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On Sharing Preferences in Social Networks

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ABSTRACT

In this paper, we study sharing in online social networks through the lens of resource-allocation. Specifically, we study whether people with large networks share as much as people with small networks. Our work shows three influencing factors in content-sharing inequality: individual sharing tendencies, sharing tendencies of one's friends, and content relevance. We then show that, content shared by an individual is determined by the number of his/her friends who are frequent sharers; thus, network composition plays a role in content-sharing.

KEYWORDS: Content-sharing inequality, Theil inequality, Online social networks, and Pareto distribution.

INTRODUCTION

Sharing is an intrinsic part of human nature, manifested in everyday experiences of tangible entities (e.g. food, wealth) and intangible entities (emotions, ideas, advice). While the sharing of tangible entities such as wealth and possessions conforms to the social norms of reciprocity and status consistency (McPherson, Smith-Lovin &Cook, 2001), the concept of sharing emotions or ideas is far less studied. Social Networking Sites (SNSs) have emerged as a significant platform in modern social discourse by facilitating sharing between users in myriad ways (e.g. likes, shares, posts, tags, followers, pins and tweets, to name a few). However, individual sharing patterns differ; some share frequently, while others merely lurk (Nonnecke & Preece, 2000). Individuals also tend to exhibit homophily (Meeker, 1971) and networks have been shown to follow the rich-get-richer pattern (Albert & Barabasi, 2002), where individuals who are new to the network are more likely to form friendships with individuals who have larger networks, than with individuals who have smaller networks. In this paper, we study the volume of content-sharing and its relationship with network size, i.e. we seek to answer the question: do people with large networks share more, less or as much as people with small networks?

To answer this question, we looked at self-reported findings of sharing tendencies of Facebook users. We borrow on the framework in (Murimi, 2016) and grouped users into one of four categories of sharers: frequent (posting at least once a day), moderate (posting at least once a week), sparse (posting at least once a month) and non-sharers (users who do not post). Users were additionally asked to provide network sizes (small or large), and the perceived sharing tendencies of friends on their network. Our results showed that users with large networks shared less than users with small networks. While the inverse relationship between network size and sharing tendencies may appear as contrary to intuition, we posit that this provides further evidence of the theory of weak ties (Granovetter, 1973). Since large networks are comprised primarily of weak ties, users are not inclined to share as much information as they would with a smaller network of friends. We call this phenomenon of inverse correlation between network size and content-sharing as the inequality of content-sharing, and analyze the various parameters affecting this inequality with the help of the Theil inequality index.

The Theil index of inequality was first proposed by the econometrician Henri Theil as a tool to measure the inequality of income distribution (Conceicao & Ferrera, 2000). Since then, numerous studies to quantify the inequality of income distribution have used the Theil index to capture effects such as public-school finances (Evans, Murry & Schwab, 1977), health outcomes (Navarro et al, 2006) and racial segregation (Reardon & Firebaugh, 2000). This paper presents the first application of the Theil index to a content-sharing inequality in SNSs, and while content-sharing and income distribution appear to be disjoint aspects of the human experience, they both exhibit a fundamental inequality in distribution –a larger portion of the wealth is generated by fewer individuals. Our findings show a similar inequality exists in content-sharing as well. Users with small networks share more content than those with large networks. We extend the heretofore limited scope of the Theil index into the realm of content-sharing in SNSs, and do so with another frequently used aspect of the unequal income-distribution literature: the Pareto distribution. The Pareto distribution, which is frequently used to model the 80/20 rule of income distribution, belongs to the family of heavy-tail distributions such as the power-law distribution and the Zipfian distribution. These heavy-tail distributions have been used to measure inequality in areas such as income, graph structure of the World Wide Web, stock returns and sizes of files, human settlements and particles (Reed & Jorgensen, 2004; Stutzmann, 2006; Zukernam, Neam& Addie, 2003; Addie, Neame & Zukerman, 2002).

LITERATURE REVIEW

The centrality of content-sharing to the social network experience has enabled a variety of studies on the nature of the content and the content-sharers themselves. In (Burke, Marlow & Lento, 2009), the authors show that newcomer sharing is directly proportional to the activity level of the newcomer's contacts. Sharing is also focused – people offer varying amounts of attention to various contacts in their networks (Backstrom et al, 2011). The authors studied this balance of attention as a function of network sizes and tie strength. Sharing content on a SNS also has the effect of reaching a wider than anticipated audience (Bernstein et al, 2013) and is not limited to the more familiar scenarios of viral online content (Berger & Milkman, 2012). In (Sleeper et al, 2013), the authors found that users frequently self-censored their posts to manage their online reputation. The content of the post and the intended audience also influenced sharing (Zhao, Lampe & Ellison, 2016). The need to present different information to different online audiences was studied through the mechanism of faceted identities in (Farnham & Churchill, 2011). The relationship between personality traits and online behavior was explored in (Gosling et al, 2011), where the authors found that an individual's personality online is an extension of their offline personality. The underlying elements behind sharing of goals and motivations, manifested as cooperative behavior and social cognition, was studied in (Dominey & Warneken, 2011). The role of content-sharing in enabling information discovery was studied in (Stutzmann, 2006). Sharing was identified as functional building block of social media alongside presence, identity, relationships, conversations, groups and reputation (Kietzmann et al, 2011). Voluntary, informal knowledge-sharing (VIKS) was studied in (Lee et al, 2004). The authors defined VIKS as serendipitous, spontaneous and extemporaneous sharing of information. VIKS interactions were noted as opportunities for learning and teaching, and social engagement. Knowledge sharing was also studied in (Leonardi et al, 2014), where the author analyzed the nature of communication between employees of a financial services organization over a new enterprise social networking site. This work studied the concept of communication visibility, where users can make inferences about their co-workers' knowledge based on the content of messages. This inference was enabled through network translucence (who knows whom) and message translucence (who knows what). A similar framework is observed on most social networking sites, where user's friends are visible to others and their activities on the network (posts, shares and likes) are visible to subsets of their contacts on the network. Settings enable users to narrow the scope of the message translucence and even network translucence – users possess the abilities to limit the number of friends who can see their network activities (Granovetter, 1973; Stutzmann 2006; Mitzenmacher 2004).

From a theoretical perspective, the inequality of content-sharing is related to the theory of weak ties (Granovetter 1973), homophily (Meeker 1971) and network structure (Albert & Barabasi, 2002). Our model of inequality in content-sharing is derived from local and global factors influencing the sharing: sharing tendencies of an individual's contacts, relevance of a post and the sharing tendency of the individual. Furthermore, our approach also applies to the model of interpersonal exchange developed in (Meeker 1971), where interpersonal exchanges is described according a framework of six elements: reciprocity, rationality, altruism, group gain, status consistency, and competition. Recent research has shown that an individual's standing in a SNS is impacted by the composition of the contacts in her network, volume of content shared (Murimi 2016) and the nature of shared content (Hajargasht & Griffiths, 2015). Finally, our measure of inequality in content-sharing in social networks is related to other metrics of inequality studied in offline social networks such as social capital (Cattell 2001) and information diffusion (Kempe, Kleinberg & Tardos, 2005). The focus of our work is to quantify the inequality of content-sharing in terms of the Theil index and to analyze the sensitivity of this index to factors such as network size and sharing tendencies of both the individual and his/her contacts.

CONTRIBUTIONS

Our main contribution is to show that sharing of content in social networks is inequitable, i.e., while one would expect that individuals with large networks would share more than individuals with smaller networks, our research shows that content-sharing follows an inverse relationship with network size. We study this inequality of content-sharing using the Theil index. We model the inequality of content-sharing using a Pareto distribution. Specifically, we study the following model: The number of posts on an individual's feed arises from the sharing tendencies of friends in his/her network. We model the number of posts that an individual makes as a function of three parameters: (a) the individuals' own sharing tendency, which can lie in any of the four categories mentioned above, (b) the number of posts that appear in his/her Newsfeed, which in turn is a function of the sharing tendencies of his/her friends on the network, and finally, (c) the relevance of the posts in one's News feed.

We consider the simple model, where the sharing tendency of an individual is fixed, i.e. if an individual is a frequent sharer, she/he remains so for the duration of network use. We also exclude other News feed items such as content recommendations and advertisements from non-individuals (such as business and other organizations) in our analysis of content-sharing. This enables us to focus on the reciprocity of content sharing between individuals. Consider a network where n_r percent of individuals have small networks and n_l percent of individuals have large networks, and $n_r \gg n_l$. The number of posts made by these individuals is Pareto distributed, i.e. n_r percent of individuals share s_r percent of posts and n_l percent of individuals share s_l percent of the posts, and $s_r \ll s_l$.

The shape parameter of the Pareto distribution has important implication is the calculation of the Theil index. We show that when the composition of the network is split evenly among small and large networks, the slope of the Theil index increases with the shape parameter. In other words, the inequality of content-sharing persists, since the individuals with small networks are expected to post less than the individuals with large networks. In this setting, we show that if the number of individuals with small networks is same as that of individuals with large networks, then the shape parameters of the Pareto distributions modeling the sharing tendencies of individuals on small networks (α) and on large networks (β) dominate the sharing patterns. Specifically, we show that as the difference between the values of the shape parameters tends to zero, i.e., $\alpha \rightarrow \beta,$ with an increase in the number of posts from individuals with large networks, there is a

Table 1: Findings of Inequality in Content-Sharing			
Network Size		Sharing Tendency	
$\boldsymbol{n_{regular}}$	78%	$\boldsymbol{s_{regular}}$	81%
$\boldsymbol{n_{large}}$	21%	$\boldsymbol{s_{large}}$	18%

corresponding decrease in the number of posts from individuals with small networks. Our hypothesis for this behavior is the underlying Pareto distribution, which assumes an inverse relationship between network size and sharing. An increase in the shared content from individuals with large networks signals the availability of less content on the news feed from individuals with smaller networks. However, as $\alpha \gg \beta$, an increase in the number of individuals with small networks or an increase in the value of α increases the number of posts on an individual's feed. This is in line with the Pareto distribution, since individuals with small networks share more than individuals with large networks. Additionally, we investigate extreme inequality of sharing in scenarios where a few individuals are responsible for all the content shared on the networks. Even in this situation of extreme inequality of content-sharing, we show that as the number of individuals with small networks increases, the inequality of content-sharing can be reduced (since individuals with small networks post more than individuals with large networks). Another method to reduce the extreme inequality is to increase the value of the sharing parameter α. As α increases, the sharing tendency of users increases, thus reducing the inequality. Finally, we show that in a network where both individuals with small networks and large networks have similar sharing tendencies($\alpha \to \beta$), the network takes on a more homogenous form. This contributes to the inequality of content-sharing since individuals with small networks would post as much as individuals with large networks and thus increase the value of the Theil index.

METHOD

A sample size of 118 students was used to obtain the data in this study. In addition to the definition of the four categories of sharers (frequent, moderate, sparse, and non-sharers) introduced above, the following terms will be introduced and defined in the context of SNSs for our study. We define content as any kind of activity performed by a user. Thus, status updates, shares, likes (and related emotion-conveyors), comments, page creation and following activities are considered as shareable content, since it has the potential of showing up on the News feed of friends in the individual's network. The average network size of our survey participants was found to be 651 friends. Thus, we categorized networks as belonging to one of two categories: small networks (1-650 friends) and large networks (greater than 650 friends). Based on the definition of the various kinds of sharers and network size categories, students were asked to answer the following questions: (a) perception of their own sharing tendency (b) preferred sharing tendency (c) percentage of friends on their network whom they would associate with a sharing tendency – for example: 40% of friends are frequent sharers, 10% of friends are non-sharers, etc. and (d) user's own network size.

Table 1 shows the inequality of content-sharing as a function of network size. Individuals with small networks (n_r) comprise 78% of the network and report sharing 81% of the content (s_r), while individuals with large networks (n_l) comprise 21% of the network and share only 18% of the content. Thus, we see that individuals with small networks share more than individuals with large networks. This inequality of content-sharing is the basis of the work in this paper, where we study the various factors influencing the inequality of content-sharing in networks. In the next section, we study the impact of three factors (a) network composition (b) sharing tendency of the self and (c) relevance of content on the content-sharing inequality.

MODEL

We use the Pareto distribution to model the sharing tendency f of an individual. The Pareto distribution is defined by a shape parameter and a scale parameter. The shape of the Pareto curve representing the inequality is influenced by the value of the shape parameter. We use the shape parameter to determine the minimum number of posts made by an individual. We denote the Pareto distribution of sharing inequality in small networks with the scale and shape parameters as x_m and α respectively. For the case of large networks, we denote the Pareto distribution with the scale and shape parameters as x_n and β respectively. We model the mean number of posts by an individual with the Pareto distribution (x_m, α), where α is proportional to the sharing tendency of the individual (s), the relevance of the posts on the feed, and the composition of the network (n).

$$\boldsymbol{\alpha \propto rns} \quad (1)$$

The composition of the network, n, is described in terms of the frequency of the posts made by users in distinct categories. The number of posts on a user's feed in terms of n_m (number of moderate sharers), n_f (number of frequent sharers) and n_s (number of sparse sharers) is given as,

$$n = (n_m)/7 + \left(n_f\right) + \ (n_s)/30 \quad (2)$$

We exclude the contributions of non-sharers in our calculations of the number of posts in (2), since their activity in invisible on one's News feed. Thus, the CDF of the Pareto-distributed sharing tendency is given as:

$$F(x) = \begin{cases} (x_m/x)^{\alpha}, & x \geq x_m \\ 1 & , x < x_m \end{cases} \quad (3)$$

Our analysis can be readily extended to the case of the Poisson Pareto Burst Process (PPBP) which has been shown in (Zukerman, Neams & Addie, 2003; Addie, Neame & Zukerman, 2002) to closely model the bursts of Internet traffic.

Theil Index

The Theil index has been used extensively (Conceicao & Ferreira, 2000) in income inequality literature to characterize the complex dynamics of inequality among rich and poor countries. Here, we use the Theil index, T_I, to characterize the inequality of content-sharing between content-rich and content-poor groups of SNS users. The value of the Theil index, as a function of the network sizes (n_r, n_l) and sharing tendencies (s_r, s_l) is derived as (Granovetter, 2006):

$$T_I = s_r \log(s_r/n_r) + s_l \log(s_l/n_l) \quad (4)$$

We model s_r and s_l as Pareto-distributed sharing tendencies as a function of the network sizes n_r and n_l respectively. Thus,

$$\boldsymbol{s_r = \alpha x_m^{\alpha} / n_r^{\alpha+1}} \quad (5)$$

$$\boldsymbol{s_l = \beta x_n^{\beta} / n_l^{\beta+1}} \quad (6)$$

<u>Case 1: Zero Inequality</u>

Here, we study the conditions under which the Theil index of inequality in content-sharing is zero when there is an equality in network composition, i.e. $n_r = n_l$. Within this constraint, we study two cases (a) the sharing tendencies of both small and large networks is similar, i.e. $\alpha \rightarrow \beta$, and (b)

Figure 1: Relationship between minimum number of posts in small $\mathbf{x_m}$ and large networks $\mathbf{x_n}$ for zero inequality in content-sharing.

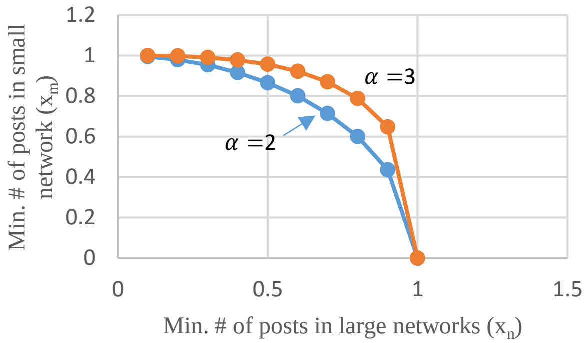
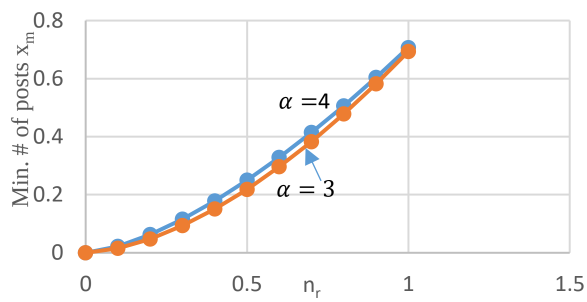


Figure 2. Relationship between network composition $\mathbf{n_r}$ and minimum number of posts $\mathbf{x_m}$



the sharing tendency of the small networks is much less than the large networks, i.e. $\alpha \ll \beta$. Substituting (6) in (5), we find that when $\alpha \to \beta$, for T_I to be equal to zero,

$$x_m = (1 - x_n^{\alpha})^{1/\alpha} \quad (7)$$

This relationship between minimum number of posts in small and large networks is depicted in Figure 1. In Figure 1, we see that, for the inequality of content-sharing to be zero, as the number of posts from friends with large networks increases, there is a decrease in the number of posts from friends with small networks. We suggest that this behavior is due to the underlying Pareto distribution, which assumes an inverse relationship between network size and sharing. An increase in the shared content from individuals with large networks signals the availability of less content on the news feed from individuals with smaller networks.

Next, we investigate the condition when $\alpha \ll \beta$ for $T_I = 0$.

$$x_m = 10\text{^}[(\log \beta + \beta \log x_n)/(\beta + 2)] \quad (8)$$

Figure 2 shows the impact of network composition on the minimum number of posts. As the percentage of people with small-sized networks (n_r) increases, the minimum number of posts seen on one's news feed increases. This is intuitive since people with small networks share more than people with large networks. The shape parameter of the Pareto distribution, α, also impacts the minimum number of posts. As the value of α increases, the minimum number of posts increases. Figure 3 shows the sharing tendency of an individual as a function of the minimum number of posts by friends in the network. As the minimum number of posts increases, there is a greater probability that at least some of them will be deemed 'shareable', and this causes an

Figure 3. Impact of Sharing Tendency on the Minimum Number of Posts

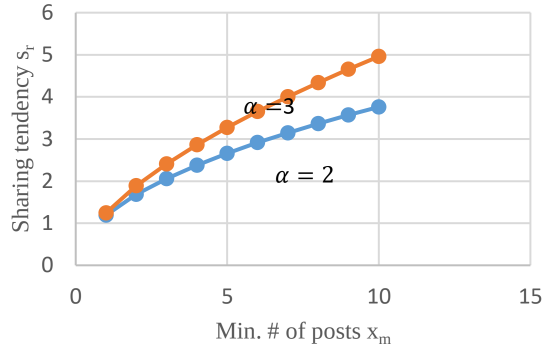
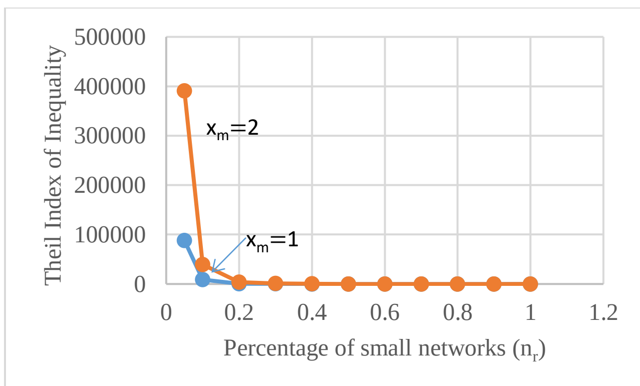


Figure 4. Extreme Sharing Tendencies



increase in the sharing tendency of the individual. Similarly, a decrease in the number of people with large networks points to a corresponding increase in the number of people with small networks.

Case 2: Extreme Sharing Tendencies

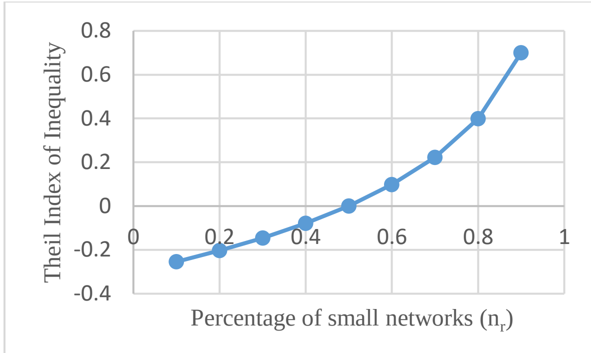
In this case, we analyze extreme sharing tendencies, i.e., what happens if $\boldsymbol{n_{regular}} \ll \boldsymbol{n_{large}}$ and $\boldsymbol{n_{regular}} \gg \boldsymbol{n_{large}}$? (i.e.1 person does 99% of the sharing and the other 99% do 1% of sharing? Figure 4 shows the conditions under which extreme inequality exists, i.e. a few individuals share majority of the content. Here, we investigate the scenario where friends with small networks comprise less than 2% of the individual's network. The value of the Theil index of inequality in this case is extremely high, and points to the fact that in such networks, content-sharing by individuals with smaller networks should be much less than content-sharing from friends with large networks. Also, as the minimum number of posts from small networks (x_m) increases, the inequality increases since the large networks are sharing less, and their reticence is helping to drive up the inequality of content-sharing.

Case 3: Homogeneous Sharing Tendencies

What happens when irrespective of network size, people share the same, i.e., $s_{regular} = s_{large}$?

$$T_I = -0.3 - 0.5\left(\log n_{regular} + \log n_{large}\right) \tag{9}$$

Figure 5. Impact of Equal Sharing Tendencies



In Figure 5, we see that when the sharing tendencies of large networks and small networks are the same, the Theil index of inequality in content-sharing increases. This trend is as expected, since content-sharing is expected to be directly proportional to network size. Yet, the inversely proportional relationship between the two is the driving factor between the inequality of content-sharing. This is amplified when the sharing tendencies are equal – as the percentage of friends with small networks increases, it implies a corresponding decrease in the percentage of friends with large networks and creates a scenario where people with small networks share more than people with larger networks.

CONCLUSIONS

The main contribution of this paper is to model sharing in social networks, and to show that the inequality of content-sharing can be realistically modeled using the Pareto distribution. The Theil index of inequality in content-sharing was used to demonstrate various scenarios of inequality by performing a sensitivity analysis to the parameters that affect content-sharing. The patterns of content-sharing in social networks initiates an intriguing new area of study that raises many questions. Among these are:

1. In this paper, we have assumed that sharing tendencies are fixed. Thus, a frequent sharer or sparse sharer does not change sharing patterns. However, in practice, sharing patterns are a function of various global (news events), regional (local events such as city-wide events) and individual circumstances (life events). We considered an extremely simple news feed; ads, trending news and sponsored content had no influence on the posts. The study of these diverse scenarios will require the development of new models.
2. Our work is based on categorizing users into two broad categories: small networks and large networks. However, even with large networks, individuals do not engage with all or most of the friends on the network. In a SNS, network size management can be accomplished in several ways: unfriending, hiding/unfollowing, creating separate sets of friends for communication or just communicating with only a specific subset of friends regularly on the network. Our work has not considered the implications of users who have large networks, but communicate only with a subset of the friends on the large network. How can the network be modeled to reflect such a structure? Does the network then resemble a homogeneous composition of individuals with small networks?
3. We focus on the inequality of content-sharing. However, there might be SNSs where content-sharing might be equitable. A study of the sharing patterns and network structures within these SNSs would be insightful in learning more about computer-mediated communication in SNSs.
4. Our model also discounts the role of non-sharers (individuals who do not share) on a social network. There are many reasons why individuals do not share: they would like the benefit of

observing the News feed from their friends, but do not want to engage with any of the content due to the nature of the online exchange, or perhaps individuals are more interested in snooping on the network and are content with being mere observers of their friends' lives on the network. Alternately, we may not be able to view an individual's posts (and thereby deem them as a non-sharer) because of the non-sharer's privacy settings. The non-sharer may have blocked an individual from viewing their posts using privacy settings. Thus, while the non-sharer is sharing, none of the shared content is visible to the blocked friend. How does a non-sharer contribute to the content-sharing inequality on the network? These and other related questions are central to the formation of social identity in SNSs and merit further research to uncover how people decide whether to share or not to share.

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