DBA3702 Assignment 1

weRready

2026-02-01

Contents

1 Part 1: Data Wrangling with dplyr

1.1 Question 1.1: Data Exploration

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    Engineeri~ Seni~         8  95000               4.5
##  2           2 Bob Martinez  Engineeri~ Lead         12 120000               4.8
##  3           3 Charlie Kim   Engineeri~ Juni~         2  65000               3.8
##  4           4 Diana Patel   Engineeri~ Seni~         7  92000               4.2
##  5           5 Eve Thompson  Engineeri~ Mana~        15 140000               4.6
##  6           6 Frank Liu     Engineeri~ Juni~         1  58000               3.2
##  7           7 Grace Okonkwo Engineeri~ Seni~         9  98000               4.4
##  8           8 Henry Wang    Marketing  Lead         10 105000               4.3
##  9           9 Iris Nakamura Marketing  Seni~         6  82000               3.9
## 10          10 Jack Brown    Marketing  Juni~         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, typeof)
```

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

```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     
```

The dataset includes information about 50 employees with 8 variables. This includes basic information, such as employee name and department, as well as quantitative information, such as salary, years of experience, performance scores, and number of projects completed.

1.2 Question 1.2: Selecting and Filtering

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) Select employees with 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    Engineeri~ Seni~         8  95000               4.5
##  2           2 Bob Martinez  Engineeri~ Lead         12 120000               4.8
##  3           4 Diana Patel   Engineeri~ Seni~         7  92000               4.2
##  4           5 Eve Thompson  Engineeri~ Mana~        15 140000               4.6
##  5           7 Grace Okonkwo Engineeri~ Seni~         9  98000               4.4
##  6           8 Henry Wang    Marketing  Lead         10 105000               4.3
##  7          11 Kate Wilson   Marketing  Mana~        14 125000               4.5
##  8          14 Nathan Lee    Sales      Lead         11 115000               4.7
##  9          15 Olivia Davis  Sales      Seni~         8  88000               4.1
## 10          18 Rachel Green  Sales      Mana~        13 130000               4.4
## # i 13 more rows
## # i 1 more variable: projects_completed <int>
```

1.2.3 f) Select employees in 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     Engineeri~ Seni~         8  95000               4.5
##  2           2 Bob Martinez   Engineeri~ Lead         12 120000               4.8
##  3           4 Diana Patel    Engineeri~ Seni~         7  92000               4.2
##  4           5 Eve Thompson   Engineeri~ Mana~        15 140000               4.6
##  5           7 Grace Okonkwo  Engineeri~ Seni~         9  98000               4.4
##  6           8 Henry Wang     Marketing  Lead         10 105000               4.3
##  7           9 Iris Nakamura  Marketing  Seni~         6  82000               3.9
##  8          11 Kate Wilson    Marketing  Mana~        14 125000               4.5
##  9          31 Eric Zhang     Engineeri~ Seni~         6  88000               4
## 10          33 George Park    Marketing  Seni~         7  80000               3.7
## 11          41 Oscar Rivera   Engineeri~ Lead         11 118000               4.5
## 12          42 Paula Hughes   Engineeri~ Mana~        16 145000               4.9
## 13          43 Quentin Price  Marketing  Lead          8 100000               4.1
## 14          47 Ulrich Weber   Engineeri~ Seni~         7  94000               4.2
## # i 1 more variable: projects_completed <int>
```

1.2.4 g) Select columns 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
```

There are two columns, *performance_score* and *projects_completed*, that meet the given condition.

1.3 Question 1.3: Sorting and Ranking

1.3.1 h) Identify top 5 highest-paid employees

```r
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 Manag~        16 145000               4.9
## 2           5 Eve Thompson Engineering Manag~        15 140000               4.6
## 3          28 Bella Moore  Finance     Manag~        14 135000               4.7
## 4          18 Rachel Green Sales       Manag~        13 130000               4.4
## 5          11 Kate Wilson  Marketing   Manag~        14 125000               4.5
## # i 1 more variable: projects_completed <int>
```

1.3.2 i) Sort by department, then performance

```r
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  Engineeri~ Mana~        16 145000               4.9
##  2           2 Bob Martinez  Engineeri~ Lead         12 120000               4.8
##  3           5 Eve Thompson  Engineeri~ Mana~        15 140000               4.6
##  4           1 Alice Chen    Engineeri~ Seni~         8  95000               4.5
##  5          41 Oscar Rivera  Engineeri~ Lead         11 118000               4.5
##  6           7 Grace Okonkwo Engineeri~ Seni~         9  98000               4.4
##  7           4 Diana Patel   Engineeri~ Seni~         7  92000               4.2
##  8          47 Ulrich Weber  Engineeri~ Seni~         7  94000               4.2
##  9          31 Eric Zhang    Engineeri~ Seni~         6  88000               4
## 10          32 Fiona O'Brien Engineeri~ Juni~         3  68000               3.9
## # i 40 more rows
## # i 1 more variable: projects_completed <int>
```

1.3.3 j) Identify employee with 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      Engineeri~ Juni~         1  58000               3.2
## 2          30 Dana Hill      Finance    Juni~         1  55000               3  
## 3          22 Victor Nguyen  HR         Juni~         1  48000               3.1
## 4          13 Maya Rodriguez Marketing  Juni~         1  52000               3.3
## 5          36 Julia Foster   Sales      Juni~         1  53000               2.9
## # i 1 more variable: projects_completed <int>
```

1.4 Question 1.4: Creating New Variables

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
```

1.4.3 m) Experience level

```
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
```

1.4.4 n) High performer flag

```
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

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
```

Managers in the Engineering department have the highest salary on average.

1.5.4 r) Individual employees' salary as % of department average

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

```
    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
```

Bella Moore from Finance department earns the most relative to their department's average, with a relative percentage of 156.37%.

1.5.5 s) Top 3 departments by performance (only considering employees with 3+ years of experience)

```
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
```

Only taking into account the work of employees with 3 or more years of experience, the Engineering, Finance, and Sales departments show the best average performance.

2 Part 2: Social Network Analysis

2.1 Question 2.1: Network Construction and Visualization

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")
```

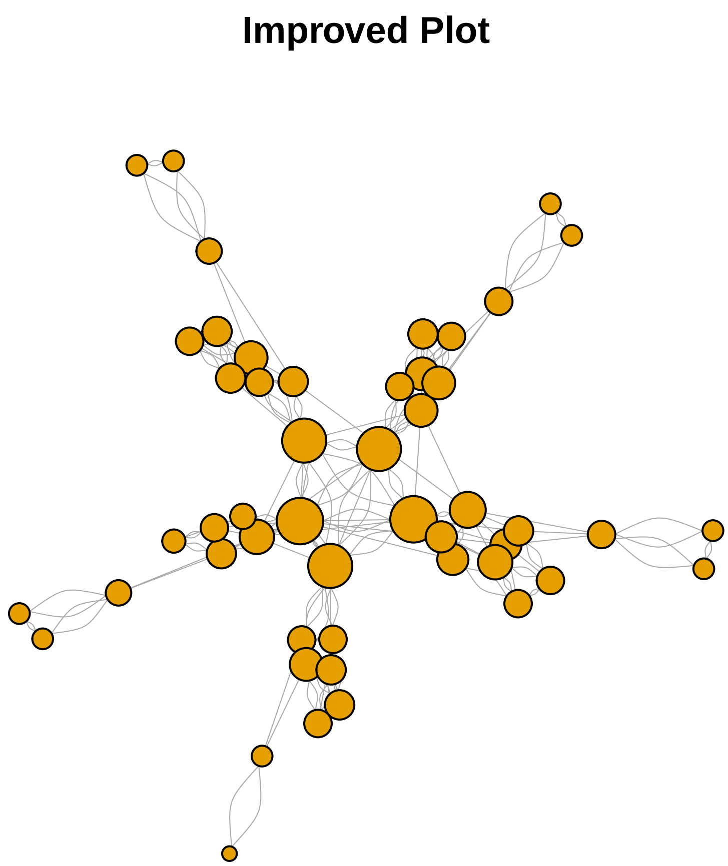
```
## Nodes: 50
```

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

```
## Edges: 207
```

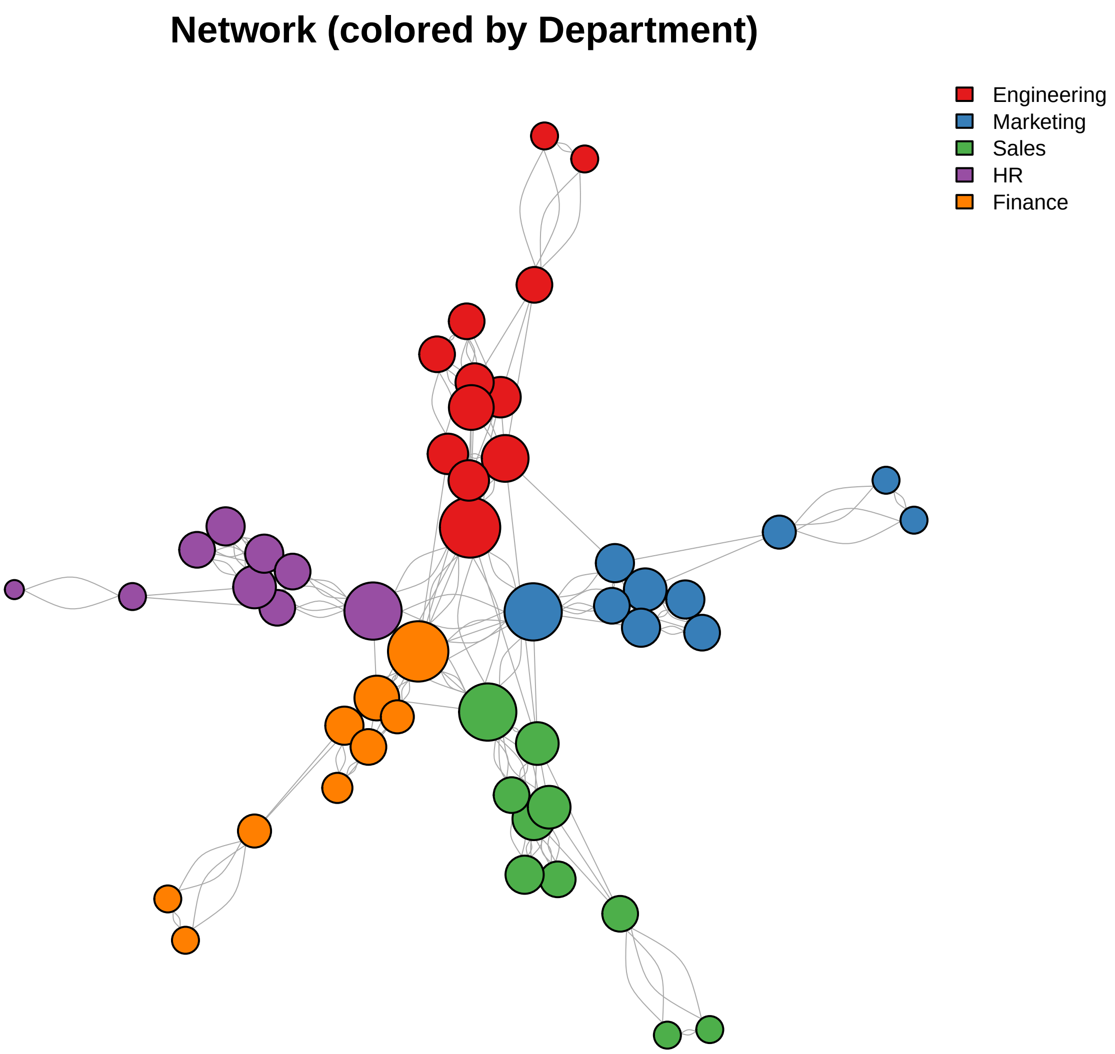
2.1.3 v) Create plot of network

```r
# v) Improved plot

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



2.1.4 w) Department-colored network

```r
depts <- V(email_graph)$department
unique_depts <- unique(depts)
colors <- brewer.pal(length(unique_depts), "Set1")
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 = "Network (colored by Department)")
legend("topright", unique_depts, fill = colors, cex = 0.7, bty = "n")
```



2.2 Question 2.2: Connected Components

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(round(lcc_size / vcount(email_graph) * 100, 1), "% of employees are in this component\n")
```

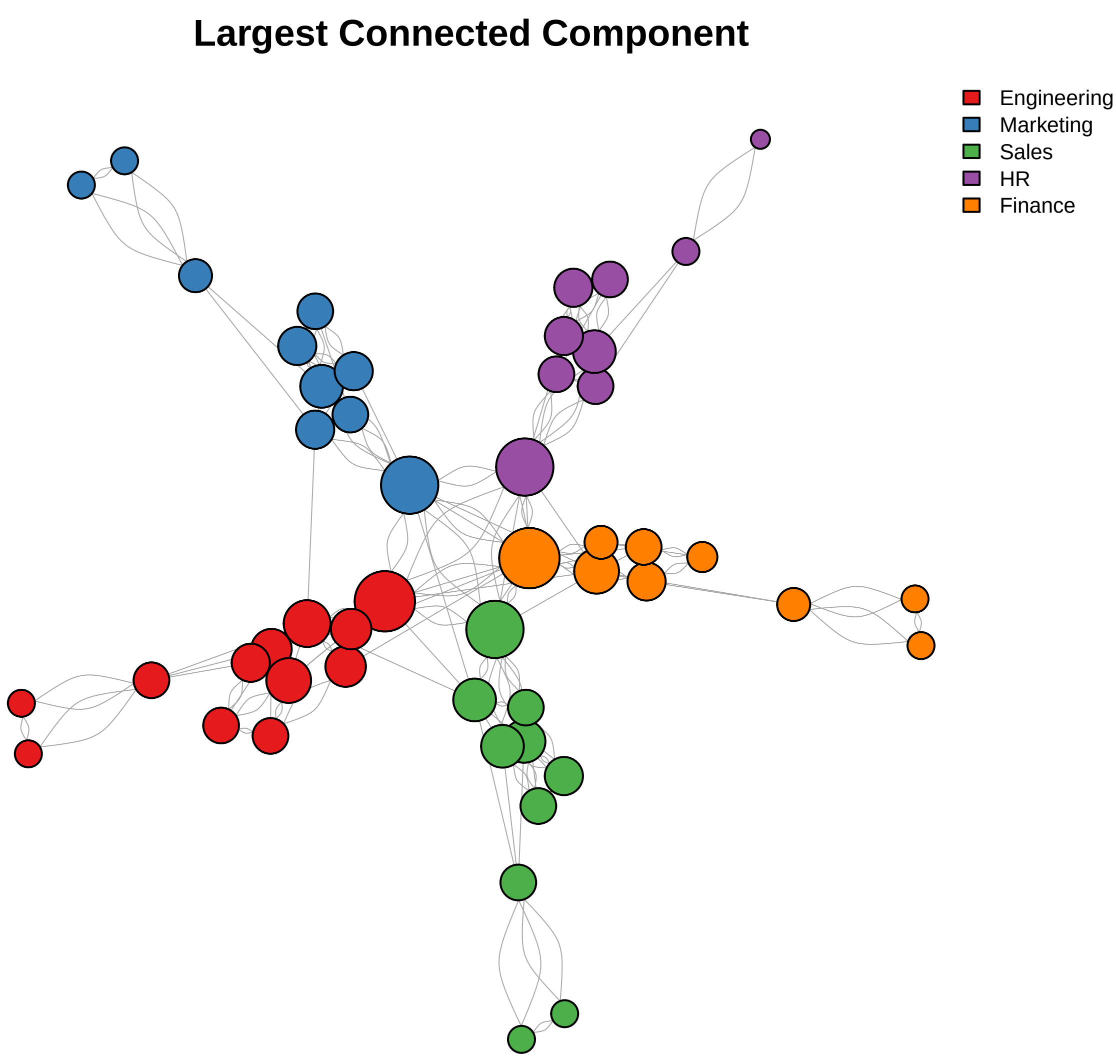
```
## 100 % of employees are in this component
```

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?

To calculate closeness centrality of nodes, every node must be reachable from every other node. If selected nodes are in different components (i.e., graph is disconnected), some distances become infinite and the calculation breaks. Focusing on the largest component helps avoid this problem and gives meaningful values that can be interpreted and compared.

2.3 Question 2.3: Centrality Metrics

2.3.1 bb) Degree Centrality

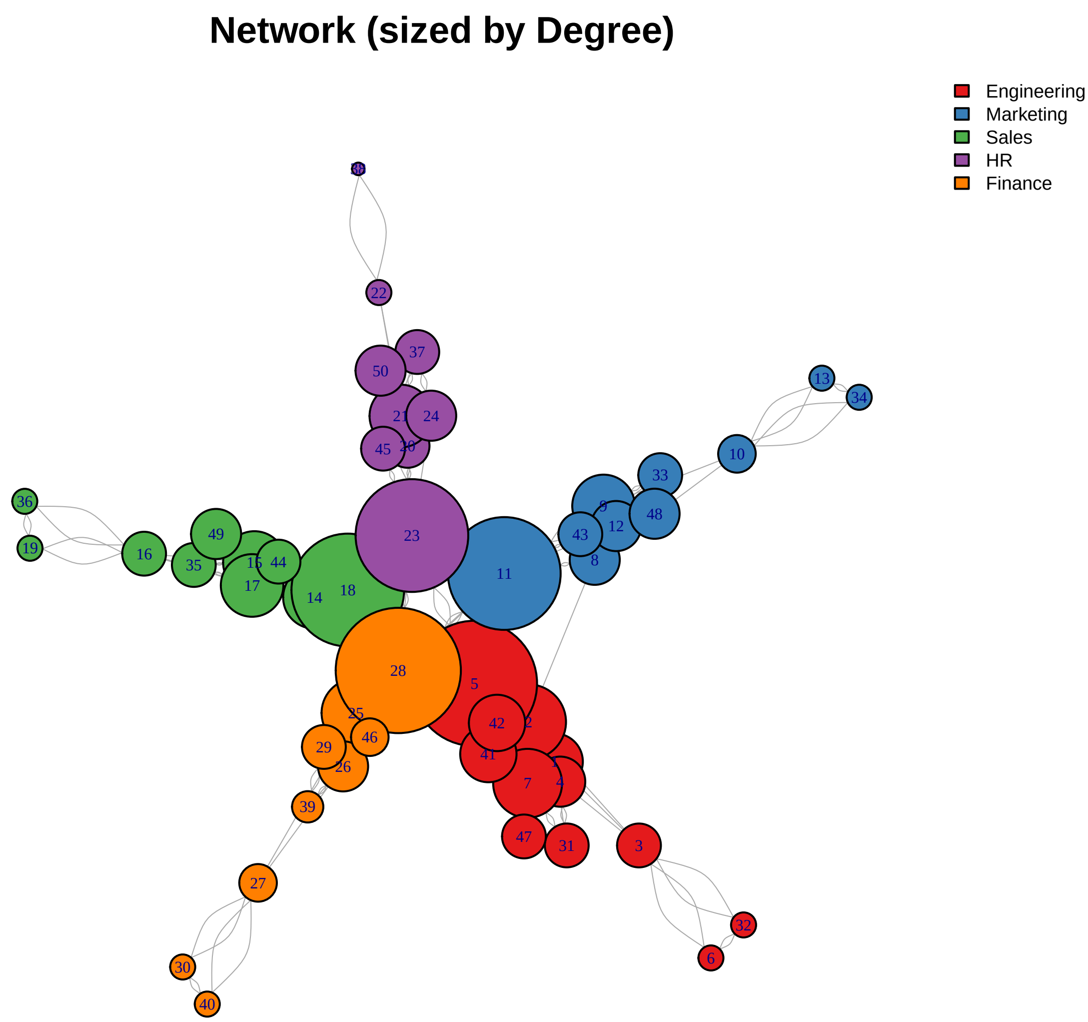
```
deg_cent <- degree(lcc)
deg_df <- data.frame(id = as.integer(V(lcc)$name), degree = deg_cent) %>%
  left_join(employees %>% select(employee_id, name), by = c("id" = "employee_id")) %>%
  select(id, name, degree) %>%
  arrange(desc(degree))

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

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

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

```
##   id          name degree
## 1  5 Eve Thompson     20
## 2 28   Bella Moore     20
## 3 11   Kate Wilson     18
## 4 18 Rachel Green     18
## 5 23   Wendy Clark     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 = "Network (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) %>%
  left_join(employees %>% select(employee_id, name), by = c("id" = "employee_id")) %>%
  select(id, name, closeness) %>%
  arrange(desc(closeness))

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

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

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

```
##   id         name  closeness
## 1  5 Eve Thompson 0.02985984
## 2 25  Yuki Tanaka 0.02925373
## 3 14   Nathan Lee 0.02920143
## 4 11  Kate Wilson 0.02884049
## 5 28  Bella Moore 0.02719201
```

High closeness means the employee can reach other employees quickly (i.e., in shorter distances) - they are central in the network. These employees are effective in spreading information fast since they are "close" to others.

2.3.3 dd) Betweenness Centrality

```r
btw_cent <- betweenness(lcc, normalized = TRUE)
btw_df <- data.frame(id = as.integer(V(lcc)$name), betweenness = btw_cent) %>%
  left_join(employees %>% select(employee_id, name), by = c("id" = "employee_id")) %>%
  select(id, name, betweenness) %>%
  arrange(desc(betweenness))

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

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

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

```
##   id         name betweenness
## 1 14   Nathan Lee   0.3380244
## 2  5 Eve Thompson   0.2884010
## 3 25  Yuki Tanaka   0.2833759
## 4 23  Wendy Clark   0.2789116
## 5  2 Bob Martinez   0.2268282
```

Betweenness measures how often an employee sits on the shortest path between other employees. An employee with high betweenness centrality is a bridge or connector. These employees control flow of information - if they do not pass something along properly or get removed, the network will be disrupted and information might not get to where it needs to go.

2.3.4 ee) PageRank

```r
pr <- page_rank(lcc)$vector
pr_df <- data.frame(id = as.integer(V(lcc)$name), pagerank = pr) %>%
  left_join(employees %>% select(employee_id, name), by = c("id" = "employee_id")) %>%
  select(id, name, pagerank) %>%
  arrange(desc(pagerank))

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

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

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

```
##   id         name   pagerank
## 1  5 Eve Thompson 0.04219373
## 2 23  Wendy Clark 0.04049384
## 3 28  Bella Moore 0.03937716
## 4 18 Rachel Green 0.03930274
## 5 11  Kate Wilson 0.03894129
```

PageRank is different from simple degree centrality because it takes into account *who* an employee is connected to. Being connected to important employees (i.e., those who are well-connected themselves) boosts an employee's PageRank score more than being connected to isolated employees. It measures an employee's direct and indirect influence instead of simply counting the number of connections.

2.3.5 ff) Comparing all metrics

```r
all_cent <- data.frame(
  id = as.integer(V(lcc)$name),
  degree = deg_cent,
  closeness = close_cent,
  betweenness = btw_cent,
  pagerank = pr
) %>%
  left_join(employees %>% select(employee_id, name, department, role),
            by = c("id" = "employee_id")) %>%
  select(id, name, dept = department, role, degree, closeness, betweenness, pagerank)

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

```
##    id          name        dept    role degree  closeness betweenness
## 1   5  Eve Thompson Engineering Manager     20 0.02985984 0.288400956
```

```
## 2   28    Bella Moore     Finance Manager     20 0.02719201 0.115949951
## 3   11    Kate Wilson   Marketing Manager     18 0.02884049 0.160501701
## 4   18   Rachel Green       Sales Manager     18 0.02606383 0.046541950
## 5   23    Wendy Clark          HR Manager     18 0.02603613 0.278911565
## 6    2  Bob Martinez Engineering    Lead     12 0.02704194 0.226828231
## 7    7 Grace Okonkwo Engineering  Senior     11 0.01952969 0.005668934
## 8   25    Yuki Tanaka     Finance    Lead     11 0.02925373 0.283375850
## 9    9 Iris Nakamura   Marketing  Senior     10 0.01954527 0.068664966
## 10  14     Nathan Lee       Sales    Lead     10 0.02920143 0.338024376
##      pagerank
## 1  0.04219373
## 2  0.03937716
## 3  0.03894129
## 4  0.03930274
## 5  0.04049384
## 6  0.03100845
## 7  0.02454985
## 8  0.02689045
## 9  0.02448814
## 10 0.02545679
```

```r
# Rankings
top10 %>%
  mutate(
    deg_r = rank(-degree),
    close_r = rank(-closeness),
    btw_r = rank(-betweenness),
    pr_r = rank(-pagerank)
  ) %>%
  select(id, name, deg_r, close_r, btw_r, pr_r)
```

```
##    id          name deg_r close_r btw_r pr_r
## 1   5  Eve Thompson   1.5       1     2    1
## 2  28   Bella Moore   1.5       5     7    3
## 3  11   Kate Wilson   4.0       4     6    5
## 4  18  Rachel Green   4.0       7     9    4
## 5  23   Wendy Clark   4.0       8     4    2
## 6   2  Bob Martinez   6.0       6     5    6
## 7   7 Grace Okonkwo   7.5      10    10    9
## 8  25   Yuki Tanaka   7.5       2     3    7
## 9   9 Iris Nakamura   9.5       9     8   10
## 10 14    Nathan Lee   9.5       3     1    8
```

Employees like Eve Thompson (employee ID: 2) and Bella Moore (employee ID: 28) rank relatively high across board - they are highly influential in the network, connected to many other employees and able to spread information quickly.

Other employees, such as Yuki Tanaka (employee ID: 25) and Nathan Lee (employee ID: 14), have high betweenness but only moderate degree, which suggests that they may not know many other employees but are still central to facilitating communication. There are also employees, such as Wendy Clark (employee ID: 23), who have a high PageRank score but moderate closeness centrality, which implies that while they may not be able to spread information fast, they have influence in the network.

In addition, managers and leads tend to show up more in the dataframe for top 10 employees, which intuitively makes sense given their coordinating role in organizations.

2.4 Question 2.4: Community Detection

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

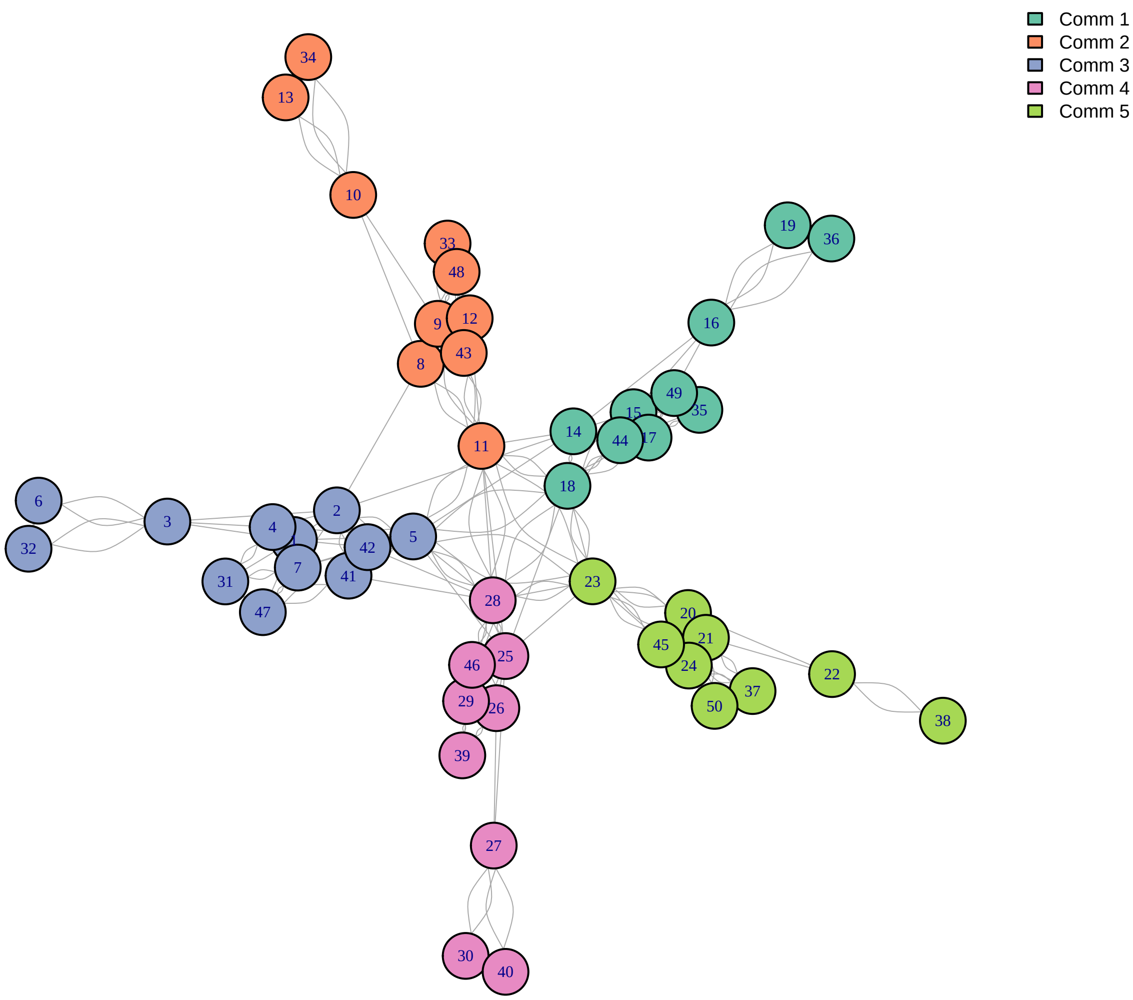
```
mem <- membership(comm)
table(mem)
```

```
## 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 = "Network (colored by Community)")
legend("topright", paste("Comm", 1:num_comm), fill = comm_colors[1:num_comm],
       cex = 0.6, bty = "n")
```

Network (colored 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
) %>%
  left_join(employees %>% select(employee_id, name), by = c("id" = "employee_id"))

xtab <- table(comm_dept$community, comm_dept$department)
cat("\nNumber of employees:\n")
```

```
##
```

```
## Number of employees:
```

```r
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 match up perfectly with departments, which makes sense given employees are more likely to work with other employees in the same department. However, this also presents a warning in that there may not be much cross-team communication happening, and certain teams could get stuck in their own silos.

2.4.5 kk) Business insights

Insights the management could take from understanding these communication communities include:

- The communities go beyond the organizational chart to show how employees actually communicate
- Employees who bridge multiple communities are valuable, as they help different groups stay connected
- If a community consists of only one department, it could be a warning sign that the community is working in silo instead of actively connecting with others
- When planning projects, changes or announcements, it is good practice to work with community leaders to spread the word quickly and effectively

3 Part 3: Integration and Insights

3.1 Question 3.1: Joining Data

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 ~ Engineeri~               4.5      9    0.0203      0.0286
##  2           2 Bob Ma~ Engineeri~               4.8     12    0.0270      0.227
##  3           3 Charli~ Engineeri~               3.8      7    0.0188      0.0799
##  4           4 Diana ~ Engineeri~               4.2      8    0.0198      0.0197
##  5           5 Eve Th~ Engineeri~               4.6     20    0.0299      0.288
##  6           6 Frank ~ Engineeri~               3.2      4    0.0164      0
##  7           7 Grace ~ Engineeri~               4.4     11    0.0195      0.00567
##  8           8 Henry ~ Marketing                4.3      8    0.0230      0.112
##  9           9 Iris N~ Marketing                3.9     10    0.0195      0.0687
## 10          10 Jack B~ 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
```

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

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

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

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

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

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

There is a positive relationship between network position and performance, but none of them are very strong. It could be the case that being well-connected helps with performance, or high performers naturally end up being more connected.

3.1.3 nn) High performers with low centrality

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

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

```
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~ Finance    Lead                4.3      6                 17
```

While employees like Tara Jenkins (employee ID: 46) do great work, they are flying under the radar network-wise. They may be specialists who do not need to talk to other employees as much, or more introverted. Management should make sure these employees are not getting overlooked for promotions simply because they are not as visible in the network.

3.2 Question 3.2: Executive Summary

3.2.1 Executive Summary for TechConnect Management

Overview

We have 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 indicates strong performance across the board. Employees have completed 612 projects in total across all departments. Moreover, we identified 23 employees who are standout performers - scoring above 4.0 and completing 10+ projects each. While there is some variation between departments, 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 employees are willing to network beyond their departments - there is a fair amount of cross-team communication. Furthermore, the communities we detected are separated by departments. While this makes sense intuitively, management may want to make additional efforts to encourage cross-department communication.

Key Employees

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

Recommendations for TechConnect

1. **Use your connectors** - The employees with high betweenness centrality are effective choices for spreading important updates or leading cross-functional projects.

2. **Watch for silos** - If any department starts communicating only internally, management may want to address it before it snowballs into significant information discrepancies across departments and serious communication issues.

3. **Do not forget the quiet high performers** - Some of your best people are not super networked, as shown by the case of Tara Jenkins. Make sure they are still getting recognized and considered for advancement, so that they feel appreciated by the company and continue to contribute to the business.

4. **Plan for departures** - It is good practice to have a backup plan in case a key bridge employee leaves the organization. Examples include cross-training employees or building additional communication paths.

5. **Think about teams** - When putting together project teams, consider who already talks to whom. Natural communication patterns can make collaboration smoother.