Unveiling Echo Chambers on YouTube: Analyzing Political Discourse and Social Dynamics Through Advanced Quantitative Methods

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Executive Summary

(150 words) – 0.3 POINTS Summarize the report. Write this as the very last thing.

- What is the main topic you are addressing?
- What are your research questions and hypotheses?
- What are your results and the main conclusion?

2 Introduction

Research on social media platforms, such as Twitter and Facebook, extensively explores echo chambers - environments where individuals connect with like-minded peers, reinforcing selective exposure to information aligning with their beliefs (Cinelli, De Francisci Morales, Galeazzi, Quattrociocchi, & Starnini, 2021). These principles, observed on social media platforms marked by informational homogeneity, apply to broader political discourse and policy debates (Jasny, Waggle, & Fisher, 2015). This suggests that the mechanisms of selective exposure observed in social media echo chambers may extend to diverse communication networks (Colleoni, Rozza, & Arvidsson, 2014). In the political domain, these tendencies contribute to polarization and extreme political positions (Colleoni et al., 2014). This harms social cohesion and trust, challenging finding common ground between political parties (McCoy & Somer, 2019) and shaping public discourse across diverse communication networks (Levy & Razin, 2019). Despite extensive research on platforms such as Twitter, the impact of echo chambers on YouTube, the second-largest social platform, remains understudied. YouTube's unique structure and user interaction patterns, distinct from platforms like Twitter, may pose challenges in recognizing and understanding echo chambers on this platform.

3 Methodology

3.1 Dataset

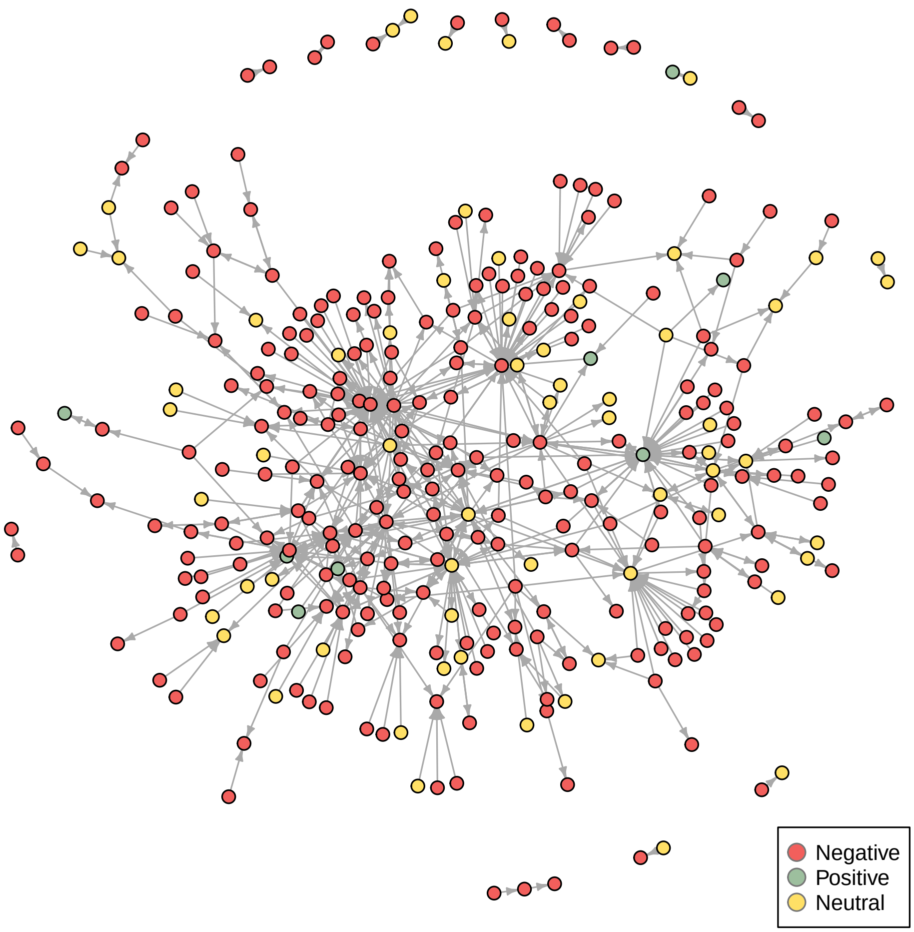

Figure 1. The plot of the network used for analysis. It shows the majority of the nodes labelled negative.

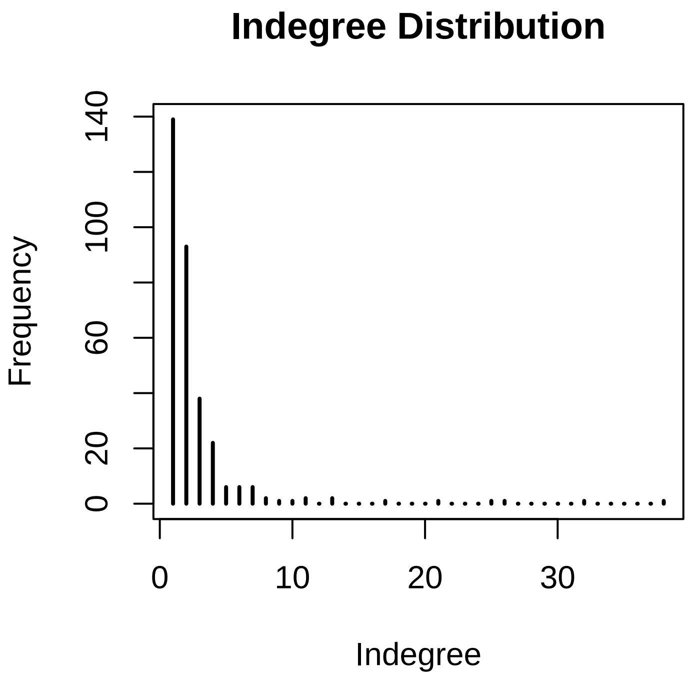

Figure 2. The plot above shows the indegree distribution for the actors in the network.

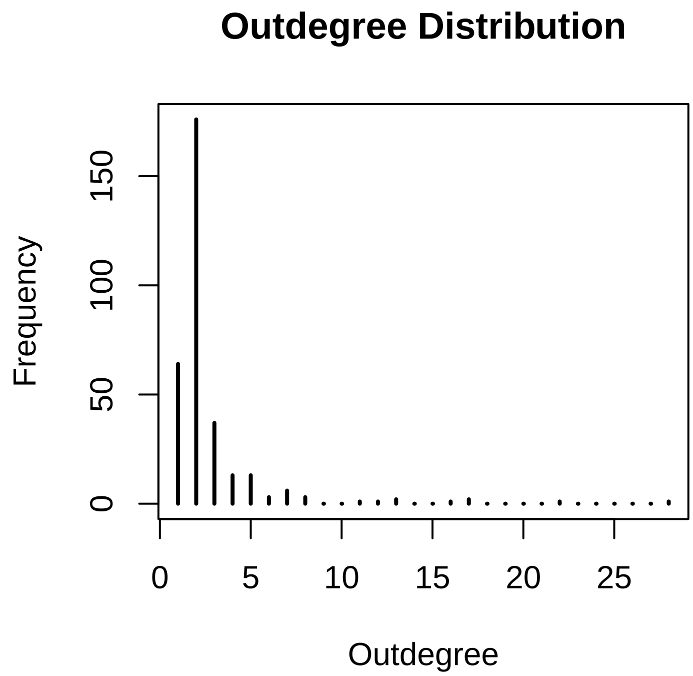

Figure 3. The plot above shows the outdegree distribution for the actors in our network.

Table 1

An overview of the reciprocal dyads.

Mutual	Asymmetric	Null
70	413	51843

3.1.1 Potential Bias.

3.2 Research Rationale

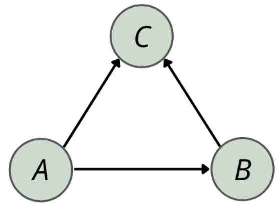

Figure 4. An echo chamber representation within the structural network configuration, also known as a transitive triad.

Table 2

Results of CUG tests.

	Empirical Value	Probability versus simulations $Pr(X >= Obs)$
Eigenvector Centrality	0.92	0.466
Degree Centrality	0.12	0
Betweenness Centrality	0.13	0.451

4 Results

Study 1:

Study 2:

5 Discussion and Conclusion

References

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences*, *118*(9), e2023301118.

Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in twitter using big data. *Journal of Communication*, *64*(2), 317–332.

Jasny, L., Waggle, J., & Fisher, D. R. (2015). An empirical examination of echo chambers in US climate policy networks. *Nature Climate Change*, *5*(8), 782–786.

Levy, G., & Razin, R. (2019). Echo chambers and their effects on economic and political outcomes. *Annual Review of Economics*, *11*, 303–328.

McCoy, J., & Somer, M. (2019). Toward a theory of pernicious polarization and how it harms democracies: Comparative evidence and possible remedies. *The Annals of the American Academy of Political and Social Science*, *681*(1), 234–271.

Appendix A

This first appendix includes all of the R chunks of code that were hidden throughout the document (using the `include = FALSE` chunk tag) to help with readibility and/or setup.

R set-up code

```
# Seed for random number generation
set.seed(42)
knitr::opts_chunk$set(cache.extra = knitr::rand_seed)
```

In Chapter 3

```
# Code for plotting the network
igraph::V(graph)$color <- "black"
igraph::V(graph) [ sentiment == 'negative' ]$color <- "#F25F5C"
igraph::V(graph) [ sentiment == 'positive' ]$color <- "#9DBF9E"
igraph::V(graph) [ sentiment == 'neutral' ]$color <- "#FFE066"

plot(
  graph,
  vertex.label = NA,
  edge.arrow.size = .35,
  vertex.size = 3,
  vertex.color = igraph::V(graph)$color
)

colrs <- c("#F25F5C","#9DBF9E","#FFE066")
graphics::legend(x = 0.75, y = -.85, c("Negative","Positive","Neutral"),
                 pch = 21, col = "#777777", pt.bg = colrs, pt.cex = 1.5,
```

```
                  cex = .8, bty = "o", ncol = 1)
```

```
# Code for plotting the indegree distribution
degree_distribution_in <- snafun::g_degree_distribution(graph,
                                                        mode = "in",
                                                        type = "count"
                                                        )
# Create a frequency plot with lines
plot(1:length(degree_distribution_in), degree_distribution_in, type = "h",
     lwd = 2, main = "Indegree Distribution",
     xlab = "Indegree", ylab = "Frequency")
```

```
# Code for plotting the outdegree distribution
degree_distribution_out <- snafun::g_degree_distribution(graph,
                                                         mode = "out",
                                                         type = "count"
                                                         )


# Create a frequency plot with lines
plot(1:length(degree_distribution_out), degree_distribution_out, type = "h",
     lwd = 2, main = "Outdegree Distribution",
     xlab = "Outdegree", ylab = "Frequency")
```

```
dyad_count <- snafun::count_dyads(graph, echo = FALSE)
# knitr::kable(dyad_count, caption = "(ref:dyad-count-table)")
apa_table(dyad_count,
          placement = "h",
          caption = "(ref:dyad-count-table)")
```

```r
# Reading file from figures directory
knitr::include_graphics(
  "SNA4DS_Report_files/figures/transitive_triad_2.png"
  )
```

Appendix B

```r
centralities_plot <- snafun::plot_centralities(
  graph,
  measures = c("betweenness", "closeness", "degree", "eccentricity"),
  directed = TRUE,
  mode = "all",
  k = 3,
  rescaled = FALSE
)
```

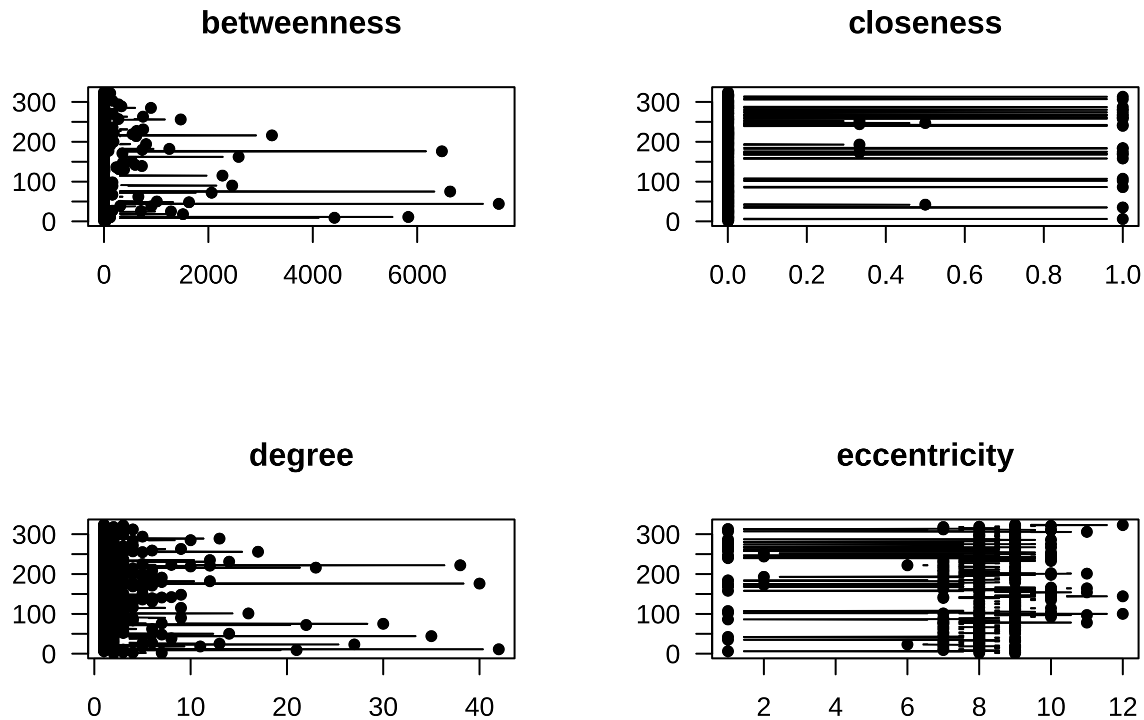

Figure 5. Plot for different centralities of our network