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MAPPING THE MUFFINS
(Understanding The Muffin Song Tweets Spread Using Social Network Analysis)

MEMETAKAN REMAH KUE MUFFIN
(Studi Analisis Jaringan Sosial pada Cuitan Tentang The Muffin Song)

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ABSTRACT
The Muffin Song is a music video that sparked debate regarding the contents of the lyrics and visuals and how social media users used it as background music of unrelated videos. Thus, we studied the interaction between social media users, focused on Twitter, to understand, map and describe the occurred interactions between users. In this study, we used quantitative approach based on Social Network Analysis (SNA). The results showed that most users have limited interactions with other users and is separate from each other. Although, many users interacted with each other strongly in a group of users. Group to group interactions also occurred, with one or more users acted as intermediary between groups.

Informasi Artikel
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ABSTRAK
The Muffin Song merupakan salah satu muatan video klip di media sosial yang memicu pro kontra baik dari isiannya maupun penggunaannya sebagai musik latar oleh pengguna media sosial. Penelitian ini bertujuan untuk melihat, memetakan dan mendeskripsikan interaksi yang terjadi antar pengguna media sosial Twitter tentang The Muffin Song ini. Peneliti menggunakan metode kuantitatif dengan berdasarkan pada analisis jaringan sosial (*Social Network Analysis* atau SNA). Hasil penelitian menunjukkan bahwa pengguna berinteraksi secara pendek dan terpisah. Meskipun begitu terdapat kumpulan pengguna yang menjalin sebuah kelompok dan berinteraksi dengan kelompok lain melalui satu atau lebih akun yang berperan sebagai jembatan informasi.

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INTRODUCTION

Dark humor is one of the many comedy genres. However, dark humor has an impact on and is related to aversive psychological states. Although dark humor can be used as a shock value like blue humor (M. S. W. Lee et al., 2020), several studies have stated that dark humor is closely related to a psychological condition called the Dark Triad (Martin et al., 2012). The Dark Triad itself is a psychological condition that is categorized as malevolent, including narcissism, psychopathy, and machiavellianism (S. A. Lee, 2019; Martin et al., 2012; Navarro-Carrillo et al., 2021).

Humor is not only conveyed in face-to-face communication, but also in mediated communication. One example is interaction on social media Twitter. Twitter is a social media with a microblogging model that allows users to send various tweets that other users can respond to. This allows for accounts whose role is to filter information (gatekeeping) on certain topics, such as political topics to humor (Holton & Lewis, 2011; Molyneux, 2015).

The Muffin Song is an audio-visual content published by YouTube user TomSka on 12th May 2018 (TomSka, 2018). Since its publication until 12th November of 2021, before YouTube changed its policy by hiding the number of dislikes (The YouTube Team, 2021), the video clip for The Muffin Song had three point eight million likes and one hundred twenty-four thousand dislikes and 232.522.286 views.

Apart from its popularity on the YouTube, The Muffin Song is also one of the most popular songs used as background music on TikTok with 271.600 uses (TikTok, n.d.). From our initial observations, this song is used in various types of videos on TikTok. As for note, The Muffin Song is a pop-EDM song composed by The Gregory Brothers, also known as Schmoyoho. This song is a kaleidoscope by combining dialogues from TomSka's series, asdfmovie, into the lyrics of the song. Thus, asdfmovie content is also contained in The Muffin Song, both visually and in the text of the lyrics.

The content of asdfmovie itself is loaded with dark humor. One of the contents and characters that are part of the title of this song is Mr. Muffin or also called The Suicidal Muffin, as the character is described as a character who wants to end his own life or have suicidal tendency. The punchline of the character Mr. Muffin itself is used as a chorus in the song The Muffin Song.

Unlike YouTube, which recently implemented policies related to suicide and self-harm, Twitter has had a sensitive media policy since 2017 and will be updated and tightened in 2022 (Twitter, 2022). Even so, from the initial data that we collected, as many as 72.856 tweets about The Muffin Song, only 1.304 tweets or 1.79% of them were marked as sensitive content.

LITERATURE REVIEW

Social media is interactive digital media through internet application-based virtual media (web app). Merriam-Webster defines social media as an electronic social network communication where users can build communities in the network to share information, ideas, messages and other content (Merriam-Webster, 2004). Social media platforms, as part of new media, are different when compared to conventional media such as television and radio. Social media, which is also known as social networking services, provides a two-way service for users to interact and share with each other (Chen & Cheung, 2019).

Social media platforms focus on user generated content as the basis for networking between users. In terms of content, social media has advantage that conventional media do not have where conventional media content is built by media organizations (Badea, 2014; Chih-Ming & Ying-You, 2020). However, social media is not without drawbacks. One issue that is often discussed in social media is the ethical issue of user privacy. There have been many cases where user privacy has been violated both by fellow users and by other parties such as the social media companies themselves. Apart from privacy, the issue of anonymity is also a problem not only in the social media environment but also in the virtual world in general (Turculeţ, 2014).

Network is something that exists in every aspect of life, starting from physical networks such as transportation networks to non-physical networks such as social networks. The study of networks is the focus of graph theory. This theory describes how a network can be formed by explaining the network elements. Graph theory has its roots in the field of mathematics studies in the eighteenth century with Leonard Euler as a pioneer based on the Konigsberg Bridge Problem. This problem explores the possibility of Konigsberg residents crossing the seven bridges in the city without crossing the same bridge more than once (Moreno Chuquen & Chamorro, 2021).

Graph is the key structure of the application of data presentation. Graphs have elements of points (nodes or vertices) which are labeled using alphabetical text (literals) or numeric (integers). Each point interacts with each other through connecting lines (edges). A graph can have more than one edge at a point. A point can also interact with itself in an interaction called looping or self-loop (Harary, 2018). This definition is described in the formula G=(V, E), where G is a graph (graph), V is data points (nodes, vertices) and E is interactions (edges). Thus, V(G) is the vertex set and E(G) is the edges set. A graph can have symmetrical (undirected) and asymmetrical (directed) interaction characteristics (Erciyes, 2021).

RESEARCH METHOD

This research is structured based on a positivistic paradigm to obtain and analyse concrete data that can be measured, reproduced and can be reverified (Grønmo, 2019).. We chose this paradigm considering that this research was conducted using hard data obtained from collecting user account data and tweets directly through the Twitter API and formulaic processing that generalizes the results where we, positioning wise, are independent of the research data. Thus, we departed from the argument that the phenomenon under study, about how Twitter users discuss The Muffin Song, is a phenomenon that can be observed objectively. Thus, we built this research with a quantitative-descriptive approach. We use this approach as a mode of uncovering complex structures (Grønmo, 2019; Leavy, 2022), such as the structure of user networks in social network analysis.

The population in this study are Twitter users, seen from the tweets queried by using keywords "#TheMuffinSong" and "The Muffin Song". The population was collected via query based on the Twitter API v2 for Academic Research key with a limited period between 12th May 2018 to 31st December 2021 as the cut-off date. We collected a total of 71.856 tweets of initial data. After going through a selection process based on English tweet labels (en) and cleaning of duplicate data, the net population used in this study was 14.017 tweets and 17.072 users involved. We limit the population with tweets labelled “en” and the users involved in the interaction of these tweets to obtain uniform data.

The data that has been collected then analyzed. In the reduction stage, the researcher converts the raw data from the results of text mining into alphanumeric text data by removing hypertext. The software used are R and Rstudio with several packages such as but not limited to dplyr, tidytext and textclean to perform data condensation/reduction as well as for data analysis and presentation. The Twitter user data that has been separated from the initial query is then used as the basis for building network maps and profiling user accounts that discuss The Muffin Song. The network map and profiling are obtained through Social Network Analysis.

RESULTS AND DISCUSSIONS

As described in research method above, data that has been collected through Twitter queries is then grouped and cleaned. Data is also reduced by deleting all entries that are not labelled as English (en). The reduction was to simplify the data to make the data uniform based on label entry in English (en). Then we will discuss in detail the processing of the collected data within the scope of Social Network Analysis. There are 14,017 interactions between users included in the selected data. Of these 14,017 interactions, there were 17,072 users involved in these interactions. At the beginning of this stage, the researcher grouped user accounts based on the year the account was created.

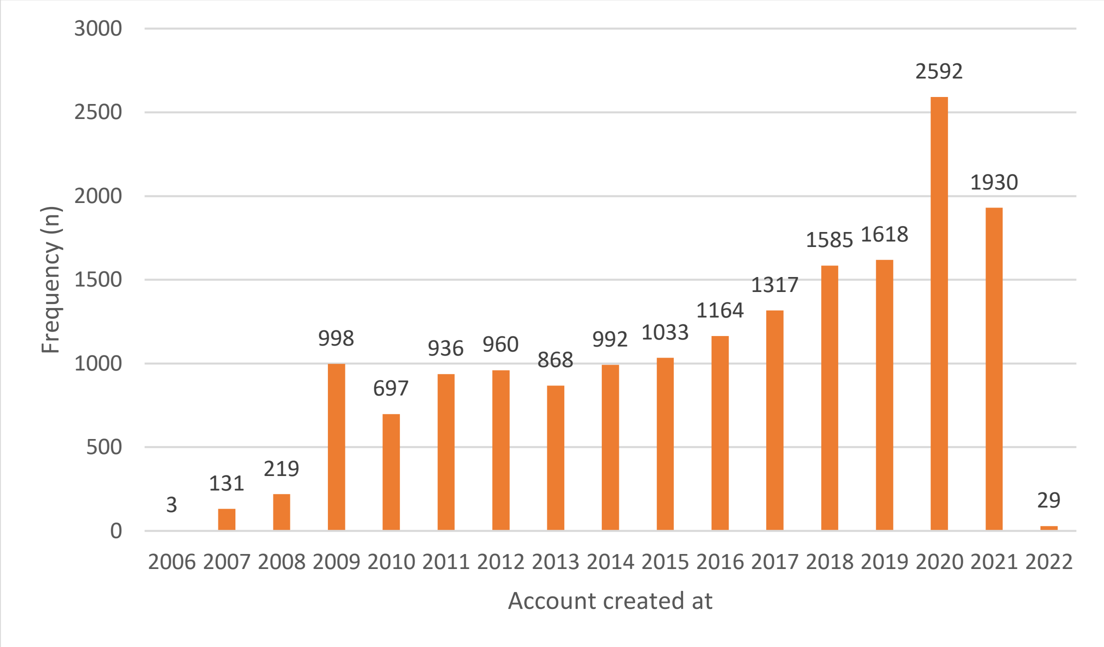

Figure 1. Account creation spread

Table 1. Mention vector sample

conversation_id	author_id	author	mentioned_user
995021176765386753	212558451	Tazer_Silvascar	thetomska
995092396030312449	743116442355138560	duplexdownfall	YouTube
995094632542294016	2811195752	ItsMiriam_	YouTube
995095722998554625	753829405	talesofayyu	thetomska
995095786286272512	1417499448	Y2Ashlee	YouTube
995097203122225152	2908720244	ZR3009	YouTube
995098098199416834	307081944	FelixSunblade	thetomska
995098582758895617	853316826171834370	itsthexstream	YouTube
995099332066951168	2982250643	TangoRose_	YouTube
995100500470022145	3055017947	ArminciaE_YT	YouTube
995100738555600896	1332672792	snlkornfeld	
995101165355384832	3628431143	NoahVehx	YouTube
995102496082116610	876401045827661824	hanngnecessary2	YouTube
….	….	….	….

Social Network Analysis (SNA) can provide valuable insights with a broad scope especially when discussing online platforms, such as Twitter. By using this method, we can explore the interaction and relationship structure of Twitter users in a network. If we look at figure 1, it can be seen that the accounts discussing The Muffin Song on Twitter are not only new accounts, but also accounts that can be considered quite "old" because they were made in the early days of Twitter.

The data used for SNA is user data (author_id and author column labels) and interactions with other users (mentions). There are interesting findings that can be seen in Figure 1. There are new accounts anomaly in which these accounts were listed as created close to or even past the data cut-off date that the researchers determined (31st December, 2021), even though in reality these accounts been involved in the interaction in previous years.

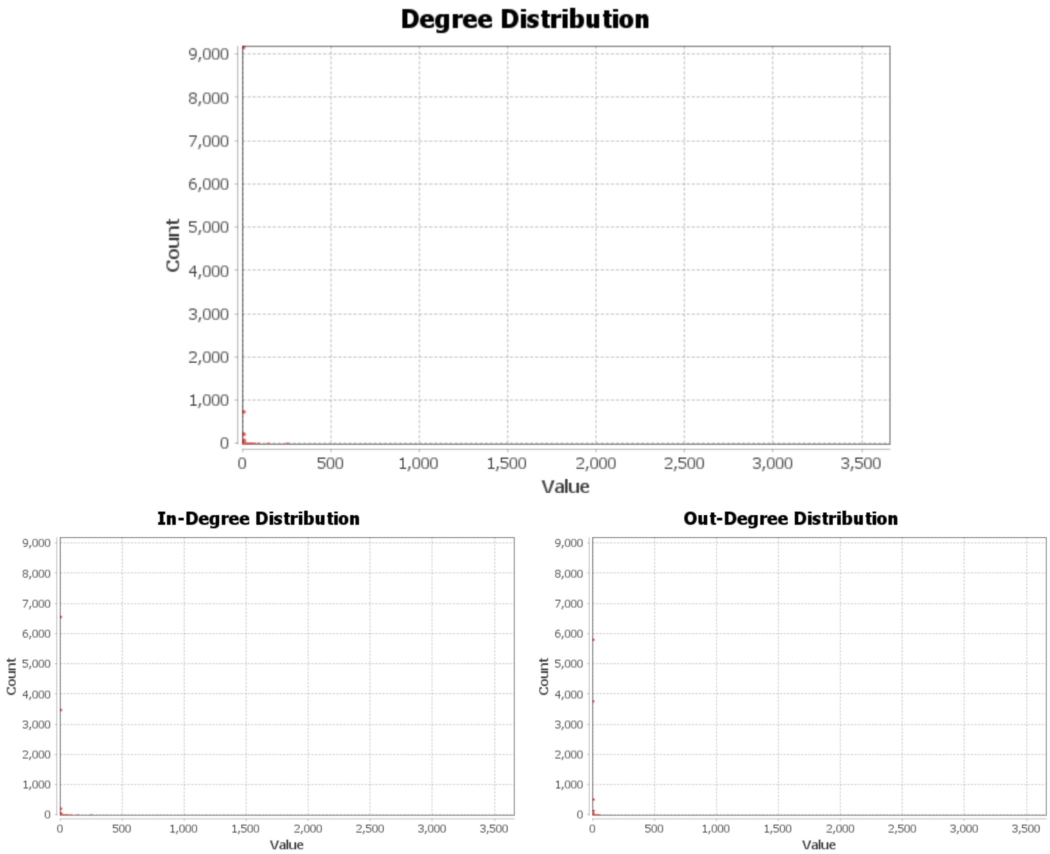

Figure 2. Degree distribution graph

After the user interaction vector is obtained, the vector table is then exported from the RStudio to be processed using Gephi. In Gephi, several calculations and data processing are done with several methods and algorithms. First, this data is used as the basis for the visualization of directed network maps (directed graph), where the interaction between data in the author column and data in the mentioned user column does not apply in both directions. The entire interaction is then calculated and condensed by calculating the frequency (n) of each interaction of the same author and mentioned users, with a total of 10.490 nodes and 9.218 edges. The data is then mapped to calculate the level of incoming and outgoing interactions for each data entry or node. Interaction data is processed to obtain an average degree and an average weighted degree. This processing resulted in an average degree of 0,879 and an average weighted degree of 1,02.

Second, the data is processed to obtain centrality distribution between nodes based on Ulrik Brandes' algorithm (Brandes, 2001). In this process, the diameter of the network and the average footprint between nodes are also mapped. This mapping produces a network size of 5 edges (each interaction between nodes or called edges is 1) with an average of 1,278.

Third, mapping of the number of strongly connected components and weakly connected components was done using Robert Tarjan's algorithm (Tarjan, 1972). The mapping results show that there are 1.898 components that are weakly connected and 10.457 components that are strongly connected.

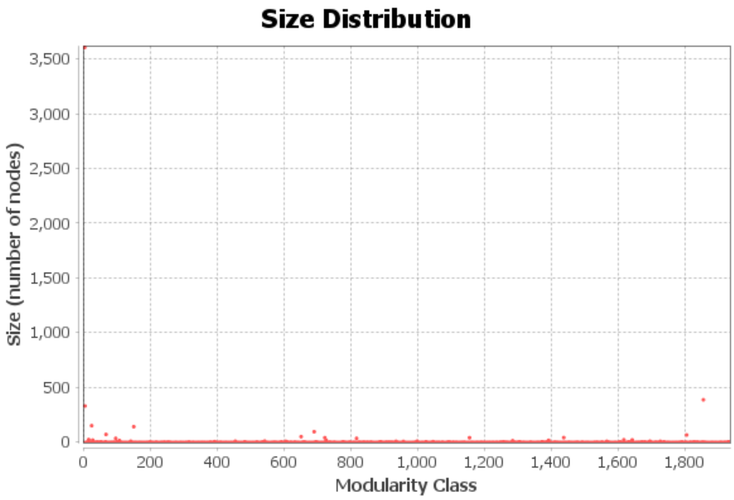

Figure 3. Modularity size distribution

Fourth, calculations are performed based on weight to obtain modularity from the data (Blondel et al., 2008; Lambiotte et al., 2008). Based on this calculation, the modularity number is 0,812 (Figure 3). In this process, 1.935 gorup of nodes or communities were detected. Using a statistical inference algorithm (Lambiotte et al., 2008; Zhang & Peixoto, 2020), a community number of 1.900 is obtained with a description length of 83.563,318. After these four stages have been carried out, the network is visualized based on the results of data processing using Gephi with a network layout based on Yifan Hu's layout generation model.

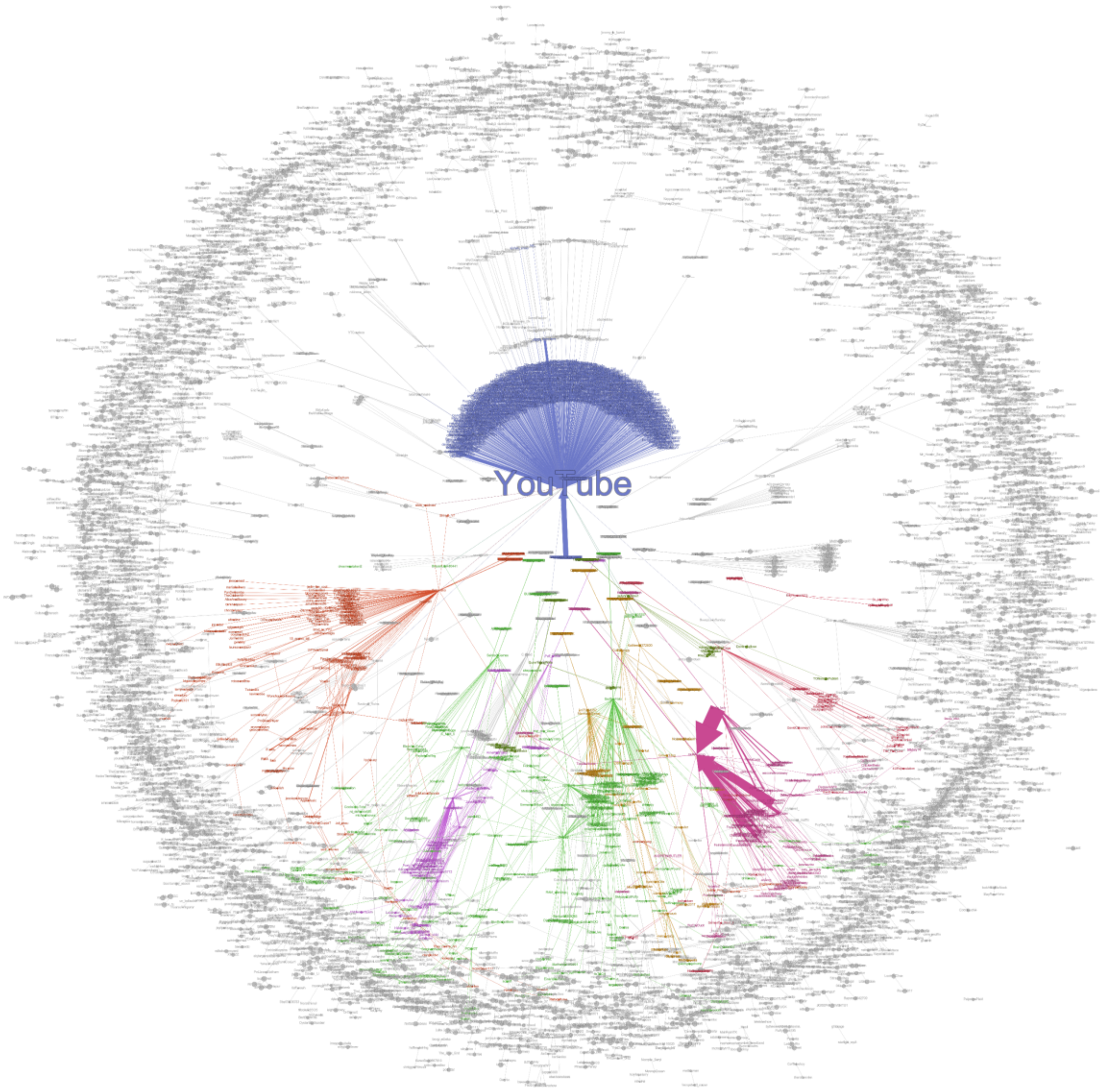

Figure 4. Directed network visualization of the interactions

We found difficulties when trying to map the distribution of user locations. We only succeeded in taking 193 data entries that had location identities and user location coordinates (see figure 5). The rest, the location column only displays unavailable (NA) or empty (NULL) labels.

Because location data cannot be retrieved through coordinates or location identity codes, we tried to map the distribution of users through location data that can be listed on Twitter user profiles. However, this method generates two new problems because the users can fill in these fields manually. The first problem is the non-uniformity of how to write the location column on the profile. The second problem is that the contents of the location can refer to fictitious locations or non-location contents. The sample of the user location data that we collected can be seen in table 2.

geo$place_id	geo$coordinates$coordinates	geo$coordinates$type
0022e3c837579650	c(174.6811, -36.5859)	Point
011add077f4d2da3	c(-73.9832, 40.6914)	Point
01cf094a554e5069	c(121.0155, 14.4359)	Point
59612bd882018c51	c(-118.4964, 34.0099)	Point
7142eb97ae21e839	c(-84.4587, 33.8844)	Point
8e9665cec9370f0f	c(-93.2782, 44.9679)	Point
c3f37afa9efcf94b	c(-97.7491, 30.2505)	Point
f1d3a53f8a3cc7e9	c(83.4574, 27.6561)	Point
0021712c0bd7eec1	NULL	NA
0022e3c837579650	list()	NA
002e24c6736f069d	NULL	NA
003e299707d0375b	NULL	NA
006a69011e2bfd34	NULL	NA
00a961d91f76dde8	list()	NA
00b8d3a173fd6ddc	NULL	NA
00c26afc77ee7aaa	NULL	NA
00c8f6113f7e9a2b	NULL	NA

Figure 5. Raw data sample on geolocation

Table 2. Sample of location data shown on profile

author_id	created_at	location
823390872163074048	2017-01-23T04:44:16.000Z	Melbourne, Victoria
621188577	2012-06-28T16:10:31.000Z	Ur mom's bed
869505796584873985	2017-05-30T10:48:31.000Z	neet
1257475220	2013-03-10T16:55:37.000Z	Bottom of the Frozen Hells
3078498494	2015-03-13T23:13:21.000Z	owo
493917154	2012-02-16T10:05:51.000Z	Sweden
498233099	2012-02-20T20:45:16.000Z	Spain without the s
810344230770057216	2016-12-18T04:41:34.000Z	Australia
2951820882	2014-12-30T10:42:54.000Z	parts unknown
20995663	2009-02-16T15:49:20.000Z	UK
753758097139695616	2016-07-15T01:08:29.000Z	You'll never know
708040128342724609	2016-03-10T21:21:36.000Z	artist | gamer | collector ♡
770246426785906688	2016-08-29T13:07:13.000Z	Deutschland
750366892322385920	2016-07-05T16:33:03.000Z	Durham Region, Ontario, Canada

Understanding user characteristics and demographics is also important for understanding how certain accounts have a large impact on interaction network. When looking at the network visualization (figure 4), it can be seen that YouTube is the account that has the highest average degree and average weighted degree. However, that doesn't mean that this account has a high level of two-way interaction as shown in figure 6.

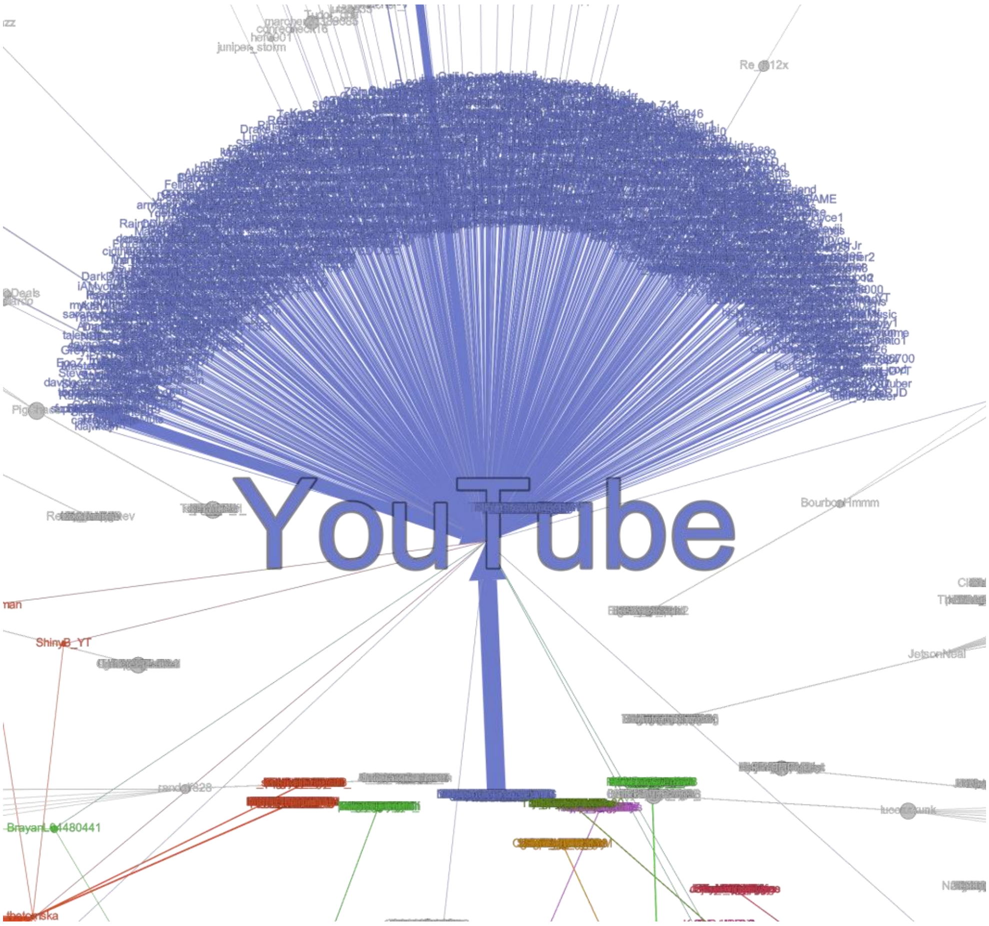
Figure 6. Directed interactions on Youtube's Twitter account

If we look in detail, the YouTube Twitter account itself is referred to by many accounts, but does not refer to other accounts at all. In the network visualization, this can be seen from the edges that point towards the YouTube account. This imbalance in the direction of interaction is also reinforced by the degree and weighted degree for YouTube nodes, where these nodes have the highest indegree (3,655) and weighted indegree (4,458) but have an outdegree and weighted outdegree level of 0. The outdegree and weighted outdegree levels indicate that a Twitter account YouTube does not interact with other users at all.

Seeing this phenomenon, the question arises, why this can happen? If we look at the tweets that mentioned YouTube accounts, it can be seen that these tweets are similar to one another.

Table 3. Tweet sample that mentioned @Youtube

text
I added a video to a @YouTube playlist https://t.co/t95d47aalH THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I liked a @YouTube video https://t.co/bu7c34mUWy THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I liked a @YouTube video https://t.co/Xar91ziXtg THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I liked a @YouTube video https://t.co/0OU2oTnBdb THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I liked a @YouTube video https://t.co/6rcfYlQDAV THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I liked a @YouTube video https://t.co/hXXxc6eWUt THE MUFFIN SONG (asdfmovie feat. Schmoyoho)
I added a video to a @YouTube playlist https://t.co/yt8zVvO7zX THE MUFFIN SONG (asdfmovie feat. Schmoyoho)

We then conducted further study by dissecting the tweet structure that mentioned YouTube. The tweets have the similar structure and consist of four parts: (1) activity tags (e.g. "I liked a [mention] video" or "I added a video to a [mention] playlist"), (2) mentions

@YouTube, (3) shortened or simplified links or hyperlinks using Twitter's (t.co) link shortener that references The Muffin Song's YouTube video page, and (4) The title of The Muffin Song's YouTube video page. These tweets are generated automatically (auto-generated) when a user connects their YouTube platform account with their Twitter platform account using the share feature. This pattern can be visualized through the following chart.

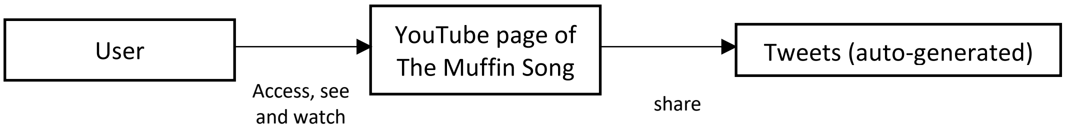

Figure 7. Pattern of cross platform interactions

This view-share pattern is known as the cross-platform spread. Cross-platform spread is the process of disseminating and sharing content, information and trends from one social media platform to another (Golovchenko et al., 2020; Shen et al., 2022). This phenomenon is a form of product of the interconnectivity and interactivity of various social media with the same range of users. This phenomenon can also encourage content to expand its visibility and impact beyond the platform from which the content was uploaded (Bode & Vraga, 2018; Deng et al., 2015; Georgakopoulou, 2015).

The phenomenon of cross-platform sharing indicates that these social media users are active not only on one platform and are active in interacting by sharing their activities (watching, liking and including The Muffin Song in their respective playlists). This view-share habit, as explained earlier, extends the visibility range of content. In doing so, accounts that share these cross-platform tweets directly increase The Muffin Song's visibility outside of the YouTube platform. This tweet also has an impact on increasing the relevance of the YouTube Twitter account by embedding @YouTube mentions in each tweet. This way, the YouTube Twitter account has social influence by establishing a strong presence passively.

The increased visibility of content across platforms also has an impact on the virality of the content. By boosting and sparking other users' interest and attention about The Muffin Song, these tweets should also be the start of a thread. However, what happens, and can be seen on the SNA network map, is that the formed network is relatively short with a network diameter of 5 edges and an average interaction length of 1,278 edges (rounded). From these findings, it can be said that the average conversation or interaction that occurs with users stops at 1-2 other users. The shortness of interaction between users can be seen from the visualization of the SNA network map, where accounts with short and interrupted interactions surround accounts that are members of a larger community and whose paths of interaction are farther away. The simplification of the visualization can be seen in the following figure.

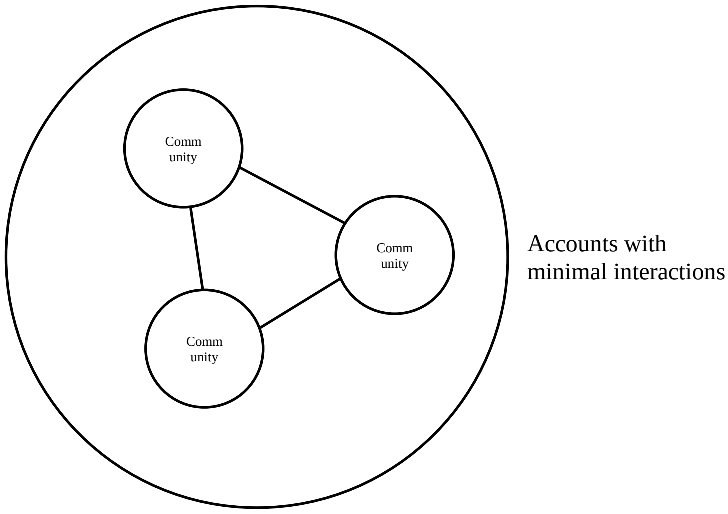

Figure 8. Simplified network

Several accounts connected in the network became important points and act as intermediaries with other nodes. The impact of these accounts as intermediaries can be seen from the amount of betwenness centrality data (Barthelemy, 2004; Brandes, 2001; Goh et al., 2003). Betweenness centrality is a measure used in SNA to identify accounts that act as a bridge of communication between communities or groups by quantifying the significance of a node among a pair of other nodes on the shortest path (Bonato & Chung, 2007; Brandes, 2001). The greater the betweenness centrality number, the greater the potential for nodes to influence the flow of information and interactions in the network (Benguigui & Porat, 2018; Laghridat & Essalih, 2023; Schoch et al., 2017).

Table 4. Accounts with high degree of betweenness centrality

Id	**closness centra lity**	**harmo nic closness centra lity**	**between ness centrality**	**pageranks**	**clustering**	**eigen centrality**
BadBoyHalo	1	1	512	0.00602	0.002261	0.037986
thetomska	1	1	500	0.01117	0.000016	0.067606
bardic_lady	0.678571	0.798246	349	0.000105	0.018116	0.000919
kaoticrequiem	0.493506	0.592105	321	0.000277	0.041667	0.002502
Laurakmonty	0.802817	0.877193	229.3	0.000082	0.05444	0.001844

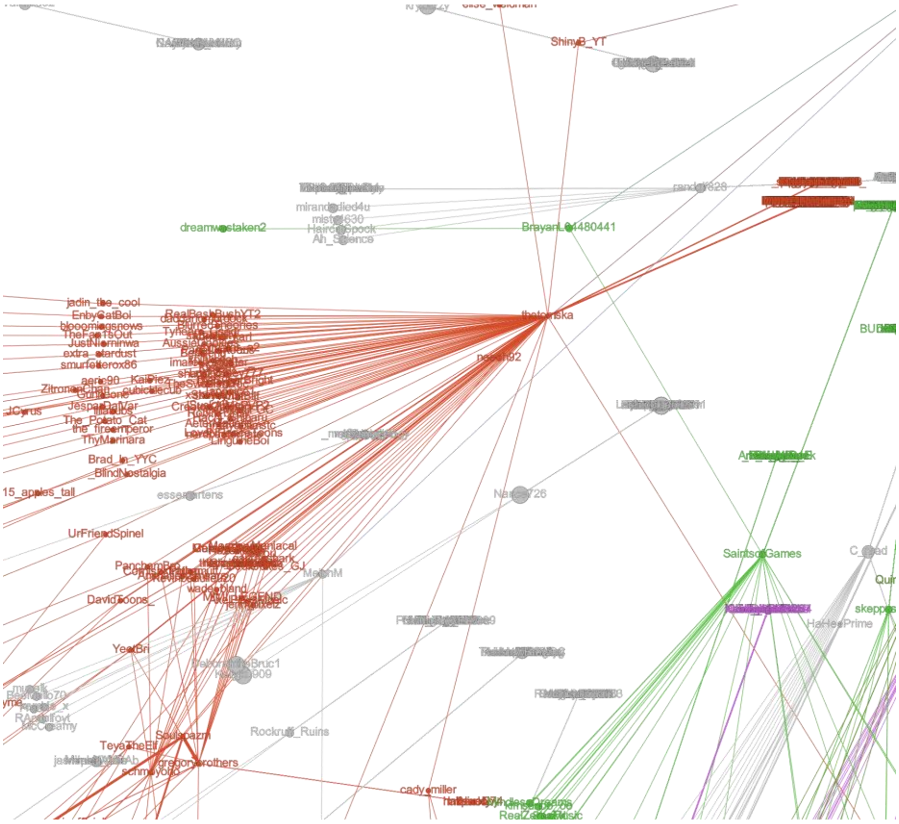

Figure 9. @thetomska shown as intermediary in the network

In contrast to the YouTube Twitter account which is the final node of the walk between nodes, accounts like thetomska for example, become nodes that are between two other nodes that are either part of a community or a bridge between communities. Thus, nodes with high betweenness centrality values can be said to act as relay points that have an outward and inward direction of interaction. Without this relay point, the network will be more separated and fractured. Nodes that have a high weighted degree as well as nodes that become bridges between nodes and influential communities in the formation of widespread understanding, because there is a mutual interaction between fellow nodes that are visible in the SNA network and those who only see the tweet but do not respond directly through reply tweets.

CONCLUSION

The accounts involved in the interactions included but not limited to accounts that have long been created, as new accounts that are less than two years old (as of the data cut-off date, which is 31st December, 2021) also present. Accounts that are frequently mentioned do not necessarily have an impact and play a role in bridging information with other accounts. An example of this finding is the YouTube's Twitter account which acted as the endpoint. On the topic of The Muffin Song, many accounts interact briefly with only one or two accounts (only 1 or 2 nodes walk). Some of the accounts that bridge the interaction are the accounts that compose the video clip for The Muffin Song (@thetomska). Apart from that, there is also the @BadBoyHalo account which also releases similarly titled Muffin Song, which is often compared to @thetomska's The Muffin Song. As we cannot get geolocation data, we refer to the location data that is listed on the user profile. This data reference is deemed unreliable and has an impact on muddling the results as the location in the user profile can be changed and modified to display things that are not related to the location such as filling it with preference pronouns (for example "♡ any pronouns ♡" or "any prns (+ neos !)") to be filled with locations that don't make sense (examples "yunhyeong abs", "Your Mom's House" and "Where u wanna be"). In addition, many location fields are filled with special characters, which makes it difficult for researchers to standardize location data.

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