The Detection of Conversation Patterns in South African Political Tweets through Social Network Analysis

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Abstract. Within complex societies, social communities are distinguishable based on social interactions. The interactions can be between members or communities and can range from simple conversations between family members and friends to complex interactions that represent the flow of money, information, or power. In our modern digital society, social media platforms present unique opportunities to study social networks through social network analysis (SNA). Social media platforms are usually representative of a specific user group, and Twitter, a microblogging platform, is characterised by the fast distribution of news and often provocative opinions, as well as social mobilizing, which makes it popular for political interactions. The nature of Twitter generates a valuable SNA data source for investigating political conversations and communities, and in related research, specific archetypal conversation patterns between communities were identified that allow for unique interpretations of conversations about a topic. This paper reports on a study where social network analysis (SNA) was performed on Twitter data about political events in 2021 in South Africa. The purpose was to determine which distinct conversation patterns could be detected in datasets collected, as well as what could be derived from these patterns given the South African political landscape and perceptions. The results indicate that conversations in the South African political landscape are less polarized than expected. Conversations often manifest broadcast patterns from key influencers in addition to tight crowds or community clusters. Tight crowds or community clusters indicate intense conversation across communities that exhibits diverse opinions and perspectives on a topic. The results may be of value for researchers that aim to understand social media conversations within the South African society.

Keywords: Social Network Analysis, Twitter Networks, Community Clusters, Network Visualisation, South African Politics.

1 Introduction

How communities form plays a significant role in understanding society and society interactions [1, 2]. In the past decade, various studies were done on the usage and influence of the internet, technology, and social media in society [3–5]. These studies indicate that social media is one of the most important means of communication in our digital society and therefore forms a significant part of what determines the views and opinions of people [6–9]. To study conversations and communities, social network analysis (SNA) emerged as a distinct research field. SNA analyses network structures in social media networks, for instance, networked communities and clusters that are established because of interactions between members. Understanding how online communities form and communicate allows us to interpret the flow of information and opinions, as well as identify notable influencers [10].

Several social media platforms are used for social media interactions, and each of these platforms became representative of a specific means of communication and user profile [11–13]. Twitter, specifically, is a microblogging platform that is characterized by the fast flow of information and opinions, often from notable influencers, as well as social mobilization [14]. These characteristics are particularly valuable when analysing political conversations within a specific society, an important capability given evidence of collective action observed globally that resulted in substantial turmoil due to protest action [15–17]. In South Africa, protest action and unrest that occurred in July 2021 were mainly organized using social media platforms [18, 19], which emphasizes the necessity to understand social media networks, conversations, and communities. In particular, in the aftermath of the looting, alleged instigators were arrested based on their social media activity, specifically using Twitter [20].

Twitter was established in 2006 and is described as a social media platform that is dedicated to the sharing of news and opinions through tweets or microblogs, which are a maximum of 280 characters long [21]. Users can follow other users without mandatory interaction, but can of course reply, retweet, or mention other users or tweets and use hashtags to markup tweets with topics. Twitter is particularly popular for expressing political and controversial opinions and Twitter's APIs, therefore, provide access to a valuable source of conversational data. This study aimed to detect the social network structures and conversation patterns within Twitter datasets surrounding specific political events during 2021 in South Africa.

Understanding the formation and dynamics of politics in social networks can provide useful insights into the interactions and changes in political communities, and might assist in the design of interventions [15, 16]. The remainder of the paper is structured as follows. The next section, Section 2, provides a brief background and summary of related work, followed by Section 3 discussing the research approach. Section 4 presents the results and findings given the SNA analysis of the datasets, and Section 5 concludes.

2 Background and Related Work

This section provides an overview of social networks and social network analysis (SNA), followed by the application of SNA on social media data.

2.1 Social Network Analysis

Social network analysis (SNA) is defined as the analysis of social (media) structures using network and graph theory [22–24]. A set or group of social actors that interact create a complex network that can be studied to gain insight into the relationships between individuals and groups within societies [25]. When studying social networks, the interactions and relations between actors are considered, and not the properties of the actors themselves [1, 26]. The identification of clusters, communities, or groups given the interactions of actors is an important objective of SNA, and groups are detected by analysing the interactions within a group as well as the interactions between different groups or clusters [8, 27]. Several algorithms exist that assist with the detection of groups or communities in networks, for instance, the Clauset-Newman-Moore algorithm [28, 29]. The algorithm detects communities by greedily optimizing using modularity [28].

The Social Media Research Foundation (SMRF) [30] was established with the distinct purpose of studying social media and uses SNA extensively. One of their research outputs is a network analysis application, NodeXL, that assists with network analysis, as well as social network and content analysis [31, 32]. NodeXL uses data from social media platforms that provide data extraction APIs such as Twitter.

2.2 Archetypical Twitter Conversational Patterns

Using NodeXL from the SMRF to analyse Twitter data, Smith et al. identified six distinct archetypical conversational patterns using network-level metrics namely density, modularity, centralization, and the fraction of isolated users [32–34]. These conversation patterns have specific characteristics that portray the conversations around specific topics, hashtags, or identities, and the patterns are briefly summarised below:

- ***The Polarized Crowd*** is a conversation pattern where a relatively small number of groups are clearly divided with dense conversations within groups but few interactions between groups. Hashtags are mostly not shared between groups. Such a pattern implies divisive and polarized discussions where groups do not argue but ignore each other. The distinct groups rely on different information sources and do not interact. Several examples of such patterns were detected within the USA, for instance as documented by the seminal work of Adamic and Glance [15] who investigated the political blogosphere of the 2004 U.S. Elections and found a distinct divide between liberal and conservative blogs.
- ***The Tight Crowd*** pattern is the opposite of the polarized crowd in that the groups are highly interconnected within as well as between groups, and have few isolates. Hashtags are shared between groups. This pattern implies that participants have interactive conversations, even arguments, and exchange ideas and opinions. Such a pattern could typically be observed when communities form at events or conferences, or when communities discuss professional topics or hobbies. Such groups support each other with information flows between members of the group [32, 35].
- ***Brand Clusters*** is a conversation pattern where groups are fragmented and there are many isolates, which indicates that there are mentions or isolated conversations about well-known brands, topics, services, or celebrities. The groups are small and interconnected, and there is a limited exchange of ideas between members of a group or between groups. Hashtags about the brand are shared between groups. Information about the topic is just passed on [32, 35].

- ***Community Clusters*** is a conversation pattern that resembles a bazaar with different stalls characterized by several even-sized groups rather than a crowd of mostly unconnected nodes [36]. Multiple medium-sized groups or hubs each have their own audience, influencers, and sources of information. Conversations are typically within a group that would entail diverse opinions on a subject with limited exchanges between groups. There are also a fair number of isolates [32, 35].
- ***A Broadcast Network*** conversation pattern is the first of two distinct hub-and-spoke patterns, which resembles a broadcast information flow typically where news from a media outlet, influencer, or agenda setters is distributed through the network [36]. The nodes are connected to the hub and are not connected, indicating that are no conversations about the topic. [32, 35].
- ***A Support Network*** pattern is also a hub-and-spoke pattern but with outgoing information flows from the hub. This pattern indicates that there are responses from the hub to the spokes, which are typically observable where "customer services for a major business are handled by Twitter service accounts" [35]. This conversation pattern could be detected where an account such as government provides services and support via social media [32, 35].

The archetypal conversation patterns detectable in Twitter data provide a mechanism to understand social media communities and their conversations, and therefore allow a unique opportunity to gain insight into the Twitter data surrounding specific political events during 2021 in South Africa.

3 Research Approach

The research approach adopted for this study is experimental and was based on the method proposed by the SMRF to detect archetypal conversation patterns in Twitter data [33]. The purpose of the study was to determine which distinct conversation patterns could be detected in the datasets collected and what could be derived from these patterns given specific South African political events. These datasets were collected because the specific political events in 2021 evoked a lot of media attention and resulted in significant Twitter activity, which made the datasets ideal candidates for conversation pattern mining. Twitter limits the number of tweets that can be collected, and all the datasets were therefore limited to a maximum of 18 000 tweets. Five datasets were collected namely:

- Dataset 1 (DS1): Tweets using the #PutSouthAfricaFirst hashtag at the beginning of May 2021. The hashtag was key in the political landscape during this time period due to xenophobia discussions [37, 38].
- Datasets 2 and 3 (DS2 and DS3): Two Twitter datasets were collected using the #VoetsekANC hashtag during two time periods, 24 August 2020 and 4 May 2021. The #VoetsekANC hashtag emerged in August 2020 in response to the frustration experienced by South Africans after more than 4 months of lockdown, the ineptitude of the government to handle the pandemic, and the constant emergence of corruption allegations [39–41]. The Twitter community

constantly urged each other to use the hashtags on every Friday, the so-called #VoetsekANCFriday.

- Dataset 4 (DS4): Twitter data surrounding the violent protests and looting in Gauteng and KwaZulu-Natal using the hashtag #SouthAfricaIsBurning in the second week of July 2021 [42, 43].
- Dataset 5 (DS5): A dataset collected early August 2021 using the identifiers "@TellUnknown OR @AZANIA_kal", which are Twitter accounts of two alleged instigators of the looting in July 2021 [20, 44].

All the datasets collected for the experiments were imported into the NodeXL application, which allows for representing tweet identities as graph vertices and interactions (that is replies or mentions) as directed edges. There is an edge for each "replies-to" relationship in a tweet, an edge for each "mentions" relationship in a tweet, and a self-loop edge for each tweet that is not a "replies-to" or "mentions". Retweets would create a new vertex.

Initial data wrangling included the removal of duplicates. The detection of groups or communities was done by applying the Clauset-Newman-Moore algorithm [28]. Several graph metrics were calculated for each dataset including the number of vertices, unique edges, and self-loops, and these metrics are summarized in Table 1. The top words, hashtags, and word pairs by frequency of mention were determined for the overall network as well as for each group within each network. The network was visualised using the NodeXL graph visualisation features that included visualising groups and interactions between groups using the Fruchterman-Reingold layout algorithm. The Fruchterman-Reingold algorithm is a force-directed iterative algorithm that results in a layout where edges are relatively similar in length for visualization purposes, but the edge length has no specific meaning [45]. The overall graph metrics of the networks are summarized in Table 1.

Table 1. Graph Metrics for the datasets

Graph Metric	DS1	DS2	DS3	DS4	DS5
Vertices	1800	2708	915	12924	799
Unique Edges	2574	6122	1496	18621	1307
Edges with Duplicates	0	3077	402	2634	1144
Total Edges	2574	9199	1898	21255	2451
Self-Loops	123	746	225	2717	80

For this experiment betweenness centrality was used for determining the top vertices since it possibly indicates more central, and arguably, more influential vertices. The top vertices ranked by betweenness centrality for the datasets are depicted in Table 2.

Table 2. Top vertices for the different datasets ranked by betweenness centrality

DS1 (#PutSAFirst)	DS2 (#VoetsekANC 1)	DS3 (#VoetsekANC 2)
mbuyisenindlozi	cyrilramaphosa	tiamontombonina
lerato_pillay	myanc	king78190744
thabe_mudzu	54battalion	sipho_nkosi
peezyjr	vivimpikashe	thokozaninala
hermajestynhla	unathi_kwaza	johnbis75624915

DS4 (#SAIsBurning)	DS5 (Instigators)
miss_zoe101	tellunknown
thearielcohen	azania_kal
nosihlemkhwana2	naomicampbell
cyrilramaphosa	ntsikimazwai
tjrmakhetha	gentlements

4 Results and Findings

In this section, the results of the analysis of each of the datasets are discussed, as well as what could be derived from the detected conversation patterns.

4.1 Dataset 1 - #PutSouthAfricaFirst

The dataset was collected from 1 800 Twitter users whose recent tweets contained "#PutSouthAfricaFirst", or who were replied to or were mentioned in those tweets. The hashtag emerged as representative of the xenophobic discussions that urged South Africans to “take their country back” and “get rid of foreigners” [37, 38]. The network was obtained from Twitter on Tuesday, 04 May 2021 but the tweets in the network were tweeted over the previous 7-day period.

This graph depicted in Figure 1 is a good example of a Broadcast conversation pattern, which is dominated by a hub-and-spoke structure with many spokes directed towards the hub [33]. This is depicted by Group 1 on the left of Figure 1. The hub is usually an influencer and the spoke vertices do not interact and therefore only link to the hub. Isolates indicate that the message has an impact beyond the hub, and some groups also exist that discuss the message between themselves (for example, Group 2 on the top right of Figure 1).

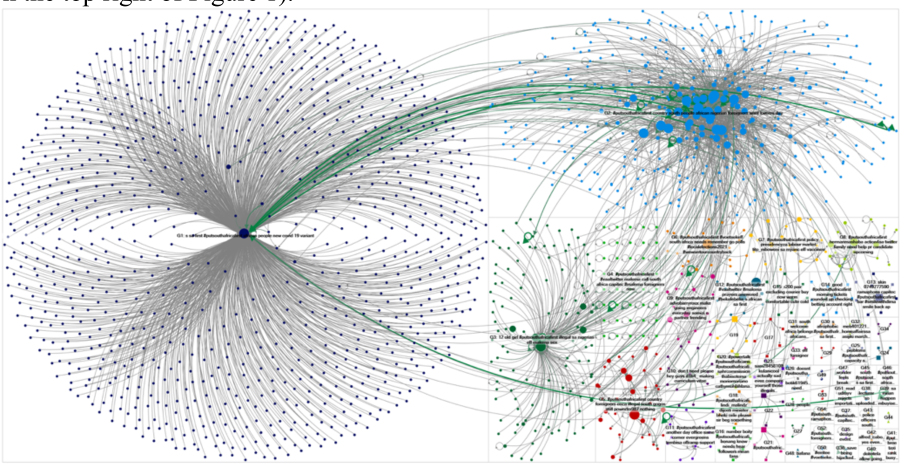

Figure 1. Conversation pattern for Dataset 1, a Broadcast pattern.

The hub vertex in this graph is *mbuyisenindlozi*, (refer to Table 2 as well, which lists the top vertices) who posted the tweet that was reacted upon to creating the spokes:

"If there was a new Covid-19 variant in Zimbabwe the border would have been long closed. The #PutSouthAfricaFirst brigade would be trending daily. But because it's India, no one said nyenye SA First. Why? It's only SA firs when it's African people- bloody self-hating hypocrites"

As is typical with the Broadcast pattern, the top hashtags are repeated in the bigger groups and this denotes the repeating of the hub's message and information (see the hashtags in Table 3).

The Broadcast conversation pattern detected is contrary to the perceptions at the time since the sentiment was that there is a large community that discusses the xenophobic topics surrounding the #PutSouthAfricaFirst hashtags [37, 38]. However, the Twitter conversation pattern indicates that there was mainly a single influencer whose message is reacted upon but very limited interaction or discussion on the topic.

Table 3: Top hashtags [1]by frequency of mention for the largest groups in Dataset 1.

Top Hashtags I Entire Graph	Top Hashtags G1	Top Hashtags G2	Top Hashtags G3
putsouthafricafirst putsouthafricafirst freedomday	putsouthafricafirst ymornings putsouthafri- cafirst backtoschool girlstalkza jobseekerssa vote putsouthafricafirst	putsouthafricafirst putsouthafricafirst freedomday	putsouthafricafirst putsouthafricafirst freedomday
putsouthafricafirst foreignersmustleavesa wewantourcountryback localelections2021 voetsekeff putsouthafricafirst voetsekanc voetseksamedia putsouthafricafirst		putsouthafricafirst foreignersmustleavesa wewantourcountryback voetsekanc voetseksamedia putsouthafricafirst ramaphosa fikilembalula putsouthafricafirst	putsouthafricafirst foreignersmustleavesa wewantourcountryback voetsekanc voetseksamedia putsouthafricafirst wewantourcountryback putsouthafricafirst

4.2 Dataset 2 and 3 - # VoetsekANC

The #VoetsekANC hashtag emerged after 4 months in lockdown in response frustration experienced by South Africans after more exposure about corruption as well as the ineptitude of the government to handle the pandemic [39–41]. The first dataset was therefore collected from 2708 Twitter users whose recent tweets contained "#VoetsekANC", or who were replied to or mentioned in those tweets. However, what was interesting about the "#VoetsekANC" hashtag is that this specific Twitter community started a campaign urging Twitter users to use the hashtag on every Friday, including the so called #VoetsekANCFriday hashtag. This was the motivation for collecting the second dataset as well. The dataset was obtained from Twitter on Tuesday on 24 August 2020 and contained the tweets that were tweeted from 31 July to 24 August 2020.

The conversation pattern of the first #VoetsekANC dataset detected is a Tight Crowd with relatively few groups that are highly connected within and between the groups. The Tight Crowd pattern implies discussions between densely interconnected

[1] The hashtag lists are depicted exactly as they appear in the tweets with the same capitalisations. Twitter users aims to use similar hashtag lists when the mention, reply or retweet.

communities and individuals, and there are few isolates in such a pattern. This pattern means that communities share and provide mutual support through social media even though slightly different perspectives allow the detection of groups using the Clauset-Newman-Moore algorithm [28].

As is typical with the Tight Crowd, hashtags are shared across groups and within the network (see Table 4), and some groups may depict a hub-and-spoke structure such as the group at the top right in Figure 2. A Tight Crowd pattern is usually observable when participants share a common interest and a common orientation.

The detected Tight Crowd conversation pattern in the dataset is somewhat surprising since the general perception is that the South African political landscape seldom converges around a specific topic [46, 47]. In the case of the initial #VoetsekANC conversation though, the Twitter communities united, shared, and supported each other, resulting in the Tight Crowd pattern, an observation shared by similar research [48].

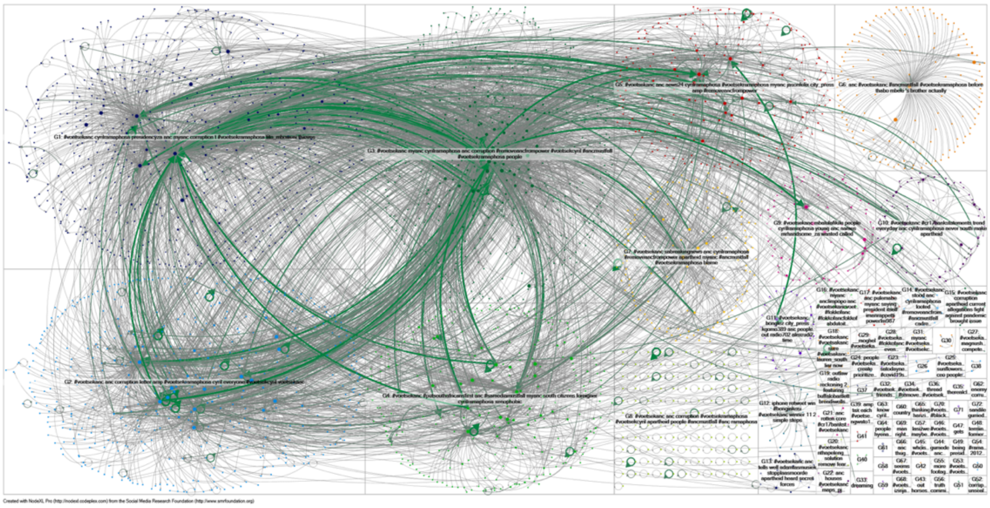

Figure 2. The conversation pattern for #VoetsekANC end of August 2020.

Table 4: Top hashtags by frequency of mention for the largest groups in Dataset 2

Top Hashtags I Entire Graph	Top Hashtags G1	Top Hashtags G2	Top Hashtags G3
voetsekanc	voetsekanc	voetsekanc	voetsekanc
voetsekanc voetsekcyril	myfokcyril voetsekanc	voetsekanc voetsekcyril	voetsekanc voetsekcyril
voetsekanc voetsekramaphosa	voetsekramaphosa voetsekanc	voetsekanc voetsekramaphosa	voetsekanc removeancfrompower
voetsekanc ancmustfall voetsekramaphosa	voetsekanc voetsekramaphosa	voetsekanc voetsekanc	ancmustfall voetsekanc voetsekcyril
voetsekanc removeancfrompower	voetsekanc removeancfrompower	redcard voetsekanc	voetsekanc voetsekramaphosa

The second #VoetsekANC dataset collected was eight months later and there were fewer vertices namely only 915 Twitter users whose recent tweets contained "VoetsekANC VoetsekEFF", or who were replied to or mentioned in those tweets in the week preceding 4 May 2021. Whilst some aspects of the pattern still resemble a Tight Crowd, there were many indicators that this pattern could better be classified as a Community Cluster. In a Community Cluster, popular topics develop evenly sized sub-groups that sometimes depict a few hub-and-spoke structures each with its own audience often centered around an influencer. Community Cluster patterns are often difficult to distinguish from the Tight Crowd or Brand Cluster patterns. However, what distinguishes a Community Cluster is that it should be possible to detect multiple conversations with an own audience, i.e., hub-and-spoke structures within groups. In Figure 3 it is possible to distinguish such structures within most of the groups, and this structure is indicative of diverse angles on a subject given different audiences each with its own influencers. Community Clusters also have fewer interactions between groups than the Tight Crowd, but more than Brand Cluster. Furthermore, the groups are medium-sized, i.e. smaller than in the Tight Crowd but bigger than in a Brand Cluster. The groups are somewhat more interconnected than found in Brand Clusters and there are fewer isolates. The pattern overall indicates different opinions and perspectives given a specific topic. The hashtags are still shared across groups and within the network as before, with variations and repetitions of #voetsekanc and #voetsekeff appearing in all groups as top hashtags.

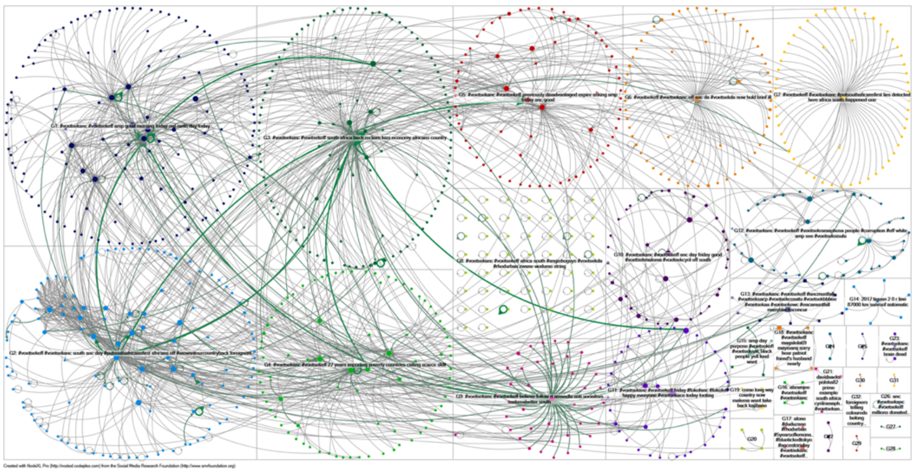

Figure 3. The conversation pattern for #VoetsekANC in May 2021

The second #VoetsekANC dataset depicting a Community Cluster implies that the Twitter communities surrounding the hashtag matured into established, separated and more isolated groups than before, each with its own audience and discussions. There are still some detectable discussions between groups, but much fewer than before, and there are relatively few isolates distinguishing this pattern from the Brand Cluster that would have smaller, less connected groups and more isolates. The implication is that even though the #VoetsekANC hashtag became established after months, it still does not depict a brand conversation pattern given the Twitter datasets. #VoetsekANC is kept alive by several communities that are often centered around an influencer (detectable by a hub-and-spoke structure within a group, see for instance the groups at the top right of Figure 3).

4.3 Dataset 4 - #SouthAfricaIsBurning

Dataset 4 is the largest dataset reported upon in this study and it was collected in the smallest timeframe. This indicates that there was intense Twitter activity about the violent protests and looting in Gauteng and KwaZulu-Natal using the hashtag #SouthAfricaIsBurning. The dataset was collected from Twitter 8:21 UTC the morning of Wednesday, 14 July 2021 and it contains 12 924 Twitter users whose recent tweets contained "#SouthAfricaIsBurning", or who were replied to or mentioned in those tweets. The tweets in the network were tweeted over the 3-hour, 40-minute period preceding 08:21 UTC.

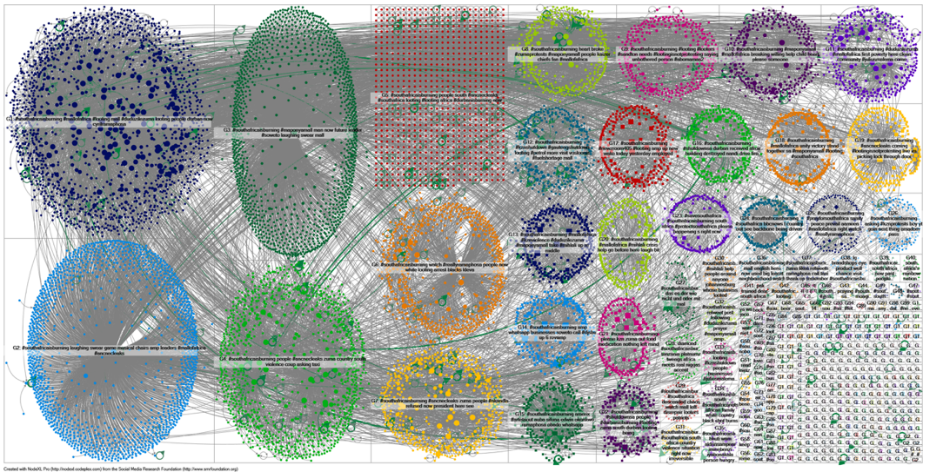

Figure 4. The conversation pattern for #SouthAfricaIsBurning of 14 July 2021

As discussed before, a Community Cluster is characterized by groups of people on Twitter that form networks with several evenly sized sub-groups and the conversation pattern depicted in Figure 4 is an example of a Community Cluster. The top hashtags are repeated across groups (Table 5), but with slight variations as each group forms its own community with conversations. The hub-and-spoke structure is also detected within several groups, which is also a defining characteristic of the Community Cluster pattern, especially given newsworthy events where news agencies would distribute news that is reacted upon.

The Community Cluster pattern is not unexpected as the unrest would naturally lead to communities forming that need to interact, share news and support each other. The specific Community Cluster pattern of Figure 4 depicts a noticeable number of interactions between groups, which is not typical of a Community Cluster but rather that of a Tight Crowd. In this case, it might be due to the topic because news about the unrest would be distributed quickly between groups given the nature of Twitter, and even though groups have their own communities, breaking news would be shared between groups.

Table 5: Top hashtags by frequency of mention for the largest groups in Dataset 4

Top Hashtags I Entire Graph	Top Hashtags G1	Top Hashtags G2	Top Hashtags G3
southafricaisburning	southafricaisburning	southafricaisburning	Southafricaisburning
southafricaisburning	southafricaisburning	ancnecleaks	maponyamall Soweto
maponyamall soweto	maponyamall soweto	southafricaisburning	
reallyramaphosa	looting jubjub indians	duduzilezuma	southafricaisburning
southafricaisburning	mihlali durban duduzilezuma sandton southafricaisburning	southafricaisburning	
ancnecleaks	southafricaisburning southafricashutdown sandton mallofafrica	southafricaisburning durban juliusmalema ancnecleaks	maponyamall southafricaisburning malema southafricaisburning mihlali

4.4 Dataset 5 – Instigators @TellUnknown OR @AZANIA_kal

The last dataset, Dataset 5, was collected early August 2021 using the identifiers "@TellUnknown OR @AZANIA_kal", which are the Twitter accounts of two alleged instigators of the looting in July 2021 [20, 44]. The dataset is different from the previous sets that used hashtags to collect the Twitter data, because the identifiers of two users were used to extract the dataset. These users are two alleged instigators identified by an investigation into the July 14 unrest [44]. The data collected was of 799 Twitter users whose recent tweets contained "@TelUnknown OR @AZANIA_kal", or who were replied to or mentioned in those tweets, extracted from Twitter on Tuesday, 03 August 2021 at 14:13 UTC and contained tweets from the 7-day period preceding 3 August.

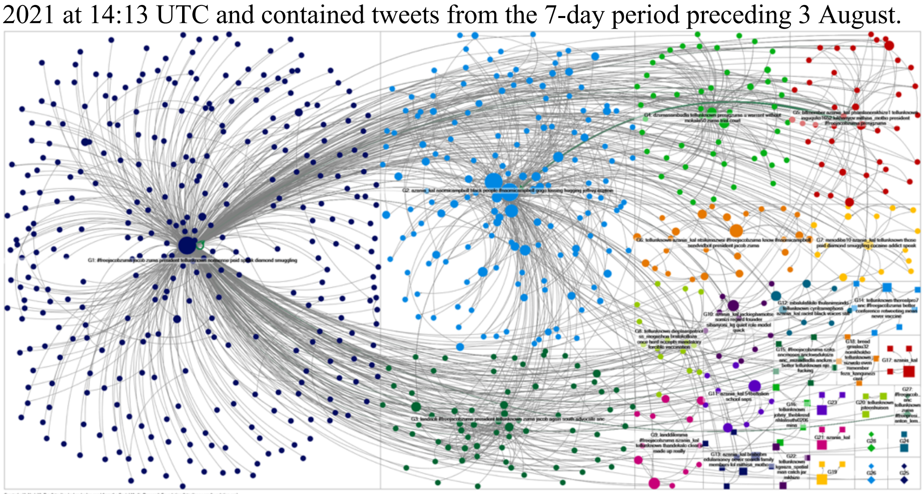

Figure 5. The conversation pattern for instigators @TellUnknown OR @AZANIA_kal of August 2021

The conversation pattern detected is a Broadcast pattern, which is not surprising given the allegations that these accounts were instigators of the violence and unrest. The top vertices for Dataset 5 depicted in Table 2 indicate that these accounts are the hubs of Group 1 (on the left in Figure 5) and Group 2 (in the middle top of Figure 5). Group 2 from @AZANIA_kal (see Figure 6) also depict a hub-and-spoke structure, but this account depicts many interactions with Group 1, suggesting a dependency on the information distributed to its followers. Normally there are some groups within a Broadcast pattern that depict internal conversations and discussion, however, in Figure 5 there are limited interactions within groups. Most groups depict a hub-and-spoke structure with vertices that only link to the hub.

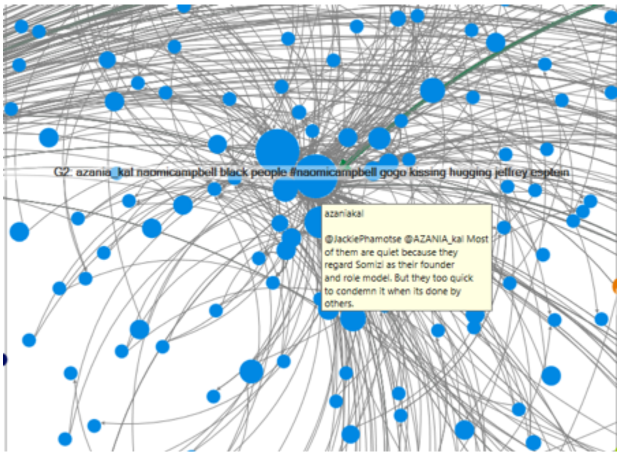

Figure 6. The hub of Group 2: identified @AZANIA_kal

The top hashtags that are repeated across the groups such as #FreeJacobZuma are also representative of the Twitter community that supported the unrest.

Table 3: Top hashtags by frequency of mention for the largest groups in Dataset 1

Top Hashtags I Entire Graph	Top Hashtags G1	Top Hashtags G2	Top Hashtags G3
Freejacobzuma	freejacobzuma	naomicampbell	freejacobzuma
Naomicampbell	Freepresidentzuma	Freejacobzuma	freejacobzuma freeikekhumalo
Freepresidentzuma	Racistbanksmustfall	Freezumanow	Freepresidentzuma naomicampbell
Racistbanksmustfall	freejacobzuma freeikekhumalo	Freepresidentzuma	Freejacobzuma
freejacobzuma freeikekhumalo	freejacobzuma ngizwemchunu bbnaija covid19sa	freezumanow freepresidentzuma cyrilramaphosa zizikodwa	freejacobzuma ancnec

	cyrilramaphosa sandton

Detecting such a strong and distinct Broadcast pattern from the Twitter dataset collected about the two instigator accounts supports the observation that these two accounts are influencers and therefore typically instigators of unrest as suspected.

5 Conclusion

Social media platforms are at present the most significant mechanism people use to communicate and express opinions. Fortunately, social media platforms also allow researchers to capture data and analyse this data to understand networks or community structures formed by the interactions. Twitter specifically, is a microblogging platform characterized by the fast flow of tweets that express information and opinions, and it became a well-used platform for the expression of political sentiments, or even mobilizing people politically. Twitter users can retweet a tweet, reply on a tweet, or mention a tweeter, and these interactions, as well as the tweets, can be mined to detect how communities organize online, as well as conversation patterns between users and groups.

This paper reports on a study that executed several experiments using a social network analysis (SNA) tool called NodeXL on Twitter datasets collected about political events during 2021 in South Africa. The purpose was to determine which distinct conversation patterns could be detected in data sets collected and what could be derived from these patterns given the South African political landscape and perceptions. The resulting graphs constructed from the datasets resemble distinct conversations patterns with specific characteristics that provide insight into the Twitter communities and conversations. The datasets collected about #PutSouthAfricaFirst and two instigator accounts expose typical Broadcast patterns meaning that the conversation is dominated by an influencer and that there are very limited discussions or conversations between users and groups. The Tight Crowd pattern extracted from the initial #VoetsekANC dataset shows surprising solidarity between users and groups with many interactions, discussions, and support and few isolates or people that do not participate in discussions. Later Twitter datasets about #VoetsekANC, as well as the unrest with hashtag #SAIsBurning, show the Community Cluster patterns, which means that sub-communities formed, each with significant discussions as well as influencers within each group, but also detectable interactions between groups.

In summary, the results indicate that conversation patterns could be detected from the Twitter datasets and that the conversations provide insight into understanding the political landscape within South Africa. Political conversations are less polarized than expected, and the conversations often manifest broadcast patterns from key influencers. In addition, conversation patterns often depict tight crowds or community clusters that reflect intense conversations across communities, and these patterns imply diverse opinions and perspectives on a topic.

Further research may incorporate relevant theory to assist with insights into the reasons why these conversation patterns develop. The results may be of value for researchers that aim to understand social media conversations within the South African society.

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