Tweether: A Visualization Tool Displaying Correlation of Weather to Tweets

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Abstract

As the generation of social media, we can instantly express how our day is going; however, unknowingly the weather can play a key role in how we are feeling. The weather may dictate our lives regardless of what may be happening. The relationship between weather and mood has been immensely studied to show that the weather does play a major factor regarding our emotions. However, how we visualize the relationship and influence between weather and human emotions remains an interesting question. Based on the natural correlation between weather and mood, we propose Tweether, *a real-time weather and tweet visualization tool, to see how Twitter users feel regarding the weather they experience. Our visualization displays a current reflection of emotions in a set of select geographic regions and also predicts possible emotions in these regions in response to the weather forecast. The visualization uses multiple layers to show the connection between geolocations, weather, and emotions. By aggregating multiple users with emotions, we create an aesthetic design in a 3D manner that is relatively free of visual clutter and it is simple to understand the relationships between weather and emotions.*

Introduction

Weather affects our daily lives, from what we wear, what activities we do, what type of transportation we use, what we eat, or even how we feel. With the increasing accuracy of weather forecasts, people can gain an idea on the type of weather they can expect for upcoming days. Activities are usually planned according to the weather outside (e.g., weddings) and alternative plans must be made in case of inclement weather. How people dress is also affected by weather; when the temperature drops people need to wear coats to stay warm. The economy is also greatly affected by the weather. Certain weather conditions can lower crop yield and cause higher prices in stores. Disastrous weather phenomena such as hurricanes, tornadoes, or even floods can cause devastation in communities resulting in homelessness, death, and destruction. Inclement weather can also cause delays in transportation on roads or via flights. We can also choose to ride our bike to work instead of driving the car if the temperature is warm enough. One thing that is an effect of all these items is how we feel:

- Are you sad that you cannot enjoy the outdoors due to rain?
- Do you love that it's raining so you can bundle up and read your favorite book?
- Do you love the snow because it's close to Christmas?
- Do you hate the winter because you want it to be spring?

These feelings are all brought out by the weather outside. One person can feel positive about a certain type of weather and one person can feel negative. Categorizing similar feelings from a large number of people may reveal some useful patterns that can help decision makers or shareholders make more appropriate decisions (e.g., carnival or sport game arrangements) with respect to weather conditions. Social media researchers can also gain benefits from these patterns by getting insights into how population behaviors may change with weather variation. However, rare visualization research exits to show the correlation between human sentiments and weather conditions. Furthermore, it remains a challenging task to depict massive and complex relationships among many objects.

In this work, we present a novel tool, named *Tweether*, a visualization of real-time Twitter and weather data to show the feelings of current users and how their emotions could fluctuate regarding the weather. We also develop a prediction model that predicts the emotions with respect to the weather forecast. Our work showcases a 3D map which highlights select clusters of weather. The correlation of tweets to weather is represented by a graph. We use texture-based edge bundling to visualize the graph for reducing visual clutter. Introducing a clear relationship between weather and tweets, the design presents a natural manner of representing correlation and revealing high-level patterns.

By using Tweether, the end-users, such as decision makers and social media researchers, can explore if the classified weather has any correlation to the majority of the population. Tweether can be used to examine if the majority of the population follows certain patterns, and how the overall sentiment changes in regards to weather. In addition, the prediction model predicts the future feelings of given weather so that public preferences could be foreseen for certain decision making.

Related Work

Visualizations correlating sentiment and weather are highly sparse, and the presence of live visualizations is also non-existent. However, there are studies showing the two portions of this work. Clustering of weather data has been done many times in the past. There are also a vast number of visualizations which indicate the sentiment of different locations.

Psychological Studies

The natural correlation of weather with emotion has been studied profusely [5, 11, 15, 17]. With various factors among the different research, the conclusions attained were broad. In general, humidity, sunshine, and temperature have the greatest effect on mood [11].

In some research on weather and mood, correlations have been debunked. There is no consistency due to seasons and time spent outside [5]. Having certain emotions regarding the season has strong links to seasonal affective disorder (SAD), where people are depressed in regards to changes of the seasons, which usually occurs during the winter. However, most psychologists believe that the weather has an impact on psychological intentions [15]. When observing serotonin levels in regards to sunshine there were strong relationships to being happy [17]. It has been found that weather may not play a big role in the positive attitude, but the negative attitude can have a correlation with weather [11].

Social Media, Weather, and Emotions

Few works present the use of Twitter data for their social media feed and some form of weather data. In comparison to our work, the following research used past data and developed a 2D graph implementation for visualization.

Work has been done using two to four years of Twitter data and correlating it with meteorological data from NOAA [8, 18]. Using urban areas in the United States as the area of interest, the tweets are passed to a sentiment analyzer that has a multi-level process. The researchers first determine keywords which are identified from public events (e.g., entertainment or natural disasters), then identify the mood state, and finally assign sentiment scores. To correlate the weather with the tweets they use a Generalized Mixed Model to display the non-linear relationship between emotion and weather. Using multiple variables for weather (temperature, temperature change, precipitation, snow depth, wind speed, solar energy, and hail), they determine the connection to hostility-anger, depression-dejection, fatigue-inertia, and sleepiness-freshness. Their results indicate that the warmer temperatures create an angrier atmosphere, lower depression, and less sleepiness, and they determine the influence of temperature to mood is trivial. Their visualization is limited to graphs [23]. Other than using urban areas in USA the researchers see relationships between temperature, humidity, and atmospheric pressure for tweets in the United States and weather data from Weather Underground. Using Linguistic Inquiry and Word Count for sentiment classification they see a pattern with temperature and emotion of every state in the United States. Using regression analysis, they find that the warmer states have a happier mood than the colder states. Their visualization is limited to a bar chart.

These works are limited in visualization and usability study. Using past data is useful for our training and testing model; however, having a live view of what Twitter users feel is what we aim for in this work.

Sentiment Analysis in Social Media

Sentiment analysis has been studied vastly. There are various methods to detect the sentiment of a sentence. However, in regards to tweets sentences may be incomplete, because a tweet is limited to 140 characters and the need to express oneself is limited to short meaningful phrases. We find abbreviations, neologisms, acronyms, hashtags, emotions, and URL's throughout most tweets. Certain features need to be extracted and some need to be filtered out. Filtering of URL's, usernames, and Twitter special words may be needed in certain scenarios [20]. Stop words (i.e., a, an, the, etc.) are also removed due to not adding any extra sentiment information. For classifying the tweets, a number of different methods are used, and the most prevalent one is the Naive Bayes classifier [20, 22]. Emotions are used as basis for sentiment classification for classifying tweets as positive or negative for the training purposes [20, 1].

Visualizations

Clustering

Although clustering of data has been extensively studied, it remains a non-trivial task to deal with temporal and time series data. Weather data needs to be clustered based on values, proximities, and changes throughout the given time span. There have been various visualization techniques for time series data. Visualizing time series data using spirals for large data sets can better identify periodic structures in data [27]. Using wavelet to transform data along a multi-resolution temporal representation to find clusters with similar trends is a useful method for exploring data in a time series fashion [28]. Applying smooth data histograms for visualizing clusters in self-organizing maps is a simple method for 2D data sets [21]. The mass majority of clustering visualizations uses k-means clustering on the basis of their algorithms [27, 28]. We choose to follow this pattern as well, as k-means is a widely used algorithm that gives reasonably good results [27, 13].

Bundling

The correlation between multiple entities (e.g., various weather and emotion patterns in our study) can be fundamentally represented as a graph. However, graph visualization remains a challenging task. Severe visual clutter can be easily incurred if we directly draw all edges as straight lines, even with some optimization techniques, such as force-directed placement of vertices or clustering of vertices [14].

To address this issue, Holten [9] proposed a concept of *edge bundling* that groups the related edges of a hierarchical graph together as a set of smooth curved bundles, and thus can significantly reduce visual clutter. Holten et al. [10] extended the original edge bundling method and presented force directed edge bundling (FDEB) for a general graph without hierarchy. Other researchers have also made similar efforts to generalize edge bundling [4, 26, 6, 7]. A few efforts have been dedicated to creating extensions in 3D space. Lambert et al. [16] presented a 3D edge bundling to visualize geographical networks on the Earth surface. Böttger et al. [3] presented mean-shift edge bundling to visualize 3D functional connectivity across the cortical regions of the brain. Their method combines FDEB and kernel density estimation edge bundling (KDEEB) [12] with an improved numerical stability.

Predictions

Using the past Twitter data set, it is desired to predict the mood for the next days. Predicting the stock market based on Twitter mood has been studied [2]. The notion that the mood of Twitter users can correlate to stocks immediately is not present; however, the mood is reflected when a few days have passed. Because the general public has strong connections with the outcome of a man-made entity, there will be some form of correlation available. In our case, however, the weather is not a man-made entity. Thus, finding a correlation between weather and mood, and then predicting the mood for the future can show zero correlations. We will address this idea later in this paper.

Approach

Implementing Tweether has multiple steps which are composed of individual and interconnected components. We use both the weather data and the Twitter data in our study. Based on the

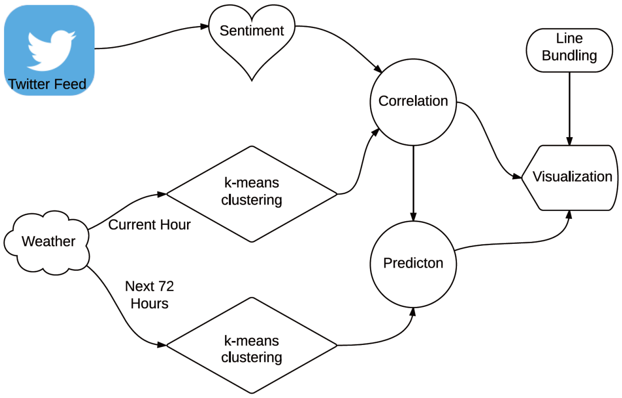


Figure 1. *The major steps of Tweether.*

clustering result of the weather data and the sentiment classification of each tweet, we compute and visualize possible correlations between these two entities. We also predict the sentiments for future times.

Tweether in its simplest form takes tweets and assigns a sentiment value which is then correlated to appropriate weather clusters. Each tweet is aligned to the map according to its geographic location. The current hour visualization and the prediction visualization have the same user interface. We represent the derived correlation as a graph, and embrace the natural link of weather up in the sky to the tweets down on the ground to implement our visualization. After we implement each of the necessary steps we can clearly see how the visualization adopts a layered design which effectively highlights the correlation of weather and emotion in space-time. The major steps of Tweether are illustrated in Figure 1.

Data Sets

We use two main data sets with respect to weather and Twitter in this work. The weather data set is generated from a climate simulation using Weather Research and Forecasting (WRF) Model [19]. The data provides hourly forecasts with up to 72 hours in the future. Each WRF file contains multiple variables in regards to weather (i.e., temperature, precipitation, wind speed, etc.). For this visualization, we choose to focus on the surface skin temperature (TSK) variable. Each TSK file is represented via a 2D array covering a regular geographic region. In this work, we use a WRF data that geographically corresponds to the state of *Nebraska*.

The Twitter data set contains the live data feed from Twitter users throughout Nebraska. The fetched Twitter data is synchronized with the weather data. Only users that have opted-in to turn on the feature of *Tweeting With Location* are selected. In addition, because Nebraska has a relatively low population with most of the land being barren, only the most populous cities are chosen. These cities include *Omaha*, *Lincoln*, *Grand Island*, *Kearney*, *Fremont*, *North Platte*, *Norfolk*, *Columbus*, and *Scottsbluff*. We use a geographic filtering process to select these cities. The Twitter data is stored in JSON format where we need to extract the coordinates of each tweet and the tweet itself.

Weather Clustering

We use clustering to extract different weather patterns from the WRF data and identify their geographic coverage. We use the k-means clustering algorithm to partition the 2D array of each time step of TSK into a set of clusters. Some clusters can be dispersed, resulting in random patterns or outliers. These outliers are removed because we assume that moods are affected mostly by comparably dominant weather patterns, and the outliers are small in space and can be changed dynamically in time. To remove outliers, we use a filtering process based on the number of data points in each cluster. If there exists a cluster that has less than one percent of the overall number of clustered elements, this cluster is removed and the data points that belong to a cluster are clustered again. This process is continued until there is no cluster that has less than one percent of the overall cluster count.

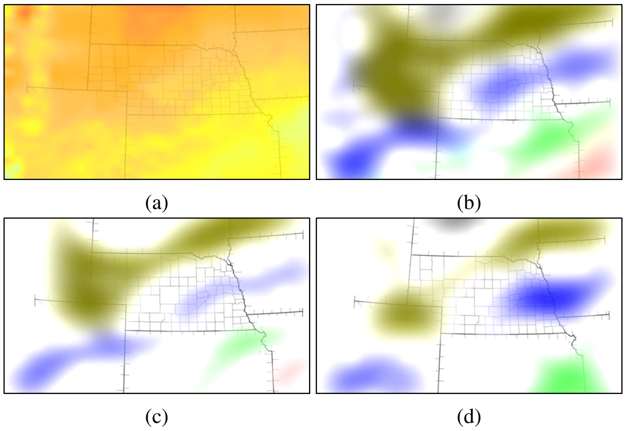


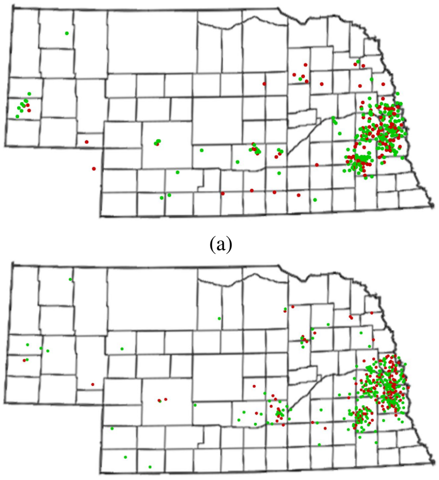
Figure 2. *(a) The geographic distribution of TSK variable at a time step. (b) The k-means result with outliers. (c) The comparably dominant weather patterns. (d) The clustering result of the forecasted weather. The color values in (a) are mapped to TSK. The color values in (b)-(d) are used to distinguish different clusters.*

To smooth any randomness in the cluster values of the 2D array, we use a low-pass filter where the cluster value of an element is determined by the values of surrounding elements. If at least 5 out of 8 neighbors have the same value, the cluster values of the element is kept; otherwise, the value is removed. We found that repeating this operation 4 times can give us sufficient smooth outcome amongst the majority of 72 hours. Figure 2 (a) shows the distribution of TSK at a certain time step. A direct use of k-means can generate many dispersed small regions, as shown in Figure 2 (b). Our method can clearly extract the dominant TSK patterns, as shown in Figure 2 (c). Figure 2 (d) shows the result of the forecasted weather.

Sentiment Classification

Each tweet can contain different attributes other than plain sentences. Due to each tweet being limited to 140 characters, the majority of users tend to use abbreviations, neologisms (e.g., noob, troll), acronyms, hashtags, emotions, or URL's. Abbreviations, acronyms, emotions, and neologisms are taken into account for training our classifier. However, a few items are filtered from certain tweets. The filtering process removes URL's, usernames, and hashtags. In some situations, it is known that hashtags can provide instant insight as to what the users are feeling [1]. However, most hashtags that we encountered contain meaningless text or sentences for tags instead of keywords.

We use the Naive Bayes classifier [20] to determine the sentiment of tweets. Robert Plutchik's theory [24] states that there



(a)

(b)

Figure 3. *The sentiment classification results and their geographic distribution of two time steps over Nebraska, where a green point corresponds to a tweet with positive sentiment and a red point corresponds to a tweet with negative sentiment.*

are eight basic emotions within two categories:

- negative - fear, anger, sadness, depression, disgust;
- positive - joy, trust, anticipation, surprise.

These emotions are the basic training portion of the classification of tweets. The synonyms for each category are taken into account and this sets up the basic foundation for the tweet classifier.

Other than acronyms we also need to take into account profanity. The use of profanity in social media is very high and it may lead to a positive or negative emotion depending on situations. To take into account how profanity is used in sentences, we fetched tweets to explore the usage of these words. We found that using these tweets to train the classifier gave a high accuracy rate in regards to profanity. In the beginning, we tried to remove any tweet with profanity; however, this drastically lowered our tweet count. We then tried to remove the occurrences of profanity in the tweet and used the remaining words as a judge of emotion, but this only worked in a few cases. For the majority of these tweets, we believe that profanity gave insights to negative moods and thus decided to take into account profanity.

Due to tweets using abbreviations and incomplete sentences, sentiment calculation is a non-trivial task. The classifier is trained using around 10,000 tweets, where each tweet is given a positive or negative score, and there were rare occurrences of duplicate tweets. Additionally, emotions may be affected by many things beyond weather, and a lot of tweets are actually neutral to the weather. All these weather-irrelative and neutral tweets are filtered out in the sentiment classification. After the classification, positive and negative tweets are identified in regards to the sentiments of words. Figure 3 shows the sentiment classification results of two time steps.

Correlation

We investigate the correlation between the patterns generated by the weather clustering and the sentiment classification. These patterns are characterized with geographic distributions. Figure 4 illustrates an example of two tweets, T_1 and T_2, and four weather clusters, W_1, W_2, W_3 and W_4. For a tweet, we want to find a weather cluster that may have the most influence on its sentiment. It is intuitive that the sentiment derived from a tweet is mostly affected by its overlapped weather cluster. If there is a naturally geographic overlap between a tweet and a weather cluster, the mapping is pure, such as T_1 and W_1 in Figure 4.

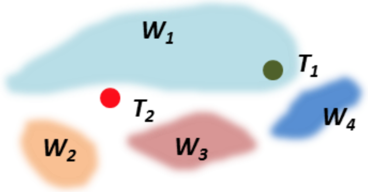


Figure 4. *The correlation between the tweets, T_1 and T_2, and the weather clusters, W_1, W_2, W_3 and W_4. T_1 is highly possible influenced by W_1 whereas T_2 might be related to one of the weathers (i.e, W_1, W_2, W_3) surrounding it.*

In situations where there is no direct overlap for a tweet to any of the weather clusters, such as T_2 in Figure 4, we explore the similarity of connections of the tweet to other clusters regardless of the sentiment it may correspond to. This is because the sentiment of the tweet can be also affected by its vicinal weather clusters. Therefore, we could quantify the correlation of the tweet to the other clusters to indicate what other clusters the tweet could map to. Particularly, we use the location of a tweet and the TSK value at the location to determine the correlation value to the points of a weather cluster using the Pearson product-moment correlation coefficient:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}, \quad (1)$$

where X is the location and the TSK value of the tweet, Y is the locations and the TSK values of all points of a weather cluster, cov is the covariance, and σ_X (σ_Y) is the standard deviation of X (Y). The correlation value of $\rho_{X,Y}$ ranges from -1 to 1. If the value is 1 (-1), it indicates a perfect positive (negative) linear relationship between X and Y. If the value is 0, it means that there is no linear relationship between X and Y. Therefore, for each tweet without direct overlapped clusters, we select the cluster that has the top value of correlation as the most influence cluster of the tweet.

Prediction

Predicting the future is mostly based on facts. We have at our disposal the current mood and the current temperature, all of the previous days tweets and the temperatures for each hour, and the predicted temperature for each hour for the next three days. Using these facts, we try to determine what the sentiment at each tweet location will be for the next three days.

Determining the mood of the current locations up to 72 hours in the future is non-trivial. Our prediction technique is based on the current hour and the previous day. We choose not to use data from earlier times because the trends today are mostly not the same a year ago, let alone a month ago. In addition to this, we should state that the long-term weather is relatively unpredictable for the state of Nebraska.

We start with a simple method of only comparing the TSK difference. If the current temperature is closer to the predicted temperature, we use the sentiment for the current hour to show the prediction. If the sentiment of the hour we are trying to pick has a closer temperature to the same hour of the previous day, we use the sentiment from the previous day.

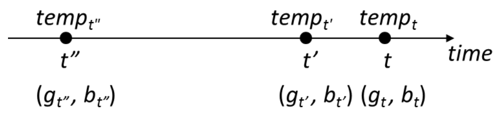


Figure 5. *The prediction model.*

However, this simple method neglects the time. Alternatively, we can consider the time difference and state that if the current hour is closer to the predicted hour we will place a higher weight on using the current hour's values; when the current hour goes further from the predicted hour, we can place more weight on the previous day value. Using this method we take the sentiment based on the percentage of the weight in terms of time.

The final method we use is a combination of above methods. As shown in Figure 5, we want to predict the sentiments at a future hour t, and we have the following information:

- t' is the current hour;
- t'' is the same hour as the predicted hour on the previous day, i.e., $t'' = t - 24$;
- $temp_t$, $temp_{t'}$ and $temp_{t''}$ are the TSK values at t, t', and t'', respectively;
- $g_{t'}$ ($g_{t''}$) is the total number of tweets with positive emotions at t' (t'') correlated to the clusters of $temp_{t'}$ ($temp_{t''}$);
- $b_{t'}$ ($b_{t''}$) is the total number of tweets with negative emotions at t' (t'') correlated to the clusters of $temp_{t'}$ ($temp_{t''}$).

Based on this information, we first compute the differences between the TSK values:

$$p_{t'} = |temp_t - temp_{t'}|; \qquad p_{t''} = |temp_t - temp_{t''}| \tag{2}$$

According to the difference values, $p_{t'}$ and $p_{t''}$, we determine the weights of the two sentiment sets:

$$w_{t'} = \frac{p_{t''}}{p_{t'} + p_{t''}}; \qquad w_{t''} = \frac{p_{t'}}{p_{t'} + p_{t''}} \tag{3}$$

Finally, we estimate the amount of tweets with positive and negative emotions, g_t and b_t, at t with respect to $temp_t$ as:

$$g_t = g_{t'} w_{t'} + g_{t''} w_{t''}; \qquad b_t = b_{t'} w_{t'} + b_{t''} w_{t''} \tag{4}$$

The method accounts directly for both the time and the temperature. We will demonstrate the details regarding how well these three methods in our empirical study.

Visualization

Simultaneously visualizing weather clusters, geographic tweet locations, and possible sentiment correlations is a challenging task. The traditional 2D weather map methods typically superimpose weather information upon a geographical map. Such a visualization can well display the two layers for the weather and tweet sentiments, where the relations between the two layers are strictly constrained by the same geographical locations. However, this is not the case when visualizing the correlations between weather and tweets. Because one's emotion could be affected by vicinal weather patterns, the traditional 2D weather map is of less help to show such relationships.

We design a novel 3D visualization to depict the analytics of weather clustering, sentient classification, and the corresponding correlation. The visualization is comprised of multiple layers. One is the weather clustering layer that has been discussed in the prior section, and the other is the geographical locations where the tweets are sent. For simplicity, we use the edges of a graph to show the emotional correlation between the layers. Also, we use color for the edges to distinguish different sentiment classification. Regarding thousands of edges would be displayed, we utilize the edge bundling technique to remedy the visual clutter. Edge bundles can also indicate how the majority of the Twitter users in the particular area feel. The interactive user operations, such as zoom-in, zoom-out and rotation, are also applied to the 3D visualization to explore the details. This visualization provides a novel and more intuitive way to present the data.

Layers

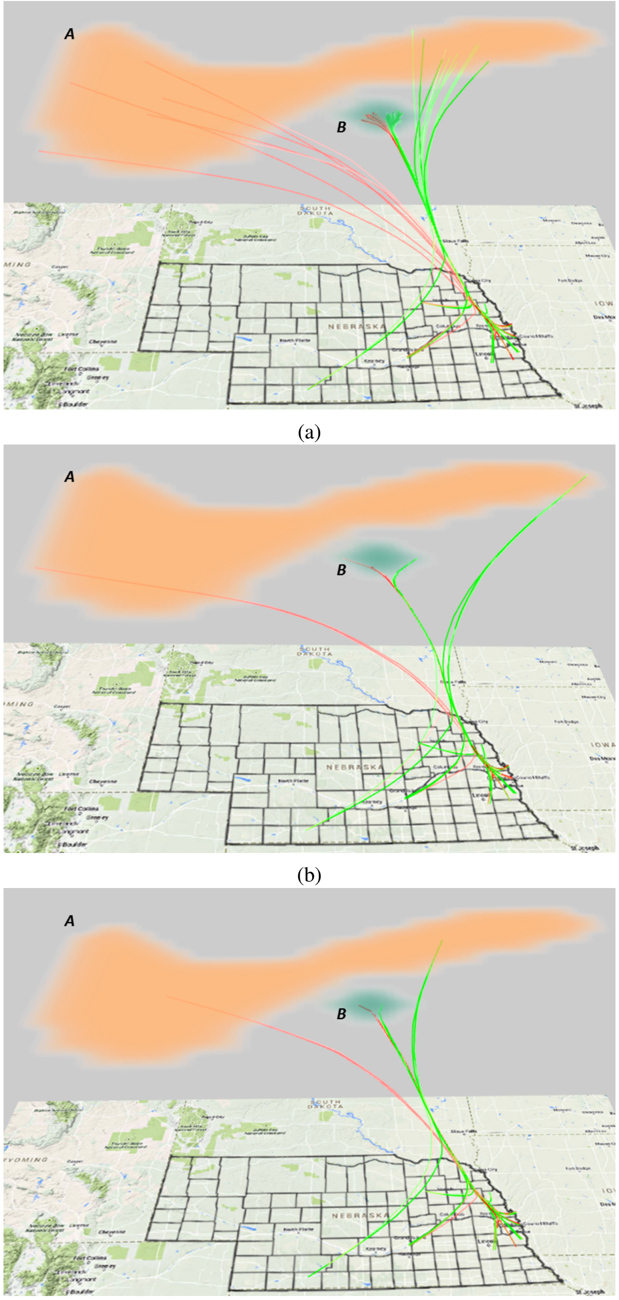
The visualization is represented by three main layers. The base layer contains the map of Nebraska and neighboring states. We have chosen to show the counties in Nebraska to gain insight on the population distribution in the state, and choose to keep the other states plain to indicate emphasis of correlation to Nebraska. Using the WRF data set for the longitude and latitude values for the map, we compute the values at intermediate locations via interpolation. We use the longitude and latitude location of each tweet to place it on the map.

The topmost layer shows the weather clusters by lifting each cluster vertically from its geographic region on the ground of map. We visualize the weather clusters using a cloud representation The middle layer contains the edges which start from the Twitter user location and ends at the weather cluster they correspond to above, according to the correlation results. We use edge bundling to succinctly display complex edges while suppressing visual clutter.

Cloud Representation

In our visualization, the weather clusters appear as clouds. Each cluster is blurred at the boundaries to remove the randomness in the cluster result, and also to make the graphical interface cleaner and aesthetically pleasing. The color of each weather cluster is mapped from purple to white with respect to lower and higher TSK values. Clusters which are not connected of the same color indicate the same conditions (i.e., similar temperature) as other locations of the state.

Because each cluster can be possibly correlated to the tweets with positive and negative emotions, we need to locate two types of edge points in the cluster for the tweets to link up to. We explore three designs on how the points should be picked. First, we assign half of one cluster to the positive emotions and the other half to the negative emotions, and randomly distribute the endpoints in the cloud. This visualization can easily generate a cluttered output, as shown in Figure 6 (a). Second, we map the tweets with positive emotions to the top rightmost point of a cluster, and map the tweets with negative emotions to the bottom leftmost point of the cluster. This method is effective until we come into situations where a tweet is related to a faraway cloud, and it will generate a long curve that crosses a big portion of screen, potentially causing visual clutter again, as shown in Figure 6 (b). Finally, we split a cluster in half and use the center points of the two halves. As shown in Figure 6 (c), this method can significantly reduce visual clutter and give the best results in our experiments.

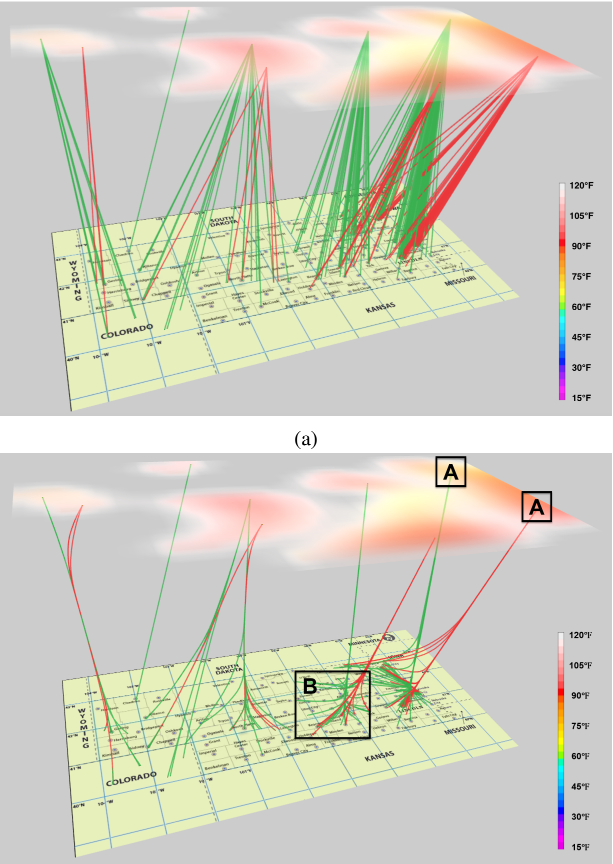


(a)

(b)

(c)

Figure 6. *Determining the best positions for indicating negative and positive tweets in the cloud repressions of clusters. (a) Use the different point of a cluster for each edge. It can easily generate visual clutter. (b) Use the top rightmost point and the bottom leftmost point of a cluster. The positive and negative endpoints in the cloud might be split up too far away that the resulting edge bundling may have a long curve cross a big portion of the screen. (c) Use the center points of the two halves of a cluster. This method is effective for both the large and small clusters,* A *and* B*, respectively.*



(a)

(b)

Figure 7. *(a) A direct visualization of the correlation graph. (b) The edge bundling result.*

Edge Bundling

Our design naturally forms a graph to represent the correlation between weather and tweets. However, visual clutter can easily occur if we directly display each edge as a straight line, as shown in Figure 7 (a). To address this issue, we adopt FDEB [10] to visualize the graph of correlation. We bundle the related edges with high compatibilities, and iteratively subdivide the edges to generate smooth curves with coherent shapes. This method can effectively reduce visual clutter in 3D.

The original paper of FDEB [10] proposed four criteria, angle, scale, position, and visibility, for edge compatibility measures. In our design, we also adopt these four compatibility measures. Hence, the 3D bundling approach is self-organizing, and the edges will be bundled according to the compatibility results. Similar to FDEB, we use an iterative simulation to refine the bundling. The simulation starts with P_0 subdivision points for each edge, and then performs C simulation cycles. During each cycle, a specific number of iteration steps I is conducted to move the subdivision points to reach an equilibrium between forces. The number of iteration steps during the first cycle is I_0. After performing a cycle, the number of subdivision points is doubled to smoothen the edges, and the number of iteration steps I is decreased by a factor R. We find that a configuration of $P_0 = 1$, $C = 6$, $I_0 = 50$, and $R = \frac{2}{3}$ leads to appropriate results in our design. Figure 7 (b) shows the edge bundling result of the same graph as in (a).

Each bundle is composed of multiple lines where each line represents one tweet. Every line corresponds to a positive or negative sentiment. The sentiment is represented in two ways. First, from the weather cluster perspective, we indicate the sentiment according to which corner of a cluster the bundle is linked to. In this way, we can easily examine the sentiments affected by a certain cluster, as shown in the two highlighted boxes marked as A in Figure 7. Second, from the tweet perspective, we associate the positive sentiments to the green bundles and the negative sentiments to the red bundles. In this way, we can intuitively convey the sentiments distribution among the tweets, as shown in the highlighted box B in Figure 7. Third, the opacity of each bundle represents the intensity of the correlation between the cluster and the tweets. The bolder the line the stronger the relationship between the two points is.

Edge bundling can effectively address the visual clutter and concisely reveal the main graph structure. However, the classic edge bundling algorithm is a serial algorithm, and it is very challenging to efficiently process a considerable number of edges. To address this, we use textures to encode the data of lines and forces, and employ GPU shaders to iteratively refine massive lines in a concurrent fashion [29]. Our parallel approach can greatly accelerate the processing of edge bundling, and interactively display a massive number of lines in the visualization. Texture is a standard feature of OpenGL and WebGL. Using texture helps deploy our visualization to various platforms portably. Our texture-based approach can interactively process and display more than two thousand bundled lines, and allow users to explore a correlation graph with a considerable size through a web browser.

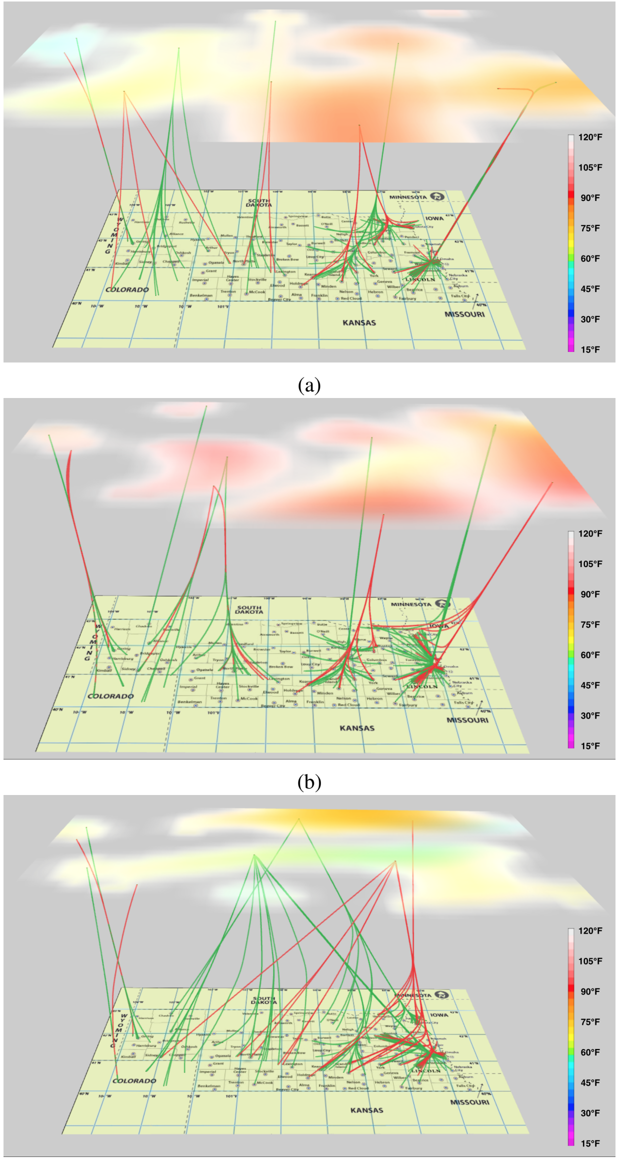
Results

Our Tweether system succinctly shows regional weather characteristics and local sentiment classification using a layered design. The edge bundling method can create smooth curves with coherent shapes and avoid visual clutter. The resulting visualization is visually aesthetic as well as directs a user's focus of attention to salient relationship between weather and mood over geographic locations and time. We implemented Tweether using JavaScript and WebGL such that the system can be viewed from any devices supporting HTML5 and WebGL.

Tweet Weather Correlation

We use the weather and Twitter data from three back to back days (from July 9th to July 11th) to see if there is any relationship between the temperature and the overall mood of people. We are lucky that during these days Nebraska has a large fluctuation in temperature such that more interesting patterns and abnormalities could be inspected in our visualization. Being on the midst of summer, we can see that the overall tweets for the colder weather will have a more positive sentiment in comparison to the hotter weather. This weather pattern also can show the potential correlation for seasonal affective disorder (SAD) [5].

We demonstrate the visualization results of three time steps across the state, as shown in Figure 8. First, the colors of the weather clusters match our expectation. In general, the afternoon of Nebraska is hot across the state during a summer. The result of Figure 8 (b) shows the temperature values are all around 85°F to 90°F whereas the morning of July 11th (Figure 8 (c)) is quite comfortable because the temperature values are generally less than 75°F. Figure 8 (a) shows the weather across the state has a significant difference during a night. The more densely populated areas like Lincoln and Omaha have higher temperatures while the west of Nebraska is much cooler. This phenomenon matches the well-known Heat Island Effect that explains why cities are hotter than countryside. We can also see that the people under the more comfortable temperature would generate more positive emotions. Figure 9 demonstrates this observation from the result of July 9th 10:00pm. The weather cluster A has a temperature of 75°F, which is comparably comfortable for human beings. In comparison to the weather clusters B, C and D, the proportion of the positive emotions appears to be the largest. Figure 10 shows the detailed statistics of sentiments across the state over these three time steps, and supports our observation. For example, in Figure 10 (a), the proportions of positive emotions are 89%, 65%, and 61% in the western, middle, and eastern Nebraska, respectively. Similar observations can be also obtained from Figure 10 (b) and (c).



(a)

(b)

(c)

Figure 8. *Tweether showing the real time mood of Nebraska correlated to the weather patterns over three time steps (a), (b), and (c) on July 9th 10:00pm, July 10th 04:00 pm, and July 11th 08:00am, respectively.*

Our visualization enables an interactive exploration and al-

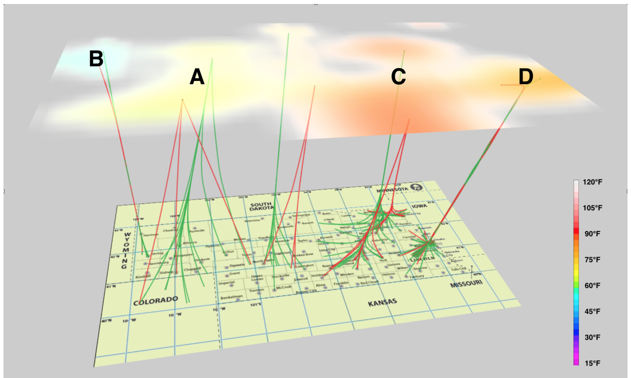
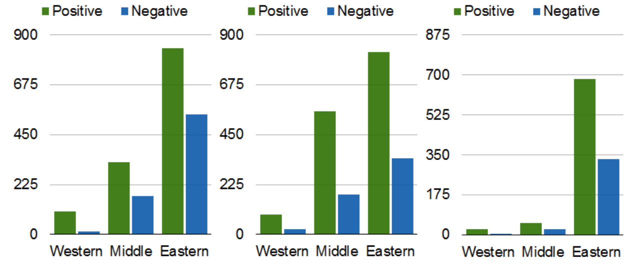


Figure 9. The tweets under the weather cluster A appear to be more positive in terms of the proportion of all tweets in that area.



(a) (b) (c)

***Figure 10.** The statistics of positive and negative tweets across the western, middle, and eastern Nebraska over three time steps (a), (b), and (c) on July 9th 10:00pm, July 10th 04:00 pm, and July 11th 08:00am, respectively.*

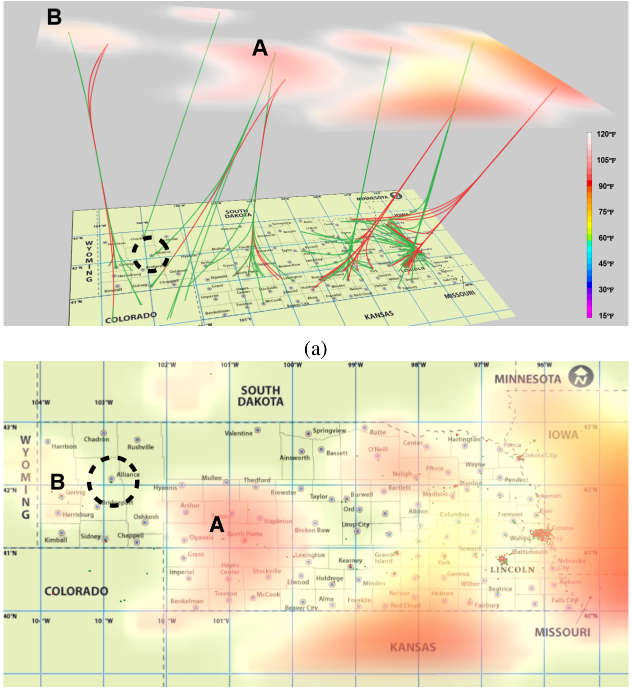
lows users to detect interesting patterns from different views. For example, in general, weather-related tweets may be affected by geographically overlapped or closet weather clouters, such as the ones of Omaha and Lincoln in Figure 11. However, we can also observe that some tweets around the small city Alliance have correlated to the cluster A on its east instead of its geographically closet cluster B, as shown in Figure 11(a). From a top view shown in Figure 11(b), we can see that although the cluster B is geographically closer to the tweets at Alliance, the cluster A has a more intensive temperature and a larger influence area. Based on our discussion on correlation in the previous section, it is possible that the correlation values of these tweets to A are larger than B. In addition, the cluster A is also relatively close to these tweets. Therefore, it is reasonable that the tweets at Alliance is more related to the cluster A other than B.

Prediction

Using the same data set we select a subset of time steps to determine if the predicted value is close to the outcome. We choose July 9th, 10th, and 11th. We collect our predictions for July 11th and compare them to the real sentiment of each hour.

Figure 12 shows the result of our prediction method at one time step. The ground truth is shown in Figure 8 (c). Figure 12 is based on our prediction method with considering both the temperature and time differences. We note that the visualization of edge bundles is very close to the ground truth.

We also quantitatively measure the errors of our prediction. We compare the number of predicted positive and negative tweets at each time step to the ones of the ground truth. For the time step in Figure 12, the relative errors for positive and negative tweets are 11% and 27%, respectively.



(a)

(b)

***Figure 11.** (a) shows a different view angle of the Figure 8 (b), and it appears that the tweets on the city Alliance is more correlated to the cluster A. (b) shows a top view revealing that although the cluster A is not closest to Alliance, it has a more intensive temperature and a larger influence area and may dominate the influence of vicinal regions.*

Interactive Web-based User Interface

Thanks to our high-performance implementation of the major steps of Tweether, particularly our new texture-based edge bundling technique, we have developed a web-based user interface in support of interactive user exploration. As shown in Figure 13, through the webpage, a user can interactively change the view angle and select the zoom level and the time step to examine the correlations in space-time. The interface also provides the aggregated information (e.g., sentiment classification) and the details of each user selected tweet. This web-based interface can facilitate the dissemination and evaluation of Tweether among a broader audience.

Discussion

There are a few aspects in regards to tweets that enforces a limit as to what we can assess. One limitation from tweets is that with a state population as small as Nebraska the chance of a user with their location enabled is relatively low. This limits the amount of tweets we can attain each hour. In the future, we would like to extend our tool to some more populous states, such as California and New York. It would be very interesting to apply our visualization to such populated areas. Some interesting observations might be gained. For example, while it may not be the case in the Midwest, rain may cause more positive sentiments other than negative ones in California because California suffers from

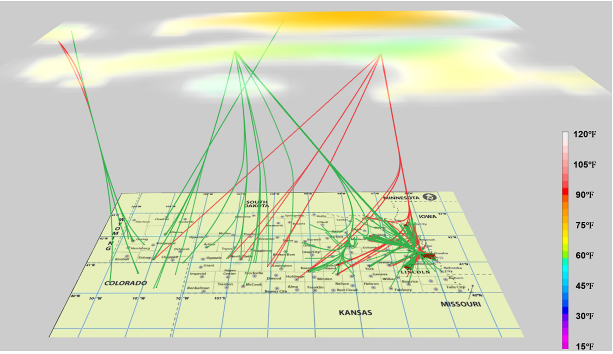


Figure 12. *The result of our prediction method for July 11th 08:00am.*

drought for years. Tweet length imposes another limitation because the complete expression of a user's feelings can be curbed in some situations. Other than Twitter's limits we need to examine the suppressed feelings of users. As Twitter is a social media hub, the need to express oneself in 140 characters may place a mask to what the user may be feeling. As proposed before there is no distinct way to determine the true feelings of a person [8]. Given this phenomena, we experimented the usage of only weather related tweets because there is a lower chance of users masking their emotions. Even in this case we saw that the majority of users use their tweets in a positive manner, so to expect a negative tweet is cynical in some sense.

Classifying the sentiment always brings errors. Humans are not known to be the most accurate at identifying the sentiment of written statements [22]. There are always certain words that can make the sentiment have a positive value instead of negative. Tweets are known to have sarcasm in terms of introducing a form of satire or irony [25]. In situations like this there are some misclassifications of sentiment.

We have experienced spring and summer weather in our current study. When we have the change of seasons it is easy to see that there is some correlation with SAD. Like most of the population, the end of summer brings new changes, and thus new feelings. We will study the sentiment changes when fall, winter, or spring approaches. Nebraska is known for its intense heat and harsh winters, but these seasons also entail vacations and family gatherings. Analyzing these aspects can also provide more insight regarding our data sets and other filtering processes that we may need.

Conclusion

In this work, we have presented a 3D visualization tool, named Tweether, that can assist analysts to explore the correlation of weather to tweets in geospace and time. We extract the dominant patterns from the weather data and classify the sentiments from the synchronized tweets. We identify the relation between weather and tweets using their geospatial relationship and the Pearson product-moment correlation coefficient. We tailor FDEB to our layered visual design and employ edge bundles to show detailed graphs of the connection between the weather clusters and the tweets. With a fine tune on graph vertex placement and edge properties, our edge bundling can significantly reduce visual clutter and clearly reveal the sentiment distribution with respect to different weather conditions in 3D. In addition, we develop a prediction model to estimate the future emotions among the tweets according to the forecasted weather. Our Tweether system integrates these data analysis models and interactive visualization, and facilities users to visually examine the connection between weather and mood and identify a possible relationship. Although researchers have presented visualizations showcasing social media sentiment or clustering of weather patterns, to the best of our knowledge we have presented here the first application to visualize the correlation between the two.

The future of this research can be expanded immensely. Although we focus on the relation to temperature in this work, the general design philosophy can be applied to precipitation, humidity, wind speed, or any other weather variables. We will conduct research regarding what the overall sentiment of people to rain, storms, and strong wind conditions. For example, there may be a significant correlation between rain amount and negative tweets [8]. We also believe that we can determine if there is a better correlation of weather to other social phenomena or events, such as road accidents, calamities from natural disasters, or even medical episodes like the flu, which can be directly impacted by the weather. Given the possible uncertainty when determining if a person's mood is truly affected by weather, we plan to involve other social phenomena or events to obtain more concrete correlation results. This work can be also expanded to other states. The outcomes in more populous states may be different. We are also interested in the states which experience less seasonal changes, and study the corresponding correlation between weather patterns and sentiments.

Other than visualization we would like to improve sentiment classifier by mining large tweet data to gain information regarding new words, such as determining sarcasm, irony, or satire, and find new linguistic patterns. This can also help improve the sentiment prediction.

Acknowledgments

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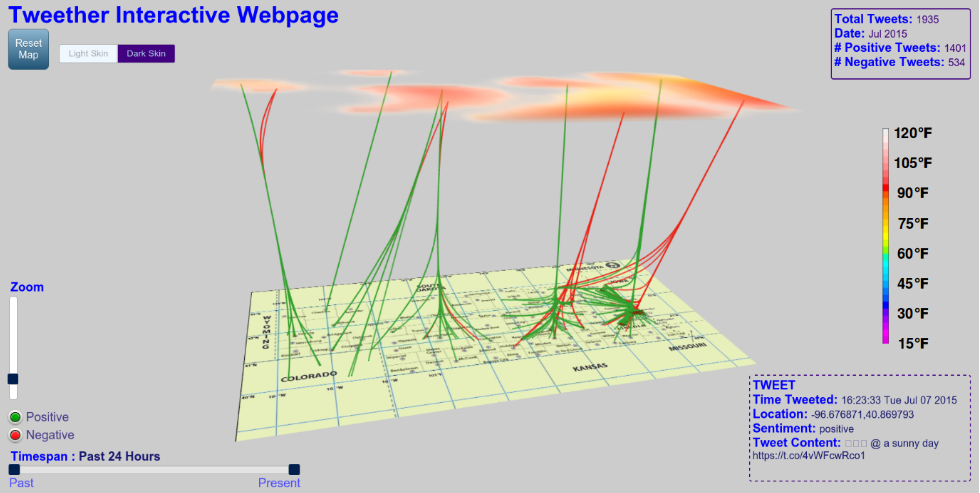

Total Tweets: 1935
Date: Jul 2015
 # Positive Tweets: 1401
 # Negative Tweets: 534

TWEET
Time Tweeted: 16:23:33 Tue Jul 07 2015
Location: -96.676871,40.869793
Sentiment: positive
Tweet Content: □□□ @ a sunny day https://t.co/4vWFcwRco1

Figure 13. *Our web-based user interface that allows multiple users to simultaneously and interactively explore Tweether in great detail.*

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