CLIMATE



CHANGE

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Introduction: The United Nations has multiple social media accounts across multiple platforms to spread awareness about its goals, mission, and objectives related to climate change. The organization creates an accessible way for people to participate in the action against climate change. It educates through facts and videos and encourages viewers to get involved in events that spread awareness on the issue. In our analysis, we sifted through two Facebook and two Twitter accounts run by the United Nations. The first account we analyzed was the UN Climate Change account. This account has nearly one million followers (~0.3% of the U.S. population) and posts anywhere from once every other day to twice daily with content related to climate change. The UN Environment Programme has a similar following but posts more frequently. Each page was created at least 13 years ago and has at least 28,000 tweets. This translates to an average of more than 2,000 tweets per year or nearly 6 tweets per day on average; thus, these accounts are very active. On Facebook, the UN Climate Change site has a little less than half of a million followers while the UN Environment Programme has one and a half million followers. The content between the two platforms is very similar and there are many instances of recycling content between the platforms. The engagement level for these sites is similar across platforms and pages. The Twitter pages generally have about 1,000-1,500 likes, less than 100 retweets, and between 100-150 comments. Facebook pages generally get less than 100 likes and 100 shares with minimal comments. The United Nations takes an active approach through social media to specify its implications; their goals with these accounts are to spread awareness through likes and retweets, and provide resources to the public; however, there is room for improvement.

Textual Analysis: Collect Twitter Data: We collected data from Twitter, using R, by utilizing the "retweet" package. When collecting data, we used one massive dataset and created five subsets of data to perform our analysis. After we secured authorization from a Twitter account, we were able to begin our analysis. After authentication, we searched for users to find the UNFCCC account. Next, we used a timeline and the favorite function to retrieve the last 100 tweets from UNFCCC and the last 100 tweets liked by UNFCCC. We used n = 100 since it takes less time to analyze this number in R compared to 10,000 and 10,000 tweets and most recent likes were subjectively not "recent" enough for our analysis. Also, we found very similar results across both bar plots (when n = 100 and when n = 10,000) suggesting that tweets over time have remained similar in tone; thus, n = 100 worked well for our study. Finally, we were able to collect data on UNFCCC's followers and accounts UNFCCC follows. This helps us analyze UNFCCC's network, related work, and connections. Followers can also serve as a potential community for the climate change-related tweets posted. We wanted to study them separately because the sentiment score is different from measuring the likes and retweets. Sentiment Analysis: For sentiment analysis, we analyzed UNFCCC's most recent tweets and generated sentiment scores across 10 dimensions. As shown in the appendix, our group generated two bar charts with different sample sizes: the first has n = 100 (this

bar chart is called "Sentiment Scores") and the second has n = 10,000. For both bar charts, the "positive" sentiment had the highest sentiment score and the "disgust" had the lowest sentiment score. Trust, fear, and anticipation also had higher scores, while sadness, surprise, and anger also had lower scores. *Word Cloud Analysis:* In creating the word cloud, the words "climate", "change", and "UN" were removed since we expect them to be used in most tweets. This allows our word cloud to better represent the other high-frequency words. After analyzing our word cloud, "cop" was the most frequent word followed by "africaclimateweek" and "simonstiell". Some other frequently used words were "climateaction" and "climatechange"; both of these words were combined into one word even after removing the words "climate" and "change". We were not surprised to see these as frequent words due to the content we are analyzing. Many of the most frequent words were hashtags, meaning that they consist of multiple words combined into one. The scale was changed from c(5, .3) to c(4, .3) to account for longer words that couldn't fit in the word cloud. Most of the words found in the word cloud fitted our expectations for posts relating to climate change; however, we were surprised to see certain hashtags were more popular than words used for basic vocabulary.

Linear Regression Analysis: *Insights About Content Generation:* To better understand the popular content regarding climate change we conducted two linear regressions analyzing the variation of sentiments among the likes and retweets. For both dependent variables (likes and retweets) we ran a regular and a logarithmic regression to analyze the results before and after the skewness was minimized. From the first regression, "likes relation", the model has a p-value of 2.653e-05. Since this value is less than 0.05, the model is significant enough to be taken under consideration; however, since the median is -278.5, which is much smaller than 0, we used the logarithmic method to remove the skewness. Despite the logarithmic model being less effective since none of the coefficients are significant, the model is still significant with a p-value of 0.02248. The "disgust" independent variable was represented as being significant (p-value = 0.0121) in the non-logarithmic model, but insignificant in the logarithmic model (pvalue = 0.0752). In the logistic regression, 10.03% of the change in the dependent variable was explained by the independent variables while 25.08% of the change in the dependent variable was explained by the independent variables in the non-logarithmic model. For the second regression analysis, regarding retweets, we followed the same line of thought and reached a similar conclusion. The first model, while significant with a p-value of 1.764e-05, was negatively skewed, so a logarithmic model had to be added. Our logarithmic model is significant since it has a p-value of 0.01489. The logarithmic model has an adjusted r-squared of 0.1113 meaning that 11.13% of the variation in the dependent variable can be explained by the independent variables. The regular model has an adjusted r-squared of 0.2508 meaning that 25.08% of the variation in the dependent variable can be explained by the independent variables.

Finally, disgust was the only independent variable significant in each model with p-values of 0.00863 in the non-logarithmic model and 0.0469 in the logistic regression model.

<u>Proposal:</u> After conducting the analysis above, we would propose a three-pronged strategy to improve the UN's current social media strategy. First and second, the organization should include more specific keywords and hashtags on its posts to lead its viewers to the desired call to action (i.e., its websites). Third, the company should strive to create partnerships with prominent and younger influencers to better reach the younger generations. All three changes will work towards generating more engagement around their platforms; this would lead to more viewers on their websites thereby increasing awareness of climate change among the general public.

Rationale: Influencer Blog Post: Astrophysicist, author, and science communicator Neil deGrasse Tyson is our chosen influencer for our blog post. His expertise in climate change and his ability to spread awareness of the issues we are writing about enhances the credibility of our post. Our blog post was split into three sections (three columns) to give readers a distinct topic in each section. The first section highlights the UN's recent climate change summit and its primary outcomes such as the fund they created to compensate vulnerable nations for climate-induced disasters. The second section is our "call to action" piece that emphasizes how devastating the effects of climate change can be. Lastly, we have a "News from Around the World" section to highlight the resilience and innovation of certain countries in combating climate change. Our three-section approach gives our blog post breadth and depth of coverage along with a digestible format for readers to scan if needed. The blue background with wind turbines is aesthetically pleasing and fitting for the discussed topics; however, we wanted to include the gas emissions to highlight the dangerous effects of our lack of action. The landing page is linked through the "Go" button. As the only button on the page, users are very likely to end up back at our landing page. Our goal is to create an easy-to-navigate blog post along with a site that is easily linked back to our landing page. Social Media Post: Addison Rae is the influencer for our social media post. Addison has obtained a large following, specifically a younger audience, and has the potential to make a large impact within her community of followers. Our post consists of representatives of the UNFCCC standing and clapping. This message implies agreement and progress to the audience. In our caption, we decided to include vocabulary that includes action and curiosity to engage the audience in making more clicks. When we compared our post to that of an influencer, we saw similarities with posts by Bella Hadid. In the past, she has called for people to make a difference in several areas such as gun violence, women's rights, and mental health. Her "call to action" posts include pictures of the organization, as well as how to contact representatives and get involved. Our social media background has fun colors and contains emoticons for applications; these features strategically align with our content. Also, the title and header include "recent" and "click here" to encourage engagement.

Keywords: The keywords we connected our blog post with include "UN, United Nations, UNFCCC, blog, climate change, and Neil deGrasse Tyson". The UN, United Nations, and UNFCCC are linked to our content as the primary organizations that handle climate change; thus, they should be keywords in our blog. Since it is a blog post, having the word "blog" link will help our readers know what format to expect with their visit. Since climate change is the theme of discussion, the word should be included so viewers know what they're referencing. Lastly, Neil deGrasse Tyson is known in the media and can generate traffic with just his name. His keyword would help our content spread with his prominent position in science. With keywords, users visiting the blog are likely to be satisfied and visit the page for longer. We identified the keywords with UberSuggest and Google Trends as seen in the appendix. Hashtags: After reviewing our initial analysis of the data extracted from Twitter regarding climate change, we wanted to select hashtags that would best relate to the most commented and mentioned topics. The word cloud highlighted many relevant keywords we could use as hashtags; however, to further relate our posts to our goals and the type of content we created, we selected the following hashtags: #UNFCCC, #blog, #climatechange, #climateaction, and #global. These hashtags include current, general, and popular topics that will spread our content to more audiences and further explain our objectives and call to action. Our selection of hashtags links our viewers to more UN climate change posts content, the release of our new blog, and resources for each person to get involved and participate. Using specific keywords will improve the click-through rates of our websites by allowing users to find our pages with ease. Summarize: Our innovative approach to this project can be seen through our symmetrical websites for easy user interaction, creativity in our social media posts, and the connectivity between the UNFCCC's website, our landing page, our blog, and our social media posts. Our expected results were to reach a wide audience, share knowledge, and promote the dangers of climate change. To achieve this, we want to push readers toward UNFCCC's e-learn courses. Our project contributes to the content generation for climaterelated topics in multiple ways. First, our selection of influencers and the content they would be able to produce allows us to reach a large target audience. Our first post was by Addison Rae on Instagram while our second was by the UNFCCC on Twitter. Our blog post encompassed Neil deGrasse Tyson and his actions against climate change. Second, the linkages between our three web pages and two posts allow us to align our material to give users a clear understanding of our message. Both the social media site and the UN climate change site were linked to the landing page with a button. With similar layouts, simple formats, and persuasive language, we believed that this would optimize clicks from users and showcase our vision for content generated on climate change. Finally, the keywords and hashtags associated with our posts will further contribute to content generation for climate-related topics as they were chosen based on popularity and association with our content.

Appendix

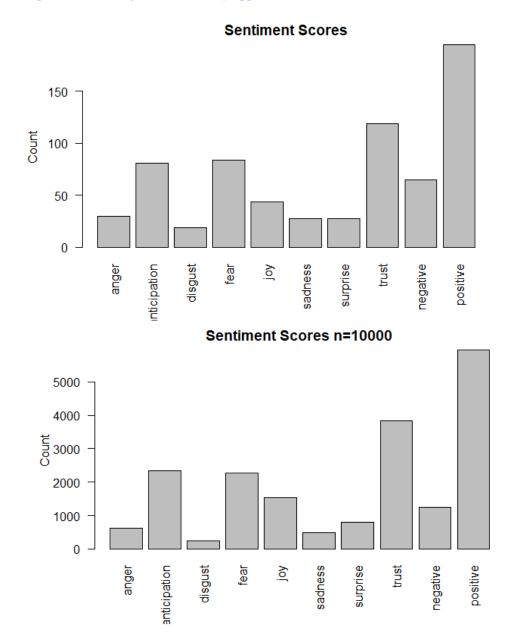
<u>Landing Page:</u> Landing Page (https://reliable-dieffenbachia-2cd41f.netlify.app/)

Blog Post: Influencer Blog Post (https://calm-begonia-873dae.netlify.app)

Social Media Post Blog: Social Media Page Link (https://cosmic-fudge-f483e7.netlify.app)

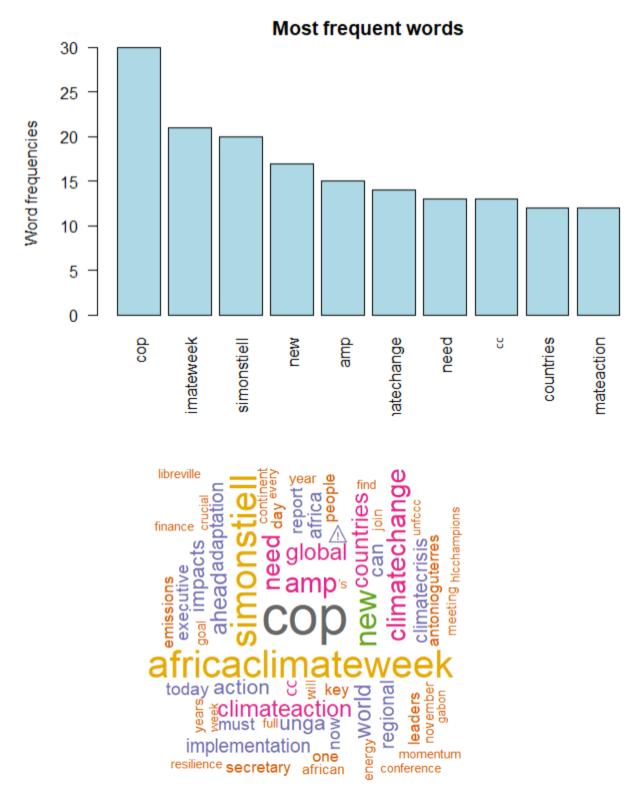
Social Media Post UN: Social Media Page Link (https://cosmic-fudge-f483e7.netlify.app)

<u>Campaign Links To Landing Page:</u> Click "Go" On https://calm-begonia-873dae.netlify.app and https://cosmic-fudge-f483e7.netlify.app



```
summary(likes_relation)
                                                                          A < X</p>
call:
lm(formula = favorites ~ anger + anticipation + disgust + fear +
    joy + sadness + surprise + trust, data = likes_combined)
Residuals:
    Min
             1Q Median
                             3Q
-7111.8 -1156.6 -278.5
                          679.4 21441.6
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)
               1217.1
                           510.3 2.385
                                          0.0192 *
anger
                470.3
                           991.9 0.474
                                          0.6365
anticipation
               -511.3
                          438.8 -1.165
                                          0.2469
                           424.6 2.561
471.4 -1.119
disgust
               3648.3
                          1424.6
                                           0.0121 *
fear
               -527.6
                                           0.2660
                                           0.8496
                123.8
                           651.1
                                  0.190
joy
sadness
                162.4
                           964.7
                                   0.168
                                           0.8667
                           679.2
surprise
                850.0
                                  1.251
                                           0.2140
               -237.7
                           339.6 -0.700
                                          0.4857
trust
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 3052 on 91 degrees of freedom
Multiple R-squared: 0.3113,
                               Adjusted R-squared: 0.2508
F-statistic: 5.143 on 8 and 91 DF, p-value: 2.653e-05
summary(likes_relation)
                                                                         /川 ☆ ×
call:
 lm(formula = log(favorites + 1) ~ anger + anticipation + disgust +
    fear + joy + sadness + surprise + trust, data = likes_combined)
 Residuals:
    Min
             1Q Median
                             30
                                     мах
 -3.4615 -0.9194 -0.3150 1.0552 3.7228
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
                                           <2e-16 ***
 (Intercept)
              5.08643
                         0.27563 18.454
              0.13176
                                            0.8063
 anger
                         0.53570
                                   0.246
 anticipation 0.10379
                         0.23697
                                   0.438
                                            0.6624
                         0.76943
                                           0.0752 .
              1.38471
                                  1.800
 disgust
                         0.25461 -0.046
                                           0.9635
 fear
              -0.01169
 joy
              -0.10628
                         0.35163 -0.302
                                            0.7631
             -0.08080
                         0.52104 -0.155
                                           0.8771
 sadness
 surprise
              0.27301
                         0.36682
                                   0.744
                                            0.4586
 trust
              0.03225
                         0.18339
                                   0.176
                                           0.8608
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.648 on 91 degrees of freedom
Multiple R-squared: 0.173,
                                Adjusted R-squared: 0.1003
F-statistic: 2.379 on 8 and 91 DF, p-value: 0.02248
```

```
summary(rt_relation)
                                                                       call:
lm(formula = retweets ~ anger + anticipation + disgust + fear +
    joy + sadness + surprise + trust, data = rt_combined)
Residuals:
             1Q Median
    Min
-3165.8 -460.0 -128.1 303.7 10074.9
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
              489.26 228.21 2.144 0.03470 *
(Intercept)
                                0.391 0.69663
anger
              173.47
                         443.52
anticipation -260.82
                         196.20 -1.329 0.18705
                                 2.684 0.00863 **
             1710.11
                         637.04
disgust
fear
              -220.32
                         210.80 -1.045 0.29871
joy
               96.63
                         291.13
                                 0.332 0.74070
                                 0.175 0.86148
               75.49
sadness
                         431.39
                                1.156 0.25074
surprise
              351.06
                         303.71
              -105.63
                         151.83 -0.696 0.48837
trust
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1365 on 91 degrees of freedom
Multiple R-squared: 0.3184, Adjusted R-squared: 0.2585
F-statistic: 5.314 on 8 and 91 DF, p-value: 1.764e-05
summary(rt_relation)
                                                                       #II ☆ ×
 lm(formula = log(retweets + 1) ~ anger + anticipation + disgust +
     fear + joy + sadness + surprise + trust, data = rt_combined)
 Residuals:
             1Q Median
    Min
                            3Q
                                   Max
 -3.2094 -0.9927 -0.1568 0.9744 3.5606
 Coefficients:
             Estimate Std. Error t value Pr(>|t|)
                                        <2e-16 ***
                      0.27504 15.393
 (Intercept)
              4.23359
              0.01519
                        0.53454
                                 0.028
                                         0.9774
                                0.228
 anticipation 0.05383
                        0.23646
                                         0.8204
                                 2.015
                        0.76777
 disqust
              1.54676
                                         0.0469 *
                        0.25406 0.105
                                         0.9166
 fear
             0.02669
                        0.35087 -0.560
                                         0.5768
 joy
             -0.19650
                       0.51992 -0.206
 sadness
             -0.10694
                                        0.8375
 surprise
             0.30791
                       0.36603 0.841 0.4024
              0.02055
                       0.18299 0.112
                                        0.9108
 trust
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 1.645 on 91 degrees of freedom
 Multiple R-squared: 0.1831, Adjusted R-squared: 0.1113
 F-statistic: 2.55 on 8 and 91 DF, p-value: 0.01489
```



Word cloud minimum frequency = 5

"Paris Agreement" could not fit on the page. It will not be plotted.

