

Network Analysis on Talent Flow Between Firms

This project explores LinkedIn-based talent movement among firms. We use network analysis to understand how employees flow between companies, identify key hubs, detect communities, and analyze network properties like assortativity and PageRank.

Load Required Libraries

```
library(igraph)

##
## Attaching package: 'igraph'

## The following objects are masked from 'package:stats':
##   decompose, spectrum

## The following object is masked from 'package:base':
##   union

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:igraph':
##   as_data_frame, groups, union

## The following objects are masked from 'package:stats':
##   filter, lag

## The following objects are masked from 'package:base':
##   intersect, setdiff, setequal, union

library(readr)
```

Load and Prepare Data

```
df_company <- read.csv("linkedin_company_metadata.csv")
df_talent_flows <- read.csv("talent_flows.csv")

# Extract edges for network graph construction
df_edges <- df_talent_flows %>% select(from, to)
head(df_edges)

##           from          to
## 1      at&t        oracle
## 2 colgate-palmolive        nike
## 3 agilent-technologies     stryker
## 4         ebay       expedia
## 5      comcast republic-services-inc
## 6         aon          aig
```

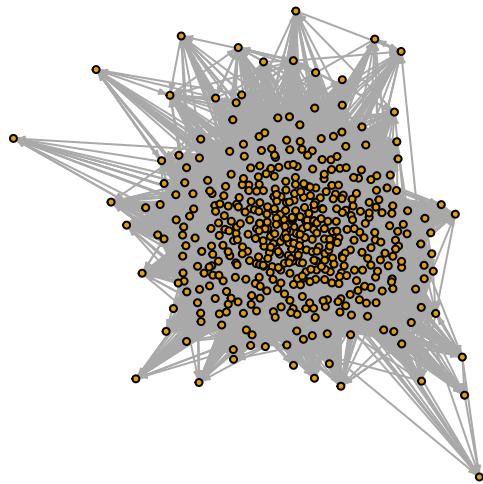
Construct Directed Graph

```
graph <- graph_from_data_frame(df_edges, directed = TRUE)
summary(graph)

## IGRAPH f954b6e DN-- 473 81114 --
## + attr: name (v/c)

plot(graph,
      vertex.label = NA,
      vertex.size = 3,
      edge.arrow.size = 0.2,
      main = "Overall Talent Flow Network")
```

Overall Talent Flow Network



Compute Degree Metrics

We examine in- and out-degrees to understand how firms attract or lose talent in the network.

```
in_degrees <- degree(graph, mode = "in")
out_degrees <- degree(graph, mode = "out")

# Top 10 firms by in-degree and out-degree
top_in_degrees <- sort(in_degrees, decreasing = TRUE)[1:10]
top_out_degrees <- sort(out_degrees, decreasing = TRUE)[1:10]

top_in_degrees

##                      ibm          accenture
##                         417                     409
## hewlett-packard-enterprise          at&t
##                           407                     406
## bank-of-america          amazon
##                           405                     405
## wellsfargo          jpmorgan-chase
##                           404                     390
## microsoft          citi
```

##	390	387
top_out_degrees		
##	ibm	at&t
##	440	437
## hewlett-packard-enterprise		jpmorgan-chase
##	432	428
## bank-of-america		accenture
##	426	419
##	ge	wellsfargo
##	417	416
##	citi	target
##	412	411

Understanding In-Degree and Out-Degree in a Talent Flow Network

The computed **in-degree** reflects how often a firm is chosen as the next career step. A high in-degree suggests a firm is an attractive destination, often due to:

- Strong market reputation
- Growth opportunities
- Competitive employee benefits
- Strategic positioning within the industry

The **out-degree** metric, on the other hand, represents how many employees are leaving a firm for other firms. A high out-degree might indicate that a firm is:

- Undergoing organizational changes (e.g., restructuring or downsizing)
- A major source of talent development (feeding into other firms)
- Experiencing talent loss due to better offers elsewhere

Examples

- **High In-Degree Firms** (e.g., IBM, Accenture, Hewlett-Packard Enterprise): These companies attract a large number of incoming employees and are considered top destinations within the professional network.
 - **High Out-Degree Firms** (e.g., IBM, AT&T, Hewlett-Packard Enterprise): These firms have significant talent outflow, which could reflect internal shifts, competitive poaching, or their role as training grounds.
-

Why Are High-Degree Firms Often Large Firms?

This aligns with earlier observations—firms with the highest degrees tend to be larger. Possible reasons include:

- **Larger Workforce:** Bigger firms have more employees, resulting in more natural inflow and outflow.
- **Diverse Opportunities:** A wider range of roles attracts a more diverse talent pool.
- **Stronger Brand Recognition:** Well-known firms are more desirable to job seekers.

- **Greater Market Visibility:** Large companies appear more often on job platforms and in professional networks.
- **More Recruitment Resources:** Bigger budgets allow for more effective hiring strategies.

In summary:

Firm size significantly impacts talent flow dynamics.

Larger companies tend to attract and release more employees due to their visibility, scale, and organizational capacity.

Analyze Degree vs Firm Size via Linear Regression

We assess how firm size (employee count) impacts talent inflow/outflow.

```

firm_data <- data.frame(name = V(graph)$name, in_degree = in_degrees, out_degree = out_degrees)
firm_data <- merge(firm_data, df_company, by.x = "name", by.y = "company_id")

model_in_degree <- lm(in_degree ~ emp_count, data = firm_data)
summary(model_in_degree)

## 
## Call:
## lm(formula = in_degree ~ emp_count, data = firm_data)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -456.46  -42.82   -3.25   47.08  143.81 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 1.366e+02 3.407e+00 40.11   <2e-16 ***
## emp_count   9.545e-04 4.365e-05 21.87   <2e-16 ***  
## ---        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 65.47 on 471 degrees of freedom
## Multiple R-squared:  0.5038, Adjusted R-squared:  0.5027 
## F-statistic: 478.2 on 1 and 471 DF,  p-value: < 2.2e-16

model_out_degree <- lm(out_degree ~ emp_count, data = firm_data)
summary(model_out_degree)

## 
## Call:
## lm(formula = out_degree ~ emp_count, data = firm_data)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -507.64  -49.69   -2.16   56.89  134.65 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 1.329e+02 3.684e+00 36.08   <2e-16 ***
## emp_count   1.055e-03 4.721e-05 22.36   <2e-16 ***  
## ---        
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
```

```
## Residual standard error: 70.81 on 471 degrees of freedom
## Multiple R-squared:  0.5148, Adjusted R-squared:  0.5138
## F-statistic: 499.8 on 1 and 471 DF,  p-value: < 2.2e-16
```

Linear Regression Results: Employee Count vs. In-/Out-Degree

To assess whether firm size (measured by employee count) influences talent movement, we ran two linear regressions:

- One with **in-degree** as the dependent variable
 - One with **out-degree** as the dependent variable
-

In-Degree Model

- **Intercept:** ~136.6
This is the expected in-degree when the employee count is zero. While theoretical (as firms can't actually have zero employees), it serves as a baseline for the model.
 - **Coefficient for emp_count:** ~0.0009545
Each additional employee is associated with an increase of approximately 0.00095 in in-degree, suggesting a positive relationship between firm size and in-degree.
 - **P-values:**
Both the intercept and the employee count coefficient are statistically significant ($p < 0.05$).
 - **R-squared:** 0.504
About 50.4% of the variation in in-degree is explained by employee count.
-

Out-Degree Model

- **Intercept:** ~132.9
Represents the expected out-degree at zero employees (again, a theoretical value).
 - **Coefficient for emp_count:** ~0.001055
Each additional employee corresponds to an increase of approximately 0.00106 in out-degree, indicating a positive relationship.
 - **P-values:**
Both coefficients are statistically significant ($p < 0.05$).
 - **R-squared:** 0.515
About 51.5% of the variation in out-degree is explained by employee count.
-

Interpretation

Both models reveal a **statistically significant and positive relationship** between firm size and degree centrality:

- Larger firms tend to have **higher in-degrees** (receive more incoming talent) and **higher out-degrees** (send out more employees).
- The R-squared values around 50% indicate that employee count is an important factor, though not the only one.
- The effect is slightly stronger for **out-degree**, but both relationships are similar in strength.

These findings support the intuition that larger firms play a central role in talent flow networks, both as talent attractors and as sources of talent.

Add Weighted Edges Based on Migration per Employee

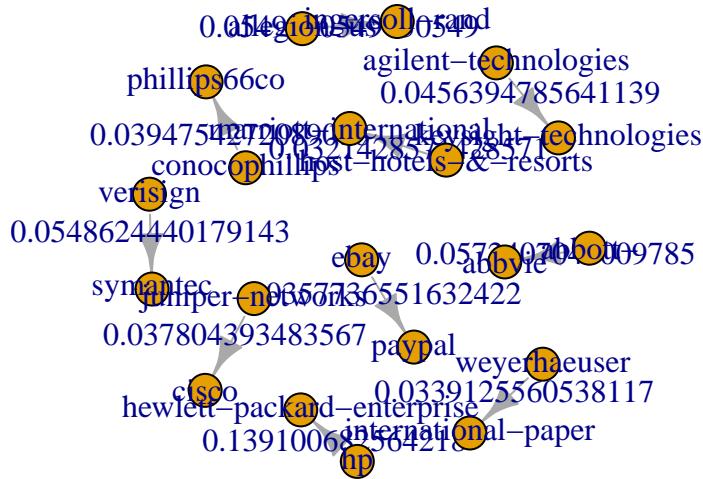
```
df_talent_flows_merged <- merge(df_talent_flows, df_company[, c('company_id', 'emp_count')],  
                                by.x = 'from', by.y = 'company_id', all.x = TRUE)  
  
df_talent_flows_merged$weight <- df_talent_flows_merged$migration_count / df_talent_flows_merged$emp_count  
  
df_edges_with_weight <- merge(df_edges, df_talent_flows_merged[, c('from', 'to', 'weight')],  
                                by = c('from', 'to'), all.x = TRUE)  
  
df_edges <- df_edges_with_weight  
head(df_edges)  
  
##   from      to    weight  
## 1 3m abbott- 8.342416e-04  
## 2 3m abbvie 5.382204e-05  
## 3 3m abiomed 2.691102e-05  
## 4 3m accenture 9.822522e-04  
## 5 3m activision 2.691102e-05  
## 6 3m      adm 5.382204e-05
```

Construct Weighted Graph

```
df_edges <- df_edges[, c("from", "to", "weight")]  
str(df_edges)  
  
## 'data.frame': 81114 obs. of 3 variables:  
## $ from : chr "3m" "3m" "3m" "3m" ...  
## $ to   : chr "abbott-" "abbvie" "abiomed" "accenture" ...  
## $ weight: num 8.34e-04 5.38e-05 2.69e-05 9.82e-04 2.69e-05 ...  
graph_df_edges <- graph_from_data_frame(df_edges, directed = TRUE)  
summary(graph_df_edges)  
  
## IGRAPH bde1cc7 DNW- 473 81114 --  
## + attr: name (v/c), weight (e/n)
```

Visualize Top-Weighted Talent Flows

```
top_edges <- head(df_edges[order(-df_edges$weight), ], 10)  
g_top_edges <- graph_from_data_frame(top_edges, directed = TRUE)  
  
plot(g_top_edges, edge.label = E(g_top_edges)$weight)
```



Network Metrics on Top Edges

```

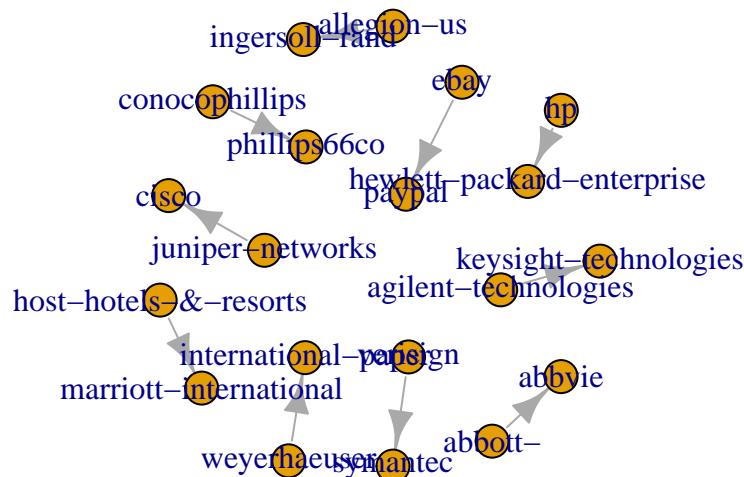
cat("Number of Nodes:", vcount(g_top_edges), "\n")
## Number of Nodes: 20

cat("Number of Edges:", ecount(g_top_edges), "\n")
## Number of Edges: 10

degree_distribution <- degree(g_top_edges, mode = "all")
cat("Degree Centrality:", degree_distribution, "\n")
## Degree Centrality: 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

betweenness_distribution <- betweenness(g_top_edges)
cat("Betweenness Centrality:", betweenness_distribution, "\n")
## Betweenness Centrality: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
plot(g_top_edges)

```



Interpreting High-Weight Edges in the Talent Flow Network

In this network, an edge's **weight** represents the proportion of employees moving from one firm (**from**) to another (**to**), relative to the size of the source firm.

A **high-weight edge** indicates a notably strong talent flow between two firms.

What Do High Weights Suggest?

- **High Employee Turnover:** The source firm may be experiencing internal change, dissatisfaction, or talent poaching.
 - **Attractive Destinations:** Destination firms may offer better career prospects, higher compensation, or stronger employer branding.
 - **Industry Trends:** High-weight edges within the same industry may reflect strong sector-specific mobility.
-

Notable Observations from the Graph

- **Spin-Offs and Restructuring:** Some connections link firms with historical ties, suggesting transitional movement after corporate restructuring.
 - **Competitive Hiring:** Edges between direct competitors may indicate aggressive talent acquisition or career-driven switches.
 - **Cross-Sector Mobility:** Movement across industries may signal broader economic shifts or emerging talent needs.
-

Summary

High-weight edges reveal meaningful dynamics in the job market—identifying firms that are central hubs of talent movement.

These patterns offer insight into employee behavior, firm reputation, and industry evolution.

For deeper understanding, further qualitative analysis may be needed, such as reviewing external factors like market conditions or firm-level strategies.

Understanding PageRank and the Random Surfer Model

The **PageRank** algorithm ranks the importance of nodes in a network based on the idea of a *random surfer*.

The Intuition

Imagine a person randomly clicking through links on a website (or navigating a network of firms). Each time they arrive at a node, they randomly select an outgoing edge to follow.

- The **more frequently** a node is visited during this process, the **higher its PageRank**.
 - The algorithm captures the idea that **important nodes are likely to be visited more often**.
-

Unweighted vs. Weighted Networks

- In an **unweighted graph**, the surfer has an **equal probability** of choosing any of the outgoing edges from a node.
- In a **weighted graph**, the surfer is **more likely to follow edges with higher weights**.

This means that in weighted networks, transitions are **biased toward stronger or more significant connections**.

As a result, nodes connected by high-weight edges are more influential, and the PageRank distribution becomes more concentrated around those nodes.

This weighted approach better captures real-world dynamics—such as employee flows between firms—where not all connections are equally likely or important.

PageRank: Unweighted vs Weighted

```
pr_unweighted <- page_rank(graph_df_edges, algo="prpack", weights = NA)
pr_weighted <- page_rank(graph_df_edges, algo="prpack", weights = E(graph_df_edges)$weight)

top_nodes_unweighted <- head(sort(pr_unweighted$vector, decreasing = TRUE), 10)
top_nodes_weighted <- head(sort(pr_weighted$vector, decreasing = TRUE), 10)

top_nodes_unweighted

##          wellsfargo             ibm
## 0.005052306 0.005042449
##         accenture bank-of-america
## 0.004941054 0.004872047
##        at&t hewlett-packard-enterprise
## 0.004823967 0.004822008
##         amazon   jpmorgan-chase
## 0.004773077 0.004701858
##        microsoft      citi
## 0.004629907 0.004615667

top_nodes_weighted

##           ibm      microsoft
## 0.02584084 0.02254956
## hewlett-packard-enterprise wellsfargo
## 0.02095859 0.02031841
##         bank-of-america   jpmorgan-chase
## 0.01918484 0.01867777
##            citi      accenture
## 0.01614856 0.01609669
##           google      oracle
## 0.01494275 0.01332736
```

Visualize PageRank Distributions

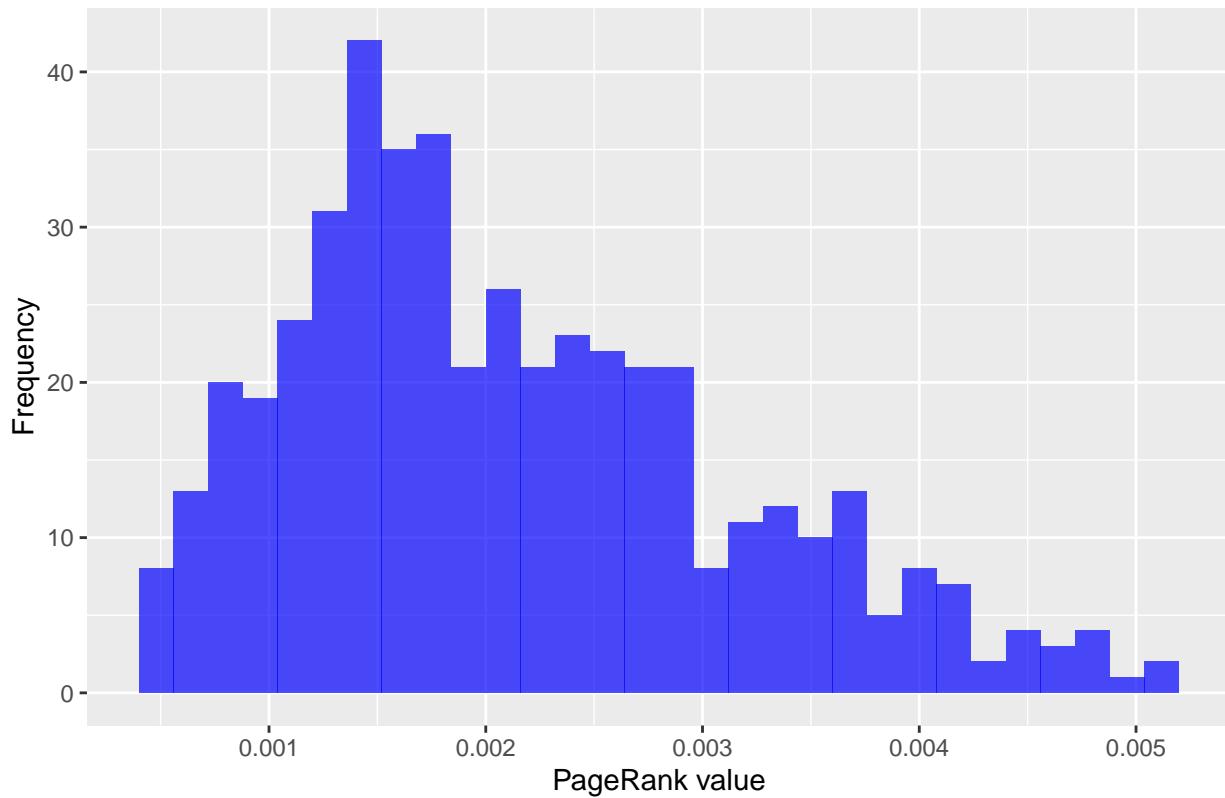
```
library(ggplot2)

df_unweighted <- data.frame(PageRank = pr_unweighted$vector)
df_weighted <- data.frame(PageRank = pr_weighted$vector)

ggplot(df_unweighted, aes(x = PageRank)) +
  geom_histogram(bins = 30, fill = 'blue', alpha = 0.7) +
  labs(title = "Histogram of Unweighted PageRank",
```

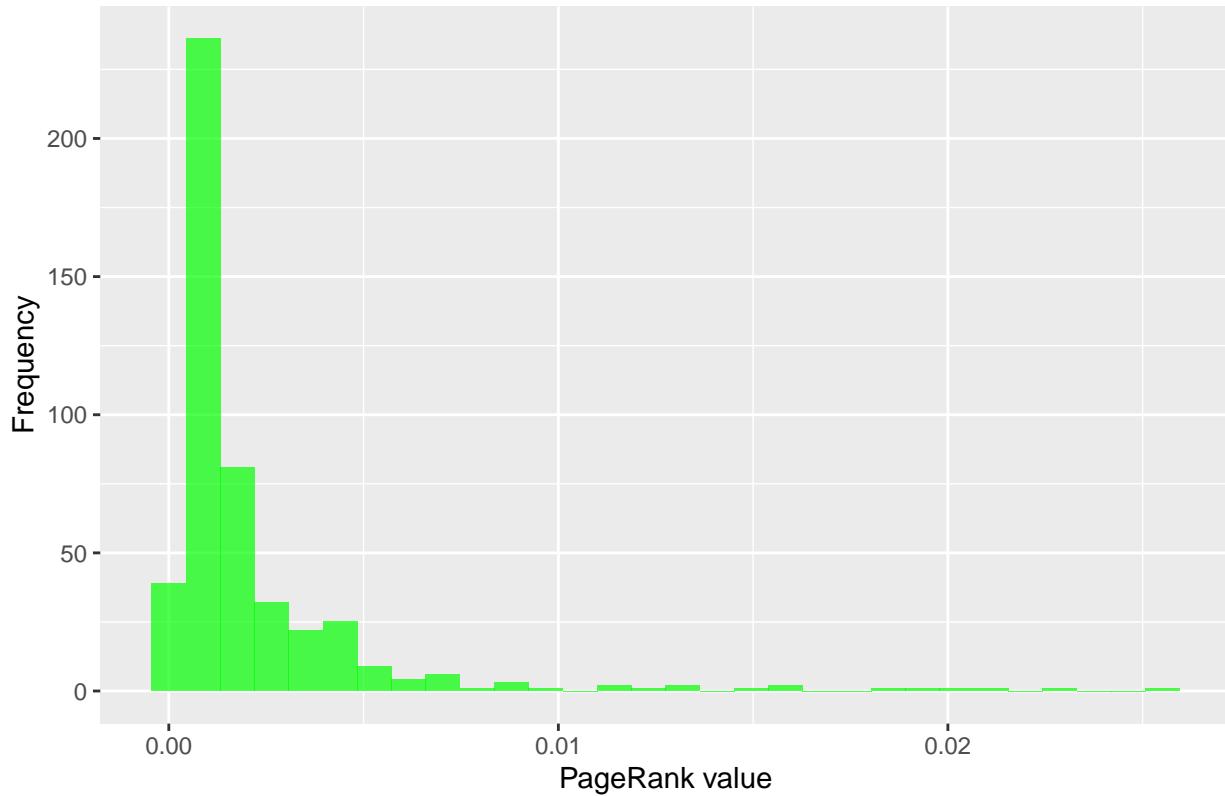
```
x = "PageRank value",
y = "Frequency")
```

Histogram of Unweighted PageRank



```
ggplot(df_weighted, aes(x = PageRank)) +
  geom_histogram(bins = 30, fill = 'green', alpha = 0.7) +
  labs(title = "Histogram of Weighted PageRank",
       x = "PageRank value",
       y = "Frequency")
```

Histogram of Weighted PageRank



The significant difference in distributions shows that the edge weights have a major impact on the importance of nodes in the network. Nodes with high-weight inbound edges are considered much more important in the weighted PageRank algorithm.

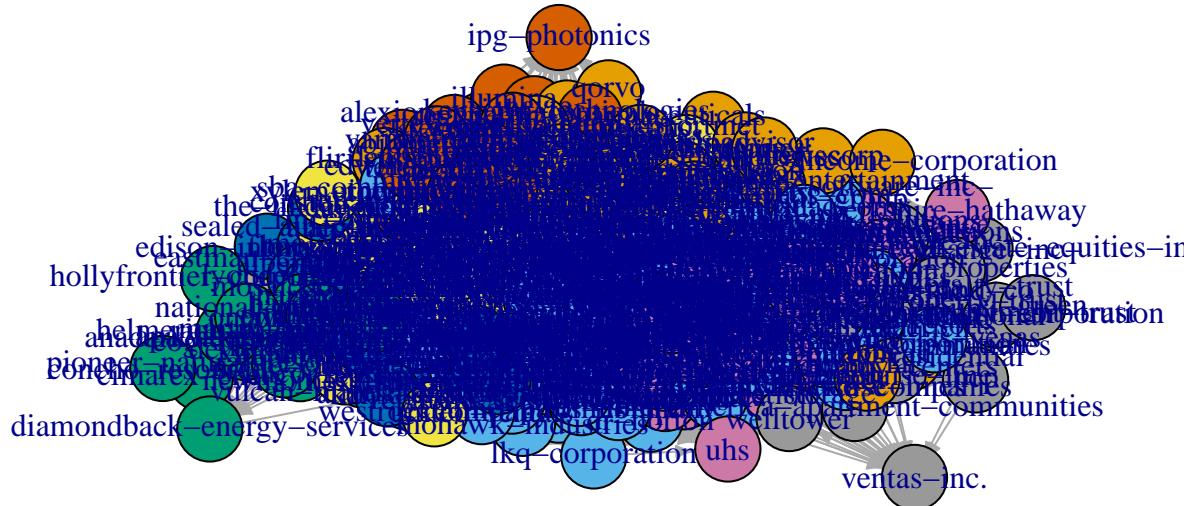
The key difference between the two calculations is that the weighted PageRank takes into account the ‘strength’ or ‘significance’ of the connections between nodes, while the unweighted PageRank does not. As a result, in the weighted PageRank, nodes that are connected by edges with higher weights will have their importance exaggerated compared to those with lower-weighted connections. This often leads to a more polarized distribution where a few nodes have much higher importance scores than the rest.

Detect Communities with Walktrap Algorithm

```
wt_communities <- walktrap.community(graph_df_edges, steps = 4)
membership <- membership(wt_communities)
sizes(wt_communities)

## Community sizes
##   1   2   3   4   5   6   7   8   9   10
##  64 120  25  80  46  39  74  17   5   3

plot(graph_df_edges, vertex.color = membership(wt_communities), asp = FALSE, edge.arrow.size = 0.5)
```



Explore Community Characteristics

```

membership_vector <- as.numeric(membership(wt_communities))
company_names <- V(graph_df_edges)$name

community_data <- data.frame(company_id = company_names, community = membership_vector)
extended_community_data <- merge(community_data, df_company, by = "company_id")

for(i in unique(extended_community_data$community)) {
  cat("Community", i, ":\n")
  community_subset <- subset(extended_community_data, community == i, select = c(company_id, community,
  print(community_subset)
  cat("\n\n")
}

## Community 4 :
##                                     company_id community
## 1                               3m          4
## 7                               adm         4
## 20                              alcoa        4
## 24                             allegion-us     4
## 29                             altria        4
## 39                            amerisourcebergen 4
## 40                             ametek         4
## 57                            avery-dennison   4
## 59                             ball          4
## 70                            borgwarner      4
## 76                           brown-forman     4
## 80                          campbell-soup-company 4
## 82                           cardinal-health    4
## 85                           caterpillar-inc    4
## 101                         church-&-dwight-co-inc 4
## 111                         colgate-palmolive    4
## 117                         constellation-brands 4
## 120                         corning-incorporated 4
## 122                           cotoy          4
## 125                         cummins-inc      4

```

```

## 127           danaher      4
## 141           dovercorp    4
## 148           eaton-corporation 4
## 150           ecolab       4
## 155           emerson      4
## 186           ford-motor-company 4
## 194           ge          4
## 196           general-mills 4
## 197           general-motors 4
## 205           hanesbrands-inc- 4
## 206           harley-davidson-motor-company 4
## 208           hasbro       4
## 212           henry-schein 4
## 218           honeywell     4
## 219           hormel-foods 4
## 225           idexx-laboratories 4
## 226           iff          4
## 231           ingersoll-rand 4
## 232           insidepmi     4
## 235           international-paper 4
## 242           itw          4
## 247           john-deere   4
## 249           johnson-controls 4
## 253           kellogg-company 4
## 256           kimberly-clark 4
## 262           labcorp      4
## 280           masco-corporation 4
## 282           mattel       4
## 284           mccormick    4
## 297           molson-coors 4
## 298           mondelezinternational 4
## 299           monster-energy_2 4
## 311           newellbrands 4
## 315           nielsen      4
## 316           nike         4
## 332           parker-hannifin 4
## 335           pca          4
## 336           pentair      4
## 338           pepsico      4
## 345           ppg-industries 4
## 349           procter-&gamble 4
## 370           rockwell-automation 4
## 378           sealed-air-corporation 4
## 384           snap-on-tools 4
## 388           stanley-black-decker-inc 4
## 396           sysco        4
## 400           te-connectivity 4
## 403           textron      4
## 405           the-clorox-company 4
## 406           the-coca-cola-company 4
## 407           the-estee-lauder-companies-inc- 4
## 409           the-hershey-company 4
## 411           the-j-m--smucker-company 4
## 412           the-kraft-heinz-company 4

```

```

## 432      united-technologies      4
## 444          vf-corporation      4
## 460          westrockcompany      4
## 461          weyerhaeuser      4
## 462      whirlpool-corporation      4
## 469          xylem-inc-      4
##           industry
## 1  mechanical or industrial engineering
## 7          food production
## 20         mining & metals
## 24  electrical/electronic manufacturing
## 29         consumer goods
## 39         hospital & health care
## 40  electrical/electronic manufacturing
## 57         packaging and containers
## 59         packaging and containers
## 70         automotive
## 76         wine and spirits
## 80         food & beverages
## 82         hospital & health care
## 85         machinery
## 101        consumer goods
## 111        consumer goods
## 117        wine and spirits
## 120        glass, ceramics & concrete
## 122        cosmetics
## 125        automotive
## 127  electrical/electronic manufacturing
## 141         machinery
## 148  electrical/electronic manufacturing
## 150         chemicals
## 155 mechanical or industrial engineering
## 186         automotive
## 194  electrical/electronic manufacturing
## 196         consumer goods
## 197         automotive
## 205         consumer goods
## 206         automotive
## 208         consumer goods
## 212         medical devices
## 218  electrical/electronic manufacturing
## 219         consumer goods
## 225         biotechnology
## 226         chemicals
## 231  electrical/electronic manufacturing
## 232         tobacco
## 235         paper & forest products
## 242         machinery
## 247         machinery
## 249 mechanical or industrial engineering
## 253         consumer goods
## 256         consumer goods
## 262         hospital & health care
## 280         building materials

```

```

## 282           consumer goods
## 284           food production
## 297           food & beverages
## 298           food production
## 299           food & beverages
## 311           consumer goods
## 315           information services
## 316           sporting goods
## 332 mechanical or industrial engineering
## 335           packaging and containers
## 336 mechanical or industrial engineering
## 338           food & beverages
## 345           chemicals
## 349           consumer goods
## 370           industrial automation
## 378           packaging and containers
## 384           automotive
## 388           consumer goods
## 396           food & beverages
## 400 electrical/electronic manufacturing
## 403           aviation & aerospace
## 405           consumer goods
## 406           food & beverages
## 407           cosmetics
## 409           consumer goods
## 411           consumer goods
## 412           food & beverages
## 432           aviation & aerospace
## 444           apparel & fashion
## 460           packaging and containers
## 461           paper & forest products
## 462           consumer goods
## 469 mechanical or industrial engineering
##
##
## Community 6 :
##               company_id community           industry
## 2             abbott-      6   hospital & health care
## 3             abbvie       6   pharmaceuticals
## 4             abiomed     6   medical devices
## 22            alexion-pharmaceuticals 6   biotechnology
## 25            allergan      6   pharmaceuticals
## 41            amgen        6   biotechnology
## 61            baxter-healthcare 6   medical devices
## 63            bd1         6   medical devices
## 66            biogen-       6   biotechnology
## 72            boston-scientific 6   medical devices
## 73            bristol-myers-squibb 6   pharmaceuticals
## 90            celgene       6   pharmaceuticals
## 131           dentsplysirona 6   medical devices
## 152           edwards-lifesciences 6   medical devices
## 154           eli-lilly-and-company 6   biotechnology
## 199           gilead-sciences 6   biotechnology
## 217           hologic      6   medical devices

```

```

## 228 illumina 6 biotechnology
## 229 ims-health 6 hospital & health care
## 230 incyte 6 pharmaceuticals
## 237 intuitive-surgical 6 medical devices
## 240 ipg-photonics 6 electrical/electronic manufacturing
## 248 johnson-&-johnson 6 hospital & health care
## 287 medtronic 6 medical devices
## 288 merck 6 pharmaceuticals
## 305 mylan 6 pharmaceuticals
## 308 nektar-therapeutics 6 pharmaceuticals
## 339 perkinelmer 6 biotechnology
## 340 perrigo 6 pharmaceuticals
## 341 pfizer 6 pharmaceuticals
## 365 regeneron-pharmaceuticals 6 biotechnology
## 368 resmed 6 medical devices
## 391 stryker 6 medical devices
## 401 teleflex 6 medical devices
## 415 thermo-fisher-scientific 6 research
## 443 vertex-pharmaceuticals 6 biotechnology
## 453 waters 6 research
## 471 zimmerbiomet 6 medical devices
## 473 zoetis 6 pharmaceuticals
##
##
## Community 2 :
##                               company_id community
## 5                      accenture 2
## 9                         adp 2
## 10                     advance-auto-parts 2
## 12                        aflac 2
## 18                     alaska-airlines 2
## 33                     american-airlines 2
## 35                     american-express 2
## 36                     american-tower 2
## 37                     american-water 2
## 52                        at&t 2
## 55                     autozone 2
## 65                     best-buy 2
## 69                        boeing 2
## 77                     c-h-robinson 2
## 83                      carmax 2
## 88                      cbs-com 2
## 93                     centurylink 2
## 94                     cerner-corporation 2
## 97                     charter-communications 2
## 99                     chipotle-mexican-grill 2
## 104                     cintas 2
## 110                     cognizant 2
## 112                     comcast 2
## 119                     copart 2
## 121                     costco-wholesale 2
## 123                     crown-castle 2
## 124                     csx-transportation 2
## 126                     cvs-health 2

```

```

## 128      darden-restaurants      2
## 129          davita            2
## 130      delta-air-lines        2
## 136      discovery-communications 2
## 137          dish-network        2
## 138          dollar-general       2
## 139      dollar-tree-stores      2
## 143          dr-horton           2
## 158          equifax             2
## 167          expeditors          2
## 168      extra-space-storage     2
## 172          fastenal            2
## 174          fedex               2
## 180          fleetcor            2
## 185          foot-locker          2
## 188      fox-filmed-entertainment 2
## 191          gap-inc              2
## 195          general-dynamics      2
## 198      genuine-parts-company    2
## 203          h&r-block            2
## 207      harris-corporation      2
## 215          hilton-worldwide      2
## 220      host-hotels-&-resorts     2
## 224          ibm                2
## 239          ipg                2
## 241          iron-mountain         2
## 243      jack-henry-&-associates   2
## 245      jb-hunt-transport-services-inc 2
## 252      kansas-city-southern-railway 2
## 260      kohls-department-stores    2
## 261          kroger              2
## 264      leggett-&-platt          2
## 265          lennar              2
## 266          limited-brands         2
## 268          lkq-corporation        2
## 269          lockheed-martin        2
## 270      lowe%27s-home-improvement 2
## 274          macy                2
## 277      marriott-international     2
## 281          mastercard           2
## 285      mcdonald%27s-corporation 2
## 286          mckesson            2
## 290      mgm-resorts-international 2
## 291          michael-kors          2
## 296      mohawk-industries        2
## 306          nasdaq-omx           2
## 319          nordstrom            2
## 320      norfolk-southern          2
## 322      northrop-grumman-corporation 2
## 327          o%27reilly-auto-parts 2
## 331          paccar               2
## 333          paychex              2
## 347          priceline-com          2
## 354      public-storage           2

```

```

## 355          pultegroup      2
## 356              pvh          2
## 359          ralph-lauren    2
## 361          raytheon       2
## 367          republic-services-inc 2
## 369          robert-half-international 2
## 371          rollins-inc.     2
## 372          ross-stores     2
## 375          sba-communications 2
## 379          sempra-energy    2
## 380          sherwin-williams 2
## 386          southwest-airlines 2
## 387          spglobal        2
## 389          starbucks       2
## 399          target          2
## 410          the-home-depot   2
## 414          the-walt-disney-company 2
## 416          tiffany-and-co   2
## 417          tjx            2
## 419          tractor-supply-company 2
## 422          tsys            2
## 424          tyson-foods      2
## 427          ulta            2
## 428          under-armour      2
## 429          unionpacific    2
## 430          united-airlines   2
## 431          united-rentals    2
## 435          ups             2
## 442          verizon          2
## 445          viacom           2
## 449          w.w.-grainger    2
## 450          walgreens         2
## 451          walmart          2
## 452          waste-management   2
## 459          western-union     2
## 465          wynn-las-vegas    2
## 467          xerox            2
## 470          yum-brands       2
##                      industry
## 5   information technology and services
## 9          human resources
## 10         retail
## 12         insurance
## 18         airlines/aviation
## 33         airlines/aviation
## 35         financial services
## 36         telecommunications
## 37         utilities
## 52         telecommunications
## 55         retail
## 65         retail
## 69         aviation & aerospace
## 77         logistics and supply chain
## 83         retail

```

```
## 88 entertainment
## 93 information technology and services
## 94 information technology and services
## 97 telecommunications
## 99 restaurants
## 104 facilities services
## 110 information technology and services
## 112 media production
## 119 automotive
## 121 retail
## 123 telecommunications
## 124 transportation/trucking/railroad
## 126 hospital & health care
## 128 restaurants
## 129 hospital & health care
## 130 airlines/aviation
## 136 entertainment
## 137 telecommunications
## 138 retail
## 139 retail
## 143 construction
## 158 financial services
## 167 logistics and supply chain
## 168 real estate
## 172 wholesale
## 174 package/freight delivery
## 180 financial services
## 185 retail
## 188 entertainment
## 191 retail
## 195 defense & space
## 198 automotive
## 203 retail
## 207 defense & space
## 215 hospitality
## 220 real estate
## 224 information technology and services
## 239 marketing and advertising
## 241 information technology and services
## 243 computer software
## 245 transportation/trucking/railroad
## 252 transportation/trucking/railroad
## 260 retail
## 261 retail
## 264 furniture
## 265 real estate
## 266 retail
## 268 automotive
## 269 defense & space
## 270 retail
## 274 retail
## 277 hospitality
## 281 information technology and services
## 285 restaurants
```

```

## 286          hospital & health care
## 290          hospitality
## 291          apparel & fashion
## 296          textiles
## 306          financial services
## 319          retail
## 320  transportation/trucking/railroad
## 322          defense & space
## 327          retail
## 331          automotive
## 333          human resources
## 347          internet
## 354          real estate
## 355          construction
## 356          apparel & fashion
## 359          apparel & fashion
## 361          defense & space
## 367          environmental services
## 369          staffing and recruiting
## 371          consumer services
## 372          retail
## 375          telecommunications
## 379          utilities
## 380          chemicals
## 386          airlines/aviation
## 387          information services
## 389          retail
## 399          retail
## 410          retail
## 414          entertainment
## 416          luxury goods & jewelry
## 417          retail
## 419          retail
## 422          financial services
## 424          food production
## 427          retail
## 428          apparel & fashion
## 429  transportation/trucking/railroad
## 430          airlines/aviation
## 431          construction
## 435  transportation/trucking/railroad
## 442 information technology and services
## 445          entertainment
## 449 business supplies and equipment
## 450          retail
## 451          retail
## 452          environmental services
## 459          financial services
## 465          hospitality
## 467 information technology and services
## 470          restaurants
##
##
## Community 1 :

```

```

##                               company_id community
## 6                           activision      1
## 8                           adobe         1
## 13                          agilent-technologies 1
## 17                          akamai-technologies 1
## 23                          align-technology   1
## 30                           amazon        1
## 31                           amd          1
## 43                          analog-devices  1
## 44                          ansys-inc     1
## 48                           apple        1
## 49                          applied-materials 1
## 54                           autodesk     1
## 74                           broadcom     1
## 79                          cadence-design-systems 1
## 105                          cisco        1
## 108                          citrix       1
## 149                          ebay         1
## 153                          electronic-arts 1
## 159                          equinix      1
## 166                          expedia      1
## 170                          f5-networks  1
## 171                          facebook     1
## 181                          flir-systems 1
## 187                          fortinet     1
## 192                          garmin-international 1
## 193                          gartner      1
## 202                          google       1
## 214                          hewlett-packard-enterprise 1
## 221                           hp          1
## 233                          intel-corporation 1
## 236                           intuit      1
## 251                          juniper-networks 1
## 255                          keysight-technologies 1
## 259                           kla-tencor  1
## 263                           lam-research 1
## 283                           maxim-integrated 1
## 292                          microchip-technology 1
## 293                           micron-technology 1
## 294                           microsoft    1
## 303                          motorolasolutions 1
## 309                           netapp      1
## 310                           netflix     1
## 313                           newscorp    1
## 326                           nvidia      1
## 329                           oracle      1
## 334                           paypal      1
## 357                           qorvo       1
## 358                           qualcomm    1
## 362                          realty-income-corporation 1
## 363                           red-hat      1
## 374                           salesforce   1
## 377                          seagate-technology 1
## 382                          skyworks-solutions-inc 1

```

```

## 393           svb-financial-group      1
## 394           symantec            1
## 398 take-2-interactive-software-inc- 1
## 402           texas-instruments     1
## 421           tripadvisor          1
## 423           twitter             1
## 438           varian-medical-systems   1
## 440           verisign            1
## 446           visa                1
## 458           western-digital       1
## 468           xilinx              1
##
##           industry
## 6           computer games
## 8           computer software
## 13          biotechnology
## 17          internet
## 23          medical devices
## 30          internet
## 31          semiconductors
## 43          semiconductors
## 44          computer software
## 48          consumer electronics
## 49          semiconductors
## 54          computer software
## 74          semiconductors
## 79          computer software
## 105         computer networking
## 108         computer software
## 149         internet
## 153         entertainment
## 159         internet
## 166         internet
## 170         computer networking
## 171         internet
## 181 electrical/electronic manufacturing
## 187         computer & network security
## 192         consumer electronics
## 193 information technology and services
## 202         internet
## 214 information technology and services
## 221 information technology and services
## 233         semiconductors
## 236         computer software
## 251         computer networking
## 255 electrical/electrical manufacturing
## 259         semiconductors
## 263         semiconductors
## 283         semiconductors
## 292         semiconductors
## 293         semiconductors
## 294         computer software
## 303         telecommunications
## 309 information technology and services
## 310         entertainment

```

```

## 313                  online media
## 326                  computer hardware
## 329 information technology and services
## 334                  internet
## 357                  semiconductors
## 358                  wireless
## 362                  real estate
## 363                  computer software
## 374                  internet
## 377                  computer hardware
## 382                  semiconductors
## 393                  financial services
## 394                  computer software
## 398                  entertainment
## 402                  semiconductors
## 421                  internet
## 423                  internet
## 438                  medical devices
## 440 information technology and services
## 446 information technology and services
## 458                  computer hardware
## 468                  semiconductors
##
##
## Community 5 :
##               company_id community      industry
## 11              aes            5        utilities
## 16          air-products      5        chemicals
## 19          albemarle       5        chemicals
## 27      alliant-energy      5        utilities
## 32          ameren         5        utilities
## 34 american-electric-power 5        utilities
## 53          atmos-energy     5        utilities
## 89          celanese        5        chemicals
## 92      centerpoint-energy 5        utilities
## 95          cf-industries    5        chemicals
## 114         con-edison       5        utilities
## 118         consumers-energy 5        utilities
## 140          dominion        5        utilities
## 142         dow-chemical      5        chemicals
## 144         dte-energy       5        utilities
## 145 duke-energy-corporation 5        utilities
## 147 eastman-chemical-company 5        chemicals
## 151      edison-international 5        utilities
## 156          entergy         5        utilities
## 164      eversourceenergy     5        utilities
## 165          exelon          5        utilities
## 169          exxonmobil       5        oil & energy
## 177      firstenergy-corp     5        utilities
## 182          flowserve        5        mechanical or industrial engineering
## 183          fluor           5        construction
## 184      fmc-corporation      5        chemicals
## 190 freeport-mcmoran-inc     5        mining & metals
## 227          ihs             5        information services

```

```

## 244           jacobs      5             construction
## 271           lyondell-basell 5             chemicals
## 276 marathon-petroleum-company 5             oil & energy
## 279 martin-marietta-materials 5             mining & metals
## 302           mosaiccompany 5             mining & metals
## 312 newmont-mining-corporation 5             mining & metals
## 314 nextera-energy-resources 5             renewables & environment
## 317           nisource      5             utilities
## 324           nrg-energy    5             oil & energy
## 325 nucor-corporation      5             mining & metals
## 346           ppl-corporation 5             utilities
## 353           pseg          5             utilities
## 385           southern-company 5             utilities
## 413           the-linde-group 5             chemicals
## 437 valero-energy-corporation 5             oil & energy
## 448 vulcan-materials-company 5             mining & metals
## 454           wec-energy-group 5             utilities
## 466           xcel-energy    5             utilities
##
##
## Community 7 :
##               company_id community
## 14           aig          7
## 26           alliance-data 7
## 28           allstate      7
## 38 ameriprise-financial-services-inc 7
## 45           anthem       7
## 46           aon          7
## 50 arthur-j--gallagher-and-co      7
## 51           assurant     7
## 60           bank-of-america 7
## 62           bb&t         7
## 64           berkshire-hathaway 7
## 67           blackrock     7
## 68           bny-mellon    7
## 75 broadridge-financial-solutions 7
## 81           capital-one   7
## 86          .cboe        7
## 91           centene-corporation 7
## 96           charles-schwab 7
## 100          chubb        7
## 102          cigna        7
## 106          citi          7
## 107          citizens-bank 7
## 109          cme-group     7
## 113          comerica-bank 7
## 135          discover-financial-services 7
## 162          etrade        7
## 163          everest-reinsurance 7
## 175          fifth-third-bank 7
## 176          first-republic-bank 7
## 178           fis          7
## 179           fiserv       7
## 189 franklin-templeton-investments 7

```

```

## 200           global-payments      7
## 201           goldman-sachs      7
## 209           hca                7
## 222           humana              7
## 223           huntington-national-bank 7
## 234           intercontinentalexchange-inc- 7
## 238           invesco-ltd        7
## 246           jefferies            7
## 250           jpmorgan-chase      7
## 254           keybank              7
## 267           lincoln-financial-group 7
## 272           m&t-bank             7
## 278           marsh-&-mcclennan-companies-inc- 7
## 289           metlife              7
## 300           moodys-corporation    7
## 301           morgan-stanley       7
## 304           msci-inc              7
## 321           northern-trust       7
## 337           people%27s-united-bank 7
## 344           pnc-bank              7
## 348           principal-financial-group 7
## 350           progressive-insurance 7
## 352           prudential-financial 7
## 360           raymond-james-financial-inc- 7
## 366           regions-financial-corporation 7
## 390           state-street          7
## 392           suntrust-bank         7
## 395           synchrony-financial   7
## 397           t--rowe-price         7
## 404           the-cincinnati-insurance-companies 7
## 408           the-hartford          7
## 418           torchmark-corporation    7
## 420           travelers              7
## 426           uhs                  7
## 433           unitedhealth-group     7
## 434           unum                 7
## 436           us-bank               7
## 441           verisk-analytics      7
## 455           wellcare              7
## 456           wells-fargo            7
## 464           willis-towers-watson     7
## 472           zions-bancorporation     7
##           industry
## 14           insurance
## 26           marketing and advertising
## 28           insurance
## 38           financial services
## 45           insurance
## 46           financial services
## 50           insurance
## 51           insurance
## 60           banking
## 62           financial services
## 64           insurance

```

```
## 67 financial services
## 68 financial services
## 75 financial services
## 81 financial services
## 86 financial services
## 91 hospital & health care
## 96 financial services
## 100 insurance
## 102 health, wellness and fitness
## 106 financial services
## 107 banking
## 109 financial services
## 113 banking
## 135 financial services
## 162 financial services
## 163 insurance
## 175 financial services
## 176 banking
## 178 information technology and services
## 179 information technology and services
## 189 financial services
## 200 financial services
## 201 financial services
## 209 hospital & health care
## 222 insurance
## 223 banking
## 234 financial services
## 238 investment management
## 246 investment banking
## 250 financial services
## 254 banking
## 267 financial services
## 272 financial services
## 278 financial services
## 289 insurance
## 300 financial services
## 301 financial services
## 304 financial services
## 321 financial services
## 337 financial services
## 344 financial services
## 348 financial services
## 350 insurance
## 352 financial services
## 360 financial services
## 366 banking
## 390 financial services
## 392 financial services
## 395 financial services
## 397 investment management
## 404 insurance
## 408 financial services
## 418 financial services
## 420 insurance
```

```

## 426          hospital & health care
## 433          hospital & health care
## 434          insurance
## 436          banking
## 441          information services
## 455          insurance
## 456          financial services
## 464          financial services
## 472          banking
##
##
## Community 9 :
##           company_id community    industry
## 15          aimco        9 real estate
## 56  avalonbay-communities      9 real estate
## 160 equity-residential       9 real estate
## 161 essex-property-trust     9 real estate
## 425         udr        9 real estate
##
##
## Community 8 :
##           company_id community
## 21 alexandria-real-estate-equities-inc-      8
## 71 boston-properties        8
## 87 cbre                    8
## 134 digitalrealty        8
## 146 duke-realty-corporation      8
## 173 federal-realty-investment-trust      8
## 210 hcp                    8
## 257 kimco-realty-corporation      8
## 273 macerich        8
## 295 mid-america-apartment-communities      8
## 351 prologis        8
## 364 regency-centers        8
## 381 simon-property-group      8
## 383 sl-green        8
## 439 ventas-inc.        8
## 447 vornado-realty-trust       8
## 457 welltower        8
##
##           industry
## 21 real estate
## 71 real estate
## 87 real estate
## 134 information technology and services
## 146 real estate
## 173 real estate
## 210 real estate
## 257 real estate
## 273 real estate
## 295 real estate
## 351 real estate
## 364 real estate
## 381 real estate
## 383 real estate

```

```

## 439           real estate
## 447           real estate
## 457           real estate
##
##
## Community 3 :
##             company_id community      industry
## 42    anadarko-petroleum-corporation      3 oil & energy
## 47    apache-corporation          3 oil & energy
## 58    baker-hughes            3 oil & energy
## 78    cabot-oil-&-gas          3 oil & energy
## 98    chevron                  3 oil & energy
## 103   cimarex-energy          3 oil & energy
## 115   concho-resources         3 oil & energy
## 116   conocophillips          3 oil & energy
## 132   devon-energy            3 oil & energy
## 133   diamondback-energy-services 3 oil & energy
## 157   eog-resources            3 oil & energy
## 204   halliburton              3 oil & energy
## 211   helmerich-&-payne        3 oil & energy
## 213   hess-corporation         3 oil & energy
## 216   hollyfrontier-corporation 3 oil & energy
## 258   kinder-morgan            3 oil & energy
## 275   marathon-oil-corporation 3 oil & energy
## 307   national-oilwell-varco  3 oil & energy
## 318   noble-energy             3 oil & energy
## 328   oneok                    3 oil & energy
## 330   oxy                      3 oil & energy
## 342   phillips66co            3 oil & energy
## 343   pioneer-natural-resources-company 3 oil & energy
## 376   schlumberger            3 oil & energy
## 463   williams-company         3 oil & energy
##
##
## Community 10 :
##             company_id community      industry
## 84    carnival-cruise-lines      10 leisure, travel & tourism
## 323   norwegian-cruise-line     10 leisure, travel & tourism
## 373   royal-caribbean          10 leisure, travel & tourism

```

Community Detection Insights

Based on the results, each detected community largely consists of firms from the same or related industries. This suggests that companies tend to form communities based on industry affinity.

Key Patterns and Implications

1. Industry Clustering

Firms within the same or similar industries tend to be more interconnected through talent flows and business relationships.

2. Strategic Alignment

Some communities may reflect strategic partnerships, supply chains, or a shared market focus.

3. Knowledge and Talent Exchange

Intra-industry communities can facilitate the flow of expertise and innovation, which are critical for competitiveness and growth.

These patterns provide insight into how industry structure influences firm interactions and highlight potential collaboration or talent movement within sectors.

Understanding Assortative Mixing

Assortative mixing describes the tendency of nodes in a network to connect with others that share similar characteristics.

In this context, assortative mixing by **industry** means that firms are more likely to connect (e.g., through talent flow or business relationships) with other firms in the **same industry**, rather than with firms from different sectors.

Compute Assortativity by Industry

```
industries <- df_company$industry[match(V(graph_df_edges)$name, df_company$company_id)]
industries <- factor(industries)

assortativity_coefficient <- assortativity(graph_df_edges, types1 = industries, directed = FALSE)
print(assortativity_coefficient)

## [1] 0.02631082
```

This concludes the end-to-end analysis of a talent flow network using `igraph` in R. The project identifies key players in employee movement, explores community and industry-level patterns, and investigates structural dynamics such as assortativity and influence.