Assignment 2: Analyzing Bluesky

Social Algorithms (S&DS 3350/5350)

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Part I: Feed Analysis

I.2 Senators You May Know Recommendation Table

Senator	Rec 1	Rec 2	Rec 3
Jeff Merkley	Tina Smith (33)	Sheldon Whitehouse (33)	Ron Wyden (33)
Kirsten Gillibrand	Tina Smith (33)	Sheldon Whitehouse (33)	Ron Wyden (33)
Maggie Hassan	Tina Smith (33)	Sheldon Whitehouse (33)	Ron Wyden (33)
Jon Ossoff	Tina Smith (33)	Sheldon Whitehouse (33)	Ron Wyden (33)
Mark Kelly	Tina Smith (33)	Sheldon Whitehouse (33)	Ron Wyden (33)
Mark Warner	Martin Heinrich (32)	Patty Murray (32)	Cory Booker (31)
Ben Ray Lujan	Alex Padilla (32)	Brian Schatz (32)	Cory Booker (31)
Adam Schiff	Ed Markey (32)	Brian Schatz (32)	Michael Bennet (30)
Brian Schatz	Chris Van Hollen (31)	Elizabeth Warren (31)	Tim Kaine (30)
Chris Van Hollen	Elizabeth Warren (31)	Tim Kaine (30)	Richard Blumenthal (28)
Maria Cantwell	Chuck Schumer (31)	Chris Murphy (25)	Jeanne Shaheen (22)
Martin Heinrich	Mark Warner (31)	Bernie Sanders (24)	Lisa Blunt Rochester (21)
Chris Coons	John Fetterman (30)	Tammy Baldwin (26)	Chris Murphy (25)
Lisa Blunt Rochester	John Fetterman (30)	Tammy Baldwin (26)	Chris Murphy (25)
Tammy Baldwin	John Fetterman (30)	Dick Durbin (13)	Jack Reed (13)
Alex Padilla	Richard Blumenthal (28)	Tammy Baldwin (26)	Chris Murphy (25)
Mazie Hirono	Tammy Baldwin (26)	Ruben Gallego (25)	Adam Schiff (25)
Ruben Gallego	Tammy Baldwin (26)	Adam Schiff (25)	Ben Ray Lujan (24)
Gary Peters	Bernie Sanders (24)	Lisa Blunt Rochester (21)	Tammy Duckworth (21)
Elizabeth Warren	Bernie Sanders (24)	Lisa Blunt Rochester (21)	Tammy Duckworth (21)
Michael Bennet	Bernie Sanders (24)	Andy Kim (17)	Elissa Slotkin (17)
Andy Kim	Jeanne Shaheen (22)	Raphael Warnock (18)	Dick Durbin (13)
Elissa Slotkin	Tammy Duckworth (21)	Amy Klobuchar (21)	Dick Durbin (13)
Tina Smith	Lisa Blunt Rochester (21)	Dick Durbin (13)	Angela Alsobrooks (7)
Cory Booker	Raphael Warnock (18)	Elissa Slotkin (17)	Dick Durbin (13)
Angela Alsobrooks	Raphael Warnock (18)	Dick Durbin (13)	Jack Reed (13)
Jack Reed	Andy Kim (17)	Elissa Slotkin (17)	Dick Durbin (13)
Richard Blumenthal	Andy Kim (17)	Elissa Slotkin (17)	Mazie Hirono (13)
Amy Klobuchar	Andy Kim (17)	Elissa Slotkin (17)	Maggie Hassan (4)
Ed Markey	Andy Kim (17)	Dick Durbin (13)	Mazie Hirono (13)
Dick Durbin	Andy Kim (17)	Mazie Hirono (13)	Jack Reed (13)
Ron Wyden	Elissa Slotkin (17)	Mazie Hirono (13)	Chris Coons (11)
Sheldon Whitehouse	Elissa Slotkin (17)	Jeff Merkley (5)	Maggie Hassan (4)
Patty Murray	Dick Durbin (13)	Mazie Hirono (13)	Jack Reed (13)
Tammy Duckworth	Mazie Hirono (13)	Jack Reed (13)	Chris Coons (11)
Tim Kaine	Mazie Hirono (13)	Jeff Merkley (5)	Maggie Hassan (4)
Raphael Warnock	Chris Coons (11)	Jeff Merkley (5)	Mark Kelly (2)
Jeanne Shaheen	Angela Alsobrooks (7)	Jeff Merkley (5)	Mark Kelly (2)
Chuck Schumer	Jeff Merkley (5)	Jon Ossoff (1)	Kirsten Gillibrand (0)
Bernie Sanders	This senator follows no other senators.	N/A	N/A
John Fetterman	This senator follows no other senators.	N/A	N/A
Chris Murphy	This senator follows no other senators.	N/A	N/A

Table 1: Senators You May Know Recommendations

Followed by ALL: None

Followed by ZERO: ['kirstengillibrand.bsky.social']

Follows ALL: None

Follows ZERO: ['sanders.senate.gov', 'fetterman.senate.gov', 'jeff-merkley.bsky.social', 'kirstengillibrand.bsky.social', 'hassan.senate.gov', 'chrismurphyct.bsky.social', 'captmarkkelly.bsky.social']

I.3 Jaccard Similarities

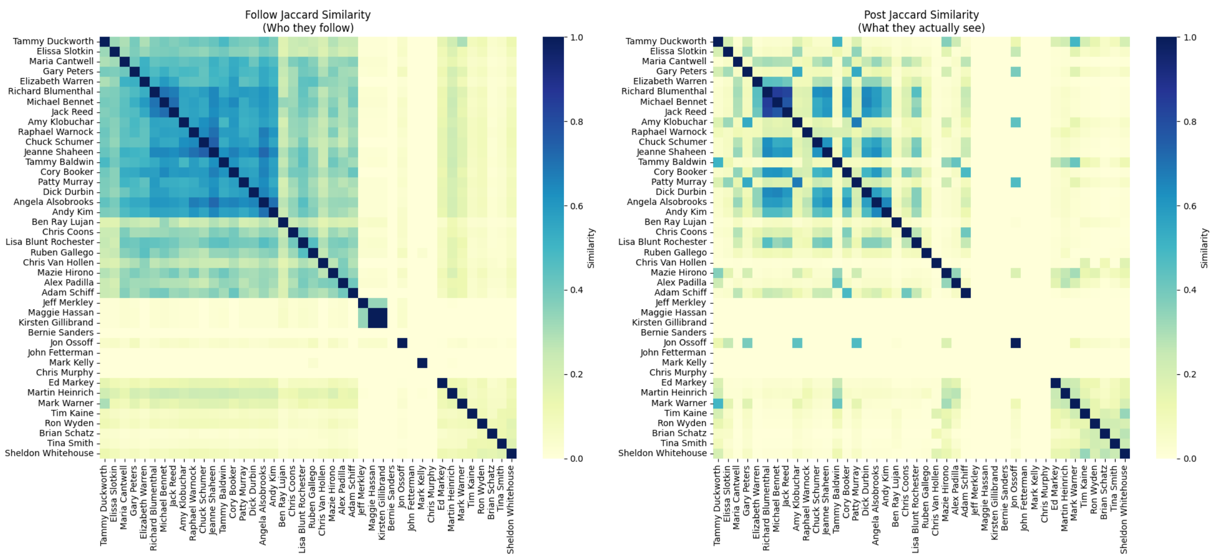


Figure 1: Jaccard Similarities Heatmap

I.4 Discussion

Follow Jaccard has a large, cohesive block in the upper-left corner, forming a broad cluster. This shows that many senators have moderately high overlap in who they follow on bluesky. There is also a smaller block in the middle more towards the lower-right, where 3 senators share overlap. Several rows/columns towards the bottom are much lighter, which shows senators whose follow lists are very different from the main cluster.

On the other hand, the Post Jaccard heatmap is a lot more sparse. The upper-left block is no longer smoothly clustered, and now contains many small 3x3 squares of clustered senators, broken up by individual senators who share similarity with other senators not in those clusters. Many of the off diagonal values are close to 0. This suggests that even when senators follow similar accounts, what they actually see on the bluesky platform in a 24-hour feed is less similar. This is likely due to variation in posting volume across followed accounts.

The left matrix has one large, smooth cluster,while the right matrix has sharper, more localized clusters of similarity. This highlights that shared follow lists do not necessarily translate to shared exposure in practice. One potential explanation could be a few high-volume posters dominating feeds and varying across senators. These heatmaps suggest that feed content similarity is more fragmented and sensitive to posting frequency and timing, even when the shared information environment of follow lists is similar.

Weighting by post volume/engagement makes the similarity structure more clustered and more unequal. Shared follows matter less than whether those shared accounts are very active or engaging.

I.4.1 Feed overlap structure

Feed overlap structure (Jaccard heatmaps): The follow-Jaccard heatmap shows a broad shared cluster, suggesting many Democratic senators follow a similar core set of accounts. The post-Jaccard heatmap is more sparse and breaks into smaller clusters, which implies that shared follows do not translate into shared exposure in practice. This points to a caucus that looks cohesive by who they follow but more fragmented in what they actually see, with a few small clusters and some low-overlap outliers.

I.4.2 Implications of feed volume differences

Implications of feed volume differences: The post-Jaccard matrix being more fragmented than the follow-Jaccard matrix matches how high-volume accounts can dominate real feed exposure. Senators that follow many high-volume accounts probably see more content and different mixtures of content than senators who follow fewer or lower-volume accounts, which could meaningfully change what they learn about constituent concerns even with similar follow lists. You can see this highlighted through the divergence between the two heatmaps.

I.4.3 Recommendation network interpretation

The most frequently recommended senators are Dick Durbin (9), Mazie Hirono (7), Elissa Slotkin (7), Andy Kim (6), and then Jack Reed / Jeff Merkley / Tina Smith / Sheldon Whitehouse / Ron Wyden / Tammy Baldwin (5 each). This suggests that these senators are located in the densest parts of the follow network and are common bridges across other senators' follow sets. Senators who follow no other senators are very disconnected are Bernie Sanders, John Fetterman, and Chris Murphy.

Part II: Reply Homophily Analysis

II.2 Gender Inference

Total repliers: 12372

Classified: 4168 (33.7%)

Female: 1553 (12.6%)

Male: 2615 (21.1%)

Unknown: 8204 (66.3%)

We found that of the 12,372 repliers, only roughly 1/3 of them could be classified with a 60% threshold to be either male or female. This large proportion of unknown may in large part be due to some limitations that the code does not address:

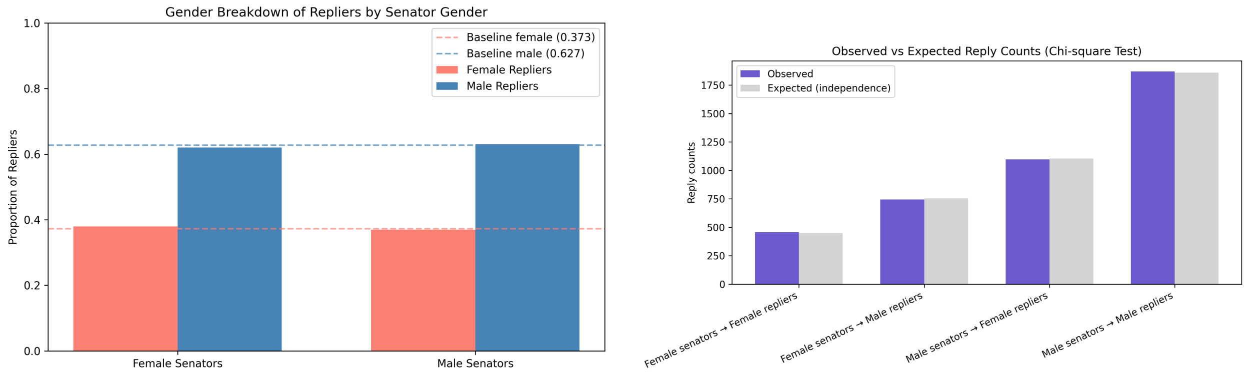
Display names sometimes are not always real names. People use nicknames (some nicknames may not appear in the SSA data), have emojis or numbers in their name, or use an alias / their username

With the SSA data only containing names registered in the US, there may be unregistered international names that won't appear in the data - therefore excluding some non-American users

Names shift in gender associations, so there may be names that are in a moment of "shift" where there is a 50/50 split in gender

It is also important to note that the 1/3 of people who were classifiable may not be representative of all repliers. This misalignment could affect the homophily estimates in the following section.

II.3 Homophily Measurement



(a) Homophily Visualization

(b) Chi Square test (observed vs. expected)

Figure 2: Homophily measurement and statistical test summary.

— Homophily Analysis —

Baseline: p_female = 0.373, p_male = 0.627

Female senators: 0.380 of repliers are female

Male senators: 0.630 of repliers are male

H_female = +0.008

H_male = +0.003

Chi-square test for homophily significance:

Chi-square statistic: 0.373

P-value: 0.541

The homophily is not statistically significant.

To test the statistical significance of our homophily findings, we conducted a chi-squared test of independence, and we found that our observed homophily coefficients were statistically insignificant with a p-value of 0.541 at an alpha level of 0.05. Thus, we find no evidence to reject the null hypothesis of replier gender being independent of senator gender.

II.4 Reply Timing Analysis

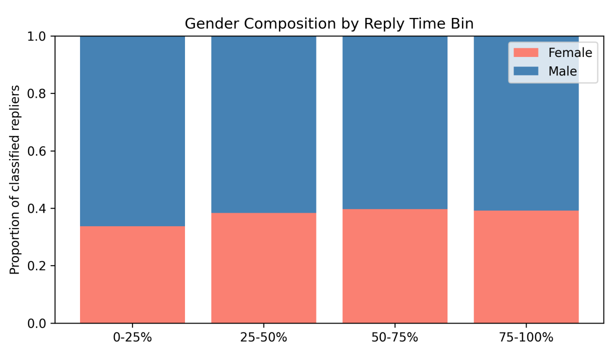


Figure 3: gender by reply time

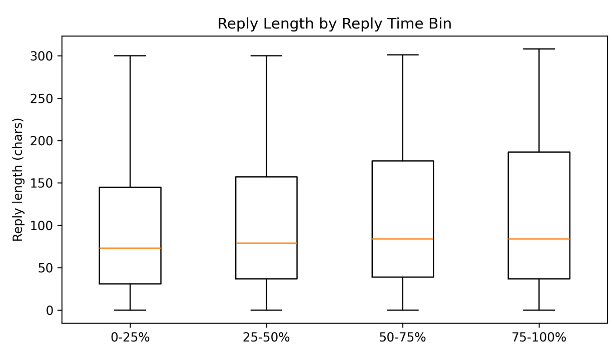


Figure 4: length of response by reply time

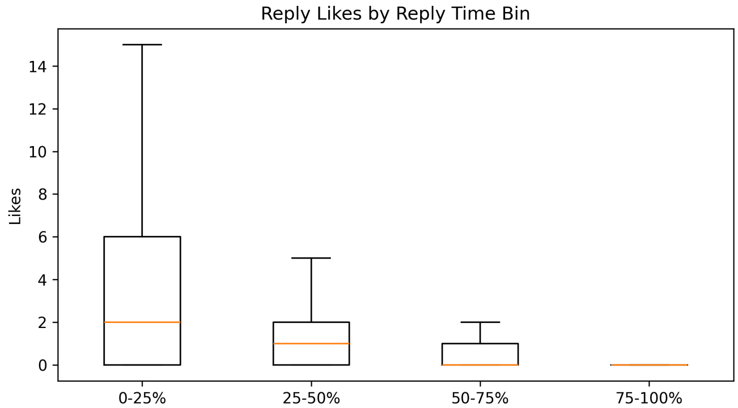


Figure 5: reply likes by reply time

The reply timing analysis reveals notable differences between early and late replies. Among posts with 50 to 200 total replies, early repliers (first 25% by timestamp) received far more engagement, averaging 9.34 likes compared to just 0.35 likes for late repliers (last 25%). This suggests that early replies gain significantly more visibility, likely because they are seen by more users as the thread grows. The gender composition of replies also shifts over time. Early replies skew more male, with 66.3% male and 33.7% female among classifiable repliers. Late replies show a higher proportion of female repliers at 38.5%, compared to 61.5% male. This shift is particularly important for interpreting our homophily results, because the Bluesky API returns at most 200 replies per post, biased toward the earliest responses. For senators like Schumer and Sanders, who routinely receive well over 200 replies per post, we are only capturing the early, more male-skewing portion of the conversation. This means our overall baseline may underestimate the true proportion of female repliers, which could in turn affect the homophily coefficients computed in the previous section. Late replies also tended to be slightly longer, averaging 116 characters compared to 99 characters for early replies.

The API reply limit thus introduces some baked-in bias that our analysis adopts. Our conclusions should therefore be understood with the caveat that the repliers we analyze may not be representative of the whole

II.5 Reflection Questions

II.5.1 Limitations of first-name gender inference

This data is US centric and binary. Trying to guess gender based on first names based on this data leads to many international, culturally specific, or non-binary names being potentially misclassified or unclassified. Display names are also often noisy (handles, nicknames, initials), and name-gender associations are not necessarily consistent across time (certain names more likely to be male/female depending on the year/decade). This leads to potentially high unknown rates or bias in who gets classified.

II.5.2 Other forms of homophily

It may be interesting/useful to try and infer geographic location from profiles or state/district, then compare reply/follow rates within vs across states/regions. It also may be interesting, on the topic of geography, to try and classify senators/users as rural vs. urban and see if there are any patterns using that discriminating factor.

We could also classify posts/replies by topic (keywords or embeddings), then measure whether senators attract replies from accounts that post on similar topics or have similar perspectives on key issues.

We could additionally compare interactions within similar time zones or posting windows (e.g., same-hour reply propensity), to see if there are trends among when people post vs. reply outside of simple temporal proximity.

Finally, we could compare committee membership or leadership roles using publicly available metadata on senators to see if there are clusters between senators who spend time together in committee or work together often, or we could see if senators seated close to each other in the senate room are more likely to follow each other or have similar followings.

II.5.3 Coverage of high-reply posts

The API returns a maximum of 200 replies per post, prioritizing the earliest responses. For posts that receive greater than 1,000 replies, this constraint captures only about 20

The 80Gender composition: Female share is lower in early replies (0.337) than in late replies (0.385).

Length: Early replies are shorter on average (99.1 characters) compared with later replies (116.0 characters).

Engagement: Early replies receive substantially more likes (9.34 on average) than later replies (0.35). These patterns highlight that the captured data disproportionately represents high-visibility, high-engagement interactions, whereas the later replies tend to be longer, less amplified, and marginally more female-skewed. Because of this, estimates of gender homophily should be interpreted with some level of caution. The results mainly reflect early-reply dynamics and might not generalize accurately to the overall reply population. Inclusion of later replies could shift some of the observed same-gender interaction rates, which could alter the magnitude or direction of homophily effects.

Part III: Platform Biases

III.1 Generalizability / partisan claims

With 41 Democrats and 1 Independent, the sample reflects a very small portion of senators and an even smaller subset of political figures. Findings are at best generalizable only to Democratic senators who chose to adopt Bluesky, rather than to the Senate as a whole or any partisan dynamics. With zero Republicans, it's impossible to make empirical claims about partisan patterns, and any claims we could make would be speculative.

III.2 How to study partisan homophily

In order to study partisan homophily, we could consider taking data from other platforms, or even a combination of different platforms, in order to get a more representative sample of varying partisan affiliations. We could look at platforms like X (Twitter), Facebook, Instagram, YouTube, and Truth Social. These have broader, more cross-party representation among elected officials.

We could then build a cross-platform list of verified senator accounts (and party labels), collect interactions (replies, quotes, mentions, reshares) over a fixed window, and then construct a partisan interaction matrix: Democrat -¿ Democrat, Democrat -¿ Republican, etc. Then, we could compare observed interaction rates to a baseline (such as expected rates based on overall platform activity), and test for independence. Finally we would report differences by platform to show how platform composition shifts homophily.

III.3 Effect of Bluesky's user base on gender homophily

If Bluesky skews heavily toward one party or demographic, the baseline distribution of replier gender is already shifted. That can produce any observed homophily (or mask it) even when we are only studying gender alone, because the pool of potential repliers is not politically or demographically neutral. This means that observed gender patterns may partly reflect platform composition instead of senator-specific preferences. For Bluesky specifically, we observed no Republican representation, and majority democratic affiliation. From outside information, we know that women are significantly more likely than men to lean towards the Democratic party. This gender homophily could be embedded in the sample through the fact that bluesky's data is almost exclusively democrats, and could bleed through into our results without necessarily representing the gender homophily we were trying to isolate.

Appendix

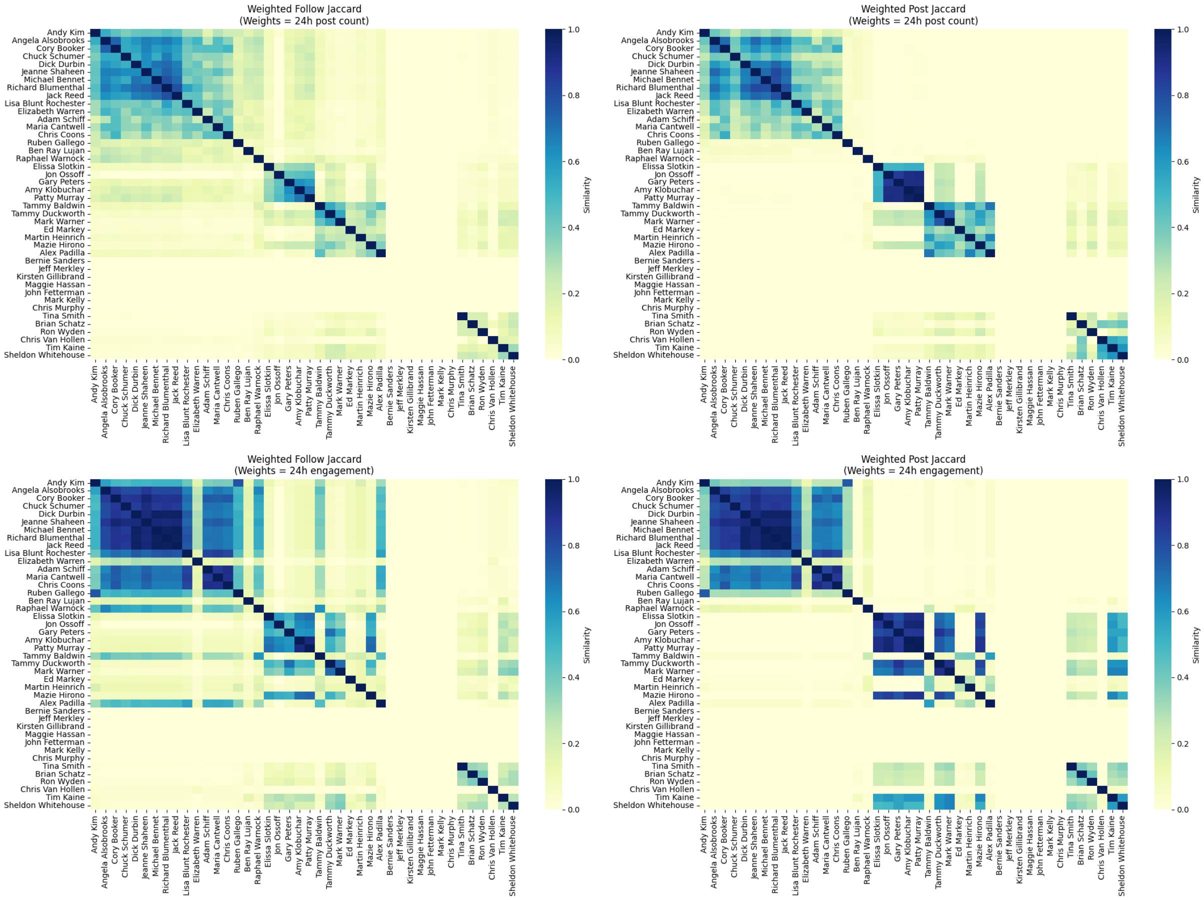


Figure 6: Jaccard Similarities Heatmap (Weighted)