Connnected Component Analysis

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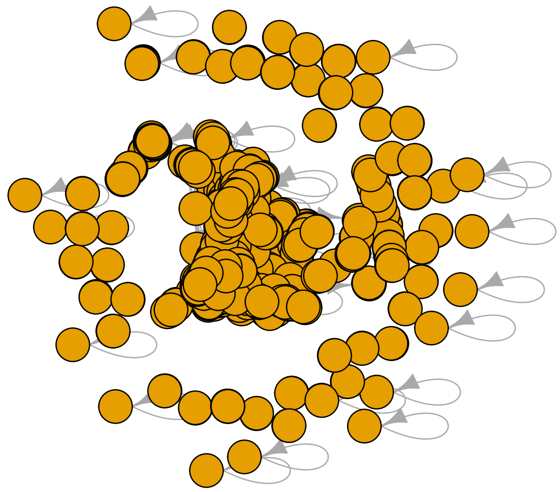
2025-12-04

Contents

1 Data Loading and Preprocessing

```r
# Load data
nodes_connected <- read.csv("data/nodes_connected.csv")
edges_connected <- read.csv("data/edges_connected.csv")
nodes_all_raw <- read.csv("data/nodes.csv")

# Filter out invalid nodes from nodes_all
nodes_all <- nodes_all_raw %>%
  filter(
    !is.na(title) & trimws(title) != "",  # Valid title
    !is.na(local_id),                     # Valid ID
    !is.na(year) & year <= 2025,  # Valid year range
    !is.na(citations) & citations >= 0,   # Valid citation count
    !is.na(references) & references >= 0, # Valid reference count
    !is.na(subtopic) & trimws(subtopic) != "",  # Valid subtopic
    !is.na(institution) & trimws(institution) != "" , # Valid institution
    !is.na(country) & country!=""
  )

# Create graph from connected component
connected_graph <- graph_from_data_frame(edges_connected, vertices = nodes_connected, directed = TRUE)
connected_graph <- simplify(connected_graph)
plot(connected_graph, vertex.label=NA)
```



```r
# Use nodes_connected as papers_df for consistency with analysis
papers_df <- nodes_connected

# Display basic information
cat("Connected component: ", vcount(connected_graph), "nodes,",
    ecount(connected_graph), "edges\n")
```

```
## Connected component:  1582 nodes, 3757 edges
```

```r
cat("Total papers in dataset: ", nrow(nodes_all), "\n")
```

```
## Total papers in dataset:  2588
```

2 Network Overview & Basic Statistics

2.1 Network Size and Structure

```r
# Calculate basic network statistics
stats_df <- data.frame(
  Metric = c(
    "Total Nodes",
    "Total Edges",
    "Average Degree",
    "Average In-Degree",
    "Average Out-Degree",
```

```r
    "Network Density",
    "Network Diameter",
    "Average Path Length",
    "Number of Weakly Connected Components",
    "Number of Strongly Connected Components"
  ),
  Value = c(
    vcount(connected_graph),
    ecount(connected_graph),
    mean(degree(connected_graph)),
    mean(degree(connected_graph, mode = "in")),
    mean(degree(connected_graph, mode = "out")),
    edge_density(connected_graph),
    diameter(connected_graph, directed = TRUE),
    mean_distance(connected_graph, directed = TRUE),
    count_components(connected_graph, mode = "weak"),
    count_components(connected_graph, mode = "strong")
  )
)

kable(stats_df, digits = 3, caption = "Network Basic Statistics")
```

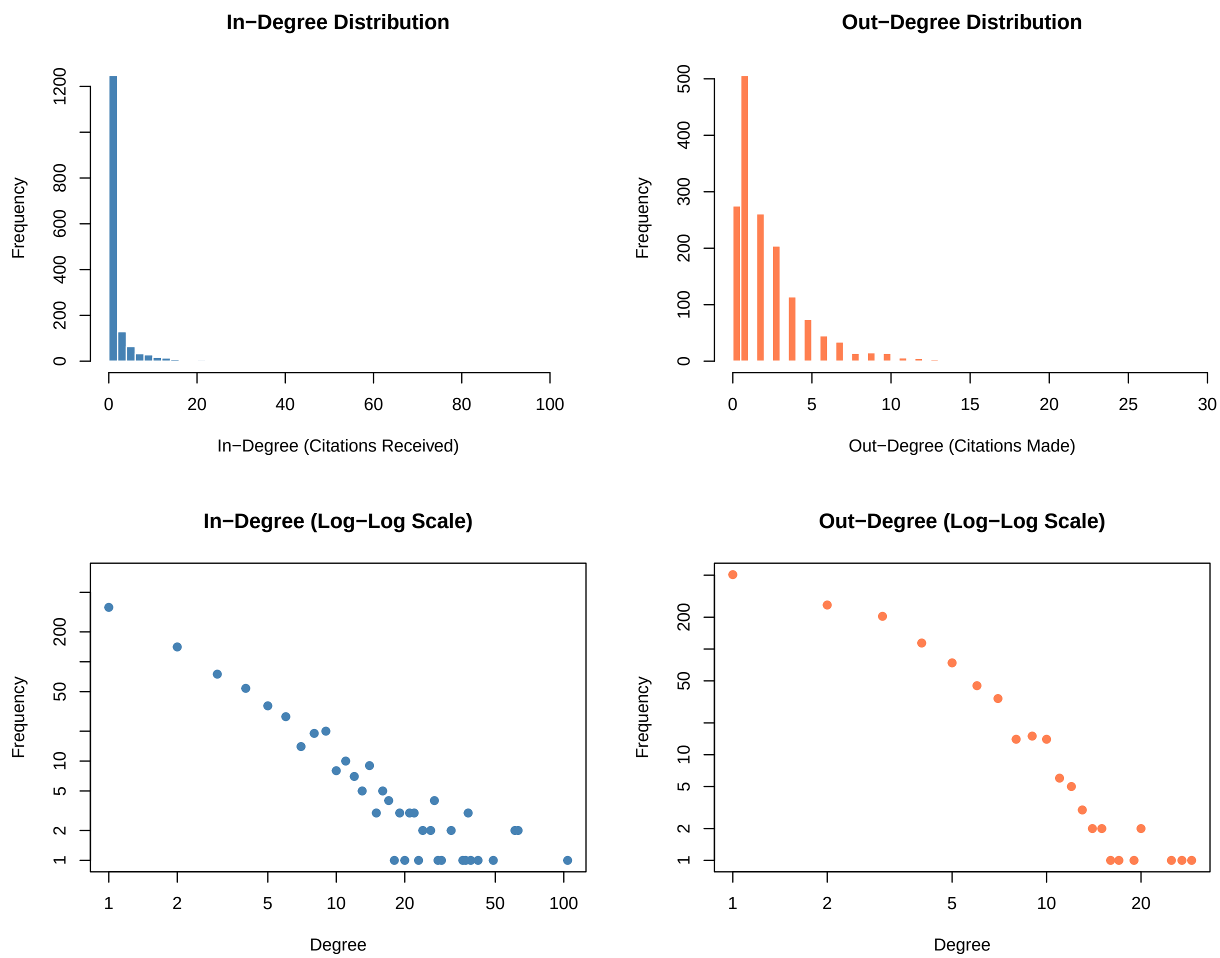
Table 1: Network Basic Statistics

Metric	Value
Total Nodes	1582.000
Total Edges	3757.000
Average Degree	4.750
Average In-Degree	2.375
Average Out-Degree	2.375
Network Density	0.002
Network Diameter	10.000
Average Path Length	3.148
Number of Weakly Connected Components	58.000
Number of Strongly Connected Components	1569.000

2.2 Degree Distribution

```r
# Calculate degrees
in_deg <- degree(connected_graph, mode = "in")
out_deg <- degree(connected_graph, mode = "out")
total_deg <- degree(connected_graph, mode = "all")

# Create degree distribution plots
par(mfrow = c(2, 2))

# In-degree distribution
hist(in_deg, breaks = 50, main = "In-Degree Distribution",
     xlab = "In-Degree (Citations Received)", col = "steelblue", border = "white")
```

```r
# Out-degree distribution
hist(out_deg, breaks = 50, main = "Out-Degree Distribution",
     xlab = "Out-Degree (Citations Made)", col = "coral", border = "white")

# Log-log plot for in-degree
in_deg_table <- table(in_deg)
plot(as.numeric(names(in_deg_table)), as.numeric(in_deg_table),
     log = "xy", main = "In-Degree (Log-Log Scale)",
     xlab = "Degree", ylab = "Frequency", pch = 19, col = "steelblue")

# Log-log plot for out-degree
out_deg_table <- table(out_deg)
plot(as.numeric(names(out_deg_table)), as.numeric(out_deg_table),
     log = "xy", main = "Out-Degree (Log-Log Scale)",
     xlab = "Degree", ylab = "Frequency", pch = 19, col = "coral")
```




```r
par(mfrow = c(1, 1))
```

3 Research Question 1: Most Impactful Papers

3.1 Multiple Centrality Metrics

```r
# Calculate multiple centrality metrics
V(connected_graph)$pagerank <- page_rank(connected_graph)$vector
V(connected_graph)$in_degree <- degree(connected_graph, mode = "in")
V(connected_graph)$betweenness <- betweenness(connected_graph, directed = TRUE)
V(connected_graph)$eigenvector <- eigen_centrality(connected_graph, directed = TRUE)$vector

# Create centrality data frame
centrality_df <- data.frame(
  local_id = V(connected_graph)$name,
  pagerank = V(connected_graph)$pagerank,
  in_degree = V(connected_graph)$in_degree,
  betweenness = V(connected_graph)$betweenness,
  eigenvector = V(connected_graph)$eigenvector
)

# Merge with paper metadata
centrality_df <- centrality_df %>%
  left_join(papers_df, by = "local_id")
```

3.2 Top 10 Most Impactful Papers (by PageRank)

```r
# Top papers by PageRank
top_papers <- centrality_df %>%
  arrange(desc(pagerank)) %>%
  select(title, first_author, year, pagerank, in_degree, betweenness) %>%
  head(10)

kable(top_papers, digits = 4, caption = "Top 10 Papers by PageRank")
```

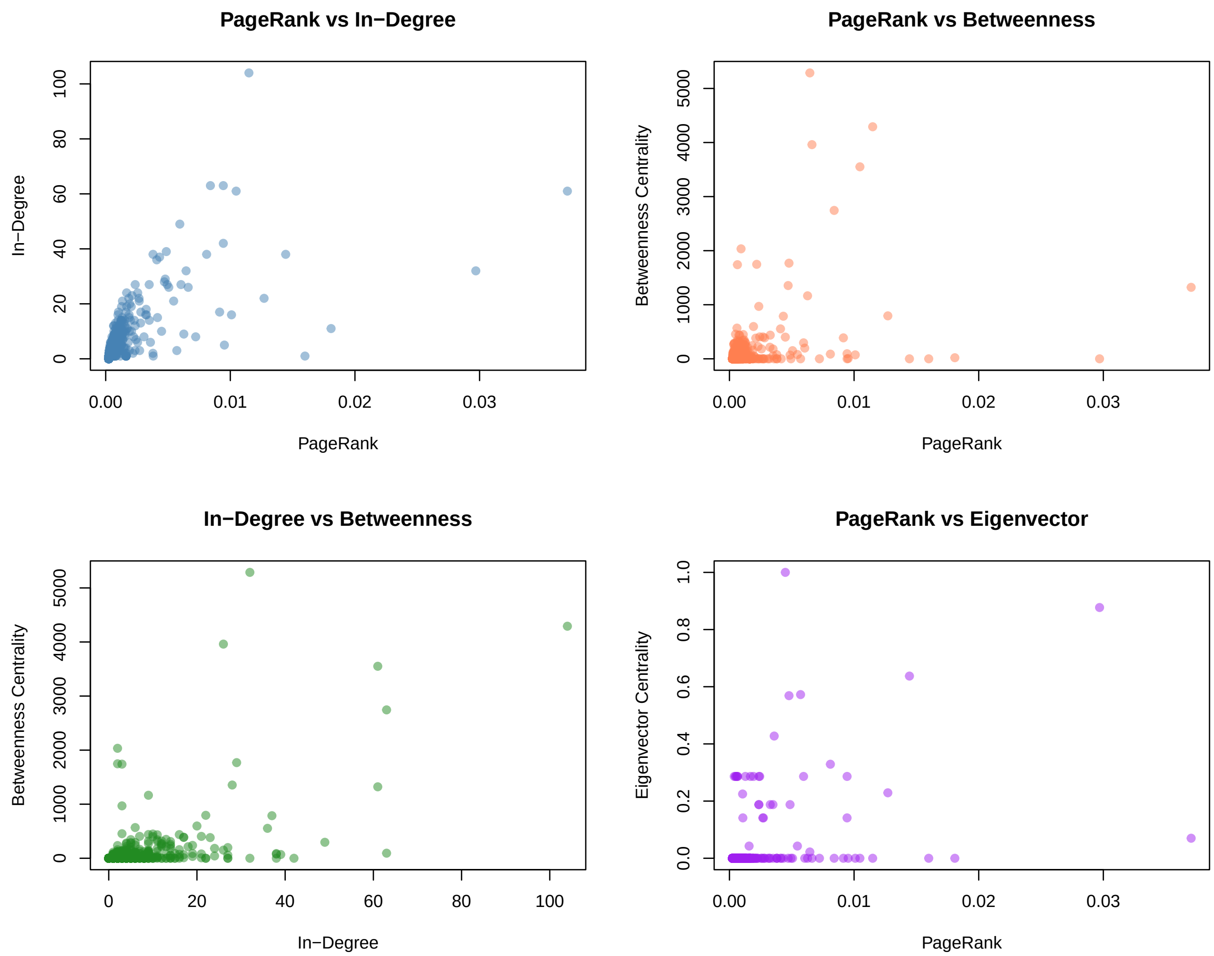
Table 2: Top 10 Papers by PageRank

title	first_author	year	pagerank	in_degree	betweenness
Artificial intelligence in healthcare	Kun-Hsing Yu	2018	0.0370	61	1321.9000
Developing specific reporting guidelines for diagnostic accuracy studies assessing AI interventions: The STARD-AI Steering Group	Viknesh Sounderajah	2020	0.0297	32	0.0000
Framing the challenges of artificial intelligence in medicine	Kun-Hsing Yu	2018	0.0181	11	19.8333
Artificial intelligence (AI) systems for interpreting complex medical datasets	Rb Altman	2017	0.0160	1	0.0000
Potential Liability for Physicians Using Artificial Intelligence	W. Nicholson Price	2019	0.0144	38	0.0000

title	first_author	year	pagerank	in_degree	betweenness
The "inconvenient truth" about AI in healthcare	Trishan Panch	2019	0.0127	22	794.5167
Large language models in medicine	Arun James Thirunavukarasu	2023	0.0115	104	4291.8181
AI in health and medicine	Pranav Rajpurkar	2022	0.0105	61	3551.0943
AI-Assisted Decision-making in Healthcare	Tamra Lysaght	2019	0.0101	16	73.0000
An Ethics Framework for Big Data in Health and Research	Vicki Xafis	2019	0.0095	5	5.0000

3.3 Comparison of Ranking Metrics

```r
# Create ranking comparison
top_by_pagerank <- centrality_df %>% arrange(desc(pagerank)) %>% head(20)
top_by_indegree <- centrality_df %>% arrange(desc(in_degree)) %>% head(20)
top_by_betweenness <- centrality_df %>% arrange(desc(betweenness)) %>% head(20)

# Scatter plots comparing metrics
par(mfrow = c(2, 2))

plot(centrality_df$pagerank, centrality_df$in_degree,
     xlab = "PageRank", ylab = "In-Degree",
     main = "PageRank vs In-Degree", pch = 19, col = alpha("steelblue", 0.5))

plot(centrality_df$pagerank, centrality_df$betweenness,
     xlab = "PageRank", ylab = "Betweenness Centrality",
     main = "PageRank vs Betweenness", pch = 19, col = alpha("coral", 0.5))

plot(centrality_df$in_degree, centrality_df$betweenness,
     xlab = "In-Degree", ylab = "Betweenness Centrality",
     main = "In-Degree vs Betweenness", pch = 19, col = alpha("forestgreen", 0.5))

plot(centrality_df$pagerank, centrality_df$eigenvector,
     xlab = "PageRank", ylab = "Eigenvector Centrality",
     main = "PageRank vs Eigenvector", pch = 19, col = alpha("purple", 0.5))
```




```
par(mfrow = c(1, 1))
```

3.4 Papers Ranking High on Multiple Metrics

```
# Normalize metrics to [0,1] for comparison
centrality_df <- centrality_df %>%
  mutate(
    pagerank_norm = (pagerank - min(pagerank)) / (max(pagerank) - min(pagerank)),
    indegree_norm = (in_degree - min(in_degree)) / (max(in_degree) - min(in_degree)),
    betweenness_norm = (betweenness - min(betweenness)) / (max(betweenness) - min(betweenness)),
    combined_score = pagerank_norm + indegree_norm + betweenness_norm
  )

# Top papers by combined metrics
multi_metric_top <- centrality_df %>%
  arrange(desc(combined_score)) %>%
  select(title, year, pagerank_norm, indegree_norm, betweenness_norm, combined_score) %>%
  head(10)
library(kableExtra)
```

```r
kable(multi_metric_top, digits = 3,
      caption = "Top Papers by Combined Metrics",
      booktabs = TRUE) %>%
  kableExtra::kable_styling() %>%
  column_spec(1, width = "15em") %>%   # title column wide
  column_spec(2, width = "2em") %>% # year
  column_spec(3:5, width="6em") %>%
  column_spec(6, width = "8.5em")      # numeric columns
```

Table 3: Top Papers by Combined Metrics

title	year	pagerank_norm	indegree_norm	betweenness_norm	combined_score
Large language models in medicine	2023	0.306	1.000	0.812	2.117
Artificial intelligence in healthcare	2018	1.000	0.587	0.250	1.837
AI in health and medicine	2022	0.278	0.587	0.672	1.536
The shaky foundations of large language models and foundation models for electronic health records	2023	0.169	0.308	1.000	1.476
Foundation models for generalist medical artificial intelligence	2023	0.222	0.606	0.519	1.346
Multimodal biomedical AI	2022	0.173	0.250	0.749	1.172
Developing specific reporting guidelines for diagnostic accuracy studies assessing AI interventions: The STARD-AI Steering Group	2020	0.800	0.308	0.000	1.108
Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension	2020	0.250	0.606	0.018	0.873
Potential Liability for Physicians Using Artificial Intelligence	2019	0.386	0.365	0.000	0.751
Creation and Adoption of Large Language Models in Medicine	2023	0.123	0.279	0.335	0.737

4 Research Question 2: Oldest Papers with Lasting Relevance

4.1 Papers with High Closeness Centrality (Sorted by Age)

```r
# Calculate closeness centrality for ALL papers
all_paper_ids <- V(connected_graph)$name
closeness_scores <- closeness(connected_graph, vids = all_paper_ids, mode = "all")

# Add closeness to centrality_df
centrality_df$closeness <- closeness_scores[match(centrality_df$local_id, names(closeness_scores))]

# Filter for papers with valid closeness (not NA or 0) and sort by year (oldest first), then by closene
oldest_papers <- centrality_df %>%
```

```r
  filter(!is.na(closeness), closeness > 0, !is.na(year)) %>%
  arrange(year, desc(closeness)) %>%
  head(10)

# Create display table
oldest_papers_display <- oldest_papers %>%
  select(title, year, closeness, in_degree)

kable(oldest_papers_display, digits = 3,
      caption = "Top 10 Oldest Papers with High Closeness Centrality (Sorted by Year, then Closeness)")
```

Table 4: Top 10 Oldest Papers with High Closeness Centrality (Sorted by Year, then Closeness)

title	year	closeness	in_degree
Exploring big educational learner corpora for SLA research	2015	1.000	1
Incremental Dependency Parsing and Disfluency Detection in Spoken Learner English	2015	0.333	1
How to Train good Word Embeddings for Biomedical NLP	2016	0.333	1
AI as evaluator: Search driven playtesting of modern board games	2017	1.000	0
Findings of the VarDial Evaluation Campaign 2017	2017	0.200	3
A Report on the 2017 Native Language Identification Shared Task	2017	0.167	1
Investigating the cross-lingual translatability of VerbNet-style classification	2017	0.004	1
What This Computer Needs Is a Physician	2017	0.000	13
Artificial intelligence (AI) systems for interpreting complex medical datasets	2017	0.000	1
Segmenting and POS tagging Classical Tibetan using a memory-based tagger	2018	1.000	1

4.2 Citation Longevity Analysis

```r
# Analyze citations to oldest papers from recent papers (2020-2025)
recent_papers <- papers_df %>% filter(year >= 2020 & year <= 2025)

# Get edges from recent papers to oldest papers
citation_longevity <- data.frame()

for (old_id in oldest_papers$local_id) {
  # Get papers that cite this old paper
  citing_papers <- neighbors(connected_graph, old_id, mode = "in")
  citing_ids <- V(connected_graph)[citing_papers]$name

  # Check which citing papers are recent
  recent_citations <- sum(citing_ids %in% recent_papers$local_id)
  total_citations <- length(citing_ids)

  citation_longevity <- rbind(citation_longevity, data.frame(
    local_id = old_id,
    total_citations = total_citations,
    recent_citations = recent_citations,
    recent_ratio = ifelse(total_citations > 0, recent_citations / total_citations, 0)
```

```
  ))
}

# Merge with paper info
citation_longevity <- citation_longevity %>%
  left_join(papers_df, by = "local_id") %>%
  arrange(desc(recent_citations)) %>%
  select(title, year, total_citations, recent_citations)

kable(head(citation_longevity, 10), digits = 3,
      caption = "Oldest Papers Still Cited by Recent Work (2020-2025)")
```

Table 5: Oldest Papers Still Cited by Recent Work (2020-2025)

title	year	total_citations	recent_citations
What This Computer Needs Is a Physician	2017	13	7
Exploring big educational learner corpora for SLA research	2015	1	1
Incremental Dependency Parsing and Disfluency Detection in Spoken Learner English	2015	1	1
How to Train good Word Embeddings for Biomedical NLP	2016	1	1
Findings of the VarDial Evaluation Campaign 2017	2017	3	1
Investigating the cross-lingual translatability of VerbNet-style classification	2017	1	1
AI as evaluator: Search driven playtesting of modern board games	2017	0	0
A Report on the 2017 Native Language Identification Shared Task	2017	1	0
Artificial intelligence (AI) systems for interpreting complex medical datasets	2017	1	0
Segmenting and POS tagging Classical Tibetan using a memory-based tagger	2018	1	0

5 Research Question 3: Subtopic Concentration

5.1 Community Detection

```
# Apply Louvain community detection
set.seed(42)
communities <- cluster_louvain(as.undirected(connected_graph))

# Add community membership to vertices
V(connected_graph)$community <- membership(communities)

# Calculate modularity
modularity_score <- modularity(communities)
cat("Modularity score:", modularity_score, "\n")
```

```
## Modularity score: 0.5981146
```

```r
cat("Number of communities detected:", length(communities), "\n")
```

```
## Number of communities detected: 77
```

5.2 Community Statistics

```r
# Calculate statistics for each community
community_stats <- data.frame()

for (comm_id in unique(V(connected_graph)$community)) {
  # Get subgraph for this community
  comm_nodes <- V(connected_graph)[V(connected_graph)$community == comm_id]
  subgraph <- induced_subgraph(connected_graph, comm_nodes)

  # Calculate statistics
  comm_size <- vcount(subgraph)
  comm_edges <- ecount(subgraph)
  comm_density <- edge_density(subgraph)

  community_stats <- rbind(community_stats, data.frame(
    community = comm_id,
    size = comm_size,
    edges = comm_edges,
    density = comm_density,
    avg_degree = mean(degree(subgraph))
  ))
}

community_stats <- community_stats %>%
  arrange(desc(size))

kable(head(community_stats, 10), digits = 3,
      caption = "Top 10 Communities by Size")
```

Table 6: Top 10 Communities by Size

community	size	edges	density	avg_degree
1	251	546	0.009	4.351
4	160	249	0.010	3.113
5	155	442	0.019	5.703
10	135	283	0.016	4.193
11	133	217	0.012	3.263
8	124	178	0.012	2.871
2	85	107	0.015	2.518
19	59	76	0.022	2.576
24	53	56	0.020	2.113
14	51	59	0.023	2.314

5.3 Predominant Topics by Community

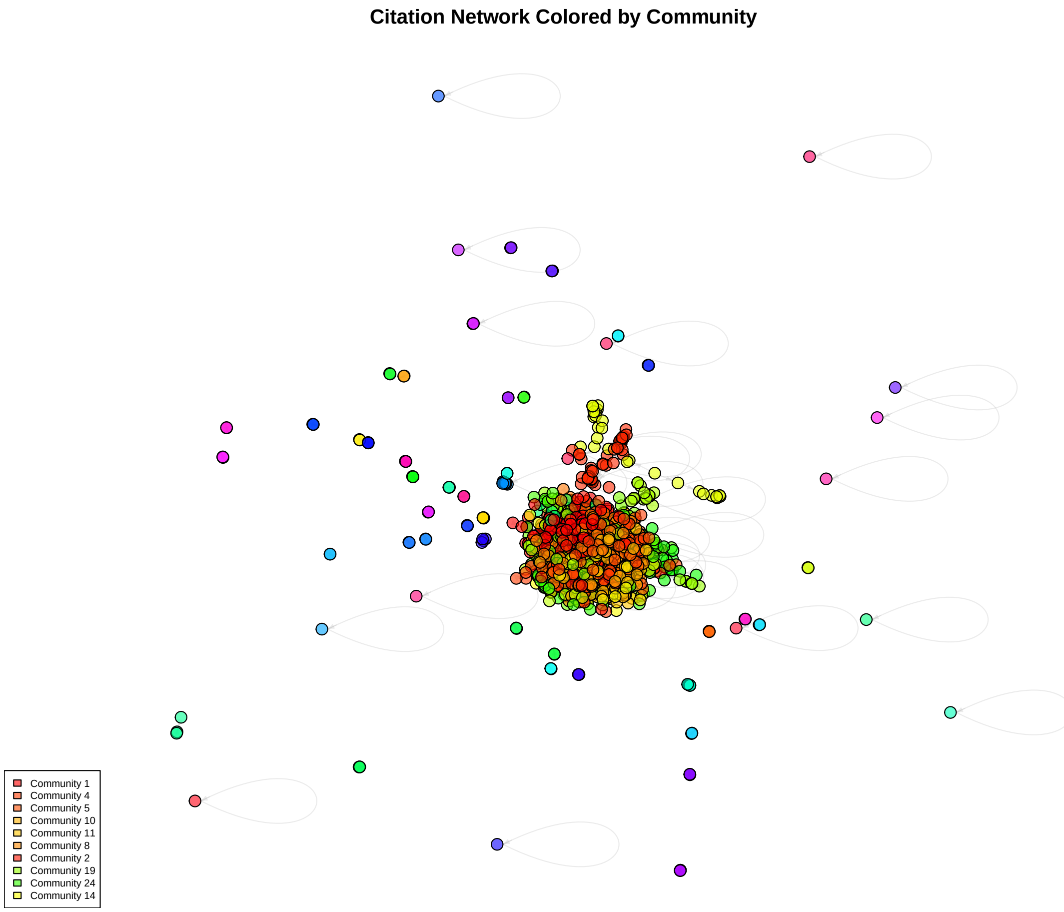
```
# Analyze subtopics within each community
community_topics <- data.frame()

for (comm_id in head(unique(V(connected_graph)$community), 10)) {
  # Get papers in this community
  comm_paper_ids <- V(connected_graph)[V(connected_graph)$community == comm_id]$name

  # Get subtopics for these papers
  comm_papers <- papers_df %>%
    filter(local_id %in% comm_paper_ids)

  # Count subtopic frequencies (subtopic is singular, not a list)
  subtopic_freq <- comm_papers %>%
    count(subtopic, sort = TRUE) %>%
    head(5)

  subtopic_freq$community <- comm_id
  community_topics <- rbind(community_topics, subtopic_freq)
}

if (nrow(community_topics) > 0) {
  kable(head(community_topics, 20), caption = "Top Subtopics by Community")
}
```

Table 7: Top Subtopics by Community

subtopic	n	community
Artificial Intelligence in Healthcare and Education	209	1
Machine Learning in Healthcare	34	1
Artificial Intelligence in Healthcare	2	1
Machine Learning in Bioinformatics	2	1
Artificial Intelligence in Games	1	1
Artificial Intelligence in Healthcare and Education	70	2
Machine Learning in Healthcare	9	2
Artificial Intelligence in Healthcare	3	2
Artificial Intelligence in Law	1	2
Machine Learning and Data Classification	1	2
Machine Learning in Materials Science	46	3
Artificial Intelligence in Healthcare and Education	145	4
Machine Learning in Healthcare	9	4
Artificial Intelligence in Healthcare	5	4
Natural Language Processing Techniques	1	4
Artificial Intelligence in Healthcare and Education	138	5
Machine Learning in Healthcare	16	5
Machine Learning and Data Classification	1	5
Machine Learning in Healthcare	2	6
Natural Language Processing Techniques	1	6

5.4 Community Visualization

```r
# Create layout for visualization
set.seed(42)
layout_fr <- layout_with_fr(connected_graph)

# Color palette for communities
num_communities <- length(unique(V(connected_graph)$community))
colors <- rainbow(num_communities, alpha = 0.6)

# Plot network colored by community
plot(connected_graph,
     vertex.color = colors[V(connected_graph)$community],
     vertex.size = 3,
     vertex.label = NA,
     edge.arrow.size = 0.3,
     edge.color = alpha("gray", 0.3),
     layout = layout_fr,
     main = "Citation Network Colored by Community")

# Add legend for top communities
top_communities <- head(unique(community_stats$community), 10)
legend("bottomleft",
       legend = paste("Community", top_communities),
       fill = colors[top_communities],
       cex = 0.6)
```



5.5 Inter-Community Connections

```r
# Calculate edges between communities
edge_list <- as_edgelist(connected_graph, names = TRUE)
edge_communities <- data.frame(
  from_comm = V(connected_graph)$community[match(edge_list[,1], V(connected_graph)$name)],
  to_comm = V(connected_graph)$community[match(edge_list[,2], V(connected_graph)$name)]
)

# Count inter vs intra-community edges
edge_communities$edge_type <- ifelse(
  edge_communities$from_comm == edge_communities$to_comm,
  "Intra-community",
  "Inter-community"
)

edge_type_summary <- table(edge_communities$edge_type)
kable(as.data.frame(edge_type_summary),
      caption = "Intra-community vs Inter-community Edges")
```

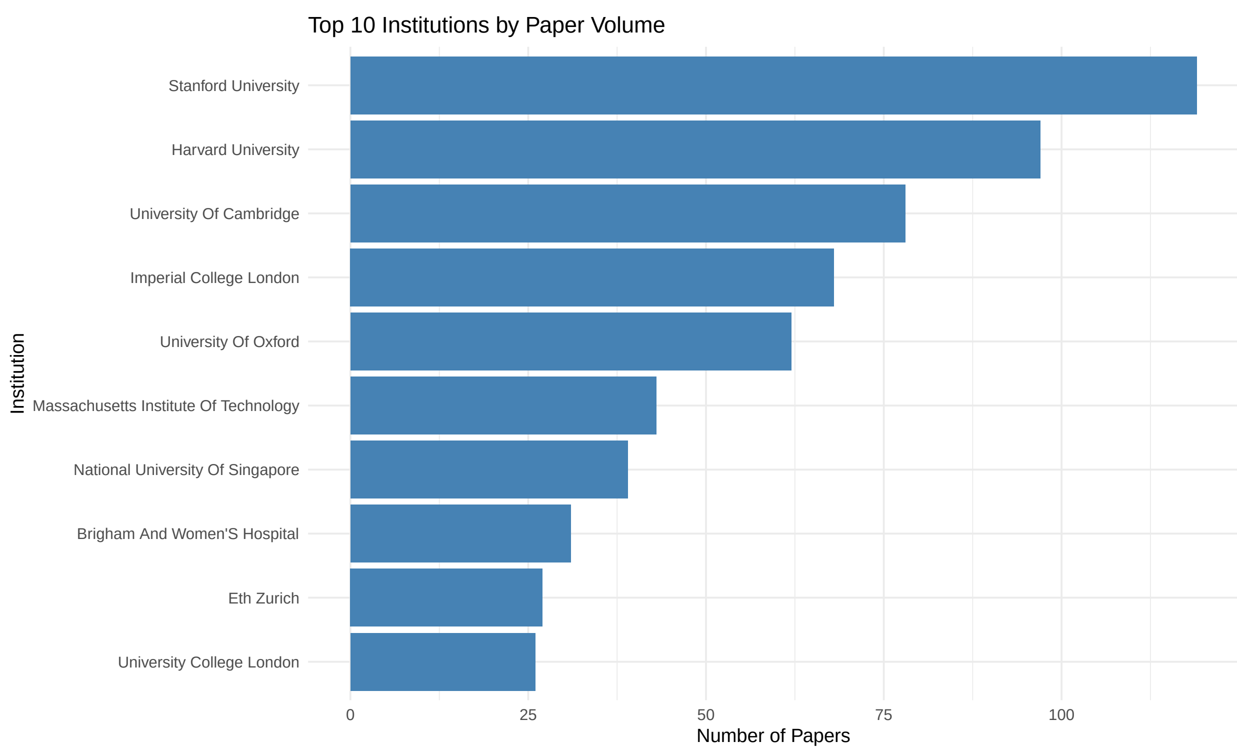
Table 8: Intra-community vs Inter-community Edges

Var1	Freq
Inter-community	1102
Intra-community	2655

6 Research Question 4: Institution/Country Output

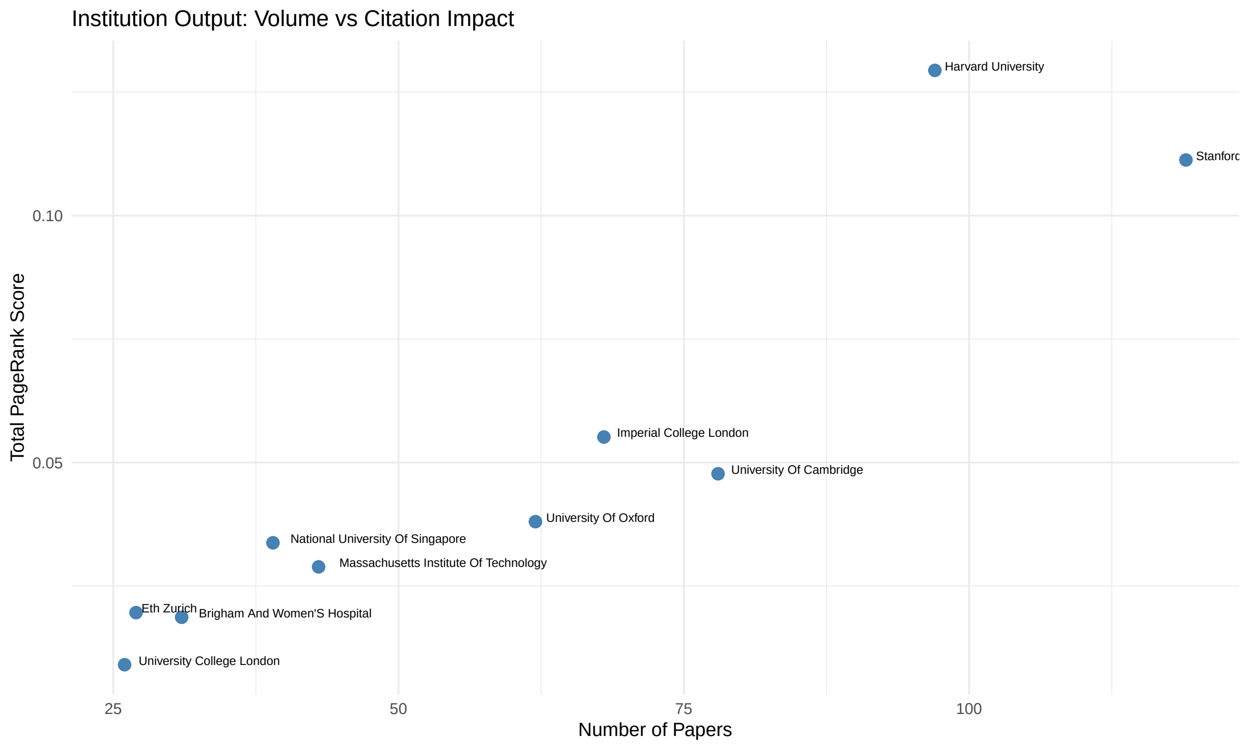
6.1 Paper Count by Institution

```
# Count papers by institution
if ("institution" %in% names(papers_df)) {
  institution_counts <- papers_df %>%
    count(institution, sort = TRUE) %>%
    head(10)

  # Bar plot
  ggplot(institution_counts, aes(x = reorder(institution, n), y = n)) +
    geom_bar(stat = "identity", fill = "steelblue") +
    coord_flip() +
    labs(title = "Top 10 Institutions by Paper Volume",
         x = "Institution", y = "Number of Papers") +
    theme_minimal()
}
```



6.2 Citation-Weighted Impact by Institution

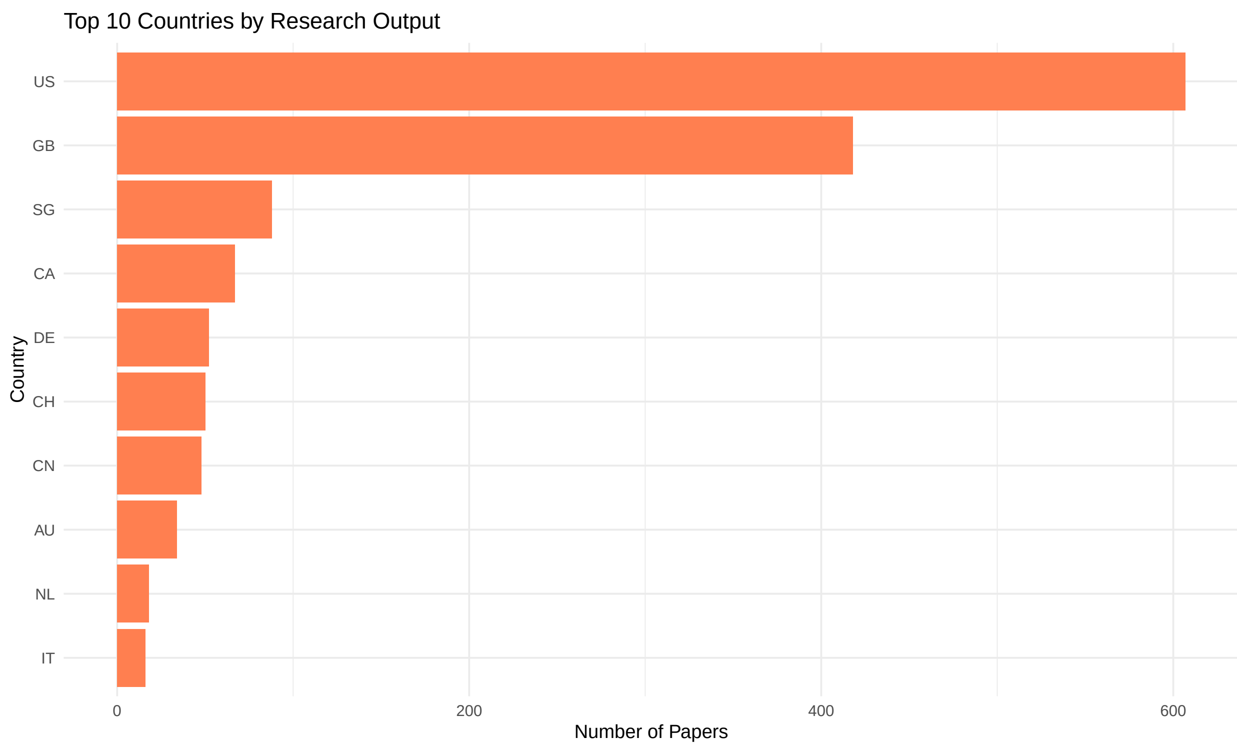
```
if ("institution" %in% names(papers_df)) {
  # Calculate total PageRank by institution
  institution_impact <- centrality_df %>%
    group_by(institution) %>%
    summarise(
      paper_count = n(),
      total_pagerank = sum(pagerank, na.rm = TRUE),
      avg_pagerank = mean(pagerank, na.rm = TRUE),
      total_citations = sum(in_degree, na.rm = TRUE),
      avg_citations = mean(in_degree, na.rm = TRUE)
    ) %>%
    arrange(desc(total_pagerank)) %>%
    head(20)

  kable(institution_impact, digits = 4,
        caption = "Top Institutions by Citation Impact")

  # Comparison plot: Volume vs Impact
  comparison_df <- institution_counts %>%
    left_join(institution_impact, by = "institution") %>%
    filter(!is.na(total_pagerank))

  ggplot(comparison_df, aes(x = n, y = total_pagerank, label = institution)) +
    geom_point(size = 3, color = "steelblue") +
    geom_text(hjust = -0.1, vjust = 0, size = 2.5) +
    labs(title = "Institution Output: Volume vs Citation Impact",
         x = "Number of Papers", y = "Total PageRank Score") +
    theme_minimal()
}
```



6.3 Country-Level Analysis

```
if ("country" %in% names(papers_df)) {
  # Count papers by country
  country_counts <- papers_df %>%
    filter(!is.na(country)&country!="") %>%
    count(country, sort = TRUE) %>%
    head(10)

  # Country impact
  country_impact <- centrality_df %>%
    filter(!is.na(country)&country!="") %>%
    group_by(country) %>%
    summarise(
      paper_count = n(),
      total_pagerank = sum(pagerank, na.rm = TRUE),
      avg_pagerank = mean(pagerank, na.rm = TRUE)
    ) %>%
    arrange(desc(total_pagerank)) %>%
    head(10)

  kable(country_impact, digits = 4, caption = "Top Countries by Research Impact")

  # Visualization
  ggplot(country_counts, aes(x = reorder(country, n), y = n)) +
    geom_bar(stat = "identity", fill = "coral") +
    coord_flip() +
```

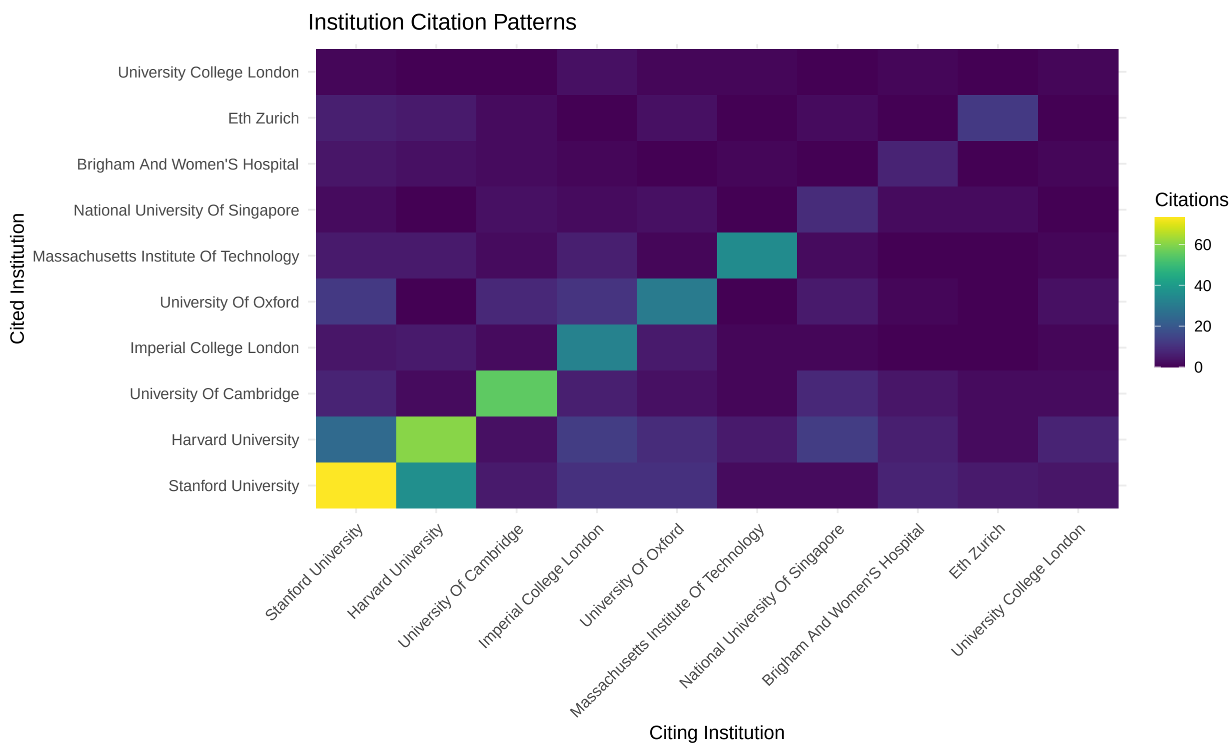
```r
    labs(title = "Top 10 Countries by Research Output",
         x = "Country", y = "Number of Papers") +
    theme_minimal()
}
```



6.4 Institution Collaboration Patterns

```r
if ("institution" %in% names(papers_df)) {
  # Find co-authorship between institutions (papers citing each other)
  top_institutions <- head(institution_counts$institution, 10)

  collaboration_matrix <- matrix(0, nrow = length(top_institutions),
                                 ncol = length(top_institutions))
  rownames(collaboration_matrix) <- top_institutions
  colnames(collaboration_matrix) <- top_institutions

  # Count citations between institutions
  for (i in 1:length(top_institutions)) {
    for (j in 1:length(top_institutions)) {
      inst_i_papers <- papers_df %>% filter(institution == top_institutions[i]) %>% pull(local_id)
      inst_j_papers <- papers_df %>% filter(institution == top_institutions[j]) %>% pull(local_id)

      # Count edges from i to j
      edges_ij <- sum(edge_list[,1] %in% inst_i_papers & edge_list[,2] %in% inst_j_papers)
      collaboration_matrix[i, j] <- edges_ij
    }
  }
```

```r
  # Heatmap
  library(reshape2)
  collab_melt <- melt(collaboration_matrix)

  ggplot(collab_melt, aes(x = Var1, y = Var2, fill = value)) +
    geom_tile() +
    scale_fill_viridis() +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    labs(title = "Institution Citation Patterns",
         x = "Citing Institution", y = "Cited Institution",
         fill = "Citations")
}
```



7 Research Question 5: Research Directions

7.1 Temporal Analysis of Citation Patterns

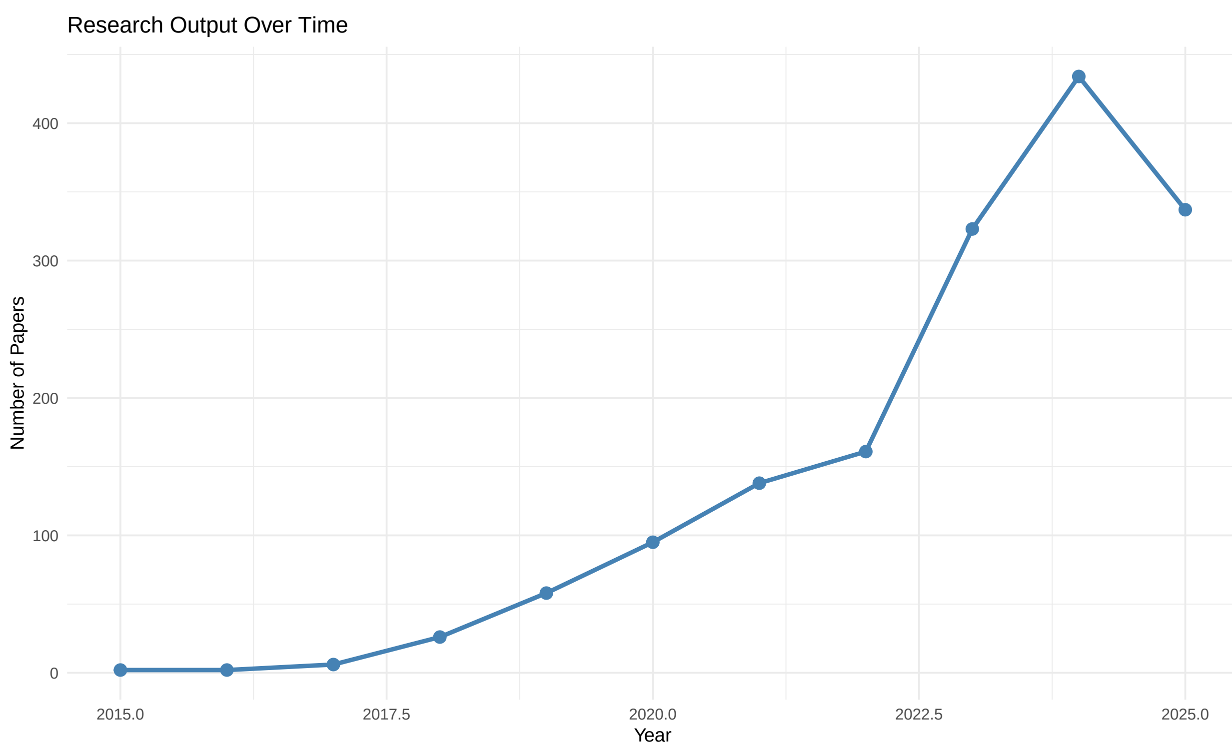
```r
# Divide into time periods
papers_df <- papers_df %>%
  mutate(era = case_when(
    year >= 2015 & year <= 2018 ~ "2015-2018",
    year >= 2019 & year <= 2021 ~ "2019-2021",
    year >= 2022 & year <= 2025 ~ "2022-2025",
    TRUE ~ "Other"
```

```
  ))

# Count papers by era
era_counts <- papers_df %>%
  count(era) %>%
  filter(era != "Other")

kable(era_counts, caption = "Papers by Time Period")
```

Table 9: Papers by Time Period

era	n
2015-2018	36
2019-2021	291
2022-2025	1255

```
# Plot papers over time
papers_by_year <- papers_df %>%
  count(year) %>%
  filter(year >= 2015 & year <= 2025)

ggplot(papers_by_year, aes(x = year, y = n)) +
  geom_line(size = 1.2, color = "steelblue") +
  geom_point(size = 3, color = "steelblue") +
  labs(title = "Research Output Over Time",
       x = "Year", y = "Number of Papers") +
  theme_minimal()
```



7.2 Emerging Bridge Papers (2022-2024)

```r
# Recent papers with high betweenness
recent_bridge <- centrality_df %>%
  filter(year >= 2022 & year <= 2025) %>%
  arrange(desc(betweenness)) %>%
  select(title, first_author, year, betweenness, pagerank, in_degree) %>%
  head(10)

kable(recent_bridge, digits = 3,
      caption = "Recent Papers with High Betweenness (Bridge Papers)")
```

Table 10: Recent Papers with High Betweenness (Bridge Papers)

title	first_author	year	betweenness	pagerank	in_degree
The shaky foundations of large language models and foundation models for electronic health records	Michael Wornow	2023	5287.655	0.006	32
Large language models in medicine	Arun James Thirunavukarasu	2023	4291.818	0.011	104
Multimodal biomedical AI	Julián N. Acosta	2022	3960.812	0.007	26
AI in health and medicine	Pranav Rajpurkar	2022	3551.094	0.010	61
Foundation models for generalist medical artificial intelligence	Michael Moor	2023	2744.235	0.008	63
QUEST-AI: A System for Question Generation, Verification, and Refinement using AI for USMLE-Style Exams	Suhana Bedi	2023	2034.000	0.001	2
Creation and Adoption of Large Language Models in Medicine	Nigam H. Shah	2023	1768.982	0.005	29
A Systematic Review of Testing and Evaluation of Healthcare Applications of Large Language Models (LLMs)	Suhana Bedi	2024	1740.675	0.001	3
AI recognition of patient race in medical imaging: a modelling study	Judy Wawira Gichoya	2022	1354.800	0.005	28
The Diagnostic and Triage Accuracy of the GPT-3 Artificial Intelligence Model	David M Levine	2023	1165.224	0.006	9

7.3 Trend-Setting Papers

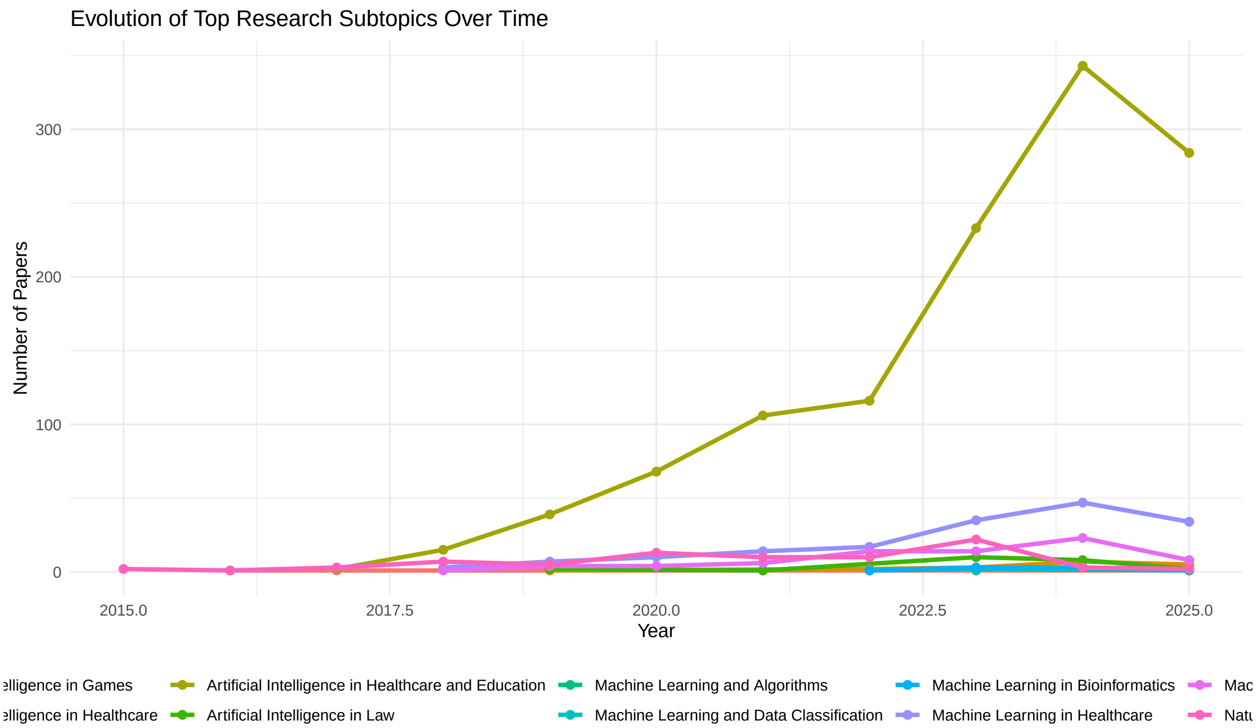
```r
# Recent papers with high PageRank (rapid impact)
recent_impact <- centrality_df %>%
  filter(year >= 2022 & year <= 2025) %>%
  arrange(desc(betweenness)) %>%
  arrange(desc(pagerank)) %>%
  select(title, first_author, year, pagerank, in_degree) %>%
  head(10)

kable(recent_impact, digits = 4, caption = "Recent High-Impact Papers (2022-2024)")
```

Table 11: Recent High-Impact Papers (2022-2024)

title	first_author	year	pagerank	in_degree
Large language models in medicine	Arun James Thirunavukarasu	2023	0.0115	104
AI in health and medicine	Pranav Rajpurkar	2022	0.0105	61
Foundation models for generalist medical artificial intelligence	Michael Moor	2023	0.0084	63
Multimodal biomedical AI	Julián N. Acosta	2022	0.0066	26
The shaky foundations of large language models and foundation models for electronic health records	Michael Wornow	2023	0.0065	32
The Diagnostic and Triage Accuracy of the GPT-3 Artificial Intelligence Model	David M Levine	2023	0.0063	9
Creation and Adoption of Large Language Models in Medicine	Nigam H. Shah	2023	0.0048	29
AI recognition of patient race in medical imaging: a modelling study	Judy Wawira Gichoya	2022	0.0047	28
Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI	Baptiste Vasey	2022	0.0043	37
GenSLMs: Genome-scale language models reveal SARS-CoV-2 evolutionary dynamics	Maxim Zvyagin	2022	0.0038	1

7.4 Evolution of Topics Over Time

```r
# Get top topics overall
all_topics <- papers_df %>%
  count(subtopic, sort = TRUE) %>%
  head(10)

top_topics <- all_topics$subtopic

# Count by year for each top topic
topic_timeline <- papers_df %>%
  filter(subtopic %in% top_topics) %>%
  count(year, subtopic) %>%
  filter(year >= 2015 & year <= 2025)

# Plot evolution
ggplot(topic_timeline, aes(x = year, y = n, color = subtopic, group = subtopic)) +
  geom_line(size = 1.2) +
  geom_point(size = 2) +
  labs(title = "Evolution of Top Research Subtopics Over Time",
       x = "Year", y = "Number of Papers",
       color = "Subtopic") +
  theme_minimal() +
  theme(legend.position = "bottom")
```



7.5 Emerging Communities (Recent Papers)

```r
# Identify communities dominated by recent papers
recent_paper_ids <- papers_df %>%
  filter(year >= 2022 & year <= 2025) %>%
  pull(local_id)

community_recency <- data.frame()

for (comm_id in unique(V(connected_graph)$community)) {
  comm_paper_ids <- V(connected_graph)[V(connected_graph)$community == comm_id]$name

  recent_count <- sum(comm_paper_ids %in% recent_paper_ids)
  total_count <- length(comm_paper_ids)
  recent_ratio <- recent_count / total_count

  community_recency <- rbind(community_recency, data.frame(
    community = comm_id,
    total_papers = total_count,
    recent_papers = recent_count,
    recent_ratio = recent_ratio
  ))
}

# Communities with high proportion of recent papers (emerging topics)
emerging_communities <- community_recency %>%
  filter(total_papers >= 10) %>%  # Only consider sizeable communities
  arrange(desc(recent_ratio)) %>%
```

```r
  head(10)

kable(emerging_communities, digits = 3,
      caption = "Emerging Communities (High Proportion of Recent Papers)")
```

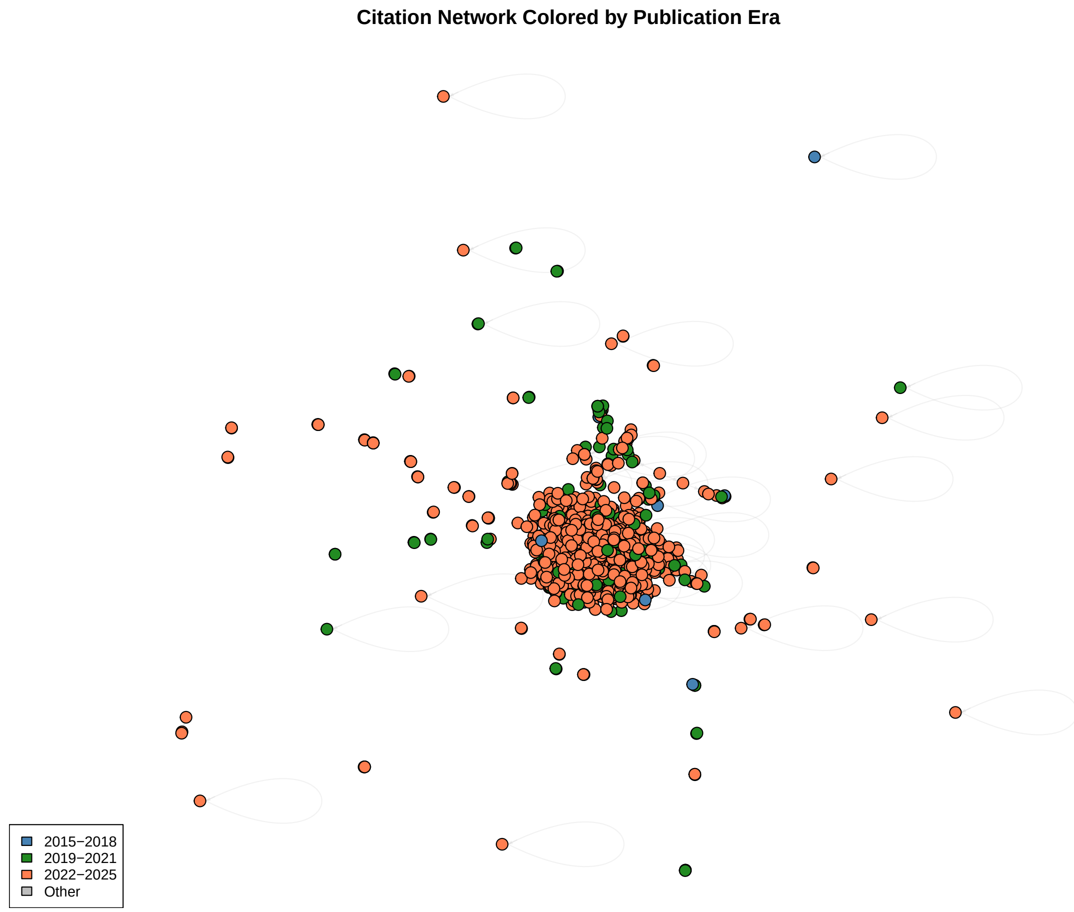
Table 12: Emerging Communities (High Proportion of Recent Papers)

community	total_papers	recent_papers	recent_ratio
1	251	247	0.984
26	19	18	0.947
19	59	55	0.932
11	133	121	0.910
7	42	36	0.857
3	46	39	0.848
17	43	36	0.837
2	85	69	0.812
14	51	40	0.784
5	155	120	0.774

7.6 Network Visualization by Publication Year

```r
# Add year to vertices
vertex_years <- papers_df %>%
  select(local_id, year) %>%
  filter(local_id %in% V(connected_graph)$name)

V(connected_graph)$year <- vertex_years$year[match(V(connected_graph)$name, vertex_years$local_id)]

# Color by era
V(connected_graph)$era <- case_when(
  V(connected_graph)$year >= 2015 & V(connected_graph)$year <= 2018 ~ 1,
  V(connected_graph)$year >= 2019 & V(connected_graph)$year <= 2021 ~ 2,
  V(connected_graph)$year >= 2022 & V(connected_graph)$year <= 2025 ~ 3,
  TRUE ~ 4
)

era_colors <- c("steelblue", "forestgreen", "coral", "gray")

# Plot network colored by time period
plot(connected_graph,
     vertex.color = era_colors[V(connected_graph)$era],
     vertex.size = 3,
     vertex.label = NA,
     edge.arrow.size = 0.2,
     edge.color = alpha("gray", 0.2),
     layout = layout_fr,
     main = "Citation Network Colored by Publication Era")

legend("bottomleft",
```

```r
        legend = c("2015-2018", "2019-2021", "2022-2025", "Other"),
        fill = era_colors,
        cex = 0.8)
```

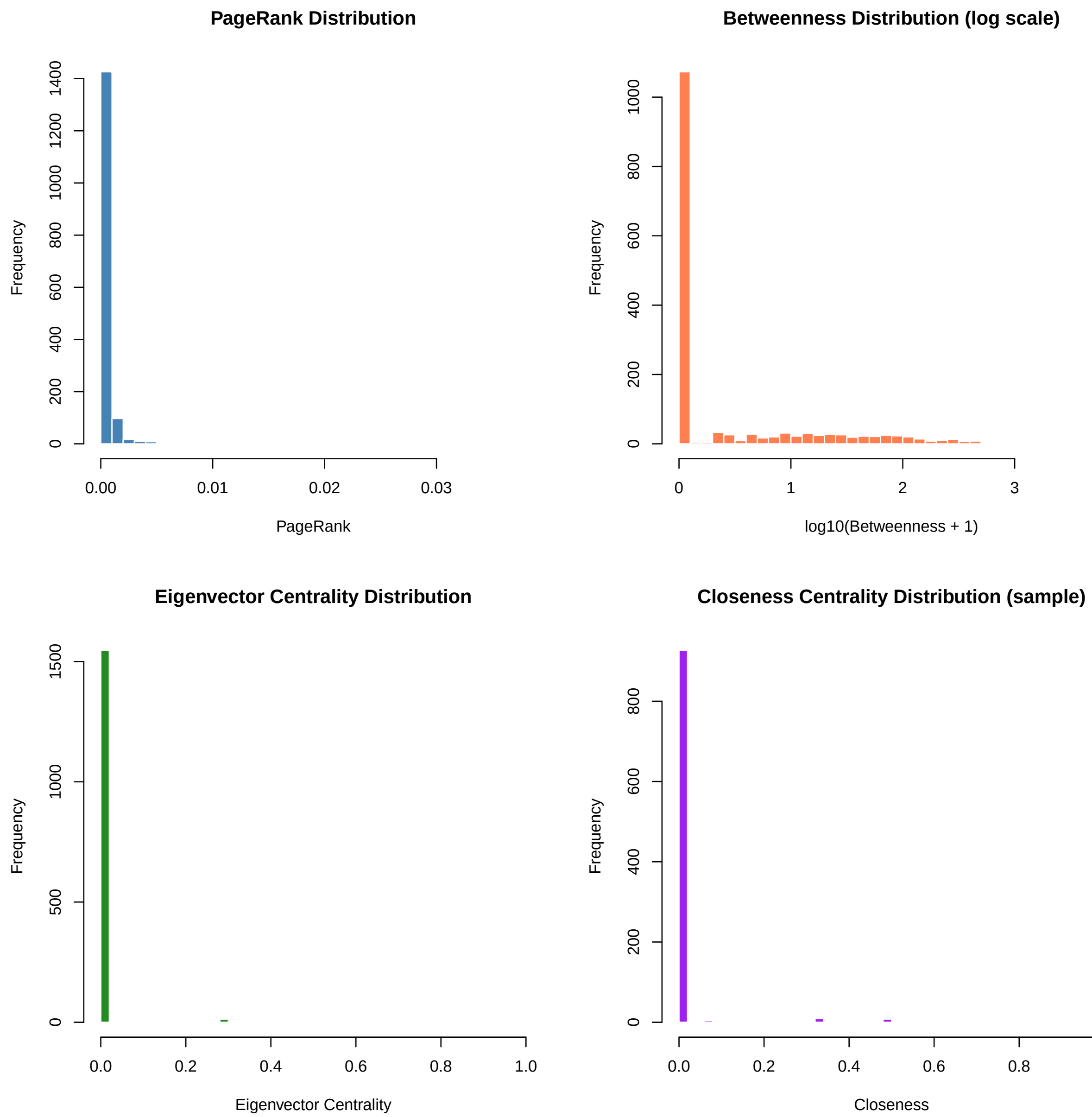


8 Advanced Network Analysis

8.1 Centrality Distributions

```r
par(mfrow = c(2, 2))

# PageRank distribution
hist(centrality_df$pagerank, breaks = 50,
     main = "PageRank Distribution", xlab = "PageRank",
     col = "steelblue", border = "white")

# Betweenness distribution
hist(log10(centrality_df$betweenness + 1), breaks = 50,
```

```r
     main = "Betweenness Distribution (log scale)", xlab = "log10(Betweenness + 1)",
     col = "coral", border = "white")

# Eigenvector centrality
hist(centrality_df$eigenvector, breaks = 50,
     main = "Eigenvector Centrality Distribution", xlab = "Eigenvector Centrality",
     col = "forestgreen", border = "white")

# Closeness centrality (sample for speed)
sample_nodes <- sample(V(connected_graph), min(1000, vcount(connected_graph)))
closeness_sample <- closeness(connected_graph, vids = sample_nodes, mode = "all")
hist(closeness_sample, breaks = 50,
     main = "Closeness Centrality Distribution (sample)", xlab = "Closeness",
     col = "purple", border = "white")
```




```
par(mfrow = c(1, 1))
```

8.2 K-Core Decomposition

```
# K-core decomposition
kcore_values <- coreness(connected_graph, mode = "all")
V(connected_graph)$kcore <- kcore_values

kcore_summary <- data.frame(
  kcore = sort(unique(kcore_values), decreasing = TRUE)
) %>%
```

```r
  rowwise() %>%
  mutate(num_nodes = sum(kcore_values >= kcore))

kable(head(kcore_summary, 15), caption = "K-Core Decomposition Summary")
```

Table 13: K-Core Decomposition Summary

kcore	num_nodes
6	35
5	230
4	459
3	724
2	1092
1	1582

```r
# Plot k-core distribution
ggplot(data.frame(kcore = kcore_values), aes(x = kcore)) +
  geom_histogram(binwidth = 1, fill = "steelblue", color = "white") +
  labs(title = "K-Core Distribution",
       x = "K-Core Value", y = "Number of Nodes") +
  theme_minimal()
```