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George Floyd Four Years After: A Data-Driven Analysis of Posts and Comments on X (Formerly Twitter)

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Abstract. The death of George Floyd in the hands of the Minneapolis Police on 25 May 2020 led to public outcry, followed by a worldwide protest against the rampant killing and humiliation of black people by the police in the western hemisphere, especially in the United States. The objectives of this study are to use data mining techniques and machine learning algorithms to better understand how the online communications emanating from X (formerly Twitter) trended during the period of the protests, and the observed characteristics of these communications. Due to the large volume of data collected from the social media platform X, two separate datasets in the form of posts (formerly known as tweets) were collected in DataFrame format using the Twitter Archival Google Sheets (TAGS). The first dataset was collected using *#BlackLivesMatter* and the second using *#GeorgeFloyd*. Using modules from the Python Pandas ecosystem specifically designed for data analytics, operations such as sentiment analysis, word count, and data visualizations such as word cloud were made possible. The social network package Gephi was found most suitable for analysing the network that evolved over the period under review. Our social media analytics of the #BlackLivesMatter dataset showed that 40% of the tweets analysed were positive, 44% were found to be neutral, and only 21% were categorized as negative by the TextBlob algorithm. A simple network was observed to have evolved due to the proximity in location of social media handles. Using the #GeorgeFloyd dataset, our analysis showed that 39% of the tweets were positive, another 39% were found to be neutral, and only 22% were considered negative by the algorithm for sentiment analysis this time around. Overall, the comments on Twitter were found to be positive and in support of the protests and clamour for change, social justice, police reforms, equality, and equity.

Keywords: BlackLivesMatter, George Floyd, social media, social network analysis, sentiment analysis, social media movements, Twitter, tweets

Introduction

On Monday, 25 May 2020, George Floyd, a 46-year-old African American was killed in police custody in Minneapolis, Minnesota, in the United States of America in broad daylight, thus sparking outrage and condemnation by many, and eventually leading to a worldwide protest by members of the Black Lives Matter movement (BLM) and their supporters. Most people were outraged at the video of the incident that went viral on social media whereby Minneapolis Police officer Derek Chauvin was seen to have knelt over George Floyd by the neck with his knees for a total of 8 minutes and 46 seconds while Mr Floyd pleaded for mercy and his life, stating severally that he could not breathe. He eventually passed out and was pronounced dead on arrival at the hospital.

Unlike previous protests, the ones following the death of Mr Floyd went on for several days and weeks. By the end of June 2020, BLM protests had taken place in all 50 states of the United States. Protests also broke out in the following: the city of London, the United Kingdom; Paris, France; Berlin, Germany; Madrid, Spain; Melbourne, Australia; Amsterdam, the Netherlands; Johannesburg, South Africa; Lagos, Nigeria; Rio De Janeiro, Brazil – to mention but a few. As of August 2020, BLM protests were still ongoing in the United States, notably in the State of Washington, which is predominately white demographically.

Aims and Objectives of the Study

The objective of the study is to use big data analytics (data mining techniques and the use of machine learning algorithms) on data collected from the social media platform X in order to better understand both how the online communications emanating from X trended during the period of the protests and the observed characteristics in the form of patterns, opinions, and insights from these communications.

Literature Review

Van Osch and Coursaris (2013) reported that "social media" are technology *artefacts*, both material and virtual, "that support various *actors* in a multiplicity of communication *activities* for producing user-generated content, developing and maintaining social relationships, or enabling other computer-mediated interactions and collaborations" [emphasis mine]. Basically, social media allows for online connection and interaction through communication (text, images, and videos) between and amongst individuals on the platform through the world wide web or via mobile applications irrespective of geographical location. According to Bruns et al. (2014), social media are often also described as social networks. Although the two terms do not mean the same thing, they are closely related.

Social Media: the communicative aspects of platforms. This means both the media we create – tweets on Twitter, images on Instagram, or videos on YouTube – and the information, ideas, and opinions we communicate through these media.

***Social Networks*:** the interconnections between people on platforms. These connections are created by and used in these communicative processes, as well as the interconnections between posts, comments, and other pieces of content we create.

The likes of YouTube, Vimeo, and Vevo have been categorized as vlogs (video blogs) due to their video sharing architecture that also makes room for responses and comments by users and followers. It is obvious from the above descriptions that the many social media platforms that are available for free usage today allow different modes of interactions and content sharing amongst users. Typically, blogs and vlogs offer interaction between a blogger (owner, operator, or manager of a weblog) and followers or users in a restricted kind of network, while the likes of Facebook and Twitter have ecosystems that allow for across user interactions in a defined network. Instagram is a mobile application that allows for the sharing of content (images and videos) amongst users, leaving room for comments. It must be pointed out that although Instagram is also accessible online as a website via a web browser, it is nonetheless essentially a mobile application with a limited web version.

Social Media Movements: Sandoval-Almazan R. and Gil-Garcia J. R. (2014) reported that information technologies were increasingly important for political and social activism, such that social media applications have recently played a significant role in influencing government decision making and shaping the relationships between governments, citizens, politicians, and other social actors. This view was corroborated by Isa and Himelboim (2018) when they observed that in the last two decades online social movements have been increasingly relying on new communication technologies and, more recently, social media, to mobilize their own members, reaching out to new ones, and engaging with key societal actors, such as news media and decision makers to bring about societal changes. Whether it is referred to as online social movements or social media movements, the use of social media platforms to plan, coordinate, organize, and mobilize a group of people effectively to take a stand and effect societal change on a particular issue of collective importance is at the core of social media movements. Ranney (2014) was of the view that a social movement is an entity formed by a group of people who come together to protest against injustices and challenge the status quo. Social movements can be local or international and may address various social issues (Isa–Himelboim 2018).

For the study, the term social media movements (SMM) is preferred because the research work is centred around the formation, sustenance, and social architecture of the online social movements that evolved from such mobilization at a specific period. Unlike traditional social movements, SMM challenges the assumption of a movement as a single interconnected component, calling for identifying subgroups within the movement (Isa–Himelboim 2018). Social-media-based activism tends to be less interconnected and often composed of distinct and often disconnected subgroups and publics (Keib–Himelboim 2016). SMM are driven by key actors who can mobilize ordinary citizens and influential members of the society. As Isa and Himelboim (2018) rightly observed, how social media movements strategically use these key users and post content to reach out beyond their immediate group of members remains understudied.

Advocacy-based Social Media Movements: Many social media movements (SMM) grew out of a spontaneous response to ongoing social issues that affects a subgroup or cross-section of society, male and female. The #BlackLivesMatter movement is one such. Formed in the U.S., BLM has gained traction across the Atlantic to places such as the United Kingdom and mainland Europe as a means of fighting systemic racism towards black people. As Bauermeister (2016) observed, social movements were often initiated by a group of actors who are the primary victims of a decision, action, or policy that drive them to protest and hold demonstrations. These actors play the leadership role throughout the movement's life cycle to achieve their goals. The BlackLivesMatter movement is not only engaged in campaigns against police brutality towards people of African descent, but it has also called for prison reforms and orientation towards the issues that affect the black communities in the diaspora. It was founded in 2013 by Alicia Garza, Patrisse Cullors, and Opal Tometi. Other notable people in the movement include Shaun King, DeRay Mckensson, Erica Garner, Johnetta Elsie, and Tet Pole.

Gender-based issues are at the forefront of most SMM. The #MeToo campaign and the #WomensMarch were all intended to fight gender-based discrimination such as sexual assault and sexual harassment, equal pay in the U.S., sexism, online bullying, racism against minorities, colourism amongst African American women, and sexism to mention but a relevant few. However, gender-related activism is not limited to the Western hemisphere of Europe and the Americas. Rape is a big issue in India and Bangladesh, while Nigeria is battling with the trafficking of women for sex and prostitution. The activities of the #BringBackOurGirls have not gone unnoticed internationally. The efforts at retrieving the 276 schoolgirls kidnapped by the insurgent Boko Haram from their dormitories in the town of Chibok, North-East Nigeria in 2014 was championed by none other than Dr Obi Ezekwesili, a former Managing Director of the World Bank. Colourism is still a big issue that affects Afro-Brazilian women. In 2013, Nayara Justino was selected and crowned as the *Globeleza*, or Carnival queen, only to be replaced quietly a few weeks later after trolls of racist slurs deemed her too dark-skinned. Some of the trolls described her as "blackie" and "monkey". TV Globo, the organizers of the Carnival pageant, secretly replaced Miss Justino with another Afro-Brazilian – a light-skinned woman named Erika Moura. It is important to note that the online verbal attacks on Miss Justino were carried out by both white and non-white Brazilians. Since that time, there have been concerted efforts by activists in Brazil to fight racism, gender-related abuses, and inclusion of non-whites in television programming.

According to Raven, Berg, and Hassenshall (2010), the elements that contribute to addressing environmental problems include scientific assessment, risk analysis, public education and involvement, political action, and long-term evaluation. These five critical elements, when set in motion accordingly, with due diligence, could help assuage some of the challenges and hazards of environmental degradation and climate change. However, the effects and importance of public education and involvement of civil society cannot be overemphasized in the fight against climate change. According to the Pew Research Center report (2017), as of August 2017, around two-thirds (67%) of Americans get their news from social media. Thus, it is important to be able to use social media as an effective platform for the dissemination of information to combat the climate crisis. This is usually termed climate and environmental communication on social media. Unlike other types of movements, climate and environmental movements are unique in that the efforts are long-term and could run into several years, even decades. Unfortunately, time creates a sort of latency or inertia to the messaging such that after a certain period the online social media campaign towards the climate crisis becomes boring due to repetitions, thus becoming less effective. Climate activists and environmental communication specialists are continually looking for creative ways to keep the public interested in the fight to prevent continuous environmental degradation and stop further damage to the ozone layer. Global warming, climate change, and now climate crisis were some of the slogans used in the last three decades to create awareness about the need to be environmentally cautious in our daily lives. According to Ibimilua F. O. and Ibimilua A. F. (2014), notable consequences of environmental degradation include loss of lives, loss of properties, loss of genetic resources, loss of habitats, climate change and global warming, biodiversity loss, as well as epidemiological threats. Others are disturbance of human activities, reduction in ecosystem adaptability, and impoverishment of communities that rely on environmental resources as their means of livelihood.

An online social network emerges when social actors (referred to as *nodes*) form connections (or links) with other actors in the network. A typical example is the online social network formed amongst Twitter users when tweets are retweeted and user handles are mentioned in tweets using the @ symbol. According to Chaudhary and Warner (2015), social network analysis (SNA), which combines both method and theory, constrains studying the individual actor in isolation because the actor is part of a network. Therefore, a *dyad*, or relationship between two individuals or actors, is the building block of the social network study. In fact, SNA combines theories from mathematics, communication, and the social sciences to better understand the dynamics of the complex interactions amongst online groups and clusters on social networks.

Social media communications via X have become widespread in many parts of the world. In Nigeria, X was used to mobilize, organize, and orchestrate the #EndSars campaign in Lagos, Nigeria, from 8 to 20 October 2020. Similar situations have been found in Hong Kong, Brazil, and many other countries in recent years. Najadat et al. (2020) reported that people in the Arab world strive to communicate their thoughts and sentiments about various political, social, and economic events in their everyday lives via Twitter, which has grown to be one of the most popular social media platforms in recent years.

Balaji et al. (2021) were of the view that the most popular data generation application platforms on the Internet are social media platforms, which makes data analysis more extensive. But it is difficult to interpret such vast amounts of data effectively, so we need a system that learns from them, like machine learning. Storing, processing, and extracting information from this vast amount of data is not an easy task. Higher storage capacity and effective processing techniques are needed. Using machine learning (ML) techniques to combine intelligence notions with intelligent learning approaches is one way to potentially obtain valuable insights and hidden patterns from the data (Balaji et al. 2021). Machine learning algorithms are particularly of importance where large datasets are involved due to their ability to extract knowledge where classical statistical methods are not applicable.

Research Methods

Due to the large volume of data anticipated from the social media platform X, data mining techniques were used in the extraction of data from social media. The extracted datasets were used for sentiment analysis using relevant natural language processing tools from the Pandas Natural Language Toolkit.

Data Collection: Two sets of data were collected from the social media platform Twitter (now X) using the Twitter Archival Google Sheets (TAGS). To have access to the data on the X platform, users must first login to their X accounts. They will then access the X application programming interface (API) via the X Developer platform (*https://developer.x.com/en/docs/x-api*). Both the API keys and tokens are required to login into the X API for data collection. API keys are typically associated with specific servers the calling application is deployed on. When the application makes an API request, the server identifies the calling application by the API key. In contrast, an API token is a string of codes containing comprehensive data that identifies a specific user. Once the API keys and tokens are inputted into the Twitter Archiving Google Sheet (TAGS, *https://tags.hawksey.info/*), access is granted into the workspace for the collection of tweets after following a series of instructions and checking the corresponding boxes and buttons on the TAGS platform. Tweets were collected by entering a search term with a hashtag (#) in the provided space on the TAGS worksheet, after which the necessary parameters were set for the search for relevant tweets based on the search term to commence. Usually, tweets from the last seven days will be returned. The returned tweets (now referred to as posts) were presented in spreadsheet format after which they were downloaded in comma-separated values (CSV) formats for onward processing. The Spyder-integrated development environment (IDE) was used for programming in the Python language for data cleansing, processing, and analysis alike using appropriate functions and modules.

For this study, the search terms used for data scraping and collection off the platform X were *#BlackLivesMatter* and *#GeorgeFloyd*. The returned tweets were then collected and saved in a comma-separated value (CSV) format by selecting the preference on the download option of the *File* menu in the TAGS.

The first set of data was collected using the hashtag *#GeorgeFloyd* between 1 and 14 June 2020. Only one of the two datasets collected was found usable. Thus, the *#GeorgeFloyd2* dataset has the attribute (18,511, 18). That is eighteen thousand five hundred and eleven instances and eighteen attributes. For the second dataset, two sets of tweets (posts) were collected over a period of four weeks (1–28 June 2020) using "#BlackLivesMatter". The collected tweets were merged into one unit (#BlackLivesMatter2020) using the concatenation (concat) function in the Python Pandas module. The data *#BlackLivesMatter2020* has a total of 67,792 instances and 18 attributes but was reduced to (67,792, 17) for further analysis, after which the column index (0) was dropped from the DataFrame using the delete function.

Data Wrangling and Cleansing: The two datasets were then subjected to wrangling and cleansing to prepare them for further analysis. Tokenization, stemming, lemmatization, and the removal of stop words were some of the operations performed on the datasets to prepare them for sentiment and social network analysis. Data wrangling or cleansing entails the removal of unwanted elements from rows or columns of a dataset.

Data Analytics: There are several modules available in the Python ecosystem for data analytics, especially in the areas of social media analytics. Modules such as *Pandas, MatPlotLib, SciPy, SciKitLearn, TextBlob, BS4,* etc. all have advanced features for doing sentiment analysis, word cloud, and data visualization such as word cloud, plots, etc. SciKitLearn has facilities for the use and application of machine learning such as logistic regression, support vector machines, naïve bayes classifiers, classification, regression trees (CART), etc. There were no predictive analytics in this study.

Sentiment Analysis: This was conducted on the two datasets using the TextBlob module from the Pandas library. Blobber is a submodule of TextBlob that is used for further pre-processing of the data before the sentiment analysis was done.

Word Cloud: The *Word Cloud* module is used to analyse and report the most common words in the tweets (posts) collected from X. This gives an indication of the direction, content, and context of the posts and discussions during the period.

Social Network Analysis (SNA) is an innovative approach that social and behavioural scientists can use in understanding online social interactions on digital platforms such as the Web 2.0. Gephi is an application designed for network analysis. It has advanced modules for the import and subsequent analysis of social networks in a variety of formats such as .csv, .txt, .xlsx, and many more. Gephi was used to analyse and report the ensuing network from the collected datasets. Most of the default parameters and settings in Gephi were found to be sufficient for this study. Gephi provided detailed analysis of the type of social networks that emerged from the George Floyd protests several weeks after the incident was reported and shared on social media.

Results and Analyses

Sentiment Analysis: This entails the categorization of an expression or a piece of text as being positive, negative, or neutral. This is useful in gauging the public perception of an item, situation, event, or phenomenon. Using the TextBlob module for sentiment analysis on the BlackLiveMatter2020 data, we have the following:

Table 1. *Sentiment analysis of tweets for #BlackLivesMatter*

S/N	Id_str	Sentiment
0	1269736037766451200	0.000000
1	1269736037410095108	0.000000
2	1269736037359726598	0.014815
3	1269736037254934530	0.00000
4	1269736037112299521	-0.250000
5	1269736036717850624	0.000000
6	1269736036629983232	-0.041667
7	1269736036462141446	0.000000
8	1269736036063744006	0.000000
9	1269736035950477312	0.000000

Percentage of positive tweets: 33.91698135473212% = **33.9%**
Percentage of neutral tweets: 44.88877743686571% = **44.9%**
Percentage of negative tweets: 21.194241208402172% = **21.2%**
Total = **100.0%**

Word Cloud: Below are the 500 most common words in the #BlackLivesMatter data that were collected and analysed. The word cloud also revealed the frequency of occurrences of specific words in tweets and retweets.

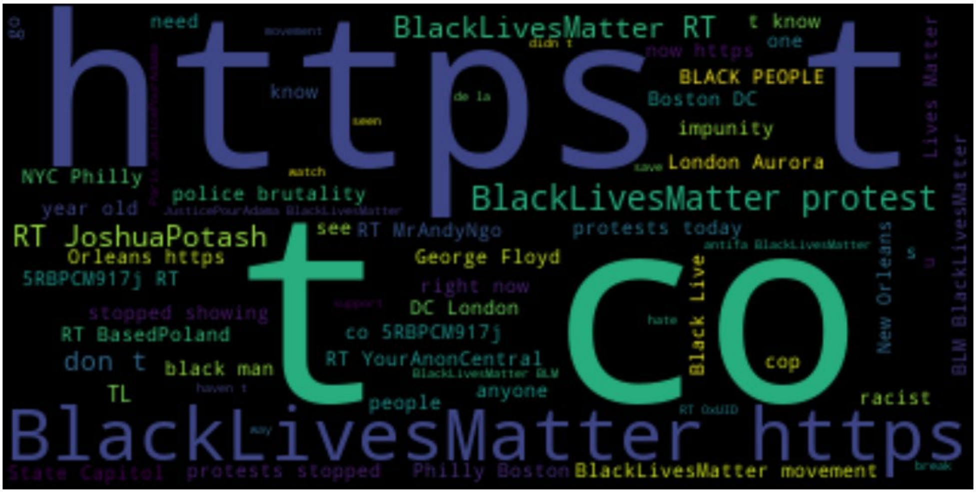

Figure 1. *Word cloud for the BlackLivesMatter2020 twitter dataset*

Word Count: This reveals the most common words in the tweets in numbers for the collected dataset.

Table 2. *Word count for the #BlackLivesMatter2020 dataset*

S/N	Word	Count
1	BlackLivesMatter	48,968
2	#BlackLivesMatter	9,493
3	Police	8,088
4	Protest	7,958
5	Black	4,774
6	Joshua Potash	4,270
7	London	3,203
8	Movement	2,742
9	Racism	2,742
10	Justice	2,540 2,464

Social Network Analysis for the *#BlackLivesMatter* Dataset

The Force Atlas option in Gephi was selected for the social network analysis, and the other parameters were set to basic options. The following network developed from the #BlackLivesMatter data (*Fig. 2*) below. Clusters were identified communities or subnetworks within the main network. Gephi was able to identify and analyse the modularity of the network (that is the tendency of a network to separate into clusters). *Table 3* below shows the results for some statistical graph measures. It is noteworthy that the network is not dynamic and is restricted (we consider the network in 30 days only – June of 2020), although in reality such networks keep growing and the shape keeps changing, and thus statistical measures such as the degree and clustering coefficient are absent, though we do indeed have clusters (subnetworks) in the graph.

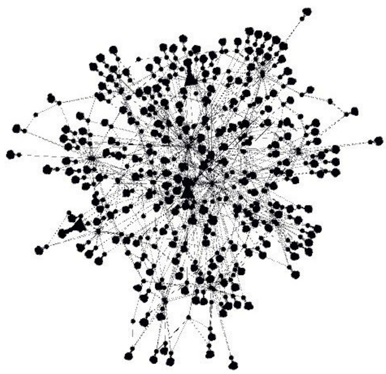

Figure 2. *A social network of the #BlackLivesMatter campaign in June 2020*

Analysing the network for the associated parameters revealed the following information as presented in *Table 3* below.

Table 3. *Network parameters for the #BlackLivesMatter2020 dataset*

S/N	Network Parameter	Value
1	Average degree	1.249
2	Average weighted degree	1.25
3	Network diameter	8
4	Graph density	0.001
5	Modularity	0.799
6	Average path length	4.94

Sentiment Analysis of the *#GeorgeFloyd2 dataset (18,511, 18)* revealed the following as presented in *Table 4* below.

Table 4. *Sentiment analysis of tweets for the #GeorgeFloyd2 dataset*

S/N	Id_str	Sentiment
0	1272120199685091328	0.050000
1	1272120189988020225	0.050000
2	1272120185764433920	-0.248810
3	1272120164071464960	0.000000
4	1272120163249410048	0.000000
5	1272120149156540418	-0.248810
6	1272120143015968776	-0.248810
7	1272120140637696001	0.050000
8	1272120132161146880	0.000000
9	1272120123558629377	-0.140909

Percentage of positive tweets: 39.01253241140881%	= **39.0%**
Percentage of neutral tweets: 39.37445980985307%	= **39.4%**
Percentage of negative tweets: 21.6076058772688%	= **21.6%**
Total	= **100.0%**

Word Cloud: Below are the 500 most common words in the #GeorgeFloyd dataset that were collected and analysed.

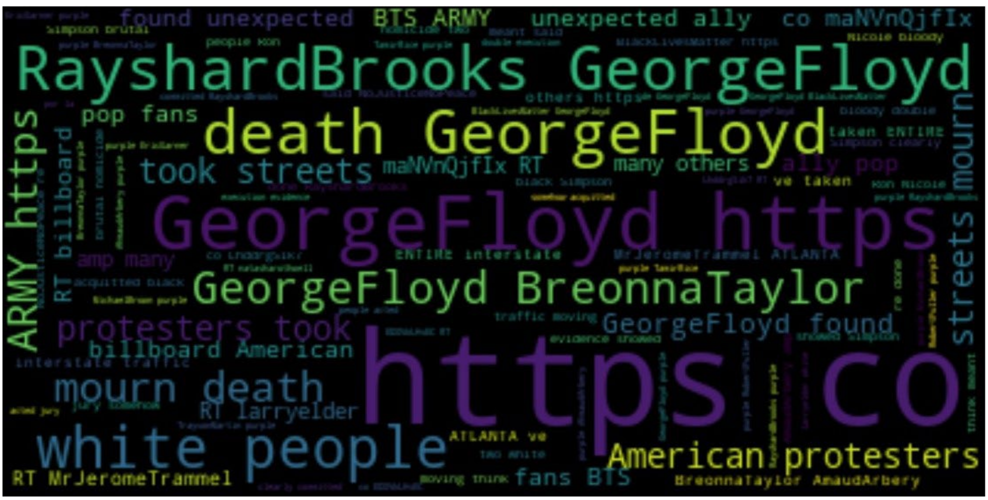

Figure 3. *Word cloud for the #GeorgeFloyd2 twitter dataset*

Word Count: Below is the word count for the most frequently occurring words in the tweets of the #GeorgeFloyd2020 dataset.

Table 5. *Word count for #GeorgeFloyd2*

S/N	Word	Count
1	George Floyd	17,155
2	Purple	6,652
3	Rayshard Brooks	3,509
4	Protesters	2,995
5	Death	2,933
6	Breonna Taylor	2,891
7	BlackLivesMatter	2,698
8	People	2,618
9	Police	2,600
10	White	2,087
11	American	1,956
12	Simpsons	1,927
13	Streets	1,827
14	Mourn	1,697
15	Unexpected	1,696

There was no social network analysis conducted for the #GeorgeFloyd2 dataset due to the small number of instances available for use. The 18,511 instances in data were insufficient to determine the type of network that resulted over the period of consideration (1–28 June 2020).

Conclusions

The *#BlackLivesMatter* dataset revealed that 40% of the tweets analysed were positive, 44% were found to be neutral, and only 21% were categorized as negative by the TextBlob algorithm. Using *#GeorgeFloyd*, our analysis showed that 39% of the tweets were positive, another 39% were found to be neutral, and only 22% were considered negative by the algorithm for sentiment analysis this time around.

Expectedly, the following words were found to be prominent within the communications in the tweets analysed: *BlackLivesMatter*, *#BlackLivesMatter*, *Police*, *Protest*, and *Black*. Surprisingly, the name Joshua Potash came up 4,270 times, the city of London 3,203 times, Movement 2,742 times, Racism 2,540 times, and Justice came up 2,464 times. These words were a clear indication of the predominant discussions, posts, and views expressed on Twitter during the June 2020 protests by the BLM movement on social media. With a modularity of 4.94, a simple social network was found to have emerged during the period under review due to the proximity of Twitter users.

The analysis of tweets collected using #GeorgeFloyd revealed an entirely different pattern for word count. The name George Floyd was found to have been mentioned a total of 17,155 times in 18,511 tweets, which is 93% of the tweets. The names Rayshard Brooks and Breonna Taylor were prominently mentioned in the tweets. Other prominent words/terms found in the tweets include *Protesters*, *Death*, *BlackLivesMatter*, *People*, *Police*, *White*, *American*, and *Simpsons*. The Simpsons was an unexpected term on the list. Available desk reference showed that the name Simpson appeared in many tweets in reference to a debunked episode of the cartoon series "the Simpsons", in which a white police officer arrested an African American male and subjected him to a physical situation by placing his knee on his neck thereby leading to protests and riots.

Overall, the protests trended well on X judging from the sentiment analysis conducted. The word count showed that the prominent terms found in the social media communication were in line with the aims and objectives of the #BlackLivesMatter movement, which is primarily about justice, police reforms, equality before the law, and probity. Finally, it must be emphasized that the results obtained from this analysis are not representative of the totality of trends observed on X in the weeks and months following the death of George Floyd. This analysis holds true only for a subset of all the tweets that emanated from X in that period.

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