6		0.3347252900760515
Combine 7		0.3164785214378319
Combine 8		0.3125057136085235
Combine 9		0.3057719434945179
Combine 10		0.2930215208853487
2019 strategy based on separate sectors in the stock market		
Informantion:	HPQ	QCM
Industry:	UAL	ALK
Consume:	HLT	CAG
Finance:	CME	JPM
Health:	ABMD	LLY
Material and Energy:	DWDP	SLB
Total return:		0.04128598653978253
Nasdaq index's 2019-till-now profit		0.14946000375402083
DOW30 index's 2019-till-now profit		0.2546661631954971

The second experiment is for whether we do 2-mode on sector-based stocks respectively will have better result. From my experiment, it is not as well as 2-mode on fund-based stocks. I think it may be due to my sample is smaller than samples from the previous experiment. I have chosen 15 mutual funds for last experiment and the 5 best-return mutual funds for this question. Thus, the return is not as good as others.

4. Conclusion and Further Work

In this paper, we demonstrate that mutual fund transactions with trustworthy rating from well-known agency can aid novice people to build a portfolio and this method can be relied on a long term. Moreover, this method can be easily extracted from the model using social network analysis and it does have better performance comparing with Nasdaq index and Dow30 index. Of course, this model has some problems: it is fitted in year-based investment and may not be fitted to quarterly or even shorter-time investment. The quarterly report we can get is much later than the managers invest and conclude. It has time-delay problem. During my process of gathering data from government website, I found that quarterly report for September will be release until November or later. Therefore, we may not be able to get the first-hand information and miss some good turns. Thus, even though is better for novice people, we still may have opportunity to improve the social network analysis to help them prevent more risks.

Acknowledgement

I would like to thank the instructor Prof. Annie Qu for giving me the opportunity to work on a data-driven project and presenting it. During this process, I have gained lots of enlightenment on the fact that the more data we can derive, the more successful our model will be. I have gained some knowledge on financial analysis based on data mining which I am interested in. I appreciate it greatly.

Reference

1. Paranjape-Voditel, P., & Deshpande, U. (2013). A stock market portfolio recommender system based on association rule mining. *Applied Soft Computing*, *13*(2), 1055-1063. doi: 10.1016/j.asoc.2012.09.012
2. Picture1 and Table was retrieved from Sankar, C., Vidyaraj, R., & Kumar, K. (2015). Trust Based Stock Recommendation System – A Social Network Analysis Approach. *Procedia Computer Science*, *46*, 299-305. doi: 10.1016/j.procs.2015.02.024
3. Freeman, L.C.. Centrality in social networks conceptual clarification. Social network 1979;1 (3):215–239.
4. Data of Mutual Fund information is retrieved from https://www.sec.gov/edgar/searchedgar/companysearch.html and you can retrieve from my github: https://github.com/avayuanyuan/stat578-final-project

Appendix:

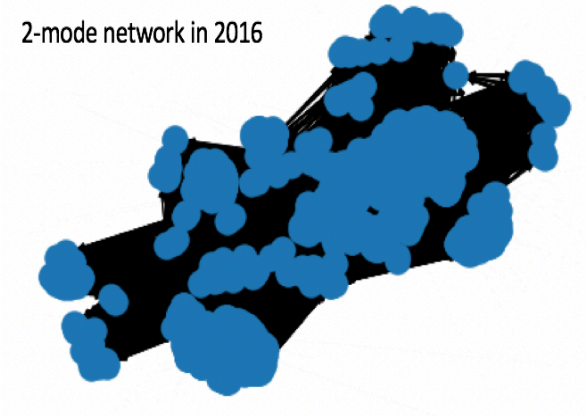
1.

Fund Name	Ticker	Morningstar Rating	Morningstar Analyst Rating	Analyst Rating Start Date	Return Since Start Date
AMG Yacktman I	YACKX	★★★★★	Gold	03/23/11	122.29
American Funds New Perspective A	ANWPX	★★★★★	Gold	07/01/99	335.79
Brown Capital Mgmt Small Co Instl	BCSSX	★★★★★	Gold	11/15/11	219.43
Brown Capital Mgmt Small Co Inv	BCSIX	★★★★★	Gold	06/11/10	315.05
Dodge & Cox Balanced	DODBX	★★★★★	Gold	09/19/05	141.59
Loomis Sayles Core Plus Bond A	NEFRX	★★★★★	Gold	12/12/12	14.55
Loomis Sayles Core Plus Bond Y	NERYX	★★★★★	Gold	12/12/12	16.34
Loomis Sayles High Income Opps Instl	LSIOX	★★★★★	Gold	10/29/18	3.07
Loomis Sayles Investment Grade Bond Y	LSIIX	★★★★★	Gold	02/22/12	25.28
PRIMECAP Odyssey Aggressive Growth	POAGX	★★★★★	Gold	10/21/11	272.52
PRIMECAP Odyssey Stock	POSKX	★★★★★	Gold	10/21/11	170.76
T. Rowe Price Blue Chip Growth	TRBCX	★★★★★	Gold	11/15/11	219.59
T. Rowe Price Capital Appreciation	PRWCX	★★★★★	Gold	11/28/12	103.73
T. Rowe Price Instl Large Cap Core Gr	TPLGX	★★★★★	Gold	12/15/17	17.05
T. Rowe Price Instl Mid-Cap Equity Gr	PMEGX	★★★★★	Gold	06/01/18	7.87
T. Rowe Price Mid-Cap Growth	RPMGX	★★★★★	Gold	11/15/11	177.82
Vanguard Mid Cap Index Admiral	VIMAX	★★★★★	Gold	10/13/10	165.12
Vanguard PRIMECAP Core Inv	VPCCX	★★★★★	Gold	09/30/11	214.63
Wasatch Core Growth	WGROX	★★★★★	Gold	04/17/13	117.94

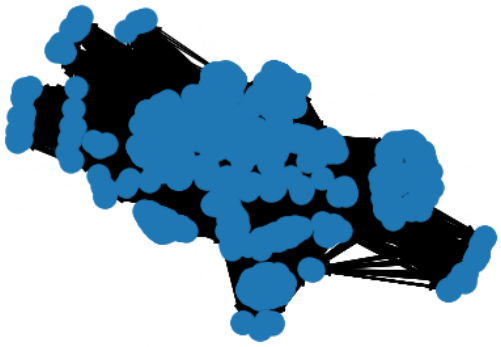
Figure 1

2.

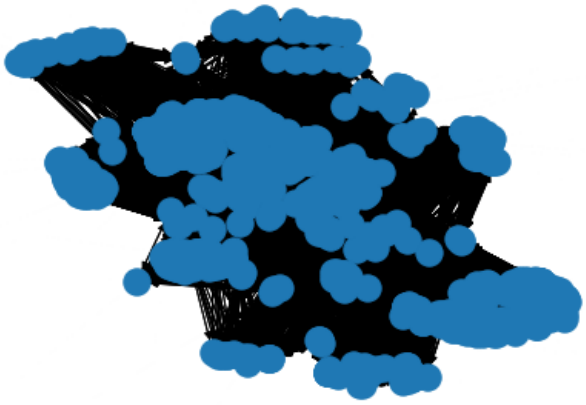
2-mode network in 2016



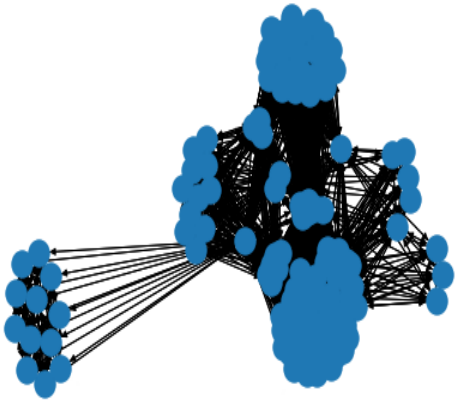
Visualization of 2-mode network of mutual funds in 2017



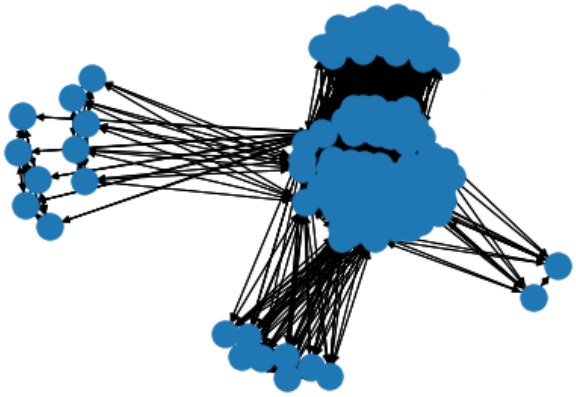
Visualization of 2-mode network of mutual funds in 2018



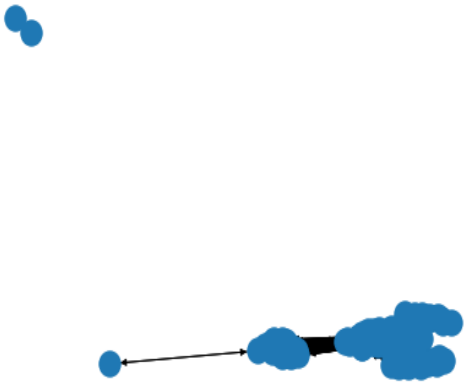
Visualization of 2-mode network of health in 2018



Visualization of 2-mode network of material & energy in 2018



Visualization of 2-mode network of industry in 2018



Stat578 Code

```
#prepocessing data
fund=['ANWPX','BCSIX','BCSSX','DODBX','LSIIX','LSIOX','POAGX','POSKX','WGROX','
VPCCX','VIMAX','RPMGX','YACKX','PRWCX','TRBCX']
stock=[[] for i in range(len(fund))]

for j in range(len(fund)):
    a='_2018.csv'
    doc=fund[j]+a

    fi = open(doc,'r',encoding='utf-8-sig')
    for line in fi:
        line=line.lstrip()
        line_str = line.split()
        if len(line_str) ==0 :
            continue
        if any("%" in s for s in line_str):
            continue
        name=""
        for k in range(len(line_str)):
            if 'Inc' in line_str[k]:
                break
            if 'Corp' in line_str[k]:
                break
            if 'Ltd' in line_str[k]:
                break
            if 'Co.' in line_str[k]:
                break
            if 'Class' in line_str[k]:
                break
            if 'PLC' in line_str[k]:
                break
            if 'SA' in line_str[k]:
                break
            if 'AG' in line_str[k]:
                break
            if '(' in line_str[k]:
                break
            if 'ADR' in line_str[k]:
                break
            if '*' in line_str[k]:
                if k==0:
                    continue
```

```
                else:
                    break
            if 'Other' in line_str[k]:
                break
            if (list(set(line_str[k]))[0] == ',' or line_str[k] == "") :
                continue
            if line_str[k][-1] == ',':
                line_str[k] = line_str[k][:-1]
            name+=(line_str[k]+'_')
        if name ==":
            continue
        if name.startswith('Total'):
            continue
        if name.startswith('_'):
            name=name[1:]
        stock[j].append(name[:-1])
    fi.close()

# create 2-mode matrix
def equal(s1,s2):
    s1l = s1.split('_')
    s2l = s2.split('_')
    l = min(len(s1l),len(s2l))
    for i in range(l):
        if (s1l[i] != s2l[i]):
            return False
    return True

def IsIn(string, List):
    for s in List:
        if equal(string,s):
            return True
    return False

summary = []
for array in stock:
    for i in range(len(array)):
        if not IsIn(array[i] , summary) :
            summary.append(array[i])

#do network analysis
import numpy as np

matrix = np.zeros((len(summary),len(stock)))
```

```
for i in range(len(stock)):
    for j in range(len(summary)):
        if IsIn(summary[j],stock[i]):
            matrix[j,i] = 1

matrix_tr=matrix.transpose()
mod_2=np.dot(matrix,matrix_tr)
np.savetxt("2018.csv", mod_2, delimiter=",")

import pandas as pd
df=pd.read_csv("2018.csv",header=None)
df.columns=summary
df['row']=summary
df.set_index('row', inplace=True)

import networkx as nx
import matplotlib.pyplot as plt
G=nx.DiGraph(df.values)
nx.draw(G)
plt.title("Visualization of 2-mode network of mutual funds in 2018")
plt.show()

# Eigenvector centrality
eig_cen = nx.eigenvector_centrality(G)
# Degree centrality
deg_cen = nx.degree_centrality(G)

# For example, as for one portfolio, how to extract data
import pandas_datareader.data as web
import datetime

eigen_ticker=['AAL','MSFT','TXN','JPM','MMC','PM','UNP','NSC','HON','DAL']
deg_ticker=['AAL', 'COG','BAC','NEP','ULTA','NCLH','SCHW','MSFT','TXN','CCL']
eigen=[]
deg=[]
for i in range(len(eigen_ticker)):
    eigen.append(web.DataReader(eigen_ticker[i], "yahoo",\
                          datetime.datetime(2018,1,1),datetime.datetime(2018,12,31)))

for i in range(len(deg_ticker)):
    deg.append(web.DataReader(deg_ticker[i],
"yahoo",datetime.datetime(2018,1,31),datetime.datetime(2018,12,31)))
```

```
#how to calculate profit from portfolio
def Profit(stocks):
    p = 0.0
    op=0.0
    close=0.0
    for i in range(len(stocks)):
        open_price = stocks[i]["Open"].iloc[0]
        close_price = stocks[i]["Close"].iloc[-1]
        op+=open_price
        close+=close_price
    p = (close - op)/op
    return p

#do combination to compare which one is better
num=5
profit_list_1 =[]
profit_list_2 =[]
while True:
    s1 = False
    s2 = False
    if num <= len(eigen):
        profit_list_1.append(Profit(eigen[:num]))
    else:
        s1 = True
    if num <= len(deg):
        profit_list_2.append(Profit(deg[:num]))
    else:
        s2 = True
    num+=1
    if (s1 and s2):
        break
```