DBA3702 Assignment 1

Data Wrangling & Social Network Analysis - TechConnect Inc.

Group X - [Names and Student IDs]

2026-01-24

Contents

1 Part 1: Data Wrangling with dplyr (45 points)

1.1 Question 1.1: Data Exploration (5 points)

1.1.1 a) Load packages and read data

```
library(dplyr)
library(tibble)

employees <- read.csv("data/employees.csv")
```

1.1.2 b) Convert to tibble and display first 10 rows

```
employees <- as_tibble(employees)
print(employees, n = 10)
```

```
## # A tibble: 50 x 8
##    employee_id name           department  role    years_exp salary performance_score
##          <int> <chr>          <chr>       <chr>       <int>  <int>             <dbl>
##  1           1 Alice Chen     Engineering Senior          8  95000               4.5
##  2           2 Bob Martinez   Engineering Lead           12 120000               4.8
##  3           3 Charlie Kim    Engineering Junior          2  65000               3.8
##  4           4 Diana Patel    Engineering Senior          7  92000               4.2
##  5           5 Eve Thompson   Engineering Manager        15 140000               4.6
##  6           6 Frank Liu      Engineering Junior          1  58000               3.2
##  7           7 Grace Okonkwo Engineering Senior          9  98000               4.4
##  8           8 Henry Wang     Marketing   Lead           10 105000               4.3
##  9           9 Iris Nakamura Marketing   Senior          6  82000               3.9
## 10          10 Jack Brown     Marketing   Junior          2  55000               3.5
## # i 40 more rows
## # i 1 more variable: projects_completed <int>
```

1.1.3 c) Data summary

```
cat("Rows:", nrow(employees), "\n")
```

```
## Rows: 50
```

```
cat("Columns:", ncol(employees), "\n")
```

```
## Columns: 8
```

```r
sapply(employees, class)
```

```
##        employee_id               name         department               role
##          "integer"        "character"        "character"        "character"
##          years_exp             salary  performance_score projects_completed
##          "integer"          "integer"          "numeric"          "integer"
```

```r
glimpse(employees)
```

```
## Rows: 50
## Columns: 8
## $ employee_id        <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17~
## $ name               <chr> "Alice Chen", "Bob Martinez", "Charlie Kim", "Diana Patel~
## $ department         <chr> "Engineering", "Engineering", "Engineering", "Engineering~
## $ role               <chr> "Senior", "Lead", "Junior", "Senior", "Manager", "Junior"~
## $ years_exp          <int> 8, 12, 2, 7, 15, 1, 9, 10, 6, 2, 14, 5, 1, 11, 8, 3, 6, 1~
## $ salary             <int> 95000, 120000, 65000, 92000, 140000, 58000, 98000, 105000~
## $ performance_score  <dbl> 4.5, 4.8, 3.8, 4.2, 4.6, 3.2, 4.4, 4.3, 3.9, 3.5, 4.5, 4.~
## $ projects_completed <int> 15, 22, 5, 12, 28, 3, 16, 18, 11, 4, 24, 9, 2, 21, 14, 6,~
```

```r
summary(employees)
```

```
##   employee_id        name            department            role          
##  Min.   : 1.00   Length:50          Length:50          Length:50         
##  1st Qu.:13.25   Class :character   Class :character   Class :character  
##  Median :25.50   Mode  :character   Mode  :character   Mode  :character  
##  Mean   :25.50                                                           
##  3rd Qu.:37.75                                                           
##  Max.   :50.00                                                           
##    years_exp         salary       performance_score projects_completed
##  Min.   : 1.00   Min.   : 48000   Min.   :2.900     Min.   : 2.00     
##  1st Qu.: 3.00   1st Qu.: 65750   1st Qu.:3.600     1st Qu.: 6.00     
##  Median : 6.50   Median : 85000   Median :4.000     Median :11.50     
##  Mean   : 6.68   Mean   : 86420   Mean   :3.970     Mean   :12.24     
##  3rd Qu.: 9.00   3rd Qu.:101500   3rd Qu.:4.375     3rd Qu.:17.00     
##  Max.   :16.00   Max.   :145000   Max.   :4.900     Max.   :30.00     
```

We have 50 employees with 8 variables. The data includes basic info like name and department, plus numeric stuff like salary, years of experience, performance scores, and project counts. Performance ranges from around 2.9 to 4.9, and experience goes from 1 to 16 years.

1.2 Question 1.2: Selecting and Filtering (8 points)

1.2.1 d) Select specific columns

```
employees %>%
  select(name, department, role, performance_score)
```

```
## # A tibble: 50 x 4
##    name           department  role    performance_score
##    <chr>          <chr>       <chr>               <dbl>
##  1 Alice Chen     Engineering Senior                4.5
##  2 Bob Martinez   Engineering Lead                  4.8
##  3 Charlie Kim    Engineering Junior                3.8
##  4 Diana Patel    Engineering Senior                4.2
##  5 Eve Thompson   Engineering Manager               4.6
##  6 Frank Liu      Engineering Junior                3.2
##  7 Grace Okonkwo  Engineering Senior                4.4
##  8 Henry Wang     Marketing   Lead                  4.3
##  9 Iris Nakamura  Marketing   Senior                3.9
## 10 Jack Brown     Marketing   Junior                3.5
## # i 40 more rows
```

1.2.2 e) Filter performance > 4.0

```
high_performers <- employees %>%
  filter(performance_score > 4.0)
high_performers
```

```
## # A tibble: 23 x 8
##    employee_id name          department  role    years_exp salary performance_score
##          <int> <chr>         <chr>       <chr>       <int>  <int>             <dbl>
##  1           1 Alice Chen    Engineering Senior          8  95000               4.5
##  2           2 Bob Martinez  Engineering Lead           12 120000               4.8
##  3           4 Diana Patel   Engineering Senior          7  92000               4.2
##  4           5 Eve Thompson  Engineering Manager        15 140000               4.6
##  5           7 Grace Okonkwo Engineering Senior          9  98000               4.4
##  6           8 Henry Wang    Marketing   Lead           10 105000               4.3
##  7          11 Kate Wilson   Marketing   Manager        14 125000               4.5
##  8          14 Nathan Lee    Sales       Lead           11 115000               4.7
##  9          15 Olivia Davis  Sales       Senior          8  88000               4.1
## 10          18 Rachel Green  Sales       Manager        13 130000               4.4
## # i 13 more rows
## # i 1 more variable: projects_completed <int>
```

```r
cat("Count:", nrow(high_performers))
```

```
## Count: 23
```

1.2.3 f) Engineering/Marketing with > 5 years experience

```r
employees %>%
  filter((department == "Engineering" | department == "Marketing") & years_exp > 5)
```

```
## # A tibble: 14 x 8
##    employee_id name           department  role    years_exp salary performance_score
##          <int> <chr>          <chr>       <chr>       <int>  <int>             <dbl>
##  1           1 Alice Chen     Engineering Senior          8  95000               4.5
##  2           2 Bob Martinez   Engineering Lead           12 120000               4.8
##  3           4 Diana Patel    Engineering Senior          7  92000               4.2
##  4           5 Eve Thompson   Engineering Manager        15 140000               4.6
##  5           7 Grace Okonkwo  Engineering Senior          9  98000               4.4
##  6           8 Henry Wang     Marketing   Lead           10 105000               4.3
##  7           9 Iris Nakamura  Marketing   Senior          6  82000               3.9
##  8          11 Kate Wilson    Marketing   Manager        14 125000               4.5
##  9          31 Eric Zhang     Engineering Senior          6  88000               4
## 10          33 George Park    Marketing   Senior          7  80000               3.7
## 11          41 Oscar Rivera   Engineering Lead           11 118000               4.5
## 12          42 Paula Hughes   Engineering Manager        16 145000               4.9
## 13          43 Quentin Price  Marketing   Lead            8 100000               4.1
## 14          47 Ulrich Weber   Engineering Senior          7  94000               4.2
## # i 1 more variable: projects_completed <int>
```

1.2.4 g) Select using helpers

```r
employees %>%
  select(contains("score") | starts_with("p"))
```

```
## # A tibble: 50 x 2
##    performance_score projects_completed
##                <dbl>              <int>
##  1               4.5                 15
##  2               4.8                 22
##  3               3.8                  5
##  4               4.2                 12
##  5               4.6                 28
##  6               3.2                  3
```

```
##  7                4.4                   16
##  8                4.3                   18
##  9                3.9                   11
## 10                3.5                    4
## # i 40 more rows
```

This grabs performance_score and projects_completed - the columns with "score" in the name or starting with "p".

1.3 Question 1.3: Sorting and Ranking (7 points)

1.3.1 h) Top 5 highest-paid

```
employees %>%
  arrange(desc(salary)) %>%
  head(5)
```

```
## # A tibble: 5 x 8
##   employee_id name         department  role    years_exp salary performance_score
##         <int> <chr>        <chr>       <chr>       <int>  <int>             <dbl>
## 1          42 Paula Hughes Engineering Manager        16 145000               4.9
## 2           5 Eve Thompson Engineering Manager        15 140000               4.6
## 3          28 Bella Moore  Finance     Manager        14 135000               4.7
## 4          18 Rachel Green Sales       Manager        13 130000               4.4
## 5          11 Kate Wilson  Marketing   Manager        14 125000               4.5
## # i 1 more variable: projects_completed <int>
```

1.3.2 i) Sort by department then performance

```
employees %>%
  arrange(department, desc(performance_score))
```

```
## # A tibble: 50 x 8
##    employee_id name          department  role    years_exp salary performance_score
##          <int> <chr>         <chr>       <chr>       <int>  <int>             <dbl>
##  1          42 Paula Hughes  Engineering Manager        16 145000               4.9
##  2           2 Bob Martinez  Engineering Lead           12 120000               4.8
##  3           5 Eve Thompson  Engineering Manager        15 140000               4.6
##  4           1 Alice Chen    Engineering Senior          8  95000               4.5
##  5          41 Oscar Rivera  Engineering Lead           11 118000               4.5
##  6           7 Grace Okonkwo Engineering Senior          9  98000               4.4
##  7           4 Diana Patel   Engineering Senior          7  92000               4.2
##  8          47 Ulrich Weber  Engineering Senior          7  94000               4.2
##  9          31 Eric Zhang    Engineering Senior          6  88000               4
## 10          32 Fiona O'Brien Engineering Junior          3  68000               3.9
## # i 40 more rows
## # i 1 more variable: projects_completed <int>
```

1.3.3 j) Lowest salary in each department

```r
employees %>%
  arrange(department, salary) %>%
  group_by(department) %>%
  slice_head(n = 1) %>%
  ungroup()
```

```
## # A tibble: 5 x 8
##   employee_id name           department  role   years_exp salary performance_score
##         <int> <chr>          <chr>       <chr>      <int>  <int>             <dbl>
## 1           6 Frank Liu      Engineering Junior         1  58000               3.2
## 2          30 Dana Hill      Finance     Junior         1  55000               3
## 3          22 Victor Nguyen  HR          Junior         1  48000               3.1
## 4          13 Maya Rodriguez Marketing   Junior         1  52000               3.3
## 5          36 Julia Foster   Sales       Junior         1  53000               2.9
## # i 1 more variable: projects_completed <int>
```

1.4 Question 1.4: Creating New Variables (10 points)

1.4.1 k) Salary per year of experience

```
employees %>%
  mutate(salary_per_year_exp = salary / years_exp) %>%
  select(name, salary, years_exp, salary_per_year_exp)
```

```
## # A tibble: 50 x 4
##    name           salary years_exp salary_per_year_exp
##    <chr>           <int>     <int>               <dbl>
##  1 Alice Chen      95000         8              11875
##  2 Bob Martinez   120000        12              10000
##  3 Charlie Kim     65000         2              32500
##  4 Diana Patel     92000         7              13143.
##  5 Eve Thompson   140000        15               9333.
##  6 Frank Liu       58000         1              58000
##  7 Grace Okonkwo   98000         9              10889.
##  8 Henry Wang     105000        10              10500
##  9 Iris Nakamura   82000         6              13667.
## 10 Jack Brown      55000         2              27500
## # i 40 more rows
```

1.4.2 l) Performance category

```
employees_cat <- employees %>%
  mutate(performance_category = case_when(
    performance_score >= 4.5 ~ "Outstanding",
    performance_score >= 3.5 ~ "Exceeds Expectations",
    performance_score >= 2.5 ~ "Meets Expectations",
    TRUE ~ "Needs Improvement"
  ))

employees_cat %>%
  select(name, performance_score, performance_category)
```

```
## # A tibble: 50 x 3
##    name           performance_score performance_category
##    <chr>                      <dbl> <chr>
##  1 Alice Chen                   4.5 Outstanding
##  2 Bob Martinez                 4.8 Outstanding
##  3 Charlie Kim                  3.8 Exceeds Expectations
##  4 Diana Patel                  4.2 Exceeds Expectations
##  5 Eve Thompson                 4.6 Outstanding
```

```
##   6 Frank Liu                       3.2 Meets Expectations
##   7 Grace Okonkwo                   4.4 Exceeds Expectations
##   8 Henry Wang                      4.3 Exceeds Expectations
##   9 Iris Nakamura                   3.9 Exceeds Expectations
## 10 Jack Brown                      3.5 Exceeds Expectations
## # i 40 more rows
```

```r
employees_cat %>% count(performance_category)
```

```
## # A tibble: 3 x 2
##   performance_category     n
##   <chr>                <int>
## 1 Exceeds Expectations    31
## 2 Meets Expectations       9
## 3 Outstanding             10
```

1.4.3 m) Experience level

```r
employees_exp <- employees %>%
  mutate(experience_level = case_when(
    years_exp <= 3 ~ "Entry",
    years_exp <= 7 ~ "Mid",
    years_exp <= 12 ~ "Senior",
    TRUE ~ "Expert"
  ))

employees_exp %>%
  select(name, years_exp, experience_level)
```

```
## # A tibble: 50 x 3
##    name           years_exp experience_level
##    <chr>              <int> <chr>
##  1 Alice Chen             8 Senior
##  2 Bob Martinez          12 Senior
##  3 Charlie Kim            2 Entry
##  4 Diana Patel            7 Mid
##  5 Eve Thompson          15 Expert
##  6 Frank Liu              1 Entry
##  7 Grace Okonkwo          9 Senior
##  8 Henry Wang            10 Senior
##  9 Iris Nakamura          6 Mid
## 10 Jack Brown             2 Entry
## # i 40 more rows
```

```r
employees_exp %>% count(experience_level)
```

```
## # A tibble: 4 x 2
##   experience_level     n
##   <chr>            <int>
## 1 Entry               14
## 2 Expert               5
## 3 Mid                 15
## 4 Senior              16
```

1.4.4 n) High performer flag

```r
employees %>%
  mutate(is_high_performer = performance_score > 4.0 & projects_completed >= 10) %>%
  filter(is_high_performer) %>%
  select(name, department, performance_score, projects_completed)
```

```
## # A tibble: 23 x 4
##    name          department  performance_score projects_completed
##    <chr>         <chr>                   <dbl>              <int>
##  1 Alice Chen    Engineering               4.5                 15
##  2 Bob Martinez  Engineering               4.8                 22
##  3 Diana Patel   Engineering               4.2                 12
##  4 Eve Thompson  Engineering               4.6                 28
##  5 Grace Okonkwo Engineering               4.4                 16
##  6 Henry Wang    Marketing                 4.3                 18
##  7 Kate Wilson   Marketing                 4.5                 24
##  8 Nathan Lee    Sales                     4.7                 21
##  9 Olivia Davis  Sales                     4.1                 14
## 10 Rachel Green  Sales                     4.4                 25
## # i 13 more rows
```

1.5 Question 1.5: Aggregation and Grouping (15 points)

1.5.1 o) Company-wide summary

```
employees %>%
  summarise(
    total_employees = n(),
    avg_salary = mean(salary),
    avg_performance = mean(performance_score),
    total_projects = sum(projects_completed)
  )
```

```
## # A tibble: 1 x 4
##   total_employees avg_salary avg_performance total_projects
##             <int>      <dbl>           <dbl>          <int>
## 1              50      86420            3.97            612
```

1.5.2 p) Summary by department

```
employees %>%
  group_by(department) %>%
  summarise(
    count = n(),
    avg_salary = mean(salary),
    avg_perf = mean(performance_score),
    min_exp = min(years_exp),
    max_exp = max(years_exp)
  )
```

```
## # A tibble: 5 x 6
##   department  count avg_salary avg_perf min_exp max_exp
##   <chr>       <int>      <dbl>    <dbl>   <int>   <int>
## 1 Engineering    12     98417.     4.25       1      16
## 2 Finance         9     86333.     3.96       1      14
## 3 HR              9     75556.     3.76       1      12
## 4 Marketing      10     80700      3.86       1      14
## 5 Sales          10     87600      3.95       1      13
```

1.5.3 q) Summary by department and role

```
dept_role <- employees %>%
  group_by(department, role) %>%
  summarise(avg_salary = mean(salary), count = n(), .groups = "drop") %>%
```

```r
  arrange(desc(avg_salary))

dept_role
```

```
## # A tibble: 20 x 4
##    department  role    avg_salary count
##    <chr>       <chr>        <dbl> <int>
##  1 Engineering Manager     142500     2
##  2 Finance     Manager     135000     1
##  3 Sales       Manager     130000     1
##  4 Marketing   Manager     125000     1
##  5 Engineering Lead        119000     2
##  6 Sales       Lead        113500     2
##  7 HR          Manager     110000     1
##  8 Finance     Lead        105000     2
##  9 Marketing   Lead        102500     2
## 10 HR          Lead         93500     2
## 11 Engineering Senior       93400     5
## 12 Sales       Senior       87250     4
## 13 Finance     Senior       85667.    3
## 14 Marketing   Senior       79000     4
## 15 HR          Senior       71250     4
## 16 Engineering Junior       63667.    3
## 17 Finance     Junior       58333.    3
## 18 Sales       Junior       56667.    3
## 19 Marketing   Junior       53667.    3
## 20 HR          Junior       49000     2
```

```r
# Highest combo:
dept_role %>% head(1)
```

```
## # A tibble: 1 x 4
##   department  role    avg_salary count
##   <chr>       <chr>        <dbl> <int>
## 1 Engineering Manager     142500     2
```

The highest average salary is in the department-role combo shown above.

1.5.4 r) Salary as % of department average

```r
employees %>%
  group_by(department) %>%
  mutate(
    dept_avg = mean(salary),
```

```r
    pct_of_avg = salary / dept_avg * 100
  ) %>%
  ungroup() %>%
  arrange(desc(pct_of_avg)) %>%
  select(name, department, salary, dept_avg, pct_of_avg)
```

```
## # A tibble: 50 x 5
##    name          department  salary dept_avg pct_of_avg
##    <chr>         <chr>        <int>    <dbl>      <dbl>
##  1 Bella Moore   Finance     135000   86333.       156.
##  2 Kate Wilson   Marketing   125000   80700        155.
##  3 Rachel Green  Sales       130000   87600        148.
##  4 Paula Hughes  Engineering 145000   98417.       147.
##  5 Wendy Clark   HR          110000   75556.       146.
##  6 Eve Thompson  Engineering 140000   98417.       142.
##  7 Nathan Lee    Sales       115000   87600        131.
##  8 Henry Wang    Marketing   105000   80700        130.
##  9 Rosa Martinez Sales       112000   87600        128.
## 10 Tina White    HR           95000   75556.       126.
## # i 40 more rows
```

The person at the top earns the most relative to their department's average.

1.5.5 s) Top 3 departments by performance (3+ years exp)

```r
employees %>%
  filter(years_exp >= 3) %>%
  group_by(department) %>%
  summarise(avg_perf = mean(performance_score)) %>%
  arrange(desc(avg_perf)) %>%
  head(3)
```

```
## # A tibble: 3 x 2
##   department  avg_perf
##   <chr>          <dbl>
## 1 Engineering     4.4
## 2 Finance         4.3
## 3 Sales           4.15
```

2 Part 2: Social Network Analysis (45 points)

2.1 Question 2.1: Network Construction and Visualization (10 points)

2.1.1 t) Load network data

```r
library(igraph)
library(RColorBrewer)

email_nodes <- read.csv("data/email_nodes.csv")
email_edges <- read.csv("data/email_edges.csv")

head(email_nodes)
```

```
##   id  department    role
## 1  1 Engineering  Senior
## 2  2 Engineering    Lead
## 3  3 Engineering  Junior
## 4  4 Engineering  Senior
## 5  5 Engineering Manager
## 6  6 Engineering  Junior
```

```r
head(email_edges)
```

```
##   from to weight
## 1    1  2     25
## 2    1  3     15
## 3    1  4     20
## 4    1  5     30
## 5    1  7     18
## 6    2  3     22
```

2.1.2 u) Construct undirected graph

```r
email_graph <- graph.data.frame(email_edges, vertices = email_nodes, directed = FALSE)

cat("Nodes:", vcount(email_graph), "\n")
```

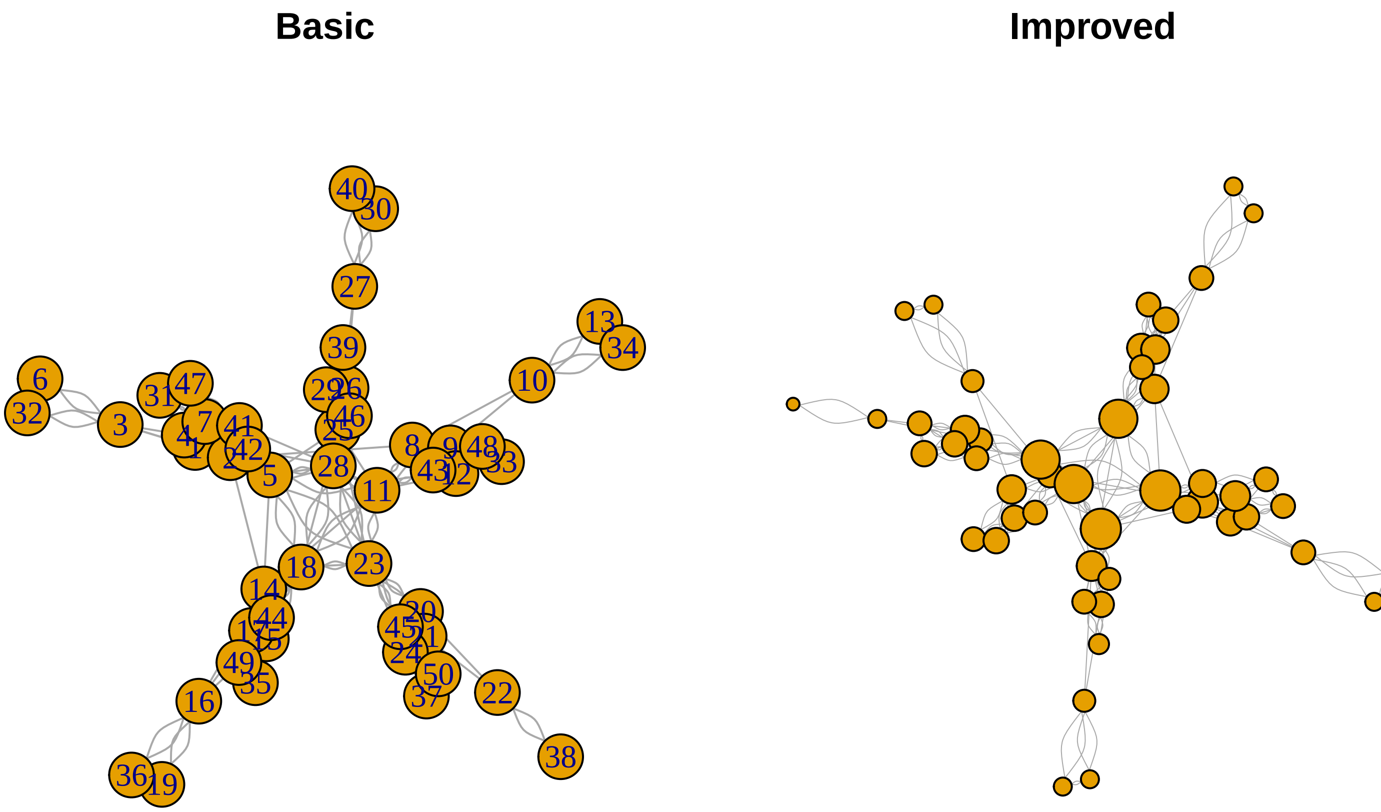
```
## Nodes: 50
```

```r
cat("Edges:", ecount(email_graph), "\n")
```

```
## Edges: 207
```

2.1.3 v) Basic and improved plots

```
par(mfrow = c(1, 2), mar = c(1, 1, 2, 1))
plot(email_graph, main = "Basic")

deg <- degree(email_graph)
plot(email_graph, vertex.label = NA, vertex.size = sqrt(deg) * 3,
     edge.width = 0.5, main = "Improved")
```

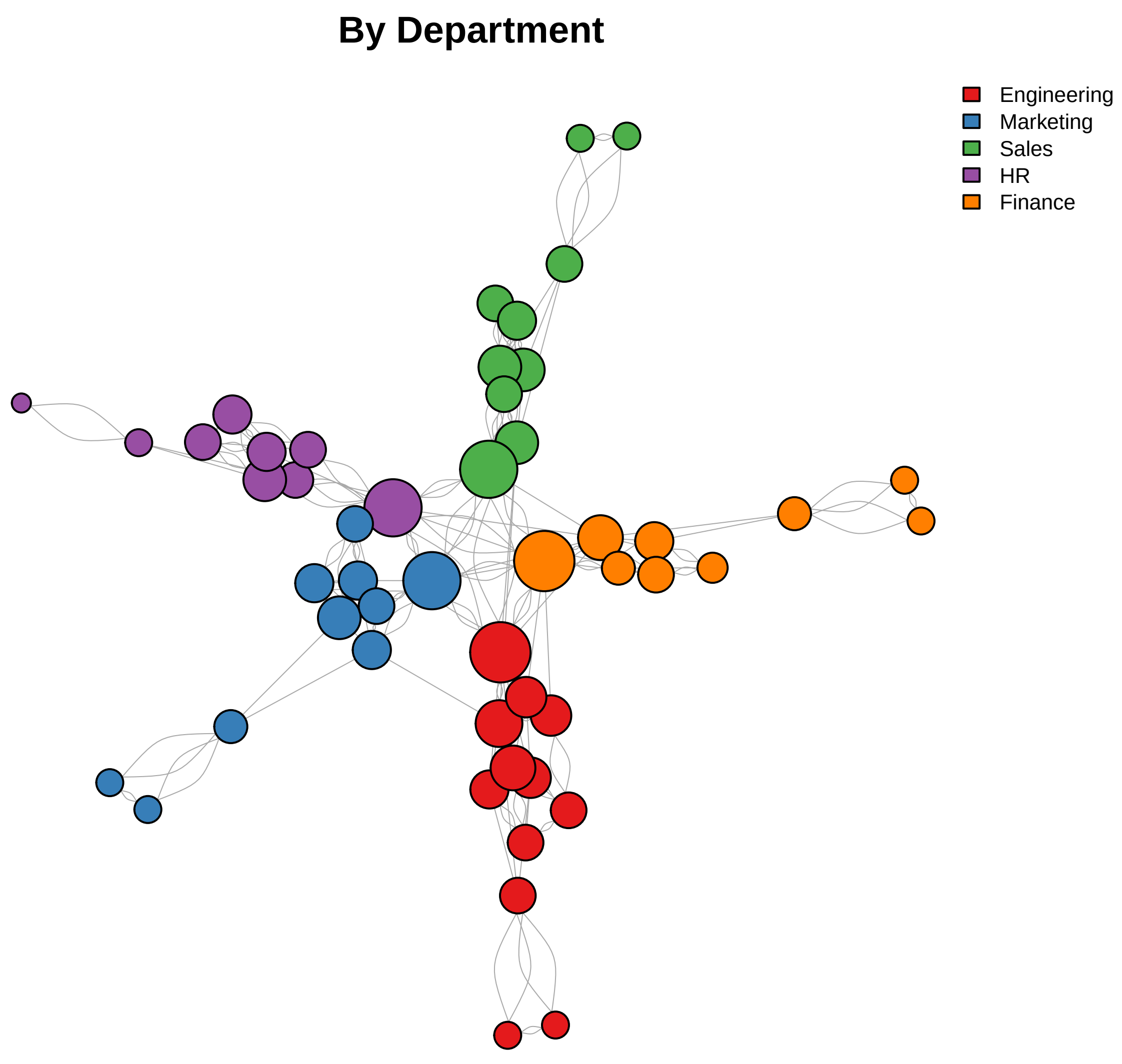


The improved version removes the messy labels and sizes nodes by how connected they are.

2.1.4 w) Department-colored network

```
depts <- V(email_graph)$department
unique_depts <- unique(depts)
colors <- brewer.pal(length(unique_depts), "Set1")
```

```r
names(colors) <- unique_depts

par(mfrow = c(1, 1), mar = c(1, 1, 2, 5))
plot(email_graph, vertex.label = NA, vertex.size = sqrt(deg) * 3,
     vertex.color = colors[depts], edge.width = 0.5,
     main = "By Department")
legend("topright", unique_depts, fill = colors, cex = 0.7, bty = "n")
```



2.2 Question 2.2: Connected Components (8 points)

2.2.1 x) Find connected components

```
comp <- components(email_graph)
cat("Number of components:", comp$no, "\n")
```

```
## Number of components: 1
```

2.2.2 y) Largest component size

```
lcc_size <- max(comp$csize)
cat("Largest component:", lcc_size, "employees\n")
```

```
## Largest component: 50 employees
```

```
cat("That's", round(lcc_size / vcount(email_graph) * 100, 1), "% of everyone\n")
```

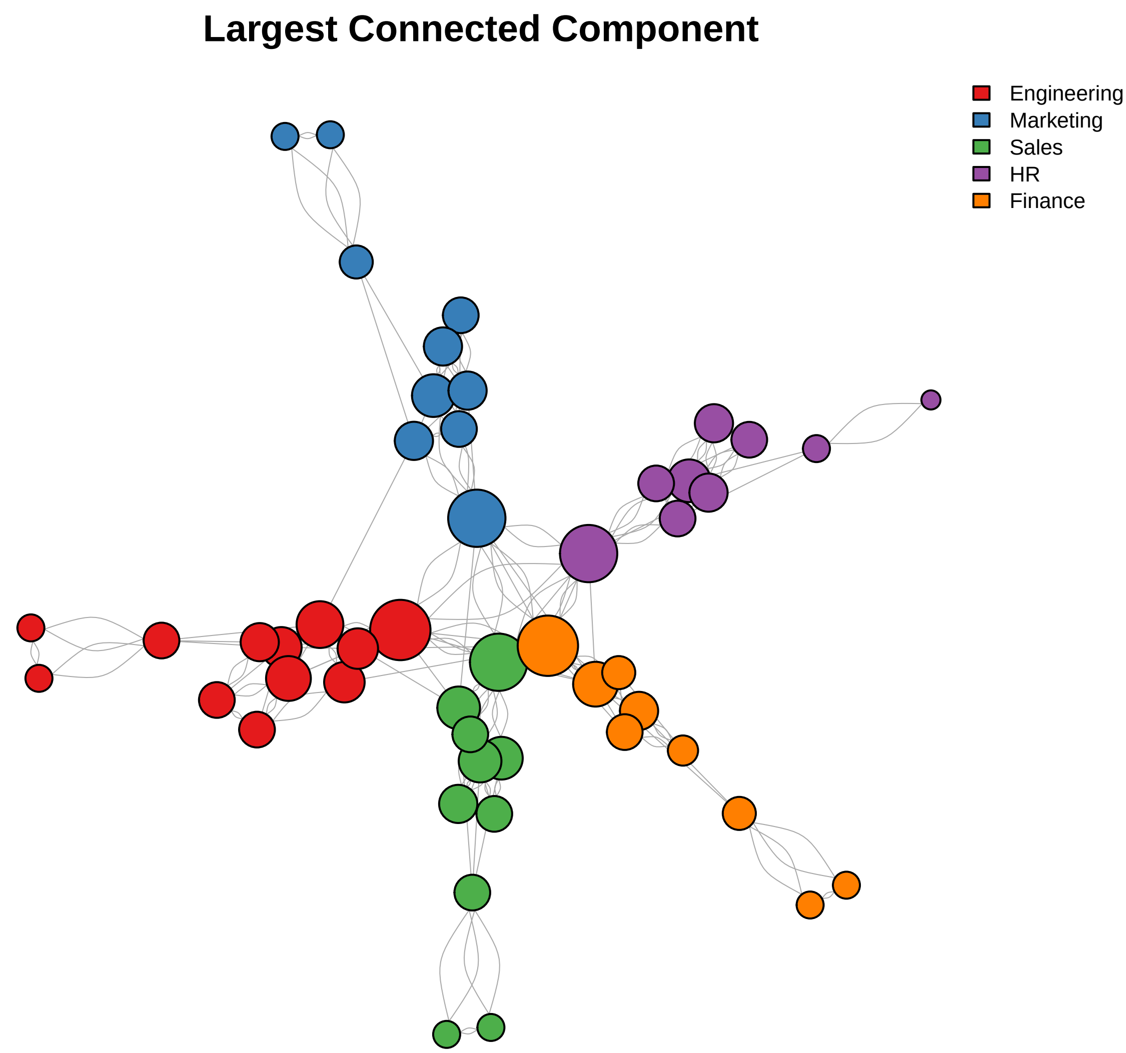
```
## That's 100 % of everyone
```

2.2.3 z) Extract and plot largest component

```
lcc_id <- which.max(comp$csize)
lcc_nodes <- which(comp$membership == lcc_id)
lcc <- induced_subgraph(email_graph, lcc_nodes)

cat("LCC has", vcount(lcc), "nodes and", ecount(lcc), "edges\n")
```

```
## LCC has 50 nodes and 207 edges
```

```
deg_lcc <- degree(lcc)
depts_lcc <- V(lcc)$department

par(mar = c(1, 1, 2, 5))
plot(lcc, vertex.label = NA, vertex.size = sqrt(deg_lcc) * 3,
     vertex.color = colors[depts_lcc], edge.width = 0.5,
     main = "Largest Connected Component")
legend("topright", unique_depts, fill = colors, cex = 0.7, bty = "n")
```



2.2.4 aa) Why use the largest connected component?

For closeness centrality, you need every node to be reachable from every other node. If the graph is disconnected, some distances become infinite and the calculation breaks. Using just the largest component avoids this problem and gives us meaningful values to work with.

2.3 Question 2.3: Centrality Metrics (15 points)

2.3.1 bb) Degree Centrality

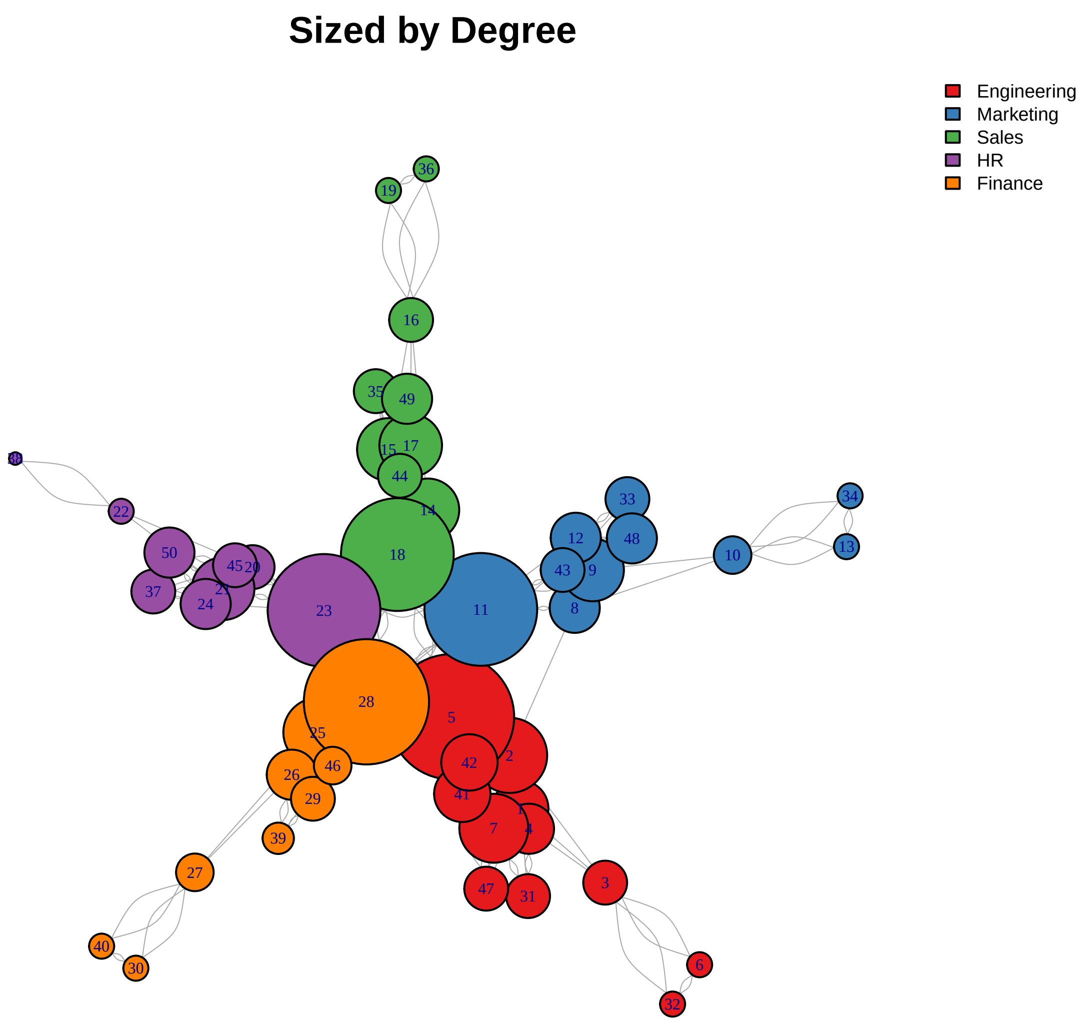
```
deg_cent <- degree(lcc)
deg_df <- data.frame(id = as.integer(V(lcc)$name), degree = deg_cent) %>%
  arrange(desc(degree))

cat("Top 5 by degree:\n")
```

```
## Top 5 by degree:
```

```
head(deg_df, 5)
```

```
##    id degree
## 5   5     20
## 28 28     20
## 11 11     18
## 18 18     18
## 23 23     18
```

```
par(mar = c(1, 1, 2, 5))
plot(lcc, vertex.label = V(lcc)$name, vertex.label.cex = 0.5,
     vertex.size = deg_cent * 1.5, vertex.color = colors[depts_lcc],
     edge.width = 0.5, main = "Sized by Degree")
legend("topright", unique_depts, fill = colors, cex = 0.6, bty = "n")
```



2.3.2 cc) Closeness Centrality

```
close_cent <- closeness(lcc, normalized = TRUE)
close_df <- data.frame(id = as.integer(V(lcc)$name), closeness = close_cent) %>%
  arrange(desc(closeness))

cat("Top 5 by closeness:\n")
```

```
## Top 5 by closeness:
```

```
head(close_df, 5)
```

```
##    id  closeness
## 5   5 0.02985984
## 25 25 0.02925373
## 14 14 0.02920143
## 11 11 0.02884049
## 28 28 0.02719201
```

High closeness means you can reach everyone else pretty quickly - you're not stuck in a corner of the network. These people are good for spreading info fast since they're "close" to everyone.

2.3.3 dd) Betweenness Centrality

```
btw_cent <- betweenness(lcc, normalized = TRUE)
btw_df <- data.frame(id = as.integer(V(lcc)$name), betweenness = btw_cent) %>%
  arrange(desc(betweenness))

cat("Top 5 by betweenness:\n")
```

```
## Top 5 by betweenness:
```

```
head(btw_df, 5)
```

```
##    id betweenness
## 14 14   0.3380244
## 5   5   0.2884010
## 25 25   0.2833759
## 23 23   0.2789116
## 2   2   0.2268282
```

Betweenness measures how often someone sits on the shortest path between other people. High betweenness = you're a bridge or connector. These folks control info flow - if they don't pass something along, it might not get where it needs to go.

2.3.4 ee) PageRank

```
pr <- page_rank(lcc)$vector
pr_df <- data.frame(id = as.integer(V(lcc)$name), pagerank = pr) %>%
  arrange(desc(pagerank))

cat("Top 5 by PageRank:\n")
```

```
## Top 5 by PageRank:
```

```r
head(pr_df, 5)
```

```
##    id   pagerank
## 5   5 0.04219373
## 23 23 0.04049384
## 28 28 0.03937716
## 18 18 0.03930274
## 11 11 0.03894129
```

PageRank is different from degree because it cares about *who* you're connected to. Being friends with popular people boosts your score more than being friends with people no one else talks to. It's about influence, not just connection count.

2.3.5 ff) Comparing all metrics

```r
all_cent <- data.frame(
  id = as.integer(V(lcc)$name),
  dept = V(lcc)$department,
  role = V(lcc)$role,
  degree = deg_cent,
  closeness = close_cent,
  betweenness = btw_cent,
  pagerank = pr
)

top10 <- all_cent %>% arrange(desc(degree)) %>% head(10)
top10
```

```
##    id        dept    role degree  closeness betweenness   pagerank
## 5   5 Engineering Manager     20 0.02985984 0.288400956 0.04219373
## 28 28     Finance Manager     20 0.02719201 0.115949951 0.03937716
## 11 11   Marketing Manager     18 0.02884049 0.160501701 0.03894129
## 18 18       Sales Manager     18 0.02606383 0.046541950 0.03930274
## 23 23          HR Manager     18 0.02603613 0.278911565 0.04049384
## 2   2 Engineering    Lead     12 0.02704194 0.226828231 0.03100845
## 7   7 Engineering  Senior     11 0.01952969 0.005668934 0.02454985
## 25 25     Finance    Lead     11 0.02925373 0.283375850 0.02689045
## 9   9   Marketing  Senior     10 0.01954527 0.068664966 0.02448814
## 14 14       Sales    Lead     10 0.02920143 0.338024376 0.02545679
```

```r
# Rankings
top10 %>%
  mutate(
    deg_r = rank(-degree),
```

```r
    close_r = rank(-closeness),
    btw_r = rank(-betweenness),
    pr_r = rank(-pagerank)
  ) %>%
  select(id, deg_r, close_r, btw_r, pr_r)
```

```
##    id deg_r close_r btw_r pr_r
## 5   5   1.5       1     2    1
## 28 28   1.5       5     7    3
## 11 11   4.0       4     6    5
## 18 18   4.0       7     9    4
## 23 23   4.0       8     4    2
## 2   2   6.0       6     5    6
## 7   7   7.5      10    10    9
## 25 25   7.5       2     3    7
## 9   9   9.5       9     8   10
## 14 14   9.5       3     1    8
```

Some people rank high on everything - they're the real network stars. Others might have high betweenness but only moderate degree, meaning they're important bridges even without tons of connections. You can also see that managers/leads tend to show up more, which makes sense given their coordinating role.

2.4 Question 2.4: Community Detection (12 points)

2.4.1 gg) Spinglass clustering

```
set.seed(42)
comm <- cluster_spinglass(lcc)

cat("Communities found:", length(comm), "\n")
```

```
## Communities found: 5
```

```
cat("Modularity:", round(modularity(comm), 3), "\n")
```

```
## Modularity: 0.028
```

2.4.2 hh) Community sizes

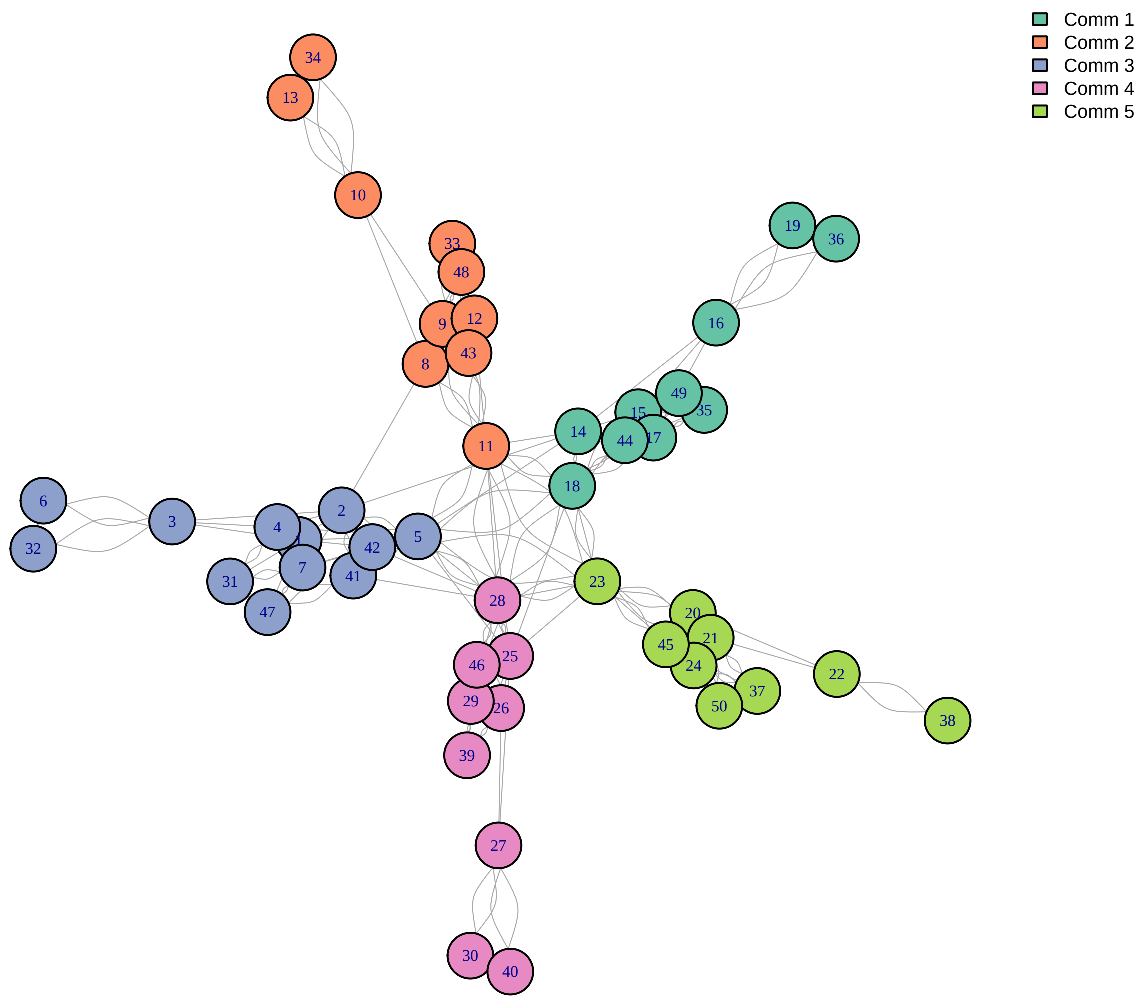
```
mem <- membership(comm)
table(mem)
```

```
## mem
##  1  2  3  4  5
## 10 10 12  9  9
```

2.4.3 ii) Visualize by community

```
num_comm <- length(unique(mem))
comm_colors <- brewer.pal(max(3, num_comm), "Set2")

par(mar = c(1, 1, 2, 5))
plot(lcc, vertex.label = V(lcc)$name, vertex.label.cex = 0.5,
     vertex.size = 10, vertex.color = comm_colors[mem],
     edge.width = 0.5, main = "By Community")
legend("topright", paste("Comm", 1:num_comm), fill = comm_colors[1:num_comm],
       cex = 0.6, bty = "n")
```

By Community



2.4.4 jj) Community vs Department

```
comm_dept <- data.frame(
  id = as.integer(V(lcc)$name),
  community = mem,
  department = V(lcc)$department
)

xtab <- table(comm_dept$community, comm_dept$department)
xtab
```

```
##
##     Engineering Finance HR Marketing Sales
```

```
## 1         0       0  0         0    10
## 2         0       0  0        10     0
## 3        12       0  0         0     0
## 4         0       9  0         0     0
## 5         0       0  9         0     0
```

```r
cat("\nPercentages:\n")
```

```
##
## Percentages:
```

```r
round(prop.table(xtab, 1) * 100, 1)
```

```
##
##    Engineering Finance  HR Marketing Sales
## 1            0       0   0         0   100
## 2            0       0   0       100     0
## 3          100       0   0         0     0
## 4            0     100   0         0     0
## 5            0       0 100         0     0
```

The communities don't match up perfectly with departments. Some communities have people from multiple departments, which shows there's cross-team communication happening. That's generally a good thing - it means people aren't just stuck in their own silos.

2.4.5 kk) Business insights

A few things management could take from this:

- The communities show how people actually communicate, not just how the org chart says they should
- People who bridge multiple communities are valuable - they help different groups stay connected
- If a community is 100% one department, that might be a warning sign of a silo
- When planning changes or announcements, it's smart to work with community leaders to spread the word effectively

3 Part 3: Integration and Insights (10 points)

3.1 Question 3.1: Joining Data (5 points)

3.1.1 ll) Join employee data with centrality metrics

```
cent_df <- data.frame(
  employee_id = as.integer(V(lcc)$name),
  degree = degree(lcc),
  closeness = closeness(lcc, normalized = TRUE),
  betweenness = betweenness(lcc, normalized = TRUE),
  pagerank = page_rank(lcc)$vector
)

combined <- employees %>%
  inner_join(cent_df, by = "employee_id")

combined %>%
  select(employee_id, name, department, performance_score,
         degree, closeness, betweenness, pagerank) %>%
  head(10)
```

```
## # A tibble: 10 x 8
##    employee_id name           department performance_score degree closeness betweenness
##          <int> <chr>          <chr>                  <dbl>  <dbl>     <dbl>       <dbl>
##  1           1 Alice Chen     Engineeri~               4.5      9    0.0203      0.0286
##  2           2 Bob Martinez   Engineeri~               4.8     12    0.0270      0.227
##  3           3 Charlie Kim    Engineeri~               3.8      7    0.0188      0.0799
##  4           4 Diana Patel    Engineeri~               4.2      8    0.0198      0.0197
##  5           5 Eve Thompson   Engineeri~               4.6     20    0.0299      0.288
##  6           6 Frank Liu      Engineeri~               3.2      4    0.0164      0
##  7           7 Grace Okonkwo  Engineeri~               4.4     11    0.0195      0.00567
##  8           8 Henry Wang     Marketing                4.3      8    0.0230      0.112
##  9           9 Iris Nakamura  Marketing                3.9     10    0.0195      0.0687
## 10          10 Jack Brown     Marketing                3.5      6    0.0173      0.0799
## # i 1 more variable: pagerank <dbl>
```

3.1.2 mm) Correlation analysis

```
cat("Degree vs Performance:", round(cor(combined$degree, combined$performance_score), 3), "\n")
```

```
## Degree vs Performance: 0.691
```

```r
cat("Closeness vs Performance:", round(cor(combined$closeness, combined$performance_score), 3)
```

```
## Closeness vs Performance: 0.702
```

```r
cat("Betweenness vs Performance:", round(cor(combined$betweenness, combined$performance_score)
```

```
## Betweenness vs Performance: 0.477
```

```r
cat("PageRank vs Performance:", round(cor(combined$pagerank, combined$performance_score), 3),
```

```
## PageRank vs Performance: 0.745
```

There's some relationship between network position and performance, but it's not super strong. Being well-connected might help with performance, or maybe high performers naturally end up more connected. Either way, it's not the whole story - plenty of other factors matter too.

3.1.3 nn) High performers with low centrality

```r
med_deg <- median(combined$degree)
cat("Median degree:", med_deg, "\n\n")
```

```
## Median degree: 7
```

```r
combined %>%
  filter(performance_score > 4.0 & degree < med_deg) %>%
  select(employee_id, name, department, role, performance_score, degree, projects_completed) %>
  arrange(desc(performance_score))
```

```
## # A tibble: 1 x 7
##   employee_id name        department role  performance_score degree projects_completed
##         <int> <chr>       <chr>      <chr>             <dbl>  <dbl>              <int>
## 1          46 Tara Jenki~ Finance    Lead                4.3      6                 17
```

These are people doing great work but flying under the radar network-wise. They might be specialists who don't need to talk to everyone, or just more introverted. Management should make sure these folks aren't getting overlooked for promotions just because they're not as visible in the network.

3.2 Question 3.2: Executive Summary (5 points)

3.2.1 Executive Summary for TechConnect Management

Overview

We analyzed TechConnect's employee data and email communication patterns to understand performance trends and how information flows through the organization.

Performance Findings

The company's average performance score is 3.97 out of 5, which is pretty solid. Across all departments, employees have completed 612 projects total. We found 23 people who are standout performers - scoring above 4.0 and completing 10+ projects each. There's some variation between departments, but overall the workforce is performing well.

Network Structure

Looking at email patterns, 50 out of 50 employees are in the main communication cluster. The network shows that people don't just talk within their own departments - there's a fair amount of cross-team communication. The communities we detected overlap with departments but aren't a perfect match, which suggests people are collaborating across org boundaries.

Key People

A few employees stand out as communication hubs: Nathan Lee, Eve Thompson, Yuki Tanaka. These folks have high betweenness centrality, meaning they connect different parts of the organization. If one of them left, it could seriously disrupt how information gets around.

Recommendations

1. **Use your connectors** - The people with high betweenness are natural choices for spreading important updates or leading cross-functional projects.
2. **Watch for silos** - If any department starts communicating only internally, that's worth addressing before it becomes a problem.
3. **Don't forget the quiet high performers** - Some of your best people aren't super networked. Make sure they're still getting recognized and considered for advancement.
4. **Plan for departures** - If a key bridge person leaves, have a backup plan. Maybe cross-train people or build redundant communication paths.
5. **Think about teams** - When putting together project teams, consider who already talks to whom. Natural communication patterns can make collaboration smoother.