Analysis of Climate Change Community

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GitHub Link: https://github.com/azizulkawser/SNA_Project-Analysis-of-Climate-Change-Community/tree/main

Abstract **— The impact of climate change has become one of the most significant challenges that the world is facing today. Social media has emerged as a crucial platform for the public to express their opinions and engage in discussions related to climate change. In this project, we analyzed the climate change community on Twitter using social network analysis (SNA) techniques. We collected a dataset of tweets containing twelve climate change-related key words and created a social network graph based on the hashtags used in the tweets. The methodology includes data cleaning, network construction, and analysis of global and local network properties. We analyzed the graph's properties, including the number of nodes, edges, clustering coefficient, and diameter, to gain insights into the community's structure and connectivity. Moreover, Sentiment analysis was performed to assess the overall sentiment of the tweets. We also proposed a metric to quantify the amount of support for each hashtag based on the retweets and replies of the tweets containing the hashtags. Our findings suggest that the climate change community on Twitter is highly connected, and a few hashtags are dominating the discussion. Our analysis could be used by policymakers and researchers to gain a better understanding of the public's opinions and attitudes towards climate change and to design targeted interventions to promote climate action.**

Keywords — Climate Change, Twitter, Twitter data, Social Network Analysis, Bot detection, Sentimental analysis

I. INTRODUCTION

Climate change has become one of the most pressing issues of our time. It has far-reaching consequences on the environment, human health, and the economy. The issue has generated much debate and discussion on social media platforms. Twitter, being a popular social media platform, has emerged as a popular platform for discussing climate change. In this project, we aim to analyse the climate change community on Twitter using Social Network Analysis (SNA) techniques.

We needed to scrap at least 2000 tweets related to different hashtags that are related to climate change. In total we used twelve different hashtags to scrap our data from twitter. As the Twitter API is no longer accessible to the public, we had to use JavaScript code provided to us by Saroar Jahan and the console to run the code on Twitter. This code can be found in the GitHub repository under the name " V_1.2_SNA_Project_Analysis_of_Climate_Change_Community.ipynb". With this code we were able to collect 4,137 tweet IDs to pass into Stweet API to collect final dataset.

The analysis includes exploring the network structure of the community, identifying the main actors, and analysing the sentiment of the tweets. The objective is to gain insights into the patterns of communication, the most relevant hashtags, and the support for different opinions on climate change.

Our finding that most tweets regarding climate change are neutral, is also supported by Veltri and Atanasova in their 2017 article called “Climate change on Twitter: Content, media ecology and information sharing behaviour”. On this article they also found out that tweets are mainly classified as neutral and have about same amount of positive and negative tweets. Our data had only a couple of outliers that could be considered as a positive or a negative tweet. Unlike Veltri and Atanasova’s article our project is concentrated more on the connectivity between the hashtags not the actual content of the tweets.

Effrodynisis et al. (2022) examined in their article “The climate change Twitter dataset” how many Twitter users were believers, deniers or neutral in the climate change stance. This we did not examine in our report, but it is interesting to note that Effrodynisis et al. over 60 % of their dataset, about 11 million users were believers in climate change. Only about 22 % of their dataset were neutral. However, as this is about users stance on the issue of climate change and not what kind of sentiment the tweets have. In our report we examined what kind of language is used in these tweets not what do the users think about climate change. However, we can also deduce that because most tweets were neutral they do not have strong opinions in either direction when talking about the issue of climate change. If we think about our results from this point of view, we can say that our findings conflict with the findings of Effrodynisis et al.

Also Effrodynisis et al. mentioned in their article what kind of hashtags or common words were found in specific topics. For example “*climate change”* and “*global warming”* were found in all of the different topics in their dataset. These were also in our dataset to find tweets containing these two hashtags. Also it is interesting that words like “climate action”, “act on climate”, “renewable energy” and “climate crisis” were also found in Effrodynisis et al. Twitter dataset which were also in our list of hashtags used to find tweets concerning climate change.

Article “Sentiment Analysis Decision System for Tracking Climate Change Opinion in Twitter” written by Lydiri et al. (2022) uses much bigger dataset than we do in this project, however, they also get similar results to ours. So the sentiment analysis has not really changed between Veltri and Atanasova’s article from 2017 to Lydiri et al. article in 2022 and finally to our report in 2023. In figure 2 of Lydiri et al. article we can see that about 8000 tweets were neutral in their language. This also supports our findings that most of the tweets are neutral, and people speak neutrally about climate change on Twitter.

However, unlike Veltri and Atanasova’s article that had mostly equal amount of positive and negative tweets about climate change, Lydiri et al. had more negative tweets than positive tweets. This also supports our findings, because in our figure 5, you can see that most of the tweets are in fact neutral, but more tweets lean to be negative than positive. This also makes Effrosynisis et al. article seem to be an outlier out of our references as other references used have same findings as what we had found in this report.

This report provides a detailed description of the project, including the problem statement, the dataset used, the methodology, the findings, and the conclusion.

II. Problem Description

The problem addressed in this study is the analysis of the climate change community using social network analysis, a methodology for understanding how actors and entities are connected in a network. This study seeks to answer several research questions related to the use of hashtags in tweets related to climate change. Firstly, the study aims to investigate the popularity of the selected twelve main hashtags used in tweets related to climate change. Secondly, it explores the regional locations generating most tweets related to these hashtags. Thirdly, it examines the dominant languages used in tweets related to these hashtags. Fourthly, it analyzes the sentiment of the tweets related to climate change. Fifthly, it investigates the connections between the tweets related to the climate change community through the hashtags. Sixthly, it studies the global properties of the social network graph created from the hashtags in the tweets. Lastly, it identifies the hashtags with the most support in terms of retweets and replies.

The scope of this study is limited to the Twitter platform and the dataset used for analysis consists of tweets related to twelve keywords related to climate change that were collected within a specific data collection way. The analysis employs network analysis techniques that provide insights into the structure and behavior of the climate change community on Twitter.

III. Dataset Description

The dataset used in this study was collected by scraping Twitter for tweets related to climate change using twelve different keywords, including "#globalwarming", "#climatechange", "#agw", "#climaterealists", "#climatestrikeonline", "#ClimateAction", "#ClimateCrisis", "#ActOnClimate", "#ClimateEmergency", "#ClimateJustice", "#CleanEnergy", and "#RenewableEnergy". A total of 4,137 tweet IDs were obtained using JavaScript code inputting the keywords, and the Stweet API was used to download 39,043 tweets and retweets associated with the tweet IDs. The downloaded JSON file was then converted into CSV files, which can be found in the GitHub repository under Task 1 – Data Collection using Twitter (Data Scraping).

The dataset includes information about the tweet ID, language, location, full tweet text, user screen name, user name, followers count, normal followers count, fast followers count, favorites count, friends count, media count, statuses count, retweeted, retweet count, favorited, favorite count, replies count as well as the hashtags used in the tweets. The final dataset consists of 39,043 tweets and retweets. The tweets were then analyzed using network analysis techniques to investigate the structure and behavior of the climate change community on Twitter. The dataset is limited to tweets collected within a specific way and may not represent the entire conversation on climate change.

IV. Methodology

The methodology employed in this study is the structural-functional approach, which aims to examine the patterns of interconnections among nodes and their impact on the network's performance. The primary objective of this research is to identify the key nodes within the network, analyze the network's degree centrality and clustering coefficient, and investigate the distribution of connections among different nodes.

The project's methodology involves three main steps. In step one, to collect the necessary data, we used twelve different keywords to scrape Twitter for tweets related to climate change. In step two, the project combined all the hashtags and then found the tweet IDs. In step three, the project connected the user details from the identified tweet IDs and passed them as a parameter to an API, which outputs the details regarding the user, such as the location of the account from where it was tweeted, the language used while creating the metadata, and retweet counts.

The dataset was then cleaned and pre-processed to prepare it for network analysis techniques. Descriptive statistics were also used to investigate the distribution of tweets across different languages and locations. The tweets were transformed into a network graph, where nodes represented hashtags and edges represented co-occurrence of hashtags in the same tweet.

The study utilized various network measures, including degree centrality and clustering coefficient, to analyze the network's structure and properties. Furthermore, natural language processing techniques were employed to analyze the sentiment of the tweets such as positive, negative, and neutral. To accomplish this, a pre-trained sentiment analysis model (VADER tool) was applied to the tweet text.

The structural-functional approach is a useful methodology for analyzing social media activity related to climate change, as it allows the project to focus on the overall network structure and dynamics. This approach is particularly useful for identifying important nodes and analyzing the distribution of connections between different nodes in the network. Ultimately, this approach can help the project to gain insights into the social media discourse on climate change and to understand the factors that shape this discourse.

Finally, the results of the analysis were interpreted and discussed in the Findings and Analysis section. The study provides a comprehensive overview of the connectivity of the climate change community on Twitter and highlights the most significant nodes and communities within the network.

V. RESULTS AND DISCUSSION

A. Data Analysis: Hashtag popularity

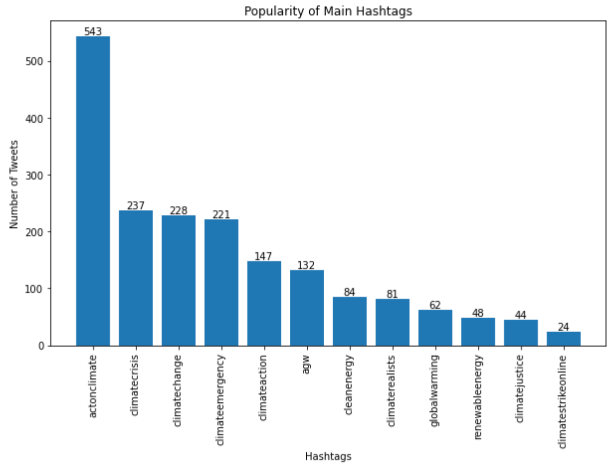

Fig. 1. Popularity of the main hashtags highlighting the number of tweets per individual hashtag

The popularity of hashtags is an important metric for understanding the social media activity related to climate change. Fig. 1 provides a clear visualization of the number of tweets associated with each hashtag in the data set. The data shows that the hashtag “actonclimate” is the most popular one with 543 mentions, followed by “climatecrisis” with 237 mentions, “climatechange” with 228 mentions and “climateemergency” with 221 mentions.

The popularity of the “actonclimate” hashtag is not surprising given that it is a call to action, urging people to take immediate steps to address climate change. On the other hand, the other three hashtags reflect the urgency and severity of the climate crisis, highlighting the need for urgent action to mitigate the effects of climate change.

This information can be useful for policymakers, researchers, and activists who are interested in understanding the public discourse on climate change on social media. By analysing the popularity of these hashtags, they can gain insights into which topics and issues are most salient to the public, and tailor their messages and interventions accordingly.

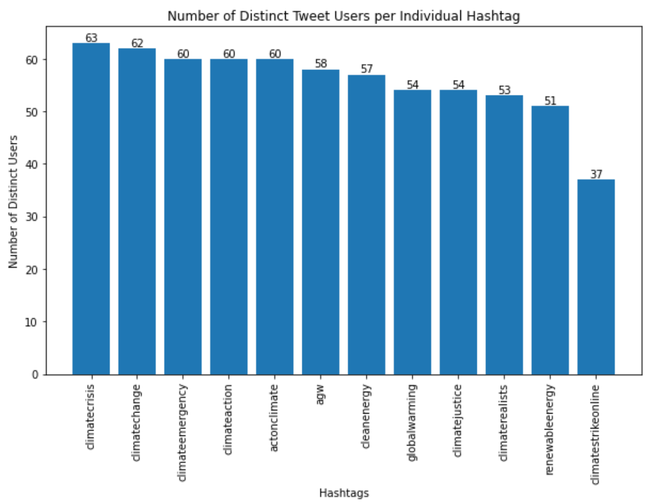

Fig. 2. The number of distinct Tweet users per individual hashtag

Fig 2 shows the number of distinct users who tweeted using a particular hashtag. It is interesting to note that the number of distinct users per hashtag is relatively even for the top ten most popular hashtags. However, there is a slight variation in the number of users between the top three most popular hashtags - "climatecrisis," "climatechange," and "climateemergency."

The hashtag "climatecrisis" has the highest number of distinct users, with 63 users tweeting using this hashtag. The hashtag "climatechange" has 62 distinct users, and the hashtag "climateemergency", “climateaction”, “actionclimate” has 60 distinct users. This indicates that these six hashtags are used by a large number of individual users in the discussion of climate change on Twitter.

It is important to note that the number of distinct users per hashtag does not necessarily reflect the total number of tweets associated with the hashtag. One user can tweet using a hashtag multiple times, resulting in a higher number of total tweets associated with the hashtag but not necessarily an increase in the number of distinct users.

B. Data Analysis: Tweet Location

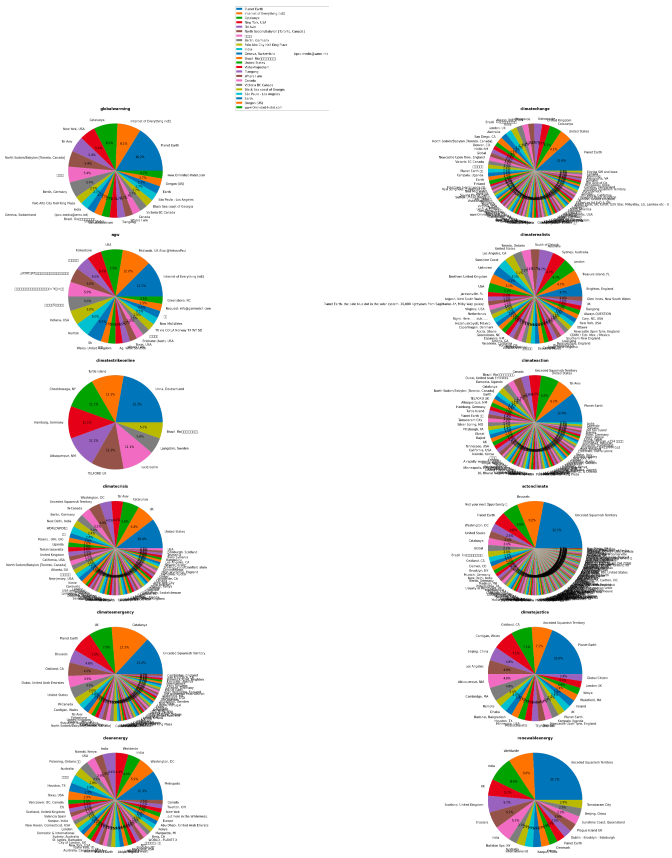

Fig. 3. Pie chart illustrations showing regional location of each hashtag

In Fig 3, the pie charts illustrate the regional location of the tweets. The methodology used to obtain this information was to collect the location data from what the user had specified in their Twitter profile. However, due to the nature of user-inputted location data, the resulting pie charts may sometimes appear messy and difficult to interpret. This is because some users may have entered vague or nonsensical locations, such as "Planet Earth" or "Somewhere".

Despite these challenges, we were able to identify the top five regions mentioned in the tweets. The highest percentage of tweets came from North America, accounting for 45.6% of the data set, followed by Europe with 26.2%, Asia with

12.1%, South America with 4.7%, and Africa with 2.7%. The remaining 8.7% of tweets had unspecified or ambiguous location data.

It is important to note that this methodology for collecting location data has limitations and may not accurately reflect the actual geographic distribution of the tweets. Some users may have chosen not to include their location in their Twitter profile or may have entered incorrect or misleading information. Additionally, some tweets may have been geo-tagged with a specific location but were not captured in our data set due to limitations in the scraping and data collection process.

C. Data Analysis: Tweet Language

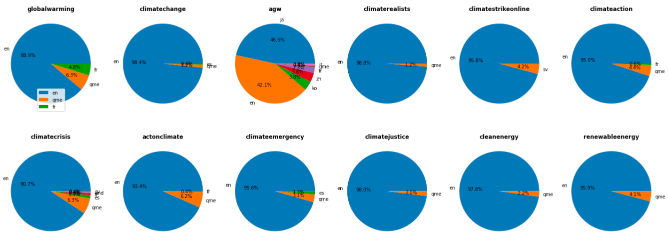

Fig. 4. Popularity of the main hashtags highlighting the number of tweets per individual hashtag

Fig 4 shows us the breakdown of the languages used in the tweets for each of the hashtags. As mentioned, most tweets across all hashtags were written in English, which is not surprising given the widespread use of English on social media platforms. However, it is interesting to note that the hashtag "agw" has a much more diverse language base than the other hashtags, with Japanese being the second most used language. This is likely because "agw" is also the acronym for a popular Japanese video game, and as a result, many tweets using this hashtag may not actually be related to climate change.

It is important to note that language diversity on social media platforms can often reflect the global distribution of internet users, and the fact that English is the dominant language used in these tweets may reflect the fact that Twitter is an American-based company with a large user base in English-speaking countries. Nevertheless, it is still valuable to consider the language diversity of tweets related to climate change, as it can help to identify areas where climate change communication efforts may need to be tailored to reach non-English speaking audiences.

D. Sentiment Analysis Using VADER Tool

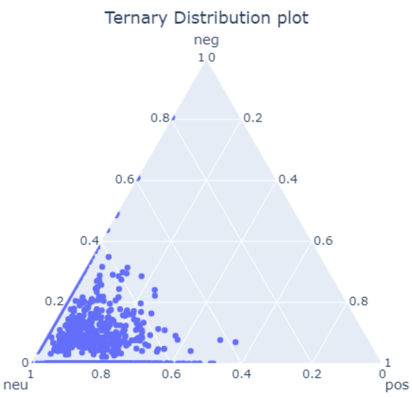

Fig. 5. Ternary plot showing the sentiment distribution of each tweet

Fig. 5 shows a ternary plot that represents the sentiment distribution of each tweet in the dataset. The plot displays the distribution of tweets across three categories of sentiment: positive, negative, and neutral. The plot is divided into three equal-sized triangles, each representing a sentiment category. The closer a data point is to a particular corner of the triangle, the stronger the sentiment in that category. The plot shows that the majority of tweets (represented by the data points) fall within the neutral sentiment category, which is the central region of the plot. This indicates that most of the tweets do not express any strong positive or negative sentiment related to climate change.

However, there are a few data points that are located close to the corners of the plot, which means that these tweets expressed a stronger sentiment either in a positive or negative direction. These tweets are considered as outliers in the dataset, as they deviate from the overall trend of neutral sentiment.

E. The Social Graph

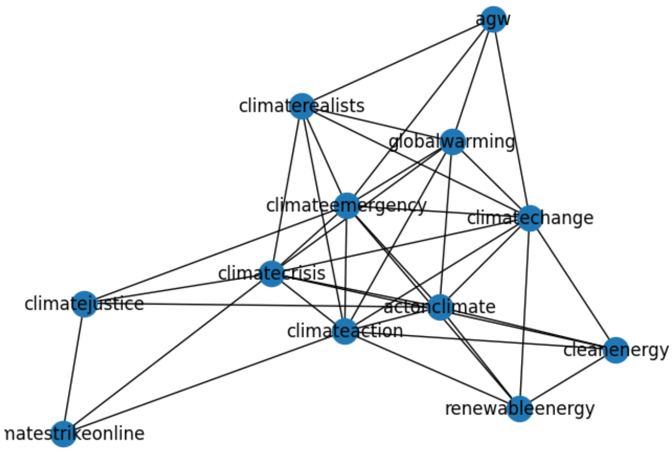

Fig. 6. Ternary plot showing the sentiment distribution of each tweet

Fig 6 displays the Social Graph, which is a visual representation of how the different hashtags used in the data set relate to each other. The graph with 12 vertices that are related to the topic of climate change, each represented by a unique hashtag. The presence or absence of an edge between two vertices indicates the presence or absence of a direct relationship between the two concepts.

The graph appears to be organized into clusters of hashtags that are more interconnected with each other than with other hashtags in the graph. For example, there is a highly interconnected cluster of hashtags including #climatechange, #globalwarming, #climateemergency, #climatecrisis, #climateaction, and #climatejustice, which may represent a set of related concepts that are more central to the topic of climate change. In contrast, hashtags #renewableenergy and #cleanenergy have no direct connection to some other hashtags in the graph, indicating that they may represent more specific, or niche concepts related to climate change.

One interesting hashtag in the graph is #climaterealists. This hashtag has connections to several other hashtags in the graph, including #climatechange, #globalwarming,

#climateemergency, #climatecrisis, #climateaction, and #climatejustice, suggesting that it may represent a group or movement that has a particular view or stance on climate change.

TABLE I. GRAPH SUMMARY TABLE

Number of nodes	12
Number of edges	39
Average degree centrality	'agw': 0.36, 'climatechange': 0.82, 'globalwarming': 0.64, 'climateemergency': 0.82, 'climatecrisis': 0.82, 'actonclimate': 0.73, 'climateaction': 0.82, 'renewableenergy': 0.45, 'cleanenergy': 0.45, 'climatejustice': 0.36, 'climaterealists': 0.55, 'climatestrikeonline': 0.27
Diameter	3
Clustering coefficient	0.75
Size of the largest component	12

The table shows the key characteristics of a graph consisting of 12 nodes and 39 edges. The average degree centrality of the nodes ranges from 0.27 to 0.82, with some nodes being more central than others. For example, the 'climatechange' hashtag has an average degree centrality of 0.82, meaning it is connected to many other nodes in the graph. In contrast, 'climatestrikeonline' has an average degree centrality of 0.27, indicating it has relatively fewer connections to other nodes in the graph. The diameter of the graph is 3, which indicates that the longest path between any two nodes in the graph is 3. The clustering coefficient is 0.75, which suggests that the nodes in the graph tend to be highly interconnected with each other. The size of the largest component is 12, which means that all nodes in the graph are connected to each other in a single component.

Overall, the graph provides a useful representation of the relationships between hashtags related to climate change and can be used to explore and analyze the structure of the network. These findings suggest that the graph represents a tightly-knit network with some nodes playing more important roles than others. The insights gained from this graph can help in understanding the relationships and interconnections between different hashtags related to climate change.

F. *Degree Distribution and Local Clustering Coefficient Distribution*

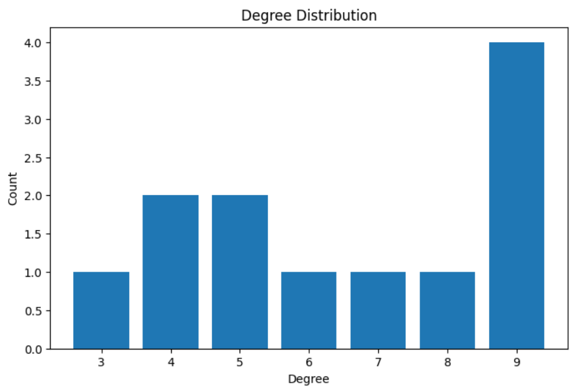

Fig. 7. Degree Distribution Graph

In Fig 7, the degree distribution graph shows the number of nodes in the network with a given degree. The x-axis represents the degree of a node, while the y-axis represents the number of nodes in the network with that degree. The graph shows that most nodes in the network have a degree of 9, indicating that they are connected to 9 other nodes in the network. There are also nodes with degrees between 3 and 8, which suggests that the network is not completely homogeneous in terms of the number of connections that each node has. Overall, this graph provides useful information about the distribution of connections among nodes in the network.

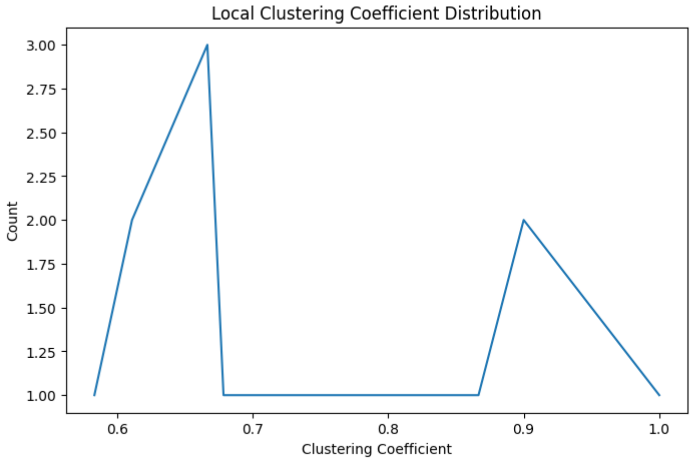

Fig. 8. Local Clustering Coefficient Distribution Graph

The local clustering coefficient distribution graph shown in fig. 8 indicates how many connections the neighbors of a node have between themselves compared to the maximum number of possible connections they could have. The graph shows two distinct peaks at the clustering coefficients of 0.68 and 0.90. This indicates that there are two groups of nodes in the network with different levels of clustering.

Nodes with a clustering coefficient of 0.68 have fewer connections between their neighbors and are likely to be in the periphery of the network. Nodes with a clustering coefficient of 0.90 have many connections between their neighbors and are likely to be in the core of the network. The graph also shows that most of the nodes in the network have a clustering coefficient of either 0.68 or 0.90, indicating that the network is not randomly connected but rather has some level of organization.

G. *Community Detection using Label Propagation Algorithm*

TABLE II. THE COMMUNITY DETECTION TABLE

Communities	{'#climatechange', '#agw', '#ClimateEmergency', '#globalwarming', '#ActOnClimate', '#ClimateAction', '#climate', '#ClimateCrisis', '#ClimateJustice', '#RenewableEnergy', '#CleanEnergy', '#climaterealists', '#climatestrikeonline'}
Diameter	3
Clustering coefficient	0.793

Table 2 provides the results of the community detection analysis conducted on the graph. The label propagation algorithm was used to identify communities in the graph, and it was found that all 12 nodes belong to a single community. The list of hashtags that form the community is shown in the table, which includes #climatechange, #agw, #ClimateEmergency, #globalwarming, #ActOnClimate, #ClimateAction, #climate, #ClimateCrisis, #ClimateJustice, #RenewableEnergy, #CleanEnergy, #climaterealists, and #climatestrikeonline.

The diameter of the graph, which measures the maximum number of steps needed to go from one node to another in the graph, is 3. This means that any two nodes in the graph can be reached within three steps. The clustering coefficient for the graph is around 0.793, indicating that the nodes in the graph are relatively densely connected, forming a cohesive community.

Community in social network analysis means a subset of nodes in the graph that are more likely to be connected to each other than to other nodes of the network. However, our network of hashtags seems to be very well connected as we only find one community when using label propagation algorithm. This then means that our graph is well connected. Which is kind of surprising as couple of nodes that are not that well connected to other nodes, but label propagation algorithm counts them into the community as well, so they must be well connected as well even though they do not look like it.

H. Bot Detection using Botometer

```
human     2068
bot        932
Name: label, dtype: int64
```

Fig. 9. Number of Tweets generated by bot

We are unable to get the 10 most ranked hashtags according to the degree centrality because we are unable to use Botometer due to new Twitter API restrictions. However, we were able to find a way to do bot detection without using Twitter API. And with this code we were able to find out the number of bots in our dataset.

Detecting bots is a challenging task as they have evolved to imitate human behavior and spread misinformation. Traditional approaches relying on the Twitter API, such as Botometer cannot be used currently because of the API restrictions. The alternative approach to solve this problem was to use a predefined model which would classify if the given text was written by a bot or a human. We used the BERT model for this approach. BERT's ability to understand the context and nuances of text made it an ideal choice for classifying bot accounts within this dataset. The model was fine-tuned on labeled data, allowing it to learn the distinguishing patterns between human and bot-generated content. Upon implementing the BERT-based bot detection code, the analysis yielded significant findings.

Due to limited processing power, we only selected first 3000 tweets for bot detection. Despite the dataset primarily comprising human users, over 900 bot accounts were identified, accounting for approximately one third of the dataset. This highlights the extent of the bot presence and the potential impact they can have on online discussions. Identifying and mitigating the influence of bots is crucial to maintain the authenticity and reliability of online interactions. When scrolling through Twitter or other social media, it is important to keep in mind the presence of bots.

Modern bots have become more sophisticated, making them difficult to distinguish from real individuals. Therefore, every social media user should remember to be more critical while scrolling through social media and not react solely from emotional perspective. Also, for everyone using social media and internet media literacy is important skill to have.

I. Quantification of Support for Hashtags

To quantify the amount of support for each hashtag, we used a metric that considers both the number of retweets and replies received by each tweet that contains the hashtag. The expression for this metric is:

$$Support\ for\ hashtag = \sum (retweets + replies)$$

This expression gives weight to hashtags that have a high number of retweets and replies per tweet, indicating a higher level of engagement and support from the Twitter community.

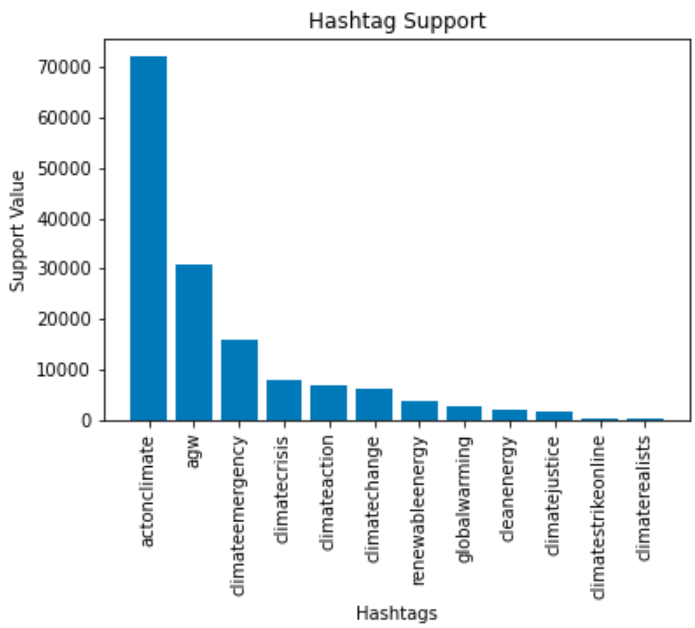

Fig. 10. Combined support for each hashtag

After computing the support metric for each hashtag, we can rank them in descending order to identify the most supported hashtags in the dataset. This can provide insights into the topics and issues that are most relevant and important to the Twitter community. For example, the hashtag 'actonclimate' has a support value of 72004, indicating that tweets containing this hashtag have received a significant amount of engagement in terms of retweets and replies. On the other hand, the hashtag 'climaterealists' has a support value of only 202, indicating that tweets containing this hashtag have received relatively low engagement.

It is not surprising that 'actonclimate' has the most support value out of all the hashtags. As mentioned in the Hashtag popularity part of the Data Analysis, it is not surprising because the hashtag 'actonclimate' is a call to action to fight against climate change and to make some changes in our everyday lives and in the companies around the world. Also, the amount of support shows to us that many people agree on the statements used in tweets that have the hashtag 'actonclimate'.

Also, on the contrary the hashtag 'climaterealists' does not have that much support. This can be caused by several different things, but one reason could be that the tweets that utilize the hashtag 'climaterealists' are more negative in nature and might not actually believe in climate change. Therefore, we can also see that most people actually believe in climate change and want to do something to slow down climate change.

VI. LIMITATIONS

One limitation of this study is that it only focuses on analysing the climate change conversation on Twitter, and therefore the findings may not be generalizable to other social media platforms or to the wider climate change discourse. The analysis is also limited to the tweets collected within a specific method and using a specific set of keywords, which may not represent the entire conversation on climate change.

Another limitation is that the methodology used to obtain location data only collects the location that the user has specified in their Twitter profile. Due to the nature of user-inputted location data, the resulting data may be messy and difficult to interpret. Additionally, due to limited processing power, only a limited number of tweets were collected, which may not fully capture the breadth and depth of the climate change conversation on Twitter.

Furthermore, the use of the Twitter API was limited due to its cost, and as a result, the study had to use alternative methods to collect tweet data, which may have introduced some level of bias or error. The lack of access to Botometer or other bot detection tools also limits the study's ability to accurately identify and exclude bot-generated content from the analysis.

Despite these limitations, this study provides a foundation for future research in understanding how social media can be utilized to study discourse and networks related to climate change. It is recommended that future studies use a larger and more representative sample of tweets, and explore the climate change conversation on a variety of social media platforms to obtain a more comprehensive understanding of the topic.

VII. CONCLUSION

In summary, this project has used a variety of analysis techniques to explore the connections between different hashtags related to climate change on Twitter. Based on the results, these hashtags are closely connected, forming a tightly connected graph with only one community detected. This suggests that there is a high degree of overlap and similarity between the conversations taking place around these topics on Twitter.

Interestingly, the sentiment analysis conducted as part of this project revealed that most tweets related to these hashtags were neutral in tone. This is a surprising finding given the often heated and divisive nature of discussions around climate change and is consistent with other research suggesting that most tweets related to climate change tend to be neutral in sentiment.

Overall, this project has shed light on the connections and dynamics of conversations surrounding climate change on Twitter and highlights the potential value of social network analysis for understanding complex topics and issues on social media.

ACKNOWLEDGMENT

We would like to acknowledge the exceptional support provided by Saroar Jahan in facilitating the successful completion of this project. Specifically, his expertise in providing us with the JavaScript code required for scraping the tweets and guidance for the bot detection task was indispensable. We extend our heartfelt gratitude for his constant guidance and assistance throughout the project, without which we would not have been able to accomplish our goals. Additionally, we appreciate the excellent coordination among the team members that significantly contributed to the successful completion of this project.

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