

# Filter Bubbles in Political Twitter Conversations

## Abstract

**Purpose:** The aim of this paper is to describe and analyse relationships and communication between Twitter actors in Swedish political conversations. More specifically, the paper aims to a) identify the most prominent actors, b) among these actors identify the sub-groups of actors with similar political affiliations, and c) describe and analyse the relationships and communication between these sub-groups.

**Design/methodology/approach:** Data were collected during four weeks in September 2012, using Twitter API. The data included 77,436 tweets from 10,294 Twitter actors containing the hashtag #svpol. 916 actors with an activity level above a given threshold were identified and categorised according to the main political blocks, using information from their profiles. Social network analysis was utilised to map the relationships and the communication between these actors.

**Findings:** The 916 actors accounted for 72% of the tweets in the data set, suggesting that political microblogging in Sweden is mostly done by a Twitter elite. The three main blocks left block (L), centre-right block (CR), and right-wing block (RW) were the most represented among these actors. The results from the social network analysis suggest that while polarisation exists in this setting, actors follow actors from other groups. However, cross-boundary communication was rare, as was re-tweeting tweets from members of other groups.

**Originality/value:** While a few papers have studied political polarisation on Twitter, this is the first to study the phenomenon using followership data, communication data, and re-tweet data.

## 1. Introduction

Twitter is a highly suitable resource for studying opinions, sentiments, and reactions regarding certain events. It can also be used for studying public conversations. Compared to other information tools on the web, Twitter allows the user greater control of information sources. From a democratic perspective it is beneficial for citizens to see things from varying points of view (Pariser, 2012, p. 5), but a problem with today's web is that information, knowledge and sociality are organised by recommender systems (Rogers 2009) also known as the "filter bubble" (Pariser, 2012, p. 9). Whereas search tools such as Google use techniques to personalise content based on the users' usage history, their own preferences and, in many cases, their friends' usage, on Twitter the information is better controlled by the user, who can choose which actors to follow. Given these allowances, Twitter is an interesting application to study. This article is focused on how different groups with separate political views connect to each other on Twitter. The main concern relates to the filter bubble. Will it be visible despite the allowances of Twitter or is this an interest-based social network that successfully connects people beyond their political comfort zone?

Twitter's potential of facilitating these kinds of discussions has been questioned. So far a number of studies have come to the conclusion that politicians' activity on Twitter largely follows one-way communication patterns (e.g. Graham et al., 2013; Sæbø, 2011). Sæbø also noted that most tweets do not support the deliberative model. However, Bruns and Highfield claimed that Twitter can provide "a simple mechanism for citizens to invoke politicians [...] in their comments, and for these thoughts to be public and visible in a way that emailed communication, telephone calls, letters, or electorate office visits are not" (Bruns & Highfield, 2013, p. 671).

Only a few studies have explored the interaction between different groups within a political conversation. These have analysed networks of re-tweets and mentions (Conover et al., 2011), overlapping of sets of followers of politicians (Kim & Park, 2012), and mentions of politicians (Bruns & Highfield, 2013). A mention (also known as an @mention) is the use of another Twitter actor's username in a tweet, which also has the function of a directed

message. This paper aims to investigate not only the @mentions, but also the re-tweets and the followership relations. Relying on networks based on messages when studying communication has drawbacks. First, it only captures active actors and not actors that have important network positions but are not as active; second, any undirected message is directed to, or intended for, all the actor's followers, or actors following any hashtag included in the tweet. Therefore, this paper explores alternative methods, using social network analysis of followership among the actors, and their communication within the hashtagged set of tweets. The analysis is focused on the most prominent actors of Swedish political conversations, regardless of whether the actors are politicians or not. Research questions are:

- To what extent do members of the different political groups relate to and communicate with members of other groups?
- How do the sub-networks comprised by these groups compare to each other with regards to connectedness, looking at a) intra-group relationships and communication, and b) inter-group relationships and communication?

From a set of tweets containing #svpol, the 916 most active and visible actors were selected algorithmically. These actors' profiles and lists of friends were then analysed, and the actors were categorised according to political preference, based on their profile descriptions. Finally, networks were created based on followership, @mentions, and re-tweets. These networks were then explored from the filter bubble perspective.

### ***1.1. The Swedish Parliament***

At the time of this study there were two political blocks in the parliament, the Red-Green block (left), and the Alliance (centre-right). One party in the parliament was not member of any block. This party was the Sweden Democrats (social conservatives with a nationalistic ethos). The Alliance consisted of the Moderate Party (liberal conservatives), the Liberal Party (liberals), the Centre Party (green, decentralised liberals), and the Christian Democrats (Christian democrats). The Red-green block consisted of the Social Democratic Party (social democrats), the Green Party (green ideologists), and the Left Party (socialists). Of the 349 representatives in the parliament, 173 were from the Alliance parties, and 156 from the Red-Green parties (The Swedish Parliament, 2013).

## **2. Other studies of politics on Twitter**

Since the application was launched in 2006, there have been a number of studies of its usage and content. Relevant for this paper are those concerning political usage. These have focused on predicting election results (e.g. Metaxas et al., 2011; Franch, 2013), tweeting during election times (e.g. Bruns & Highfield, 2013; Moe & Larsson, 2013; Larsson & Moe, 2011), predicting political preferences and affiliations (e.g. Golbeck & Hansen, 2011; Pennacchiotti & Popescu, 2011), examining the correlation between political opinion polls and sentiment words (e.g. O'Connor et al., 2010), and usage by political leaders or governmental organisations (e.g. Lassen & Brown, 2011; Aharony, 2012, Hsu & Park, 2012; Cho & Park, 2012). This section highlights studies that are relevant for this paper, i.e. studies that are hashtag based and network based studies of political Twitter usage. The section ends with a number of studies of polarisation on Twitter.

One major topic of interest has been the conversations in conjunction with elections. Bruns and Burgess (2011) described key patterns of activity as well as thematic foci during the 2010 Australian election by following the hashtag #ausvotes. They found that activity was often event-related and peaked during election day. A similar finding was made by Larsson and Moe (2011) in their study of the Swedish 2010 election. They tracked the hashtag #val2010, and did a social network analysis based on @mentions and re-tweets of and by the most active actors. At state level, political activity and campaigning was studied by Bruns and Highfield (2013) as they followed members of the parliament and alternative candidates during the 2012 state election in Queensland, Australia. Apart from this, they also tracked #qldvotes and compared the activity around the candidates with the overall hashtagged activity.

Among their findings was the conclusion that ordinary Twitter users are @mentioning the politicians to talk about them rather than for conversational purpose.

Some studies have focused on more general political conversations on Twitter. In a Canadian setting, Small (2011) applied content analysis to tweets containing the political hashtag #cdnpoli to investigate who uses the hashtag, what the nature of tagged tweets is, and to what extent Twitter enables political conversation and participation. Mass media actors contributed to about 10% of the tweets, whereas politicians accounted for less than 2%. Tweets were focused mainly on informing, but very few tweets could be identified as reporting of news (Small, 2011). The Austrian political discussions were studied by Ausserhofer and Maireder (2013), with a focus on relations between political actors and citizens. This was contrasted with articles published by newspapers during the same period of time. It was concluded that the Austrian political Twittersphere was dominated by an elite of political professionals, but also that the discussions were open to participating citizens.

Few examples exist regarding polarisation on Twitter. Conover et al. (2011) examined political polarisation during the 2010 US congressional midterm elections by analysing re-tweet and @mention networks, and found that the former revealed a polarised structure, but also that the latter did not indicate polarisation. It was concluded that users might try to provoke an interaction by injecting partisan content into the opposing actors' timelines. Kim and Park's (2012) study of followers of five Korean politicians from four different parties showed little overlaps between the sets of followers, suggesting that polarisation exists in the chosen context. The aforementioned study of Bruns and Highfields (2013) also included an analysis of cross-boundary communication, showing that Twitter actors @mention other actors from not just one, but several different political groupings. It was also shown that cross-boundary @mentioning existed between the party organisations.

### **3. Method**

The following section describes and discusses issues of how to access Twitter data, the algorithm for identifying the most active and visible actors, the analysis of profile descriptions, and the analysis of networks.

#### **3.1. Data collection**

For gathering Twitter data, an adapted version of yourTwrapperKeeper was used. Some changes were needed to make the software comply with Twitter's new developer rules. Data were collected by tracking the hashtag #svpol during four weeks in September 2012. This is "a manageable and low-cost alternative" (Bruns & Stieglitz, 2013, p. 92). The goal is not to capture the entire conversations, but rather a sample of it. The main focus here is to map the relationships and the communication among the participating actors. According to Bruns (2011), studies of @mention patterns within a set of tweets containing a hashtag can identify the most central users within the topical network of the hashtag. This paper extends the method by also including followership networks. Using only tweets matching a given hashtag entails that a large portion of replies to messages will be missing. Bruns (2011) points out that a hashtag-based study captures the beginning rather than the conclusion of conversations. Hence, most @mentions in this dataset are more of initiatives to conversations.

In the dataset used for this paper 10,294 actors were present. To make a manual categorisation of actors possible, a subset containing the top tweeters was created algorithmically by first filtering out the actors contributing with less than five tweets during one week and then calculating an authority score for the remaining actors. Drawing on Anger and Kittl (2011), an authority score was here calculated from the activity and the visibility of each actor, as well as its probability of spreading a message throughout the network. A weighting scheme was used to calculate the scores (Table 1). These metrics are based on the assumption that activity and spreadability are important, therefore original tweets and original tweets re-tweeted by other actors receive a higher weight. But conversation rate is also considered important, so directed tweets get a higher weight than a re-tweet by the actor. A re-tweet passes a message on to a wider audience, as well as it can indicate agreement with the content, so the number of re-tweets is also part of the score.

[insert Table 1 about here]

The list of actors was sorted by the average value, and the top 500 were kept. At the end of the four weeks the lists of actors were aggregated into one final list of 916 actors. These are labelled authorities in this paper. The goal was to focus the analysis on actors that at some stage contributed sufficiently to the conversations whilst still having the possibility of making a qualitative analysis of the actors. This method captures the actors with a relative contribution to the conversations, as well as it captures different types of actors. An actor can be included because of frequent tweeting, being frequently tweeted to, or having its tweets re-tweeted frequently, or having a high score on all of the metrics. Previous studies have shown that political conversations on Twitter are dominated by a small number of users (e.g. Jürgens et al., 2011; Bruns & Highfield, 2013), and this study is no different with the 916 actors accounting for 72% of all tweets.

After the data collection period, the four lists of authorities were aggregated into one final list of actors. The final list comprised 916 actors of which 17 had protected profiles. Tweets posted by an actor with a protected profile are retrieved by the application, but data about the actor, such as his/her friends, followers and profile data cannot be retrieved, so these 17 actors were excluded from the analysis. The profile data, which include a description of the actor written by the actor itself, of the remaining 899 actors were collected alongside the lists of the actors' friends. A friend limit of 15,000 was set to prevent the system from spending too much time on potential spam accounts with an unrealistic number of friends. All the Twitter IDs were re-coded for ethical reasons so that no political views could be associated with a physical person.

There are some issues that have implications on the result. boyd et al. (2010) concede that there is no agreed-upon syntax for a re-tweet, but that the prototype is "RT @user Text". A problem is, however, that Twitter's re-tweet button embeds the tweet in the actor's timeline without adding RT and the original tweeter's username (Bruns, 2011). The compromise solution was to follow the prototype "RT @user Text", accepting that some re-tweets cannot be captured. It should also be noted that not all replies are hashtagged, so the network of @mentions underestimates of the follow-on communications (Bruns & Stieglitz, 2013). With the lack of replies, the @mention analysis is merely an analysis of initiatives to conversations, rather than an analysis of conversations.

### **3.2. Analysing data**

All the profile descriptions were analysed manually by two people. Following the groupings in the parliament, the actors were categorised into the left block (L; 136 actors), the centre-right block (CR; 116), the right-wing block (RW; 62), and other blocks (23), based on the content in their profile descriptions. In some cases, the Twitter account could be associated with a known politician, and the political block was then determined by the party the politician was a member of.

Social network analysis was utilised to map the relationships and the communication between actors. In social network analysis, nodes (the actors) are connected by arcs or edges representing the relationship between the nodes. The information this analysis provides can be used to contextualise the relationships and the activities in the conversations. Of interest here is the relationships and communication within the groups and between the groups. While the focus of the paper is to analyse the relationships and communication across the block boundaries, knowledge of relationships and communication within the blocks is valuable to contextualise the inter-block findings. For example, are members of a block more willing to communicate with each other than with members of another block, and if so, to what extent? Different types of networks were created using the Gephi software (Bastian et al., 2009), and laid out using the ForceAtlas 2 algorithm. The networks, with disconnected nodes excluded, are:

1. Followership network (893 nodes, 48,401 edges), where edges are drawn from an actor to the actors the actor follows.
2. Communication network (693 nodes, 3,995 edges), where edges are drawn from an actor to the actors he/she has @mentioned.

3. Re-tweet network (851 nodes, 6,417 edges), where edges are drawn from an actor to the actors he/she has re-tweeted.

Two network metrics are used in this paper. These are *density* and *degree centrality*, where density is an indicator of connectedness of a network, given as the number of connections in a graph divided by the maximum number of connections, and degree centrality is an indicator of how central a node is, given as the number of connections the node has with other nodes (Wasserman & Faust, 1994, pp. 129, 178). This paper uses two versions of degree centrality: normal and weighted, where the latter takes the number of interactions (@mentions and re-tweets) as a weight.

Finally, the actors were divided into groups based on their activity (see Bruns & Stieglitz, 2013). The groups follow a 90/9/1 division where the 1% most active actors form one group. The activity is also broken down into these actions:

- Original tweets: original statements not including @mentions,
- @mentions: mentions of other actors including messages directed to other actors but excluding re-tweets,
- Re-tweets, and
- Tweets containing URLs.

Of the 916 authorities, 103 belonged to the top percentile, and 706 to the next nine percent group. 107 actors were not in the top 10 percentile group.

## 4. Results and discussion

The nodes in the network graphs are sized according to their degree centrality value, that is, the total number of connections with other nodes. In the @mentions and re-tweet graphs, the weighted degree is used, which is the total number of @mentions and re-tweets.

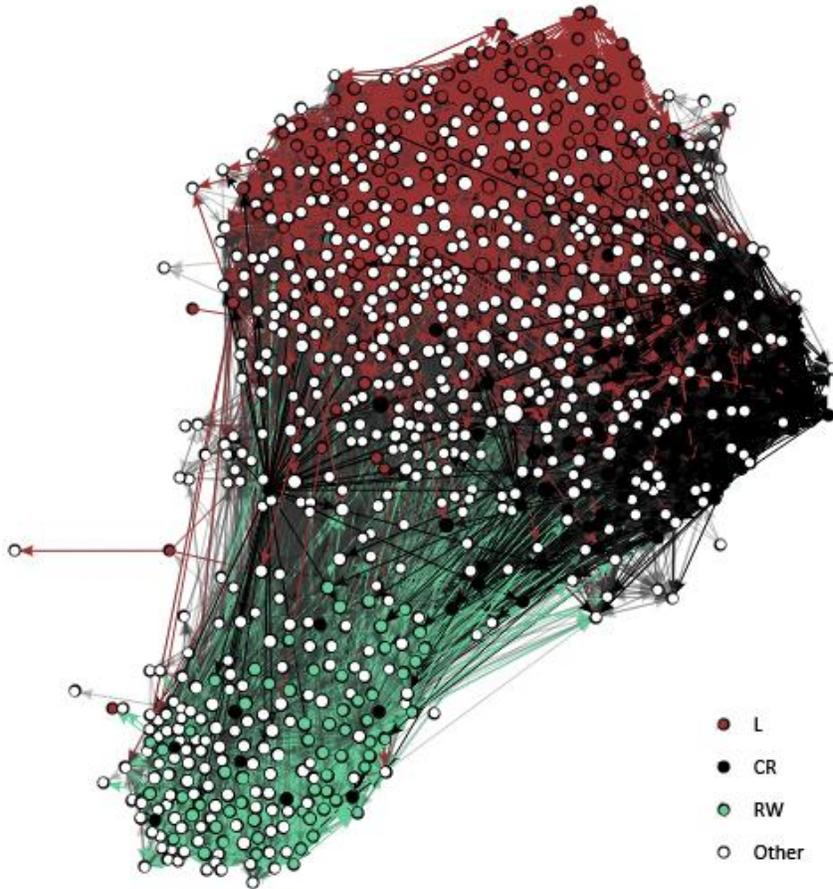
### 4.1. Group level analysis

The followership graph (Figure 1) reveals that the members of the three main groups are clustered together. More than 95% of the actors within these groups follow fellow group members. At the bottom left, the RW group (green) is somewhat distant to the other groups, even though there are some CR actors (black) situated close by or even within the RW cluster. There are more connections between CR and L actors, and as a consequence these clusters are closer in the graph. The network analysis shows that the actors follow actors from other groups to some extent (Table 3). The strongest connections between two groups are between L and CR. The average CR actor follows and is followed by 7 L actors. The average L actor follows and is followed by 6 CR actors. There is very little connection between L and RW. Looking at the network as a whole, actors from all three groups follow an equal number of actors from other groupings (41 friends), but the right-wingers have more followers per actor (48; CR: 42; L: 37). When taking the whole network into account, RW has slightly more friends (65; CR: 63; L: 62), and more followers per actor than the other two (72; CR: 64; L: 57).

[insert Table 2 about here]

The groups differ from each other regarding intra-group followership. RW is by far the densest network with a density of 0.38 (Table 2). All networks have a similar average degree, but as the RW group is smaller, these connections are also distributed over fewer actors. CR and L have a similar density value, with the former being slightly denser than the latter. All three networks are denser than the network as a whole.

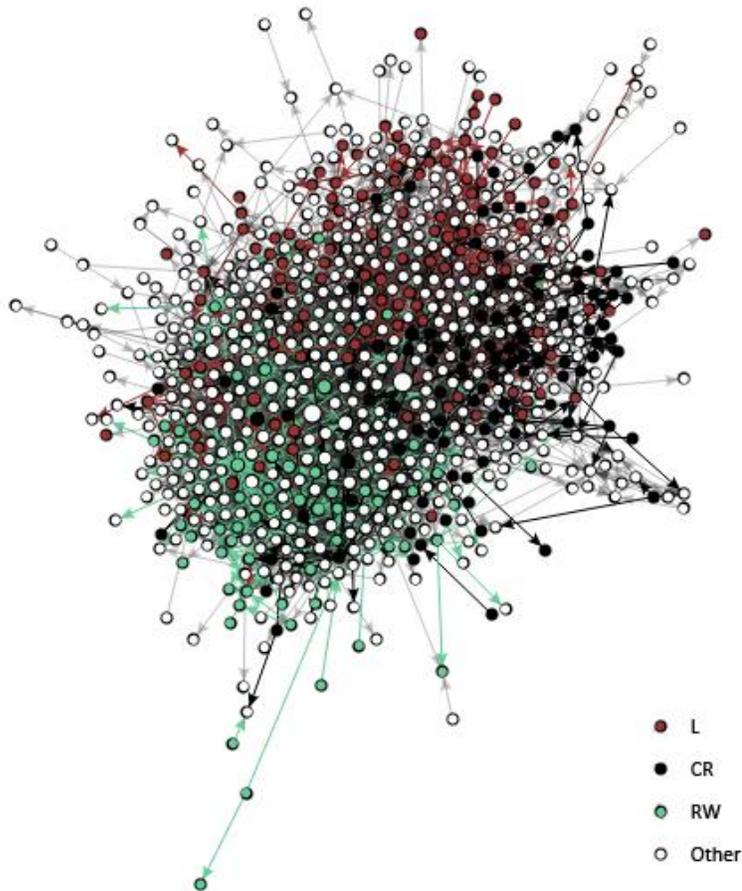
[insert Table 3 about here]



**Figure 1. Followership graph. Nodes and edges are coloured by their block affiliations. Red: left block, black: centre-right block, green: right-wing block, white: other blocks and unknown actors.**

Contrary to the followership graph, the @mentions graph (Figure 2) is very sparse, but the figures reveal interesting findings (Table 4). Overall, RW actors send significantly more messages than members of the other groups. RW is also the only of these three groups that sends more messages than it receives. L actors are the least active when regarding messages sent. CR and L have a reciprocal communication, with 73 CR messages sent to L and 75 messages sent in the opposite direction. The communication between CR and RW is also fairly reciprocal, with 69 messages from CR and 62 from RW. However, RW sent 111 messages to L, but only received 19. The intra-group activity differed among the groups. RW actors communicate significantly more with each other than with the other groups. The RW network is much denser than the other two and has a significantly higher average weighted degree (Table 2).

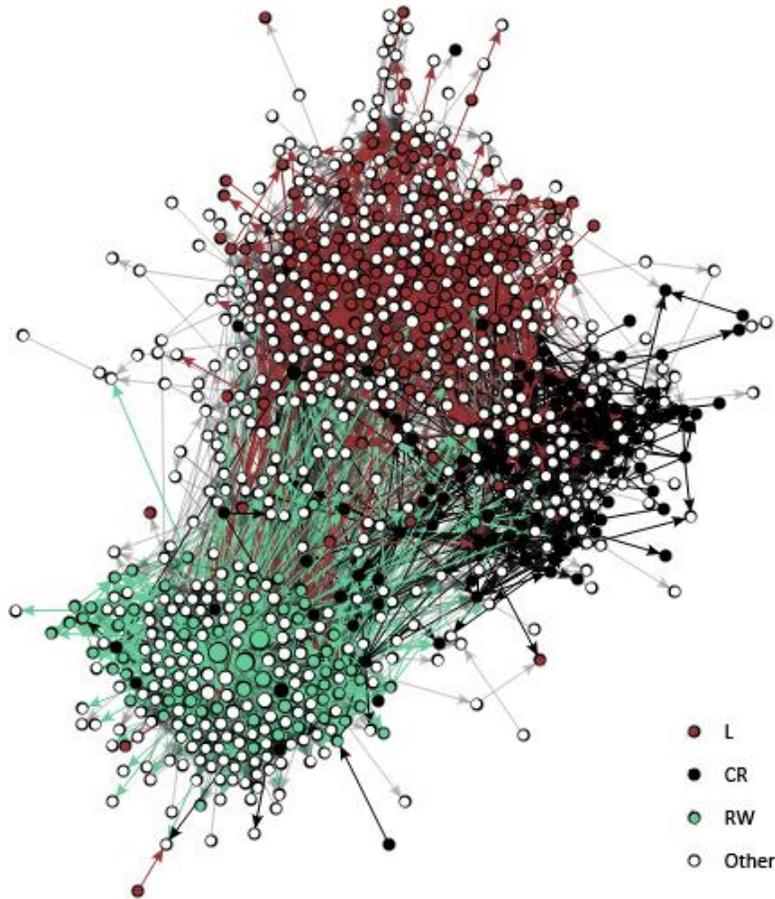
[insert Table 4 about here]



**Figure 2. @mentions graph. Nodes and edges are coloured by their block affiliations. Red: left block, black: centre-right block, green: right-wing block, white: other blocks and unknown actors.**

The re-tweet graph (Figure 3) mirrors the followership graph, but is sparser. There is a significant difference in the messaging behaviour compared with the re-tweet behaviour. Table 5 shows the total number of re-tweets performed by the groups in the “Out” columns and the total number of re-tweets of the own tweets in the “In” columns. For all main groups, a large share of the re-tweets made by group members are re-tweets of messages posted by other group members. RW actors are the far most frequent re-tweeters with a total of 4427 re-tweets (L: 1,606; CR: 976). RW actors also have more tweets re-tweeted (2,922; L: 1,275; CR: 1,216). Re-tweeting tweets from one of the other two main groups was generally not as common as @mentions, even though RW actors re-tweeted CR messages 267 times.

[insert Table 5 about here]



**Figure 3. Re-tweet graph. Nodes and edges are coloured by their block affiliations. Red: left block, black: centre-right block, green: right-wing block, white: other blocks and unknown actors.**

Table 6 shows the differences between the networks. The @mention network does not show signs of polarisation. Actors within the blocks seem to be as willing to communicate with members of other blocks as with members of their own block. All groups have an @mention ratio close to 1, which gives little support for polarisation. RW is the exception when comparing followership and re-tweets network. It is the only block with a followership ratio that is close to the re-tweet ratio. As the last section revealed, RW actors do re-tweet tweets from other blocks to a larger extent. Overall though, the re-tweet network is more polarised than the followership network. As the hashtagged set of tweets do not contain replies without the hashtag, the @mention network cannot function as an indicator of polarisation.

[insert Table 6 about here]

#### **4.2. General statistics**

Of the 77,436 gathered tweets, 45% were original tweets, 18% included @mentions, and 37% were re-tweets. 51% contained a URL. So far, very different results have been reported. Larsson and Moe (2011) found 60.2% original tweets, 32.8% re-tweets and 7% directed messages. Small (2011) found that 7% of the tweets were @mentions and commented re-tweets.

The analysis of the activity by user percentile groups (Figure 4) shows similar results as Bruns and Highfield (2013). The least active 90% did not contribute as much as the other groups. When they did, a larger percentage of their tweets were re-tweets. The share of @mentions is larger in the top 1% group, and the top 10% has a larger share of

original tweets. The use of URLs was very similar across all groups, even though the least active group had a marginally larger share of tweets including URLs than the other groups. A difference between these results and those of Bruns and Highfield is that a larger share is comprised by original tweets in this set, at the expense of @mentions.

When comparing the three main political groups (Figure 5), a different pattern emerges. Although all groups posted a similar amount of original tweets, and, except for the left block, a similar amount of @mentions, the right-wingers posted far more re-tweets. 49.6% of their tweets were re-tweets, which is quite similar to the least active 90% group.

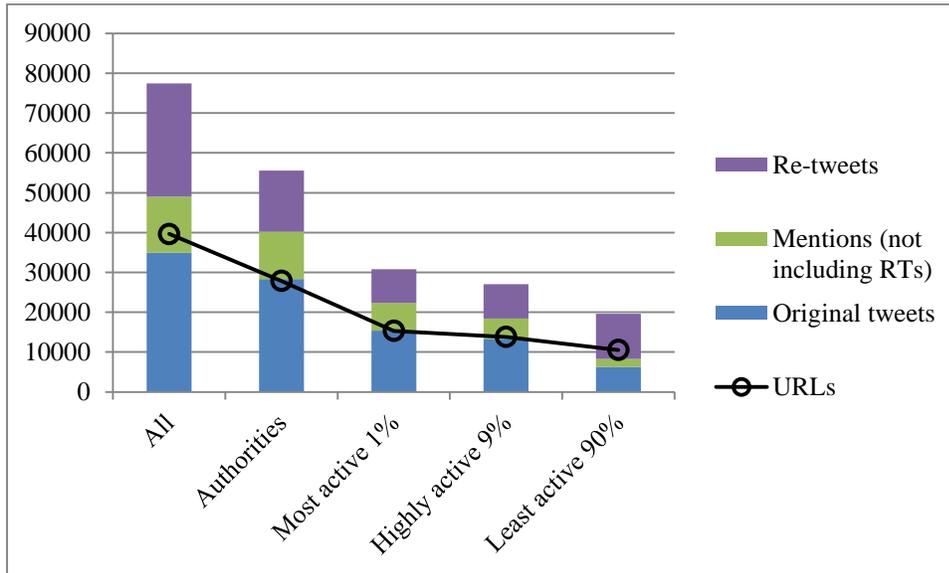


Figure 4. Activity by actor percentiles, compared to the whole group of actors, and the group of authorities.

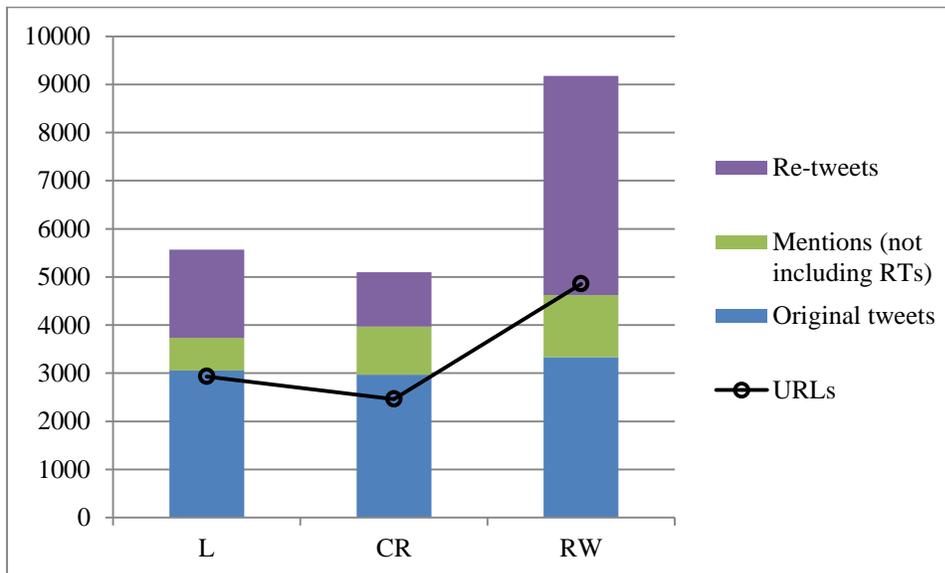


Figure 5. Activity by main political groups.

## 5. Conclusions

This paper analysed communication and relationships across political boundaries by using three different kinds of networks. Cross-boundary relationships exist, with a stronger connectedness between the left and centre-right blocks.

This is perhaps not surprising when considering that both blocks include actors that ideologically-wise would be positioned near the centre of the left-right scale. The communication network was quite sparse, which is partly due to the hashtagged dataset not including replies without the hashtag. Least active in initiating conversations were actors of the left block. The communication across boundaries was fairly reciprocal with one exception. The right-wingers sent 111 messages to left block members, but received only 19. The re-tweet network is more polarised than the other two, as the actors mainly re-tweeted tweets from their own group. It is possible that the actors re-tweet actors they follow, but this paper did not investigate that relation. The right-wingers were the most frequent re-tweeters with 49.6% of their messages being re-tweets. This is interesting considering that they were very active as a group, but when looking at the overall statistics, only the least active 90% had a comparable re-tweet share.

The analysis of these networks revealed clear examples of filter bubbles, but also that people are using the allowances of Twitter to create connections beyond the bubbles. All the relationships sub-networks were denser than the network as a whole, and more than 95% of actors within a block followed their fellow block members, but the three main groups have also produced different bubbles. The one that is most different from the others is the RW group, which is much denser in all three networks. Its actors are more outreaching, as well as they attract more followers per actor. The numerically strong representation, and the high activity, of right-wingers is an interesting finding. As Larsson and Moe (2011) suggested, there is a potential of the Twitter platform to function as a means of outreach for minority actors. The other blocks have stronger representation in the parliament, which might entail a more restrictive usage of social media, and they have also had a strong standing in the traditional media. But these blocks also differ from each other, with CR actors more often @mentioning other actors, and L actors more often re-tweeting. CR actors are least active in re-tweeting, but on the other hand, get re-tweeted more often than they re-tweet. This clearly indicates that behaviour is different within sub-groups of the conversations, and that research needs to look beyond the holistic view of the conversations. It will be interesting in further research to see if these kinds of filter bubbles, with their different characteristics and the levels of cross-boundary followership and communication, are a specific Swedish phenomena or something that can be identified in other political cultures as well. Also of interest would be to compare the relationships and activity during non-election times, as in this paper, with election times.

There are some points that need to be addressed qualitatively. First, RW actors sent far more messages to L than vice versa. As these groups are supposed to be farther from each other than other groups in this setting, and the aforementioned relationship analysis confirms this, it would be tempting to follow up on Conover et al. (2011) and investigate if actors are trying to provoke interaction with actors from other groupings. The nature of the @mentions would be an interesting subject to investigate as well. Are they used as, for example, substitutes for politicians' names as suggested by Bruns and Highfield (2013), or are these tweets truly conversational? Second, RW actors were re-tweeting the other groups more often than vice versa. Given that they have more followers per actor, they help other groups to spread their messages. But what is the type of messages re-tweeted, who are the actors that re-tweets, and who are they followed by? The possibilities and habits of modifying messages when re-tweeting (boyd et al., 2010) also makes it possible to attribute content to someone who is not responsible for it, or to modify the content that someone was responsible for. This entails that the audience viewing a re-tweet may on one hand be notified of a conversation they might be interested in, but, on the other hand they may also get the wrong idea of an actor's opinion should the message have been altered. As Murthy puts it, "when tweets are re-tweeted, they become re-embedded into the situated present of the recipient. [...] with Twitter, the audience range is not always in congruence with the perceptual range of the original Twitterer." (Murthy, p. 1068) For these reasons, cross-boundary re-tweets need to be analysed qualitatively in order to find out why an actor from one group is re-tweeting an actor from another group.

Finally, the combination of followership and communication data enable us to find both actors that are well connected through followership but not active in their communication, and actors that are active in their communication but not well connected. This was not investigated further in this paper, but for future studies, it could be interesting to find what kind of actors that are well connected but less active, and vice versa.

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Aspect	Metric	Description	Weight
<b>Outbound activity</b>	Original tweets	The number of tweets that are not re-tweets or @mentions	2
	Directed tweets	The number of @mentions	1.5
	Re-tweets	The number of re-tweets posted	1
	Outbound conversation	The number of actors @mentioned by the actor	1
<b>Inbound activity</b>	Received tweets	The number of tweets received	1
	Inbound conversation	The number of actors @mentioning the actor	1
<b>Spreadability</b>	Tweets re-tweeted	The number of own tweets re-tweeted by other actors	2
	Actors re-tweeting	The number of actors that have re-tweeted a tweet posted by the actor	1

Table 1. Metrics for the calculation of the authority score.

	Followership		@mentions		Re-tweets	
	Density	Avg degree	Density	Avg w. degree	Density	Avg w. degree
<b>L</b>	0.15	20.49	0.004	0.69	0.018	4.6
<b>CR</b>	0.19	21.9	0.006	1.52	0.018	3.46
<b>RW</b>	0.38	22.28	0.029	2.77	0.096	23.29
<b>Overall</b>	0.06	52.84	0.005	8.57	0.008	4.92

Table 2. General network statistics.

Group	L		CR		RW		All other groups		Total	
	Out	In	Out	In	Out	In	Out	In	Out	In
<b>L (n = 136)</b>	20.49		5.89	5.84	0.45	0.63	41.21	36.85	61.70	57.33
<b>CR (n = 116)</b>	6.84	6.91	21.90		2.08	2.27	41.01	42.29	62.91	64.19
<b>RW (n = 62)</b>	1.37	0.98	4.24	3.89	22.28		41.76	48.61	64.71	71.56

Table 3. Cross-boundary followership, average per actor.

Group	L		CR		RW		All other groups		Total	
	Out	In	Out	In	Out	In	Out	In	Out	In
<b>L (n = 136)</b>	94		75	73	19	111	282	876	376	970
<b>CR (n = 116)</b>	73	75	176		69	62	497	841	673	1017
<b>RW (n = 62)</b>	111	19	62	69	172		701	793	873	965

Table 4. Cross-boundary communication, number of @mentions.

Group	L		CR		RW		All other groups		Total	
	Out	In	Out	In	Out	In	Out	In	Out	In
<b>L (n = 136)</b>	626		65	39	22	34	980	649	1,606	1,275
<b>CR (n = 116)</b>	39	65	401		48	267	575	815	976	1,216
<b>RW (n = 62)</b>	34	22	267	48	1,443		2,984	1,479	4,427	2,922

Table 5. Cross-boundary re-tweets.

Group	Followership ratio	@mention ratio	Re-tweet ratio
<b>L</b>		3.23	1
<b>CR</b>		2.46	1.24
<b>RW</b>		4.09	0.99

Table 6. Comparison between networks. The ratio is own group/the other two groups.