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Analyzing Trends in Public Sentiment Regarding Climate Change Through Posts on X [formerly Twitter]

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ABSTRACT: The purpose of this paper is to view how public sentiment regarding climate change has shifted over time and to identify any trends in opinion that could prove useful for future climate change and general sentiment analysis. Positive sentiment is defined as the post having a positive emotion while a negative sentiment is defined as a post having a negative emotion. The primary hypothesis was that the average sentiment would remain slightly negative over time (H1). This study analyzes the relationship of location, popularity metrics, and emojis to sentiment in posts from the social media platform X, formerly known as tweets on Twitter. The hypothesis for emojis' relationship to the sentiment of a post (H2) was that a post with an emoji is more likely to have a positive sentiment. This hypothesis was to determine if emojis can be used as a sentiment indicator in the future. For the locations, the prediction (H3) was that even in countries/groups, there would not be a consensus or similar sentiment. The results did not align with H1; instead of a continuous slightly negative view, the average remained neutral over the years 2015-2022. However, the results did confirm H2 by showing the sentiment of a post with an emoji tended to have a higher sentiment than a post without one. A "weighted popularity", which accounted for likes in addition to the original post's sentiment, was used to confirm the findings of average sentiment per year. The results regarding location show a distribution of sentiment that doesn't lean one way or another when close together, which aligns with the location-related hypothesis (H3).

KEYWORDS: Systems Software; Earth and Environmental Sciences; Language and Operating Systems; Robotics and Intelligent Machines; Machine Learning; Climate science.

Introduction

Researchers have turned to social media due to its vast data and honest opinions to understand better public perception of controversial topics such as climate change.[1] The large amounts of data have led to the development of ways to quickly process and understand the overall sentiments without manually analyzing each post, formerly known as a tweet, individually. The creation of sentiment analyzers has led to discoveries surrounding the correlation between sentiment regarding climate change and gender, location, and politics.[2] Researchers hope that as this practice becomes more commonplace, it will make sentiment analyzers and their addition to polling more effective.[3] They have also developed new ways to process and organize data through semantic networks.[4] However, one part of text-based posts often omitted by researchers is the emoji. They are often daunting to incorporate due to their changing meaning and the possibility of indicating sarcasm and humor. This leads to them being omitted or posts with emojis removed from samples.[5] This paper aims to fill the gap in research surrounding emojis in sentiment analysis.

Methods

Data Sets and Cleaning:

The three datasets are publicly available at Kaggle.com. They were processed by using Python, Jupyter Notebooks, and Google Sheets. For the coding, pandas, emojis, print_function, and matplot.lib.pyplot were imported. Each contained various metrics and different pieces of information about the posts, spanning from 2015 to 2022. The three sets are distinguishable by the periods they cover: 2015 to 2018, 2020, and 2022. All of these are stored as CSV (Comma Separated Values) files. Some contain posts (string data) and numerical values representing the post's popularity. The 2015-2018 set had a pre-existing human-assigned sentiment tag. Only the data set for 2022 contains emoji data. I cleaned the data by removing random characters that appeared during downloading, removing the "RT" if it was a response to a post (RT signifies re-tweet/post), and lemmatized the sets. Lemmatization involves simplifying the words so they are easier for the sentiment analyzer to understand.

I also cleaned the data by checking for repeat posts and ensuring the vocabularies were proportional to the number of posts in each set. The dataset for 2015-2018 had no null values, while the data sets for 2020 and 2022 did have null values. The 2020 dataset had null values in the location column, which were omitted during the mapping process. Data cleanup was needed because people could manually input their locations. Since there are under 400 posts in this set, locations set to "Earth", "Global", only emojis, and other locations the geolocator would run into issues. So, they were manually removed. In addition, local spellings of places sometimes differ from how they are spelled in the USA: this made it very difficult to write a program to convert the human-made locations into something understandable to the geolocator function, so manually going through each location was the only option. The 2022 dataset has null values mostly under the emoji column when there is no emoji in the post; There are also occasional null values in the popularity metrics. None of the datasets have null values that make the data unusable- this would mean not having text in the post field. This meant null values were only removed for a test when tests on a column contained null values. For the 2020 and 2022 datasets, the exact times of when the post was posted were available. For the 2015-2018 set, only the post ID was given. However, by reverse engineering the generation of post IDs, I was able to determine the date of the 2015-2018 posts and get a more precise dataset. Each data set had different information available or found (**Table 1**).

Table 1: Summary of known information: After data clean-up, these were the known aspects of each dataset. This data reveals what each dataset is appropriate to test which hypothesis. All can be used to test sentiment over time, 2022 is the only one that can be used for emojis, and the combination of 2020 and 2022 can be used to review popularity.

Data Set	Post/Tweet ID	Exact Timestamp	Retweets	Likes	Location	Emojis
2015 to 2018	☑	☑	☐	☐	☐	☐
2020	☑	☑	☑	☑	☑	☐
2022	☐	☑	☑	☑	☐	☑

Machine Learning:

All the posts were scanned through NLTK's pre-trained sentiment analyzer, VADER (Valence Aware Dictionary for Sentiment Reasoning). "Topic Modeling and Sentiment Analysis of Global Climate Change Posts" used VADER, making it a reliable option. VADER outputs four values after reading a string of text: how positive it is, how neutral it is, how negative it is, and a compound value that ranges from -1 to 1, which shows what VADER thinks the overall sentiment is. The VADER results were compared to the polarity labels in the 2020 set to test its accuracy. However, since the 2020 polarity ranges from -0.5 to 0.6 and the VADER compound sentiment label ranges from -1 to 1, polarity times 2 was compared to VADER. To check the accuracy, I used MSE (mean square error) by subtracting VADER's prediction from polarity and summing the squares of each of these values.

In the 2020 dataset, the MSE was 0.1878. The sentiment was overall positive, the same as the polarization VADER was being compared to, making it the sentiment analyzer for the entire study and applied to the rest of the datasets.

Result and Discussion

Results:

To find the overall sentiment, sentiment given by VADER was averaged in each data set. After the exact timestamps for the posts into the 2015-2018 dataset were found, they were split by year (**Table 2 and Figure 1**). Then, to find the confidence intervals, the total climate change tweets for each year was required.[6,7] To find standard error, I used the equation (standard deviation)/(square root of population total) for each year. Since I wanted a 95% confidence interval, I used a z-score of 0.975, which equates to 1.96 standard errors.[8] In Table 2, the data set total, the yearly climate change tweet total, and 95% confidence intervals are shown.

Table 2: Average sentiments per year and confidence intervals. These low standard error values reveal the reliability of using the mean values.

Year	2015	2016	2017	2018	2020	2022
Average Sentiment	0.0035	-0.0372	-0.0331	-0.0033	0.0005	-0.0020
Total Climate Change Posts on X	1,000,000	990,000	1,200,000	1,100,000	5,600,000	5,400,000
Posts in Data Set	3,545	14,067	19,229	7,102	396	9,050
Standard Deviation	0.0020	0.3240	0.5100	0.2667	0.6945	0.5884
Standard Error	0.000002	0.00033	0.00047	0.00025	0.00029	0.00025
95% Confidence Interval	(0.00350, 0.00350)	(-0.03784, -0.03660)	(-0.03402, -0.03218)	(-0.00380, -0.00281)	(-0.00007, 0.00107)	(-0.00249, -0.00151)

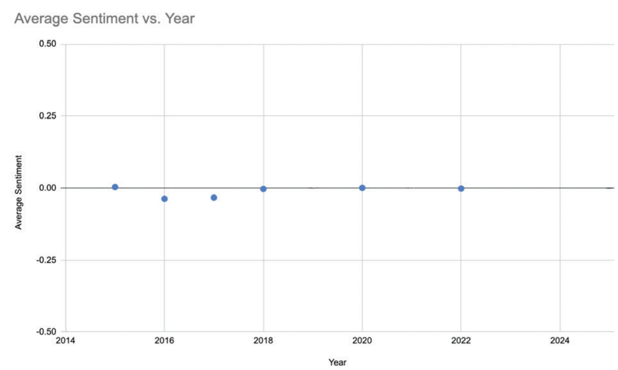

Figure 1: 2015 to 2022 Posts Plotted by Sentiment. The low variance shown in the table demonstrates the consistent sentiment over time.

The timestamps were either given by the datasets or obtained by reverse engineering the post ID. The sentiment is on a scale from -1 to +1 given by VADER. The more negative a sentiment is, the more negative the overall mood of the post is, and the more positive it is, the opposite is true.

The average sentiments remained from -0.04 to 0.04. The geo-tagged posts were plotted on a map based on longitude and latitude to search for general trends between sentiment and location (**Figure 2**).

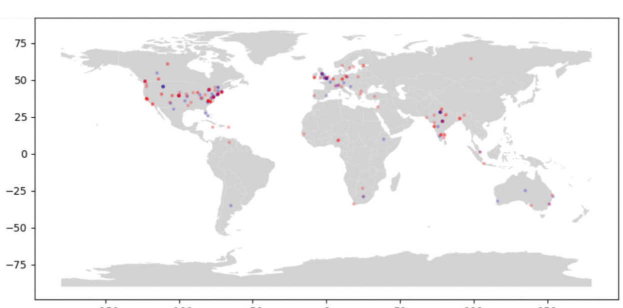

Figure 2: 2020 Posts Plotted by Location and Sentiment: Blue dots correspond to negative sentiment, and red dots correspond to positive sentiment. Each point has an opacity of 20%. Darker dots mean more posts in the same region. This map reveals that many of the tweets in the set represent the US, Europe, and India. The darkest dots were a dark purple, showing the extreme and plentiful opinions about climate change.

No general trend was found connecting sentiment to location. The 2020 and 2022 datasets included various popularity metrics, including comments, likes, reposts, and friends of the user. This research used an algorithm to increase the weightage of a post by factoring in the number of likes. Only likes were considered in "weighted popularity" because the metric had the same sentiment as the original post. This weighting algorithm did not consider the number of comments, friends, or reposts since they are complex in agreeing or disagreeing with the original post. A post's "weighted popularity" was calculated by raising the number of likes to 1.01 power and then multiplying it by the sentiment given by VADER. This was accomplished on Google Sheets (**Table 3**).

[“weighted popularity” = (Number of Likes^1.01) * sentiment]

Table 3: Weighted vs. Unweighted Sentiment: The number of likes in the 2020 and 2022 datasets was used to calculate a weighted sentiment to confirm the average sentiment. This was to ensure the average sentiment and the posts that would get the most support were either both positive (2020) or both negative (2022). The consistency of being positive or negative in 2020 and 2022 between the weighted and non-weighted mean reveals that the number of posts is a proper indicator of sentiment since they are also the most supported posts.

Year	Weighted Popularity	Sentiment without regard for popularity
2020	1.730	0.000474
2022	-1.406	-0.00196

This test was to see if the average sentiment of posts was the same with and without these calculations that accounted for the popularity of each post. The weighted mean with regard to popularity was calculated to ensure that the mean was the correct indicator of sentiment. If, for example, there were far more negative tweets, but the positive tweets were fewer with higher engagement, then there would be more positivity, but the mean would report there is more negativity. The weighted mean checks that if one considers the number of likes, it aligns with the mean. The average 2022 sentiment with no account of popularity was -0.00196. The “weighted popularity” was -1.406. Since the popularity of the posts remained negative, it reinforces the finding that the average 2022 sentiment was indeed negative. For the 2020 sentiment, the weighted sentiment confirmed that the sentiment was indeed positive because the positive posts were the majority and got the most likes. One unique aspect of this (paper/study) is its look at emojis. Typically, published papers omit emojis. One important aspect to note about this test is that emojis were omitted from the text analyzed by VADER- they were stored in a separate column. This test aims to determine if emoji use or a specific emoji can indicate whether the post had a positive or negative sentiment. This section will only look at the posts of 2022 and compare them to the overall posts for 2022 because this is the only dataset with emojis. The average sentiment of all posts in 2022 was -0.001963303867. Only looking at the sentiments of posts that contain emojis, the average was 0.03120150943 (**Table 4**).

Table 4: Emoji vs. No Emoji Sentiment. The emoji-only posts have a positive sentiment, while the average of all the 2022 posts is negative, demonstrating that emojis can be used as a positive tone indicator overall.

	2022 emoji-only posts	2022 All Posts
Average Sentiment	0.0312	-0.0020
95% Confidence Interval	(0.03112, 0.03127)	(-0.00249, -0.00151)

To test the hypothesis that the emojis will have a greater sentiment, one must refer to the confidence intervals. Since the mean without and without the emojis does not fall into the confidence interval of only emojis, the null hypothesis that the sentiments are the same can be rejected. Therefore, the conclusion is that tweets with emojis have a more positive sentiment than tweets without emojis. This demonstrates the use of emojis suggests a more positive sentiment.

Discussion:

The findings show that sentiment regarding climate change from 2015 to 2022 on X averages is neutral. This does not mean that the majority of sentiments are neutral; instead, there is a strong split in opposing views. Another finding that supports the strong division in opposing views is in the map (Figure 2). There was no clear trend linking the sentiment of a post and its location. This may have been because of faulty tagging on behalf of X users. 150 posts out of 396 had to be removed from the 2020 dataset to remove faulty labels. So, it is still being determined whether there is simply no trend between the location of a post and its sentiment or whether there was not a large enough dataset. The weighted popularity test confirmed that averaging the sentiment of posts is an accurate way to find the sentiment for that year. By factoring in the post's popularity in terms of likes, there was a clear indication that in 2020, most climate change posts were positive (unweighted average). They gained the most support (weighted average), while in 2022, most climate change posts were negative, and they gained the most support.

By comparing the sentiments of the overall 2022 posts and only the ones with emojis, there was an evident boost in positivity when looking at posts that contained emojis. This may have been the case because emojis, even though they can mean different things in different situations, are often used in an informal, silly, or light-hearted manner. This is supported by a meta-study which found emojis are used as a mood-relaxer.[9] For such a controversial topic such as climate change, this may offer a reason as to why a mood-relaxer led to a more positive sentiment. Emojis can be used as a core concept in sentiment analysis, which demonstrates the importance of these findings.[10]

Researchers have looked at posts surrounding climate change to understand best how location, gender, and climate events affect sentiment on environmental issues. A study conducted by professors at Cleveland and North Carolina State University examined over 300,000 posts across the globe. They utilized geospatial and temporal perspectives in their research. The study revealed an overall negative (an unhappy emotional state) reaction to climate issues. This reaction was often in di-

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rect response to real-life events or influential posts, such as one by former President Donald Trump.[11] They also discovered extreme weather events had a direct correlation to sentiment. In a study that looked at posts following the disastrous Hurricane Irene by viewing posts from impacted areas, the analysis revealed how gender affected sentiment and levels of concern leading up to the hurricane.[12] The results demonstrated in both of these research papers show that it wasn't exactly their location that affected sentiment but their proximity to a natural disaster. The findings of this paper demonstrate that despite these spikes caused by natural disasters and politicians, averages are an overall neutral sentiment. Although 44,000 posts were used in this paper, it is important to note that it is only a small fraction of all climate change-related posts. In addition, with the current change of leadership in X, its rebranding, and new rules of use, X may not be a viable option in the future for researchers to get all of the public's data accurate. As of February 9th, 2023, X's policies have eliminated free APIs and created paid subscriptions for up to $210,000 per month for accurate and large amounts of data.[13] However, this research is not exclusive to X and can be used and applied to other posts, such as Meta's new social media app, Threads. Another limitation is caused by the sentiment analyzer's ability only to analyze English. This causes a sample set that caters to the bias for English speakers. There is skepticism surrounding the effectiveness of sentiment analysis since current systems, including the one used in this paper, are behind on ever-changing slang.[14] However, it is important to remember that social media polling cannot be a standalone indicator of sentiment. As the studies aforementioned in the Introduction state, social media sentiment is a helpful addition to polling.

Conclusion

These findings disprove H1, but they prove H2 and H3. There was an overall neutral average sentiment regarding climate change from 2015 to 2022, posts with emojis had a higher average sentiment, and there was no clear consensus in sentiment in geographic regions. Since VADER is a general sentiment model and all cleaning could be applied to any dataset, it can easily be generalized to data in fields other than environmental science. With this, it could impact researchers' understanding of emotional state over time regarding politics, weather, and popular culture. Although social media should not be used as a substitute for polling, it allows researchers to analyze opinions users post. One limitation of this study is the need for more editing on the sentiment analyzer. Instead, many analyzers, including VADER and LSTM, were used. The most accurate one (VADER) was chosen rather than tweaking and focusing on a singular model that could have made the sentiment labels more accurate.

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