CSCE 474: Temporal and Spatial Sentiment Analysis of Twitter Data: University of Nebraska-Lincoln

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I. Introduction

The advent of twitter dramatically increased the generation of publicly available content. In 2021, 217 million active users visited the platform daily during quarter four. [1] For better or worse, Twitter discourse is a substantive driver of public opinion. Large quantities of tweets with negative sentiment can potentially impact consumer behavior and product sales. As a result, the analysis of sentiment is essential for the effective marketing of an entity.

We performed sentiment analysis on Twitter data with locations and keywords related to the University of Nebraska. To analyze this data, we performed spatial clustering and produced visualization to gauge sentiment in a geographic location.

II. Objectives

1. Data preparation to collect, clean, and format Twitter data containing keywords or geocoordinates related to the University of Nebraska.
2. Sentiment analysis of compiled Twitter data.
3. Spatial analysis using our sentiment analysis results to discover patterns relating to tweets' location of origin.
4. Visualization of data to aid in the recognition of trends.

III. Related Work

Previous studies have been conducted which detail the process of performing sentiment analysis on tweets and other forms of social media. Kharde and Sonawane detailed one such process in their study. Their paper focuses heavily on the process for sentiment analysis including steps such as preprocessing the dataset, feature extraction, machine learning, and other various sentiment approaches. [2]

Another study by Alruily and Shahin developed a new sentiment analysis model on Twitter data. This study in particular used a dataset of tweets relating to 22 different Saudi universities. This study differs from our proposed method as it focused on creating an improved sentiment analysis model for the Arabic language rather than analyzing the tweets themselves. [3]

In the study by Hu et. al, the researchers performed spatial and temporal sentiment analysis on tweets. The study used general geo-tweet data from 2016 for the analysis. They discovered spatial patterns particularly among positive sentiment tweets. More importantly, this study proved the viability of using spatial and temporal analysis with Twitter data. [4]

IV. Datesets

A. Sources

The project primarily references data from Twitter that is being accessed via API through a Python package. The data is gathered via a set of inputs that configure a query to the API. We have access to historical data which makes temporal analysis possible. The data is formatting consistently but contains a large number of missing values due to user privacy preferences. Generally speaking, the initial quality of the data is relatively high in relation to most data sources.

B. Attributes

At a high level, the available attributes describe the context of the tweet, the content of the tweet, and the user of the tweet. Each tweet has the potential to have up to 47 attributes. Some specific examples of attributes would be URL, date, content, ID, user, language, etc. The majority of the attributes are nominal, with a few being numeric or alternative types. We have narrowed our dataset down to have a total of 12 attributes as defined in Table I.

TABLE I. Tweet Data Attributes

Attribute	Description
id	Unique identifier
date	Date of the tweet
url	Direct URL to the tweet
user	User object who posted the tweet
replyCount	The number of replies to the tweet
retweetCount	The number of times the tweet has been retweeted
likeCount	The number of likes of the tweet
quoteCount	The number of tweets which quote the tweet
lang	The language of the tweet
coordinates	The geographical coordinates of the tweet
place	A common name for the location of the tweet
content	The text or media that is presented in the tweet

C. Size and Scope

The number of available tweets that we have access to is in the billions, which is much larger than the scope of this project. As a result, we refined our scope to focus primarily on tweets that reference the University of Nebraska-Lincoln (UNL). In order to retrieve said tweets, we used keywords such as "husker", "cornhusker", "UNL", "University of Nebraska-Lincoln", and "Devaney Sports Center". Our temporal scope remained unbounded, and the first recorded Tweet referencing UNL is from 2008.

In order to perform spatial analysis from various origins, we also collected geotagged data centered on three universities – University of Nebraska-Lincoln (Love Library), University of Nebraska-Omaha (Criss Library), and University of Nebraska-Kearney (Calvin T. Ryan Library). We gathered all geotagged tweets within a 25 mile radius of the university libraries. The tweets were not gathered using keywords, so they were only related by their point of origin. The exact size of the datasets and the percentage of the tweets that had appropriate geotagging can be seen below in Table II and Table III.

TABLE II. KEYWORD DATA SIZE

Keyword	Total Entries	Geotagged Entries	Geo %
"Cornhusker"	26447	1245	4.7
"Cornhuskers"	50346	2268	4.5
"Husker"	405936	24259	6.0
"Huskers"	1119918	69147	6.2
"UNL"	155212	6651	4.2
"University of Nebraska-Lincoln"	4134	148	3.6
"Devaney Center"	2261	74	1.4
"Devaney Sports Center"	607	25	4.1
"Bob Devaney Center"	102	9	8.8
"Bob Devaney Sports Center"	397	14	3.5
"Lied Center"	3394	156	4.6
"Lied Center for Performing Arts"	49	4	8.2
"Pinnacle Bank Arena"	4665	288	6.2

TABLE III. GEOLOCATION DATA SIZE

Location	Total Entries	Geotagged Entries	Geo %
Love Library (UNL)	1310321	1262080	96.1
Criss Library (UNO)	3787610	3608659	95.3
Calvin T. Ryan Library (UNK)	149894	148011	98.7

V. DATA PROCESSING

A. General Procedure

The general procedure used for data processing focused on the retrieval of data, formatting of data, and cleaning of data. The retrieval process used a Python package, Snscrape, to access the Twitter API and query for individual tweets. The tweets returned were based on a simple query that used a keyword and time frame. For each tweet that was retrieved, the data within was formatted into a tweet class that allowed easy access to all of its properties. The desired properties of the tweet class were then referenced and saved to a csv file. This process allowed us to have a careful hand in the selection of relevant attributes while removing any irrelevant attributes.

B. Tool Selection

Multiple tools were considered for the retrieval of Twitter data. Sprinklr was the first tool examined. The access from Sprinklr provided automatic analysis on special topics and keywords. We ultimately decided to move past Sprinklr because of the limited number of tweets and the lack of keyword flexibility. This functionality may be possible with Sprinklr, but we found the documentation to complete the necessary tasks to be sparse.

As an alternative to Sprinkler, the next tool examined was a Python library called GetOldTweets3. Despite being relatively well documented, GetOldTweets3 was out of date and no longer compatible with the Twitter API. This led us to look into another Python library called Snscrape. Snscrape interfaces with multiple social media platforms, however, we only used the Twitter module. Snscrape documentation was very limited, but user guides on various forums aided in the implementation. Snscrape was able to easily query for tweets using highly flexible parameters. The resulting tweet objects could be configured to retain only the relevant attributes. As such, Snscrape was the tool selected for data retrieval.

C. Data Problems

One of the major problems of the data set is the large number of missing values due to user privacy preferences. This should have minimal impact on the project because the majority of attributes of interest are required. The main property that was of concern is the location. The location was used to perform a geographical analysis of tweet sentiment. Therefore, the missing data simply reduces the number of data points that we are able to use to support the analysis.

D. Data Filtering

The data can be filtered when retrieving the data from Twitter itself. The generator allows for specific parameters such as a time frame and keyword which produced specific results. After the generation process, the data was stored in a CSV which can be imported into a series of scripts written in R as shown in Table IV and V.

Once our script imports the CSV files, we first remove all duplicate data that may occur due to having each CSV file from Snscrape representing the results of one keyword. We then filter for tweets that contain latitude and longitude metadata, as we are only interested in tweets with this information for our geolocation visualization. Out of the 2,404,779 keyword tweets in our dataset, only 127,178 keyword tweets contained coordinate information. The distribution of this data can be seen above in Table II and Table III. Our script first imports the dataset as a dataframe, returns only the text of the tweet, removes formatting characters (such as \n), and removes emojis.

The script then exports this data as a CSV file for the sentiment analysis programs to score each of the tweets for a positive scale (1 to 5) and a negative scale (-1 to -5). Once both sentiment analysis programs output their files as shown in Table IV and Table V, our script then imports the predicted scores to be merged back to our dataset to be analyzed within the script for a basic visualization of a change in overall scores of tweets over time. For the purposes of this analysis, the positive scores and negative scores are added to produce a single overall score. We then export this dataset as a CSV file to be used on Weka for k-means cluster analysis and Tableu for further location-based visualization.

TABLE IV. SENTISTRENGTH OUTPUT ATTRIBUTES

Index	Tweet content	Positive	Negative
1	"Literally someone take Jojo Domann. Hes a stud."	1	-1
2	"Shocked Jojo hasn't goteen drafted yet. Figured his tea…"	1	-3
3	"4 more Huskers getting drafted today Jojo Allen Tou.."	1	-1
4	"AFL almost looks a sport when umpires don't pay 50m.."	1	-1
5	"The Great Wall of Tommy #AFLCatsFreo"	3	-1
6	"SDK is a tall man. But hes growing every week #AFL…"	1	-1
7	"No Danger no Geelong #AFLCatsFreo"	1	-2
8	"Is it a thing for Geelong to head to the pub for a 2nd …"	1	-1
9	"Addison transferring to USC BEFORE being in the port…"	2	-3
10	"Cam Taylor-Britt said his visit with the #Bengals two …"	3	-1
11	"INFORMATION at 20:56 road open at NB JFK on ramp …"	1	-1

TABLE V. SENTISTRENGTH-SE OUTPUT ATTRIBUTES

Index	Tweet content	Positive	Negative
1	"See our latest #Bellevue, NE #Retail job opportunity a…"	1	-1
2	"Update on Cornhusker AD Trev Alberts record at Nebr…"	3	-1
3	"I'm guessing that there will soon be some office space…"	1	-1
4	"If youre traveling north on Highway 75 this morning b…"	1	-1
5	"Cornhusker fans today?"	1	-1
6	"I watched the Nebraska Cornhusker women's bowling…"	2	-1
7	"Will Pop Watson III has announced his commitment to…"	1	-1
8	"Annual Luncheon today at the Cornhusker Marriott! …"	1	-1
9	"#EclipseAwards | Campen Caballo Maduro : KNICKS G…"	1	-1
10	"I'm a different individual (cornhusker)"	1	-1
11	"I expect the refs to completely blow this game now th…"	1	-1

VI. EVALUATION

A. Software Used

The sentiment analysis tools we use for our project are: SentiStrength[5] and SentiStrength-SE[6]. These are commonly used sentiment analysis tools in academic literature. We use a series of scripts to run our dataset against all of the tools that we plan on using to have a general idea of the sentiment expressed in each Tweet.

SentiStrength is a tool by M. Thelwall et al.[5] that was designed when most tools of its time were commercially oriented by being trained using marketing data. SentiStrength was designed to take language in social media into account, because online communication in English frequently does not follow conventional grammar and spelling. In SentiStrength, two sentiment Strengths, positive and negative, scale from: -1 (not negative) to -5 (extremely negative) and 1 (not positive) to 5 (extremely positive).

SentiStrength-SE is a modified version of SentiStrength by M.R. Islam et al.[6] that was designed to address the limitations of sentiment analysis tools that were designed for the general public. Domain-specific use of vocabulary means that the expressed sentiment of a word can change depending on what domain it is used in, and the authors trained their tool on software repository conversations to more accurately predict the sentiment expressed by software developers.

M.R. Islam et al. made the comparison of the accuracy of SentiStrength and SentiStrength-SE using precision, recall, and F-score metrics with the "Gold Standard" dataset from N. Novielli et al. [7], a manually annotated dataset of 4,800 Stack Overflow conversations. In this comparison, the overall precision, recall, and F-scores were 61.69%, 78.54%, and 62.02% respectively for SentiStrength and 73.58%, 85.43%, and 79.06% respectively for SentiStrength-SE.

Tableau Public is a desktop tool used to create data visualizations. Tableau has a wide array of visualization options, from simple charts, table and graphs, to more complex visualization utilizing spatial and temporal dimensions. For our project, we made use of the density map visualization to identify locations with greater or fewer numbers of data points [8].

Weka is another desktop tool that can be used for a large variety of data processing and data analysis tasks. The data analysis presented in this paper utilized Weka to perform clustering on geotagged tweets. A density-based clustering algorithm and KMeans were used. Additionally, Weka provides a visualizer which was used to create basic visualizations of the clustered data. [9].

B. Approach

Sentiments were graded based on two metrics obtained through SentiStrength and SentiStrength-SE. These were the number of positive sentiments and negative sentiments. These elements were summed to produce a total sentiment for a tweet, (i.e., if positive is 4 and negative is -2, overall score for the tweet will be 2). In order to evaluate the validity of the tools, a few tweets were manually validated to ensure that the machine-detected sentiment matched the human-detected sentiment.

After filtering the data, the sentiment analysis was evaluated on trends over time from the average scores from SentiStrenth and SentiStrength-SE. We compared this data with Sprinklr results to compare how the systems evaluated sentiments. In order to validate the temporal analysis, the generated visualizations were manually examined. Over the several years the data spanned, seasonal patterns would be expected.

A few techniques were used to evaluate the results of the spatial analysis. We utilized the KMeans algorithm to cluster the data, so we created an elbow graph in order to select the ideal number of clusters. The resulting clusters were then manually examined to ensure that the spatial plotting was correct and the clusters were valid. Manual examination was aided through the use of visualization from Weka Explorer and Tableau.

VII. Results and Analysis

A. *Temporal Sentiment Analysis*

The general sentiment of tweets that refer to UNL is shown to lower over time as denoted by the blue Loess lines in Figure 1. Loess regression was chosen to represent the general trend of our data because it is a non-parametric test as we did not have any assumptions on the distribution of our data. When looking at the black lines that represent average values, it can be seen that the average sentiment for each month also fluctuates depending on the time of year for both sentiment analysis tools. The average sentiment of tweets that refer to UNL is at its peak at around April and valleys at around December of each year.

SentiStrength-SE[6], as mentioned above, was trained on a dataset consisting of comments and conversations in software repositories. Due to this, we hypothesized that tweets evaluated SentiStrength-SE would be predicted as mostly neutral. In practice, the opposite occurred, shown in Figure 2. SentiStrength-SE shows similar average scores of all tweets from March 2010 to around June 2017. However, after this point, scores began to diverge significantly, disproving our original hypothesis.

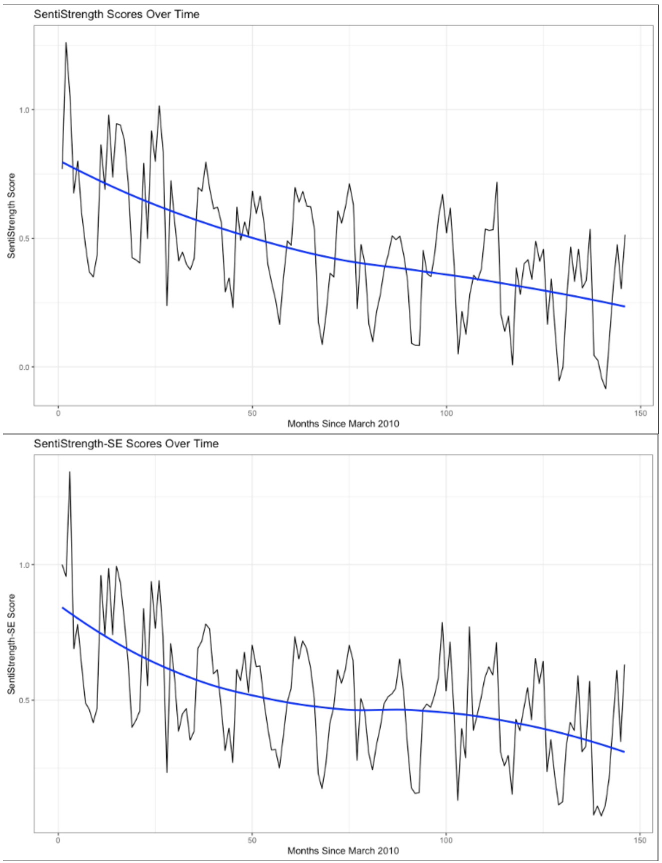

Fig. 1. Average sentiment scores of tweets from SentiStrength (top) and SentiStrength-SE (bottom) over time. The blue line indicates Loess regression to visualize the overall change over time.

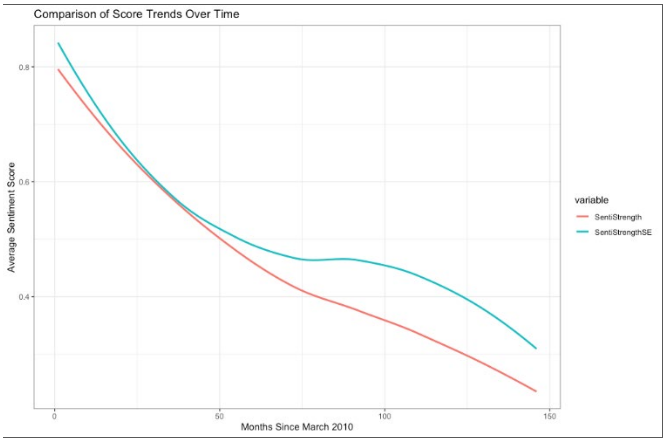

Fig. 2. Comparison of Loess regression lines from Figure 1. The magenta line indicates SentiStrength-SE and the teal line indicates SentiStrength

B. *Weka Spatial Analysis*

The spatial analysis performed on the geotagged keyword tweets uncovered some minor insights in the spatial trends across the United States and the world. In the comparison of the tools, we found that SentiStrength did not provide meaningful spatial trends within the United States. However, in the SentiStrength results, the cluster that represented the rest of the world, as designated by the color pale pink in

Figure 3, was significantly positively skewed. The peak of said distribution was at a sentiment score of +2.

In the examination of the SentiStrength-SE results, more spatial clusters were discovered than the SentiStrength analysis. Referencing Figure 4, separate clusters can be found for northern United States, southern United States, Europe, and the rest of the world. Additionally, a loose clustering can be found in the north-eastern United States - cluster1 designated in red in Figure 4. After viewing the associated sentiment, the northern and southern United States were uninteresting since they represented the neutral values for each respective area of the country. The north-eastern cluster was relatively interesting because this cluster represents the very high sentiment tweets within the United States. This finding tells us that tweets generally contain positive sentiment in the northeast portion of the country. The other new discovery was regarding the Europe cluster. The analysis found that Europe - cluster 6 designated by yellow-orange in Figure 4 - heavily favored positive sentiment toward UNL. This is a refinement of the previous discovery that the world excluding the United States skewed toward positive sentiment.

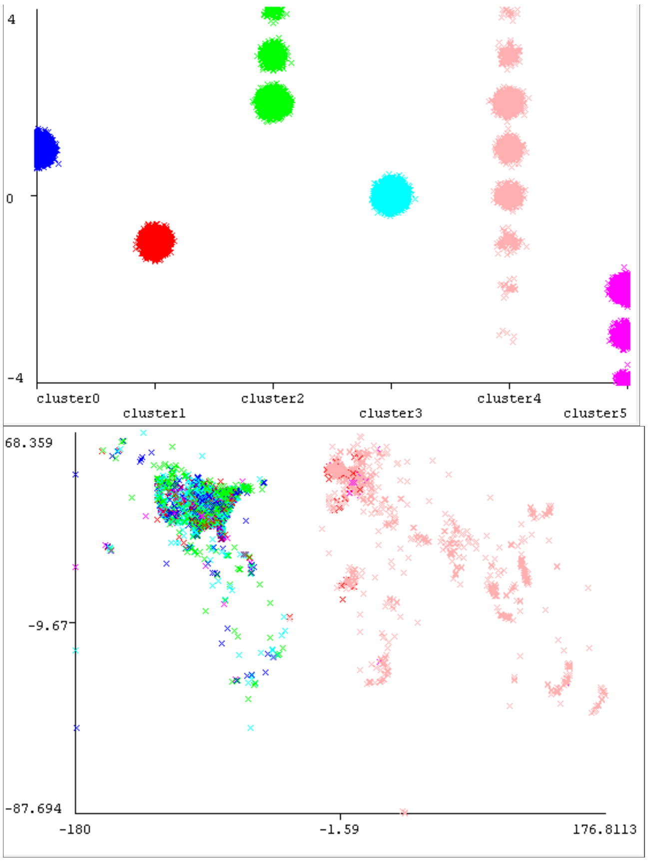

Fig. 3. Clusters vs Sentiment score (top) and longitude vs latitude (bottom) of SentiStrength analysis.

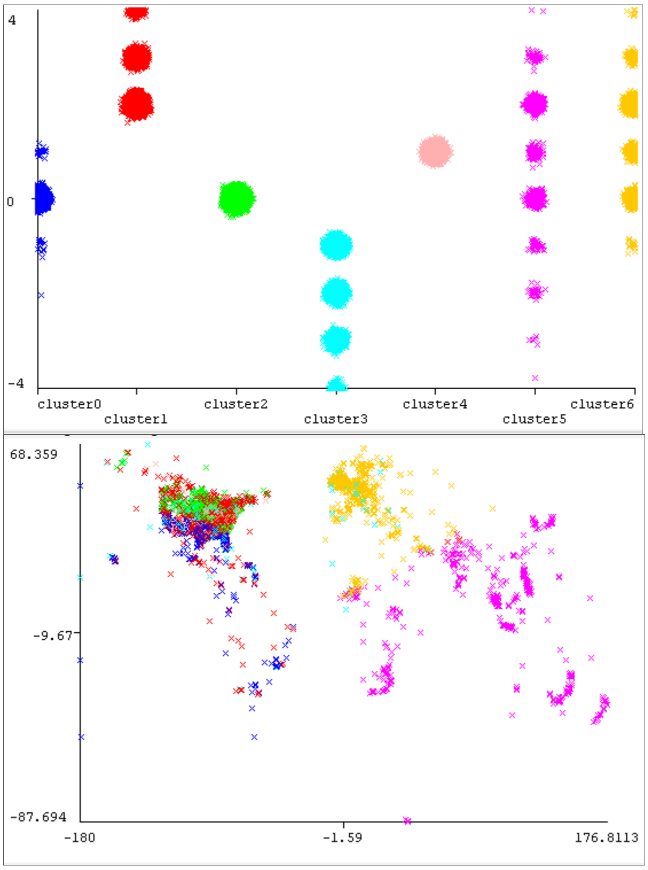

Fig. 4. Clusters vs Sentiment score (top) and longitude vs latitude (bottom) of SentiStrength-SE analysis.

In an attempt to discover new findings, an analysis of the average values between SentiStrength and SentiStrength-SE were used in spatial analysis. We did not find any new significant findings from this analysis. The average values reaffirmed the international sentiment once again. The corresponding graphs can be found in Figure 5.

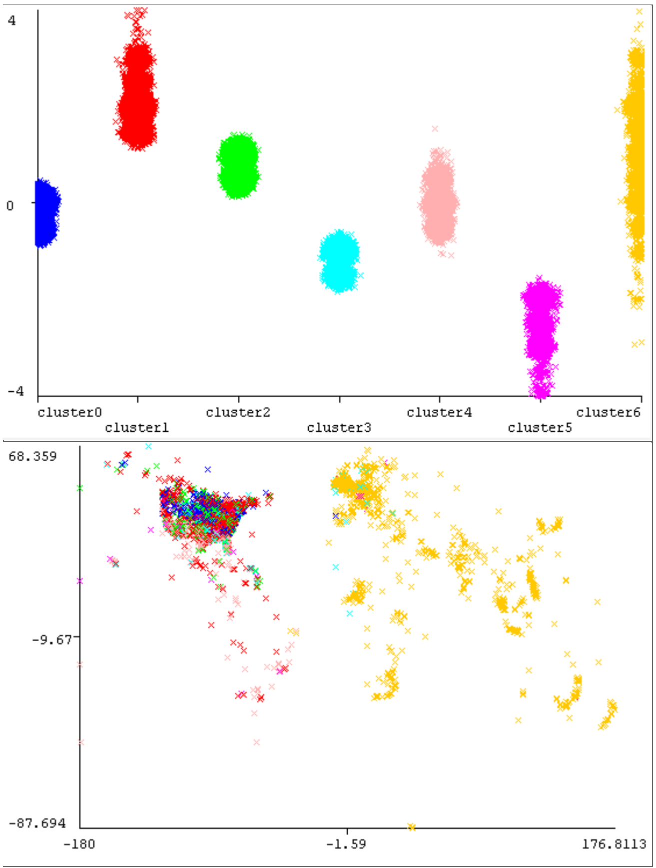

Fig. 5. Clusters vs Sentiment score (top) and longitude vs latitude (bottom) of SentiStrength-SE analysis.

Overall, the WEKA spatial analysis through clustering proved to be fruitful in a few minor ways. The results point to positive sentiment in a European cluster, international cluster, and a loose northeastern United States cluster. The results from the SentiStrength-SE sentiment were more useful for spatial clustering than SentiStrength and the average values of SentiStrength and SentiStrength-SE.

C. *Tableau Spatial Analysis*

In addition, Tableau Public was used to visualize spatial trends of tweets posted within 25 miles of UNL, UNO, and UNK. As featured in Figure 6, the data is far too dense to interpret when all data points are displayed. To combat this, we employed a density map that averages data points within a given area and assigns and creates one data point containing the average. This is more useful for examining the sentiment of larger geographic areas than individual precise geocoordinates.

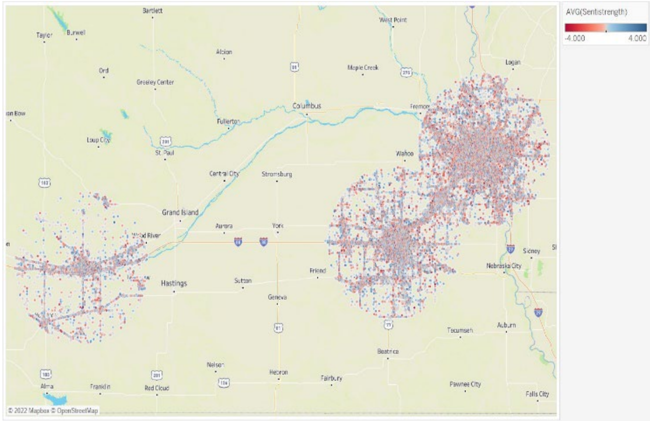

Fig. 6. All geolocated tweets within 25 miles of Omaha, Lincoln, and kearney with associated sentiment score. Scores in blue indicate positive sentiement and scores in red inidcated negative sentiment. The Color Scale for subsuquent figures is availabe in the top right corner.

To begin with the density map, we first created a heatmap that showed us locations where high and low volumes of tweets were sent as shown in Figure 7. As expected, the city centers contain the highest density of tweets, and rural areas have much more sparse tweet coverage. As we associate average sentiment with density, the map becomes entirely different. For clarity, we do not specify to what degree each area is positive or negative, only which direction it leans and how dense the area is. As depicted in Figure 8, the overall sentiment leans negative in most of Omaha, whereas sentiment leans positive in most of Lincoln and Kearney.

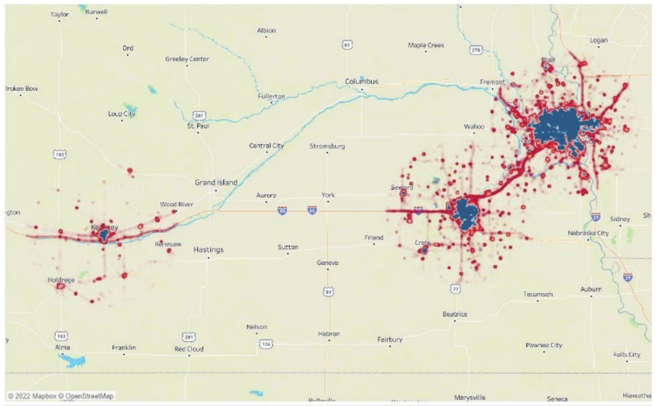

Fig. 7. Denisty map of tweets of all tweets located within 25 miles of Omaha, Lincoln, and Kearney. Scores in red indicate low tweet density, while scores in blue indicate high tweet density.

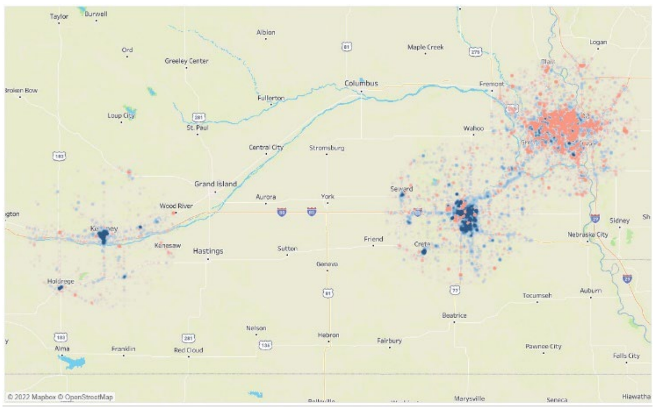

Fig. 8. Density map of all tweets located within 25 miles of Omaha, Lincoln, and kearney with associated average sentiment scores. Socres in blue indicate positive average sentiment in an area, while socres in red indicate negative average sentiment in an area.

For further analysis, we will examine the metro area of Lincoln. Using Figure 9, we determined the location with the most high-density tweet areas is University of Nebraska-Lincoln campus. Aside from campus, high density regions are scattered through the city. When examining average sentiment in the greater Lincoln area using Figure 10, we find that positive and negative regions are scattered throughout Lincoln. Three main trends emerged. First, as well as containing extremely high density, University of Nebraska-Lincoln leans positive throughout most of campus. Second, when excluding the UNL campus, North Lincoln has an even distribution of positive and negative area and contains several high-density areas with positive and negative sentiment. Finally, South Lincoln leans positive throughout most of the area with occasional small pockets of low and high negativity.

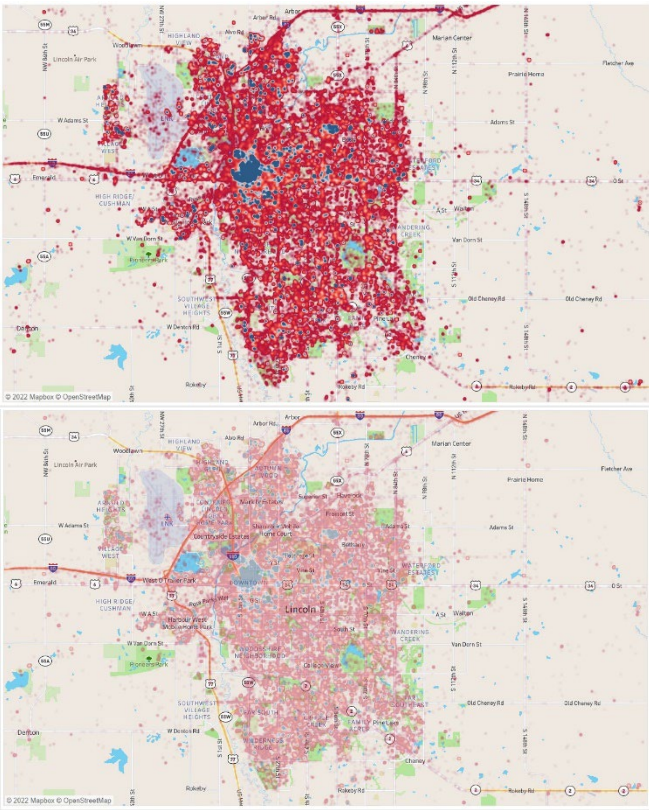

Fig. 9. Denisty map of tweets of tweets located in Lincoln (top) and an identical map with partial transparency to view underlying geographic areas (bottom). Scores in red indicate low tweet density, while scores in blue indicate high tweet density.

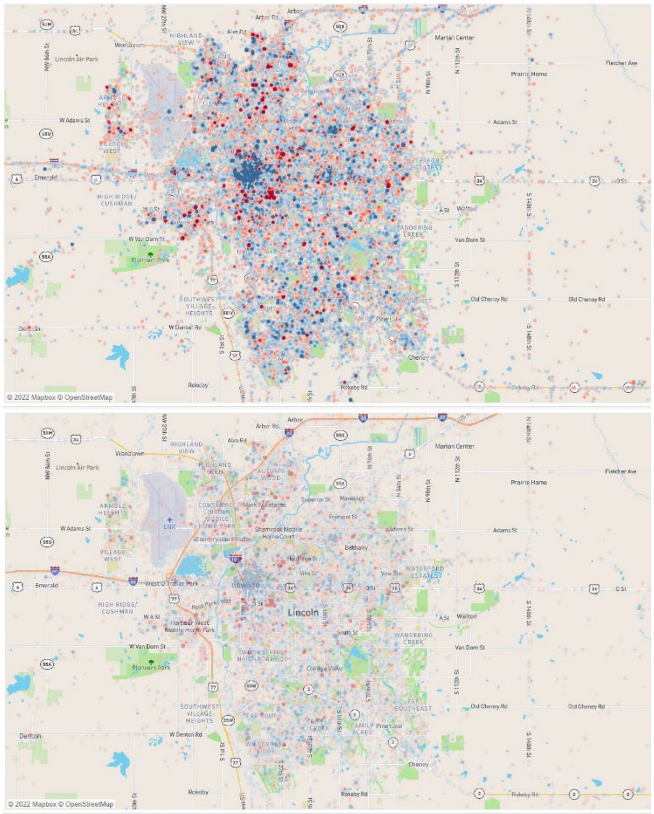

Fig. 10. Density map of all tweets located in Lincoln with associated average sentiment scores (top) and an identical map with partial transparency to view underlying geographic areas (bottom). Socres in blue indicate positive average sentiment in an area, while socres in red indicate negative average sentiment in an area.

Our final level of analysis is at the campus level. The UNL campus is the largest high-density area in our map and requires closer inspection to glean trends from the visualization. Upon examination of Figure 11, high density areas consist of popular student locations such as residence halls, parking garages, the library, and the student union. While each of these areas contains largely mixed sentiment, some small patterns can be found. As represented by Figure 12, there are several high-density areas throughout the parking garages, the library, and the student union where the sentiment is negative. Positive sentiment exists in these areas but is less dense than negative sentiment. Around Memorial Stadium and the residence halls, positive sentiment account for a much larger area than negative sentiment. Nonetheless, high density negative pockets still exist within the residence halls as well, and the positive sentiment within the residence halls is less dense than some negative pockets.

Fig. 11. Denisty map of tweets of tweets located with the UNL campus (top) and an identical map with partial transparency to view underlying geographic areas (bottom). Scores in red indicate low tweet density, while scores in blue indicate high tweet density.

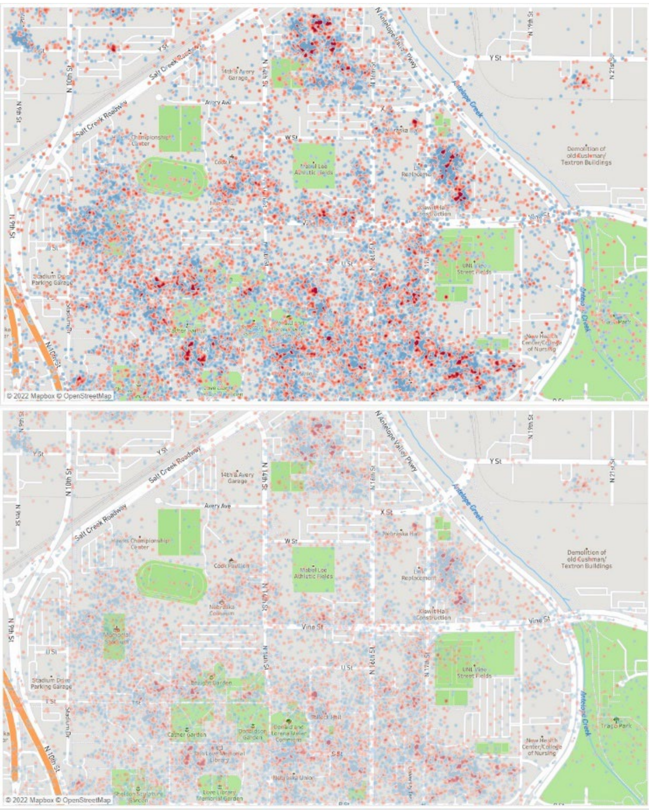

Fig. 12. Density map of all tweets located within the UNL campus with associated average sentiment scores (top) and an identical map with partial transparency to view underlying geographic areas (bottom). Socres in blue indicate positive average sentiment in an area, while socres in red indicate negative average sentiment in an area.

In review, tweets gathered based on geolocation can be quite dense, so density maps were used to determine the sentiment over a specific geographic area. Tweets from Omaha lean negative whereas tweets from Lincoln and Kearney seem to lean positive. When examining Lincoln, UNL was the largest area of high density in Lincoln. Finally, when examining the geographic area of UNL more closely, high density negative areas began to appear more frequently than high density positive areas, even though the UNL campus leans positive overall.

VIII. FUTURE WORK

Comparisons between more sentiment analysis tools can be made. While we attempted to use Sprinklr's dataset to compare against the use of SentiStrength and SentiStrength-SE, there are more tools published in current literature that can be used to do a broader comparison between tools. Some of these tools include the Python NLTK toolkit[10] and Stanford CoreNLP[11], a tool implemented by R. Socher et al. determined the sentiment of a given sentence by generating a sentiment parse tree and was trained using movie review data. One notable aspect of using sentiment analysis tools was that none of them took the usage of emoji into consideration for the sentiment score. Therefore, future work can also involve using SEntiMoji by Z. Chen et al.[12] that employs the use of emoji as noisy labels of sentiment.

TABLE VI. SHARE OF WORK

Group Member	Percent	Work
Kang-il Park	25%	Data preprocessing, Sentiment analysis of dataset, Temporal analysis & visualization, and report
Dominic Pelini	25%	Geo-sourced Twitter data retrieval, Tableau Visualizations, presentation, and report.
Alex Rechsteiner	25%	Proposal design, alternate analysis, presentation, report
Chris Wieskamp	25%	Keyword Twitter data retrieval, Weka clustering and spatial analysis, presentation, and report.

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