Twitter use by the dementia community during Covid-19: A user classification and social network analysis

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Abstract

Purpose: The study aimed to examine how different communities concerned with dementia engage and interact on Twitter.

Methodology: A dataset was sampled from 8,400 user profile descriptions, labelled into five categories and subjected to multiple machine learning classification experiments based on text features to classify user categories. Social network analysis (SNA) was used to identify influential communities via graph-based metrics on user categories. The relationship between bot score and network metrics in these groups was also explored.

Findings: Classification accuracy values were achieved at 82% using support vector machine (SVM). The SNA revealed influential behaviour on both the category and node levels. About 2.19% suspected social bots contributed to the Covid-19 dementia discussions in different communities.

Value: The study is a unique attempt to apply SNA to examine the most influential groups of Twitter users in the dementia community. The findings also highlight the capability of machine learning methods for efficient multi-category classification in a crisis, considering the fast-paced generation of data.

Keywords: Twitter, user profiling, social network analysis, bot, dementia, Covid-19

1. Introduction

A large sector of the ageing population with dementia are at risk of being impacted by the Covid-19 pandemic (Wang *et al.*, 2020). People with dementia (PWD) might have limited abilities to access and process reliable information and safety procedures regarding Covid-19 (Xie *et al.*, 2020)(Wang *et al.*, 2020). Thus, in order to make informed decisions on their behalf and plan ahead, families and carers need accurate information about risk reduction and home care (Alzheimer's Disease International, 2020). PWD run the risk of being hospitalised during this period due to the negative effects of long-term social isolation and anxiety, which can lead to behavioural changes, confusion, and even delirium (Alzheimer's Disease International, 2020).

Information dissemination can have a detrimental effect on the efficacy of safety measures governments put in place to handle crises (Cinelli *et al.*, 2020). Researchers are challenged to ascertain how information is sought after in demanding public health situations, such as the Covid-19 pandemic, as well as how information is presented and absorbed, especially considering the filtered information dispersion by news cycles (Cinelli *et al.*, 2020). The information science field should critically consider the fact that global health crises often give rise to information crises (Xie *et al.*, 2020) . To help populations cope with global pandemics, engage with their after-effects and be better equipped for the next crisis, a critical question should be explored: What explicit steps can information scientists take to better aid this process? (Xie *et al.*, 2020). Health information sources regularly circulate both accurate and false information on social media, with incorrect information tending to soar during pandemics (Pennington, 2020) (Chan *et al.*, 2020). This is true for all social media platforms (e.g., Facebook, Instagram), but Twitter takes the lead (Chan *et al.*, 2020). The Twitter platform is a common source of information during crises or emergencies, as illustrated by the current pandemic. Dementia is one of the top five most discussed health conditions on Twitter (Zhang and Ahmed, 2019). Studies by (Robillard *et al.*, 2013), (Danilovich *et al.*, 2018) and (Alhayan and Pennington, 2020) have reported engagement by different stakeholders, ranging from patients to physicians, in the Twitter dementia community. Therefore, it is vitally important to understand the interaction between users in this vulnerable community. This study set out to apply a supervised machine learning approach for non-binary classification to help identify categories of users participating in dementia-related communities. Social network analysis (SNA) was employed to reveal influential categories during emergency situations (i.e., Covid-19) in the dementia community and to understand the interaction and flow of information between different user categories.

2. Related Work

The related work comes from three perspectives: studies of dementia on social media, studies of SNA and user profiling on social media.

2.1. Dementia on Twitter

The topic of dementia on Twitter has attracted various scholars due to the rapid increase in the use of Twitter by the dementia community. Robillard et al. (2013) analysed 920 tweets within 24 hours to determine who was sharing information about dementia on Twitter, what sources of information were promoted and which dementia-related themes were most dominant. In terms of user types, the manual analysis revealed that health information sites, news organisations, commercial entities and health professionals were at the top. Most of the tweets analysed contained links to other websites and did not include personal information, experience or research findings about the disease or how to prevent its risks. Another work by (Oscar *et al.*, 2017) collected 31,150 Alzheimer- and dementia-related tweets and used 311 random tweets (representing 1% of the total), manually coded, as input for a machine learning (ML) algorithm to automatically code the remaining tweets (99% of the dataset). The manual coding resulted in six different dimensions (i.e., informative, joke, metaphorical, organisation, personal experience and ridicule). The study found that the semi-automated coding procedure replicated manual coding reasonably well and noted that more than 21% of the tweets stigmatised dementia. A similar study conducted by (Cheng *et al.*, 2018) analysed 398 tweets about dementia from 28 different countries, circulated within two months. The authors found that most of the users were from the United States and the United Kingdom. Thematic analysis was used to classify the users into four categories (general public, health care field, advocacy organisation and public broadcasting). The general public category was further classified into five subcategories: mental health advocate, affected persons, stigmatisation, marketing and other. Content analysis of the 'general public' tweets was also performed, which identified the two most common themes, namely stigmatisation and mental health advocacy. In a recent study by (Robertshaw and Babicova, 2021), the authors collected 860,383 dementia-related tweets based on five search terms (dementia, Alzheimer's disease, vascular dementia, Lewy body dementia and frontotemporal dementia) over a six-week period. Linguistic inquiry and word count were used to analyse and investigate these terms for their emotional tone, sentiment, clout, analytical thinking and authenticity. It was revealed that the majority of tweets referred to 'dementia' and 'Alzheimer's' (48.63% and 49.95%, respectively). The term dementia was used in positive and personal tweets, while Alzheimer's was discussed in a more technical and detached way. The results showed that dementia is still mostly stigmatised, as revealed by the overall negative emotional tone of the tweets.

Thus far, to the best of our knowledge, none of these studies explored the types and interactions of users generating dementia information on Twitter. Although SNA conducted among different user types has been applied in other contexts (e.g., hate speech, health misinformation, crisis) as discussed below, this has not been done in the dementia context.

2.2. Social Network Analysis on Social Media

To define the characteristics of Twitter communities, studies focus on propagation networks, which are usually formed by retweeting (reposting) behaviours as a credibility indicator on Twitter. Retweeting indicates the proof of acceptance of information as credible and worthy of further dissemination. Several studies in different domains have looked into analysing Twitter communities composed of different types of users or tweets. For example, studies on hate speech manually classified hateful and non-hateful users on Twitter (Ribeiro *et al.*, 2018) and Gab (Mathew *et al.*, 2019). This was followed by a graph to represent the interactions and characteristics of the two groups, including network characteristics and activity patterns. Ribeiro *et al.* found hateful users on Twitter to be densely connected in the graph (Ribeiro *et al.*, 2018). Additionally, the account age of hateful users was newer, and their tweets were more negative. Similar findings in (Mathew *et al.*, 2019) established that hateful users on Gab were more closely related to each other than to non-hateful users, generating nearly a quarter of the content on Gab, despite representing a mere 0.67% of the users overall. Evkoski *et al.* addressed similar issues in the context of Slovenian hate speech tweets, which were classified into acceptable and unacceptable speech categories by training a deep learning classification model (Evkoski *et al.*, 2021). A retweet graph explored the popularity of influential users and tweets between the tweet categories. By inspecting the main sources of unacceptable tweets, it was found that they could be attributed to anonymous, closed or suspended accounts. Far fewer unacceptable tweets were disseminated in the categories Institutional and Media than in the Individual category. Overall, the number of hateful retweets was found to be considerably higher than non-hateful tweets.

The health context is also very important, as shown in a recent study (Milani *et al.*, 2020) that manually classified visual images in Twitter discourses into pro- and anti-vaccination sentiments. Thereafter, SNA was performed to understand who the key influential actors were and how image flow was shared between or within the two communities. The study found that parents and activists were among the most influential anti-vaccination groups, whereas non-governmental organisations and health professionals tended to be pro-vaccination. Moreover, the pro- and anti-vaccination groups were total opposites, barely communicating with each other. In the Covid-19 context, (Xing *et al.*, 2021) incorporated SNA and the text clustering method to categorise people's opinions on Covid-19-related topics, based on various themes. The findings showed how user interaction networks and public opinions changed over time during the pandemic. Another study by (Memon and Carley, 2020) manually annotated the tweets related to different types of Covid-19 information and misinformation. The study aimed to understand how two communities spread information during Covid-19, in terms of network characteristics, linguistic variants, bot presence and association with other communities. The first community consisted of users who actively posted tweets containing misinformation, whereas the second community's users posted true information. The misinformed communities were observed to be denser than the informed communities. Bots were actors in both communities; however, a higher number of bots occurred in the misinformed community than the informed community. Likewise, the strength and effectiveness of network features were shown when linguistic, sentiment and profile features were compared to distinguish between the authors of either legitimate information or misinformation (Zhao *et al.*, 2021). In conclusion, the reported studies aimed to identify the characteristics of different communities formed by two different user or tweet categories for understanding user behaviours. The tweet classifications or user profiling in these works involved analysing Twitter accounts manually, which is highly labour intensive. Therefore, the machine learning approach was used to automatically profile the users, which is discussed in the next section.

2.3. Twitter User Profiling

Various studies have utilised ML algorithms for classifying user profiles based on different features for different purposes. In the public health domain specifically, (Park *et al.*, 2016) applied a ML technique to categorise all users whose tweets related to oral cancer into two binary classes: individuals and organisations. The labelled data was based on user profile descriptions only. The Naïve Bayes classifier achieved 91.5% for the task. Also, (Kim *et al.*, 2017) developed a classifier to automatically place Twitter users into different categories in order to identify sources of tweets on e-cigarette topics. The categories were informed agencies, individuals, vape enthusiasts, spammers and marketers. The data was labelled by experienced data coders by considering the profiles of handlers and timelines. The classifier was not only trained on user profile descriptions but also on features such as user metadata and tweeting behaviour. The Gradient Boosting Regression Trees (GBRT) algorithm achieved the best F1 (82.5%). Another general user classification study in the health domain was performed in (Zhang and Bors, 2019). Relatively simpler features of user profiles were used in the classification strategy instead of more complex features. The data consisted of tweets collected using 379 disease hashtags from Twitter. Utilising the bio of each of the users or the 20 most recent tweets in the absence of a bio, six different types were identified as stakeholders in this domain. For features extraction, three approaches were applied: 1) content-based features, extracted from the user profile instead of the contents of posted tweets; 2) behaviour-based features such as the number of tweets created by a user, favourites of the user, number of friends, followers and number of lists a user has and 3) the use of dictionaries to extract features from a user profile description. The assumption is that a particular class of users may use a set of typical lexical expressions that distinguish them from other classes. In contrast with the other domains, the best result obtained in this study was only 59% in terms of the F1 score, proving that user classification in the public health domain is more complicated than in other domains.

2.4. Study Objective

According to existing literature reviews, empirical research is lacking on information dissemination on social media among different parties of interest in the dementia domain, this lack motivated this study. Another motivation for this study is the lack of studies related to automatic user classification in the dementia community, using simple text features. Although a noteworthy attempt was made to produce automated categorisations of user profiles, for example to identify the sources of tweets related to 379 diseases proposed by (Zhang and Bors, 2019), these general classification results do not provide promising accuracy values desired in the specific health information domain. Since a single set of features cannot be used on different domains with the same success, due to changes in datasets, it is imperative to test the best features suited for this unique research topic.

Information flow and relations among different categories, using network graphs, were not explored in these studies (Zhang and Bors, 2019) (Kim *et al.*, 2017). In addition, previous work primarily used SNA on binary classifications of users or tweet groups. In contrast, this study sought to apply SNA on several groups of users to obtain further insights as to how different types of user groups interact through the network. Therefore, this study is intended to fill a gap in our knowledge of how dementia information is shared on Twitter, applying ML methods to classify different user categories, to reveal the influential categories, to show the relationships between the different user categories and to identify influential dementia information authors on Twitter, through metrics provided in graph theory. Although it is critical to recognise the validity of tweet origins, information dissemination via Twitter, whether fact or fiction, is compromised by the use of bots. Yet the role of bots in important health information dissemination in the midst of a pandemic cannot be ignored, specifically to protect this vulnerable part of society (i.e., PWD) against their negative impact. On Twitter, a bot is an automated programme that controls profile behaviour, such as posting tweets and re-tweeting, by calling on available Twitter API features (Chu *et al.*, 2012). Bots can be utilised for positive, negative or harmless purposes, working in a coordinated fashion on the social network (Yang *et al.*, 2019). Therefore, the study also evaluates the role and proportion of bots in these categories and their network behaviour. To this end, the following research questions were posed: 1) How can user categories participating in dementia communities on Twitter be classified? 2) What are the most influential categories and nodes during Covid-19? 3) What is the relationship between a user's bot score and network metrics?

3. Methodology

3.1. Data Collection

Two datasets containing Twitter user description information (bio) were used for this study. A bio is a valuable source for user profiling (Zhou and Na, 2019). The first was a training dataset from a previous study by (Alhayan and Pennington, 2020) and the second a Covid-19 Twitter user dataset for user category classification. The first dataset was sampled from 8,400 profile descriptions of users whose tweets during a three-month period contained the words 'dementia' or 'Alzheimer'. Based on their profile descriptions, the users were classified into eight main categories, by manual annotation. The category descriptions are provided in Table I. The Organisations, Promoters, News and Books/Apps categories showed overlapping profile descriptions and were therefore merged into one category, called Organisations, which reduced the total number of categories from eight to five to improve the classification accuracy values. For the training dataset, a random sample was selected in order to have approximately 500 profiles from each category. The second Twitter user dataset was collected between 1st January and 30th April 2020. The tweets contained the keywords Covid19 OR coronavirus AND dementia OR Alzheimer OR Alz. By using the standard

Twitter API, publicly available features of tweets, such as the retweet count and user profile description of the tweeter, were obtained. A total of 11,354 tweets were collected, with 4,097 getting at least one retweet, and only 3,770 were relevant to dementia/Alzheimer. If retweeting occurred more than 100 times, only the 100 most recent retweeter information, including profile descriptions, were obtained due to a Twitter API limit. A total of 13,679 user profiles tweeted and retweeted. The English bot scores for the tweeter and retweeter profiles were then retrieved using Python BotOrNot API (Yang *et al.*, 2019).

3.2. Data Preprocessing

Different preprocessing steps were applied to the profile descriptions in the training dataset. For the profile descriptions in the categories, all words were converted to lowercase; broken Unicode characters, such as mojibake/garbled HTML entities, were fixed; and contractions were resolved. To fix broken Unicode characters, the FtFy [1] library (Python 3.7) was used. Word contraction was resolved using the Contraction library [2], which is capable of resolving contractions (and slang) by simple replacement rules of commonly used English contractions, such as 'you're' to 'you are' and 'gotta' to 'got to'. Next, the emojis and singular pronouns in the profile descriptions were replaced with more generic single words 'EMOJI' and 'SINGULAR'. Applying generalisations on these text features can help to reduce feature spaces and increase the weight of these labels of the category, and thus optimise the classification results. For example, Individuals' profiles often use singular pronouns, while those of Organisations/Care Providers often use plural pronouns.

3.3. Features Selection Technique

The next stage was the process of extracting numerical features from the text. The Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer was applied using the Scikit-Learn library [3] to convert words in users' profile description n-dimensional vectors. Generated vectors at the word level (ngram (1, 1)) considered the top max features ordered by term frequency across the corpus.

3.4. Models Training and Evaluation

To find the best model for classifying the user categories of the second dataset, four common classification algorithms were tested and compared: Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB) and Support Vector Machine (SVM). The train/test split ratio was set to be 75/25 throughout all the classifiers. Figure 1 illustrates the approach used in developing the classifier. The accuracy achieved for SVM, NB, RF and DT to classify the categories are 82%, 81%, 75% and 67%, respectively. This indicates that the SVM and NB classifiers provided the best accuracy. Different performance measurements, such as precision, recall and F1-score for both SVM and NB, are provided (Table II).

The precision of both classifiers ranged between 72% and 90% and the recall between 73% and 92%. However, the results show that the SVM provides better precision values for all categories except 3 and 5, as compared to other categories for the NB classifier. This is possibly due to more common words or features in categories 3 and 5, which may have led to misclassification. The SVM achieved the best performance, with an F1-score of 82% in 10-fold cross validation for the five classes. The confusion matrix of SVM and NB provided in Table III illustrates the predicted and actual labels for all categories.

3.5. Social Network Analysis

SNA was performed to understand the information flow among the classified categories from the second dataset. A directed retweet graph D (V, E) among all five categories (macro level) was formed by the Gephi tool [4] (Figure 2). V is the vertex (node), which represents all the users in each category. E is the edge; there is an edge between two nodes if there is a retweeting relationship between them, and the edge is directed from the re-tweeter to the tweeter. The vertex with the terminating arrow represents the tweeted category. Considering the complexity of the graphs due to the large number of nodes (13,679), the edges with less weight (1 and 2) were removed. This graph shows the influence of one category on another, in terms of the number of retweets. Along with category-level analysis (macro level), individual nodes were also analysed (micro level) to understand collective behaviour (Figure 3). Thus, network analysis metrics, such as centrality measures and others, were used. Centrality is a metric of a node's (user's) importance in a given network. Different types of centralities have slightly different meanings in Twitter networks. The network metrics used are defined as follows: **Out-degree centrality:** the number of edges flowing from a selected node to a range of other network members (Cherven, 2015). In this study, high out-degree refers to users who get many retweets. **In-degree centrality:** the number of edges flowing in towards a selected node from a range of other network members (Cherven, 2015). High in-degree, in this study, refers to users who retweet a lot. **Modularity:** to measure clustering in a given network. Cluster basically refers to the nodes with strong relationships, which are thus highly connected (Cherven, 2015). **Betweenness centrality:** indicates the most direct path between otherwise disconnected clusters (Cherven, 2015). It assesses the potential of a node for control of communication in the community (Freeman, 1978). **Closeness centrality:** measures how close a node is to the other nodes in the network (Cherven, 2015). It rates the ability of a node to instantly communicate with others without having to go through several intermediaries (Freeman, 1978). **Eigenvector centrality** is being connected to nodes with a high level of influence. In this case, it means not only being connected to many other nodes but also being connected to the most highly influential nodes (Cherven, 2015). **PageRank** is a variation of the eigenvector centrality measure and is used to rank web pages in the Google search engine. To identify the most important node, it takes into consideration the incoming connections and weighs their relative importance (Cherven, 2015).

Results

The total numbers of tweeters and re-tweeters in the classified categories are shown in Figure 3. The highest number of tweeters is in the Organisations category (category 3, Figure 3a), while the re-tweeters are highest in the Individuals category (category 1, Figure 3b). The average bot score of all users is less than 2. To understand the role of bots within the groups, the BotOrNot scores were used to identify potential bot-like accounts. The total number of users with an English bot score of greater than 4 and a CAP greater than 0.50 is 299. Whereas the English bot score range 1–5 indicates that a user is likely to be a bot, the Complete Automation Probability (CAP) ranges from 0–1, based on Bayes' theorem, which is a more meaningful way to judge whether an account is automated or not. Manual inspection of these profiles showed that only five were original tweeters and all other profiles were re-tweeters. Further inspection of the user categories of these re-tweeter(s) resulted in the following numbers of accounts: Individuals (32), Professionals (54), Organisations (52), Care Providers (23) and Empty/Unknown (133). The professional accounts included researchers and medical doctors.

3.6. Macro- and Micro-Level Analysis

Various network metrics were used on the macro-level analysis (category-level) to measure the influential category. Based on the high out-degree of the Organisations category (Figure 2), it was observed to be highly influential because all other categories, except Care Providers, retweeted the posts of the Organisations category. However, Individuals and Empty/Unknown are also influential categories because individual profiles in these categories have high PageRank values (Table IV). In order to measure the influencer node (user), micro-level analysis in different categories in terms of metrics such as weighted in-degree, weighted out-degree and eigenvector centrality were performed. Table V is sorted based on these three variables respectively, after considering only the top 10 users. It shows that nodes with the highest in-degree have zero out-degree in all cases. This means that there is a negligible influence of such users on only circulating tweets in the network. For out-degree, it can be seen that category 3 (Organisations) is prominent in the list with most of the retweets. Similar to high in-degree profiles, out-degree profiles do not show a high in-degree, which means that although many users largely retweet the tweets from Organisations profiles, Organisations' profiles do not retweet other profiles very often. The role of category 3 appears to be that of the information disseminators in the networks. The next important measure is eigenvector centrality, which shows that category 1 (Individuals) users are more influential. Furthermore, identifying the influencer node (user) type within communities is equally important; thus, (Figure 4) was plotted to highlight the communities in which colours are assigned to nodes based on their cluster. These clusters were generated using a 'modularity' community detection algorithm. The largest cluster (purple), which has a high modularity value, contains 10.16% of the total number of nodes. A subset of nodes has a very high betweenness centrality score (demonstrated by node size) inside the cluster, showing the influence of the node. These influential nodes belong to the Professionals or Organisations categories. There are also sub-clusters in a cluster, indicating more than one influencer profile in the whole cluster (blue). Sub-clusters are identified (red, black and green) with relatively low modularity values and have local influential users that are connected to a single node.

3.7. Network Metrics with User Categories and Bot Scores

To explore the relationship among different social network metrics with the English bot score and user category, initially scatter plots were used, as displayed in Figure 5. Important metrics, such as in-degree, out-degree and eigenvector centrality are plotted against user bot scores, as well as user categories. If in-degree is high, it means the profile is important due to the high amount of retweet activity. Similarly, if out-degree is high, it means the profile is influential due to being retweeted by many other profiles.

Assuming 2.5 is the threshold bot score, the most retweeted accounts are more likely to be human (Figure 5a). Also, a high number of retweets originated from users with a bot score of greater than 2.5 (Figure 5b). The profiles with high eigenvector centrality values have a bot score of less than 2.5 (Figure 5f), which means the most influential users are more likely to be humans, not bots. However, there are three profiles showing a high bot score with a noticeable eigenvector centrality value score.

On the other hand, the same metrics against category type are shown in Figures 5c, 5d and

5e. A few profiles in categories 1 and 5 (Individuals and Unknown/Empty) showed high retweet activity, whereas only category 3, Organisations' posts, were highly retweeted. This indicates that the users in categories 1 and 5 showed interest in different tweets about the guidelines provided by Organisations to keep up with Covid-19 information, as well as the guidelines posted by category 3 users. Other categories' posts have a retweet count of less than 1,000 (Figure 3d). Similarly, in all categories, there are few profiles that show an eigenvector centrality value of greater than 0.3. The most influential user belongs to the Individuals category, specifically to a caregiver, as referenced from the profile bios.

To further understand the relationship between bot score and network metrics, correlation analyses between bot score and other network-related metrics, such as in-degree, out-degree, eigenvector, closeness, betweenness and modularity values were also performed. According to the central limit theorem, in large samples (> 30 or > 40), the sampling distribution tends to be normal, regardless of the shape of the data (Elliott and Woodward, 2007), so parametric tests were used to estimate the relationships between the variables. Pearson's r shows all relationships to be statistically significant, with a p-value of < 0.01. The statistically significant correlation of the bot score is positive with weighted in-degree and modularity class ($r = 0.053$, $r = 0.033$), while it is negative with the closeness-centrality measure ($r = -.032$). Although the correlation values are small, this suggests that the importance of these metrics cannot be undermined in a credibility assessment.

4. Discussion

The objective of the study was to identify different categories of users that participate on the Twitter platform in order to understand which ones are influential, especially in the context of widely shared health misinformation and disinformation disseminated to a vulnerable group, such as PWD, during a global pandemic. Generally, ML methods were used to categorise users, after which macro- and micro-level SNA were applied to those categories. Furthermore, bot-like node presence within different categories and the relationship between different network metrics with the bot score were explored.

The datasets used were comprised of authors of dementia-related tweets, as well as retweeters, in the context of the early stages of the Covid-19 pandemic. Different classifiers using TF-IDF vectors of profile descriptions were tested and evaluated. The best performing model for user classification was the SVM method, which performed relatively well in classifying different types of Twitter users. Based only on user profile descriptions for feature extractions, good precision and recall with satisfying accuracy values were achieved for this task. The F1-score for all user types ranged from 73% to 91%. This is different from the classification in (Zhang and Bors, 2019), which relies on both content-based, including dictionary-based and lexical features extracted from the bio, and behaviour features related to the user (e.g., number of followers), whereas the technique used in this study only considered user bios to extract the features. (Zhang and Bors, 2019) obtained 59% in terms of F1 score, which shows lower performance for all the classifiers compared to the results of the classifier in this study. The major reason for this could be the heterogeneous dataset in (Zhang and Bors, 2019), while it is homogenous in this study's dataset. The data consists of tweets containing information related to 379 disease hashtags. Consequently, the data is further generalised by using common words rather than less specific words compared to a single health condition (dementia) dataset. Therefore, the overall performance of different classifiers applied to the data is better than that of the benchmark's best performing SVM classifier.

Although micro-level (node-level) SNA has been employed in many studies to identify the most influential nodes in two communities, as explained in Section 2.2, this work performed both macro-level (category-level) and micro-level (node-level) SNA to address the second research question. This allowed us to not only understand the influential nodes in the different communities but also to identify the influential categories and the interactions between them. Influence measures identified that the Organisations category had the highest in-degree value (Table IV), indicating that Organisations influenced other categories in terms of the number of retweets. This suggests that different user groups which are highly engaged with tweets concerning dementia are originated from Organisations. All other categories, except Care Providers, noticeably retweeted the posts of the Organisations category, as shown in Figure 2. Also, it was found that the Individuals category had the highest in-degree value as shown in (Table IV), which suggests that individuals are most responsible for tweet circulation (retweeting). The Individuals and Empty/Unknown categories had the highest PageRank (0.28) (0.24) respectively (Table IV). This can explain their importance as categories in the network, because a high PageRank score indicates that other important network categories interact with that category.

A cluster of nodes belonging to different user categories with high modularity values reflecting high coherence was revealed. Influential nodes within the cluster were found to belong to the Professionals or Organisations categories.

Regarding the influencer nodes on the whole network, the micro-level analysis of the 10 top users revealed profiles with the highest in-degree belonging to different categories, showing zero out-degree in all cases. Furthermore, most profiles with high out-degree belong to Organisations, and none of these profiles show a high in-degree value. This was different from the study by (Kim and Hastak, 2018), where they found that out-degree, in-degree and eigenvector centrality for all the top 10 nodes during the Louisiana flood disaster belonged to Individuals rather than emergency agencies or organisations. This shows the importance of identifying the type of both influential categories (group) and influential nodes with various centrality measures in a given network.

Although it is important to report the propagation of bot accounts participating in a network community by quantifying them, as in COVID-19 misinformation communities (Memon and Carley, 2020), and in the context of dementia (Alhayan and Pennington, 2020), understanding the network behaviour of these accounts is also essential. Therefore, this study sought to identify and discuss the potential relationships between users' bot scores and social network features. The bot score was statistically significant and positively correlated with weighted in-degree and modularity class. Correlation with in-degree pointed to a positive correlation of profiles' bot scores with the number of retweets. This indicated that a group of users in the dataset might use tools to populate their accounts by retweeting dementia-related posts. On the other hand, bot scores were negatively correlated with the closeness centrality measure. Nodes deemed central and close to most of the nodes on the network had lower bot scores and were more likely to be humans than bots. While our study detected a correlation between network features and user bot score, the work by (Zhao *et al.*, 2021) revealed network features related to health misinformation creators as well. These achieved relatively lower closeness centrality values when compared to the legitimate authors (0.2848 vs. 0.3011) while reflecting a higher degree of centrality (0.0076 vs. 0.0068) and a higher betweenness of centralities values (0.0076 vs. 0.0054).

5. Theoretical Implications

Despite the rapid increase in employing SNA, which is based on graph theory, in different social media research, its application in certain contexts (i.e., dementia community) remains limited. Therefore, the proposed method for the present study, that of combining SNA and user classification, proved to be efficient at identifying the influential users in order to characterise and measure a social structure, especially given its superiority in large dataset processing.

6. Practical Implications

During the pandemic lockdowns, Twitter became highly popular as an information sharing outlet in all domains, including dementia information, while also discouraging misleading information. PWD are a vulnerable population within society that is more likely to be seriously affected by regulations to reduce the spread of Covid-19, as they generally do not manage changes to their routines well. PWD and their carers need reliable information sources in order to stay safe in these challenging circumstances. The study method can help dementia stakeholders develop a deeper understanding of their online social communities. The study's findings can inform dementia stakeholders on how to improve their communication strategies by making use of different influencers to assure reliable pandemic information dispersion on social media.

7. Conclusions

Although SNA has been widely applied to social media data, this study is a unique attempt to examine the network structure and the most influential groups of Twitter users in the dementia community. An important contribution is the integration of machine learning-based classification results with SNA to determine influential groups and nodes in the network. This resulted in understanding the different types of influential communities involved in Twitter as a channel of communication during emergencies. This approach is generic and can be applied to any domain of any text-based social media platform. Furthermore, this study revealed some network features that contribute to bot behaviour in the context of specific health information, which can be considered in credibility assessment. The study has some limitations that may lead to interesting directions for future research. Firstly, to improve the user classification accuracy, advanced algorithms (e.g., deep learning models) could be used. Secondly, our characterisation only considered the behaviour of users. Tweet content analysis, for example whether it contains misinformation or not, was not considered. It would be interesting to analyse the flow of misinformation within the network.

Notes

1. https://pypi.org/project/ftfy/
2. https://github.com/kootenpv/contractions
3. https://scikit-learn.org/
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Table I: User Categorization Codebook (Alhayan and Pennington, 2020)

Category	**Sub-category**	**Description of Qualifying User Account**
Individuals - Professionals	Medical Professionals (IP-MP)	Individual users who include professional medical titles (as recognized by health practitioner registrations boards) in their biographical descriptions, e.g., doctor, registered nurse, nurse, physician, neurologist etc. or academic titles, e.g., professor of clinical neuropsychology, professor of integrative medicine, etc.) Examples of terms and/or phrases indicate medical titles you may find in their descriptions including, but not limited to: [Neurologist] [Neuro-surgeon] [Neuro-psychologist] [Organizational Psychologist] [Social geriatrician] [Occupational Therapist] [Re-habilitation Consultant] [Mental health specialist] [Nursing home doctor] [Biomedical Scientist] [Speech pathologist] or combinations of the above.
	Health Activist (IO-HA)	Individual users who are dementia/Alzheimer's/mental health advocates or who are involved in active campaigning with the purpose of bringing about human or social change in the field of healthcare.
Individuals - Other	Caregiver (IO-C)	Formal/informal caregivers who provide care to person with dementia, regardless of whether he/she has medical qualifications or an occupation relating to the field of dementia/Alzheimer's disease.
	Artist (IO-A)	Individual users notable for their fame in art, such as music, photography, or visual arts.
	Marketer (IO-M)	Individual users who specialize in marketing to promote their own products, books or equipment or work on the behalf of a company/organization to promote products, books, equipment, etc.
	Author (IO-AU)	Individual users who are expert writers and publish written material in works such as books, newspapers, magazines, etc.
	Others (IO-LP)	Individual users who do not belong in the above categories.
Entities	General Organizations (E-G)	These include government/public organizations, private organizations, non-profit organizations, interest groups, or charities that provide emotional support, activities, research, arrange seminars and develop communities.
	Homecare Providers (E-OCP)	Entities including profit or non-profit home care-providers or providers of services specifically for people with dementia and/or their caregivers and families. It may include agency or web directory help to find senior care-providers. Bio-descriptors may include phrases such as home care assistance, care-giver services, carer-services, nursing services, caregiver training, private duty home care, mobility assistance, memory care, re-habilitation, health and wellbeing services, music therapy etc.
	Promoters (E-P)	Promoters include technology and product development companies related directly to healthcare (e.g. devices, pharmaceuticals, biotechnologies). They also include marketing companies providing services or products not related directly to healthcare (e.g. law services, food, furniture).
	Media (E-MN)	Media includes electronic media such as news channels (BBC, CNN), print media such as newspapers (New York Times), research media (journal articles, research papers etc.), websites or social media profiles (Face-book, Instagram) to provide tips and information related to health.
Books and Apps	Books (E-B)	An account for book publishers, tweeting about collections of books or a specific published book.
	Dementia App (E-AD)	An account for a software program/app/tool /game/system that is specifically designed to serve people with dementia or Alzheimer's disease, their families and caregivers.
	Health App (E-AH)	An account for a software program/application/tool that is designed to increase general health and well-being.
Empty and Unknown	Unknown	Unknown includes places or events (e.g. conferences).
	Empty	The Empty category refers to profiles without descriptions.

Table II: Classification Results of NB and SVM

	Category	Precision	Recall	F1-score	Support
NB	Individuals	0.83	0.73	0.78	139
	Professionals	0.81	0.78	0.80	118
	Organizations	0.78	0.76	0.77	133
	Care Providers	0.84	0.82	0.83	120
	Empty + Unknown	0.78	0.97	0.86	103
Weighted Avg		**0.81**	**0.81**	**0.80**	**613**
SVM	Individuals	0.85	0.79	0.82	139
	Professionals	0.84	0.85	0.84	118
	Organizations	0.72	0.73	0.73	133
	Care Providers	0.82	0.86	0.84	120
	Empty + Unknown	0.90	0.92	0.91	103
Weighted Avg		**0.82**	**0.82**	**0.82**	**613**

Table III: Confusion Matrix for NB and SVM

NB Classifier						
Predicted						
Actual	**Category**	Individuals	Professionals	Organizations	Care Providers	Empty + Unknown
	Individuals	102	15	9	3	10
	Professionals	13	92	3	2	8
	Organizations	7	4	101	14	7
	Care Providers	1	2	14	99	4
	Empty + Unknown	0	0	3	0	100
SVM Classifier						
Predicted						
Actual	**Category**	Individuals	Professionals	Organizations	Care Providers	Empty + Unknown
	Individuals	110	10	12	4	3
	Professionals	10	100	5	1	2
	Organizations	7	7	97	18	4
	Care Providers	1	4	14	103	1
	Empty + Unknown	1	1	6	0	95

Table IV: Network Metrics

Category	Bot Score (Avg)	In-Degree	Out-Degree	Degree	Page Rank
Individuals	0.92	6661	2455	9116	0.28
Professionals	0.75	4043	3346	7389	0.18
Organizations	1.03	4259	12829	17088	0.21
Care Providers	1.34	1167	750	1917	0.08
Empty + Unknown	0.87	5172	1922	7094	0.24

Table V: Top users based on (Weighted In-degree, Out-degree, Eigenvector-Centrality)

Weighted In-degree			Weighted Out-degree			Eigenvector-Centrality		
Category	**Bot-score**	**In-Degree**	**Category**	**Bot-Score**	**Out-Degree**	**Category**	**Bot-Score**	**Eigen-Centrality**
1	2	155	3	2.3	2925	1	0.8	1
5	1.6	106	3	0.4	483	1	0.2	0.36
3	3.5	89	3	1.1	348	1	0.5	0.35
1	0.4	88	3	1.1	317	5	3.2	0.31
5	1.2	86	2	1.1	279	2	1.3	0.28
1	0.8	80	3	1.4	168	1	1.1	0.26
5	1.7	78	3	1.2	144	3	1.3	0.25
1	0.5	77	5	2.2	72	3	2.1	0.25
3	1	69	1	1	50	4	1.1	0.25
2	2.1	66	3	2.4	50	1	0.3	0.23

Fig. 1: Classifier Training Process

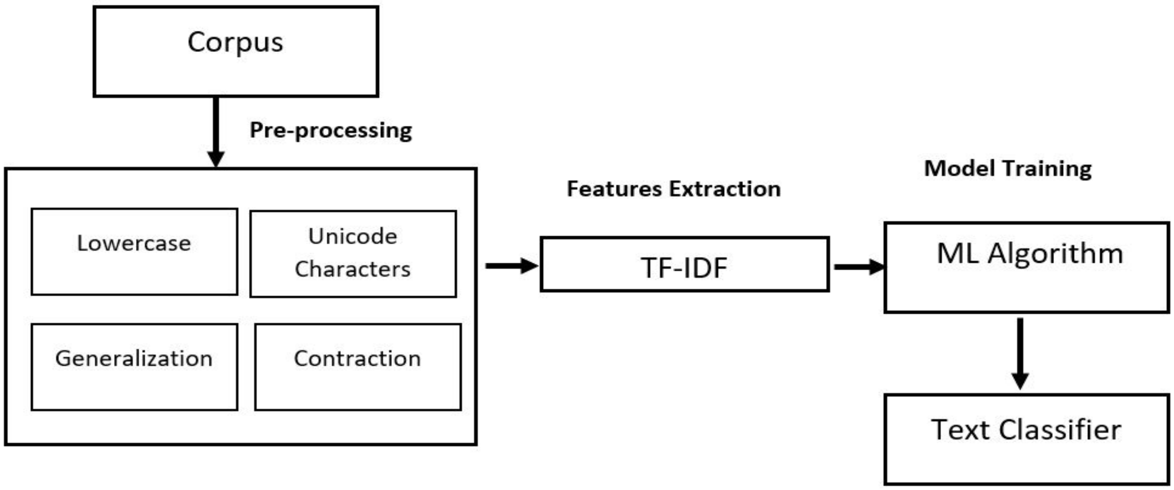


Fig. 2: Macro Network Analysis of Tweets and Retweets among Categories

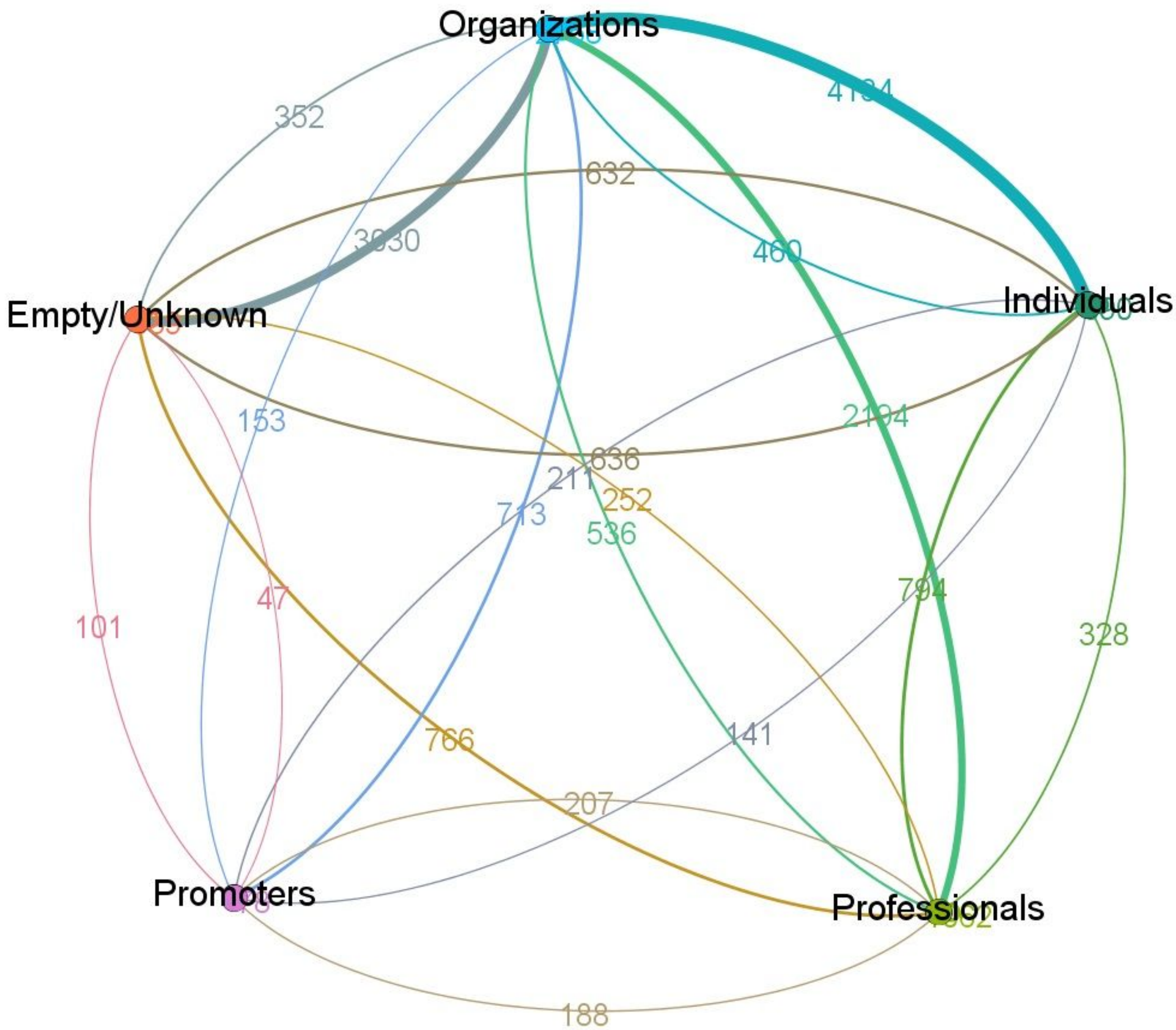
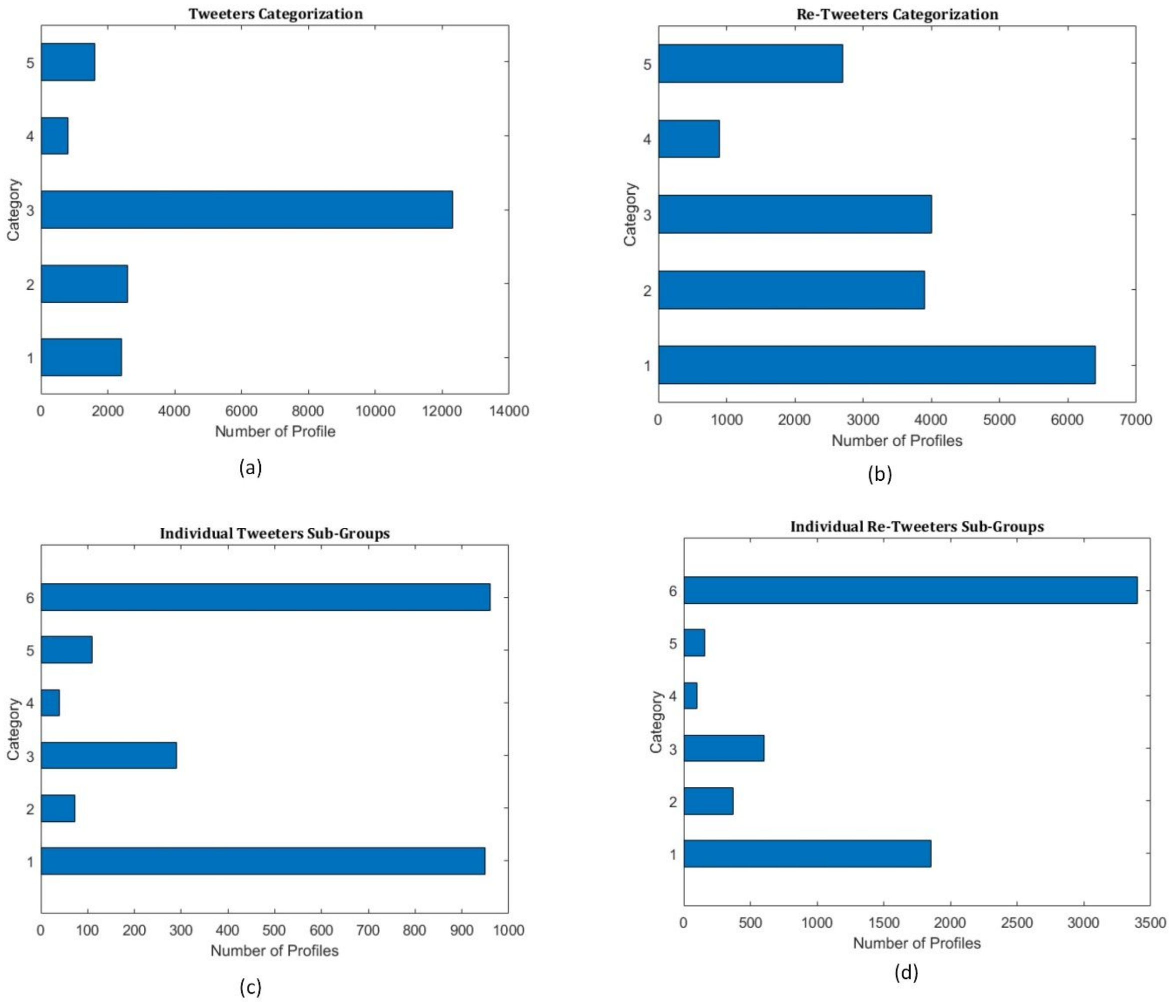


Fig. 3: Tweeter vs Re-tweeters by categories



(a) (b) (c) (d)

Fig. 4: Modularity and Betweenness Centrality at Micro Level

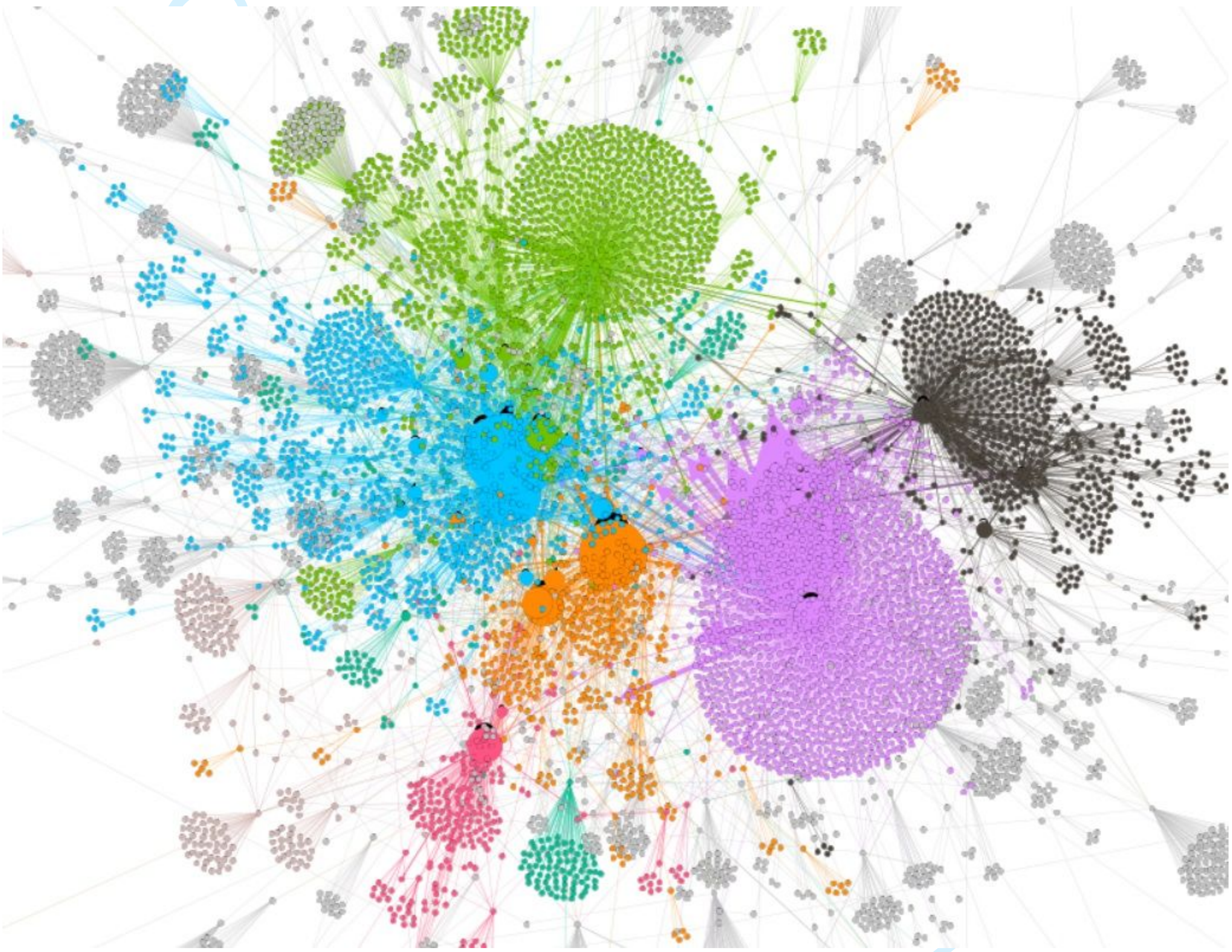


Fig. 5: Bot-Score vs Network Metrics and Categories