Tweether: A Visualization Tool Displaying Correlation of Weather to Tweets

Fig. 1. Tweether showing the real time mood of Nebraska.

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 dictates 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 to our emotions. However, how much weather affects us and how we display the relationship using social media remain interesting questions. Based on the natural correlation between weather and moods we propose *Tweether*, a real-time weather and tweet visualization, to see how Twitter users are feeling. This 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 locations, weather, and emotions. By aggregating multiple users with similar emotions, we create an aesthetic design that is free of visual clutter and is simple to understand in a 3D manner.

Index Terms—Time series, weather, clustering, sentiment classification, prediction, line bundling, correlation

1 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 for 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 raining?
- 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. In this work, we showcase 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. Having the weather forecast in the future, the emotions in current regions can be predicted.

We see if the weather has any correlation to the majority of the population and we try to predict the future feelings of given weathers. For example, when thinking about warm and sunny weather we naturally assume the majority of the population will be happier in comparison to dreary or cold temperatures. We plan to examine if the majority of the population follows such patterns. We will also examine how the overall sentiment changes when we filter tweets so only tweets in regards to weather are displayed.

It is not enough to just determine the correlation between emotion and weather, but a novel visualization is necessary. 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 line bundling to visualize the graph to reduce visual clutter. Introducing a clear relationship between weather and tweets, the design presents a natural manner of representing correlation.

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2 RELATED WORK

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

2.1 Psychological Studies

The natural correlation of weather with emotion has been studied profusely [1, 4, 7, 10, 16]. With various factors among the different research, the conclusions attained were broad. Humidity, sunshine, and temperature have the greatest effect on mood [1].

In some research on weather and mood, correlations have been debunked. There is no consistency due to seasons and time spent outside [4]. 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 [7]. When observing serotonin levels in regards to sunshine there were strong relationships to being happy [10]. 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 [16].

2.2 Social Media, Weather, and Emotions

When dealing with the correlation of weather with emotion the research is fairly sparse. Few work presents the use of Twitter data for their social media feed and some form of weather data. However in comparison to our work the following research was computed on past data and used a 2D graph implementation to visualize the data.

Work has been done using two to four years of Twitter data and correlating it with meteorological data from NOAA [7, 14]. 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. They first determine keywords which are identified from public events (e.g., entertainment or natural disasters), they 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 [7]. Other than using urban areas in USA they 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 saw a pattern with temperature and emotion of every state in the United States. Using regression analysis the find that the warmer states had a happier mood than the colder states. Their visualization was 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.

2.3 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, emoticons, and URL's throughout most tweets.

Certain features need to be extracted and some need to be filtered out. Filtering of URL's, usernames, Twitter special words, and emoticons may be needed in certain scenarios [14]. Stop words(i.e., a, an, the) 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 Naive Bayes classifier [14]. Emoticons are used as basis for sentiment classification for classifying tweets as positive or negative for the training purposes [12, 14].

Using emoticons for classifying training data is novel; however, most tweets gathered in the live feed have a very low count of emoticons. Thus, emoticons are not employed in our method. Filtering of URL's and usernames is used for our method. We also add the filtering process to drop phrases beginning with hashtags.

2.4 Visualizations

2.4.1 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 [19]. 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 [17]. Applying smooth data histograms for visualizing clusters in self-organizing maps is a simple method for 2D data sets [20].

The mass majority of clustering visualizations uses k-means clustering on the basis of their algorithms [17, 26]. We choose to follow this pattern as well, since K-means is a widely chosen algorithm; primarily due to it being a simple clustering algorithm [26].

2.4.2 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. A direct drawing straight lines for all edges can easily incur severe visual clutter, even with some optimization techniques, such as force-directed placement of vertices or clustering of vertices [13].

To address this issue, Holen [8] 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 cluster. Holen et al. [9] 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 [3, 25, 5, 6]. Few efforts have been dedicated to creating extensions in 3D space. Lambert et al. [15] presented a 3D edge bundling to visualize geographical networks on the Earth surface. Böttger et al. [2] 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)* [11] with an improved numerical stability.

2.5 Predictions

Using the past Twitter data set it is necessary to predict the mood for the next days. Predicting the stock market based on Twitter mood has been studied [27]. 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.

3 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 (Section 3.1). Based on the clustering result of the weather data (Section 3.2) and the sentiment prediction of each tweet (Section 3.3), we correlate these two entities (Section 3.4). We represent the derived correlation as a graph, and use line bundling for visualization (Section **??**). In addition, we also

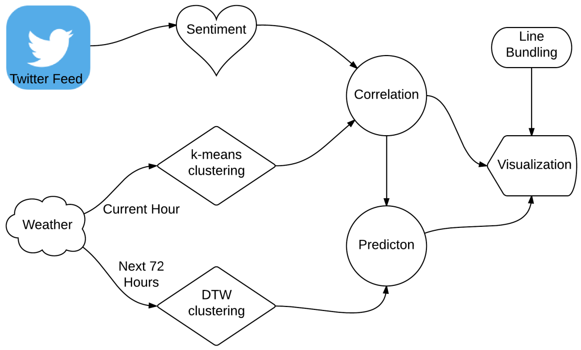


Fig. 2. The major steps of Tweether

predict the sentiment for future times (Section 3.5). The steps are illustrated in Figure 2.

Tweether in its simplest form takes tweets and assigns a sentiment value which is then correlated to the nearest weather cluster. 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 embrace the natural link of weather up in the sky to the tweets down on earth to implement our visualization (Section 4). After we implement each of the necessary steps we can clearly see how the visualization adopts a layered implementation which effectively highlights the correlation of weather and emotion in space-time.

3.1 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 [18]. 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 the WRF data that geographically corresponds to the state of Nebraska.

The Twitter data set contains the live data feed from Twitter users throughout Nebraska and 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 fairly 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. Due to some cities being on the border of Nebraska such as Omaha, the Twitter data needs to have a second filter which removes any tweets that do not have any relation with Nebraska.

3.2 Weather Clustering

We use clustering to extract different weather patterns from the WRF data and identify their geographic coverage. The clustering of weather differs depending on if looking at the current hour or the predicted values for the next 72 hours. For the current hour of weather, we use the k-means clustering algorithm. For the forecasted weather, we use a modified k-means algorithm.

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 dominated 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 which has less than one percent of the overall number of clustered elements, this cluster is removed and the data points which belong to a cluster are clustered again. This process is continued until there is no cluster which has less than one percent of the overall cluster count. For the forecasted weather, we used a modified k-means algorithm to measure the similarity between two successive hours; where we use the difference between two hours for the similarity.

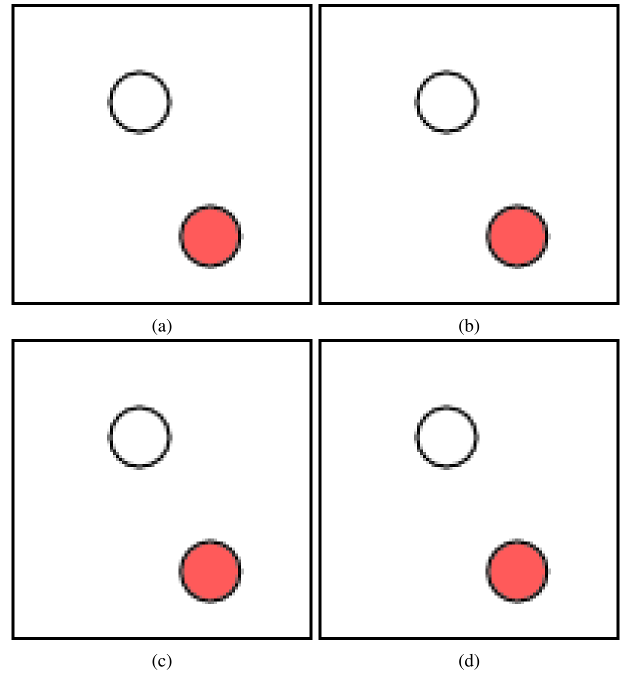


Fig. 3. (a) The distribution of TSK variable at a time step. (b) The k-means result with outliers. (c) The comparably dominated weather patterns. (d) The clustering result of forecasted weather using DTW.

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 to ensure smooth clusters can give use sufficient smooth outcome amongst the majority of 72 hours. Figure 3 (a) shows the distribution of TSK at a certain time step. A directly use of k-means can generate many dispersed small regions, as shown in Figure 3 (b). Our method can clearly extract the dominated TSK patterns, as shown in Figure 3 (c). Figure 3 (d) shows the result of forecasted weather.

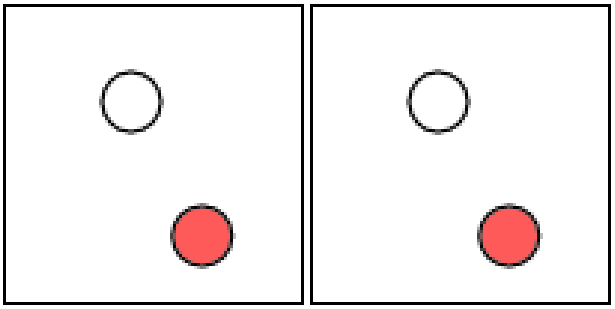
3.3 Sentiment Classification

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, emoticons, or URL's. Abbreviations, acronyms, and neologisms are taken into account for training our classifier. However, a few items are filtered from certain tweets. The filtering process removes emoticons, URL's, usernames, and hashtags. In some situations, it is known that hashtags can provide instant insight as to what the users are feeling [14]. However, most hashtags that we encountered contain less meaning text or sentences for tags instead of keywords.

We use a Bayes classifier [14] to determine the sentiment of tweets. Robert Plutchik's theory [22] states that there are eight basic emotions: check reference

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

These emotions are the basic training portion of the classification of



(a) (b)

Fig. 4. The sentiment classification results of two time steps

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 the situation. 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, which however 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, which however only worked in a few cases. For the majority of these tweets, we believed that profanity gave insight 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 was given a positive and negative score, and there were rare occurrences of duplicate tweet, and it was made sure that there was an equal portion of positive and negative tweets in regards to words where sentiment could go either way. Figure 4 shows the sentiment classification results of two time steps.

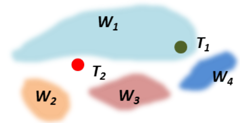
3.4 Correlation

We investigate the correlation between the patterns generated from the weather clustering and the sentiment classification. These patterns are characterized with geographic distributions. Figure 5 (left image) illustrates an examples of two tweets, T_1 and T_2, and four weather clusters, W_1, W_2, W_3 and W_4. It is intuitive that the sentiment derived from a tweet is mostly affected by its overlapped weather cluster. We call such a cluster as the *primary* cluster of a tweet. If there is a naturally geographic overlap between a tweet and a weather cluster, the mapping is pure, as T_1 and W_1 in Figure 5. In situations where there is no direct overlap for a tweet to any of the weather clusters the nearest cluster is used, as T_2 and W_1.

Other than the natural link between the primary cluster and the tweet, we explore the similarity of connections to other clusters. This is because the sentiment of a tweet can be also affected by its vicinal weather clusters. Therefore, disregarding the primary cluster, we quantify the correlation of the tweet to the other clusters to indicate what other clusters the tweet could map to. In particular, we use the location of a tweet and the TSK value at the location to determine the correlation value to the points of other clusters using the Pearson product-moment correlation coefficient: we determine the similarity of each tweet to the weather clusters:

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

where *cov* is the covariance, and σ_X (σ_Y) is the standard deviation of X (Y). Here, X and Y are ... 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.



	Primary	Secondary	Tertiary
T_1	W_1	W_3	W_2
T_2	W_1	W_4	W_3

Fig. 5. The correlation between the tweets, T_1 and T_2, and the weather clusters, W_1, W_2, W_3 and W_4. The left image shows the geographic distribution of the tweets and the weather clusters. The right table shows the primary, secondary, and tertiary weather clusters of T_1 and T_2.

In most cases, the secondary and tertiary mapping have the same sentiment since the best fit is a cluster close by with a similar temperature.

This correlation is only available for the current hour. For each tweet, we use the top two relations to other clusters which we deem the *secondary* and *tertiary* clusters, respectively.

Figure 5 shows the primary, secondary and tertiary clusters of T_1 and T_2 respectively.

3.5 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 two days. Using these facts, we try to determine what the sentiment at each location which people are currently tweeting from will be for the next two days.

Determining the mood of the current locations up to 72 hours in the future is a non-trivial task. 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 definitely 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 strategy by comparing the temperature 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.

However, this simple strategy cannot.... Depending on the hour we are trying to predict, we state that if the current hour is at most five hours ago we will place a higher weight on using the current hours values, however when going past five hours we place more weight on the previous days values, where the further we are from the current hour the less weight it plays. Using this method we take the sentiment based on the percentage of the weight.

The final method we use is a combination of above methods. We first determine the closest temperature value to the hour we are trying to predict the sentiment. Then, based on the difference, we determine the weight the two different sentiment sets place (3). As we see in (2) X and Y represent the current temperature and the previous day's temperature respectively, and Z represents the temperature of the hour that we are trying to predict. The number of good and bad sentiment lines is calculated in (4), where G and B represent the number good and bad tweets predicted by using the good and bad tweets of X and Y. The details regarding how well the different methods performed will be seen later on in the case studies.

p_1 and p_2 represent the difference between the temperatures

$$p_1 = |Z - X| \qquad p_2 = |Z - Y| \quad (2)$$

w_1 and w_2 represent weight of the temperatures

$$w_1 = \frac{p_2}{p_1 + p_2} \qquad w_2 = \frac{p_1}{p_1 + p_2} \quad (3)$$

g_x, g_y, b_x, and b_y represent the amount of good and bad tweets in X and Y

$$G = g_x w_1 + g_y w_2 \qquad B = b_x w_1 + b_y w_2 \quad (4)$$

4 VISUALIZATION

The novelty of this work is pictured through the 3-dimensional visualization. The visualization is comprised of multiple layers where there is a natural visual connection between the layers. Many different methods could represent this data correlation however, we have created a novel visualization where the weather above affects the people below. The layers are connected via line bundles to dictate how the majority of the Twitter users in Nebraska are feeling.

4.1 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, however we choose to keep the other states plain to indicate emphasis of correlation to Nebraska as shown in Figure 6.

On the map of Nebraska, there are red circles which indicate the area that Twitter users are posting from. The radius of the circle corresponds to the amount of people posting tweets in the vicinity. Using the WRF data set for the longitude and latitude values for the map, we obtained the intermediate values via interpolation. For each tweet location, the euclidean distance is calculated to get the nearest longitude and latitude location.

The middle region contains the line bundles which starts from the Twitter user location and ends at the weather cluster they correspond to above depending on the sentiment. The topmost layer is the weather clusters.

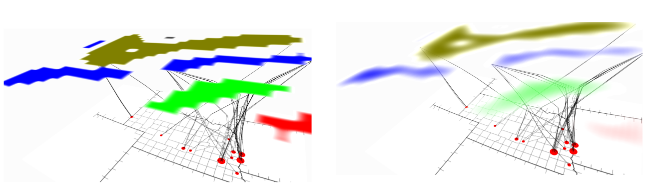
The middle region contains the line bundles from the Twitter user location to the weather cluster they correspond to above depending on the sentiment.The topmost layer is the weather clusters.

4.2 Cloud Reperesentation

Each cluster is represented by a different color. Clusters which aren't connected of the same color indicate the same conditions such as similar temperature, in other locations of Nebraska as seen in Figure 6.

Once the cluster for each hour was attained we needed two edge points for the data to link up to. These two edge points correspond to positive and negative emotions. We had different ideas on how the points should be picked. At first we were thinking to give half of one cluster to the positive emotion and the other half to negative emotions. This method seemed like a good idea at the beginning however in the visualization the output looked cluttered as seen in Figure 7(a). The second method we tried split the cluster in half and used the center points of the two half's. This was also a good idea until we came into situations where the cluster was represented by a very small amount of data points causing the visualization to look awkward. (Figure 7) We finally decided on a method where for each cluster the positive tweets would map to top rightmost point in the cluster and the negative tweets would map to the bottom leftmost point. This reduced visual clutter and helped in situations where the cluster size is fairly small. (Figure 7)

In our visualization, the clusters appear as clouds. Initially, we had the user space and the weather space flipped, however, we believe that the way we present the data is novel and more intuitive. Each cluster is blurred at the boundaries to make the graphical interface cleaner and aesthetically pleasing as seen in Figure 6(b).



(a) Before blurring (b) After blurring

Fig. 6. Clustering of the weather. In this hour we see five different clusters. The blue cluster is seen in three different locations.

4.3 Line Bundling

Each bundle is composed of multiple lines where each line represents one tweet. Every bundle represents positive or negative sentiment. The sentiment is represented in two ways. Depending on which corner the bundle is linked to indicates the sentiment, also the more intuitive notion is the color of the bundle. Naturally we associate the positive sentiments to the green bundles and the negative sentiments to the red bundles.

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. The primary cluster has a stronger hue in comparison to the secondary and tertiary clusters. Both of these links will have a staggered decrease of intensity of color. Thus, we state that the more prominent the link between the tweet and the cluster the higher the opacity of the line.

5 CASE STUDIES

For our work, we have two goals. We first want to determine if there is any correlation between weather and mood. Secondly we would like to determine if our predicted mood is correct.

5.1 Tweet weather correlation

We use two data sets to show our visualization. Using weather and twitter data from two back to back weekends we see if there is any relationship between the temperature and the overall mood of people. We are lucky that the days we chose show warmer changes in weather. Being on the brink of Spring we predict that the overall Tweets for the warmer weekend will have a more positive sentiment in comparison to the colder weekend. This weather pattern also can show any correlation we find for Seasonal Affective Disorder.

5.1.1 All Tweets

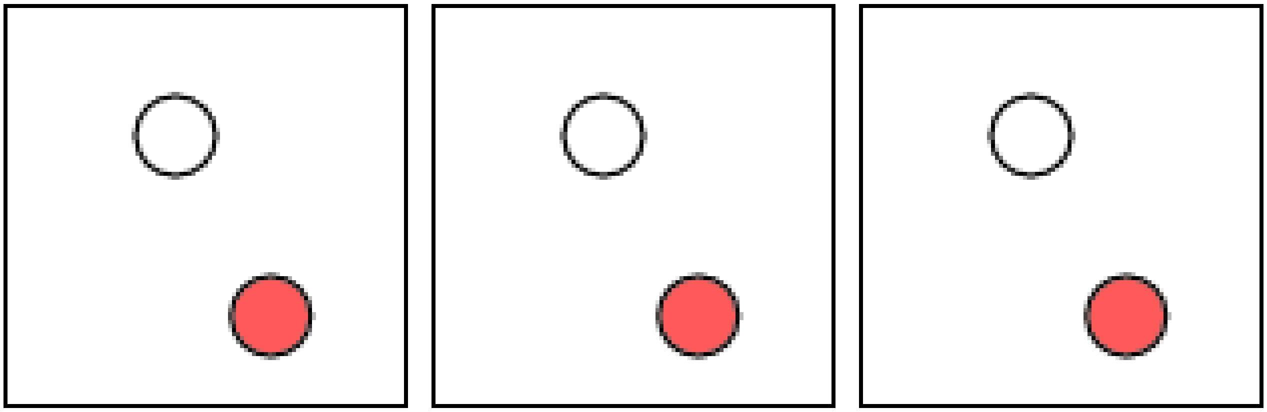
Of all the cities, we see that Omaha and Lincoln have the most tweets, so we will use these two cities to display our results. The weather patterns of the two weekends are shown in Figure 8(a). As seen in the figure, we choose to look at times where most of the population is awake (i.e. noon to 11 PM). From Figure 8(b) we can see the tweets and their sentiment for select days through the two weeks, where more emphasis is placed on the first week and less on the later. Each date has a positive and negative count, where we see that the pattern throughout is that the positive tweets outweigh the negative tweets. Another pattern that we see is that as the temperature increases the number of tweets increase however we see that more people tweet on Saturday than on Sunday. We think that this has to do with a number of factors; people go to church on Sunday where they choose to be among family, they do work around the house, or they don't have any eventful things which they feel they need to share.

We do not see that with the change of temperature that there is a clear trend of more positive tweets versus negative tweets. The number of positive tweets is at least half the amount of negative tweets. The only item that we could see which may be weather related is that the amount of negative tweets is percentage wise far more in the colder temperatures in comparison to the warmer temperatures. In lieu of not finding any clear results, we look at tweets only with words related to weather to see if we find any trends.

5.1.2 Weather related tweets

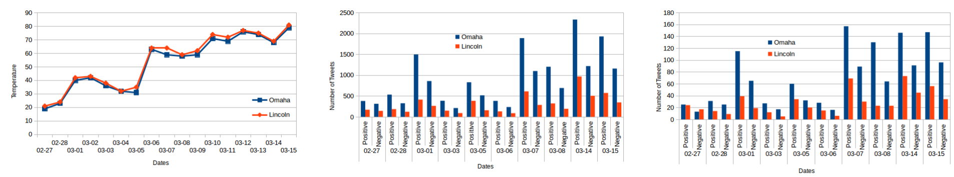
Other than using all the tweets we collected we filter the collected tweets for weather-related terms. (i.e. snow, sunny, warm, cold, rain, etc.) We wanted to see if there was a stronger correlation in this situation compared to using all the tweets collected. In this situation, we are unfortunately limited to a few tweets. As we see in Figure 8(c) we see that the number of tweets drastically reduces to at most slightly less than 160 tweets for one day.

Fortunately, we are able to see a pattern with weather and positive tweets. There is a spike of tweets when there is warmer weather. This pattern is seen in both sets of tweet data sets. However, we are now able to confirm that the correlation is due to weather. As the weather increased slightly on March 1st we see a spike in amount of tweets



(a) Half good half bad (b) Half good half bad centers (c) Corners

Fig. 7. Determining the best position for indicating negative and positive tweets in the cloud clusters.



(a) Temperatures in Omaha and Lincoln (b) Sentiment of Omaha and Lincoln Tweets (c) Sentiment of Omaha and Lincoln Tweets

Fig. 8. The comparison of weather to sentiment.

overall(Figure 8(b)) and also when the tweets had weather-related words(Figure 8(c)). We can also see that in Figure 8(c) that with the warmer weather the number of tweets in relation to the weather increased by approximately twice the amount. We still see the trend of more positive tweets in comparison to negative tweets when using the filtered data set.

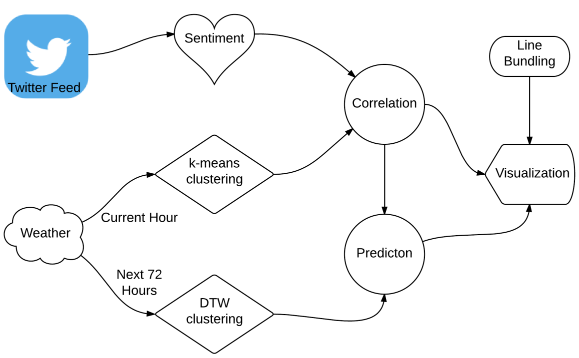


Fig. 9. Accuracy of the different prediction methods

5.2 Predicted?

Using the same data set we select a subset of two weekends to determine if the predicted value was close to the outcome. We chose March 6th, 7th and 8th for weekend one and March 13th, 14th and 15th for weekend two. The first weekend has between 10 to 20 degrees difference to the second weekend to take into account any change in weather patterns. We collect our predictions for Saturday and Sunday and compare them to the real sentiment of each hour. Again we focus on the two most populous cities in Nebraska; Lincoln and Omaha.

As we see in Figure 9 the accuracy of the three methods we used are shown.

6 Discussion

We used a large data set to determine if there was any noticeable correlation, and we filter the data set to determine if this could provide a better indication of correlation. We saw that most of the tweets were positive in colder and warmer temperatures, however, the number of tweets increased as the temperature rose. We observed the number of positive tweets percentage wise was much higher when the temperature rose. Even though, our initial aim was to find a distinct answer to the question: Does the weather affect mood?, we were not able to gain concrete results. We were able to find other patterns from our analysis.

Our bundling methods created smooth curves to create an aesthetic design. ....

We were able to determine the possible sentiment of users in select regions, even with lower a population. The results show ......

Correlating tweets to weather patterns is not a trivial task and requires multiple steps which can create errors at each step. Having a multi-step process the chance of error from classification can occur.

There are a few items in regards to tweets that enforces a limit as to what we can assess. One drawback from tweets is that with a state population as small as Nebraska the chance of a user with their location enabled is minute. This drastically limits the amount of tweets we can attain each hour. Another limitation in some situations is tweet length since this may cause the complete expression of a user's feelings to be curbed. Other than Twitters limits we need to examine the suppressed feelings of users. Since 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.[3] Due to this phenomena we proposed the usage of only weather related tweets, due to there being a low chance of users masking their emotions. Even with this 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 error. Humans aren't known to be the most accurate at identifying the sentiment of written statements. [21] When bringing in our own classifier, we believe that it can be improved. There are always certain words that can make the sentiment have a positive value instead of negative. Tweets are known to have sarcasm in them to introduce a form of satire or irony. [23] In situations like this there are some misclassifications of sentiment.

We believe that using the current weather limits us on other seasons which are approaching. So far, we have experienced winter and spring weather. When we have the change of seasons it's easy to see that there is some correlation with SAD. Like most of the population, the end of winter brings new changes, and thus new feelings. However, we don't know how the sentiment will change when summer, fall, or winter approaches. Nebraska is known for its intense heat and harsh winters, but these seasons also entail vacations and family gatherings. Analyzing these things can also provide more insight regarding our data sets, and what other filtering processes we may need.

7 Future Work

The future of this research can be expanded immensely. There are various aspects we can add to the existing work, or even alter the existing work. For altering existing work, we would like to in the future make a cleaner looking visualization. Currently, there seems to be some rigidness to the design where corners could be smoothed have a clearer indication of what places link up to where. We also feel that we can make the design more intuitive without adding additional elements. Other than visualization we would like to implement a better sentiment classifier. Just by polling more tweets and gaining information regarding new words, determining sarcasm, irony, or satire, and finding new linguistic patterns we believe we can gain a better classifier. Additionally we would also like to improve the sentiment prediction.

For supplementing this work, we have a few items which we believe we can add. This work as of now only sees the relation to temperature, but this study could be extended to be applied to precipitation, humidity, wind speed, or any other weather variables. There may be a significant correlation between rain amount and negative tweets. As we approach warmer climates we can conduct research regarding what the overall sentiment of people to rain, storms, and strong wind conditions. We also believe that we can determine if there is a better correlation of weather to other variables, possibly ones which are directly impacted by weather such as road accidents, calamities from natural disasters, or even medical episodes like the flu. Since there is no real way to determine if a person's mood is truly affected by weather we think using some other variables can provide more concrete correlation results.

This work can be expanded to other states and see if in more populous states the outcome would be more different. We also think that states which don't experience much seasonal change will have very different outcomes and not reflect any correlation between weather patterns and sentiment.

8 Conclusion

In this paper, we introduced Tweether, a visualization tool for displaying the correlation of weather to tweets. Other than making a novel visualization to showcase correlation between weather and sentiment our main goal was to determine if there was any correlation between usage of social media and weather patterns. Using two data sets, we were able to determine that there is some correlation with the amount of tweets related to weather when it is warm in comparison to the colder weather.

Visualizations showcasing social media sentiment has been done many times before, and similarly clustering of weather has been implemented numerous times before. However, there have been few to none works out there which try to find the correlation between the two.

We realized that this work can be expanded to apply to many different scenarios, but we chose to apply it to a question that has been asked for centuries. ...

Our prediction technique worked for...

The line bundling implemented in this visualization is an entity on its own and should be applied to many different works. ...

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