Retweets Distort Exposure to Polarized Information

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ABSTRACT
The growing prominence of social media in public discourse has led to greater scrutiny of the quality of information spreading online and the role that polarization plays in this process. However, studies of information spread on social media platforms like Twitter have been hampered by the difficulty of collecting data about the social graph, specifically follow links that shape what users see in their timelines. As a proxy of the follower graph, researchers use retweets to construct the diffusion graph, although it is not clear how these proxies affect studies of online information ecosystems. Using a dataset containing a sample of the Twitter follower graph and the tweets posted by users within it, we reconstruct the retweet graph and quantify its impact on the measures of exposure. While we find that echo chambers exist in both networks, they are more pronounced in the retweet neighborhood. We compare the polarization of information users see via their follower and retweet graphs to show that retweeted accounts systematically share more politically extreme content and misinformation. This bias cannot be explained by the activity or polarization within users’ own social neighborhoods but by the increased attention they pay to more polarized sources. Our results suggest that studies relying on the follower graphs underestimate the polarization of information users pay attention to online.

CSCS CONCEPTS
• Networks → Network types; • Information systems → Social networks.

KEYWORDS
information propagation, social network comparison, misinformation, polarization

ACM Reference Format:
Ashwin Rao, Fred Morstatter, and Kristina Lerman. 2018. Retweets Distort Exposure to Polarized Information. In Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference acronym ’XX’). ACM, New York, NY, USA, 10 pages. https://doi.org/XXXXXX.XXXXXXX

1 INTRODUCTION
Social media has become a popular platform for sharing information. Its wide reach and low barriers to entry, however, have raised concerns about the quality and validity of online information. Misinformation spreads easily online with adverse outcomes for society. Health misinformation about the Covid-19 pandemic, for example, has been implicated in resistance to virus mitigation measures such as masking and vaccination [30].

Previous research on the influence and impact of misinformation focuses on identifying accounts that promote misleading health claims, such as the “disinformation dozen” [21] during the pandemic. However, the influence of these accounts on the information their followers receive and their beliefs is complex and cannot be quantified simply by the volume of messages these accounts generate, their number of followers or centrality within the follower graph. To understand the joint influence of social media accounts on shaping the exposure to information and misinformation, researchers have examined the role of network structure [1, 20], particularly, the formation echo chambers, wherein people follow accounts that expose them to information that is congruent to their existing beliefs. Studies of online echo chambers (e.g., [9, 25]) have typically used the follower graph and show that people followed accounts whose beliefs and opinions coincided with their own. This is important, because “friends”, i.e., the accounts users follow, largely determine what information people see. Existence of echo chambers suggests that people see information that aligns with their own beliefs, a phenomenon that can radicalize people and reinforce harmful beliefs.

Collecting follower graph information to construct the echo chambers, however, is highly non-trivial due limitations of the Twitter API. As a result, the friend/follower links remain largely unobserved. While retweets have been associated as a proxy for agreement [7, 22], their role in exposures is unexplored. Retweeting refers to the practice of re-sharing another user’s posts, and it is the mechanism of information diffusion on Twitter [11, 23, 33, 35]. However, there is little understanding about how well these retweet links capture the information people see via their follower (friend) path. As a result, we do not know the relationship between the echo chambers in the follower and the retweet graphs nor whether the latter creates a good proxy of information exposure.

In this work we compare local neighborhoods in the follower and retweet graphs and explore how they affect our estimates of the information people see online. We organize our research around the following questions:

RQ1 What is the relationship between friends (i.e., accounts a user follows) and retweet friends (i.e., the accounts the user retweets)?
2 RELATED WORKS

Previous studies have leveraged follow/friend relationships in inferring individual political preferences [3], assessing characteristics of echo chambers [2, 3, 16] and quantifying ideological exposure [3, 14, 17, 24]. The common assumption underlying these studies is that users are more likely to follow individuals who are ideologically similar to them. Other quantification of the echo chamber effect on social media platforms like Twitter rely on retweet and mention interactions between individuals [11, 33]. While some studies have found strong ideological clustering [10, 12, 16, 17] others have highlighted the existence of cross-ideological exposures [2, 3].

In order to better understand echo chamber effects one needs to better characterize exposures. The proliferation of content generated on social media has brought with it an overload of information. A survey based experiment [6] showed the users of micro-blogging platforms like Twitter are the worst affected with nearly two-thirds of the users feeling overloaded with information. Studies on Twitter and Sina Weibo [15, 29] have found that users who have many friends needed repeated exposures to the same content before they re-shared it. These highlight the importance of factoring in the user attention span while characterizing exposures. One way to do so is by directly looking at the content re-shared (or retweeted on Twitter) by individuals as an unified abstraction of such repeated exposures. Moreover, a follow relationship between two users need not necessitate ideological similarity and could arise out of mere curiosity. While several studies have explored factors affecting retweetability of content and retweet information cascades [26, 27, 34, 36], not many of them have explored their role in user exposures. While comparisons of the structure of follower and retweet networks have been done before [5], a comparison of exposures from neighborhoods in these networks has remained unexplored.

The growing influence of content curation algorithms on user timelines has motivated research in understanding how content exposures are affected [4, 18]. There is an active debate on how one can address echo chambers [32]. One viewpoint argues that cross-ideological exposure can mitigate echo chambers [13] while others have argued that the control over exposure to cross-ideological content lies with the user themselves [2]. This finding suggests the presence of selective attention and motivates us to quantify exposures in the absence of influence from recommendation systems to better understand the dynamics of what users pay attention to. More specifically, we can investigate whether users resort to selective attention in a reverse chronological ordering of timelines and if so, how can retweet exposures be leveraged to understand this.

Misinformation and more recently, anti-science attitudes have been associated with political partisanship [25, 28]. Assessing exposures along two different dimensions of politics and factual quality of content can yield robust inferences of local neighborhoods in the follower and retweet graphs.

3 DATA AND METHODS

3.1 Twitter Data

Data collection was based on a study of the 2012 US elections [31], which tracked discussions of initiatives on the California ballot. These initiatives proposed new laws on a variety of topics, from labeling genetically modified foods and abolishing the death penalty, to school funding, which Californians then voted for (or against) in the November elections. The study identified 81 users active in the discussion these ballot initiatives. Using snowball sampling, researchers expanded this set to 5,599 such accounts, who we refer to as seed users.

Follower graph: Starting in March 2014, we queried Twitter to identify the accounts each seed user follows, which we refer to as friends or follower graph friends. We continued to query daily through September 2014 to identify any new friends of seed users.
This subset of the Twitter follower graph has over 4M users with over 17M edges.

We also collected the messages seed users and their friends posted over this time period, roughly 81.2M tweets, of which 22.7M were retweets. At the time of data collection, Twitter showed tweets posted by friends in reverse chronological order in a user’s timeline. We were therefore able to reconstruct the timeline for each seed user and quantify information exposure. For of this study we consider tweets from May 2014 through September 2014, or 43.4M tweets of which 14.8M are retweets.

**RT graph:** To create the retweet graph, we identified retweets (RTs) among the messages posted by seed users, and created links from retweeted accounts. The *retweet graph* aggregates retweet links over all seed users. The tweet object specifies whether it is a retweet and provides information about the individual retweeting it and the individual who originally posted it. Intermediate retweet chains are not recorded in the tweet object. Note that we do not actively collect all tweets generated by RT friends. If a RT Friend is not a friend of a seed user, it may be the case that we don’t factor in all their tweets.

**Limitations:** Note that the data set has some limitations. The data was collected before Twitter introduced algorithmic timeline personalization in 2016, so it does not reflect how users are exposed to information now. However, this has a benefit, in enabling us to study the impact of friends on the information users see without the confounding effects of algorithms. Also, Twitter still allows users to select to see tweets in reverse chronological orders and other social platforms, such as Mastodon and Instagram, also allow content to be shown in reverse chronological order. This adds to our study’s relevance.

Another limitation that seed users set is heavily biased. Most of the people discussing ballot initiatives in California election are liberal, which contributes to the dearth of conservatives in our sample. Despite these limitations, we believe that this unique data offers an unprecedented opportunity to study exposure in online social networks.

### 3.2 Measuring Polarization

Following existing studies [9, 19, 25, 28], we leverage URLs shared in tweets to quantify political orientation. We measure polarized orientation along two dimensions: political and factual. The political dimension represents political orientation from hardline liberal (0) to hardline conservative (+1). The factual dimension captures content factuality from Very Low (0) to Very High (+1). Media Bias-Fact Check\(^1\) (MBFC) provides partisan and factual scores for thousands of Pay-Level Domains (PLDs). Political partisanship is categorized as Left/Hardline Liberal (0), Left-Center (0.25), Least-Biased/Center (0.5), Right-Center (0.75), Right/Hardline Conservative (1). Factuality or reporting quality of PLDs is categorized along the scale Very Low/Low (0), Mixed (0.33), Mostly Factual(0.66), High/Very High (1).

**Individual Orientation.** To calculate the orientation of information a user shares, we aggregate their tweets and average domain scores of embedded URLs along the political and factual dimensions (Eqs. 1 and 2). Here \(\Pi(d)\) and \(\Phi(d)\) are functions that return the political and factual polarity of domain \(d\). Our measures of user \(u\)’s political \((p_u(u))\) and factual \((f_u(u))\) scores are similar to political orientation and propensity for misinformation used in previous works [25, 28]. These scores give the ideological polarization of information the user shares. Given the set of domains \(D(u)\) that a user shares, we define \(p_u(u)\) and \(m_u(u)\) as:

\[
\begin{align*}
    p_u(u) &= \frac{1}{|D(u)|} \sum_{d \in D(u)} \Pi(d) \\
    m_u(u) &= \frac{1}{|D(u)|} \sum_{d \in D(u)} \Phi(d)
\end{align*}
\]

**Information Exposure.** Previous works [9, 25] quantified polarization of a user’s neighborhood by averaging over each friend’s political (or factual) orientation. However, this ignores the large variation of friends’ activity, with each friend contributing equally to neighborhood polarization, regardless how many messages the friend posts. In contrast, we estimate the polarization of information users see through the follower (or retweet) graphs by aggregating all tweets user’s friends (resp. retweet friends) shared and averaging their domain scores. These scores measure the polarization of exposure. By aggregating over friends tweets, our measure gives more weight to active friends. Let us denote the relationship between two nodes using \(\rho\) where, \(\rho \in \{friend, retweet \ friend\}\). \(D(\rho)\) denotes the domains shared by a user’s friends (or RT friends). Equations 3 and 4 specify political and factual exposure scores.

\[
\begin{align*}
    p_u(u, \rho) &= \frac{1}{|D(\rho_u)|} \sum_{d \in D(\rho_u)} \Pi(d) \\
    m_u(u, \rho) &= \frac{1}{|D(\rho_u)|} \sum_{d \in D(\rho_u)} \Phi(d)
\end{align*}
\]

We denote exposures via the follower graph \((\rho = f)\) as \(p_u(u, f)\), \(m_u(u, f)\) and for the retweet graph \((\rho = r)\) as \(p_u(u, r)\), \(m_u(u, r)\). Not all seed users generated ideological content, leaving us with roughly 2.8K seed users who were exposed to polarized information. We also scored the friends and RT friends of seed users, a total of 92K users.

### 4 RESULTS

We study how the observed retweets affect the estimates of ideological polarization of information seen online. We first show that retweets systematically distort information exposure by magnifying extreme polarities. To explain the origin of bias we have to take into account the interplay between user polarization, activity and attention.

#### 4.1 Friends vs Retweet Friends

First, we analyze the relationship between the friends the seed users follow and their retweet friends. As a reminder, we define a *retweet friend* (or *RT friend*) of a seed user as the account the seed user has retweeted \(k\) or more times, where \(k\) is a threshold we vary from one to 10.

We calculate the share of friends who have been retweeted at least once by each seed user. Figure 1(a) shows the distribution of this quantity. Retweet friends are a sparse approximation of the

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\(^1\)http://mediabiasfactcheck.com
follower graph: roughly 90% of the seed users retweet fewer than 10% of their friends.

Next, we assess the overlap between friends and retweet friends: what fraction of a seed user’s retweets are retweets of their friends’ content. On average the overlap between users’ friends and retweet friends is 0.69, and for roughly half of all seed users, 72% of the content they retweet comes from their friends (Figure 1(b)).

To study how users distribute their attention over friends, we look at the overlap between friends and RT friends changes as we increase the threshold that defines the minimum number of times a seed user needs to retweet an account for it to be considered a retweet friend. As we increase the threshold from one to ten, we find that users retweet a higher fraction of their friends’ tweets. Figure 1(c) shows how the change in average overlap between friends and RT friends as a function of threshold. When the threshold is two, meaning a seed user has to retweet an account at least twice to be counted an RT friend, the average overlap between friends and RT friends is 0.89. These results suggest that users give their friends sustained attention. Unless otherwise stated, we use ≥ 1 retweet interactions as the threshold for an individual to be considered a user’s RT friend.

4.2 Information Exposure via Friends vs RT Friends

Users select which accounts to follow in order to see the messages they post. Friends, therefore, shape the information users see online. We compare how what users see changes based on whether we aggregate messages from friends or RT friends when estimating exposure.

4.2.1 Echo Chambers. People tend to follow others with similar beliefs and opinions [25], creating echo chambers that expose them to information compatible with pre-existing opinions. To demonstrate the existence of echo chambers in the retweet and follower graphs, we bin seed users into five groups politically: Liberals ($p_s < 0.2$), Liberal Moderates ($0.2 < p_s < 0.4$), Least Biased ($0.4 < p_s < 0.6$), Conservative Moderates ($0.6 < p_s < 0.8$) and Conservatives ($p_s ≥ 0.8$). Note that Least Biased group can also be called Moderates or Centrists. We also bin seed users into based on their factual sharing $m_s$: Factual ($m_s ≥ 0.8$), Mostly Factual ($0.5 ≤ m_s < 0.8$), Mixed ($0.2 < m_s ≤ 0.5$) and Misinformative ($m_s ≤ 0.2$). For each seed user we calculate the share of friends and retweet friends from each political and factual group. Figure 2 shows results. The share of friends with the same political orientation is highest among all political groups, and more pronounced for retweet friends (Fig. 2(a) (ii)) than for friends (Fig. 2(a)(i)). We see similar results for the factual dimension (Fig. 2(b) (i) and (ii)). This suggests that users generally tend to surround themselves with friends and retweet friends who are ideologically similar to them, which is representative of an echo chamber.

Figure 2 shows that the echo chamber effect is more pronounced in the retweet neighborhood: i.e., users have a higher share of friends with the same ideology in the retweet graph than in the follower graph. To validate, we calculate the proportion of RT friends and friends from each ideological group for each seed user. The proportion is defined as the ratio of number of friends or RT friends in an ideological group and the total number of friends or RT friends the seed user has. We then take the difference in proportions for each seed user across the four factual groups and five political groups and calculate the mean. Figure 3(a) and (b) shows the difference along political and factual dimensions respectively. Liberals have 3% more liberal friends in their RT neighborhood, and Liberal Moderates have a few more liberal moderate friends in their retweet neighborhood. The difference is highest for conservative moderates: they have 12% more conservative moderate friends in their retweet neighborhood and fewer liberal friends. We see similar trends along the Factual dimension. Factual users have a few (1.2%) more factual friends in their retweet neighborhood, but users who share a mix
with more conservative content. Retweet exposures are shifted to the left (mean of 0.25) and have higher variance ($\sigma^2 = 0.02$ compared to $\sigma^2 = 0.009$ for exposure via friends). According to the parametric Student’s t-test, these distributions are significantly different ($p < 0.001$). The higher variance suggests that RT friends expose users to more ideologically extreme content.

Figure 4(b) compares the factuality of information posted by friends and RT friends. The difference in the distributions of factual scores is statistically significant ($p < 0.001$), suggesting that RT friends are not a good proxy for estimating exposure to misinformation. The factual exposure through retweet friends also has higher variance ($\sigma^2 = 0.02$) compared to exposures through friends ($\sigma^2 = 0.006$), which suggests that RT friends substantially exaggerate the amount of both misinformation and factual content people see.

4.2.3 Retweet Exposures are Systematically Biased. Next, we show that retweet friends systematically distort estimated polarization of information people see. To quantify the distortion, we define $\Delta p_u = p_u(f) - p_u(r)$, the difference in political exposure through friends and RT friends. Figures 5(a)–(d) show $\Delta p_u$ as a function of seed user’s political score $p_s$. The correlation between $\Delta p_u$ and $p_s$ is negative, which means that information posted by user’s RT friends is more polarized than the information posted by user’s friends, and the discrepancy is larger for more polarized users. Retweet friends expose conservative users to more conservative content than they would see their friends post, and likewise, they expose liberal users to more liberal content than they see their friends post. Therefore, for all users on either side of the political spectrum, exposures computed through the follower graph underestimate the extent to which individuals pay attention to polarized partisan information. Exposure bias can be substantial: for users at the extremes of the political spectrum, the difference in exposure scores can be $0.2–0.4$, or enough to shift the exposure from center-right to right.

We also find that users pay more attention to their politically more extreme friends. As we increase how much attention users pay to friends (by varying the retweet threshold), we find that exposure bias increases. As we raise the retweet threshold in Fig. 5(a)–(d), the Pearson’s correlation decreases from $r = -0.13$ ($p < 0.001$) threshold of $\geq 1$ to $r = -0.44$ ($p < 0.001$) for threshold of $\geq 10$. Together with Fig. 1(c), these findings suggest that users pay more attention to friends who post more politically extreme content.

We see a similar bias with respect to content factuality. Figure 5(e)–(h) show the difference in factual exposure through friends and retweet friends $\Delta m_u = m_u(f) - m_u(r)$ as a function of the user’s factual score $m_s$. We see that as $m_s$ increases, $\Delta m_u$ decreases. This suggests that for users who share more factual content, the follower graph underestimates how much factual content they see, and for users who share less factual information, it underestimates how much misinformation they see. The bias is substantial, equivalent to moving up an MBFC category at extremes of the spectrum.

Similar to Fig. 5(a)–(d), we see decreasing negative correlation in Fig. 5(e)–(h) accompanying the increase in threshold on retweet interactions. The correlation decreases from $r = -0.15$ ($p < 0.001$) when the retweet threshold is $\geq 1$ to $r = -0.51$ ($p < 0.001$) when the retweet threshold is $\geq 10$. This suggests that users pay more

Figure 3: Retweet networks distort echo chambers. The plot shows the mean difference in the share of friends (RT friends - friends) from each ideological group of seed users across (a) political and (b) factual dimension. Conservative moderates have more conservatives and fewer liberals in their retweet neighborhood than in their follower graph neighborhood. Similarly, people sharing misinformation have fewer factual friends in their retweet neighborhood. Note there are too few conservatives in our sample for analysis.

4.2.2 Retweets Skew Exposure to Polarized Information. At the time of data collection, Twitter did not personalize a user’s timeline, but displayed tweets by friends in reverse chronological order. As a result, friends defined what content users saw. How does using retweet friends’ posts to calculate exposure affect what information users see? Figure 4(a) compares the partisanship scores of the information seed users’ friends post (blue bars) to the information their retweet friends post (orange bars). Exposure to political information via friends (blue bars) is approximately normally distributed around the mean of 0.27. Partisanship scores smaller than 0.5 are associated with more liberal content, while scores higher than 0.5
4.3 Origins of Exposure Bias

Why are exposures through the retweet friends more polarized and diverse than exposures through the follower graph? Polarization could be amplified by Twitter’s curation algorithms, which recommend politically more extreme content [8]. However, during the time of data collection Twitter was not yet personalizing timelines, so algorithmic amplification does not explain the observed effect. We therefore explore alternate explanations. 1) Are highly polarized users more active? If so, then their ideologically extreme content is more available for others to retweet. Alternately, if highly polarized users were more 2) Do users pay more attention to the attention to highly factual or highly misinformative friends depending on their own propensity for misinformation.

As we increase the retweet threshold from one to two, the number of seed users who repeatedly retweet others decreases. There are roughly 450 seed users for RT threshold of ≥10. The correlations between Δp_e and p_s and, Δm_e and m_s, still hold for these 450 seed users.

Figure 4: Retweets distort exposure to partisan and factual information. (a) Distribution of political exposures through the follower and retweet graphs. (b) Distribution of factual exposures through the follower and retweet graphs.

Figure 5: Retweets distort exposure to partisan information. As the overlap between retweet friends and friends increase with an increase in frequency of retweet interactions between a seed user and their retweet friend, we see an increased distortion in exposures. (a–d) Difference in political exposure Δp_e as a function of seed user’s political score p_s as we increase the threshold defining how many times a seed user retweets an account for that account to be counted as a retweet friend. (e–h) Difference in factual exposure Δm_e as a function of seed user’s factual score m_s as we increase the threshold defining a retweet friend. Darker shade of color represents increasing correlation.
more extreme content? If so, they may preferentially retweet more polarized content.

4.3.1 Are Polarized Users More Active? Leveraging equations 1 and 2, we quantify political and factual orientations of all users in our dataset, including seed users, their friends and retweet friends. We then split all users into five groups politically: Hardline Liberals/Liberals (\( p_L \leq 0.2 \)), Liberal Moderates (0.2 \(< p_L \leq 0.4 \)), Least Biased (0.4 \( \leq p_L \leq 0.6 \)), Conservative Moderates (0.6 \(< p_L \leq 0.8 \)) and Conservatives (\( p_L \geq 0.8 \)). We also split users into four groups based on their factual sharing \( m_f \): Factual (\( m_f \geq 0.8 \)), Mostly Factual (0.5 \(< m_f \leq 0.8 \)), Mixed (0.2 \(< m_f \leq 0.5 \)) and Misinformative (\( m_f \leq 0.2 \)). Aggregating users into political and factual groups allows us to highlight the differences in who gets retweeted by the different groups.

One argument to explain the higher variance of retweet exposures in Figure 4 is that highly polarized users are more active, so they offer more content to retweet. Another argument could be that, given the number of friends a user has is significantly larger than the number of retweet friends, there is "reversion to the mean" that makes exposures via friends look less diverse.

We find that the higher variance of retweet exposures cannot be attributed to either of the two reasons. To demonstrate this, we first compare the activities of politically and factually extreme groups and moderate groups. We find no statistically significant difference in activity between the Liberals and Liberal Moderates by means of the non-parametric Mann-Whitney U Test. Similarly, we don’t find a statistically significant difference in activity between the Hardline Conservatives and Conservative Moderates. This can also be seen in the boxplots in Figure 6(a). We do not find any statistically significant differences in activity factual and misinformation groups (Fig. 6(c)).

To determine whether increased availability of extreme content explains why retweet exposures are more polarized, we select a random subset of friends equal to the number of RT friends a user has, weighted by the friend’s activity. We then compare information exposure via this subset of friends to exposure via retweet friends. Given that we are comparing an equal number of friends and retweet friends, we can test to see if the low variance of the friendship exposures in Figure 4 is due to the disparity in number of friends and retweet friends for a seed user. Given that we are weighting friends by their activity we can also test whether higher activity plays any role in making retweet exposures appear more diverse.

Let us assume that a seed user \( u \) has \( |\theta_f| \) friends and \( |\theta_r| \) RT friends. More active friends would have a higher chance of being sampled and would ideally expose that are akin to retweet exposures. We repeatedly sample (1000 times) \( |\theta_f| \) number of friends without replacement from \( |\theta_f| \) to get \( |\theta_r| \). Assigning polarities to domains extracted from tweets generated by users in \( \theta_f \), we calculate the political and factual exposures using Equations 3 and 4.

We then compute the average exposures over the number of trials to obtain random friend exposures and compare them to the retweet exposures. Figures 7 compares the distribution of political and factual exposures from retweet friends, friends and random friends. We find that the random-friend exposures along the factual and political scale remain more or less as varied as the friendship exposures. The variances of political retweet, friendship and random friend political exposures are 0.02, 0.009 and 0.006 respectively. The variances of retweet, friendship and random-friend factual exposures are 0.02, 0.006 and 0.007 respectively. We run F-tests to test the reliability of these observations and find that the differences in variance are statistically significant at \( p < 0.001 \).

These findings suggest that increased availability of content from active and (or) ideologically extreme accounts does not explain the higher variance and ideological polarization of retweet exposures. Instead, we argue that preferential retweeting amplifies polarization because individuals choose to retweet more extreme content. The selective attention to ideologically extreme content suggests that follower graphs do not adequately represent echo chamber effects.

4.3.2 Selective Attention to Ideologically Extreme Content. An initial reasoning for retweet exposures being more extreme might be that friends on the ideological extreme are retweeted more frequently. To test this hypothesis, we count the number of times users in each political and factual group were retweeted. The box-plots in Figure 6(b) and (d) show the number of times users were retweeted in each of the political and factual groups respectively. We see that hardline liberals and conservatives are retweeted more than liberal moderates and conservative moderates. These findings are confirmed by means of a Mann-Whitney U Test which shows statistically significant differences between hardliners and moderates (\( p < 0.001 \)). However, this reasoning does not hold for the factual dimension. In Figure 6(d), we see on one end that the Factual group gets retweeted significantly less (Mann-Whitney U; \( p < 0.001 \)) than the Mostly Factual group. On the other end, we don’t find any significant differences between the Misinformative and Mixed groups.

To understand why retweet exposures are more diverse, it is important to not only understand who is getting attention but also who is paying attention to whom. To measure this, for each political and factual grouping, we calculate how much attention (via retweets) users in each group pay to the other groups. Figure 8 shows the fraction of times users in each political (a) and factual (b) group retweet others from different groups. Along the political dimension, we find that Hardline Liberals devote roughly 39% of their retweets to other Hardline Liberals and roughly 49% to Liberal Moderates. Liberal Moderates retweet other Liberal Moderates or Hardline Liberals 82% of the time. Conservative Moderates retweet other Conservative Moderates or Hardline Conservatives 36% of the time. Hardline Conservatives retweet Hardline and Moderate Conservatives 51% of the time. Given the liberal bias of our dataset, the retweet preferences for conservative groups appear subdued. These observations show that most users across the political spectrum pay attention to others who are at least as polarized as they are, devoting significant attention to the more extreme accounts. This explains the higher density for retweet exposures along the extremes in Figure 4(a) and the distortions in retweet exposures as political sharing becomes hardline (Figure 5(a)-(d)).

Along the factual dimension the effects are much stronger which is reflected in the much larger densities at the extremes in Figure 4(b). We observe that Factual users retweet other factual users about 68% the time. Users in the Mostly-Factual group retweet
5 CONCLUSIONS

Network connections expose users to information. Exposures have been studied by analyzing the accounts users follow. An alternative approach is by analyzing retweet interactions thereby capturing what users pay attention to. However, it is not generally known how well these representations of exposure agree. Leveraging factual and political polarities at scale of pay-level domains, we quantify users’ own polarization, as well as the polarization of the information they receive via their network connections, i.e., their exposure. We then used this measure to compare our estimates of exposure via the follower and retweet networks. Relying on the retweet network to measure the information people see systematically distorts its polarization compared to what users see their friends in the follower network post. This methodology reveals several key insights into the nature of information exposure in online environments.

We find a significant correlation between a user’s polarization and the polarization of the information they see in both networks, which points to the existence of echo chambers, i.e., ideologically similar friends who expose users to information that aligns with users’ own attitudes. However, we find that friendship network consistently underestimates what users pay attention to. While all users may seem to follow other liberal or factual individuals irrespective of their political or factual groups respectively, we find that more conservative and less factual seed users retweet/pay attention to other conservative or less factual individuals. We also find that liberal and factual users tend to retweet a higher fraction of liberal and factual individuals than what they follow. These differences between what users follow and retweet highlight that looking at all friends to quantify exposures may in fact subdue the extent of polarization.

We then studied differences in ideological and factual exposure resulting from different networks. We find that the retweet networks distort a user’s perceived polarization, both in terms of partisanship and factuality of content seen. The distribution of retweet exposures are consistently more ideologically extreme than friendship exposures. We find that as users become more extreme, both ideologically and factually, the retweet exposures become more extreme than friendship exposures. We also see that the distortion of retweet exposure increases when we consider individuals with.

Figure 6: Number of tweets shared by users (activity) and the number of times users in an ideological group were retweeted. (a) Number of tweets shared of each pole by users in each ideological group. (b) Number of times users in each political group were retweeted. (c) Overall activity for users in each factual group. (d) Number of times users in each factual group were retweeted.

Figure 7: Compares the distribution of retweet ideological exposures with random friend exposures. (a) makes the comparison for the political dimension while (b) makes it for the factual. Retweet exposures are ideologically extreme in comparison to random friend exposures on average.
whom the user shares an increasing amount of retweet interactions. This indicates that users tend to pay increased attention to individuals who expose them to more polarized content.

Finally, we investigate the reason behind retweet exposures being more extreme. Given that the dataset was collected before November 2014 the distortions cannot be attributed to algorithmic curation of timelines. We then assess if highly polarized individuals are more active and if this translates into an increased availability of ideologically extreme content for users to retweet. Activity across user groups remain almost similar along both dimensions. While we find that hardline users on the political axis tend to get retweeted more often than others, highly factual and misinformative users on the factual axis aren’t the most retweeted. We also show that increased activity has no role to play in users choosing to retweet highly polarized users by means of a randomized trial experiment.

By focusing on not just who was retweeted but factoring in who made the retweet we find that, individuals prefer to pay attention to others who are at least as polarized as them. We see that a large proportion of retweets are of others who are at least as polarized as the user. Given that this finding applies to all users in our dataset with at least one friend and retweet friend, and not just seed users, we can generalize the results from the Echo Chambers subsection. We therefore argue that by relying on friend/follow relationships to quantify exposures, previous studies underestimated the extent of polarization and users preference for more hardline/extreme content. These results point to important considerations for researchers studying polarization through the lens of social media. Studies should factor in user attention span when quantifying exposures. Owing to the proliferation of content produced it is impractical to assume that users can pay any attention if not equal attention to all their friends. Repeated interactions between users can be a viable proxy to assess what users pay attention to. While users may appear to follow a diverse set of individuals researchers can focus on who they pay more attention to in order to identify the true extent of polarization. The fact that these preferences existed prior to personalization algorithms highlights an inherence which can be exacerbated by content curation.

Figure 8: Retweet Preferences for Political and Factual Groups. (a) Shows the retweet preference for political groups. The y-axis represents the fraction of times users in a particular political group, identified by the x-axis, retweet other users across political groups. (b) Shows the retweet preference for factual groups. The y-axis represents the fraction of times users in a particular factual group, identified by the x-axis, retweet other users across factual groups.

5.1 Limitations and Future Work

Our study has the following limitations which should be taken into account. The set of seed users whose friendship links we collected have a strong liberal bias which could be a limitation. Additionally, we only look at tweets and retweets made by seed users and their friends. While we have data about the friends of seed users we don’t have data about the friends of friends. This creates sinks in the network because two friends of a seed user can have a link between them if one of them is also a seed user. This can hamper comparisons of network structure. In addition, any study of exposure done today would have to account for Twitter personalization algorithms, which may further exacerbate exposures. Media Bias-Fact Check by no means provides an all encompassing list of Pay-Level Domains and one can explore other sources such as NewsGuard, Adfontes Media etc. A comparison of these exposures with exposures from exposures from personalized timelines of today could be an interesting direction for future research.

5.2 Ethical Considerations

The study was reviewed by the institutional review board and determined to be exempt. The Twitter data that we collect is only representative of English language speakers in the United States and is by no means representative of the general population. One way we can overcome this is by building multi-lingual approaches and probably expanding to tweets from across the world. Another ethical shortcoming could we the implication that findings on Twitter reflect real world phenomena. Twitter tends to be biased towards liberals and is mostly used by the younger population thereby not being representative of the real world. Additionally, given that our seed users set is comprised of mostly liberal users, this bias is somewhat exacerbated. A better approach to overcome this could be by having an equal number of liberal and conservative users. Political sharing behaviors are personal to the individual and in order to preserve anonymity we remove screen names from tweets.

ACKNOWLEDGMENTS

Anonymized for review process.
