		Followed	
		No	Yes
Listed	No	W	X
	Yes	Y	Z

Figure 1. Relationship between Listing and Following

Here W, X, Y, Z represent the corresponding sets and n (W), n(X), n(Y) and n (Z) their respective cardinalities. For any curator i, W will be the have the highest cardinality. We can define three metrics to examine the relationship between listing and following.

$$CF_{Ratio} = \frac{n(Z)}{n(Y)+n(Z)}$$

$$CM_{Ratio} = \frac{n(Z)}{n(X) + n(Z)}$$

$$MF_{Ratio} = \frac{n(Y)}{n(X)}$$

Thus, CF Ratio is the fraction of people a curator is following out of all the people that she has listed across one or more of her public lists. On the other hand, CM Ratio is the fraction of people that a curator has listed at least once (across all his public lists) out of all the people that she is explicitly following. Finally, the MF Ratio is a measure that compares the relative strength in numbers of those who are only listed to those who are only followed.

To examine the relationships between subscribing and following, we similarly identify 4 disjoint sets in the universe of Twitter users (Figure 2).

		Followed	
		No	Yes
Subscribed	No	A	B
	Yes	C	D

Figure 2. Relationship between Subscribing and Following

*Subscribed in this case indicates that they belong to the lists to which the curator has subscribed.

Similar to the metrics defined in the previous case, we define the following ratios

$$CS_{Ratio} = \frac{n(D)}{n(C) + n(D)}$$

$$CFS_{Ratio} = \frac{n(D)}{n(B) + n(D)}$$

$$SF_{Ratio} = \frac{n(C)}{n(B)}$$

These three metrics together define the relationship between following explicitly and following by subscribing to a list.

4. DATASET AND ANALYSES

A dataset for analysis was collected during December 2012. We identified a random sample of 100 Twitter curators –and collected the set of users they are following, the members of the lists they have created and members of the lists to which they have subscribed. The initial data about lists and their members was collected from listorious.com. We used the Tweepy module in python to collect the membership and following data. All together our dataset has 1183 lists that were curated and 984 unique lists to which there were subscriptions.

The CF Ratio had an average value of 0.43 with a median of 0.42 (σ = 0.28) meaning users on an average follow only 43% of the people they list. The CM Ratio had an average value of 0.28 (σ = 0.23) with a median of 0.21 meaning users list a mere 28% of the people they follow. However the fact that the standard deviations were substantial indicates that there is a large user specific heterogeneity. We also found that the MF Ratio had an average of 58.46 (σ = 501.26) with a median of 0.27 meaning for some users listing is the primary form of information consumption while for others it is following explicitly. Together these results point out that members in a curators list are not the ones they follow and vice versa.

The average CS ratio was 0.11 (σ=0.13) with a median of 0.06 indicating that curators follow a meager 11% of the members in the lists they subscribe to. A paired t-test on the CF and CS Ratios for these users indicated that (t-value =11.73, $p<0.001$) the CF Ratio was significantly higher meaning curators follow a greater fraction of the people they list than members of the lists to which they subscribe. Further, the average CFS ratio was 0.09 (σ=0.10) with a median of 0.05 indicating that a mere 9% of the people that a curator follows are also members in the lists to which they subscribed. We also found significant differences between the CM and CFS Ratios (t-value=7.9, $p<0.001$) meaning that out of all the people that a user follows, a greater fraction are members of the lists they have created than the lists to which they have subscribed. These two ratios provide evidence for the fact that the people users follow are substantially different from the members of the lists they subscribe to. Finally the fact that the SF Ratio had a mean of 5.03 (σ = 25.2) with a median of 0.54 shows that some users prefer to consume information primarily through following while others through subscribing.

5. CONCLUSION IMPLICATIONS AND ONGOING WORK

We have investigated relationships between three forms of information consumption on Twitter viz., following, listing and subscribing by developing a systematic framework and defining specific measures for pairwise analysis. Our results show that these forms of information consumption are significantly different from each other. We also show that Twitter users follow a greater fraction of the people they list than the people in the lists to which they subscribe. Similarly, users list a greater fraction of the people they follow as compared to the fraction of the users in the lists to which they subscribe. Finally we show that there is considerable user specific heterogeneity in terms of preference for each form of information consumption. Our framework has implications for developing improved models of information propagation and diffusion on Twitter. Most current models consider following as the only form of information consumption[1, 10].It also has implications for list recommendations i.e. for adding members to lists, subscriptions to lists, follower recommendations, and for merging/splitting of lists.

While our research points to interesting results about forms of information consumption, we are continuing extend it in several directions. First, this paper reports on an analysis of a sample of 100 Twitter list curators and it is primarily a static analysis. In our ongoing work we are collecting and analyzing a larger sample to provide stronger evidence for the results of this research. Second, our work examines the relationship between 3 forms of information consumption at a specific point in time. There may be a temporal relationship between these forms. For example, it is possible that a user follows someone first and then decides to list him or vice versa. In our ongoing work we are building a framework for temporal analysis of such relationships while leveraging our static framework. Finally, based on the fact that some curators primarily prefer one form of information consumption over others, it would be interesting to see how these patterns are manifested in the tweeting activity. Our ongoing work is to examine the differences between tweeting, retweeting and mentioning behaviors of these users.

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