CMP 7202

W EB SOCIAL MEDIA ANALYTICS AND VISUALIZATION

An article presented as a part of the degree's essentials of
MSc in BIG DATA ANALYTICS at the
School of Computing and Digital Technology
Birmingham City University, Birmingham,
United Kingdom (UK).

MAY 2023

Module: CMP 7202 Web Social Media Analytics and Visualization.

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Contents

1 Introduction: -

The study of social media data and the use of data analytics technologies on the given data to retrieve insights and patterns are combined in the disciplineof web social media and analytics and visualization. Twitter, LinkedIn, Insta- gram, and Facebook are popular social media sites for this kind of study where users have access to a large indefinite amount of data in real.

The findings of social media analytics may be presented and understood better through visualization. This may be able to see links, patterns, and trends in the data that the raw data might not be able to. Network diagrams, heat maps, and word clouds are visualization methods of research.

The process of Twitter Analysis includes gathering, processing, and analyz- ing Twitter data using a variety of analytical tools. To examine the connections between entities on Twitter techniques known as graph analytics is utilized. Communities, influence patterns, and groups of users with comparable preferences and habits can be shown.

A method for locating and separating topics or themes from massive volumes of text data is Topic Modeling. It helps analyze tweets and locate important topics or conversations that are taking place on Twitter. Using Natural Language Processing (NLP) to ascertain the tone, mood, or emotion represented ina tweet is an approach to Sentiment Analysis.

2 Twitter Analysis on ‘September Attack 9/11’:

Twitter has developed into a crucial tool for people to share and manage information during crises. It wasn’t even a factor when the ‘September 11’ attack happened. In the days and weeks that followed the attacks, Twitter was inundated with postings from people seeking to understand what had happened and support for the people impacted Evans, Cordova, and Sipole 2014. The feeling of community that developed during the Twitter conversations around September 11 became one of the most powerful elements. Since the ‘9/11’ attacks, Twitter has persisted in remaining a crucial tool for facilitating information sharing and fostering interpersonal connections among users in unspecified future emergency situations. This data set is scraped form Twitter tweets on ‘September Attack 9/11’ Awan 2014.

2.1 Highest-Volume Tweets Word Cloud

The collection of rules generates a word cloud visualization based on the textual content information. The textual content statistics are wiped clean by deleting any instances of the terms ‘September’, ‘redirect’, ‘year’, ‘previous revision’, and ‘line’ in Figure-1. The most commonly used phrase in the text facts is shown in a word cloud that is created using the wiped-clean text record.

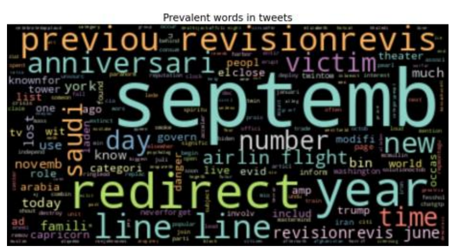

Figure 1: Twitter Word Cloud.

The top 20 Twitter customers with the most tweets referencing the studied information are represented in the Figure-19. The pinnacle user’s usernames are displayed on the y-axis, even as the number of tweets posted is displayed onthe x-axis. ‘DavidCranmerlUNI’, with the maximum number of tweets, has sent out more than 208 tweets that are linked to the studied facts of the September Attack. ‘NBCNightlyNews’, with the 20th highest number of tweets, has sent out about 9 tweets.

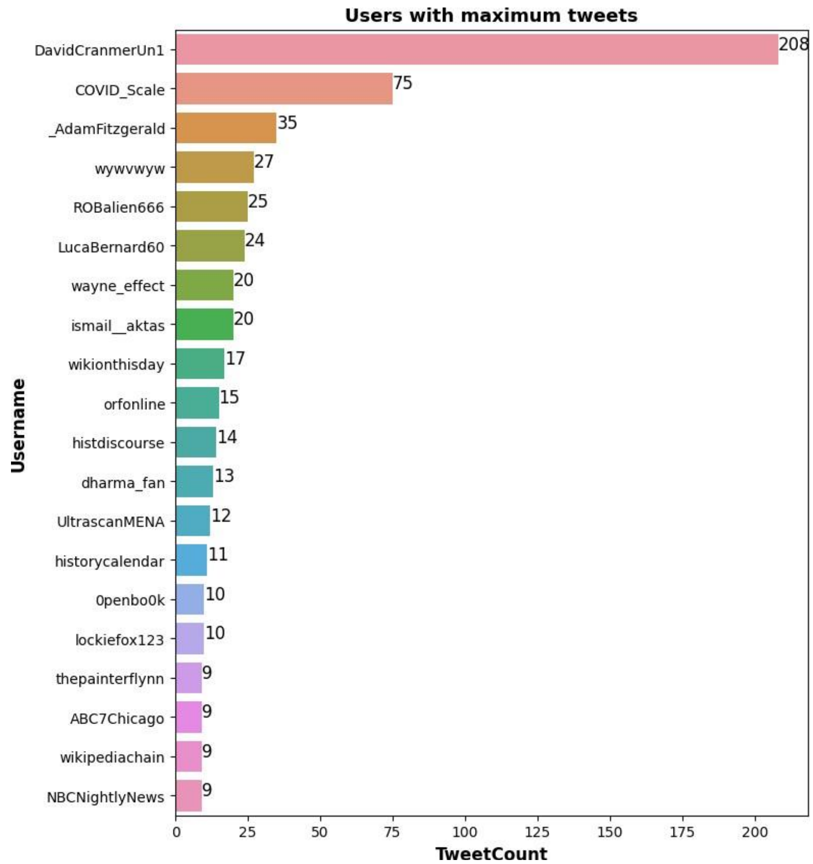

Figure 2: TOP 20 Tweets of Individual Users on September Attack.

2.2 Tweets of Unique Values, Sources

In the resulting bar plot Figure-3, the number of the unique values for each column is shown as a vertical bar. The fantastic values present in each column are shown by the length of each bar. The 'Datetime' column contains 6700 precise values, the 'tweetid' column contains 40 specific values, the 'text' contains 5000 precise values, and the 'Username', 'Language', 'Source', and 'Location' are as follows.

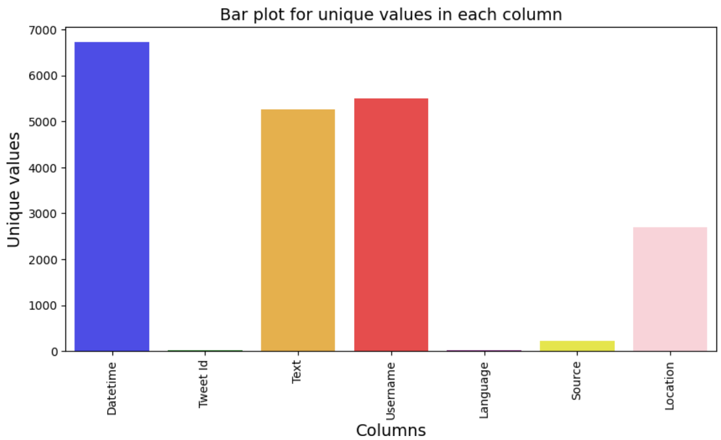

Figure 3: Twitter BAR PLOT of Fantastic Values.

The top 10 systems for the tweet booklet are displayed in a bar graph. The number of tweets posted from each consumer platform is parallel to the consumer platforms in Figure-4.

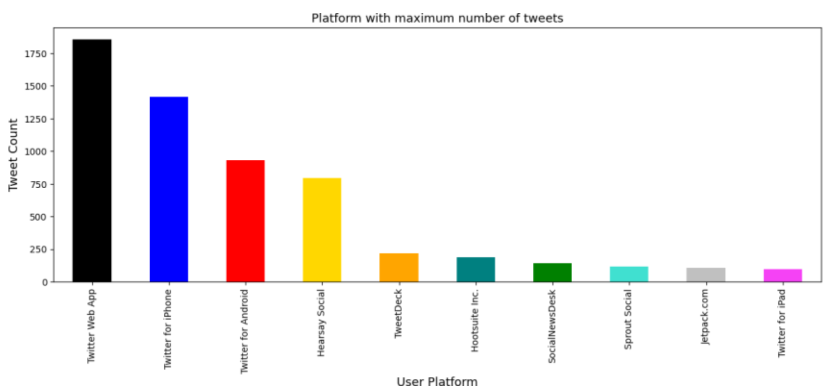

Figure 4: TOP 10 Tweeter Sources to Tweets.

The graph famously shows that the platform with the maximum number of tweets is the 'Twitter Internet app', with 1860 tweets, observed with the aidof 'Twitter for iPhone' with 1400 tweets, Twitter for Android with 900 tweets, Hearsay Social with 750, and Tweets Deck with 250 tweets in Table-4. These effects suggest that the majority of tweets on the problem have been published by both mobile and web-primarily-based Twitter consumers.

SOURCE	TWEET COUNT
Twitter Web App	1860
Twitter for iPhone	1400
Twitter for Android	900
Hearsay Social	750
TweetDeck	250

Table 1: TOP 5 Tweeter Sources.

2.3 Sources of Tweets:

The distribution of tweet sources may be easily seen using the pie chart, which is a visual representation of the data. The 'Top 5 Sources for tweets within the United States are displayed in the following pie chart Figure-5. The source of '42.4 percent' of tweets is the 'Twitter net app'. With '21.2 percent' of tweets, Twitter for iPhone is the source with the second-most variety of tweets, while '24.2 percent' of tweets come from 'Twitter for Android'. 'I simply need to tweet' and 'Tweet Deck' are the alternative two resources, accounting for '7.6 percent' and '4.5 percent' of tweets. The chart gives insightful statistics on the most commonly used Twitter asset in the United States.

A pie chart displaying the proportion of tweets from the top five resources used in India with the place information in the data set. The most popular supply is the 'Twitter net app' which has a share of '10.4 percent', observed via Tweet Deck with '45.8 percent', Jetpack.com with '22.9 percent', Twitter for Android with '16.7 percent ', and Twitter for iPhone with '4.2 percent' in Figure-6. This pie chart presents a visual deception of the tweet assets utilized in India andmay be beneficial in providing information on how consumers use their tweets.

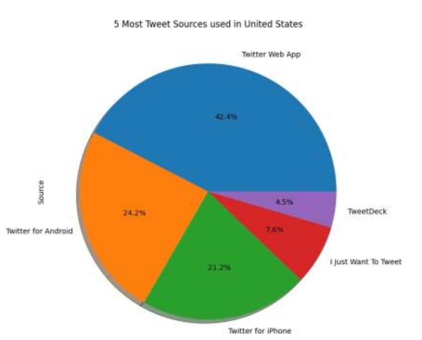

Figure 5: Pie Chart of Top 5 Twitter Sources in the United States.

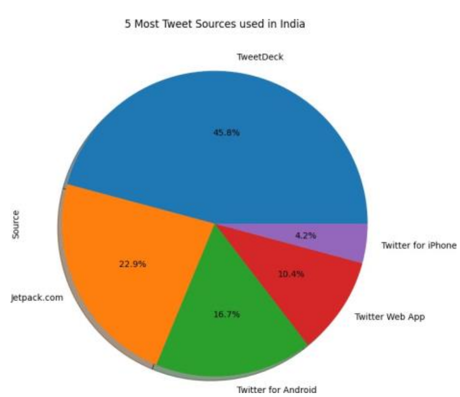

Figure 6: Pie Chart of Top 5 Twitter Source in India.

Users who identified Australia as their tweet location are known to have used the top 5 five Australia tweet sources in Figure-7. Since the 'Twitter web app' charges for almost all tweets, it has been used to send '43.8 percent' of all tweets. The next and third most often used assets were Twitter Media Studio and Twitter for Android. Grabyo and Tweet Deck were last in terms of how frequently they are used.

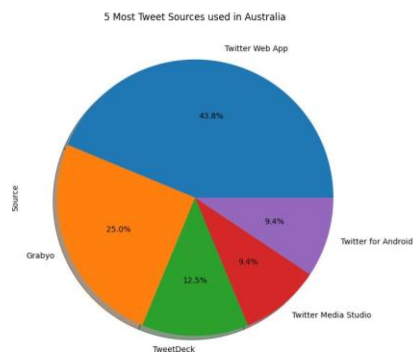

Figure 7: Pie Chart of Australia

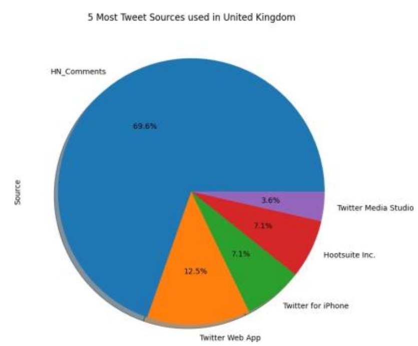

Figure 8: Pie Chart of United Kingdom

Furthermore, in the United Kingdom 'HN-Comments' are the most usedtweet source with '69.6 percent'. Tweet with Twitter web app used by '12.5 percent', Twitter for iPhone and Hootsuite Inc are used '7.1 percent' for each, and rest '3.6 percent' of Twitter Media Studio in Figure-8.

2.4 Evaluation of Twitter Location:

A heat map is an effective tool for studying data distribution and identifying trends or patterns. To aid future manual information collection efforts, it may also be used to pinpoint coverage gaps in the data set. The number of data points in a positive zone is represented by color, with denser shades denoting more data points. In the following heat map, most of the sites are concentrated in the 'United States', 'India', 'Australia' and the 'United Kingdom' Figure- 9 and Figure-10. The heat map also makes any grouping or arrangement offacts suggestive. Particular geographical areas within the four countries are overrepresented in the study because of the excessive density of websites in those four countries.

Figure 9: Topographical HEAT MAP Tweets OF ‘UNITED STATES’.

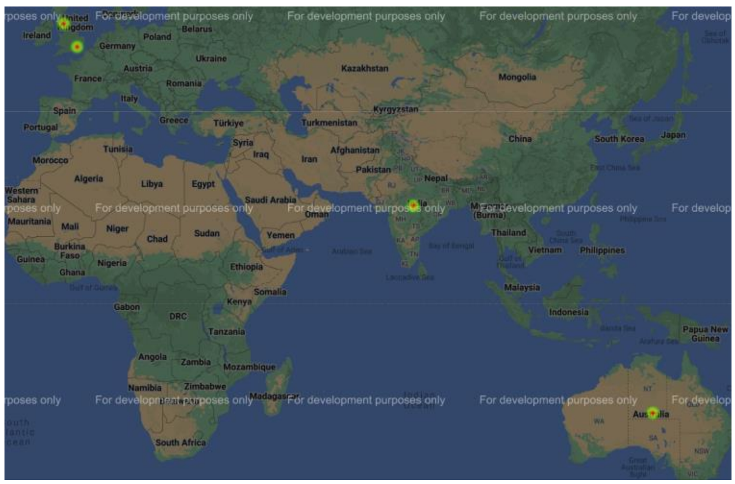

Figure 10: Topographical Heat Map Tweets of ‘INDIA’, ‘UNITED KINGDOM’, AND ‘AUSTRALIA’.

3 Sentiment Analysis on FIFA WORLD CUP 2022: -

Twitter Sentiment Analysis is a form of (NLP) Natural Language Processing that seeks to categorize statistics into neutral, positive, and negative attitudes. The tweet's sentiment regarding the 'FIFA WORLD CUP 2022' has been examined in some of the research and projects using Twitter sentiment analysis Nuñez Franco 2023. A sentiment observation of tweets at the FIFA WORLD CUP 2022, the bulk of them are beneficial. This is most likely a result of the FIFA WORLD CUP, a vast athletic event that is watched by human beings all around the globe. The Pandas data frame contains the sentiment analysis of the input tweets. This data set is sourced from Twitter Scrape 'FIFA WORLD CUP 2022' where values of Datatime, Tweetid, Text, Username, Language, and Source 6,000 tweets.

3.1 FIFA Tweet Subjective distribution and Tweet Sentiment, Polarity.

The sentiment analysis collection of tweets about a certain subject. The 'SentimentChecker' characteristics take a list of tweets as enter analyses each tweet's sentiment using the 'TextBlob' library and generate pandas' 'DataFrame' with columns for the tweet's subjectivity, polarity, and sentiment in Figure-11. The subjectivity rating varies from 0 (goal) to 1 (subjective), while the polarity rating runs from -1 (maximum negative) to at least 1 (maximum positive) Barnaghi, Ghaffari, and Breslin 2015.

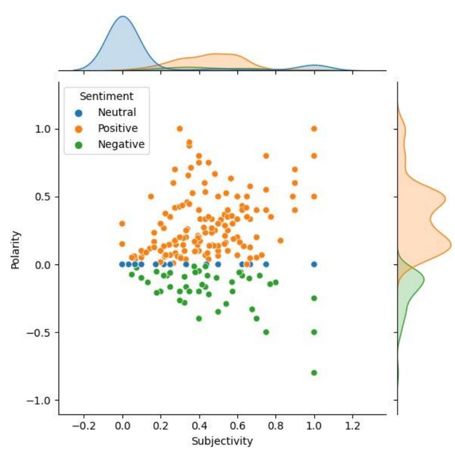

Figure 11: FIFA TWEET Sentiment Analysis of Polarity and Subjectivity.

Depending on the polarity score, the sentiment is labeled as both high quality, negative or neutral in the given graph where orange prefers to be positive, blue refers to neutral, and green is negative. The 'JointPlotter' feature gener- ates a combined plot that presents the distribution of the tweets' subjectivity and polarity ratings. The 'Sentiment' option is chosen, and as shown in the result Figure-12, the plot presents the sentiment of every tweet in three distinct colorings: orange for positive sentiment, blue for neutral sentiment, and green for negative sentiment.

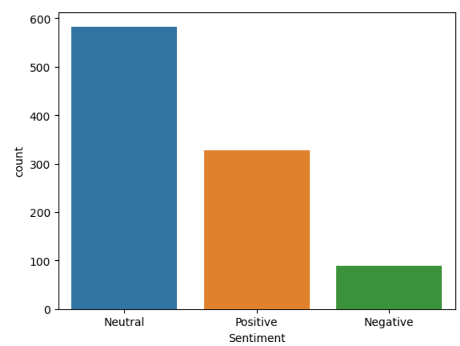

Figure 12: Sentiment Analysis on FIFA TWEETS COUNTS.

3.2 Neutral Sentiment Word Frequency Distribution and Word Cloud distributed by sentiment:

In Neutral Sentiment, the word cloud visualizes the frequency of the most time-honored terms within the textual content statistics. Three terms are blanketed on this word cloud: 'World', 'FIFA', and 'CUP' with frequencies of 520, 518, and 510 Figure-14.

Figure 13: Neutral Sentiment Analysis Word Cloud.

Figure-13These words are portrayed in larger font sizes than less commonplace terms on the grounds that they appear more often inside the text statistics. The ‘subset’ was to generate a word cloud.

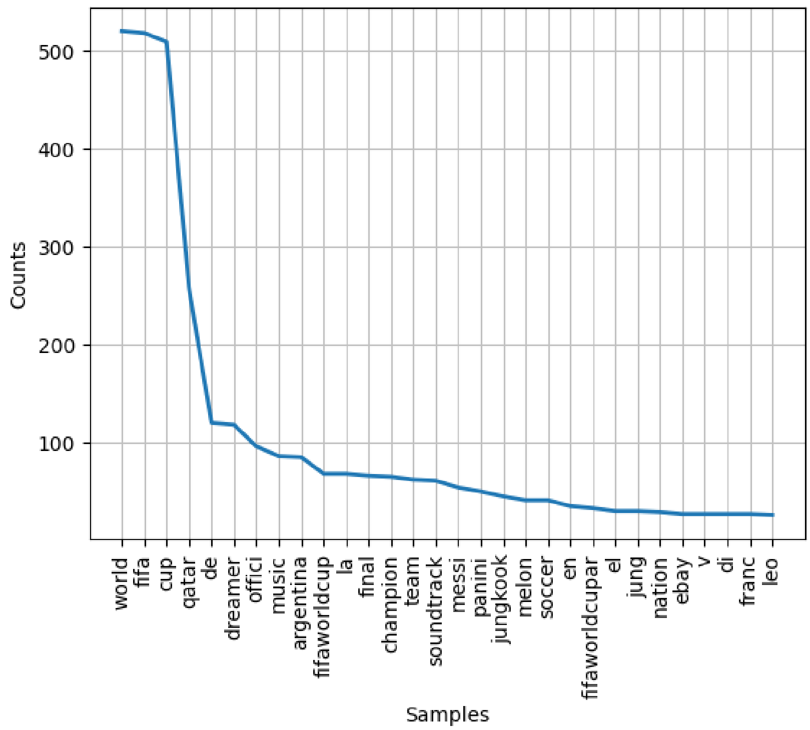

Figure 14: Neutral Sentiment Analysis Frequency Distribution.

3.3 Positive Sentiment Word Frequency Distribution and World Cloud distributed by sentiment:

A word cloud is made using the text data set contained within the ‘subset’ field. In Positive sentiment, the word cloud visualizes the frequency of the most time-honored terms within the textual content statistics.

Figure 15: Positive Sentiment Analysis Word Cloud.

The top 3 terms in frequency and word cloud are ‘WORLD’, ‘CUP’, and ‘FIFA’ in Figure-15 with the frequency of 310, 290, and 260. These words are portrayed in larger font sizes than terms on the grounds that appear more often inside the text statistics in Figure-16.

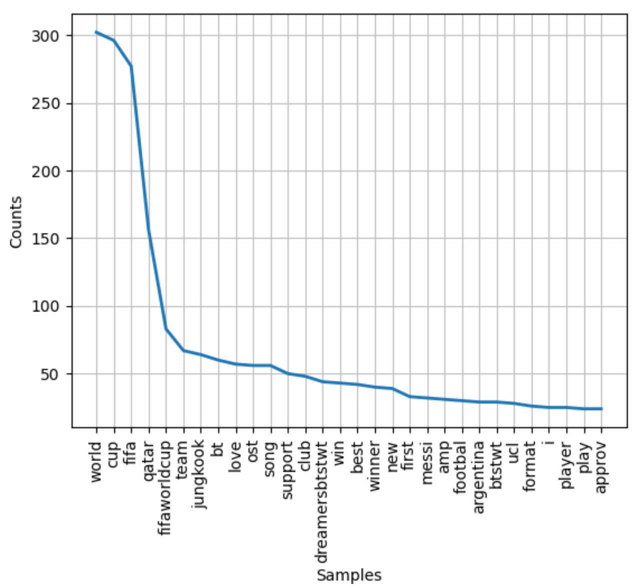

Figure 16: Positive Sentiment Analysis Frequency Distribution.

3.4 Negative Sentiment Word Frequency Distribution and Word Cloud distributed by sentiment:

The textual content data set inside the 'subset' variable creates a word cloud. The phrase cloud in Negative Sentiment depicts the frequency of the most frequently occurring phrases in the textual content data set. Three phrases covered on this word cloud are 'FIFA', 'WORLD', and 'CUP' in Figure-18 with which frequency levels from 150, 91, and 89.

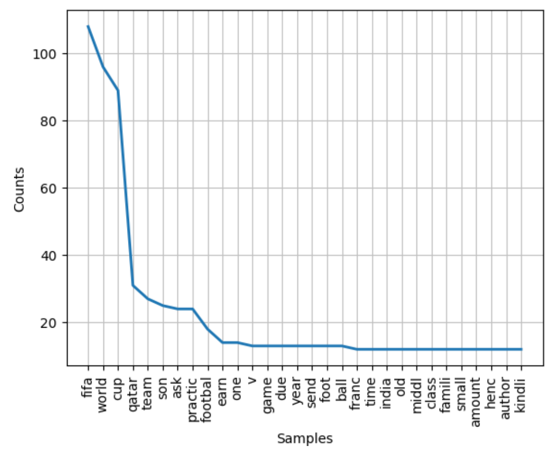

Figure 17: Negative Sentiment Analysis Frequency Distribution.

When it reaches to next word 'Qatar' it quickly drops to 30 in Figure-17. Due to the fact that they appear more frequently in the text data, these phrases are shown in larger font sizes than significantly less common terms.

Figure 18: Negative Sentiment Analysis Word Cloud.

4 News API Article and Topic Modeling Analysis:

Information items on the 'NBA LEAGUE 2021-22' topic matter had been identified using the News API Williams 2021. The article headlines are then merged using a loop over each one into a single string called text combined. After the first 200 characters of this string have been printed, a few articles on recent developments in the NBA, such as a new labor agreement, marijuana legalization, and player's prediction for the 'Most Valuable Player' for the 2021-2022 season, are then made available for viewing. It is possible to do additional analysis of this text as subject matter modeling or sentiment analysis.

4.1 Articles Analysis

In the given article of NBA there are 12 articles to analyze where Authors, Title, and Publish Date. The article's substance as well as the identification of the author's arguments' strong and weak points are the goals of the article analysis. Summarizing the article's main ideas and examining the author's writing style and tone are common aspects of article analysis.

AUTHOR	TITLE	PUBLISHED
'TIM REYNOLDS'	'NBA and Players Reach Deal for a New Labor Agreement'	'2023-04-01'
'Shruti Rajkumar'	'NBA To Lift Marijuana Ban For This Season In New Contract'	'2023-04-02'
'Doric Sam'	'NBA Players Feel Joel Embiid Was 'More Deserving'	'2023-04-19'
'Leonard Solms'	'What Tigers coach Rasheed Hazzard learned from Kobe'	'2023-04-24'
'Scott Polacek'	'Kevin Garnett to Ben Simmons'	'2023-04-02'
'Jonathan Givony'	'French lottery hopeful Rupert enters NBA draft'	'2023-04-19'
'Susan M. Shaw'	'Should The WNBA's Players Association Change Draft'	'2023-04-17'
'NBC Sports'	'DeMarcus Cousins reportedly signs in Puerto Rico'	'2023-04-11'
'Benjamin Mayo'	'Apple TV+ shows and movies'	'2023-04-28'
'Tim Casey'	'These Former University Of Kentucky Basketball'	'2023-04-24'
'Brad Adgate'	'The 2022-23 NBA Season In Review And A Look Ahead'	'2023-04-19'
'Andrew Lopez'	'The Rockets are ready to move past their rebuild'	'2023-04-06'

Table 2: Caption

4.1.1 Word Cloud And Word Frequency Analysis:

The FreqDist of clean text titles suggests there are 352 particular phrases in the clean text listening and a total of 578 world results in the clean test list. This parameter after cleaning the text from the list, then it carries out the subsequent actions. The frequency distribution of the words in clean text using NLTK library Eckert 2012.

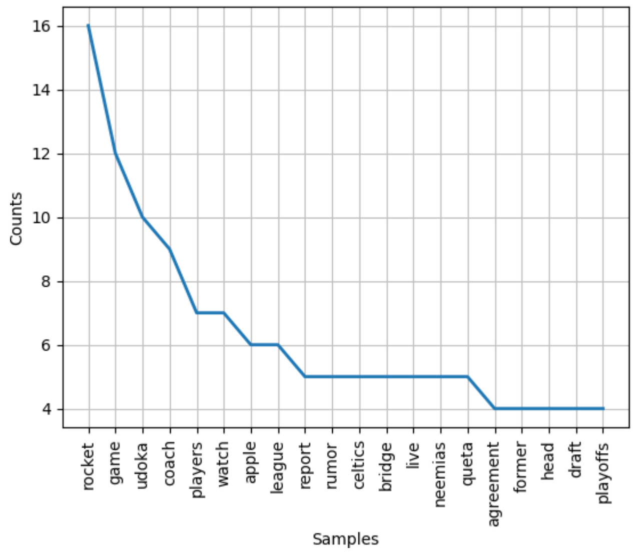

Figure 19: NBA LEAGUE 2021-22 Article Analysis Frequency Distribution.

The calculated filtered dictionary frequency distribution, then a graph (no) shows the frequency distribution of the top 20 terms in the filtered lexicon. In Figure-20, the word cloud shows the top 100 terms in it, ordered by frequency. The top 30 terms from the filtered vocabulary and plot their frequency distribution in the bar chart Figure. In the given bar chart Figure-21. the phrase 'rocket', 'game', 'Udoka', 'coach', and 'players' are the top 5 words in the content of frequency of NBA LEAGUE.

Figure 20: NBA LEAGUE 2021-22 Article Analysis Word Cloud.

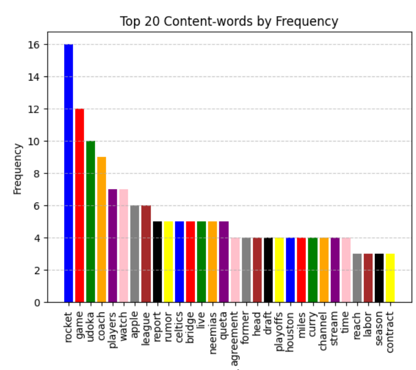

Figure 21: Top 20 Content words by Frequency.

4.2 Topic Modeling:

The range of subjects increases, the perplexity score declines, even as the coherence score fluctuates first of all between increasing and decreasing. A trade-off between these two metrics can be used to determine the appropriate number of topics Bicalho et al. 2017.

TOPIC	Perplexity	Coherence Score
2	-6.6129	0.2749
3	-6.691	0.2856
4	-6.7596	0.2819
5	-6.8185	0.2747
6	-6.8704	0.2784
7	-6.9168	0.2752
8	-6.9588	0.2705
9	-6.9970	0.2721
10	-7.0322	0.2720

Table 3: TOP 5 Tweeter Sources.

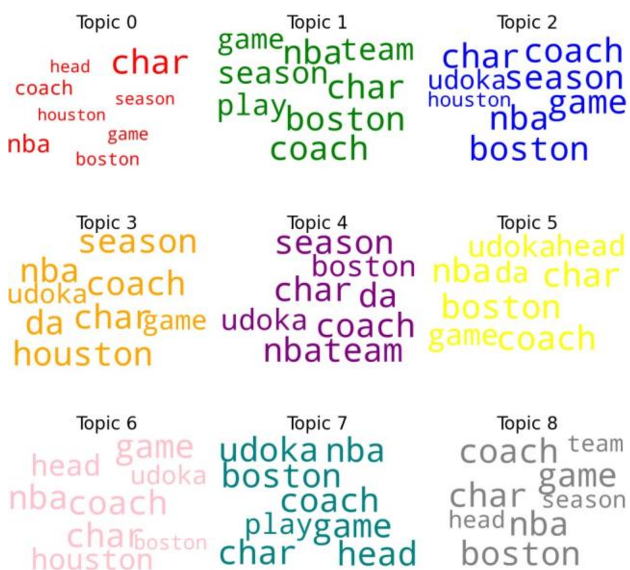

Figure 22: NBA LEAGUE 2021-22 Topic Modeling Frequency Distribution.

The coherence score for the version with three topics is the highest ‘0.2856’, while the perplexity rating for the version with six topics is the lowest (-6.8705).

Therefore, depending on the particular necessities of the analysis, an appropriate number of subjects could be 3 or 6.

Perplexity	Coherence Score
-6.8705	0.2856

Table 4: The Compute Perplexity and Coherence Score.

4.2.1 Frequency distribution and Word Cloud Analysis:

In the given Figure-29 shows the top 30 most common terms in the corpus of articles. Each word count is displayed on this plot together with its associate word. 'Season', 'game', 'NBA team', and 'watch' are the top phrase in the given plot, with values ranging from 200 to more than 1200. The terms most often used in the compiled articles Zhao et al. 2016. The blended text from all collected articles is plotted as a word cloud.

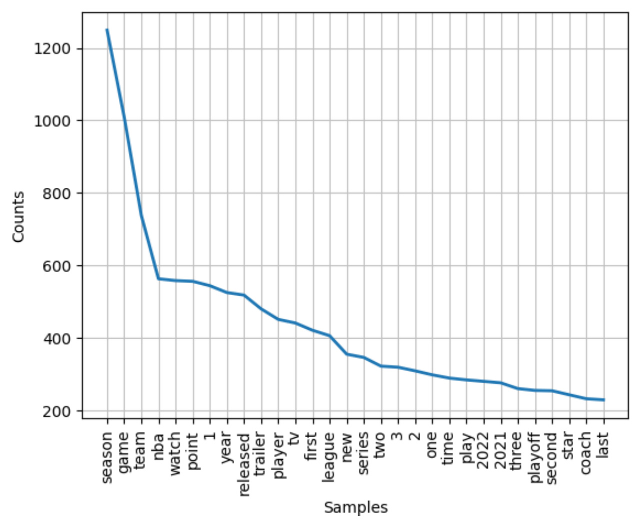

Figure 23: NBA LEAGUE 2021-22 Topic Modeling Frequency Distribution.

The magnitude of each phrase within the word cloud, which is 'season', 'sports crew', and 'NBA watch', displays how regularly it appears inside thetext. The plot, visible depiction of the most frequently used phrases inside the complied articles, and also provide insights into the subject addressed in the article.

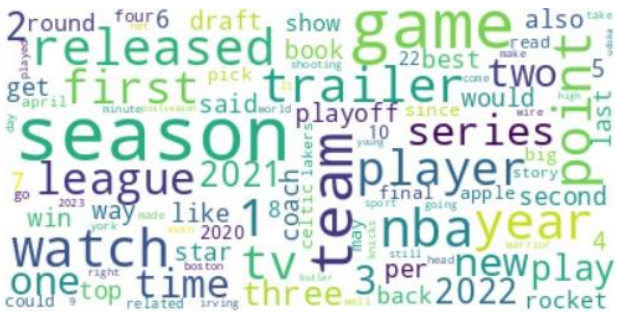

Figure 24: NBA LEAGUE 2021-22 Topic Modeling Word Cloud.

4.2.2 Article Ranking Analysis:

The Figure-25seems to be the outcome of applying a topic modeling to a collection of web pages associated with the search term ‘NBA LEAGUE 2021-22’.

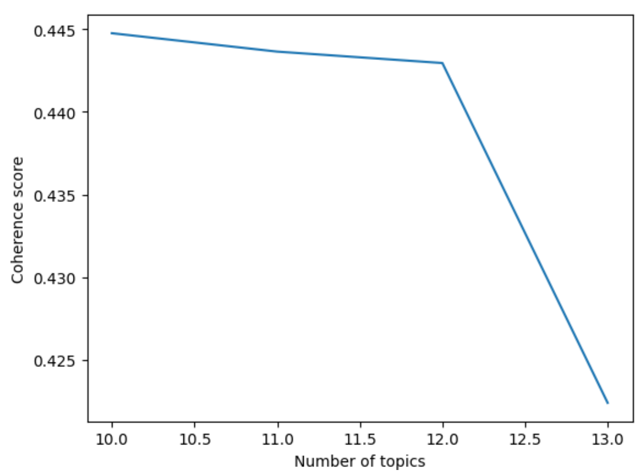

Figure 25: NBA LEAGUE 2021-22 Article Ranking Analysis.

It displays the top 10 terms for a specific subject, together with the weights assigned indicated by the numbers adjacent to it, with higher specific values signifying greater importance. In the below tables from Table-5 to Table-14 with the values of WEB pages and Best Valuation.

WEB Page	Best Valuation
watch	0.373
released	0.369
trailer	0.352
season	0.326
tv	0.317
series	0.164
1	0.159
book	0.145
2022	0.131
show	0.126

Table 5

WEB Page	Best Valuation
game	0.429
team	0.254
point	0.227
nba	0.177
season	0.167
released	-0.152
year	0.148
trailer	-0.146
player	0.142
watch	-0.134

Table 6

WEB Page	Best Valuation
game	-0.353
Irving	-0.264
butler	-0.203
year	0.201
season	0.163
heat	-0.144
player	0.112
curry	-0.112
6	0.111
lakers	-0.101

Table 7

WEB Page	Best Valuation
year	0.265
6	0.250
position	0.199
weight	0.192
1	0.191
draft	0.170
3	0.168
playoff	-0.156
pick	0.140
season	-0.138

Table 8

WEB Page	Best Valuation
team	0.342
year	0.224
point	-0.221
city	0.208
league	0.177
game	-0.175
knicks	-0.144
york	-0.143
cleveland	-0.141
would	0.140

Table 9

WEB Page	Best Valuation
new	0.208
playoff	-0.207
city	0.206
york	0.181
season	-0.171
sport	0.154
cleveland	0.145
postseason	-0.144
lake	0.141
brunson	0.128

Table 10

WEB Page	Best Valuation
player	0.241
city	-0.195
coach	0.176
said	0.173
lake	-0.156
season	0.144
rocket	0.142
bridge	0.142
guy	0.138
playoff	-0.137

Table 11

WEB Page	Best Valuation
nba	-0.222
west	0.202
league	-0.186
season	-0.155
net	0.150
guy	0.147
seed	0.142
would	0.136
bridge	0.125
phoenix	0.118

Table 12

WEB Page	Best Valuation
embiid	-0.205
said	0.176
new	0.164
joki	-0.154
rocket	0.142
100	-0.126
lopez	-0.123
bridge	0.123
game	0.121
minute	-0.121

Table 13

WEB Page	Best Valuation
season	-0.302
bridge	0.242
seed	-0.154
net	0.139
guy	0.136
point	0.136
star	0.130
team	-0.129
playoff	0.125
stats	0.120

Table 14

5 Network Graph Analysis on Instagram:

A community with ‘16210 nodes’ and ‘28308 edges’ is present in the centrality as the result. The nodes have a median degree of ‘3.49’

Total No. Of Nodes	Total No. of Edges
16210	28308

Table 15: NODES AND EGDES OF INSTAGRAM

5.1 Betweenness Centrality:

Measures of a node's significance in a network include betweenness centrality. It determines the proportion of shortest routes that traverse a certain node between all pairs of nodes inside the graph, and have the highest betweenness centrality Brandes 2001. The graphic shows the betweenness centrality of each node, with every node's size in keeping with its betweenness centrality. These nodes are regularly called 'connectors' or 'bridges'.

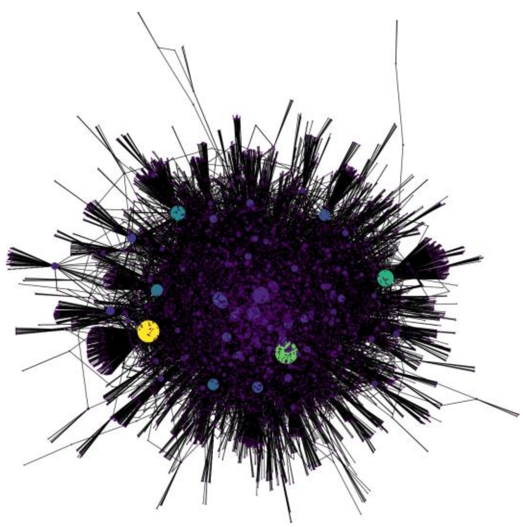

Figure 26: NETWORK GRAPH OF BETWEENNESS CENTERLAITY

The node with the highest betweenness centrality is highlighted with 'red' accents to draw attention to them. These nodes are all positioned in the network's core Figure-27. The lowest betweenness centrality is found in the outermost nodes of the community. The relevance of nodes with frequent and excessive betweenness centrality varies in Table-16.

SERIES	NODE
1	69
2	682
3	106
4	579
5	778

Table 16: TOP 5 NODE OF BETWEENNESS CENTRALITY.

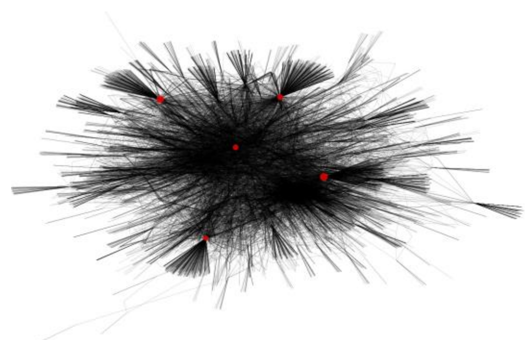

Figure 27: HIGHEST NODE GENERATED BY BETWEENNESS CENTRALITY.

5.2 Degree Centrality:

The number of edges a node is measured by the degree of centrality. With adegree centrality of 0.0726 in this instance, the first node 682, has the greatest degree of centrality inside the community, which is far more related to the wholeof different nodes Kostygina et al. 2021. Indicating that they're also quite linked nodes within the network are the 2 and 3 with node values 69 and 106 which also have a high degree centrality in Table-17. The community graph is visualized using the figure, where nodes are represented by circles and edges by strains. Each circle's diameter corresponds to the degree centrality of the node.

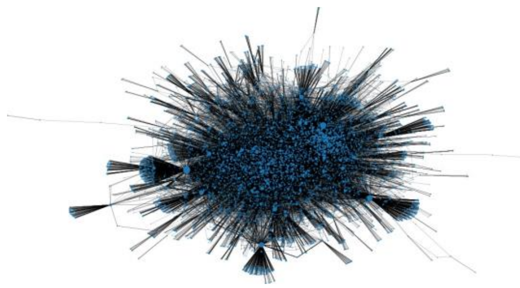

Figure 28: NETWORK GRAPH PRODUCED BY DEGREE CENTRALITY.

SERIES	NODE
1	682
2	69
3	106
4	778
5	624
6	427
7	78
8	611

Table 17: Top 8 Most NODE in DEGREE CENTRALITY.

5.3 Eigenvector Centrality:

Eigenvector centrality is used to determine a node's significance in a network. Nodes with a higher eigenvector centrality are more massive than nodes with a low eigenvector centrality. They have a larger impact on how information and resources move across the community. These nodes have excessive centrality rankings primarily based on their capacity to affect or be impacted with the aid of other nodes within the community Ruhnau 2000. The determination produced suggests a community plot with node colors representing their degree centrality values, and node sizes representing their eigenvector centrality values.

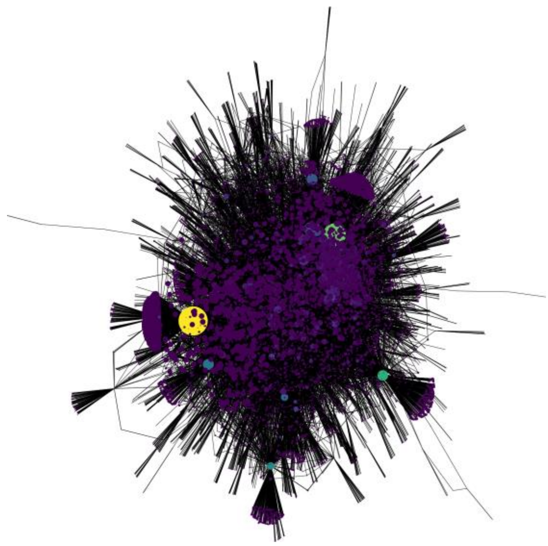

Figure 29: NETWORK GRAPH GENERATED BY EIGENVECTOR CENTRALITY.

It means that the min and max values for the x-coordinate are -0.9293 and 1.0423, and the min and max values for the y-coordinate are -1.1909 and 1.0089. The numbers are the coordinates of the center of the network in Table-18. The center of the network is the point that is closest to all other points in the network. In the following figure, the center of the network is located at the coordinates.

SERIES	NODE
1	682
2	69
3	77
4	321
5	208

Table 18: Top 5 Most NODE in EIGENVECTOR CENTRALITY.

5.4 Community Detection:

The Figure is displayed as a list of nodes for each community that the Louvain set of rules detects Ghosh et al. 2018. The node locations are established using the NetworkX library spring format technique. Network illustrations with nodes colored following networks.

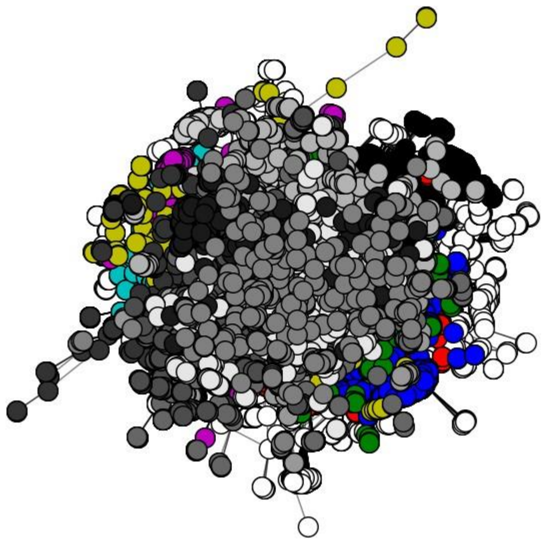

Figure 30: COMMUNITY NETWORK CLUSTER.

Even though nodes representing the same community share the same color, each community and the distribution of nodes in Table-19 among the various groups can both be observed in the figure Ferrara, Interdonato, and Tagarelli 2014. A network diagram with totally distinct forms for each community's nodes. The form and distribution of nodes among groups, the 'Louvain Method' are used to display the group of community in which length appears to be '34'. Where communities begin from 6, 281, 526 and go to 16674.

SERIES	NODE
i	287
ii	3468
iii	15389
iv	31894
v	47447

Table 19: Top 5 Communities Detects.

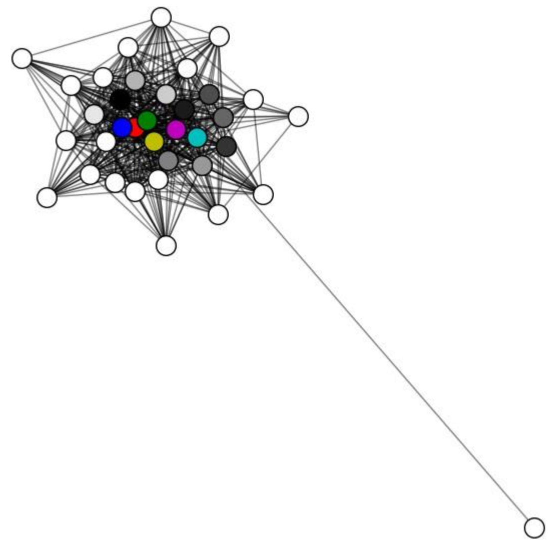

Figure 31: COMMUNITY DETECTION GRAPH.

6 Summarize Extractive on UK Recession:

6.1 Content Summarize of Recession in United Kingdom:

British economic growth of 0.1 percent within the fourth sector of 2022 avoided a droop. The primary causes of growth have been an increase in travel demand and a lift to family budgets from nationwide invoice subsidies. The economic system is cautious, as seen by the reality that enterprise investment has declined. The first quarter of 2023 is expected to see a 0.1 percent decline in the GDP, according to the Bank of England, but the next 3 months will seelittle growth. Major contributors to the improving financial outlook encompassa sturdy activity market and falling global power charges. However, matters could possibly deteriorate all over again if recent turmoil inside the worldwide banking system prompts lenders to tighten credit scores.

6.2 Recession in London Content Summarize:

LONDON, March 31 (Reuters) - Britain's economy avoided a reces- sion as it grew in the final months of 2022, according to official data which showed a boost to households' finances from state energy bill subsidies but falling investment by businesses. With the economy still hobbled by high inflation and worries about a weak growth outlook, gross domestic product (GDP) increased by 0.1 percent between October and December after a preliminary estimate of no growth.GDP in the third quarter was also revised to show a 0.1 percent contraction, a smaller fall than initially thought, the Office for National Statistics (ONS) said on Friday. Two consecutive quarters of contraction would have represented a recession.

Ruth Gregory at Capital Economics said Friday's figures showed high inflation had taken a slightly smaller toll than previously thought. "But with around two-thirds of the drag on real activity from higher rates yet to be felt, we still think the economy will slip into a recession this year," she said. The ONS said Britain posted a shortfall in its current account in the fourth quarter of 2.5 billion pounds (3.1 billion dollars) or 0.4 percent of GDP. Excluding volatile swings in precious metals, the shortfall fell to 3.3 percent of GDP from 4.2 percent in the third quarter. The ONS said increased foreign earn- ings by companies, particularly in the energy sector, helped narrow the deficit. Britain's financial account surplus - which shows how the current account deficit was funded - comprised large net inflows of short-term, "hot" money.

The Average Sentence Value of the given 'Recession Content' is **'133.0909'**.According to the research, the UK is the high-quality-appearing G7 financial machine that has now not yet absolutely recovered from the COVID-19 epidemic.

This is probably because of a range of factors, inclusive of the United Kingdom's selection to exit the European Union, which has made it harder for groups to conduct business with other nations. The article's important point is that although the UK's monetary area regularly recuperating from the pandemic, there are nevertheless many pressing troubles that need to be tackled.

7 Conclusion:

Understanding the importance and distribution of the network's nodes through a look at network topology and centrality metrics may additionally assist in gaining a better understanding of how facts and assets move throughout the community. The 2021–22 NBA League season saw a variety of modifications and improvements. It is beneficial to utilize Twitter sentiment evaluation to research what the general public thinks about various issues.

Twitter has developed into a critical tool for facts to change at some point in emergencies. It is usually recommended that Twitter sentiment evaluation be a useful tool for gauging popular opinion on quite a few subjects, which includes the FIFA World Cup. Overall, the texts emphasize the influence social media has on public debate and the importance of using these channels responsibly and thoughtfully.

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