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Tweet Emotion Mapping: Understanding US Emotions in Time and Space

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***Abstract*—Twitter is one of the most popular social media platform where users post their views and emotions on a regular basis. Consequently, Twitter tweets have become a valuable knowledge source for emotion analysis. In this paper, we present a new framework for tweet emotion mapping and emotion change analysis. It introduces a novel, generic spatio-temporal data analysis and storytelling framework and its architecture. The input for our approach are the location and time were and when the tweets were posted and an emotion assessment score in [-1, +1], with +1 denoting a very positive emotion and -1 a very negative emotion. Our first step is to segment the input dataset into batches with each batch containing tweets that occur in a specific time interval, for example weekly, monthly or daily. Next, by generalizing existing kernel density estimation techniques, we transform each batch into a continuous function that takes positive and negative values. Next, we use contouring algorithms to find contiguous regions with highly positive and highly negative emotions for each of the batch. After that, we apply a generic, change analysis framework that monitors how positive and negative emotion regions evolve over time. In particularly, using this framework unary and binary change predicate are defined and matched against the identified spatial clusters, and change relationships will then be recorded, for those spatial clusters for which a match occurred. Finally, we propose animation techniques to facilitate spatio-temporal data storytelling based on the obtained spatio-temporal data analysis results. We demo our approach using tweets collected in the state of New York in June 2014.**

***Index Terms*—Sentiment analysis, Tweet Emotion Mapping, Spatial Clustering and Hotspot Discovery, Emotion Change Analysis, Kernel Density Estimation, Spatio-Temporal Data Storytelling**

I. Introduction

Emotions are a mandatory part of human nature that can be considered as hereditary. They can play an important role in how we think and behave. The emotions we feel each day can compel us to take action and influence the decisions we make about our lives [1]. To convey our emotions, we use the language. Automatically identifying emotions expressed in the text has a number of applications, including customer relation management, determining the popularity of products and governments [2], and improving human-computer interaction [3] [4].

With the strong development of social media, tracking emotions becomes easier, faster and more reliable than using the traditional public surveys or polls [5]. With the rapid global proliferation of microblogging websites, there has been growing interest in using this existing source of easily accessible data to extract social science knowledge. Twitter as an example has evolved to become a great tool with various kind of information. People can post real-time messages regarding their opinions on a variety of topics, discuss current issues, complain, and express many kinds of emotions. Thus, user generated content on Twitter (produced at an enormous rate of 340 million tweets per day) provides a rich source for gleaning people's emotions, which is necessary for a deeper understanding of people's behaviors and actions [6]. During the last years, Twitter has been the subject of extensive research and analysis [7] [8] [9]. Twitter analysis research has concentrated on sentiment analysis, which categorizes tweets as positive, negative or neutral. The majority of the existing approaches focus on the lexical content of a tweet to measure the emotion it expresses. Batool et al. [10] have proposed a technique that identifies keywords, entities and synonyms from a tweet to do sentiment analysis. Venugopalan et al. [11] have developed another framework that uses domain independent and domain-specific lexicons to identify the sentiments expressed by users in their tweets.

In this paper, we focus on measuring and summarizing the well-being of large populations and how their happiness evolves over time. A novel spatio-temporal data analysis framework will be introduced in this paper to facilitate emotion mapping and change analysis and the creation of animations to facilitate spatio-temporal data storytelling Two other projects were interested in the measuring happiness: The Hedonometer project [12] uncovers and explains the temporal variations in happiness and provides a website and visualizations to display its findings on a day-to-day basis. The second project is the UN World Happiness Report 2018 [13] which ranks 156 countries by their happiness levels. This is a accomplished by relying on citizens to fill out questionnaires that inquire six key variables that are believed to play a key role for measuring happiness:

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well-being: income, healthy life expectancy, social support, freedom, trust, and generosity.

However, the mentioned research lacks spatio-temporal data analysis and storytelling capabilities and the goal of our current research is to provide such capabilities. To the best of our knowledge, our project is the first research project that analyzes, summarizes and animates how spatial clusters of highly positive and negative emotions appear, continue, disappear, intensify, grow and shrink in time and space. Geo-tweets are used in this paper as the knowledge source to measure happiness.

This paper's main contributions include:

- It introduces a novel, generic spatio-temporal data analysis and storytelling framework and its architecture.

- It introduces emotion-weighted density estimation, which generalizes classical kernel density estimation, to consider emotion values associated with tweets and uses contouring algorithms to identify positive and negative emotion regions.

- It provides a novel, generic change analysis framework to capture and summarize the evolution of positive and negative emotion regions.

The remainder of the paper is organized as follows. Section II introduces the architecture of the proposed emotion analysis system. Section III introduces the proposed emotion-weighted density estimation approach and discusses our spatial clustering approach to identify positive and negative emotion regions. Section IV introduces an emotion change analysis framework and briefly discusses how to facilitate emotion evolution storytelling. Finally, section V summarizes and discusses our research result.

II. Architecture of the Proposed System

In this section, we describe the architecture of an integrated framework for tweet emotion mapping, change analysis and storytelling. Fig, 1 depicts the architecture of the system we are currently developing. The input for our system are the location and time where and when the tweets were posted and an emotion assessment score in [-1, +1], with +1 denoting a very positive emotion and -1 a very negative emotion. This input is processed as follows. First, we partition the input dataset of emotion-annotated tweets into consecutive temporal batches. For example, geo-tweets that were recorded for the month of June 2018 in New York, might be transformed into 30 batches with each batch containing the emotion-annotated tweets of a single day.

Next, we apply an emotion-weighted density estimation approach to transform each batch into a continuous function that takes positive and negative values—the obtained values are proportional to the degree of happiness/unhappiness at a measuring point. Next, a contour-based spatial clustering algorithm is applied to the continuous functions that were obtained in the previous step to identify contiguous regions with highly positive and highly negative emotions for each batch. Next, a generic, change analysis framework will be employed to summarize how positive and negative emotion regions evolve over time. Finally, a spatio-temporal data storytelling component creates animations and narrative based on the obtained spatio-temporal data analysis results. We also provide navigational capability to the user. User can navigate through the emotion-weighted density functions, spatial clusters and change graphs and display these emotions.

Details about the different components of our proposed emotion mapping and analysis framework will be discussed next in Sections III and IV. As the design and implementation of the spatial-temporal data storytelling component has not been completed yet, this component will only very briefly discussed at the end of Section IV.

III. Creating Positive and Negative Emotion Clusters

A. Dataset Creation

We have used the "Geotagged Twitter posts [14] from the United States" in our experiments. This dataset consists of the geotagged Twitter posts' Ids from within the United States. The data is provided as files per day. We next use the twarc python package to rehydrate the tweet Ids and obtain the tweet data in the JSON format. Rehydrate command essentially reads the tweet Id and using Twitter's status/lookup API writes the corresponding tweet in a JSON file. The JSON file is next converted into a CSV file which contains the timestamp, longitude, latitude and the text of each tweet. The text of the tweets is then preprocessed using the Preprocessor python library. This library helps in cleaning, parsing and tokenizing the tweet data by identifying URLs, hashtags, smileys, etc.

The next task is to assign an emotional score to each tweet. We use the Python package VaderSentiment for this purpose. VADER stands for Valence Aware Dictionary and Sentiment Reasoner [15]. It is a sentiment analysis tool specifically built for the sentiments expressed in social media. VADER uses lexicon of commonly used sentimental words to rate each tweet. For each tweet, the analyzer parses the tweet and then checks its lexicon for the sentimental words. Finally, the weighted average of sentimental words is returned as the final emotional score; the obtained scores range in [-1,1].

1) Emotion-weighted Density Estimation: Traditional density estimation techniques consider only the spatial dimension of data points ignoring non-spatial information. In this paper, we propose a novel density estimation technique called emotion-weighted density estimation. It differs from the traditional density estimation by additionally considering a non-spatial, continuous variable of interest in its influence function. The new influence function is defined as the product of a traditional, kernel density estimation influence function and the variable of interest, which takes values in [-1,1], representing negative, neutral, and positive emotions.

Throughout the paper, we assume that datasets have the form $(< location >, < variable\_of\_interest >)$. More formally, a dataset O is a set of data objects, where n is the number of objects in O belonging to a feature space F.

$$O = \{o_1, o_2, ..., o_n\} \subseteq F \quad (1)$$

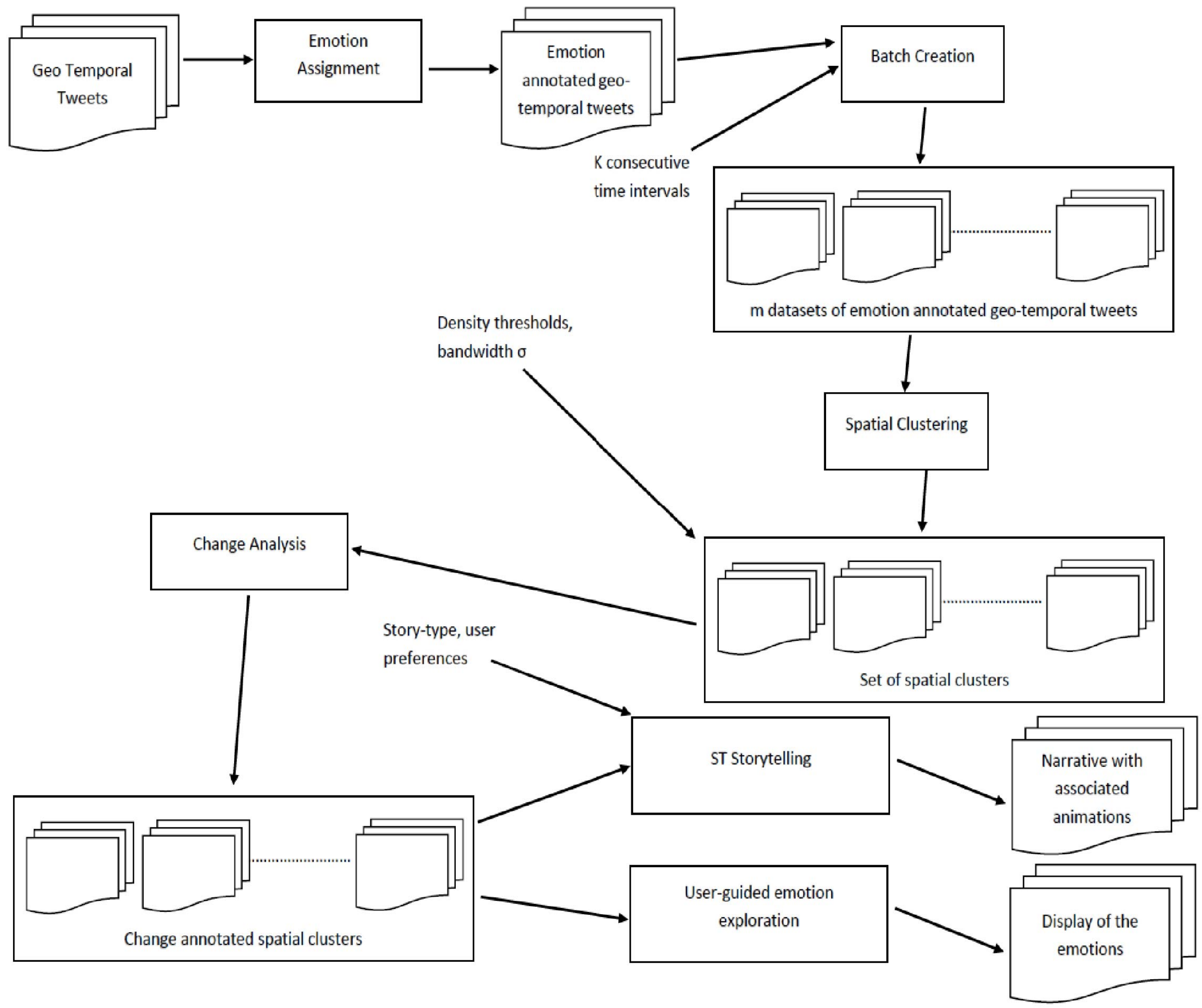

Fig. 1: Architecture of the proposed framework

We assume that objects $o \in O$ have the form $((x, y), e)$ where (x, y) is the location of object o, and e denoted as $E(o)$ in the following is the value of the variable of interest of object o. The distance between two objects in O say $o_1 = ((x_1, y_1), e_1)$ and $o_2 = ((x_2, y_2), e_2)$ is measured as $d((x_1, y_1), (x_2, y_2))$ where d denotes a distance measure. Throughout this paper d is assumed to be Euclidian distance.

In general, density estimation techniques employ influence functions that measure the influence of a point $o \in O$ with respect to another point $v \in F$; moreover, a point o's influence on another point v's density decreases as the distance between o and v increases. In contrast to past work in density estimation, our approach employs weighted influence functions to measure the density in datasets O: the influence of o on v is measured as a product of $E(o)$ and a Gaussian kernel function. In particular, the influence of object $o \in O$ on a point $v \in F$ is defined as:

$$f_{influence}(v, o) = E(o) * e^{\frac{-d(v,o)^2}{2\sigma^2}} \tag{2}$$

If $\forall o \in O$, $E(o) = 1$ holds, the above influence function becomes a Gaussian kernel density function, commonly used for density estimation. The parameter σ determines how quickly the influence of o on v decreases as the distance between o and v increases.

The accumulated influence of all data objects $o \in O$ on a point $v \in F$ is used to define a density function $\psi^O(v)$, as follows:

$$\psi^O(v) = \Sigma_{o \in O} f_{influence}(v, o) \tag{3}$$

For the purpose of this research we assume that $E(o)$, where $o \in O$ is assumed to be a tweet, taking emotion values in [-1,1]. Our goal is to identify contiguous, *positive emotion spatial regions P* for which the $\psi^O(p) > \theta_1$ for all objects

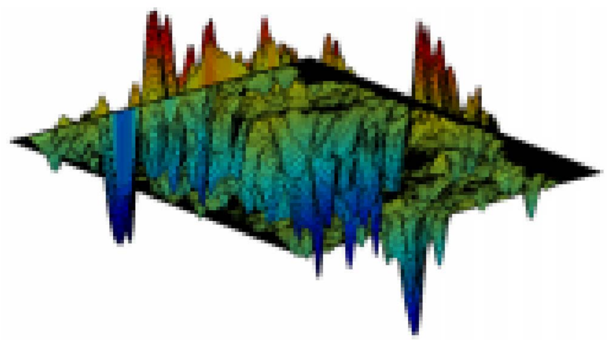

Fig. 2: Example of an Emotion-Weighted Density Function

$p \in P$ and to identify contiguous, *negative emotion spatial regions* N for which $\psi^O(p) < \theta_2$ for all objects $n \in N$. Moreover, it is possible that the objects x belonging to a region X take values close to 0 for $\psi^O(x)$; in this case, there are two possible explanations for this to happen:

1) There is a balance of negative and positive emotions in region X or
2) Region X is very sparse with respect to tweets; therefore, its density is low.

However, the distinction between these two cases is not very relevant for the for the propose of this research, as we focus on finding regions for which ψ takes values significantly larger and smaller than 0.

In summary, according to our previous discussion, the influence of tweets far away from the query point v is much less than the influence tweets nearby v; furthermore, very positive or negative emotion tweets having very high/low emotion values have a stronger influence than tweets whose emotion values close to 0; that is, the proposed emotion-weighted density estimation approach "balances" these two forces. Finally, it should be noted that the proposed emotion-weighted density estimation approach creates a density function that takes positive and negative values, as depicted in Figure 2. This might look unusual to some readers; however, in a well-known book on density estimation Silverman observes *"there are some arguments in favor of using kernels that take negative as well as positive values..."* [16].

B. Obtaining Positive and Negative Emotion Spatial Clusters

Once the continuous function $\psi^O(v)$ has been obtained the next step is to obtain positive and negative emotion regions which are contiguous regions in space whose density is either above θ_1, or below θ_2—with θ_1 and θ_2 being the density thresholds. Generalizing our spatial clustering work that originally operates on traditional density functions [17], we employ contouring algorithms to obtain positive and negative emotion regions as polygons; our approach supports polygons with holes. We will describe this process in more detail in the next paragraph.

The first step is to divide the dataset into a number of grids. Next using the spatial density function $\psi^O(v)$, obtained in the last step, we calculate the density values for all the grid intersection points. These density values are then weighted with the average of the emotional scores of the nearby grid cells. That is, for each grid intersection point, we find all the emotional scores that lie in the four neighboring cells and then take their average. Next, using the product of the density values with the emotional scores for all intersection points as an input, we call the CONREC [18] contouring algorithm to compute the contour lines for all density thresholds.

Next, in a post-processing process, spatial cluster polygons are computed as polygons from those contour lines. Challenges of this post-processing step include: a. creating closed contour lines for contour lines that lie on the boundary of the observation area, b. distinguishing between holes and spatial clusters and c. removing small and insignificant clusters. More details about this post-processing step have been discussed in [17].

In summary, the output of this step is a set of spatial clusters with each spatial cluster being described by: a polygon describing its scope, the average and standard deviation of emotion values of tweets that are inside of the spatial cluster polygon, and the density thresholds for which the spatial cluster was obtained.

C. Spatial Clustering Results

We have run the framework for tweets in New York State from June 1 to June 16, 2014 for four different density threshold values. We have used daily batches in our experiments. Figures 3 and 4 depict the spatial clustering results we have obtained for tweets that were posted on June 1 and June 2, respectively. In the figure red polygons depict high negative emotion clusters, blue polygons depict medium negative emotion clusters, orange polygon depict high positive emotion clusters, and green polygons depict medium positive emotion clusters. As we can see, overall there are more positive emotions. One of the interesting observation is that June 1 seems to have more clusters than June 2. This can be attributed to the fact that June 1 was a Sunday and, therefore, people were more active on the social media. We also see that the spatial clusters are more concentrated in the cities, like Buffalo and New York City, for example.

Focussing on the New York City tweets, we see that the positive emotions deintensifies from June 1 to June 2. The orange postive emotion clusters from June 1 and June 2 are not similar. For the orange color clusters there is a significant change, however, the green cluster does not change much. Also the small red cluster that was cutting the green cluster on June 1 disappears on June 2. Therefore, though the big green cluster contain three orange clusters both on June 1 and June2, thos on June 2 are smaller in size and in different locations. On June 1, we have three highly positive clusters in the area. But when we look at June 2, the size of the clusters is reduced. For Rochester, the positive emotion cluster denoted by orange color loses intensity going from June 1 to June 2. The highly positive emotion cluster denoted by green color moves north.

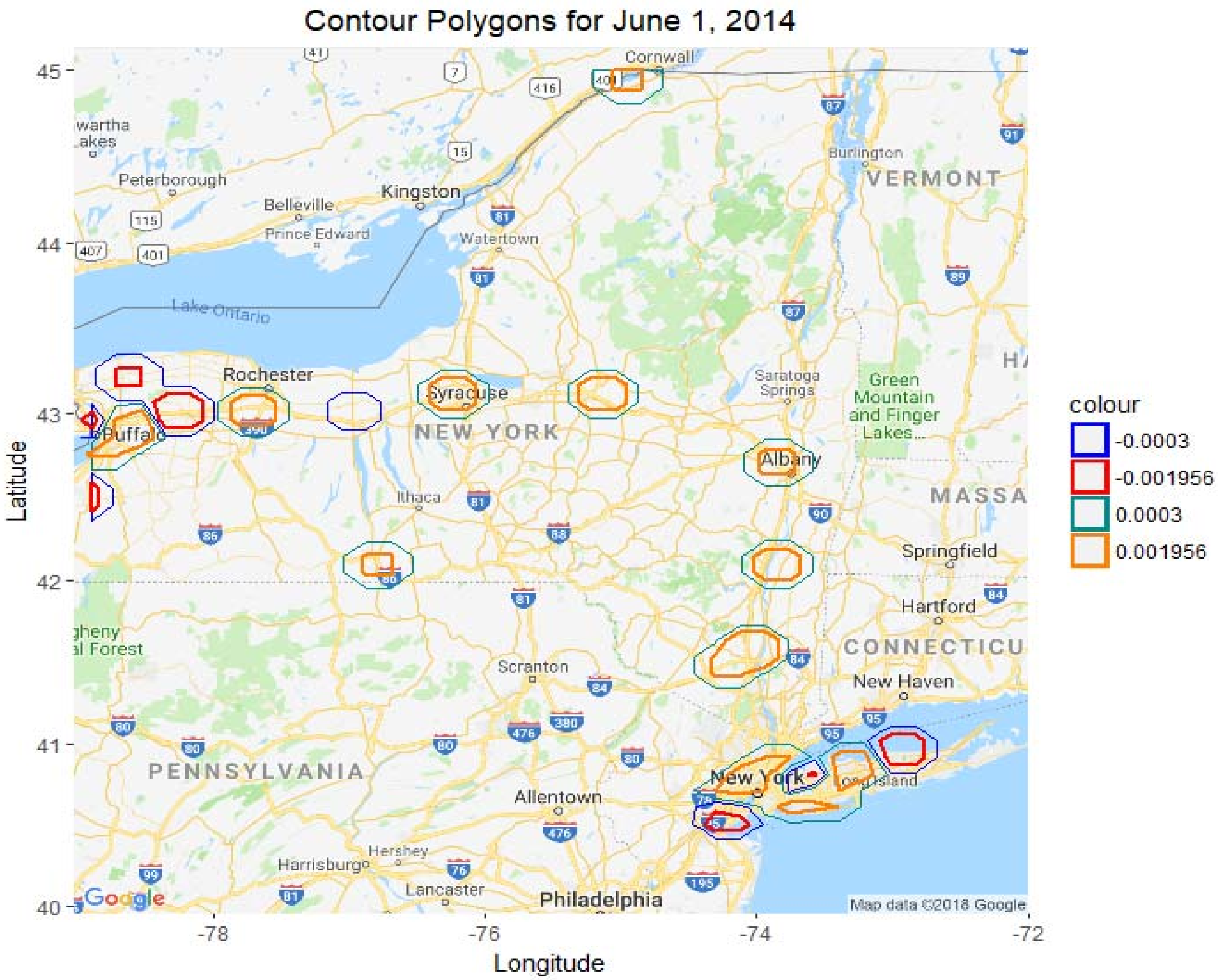

Fig. 3: Spatial Clusters for June 1, 2014

IV. Analyzing and Animating Emotion Change over Time

A. Analyzing Change of Emotions

Analyzing change in spatial data is critical for many applications including developing early warning systems that monitor environmental conditions, detecting political unrest and crime monitoring. Addressing this need, our framework detects and analyzes how the patterns of emotion change over time and space; in our particular approach change is analyzed by comparing sets of polygons which represent spatial clusters for a particular time window/batch that have been created with the methods we described in Section 3.

As shown in Figure 1, the input of the change analysis component is a set of spatial clusters, each of which is characterized by a scope polygon, average emotion value, and an emotion standard deviation, and a density-threshold. Each spatial cluster belongs to a single batch.

Emotion change analysis is conducted by analyzing particular relationships between polygons belonging to different batches. This is done by introducing a set of change predicates that refer to spatial clusters—belonging to different batches—and their average emotion values and other emotion value statistics. If a change predicate is satisfied, a relationship between the spatial cluster in question and another spatial cluster is present and will be recorded. In general, the output of the change analysis process is a change graph that represents the spatial clusters that occurred in various batches as nodes, and whose edges represent particular types of change relationship that holds between a pair of spatial clusters. Examples of change types include continuing spatial clusters, shrinking spatial clusters, continuing spatial clusters whose emotion intensity significantly changed. Moreover, relationships of a

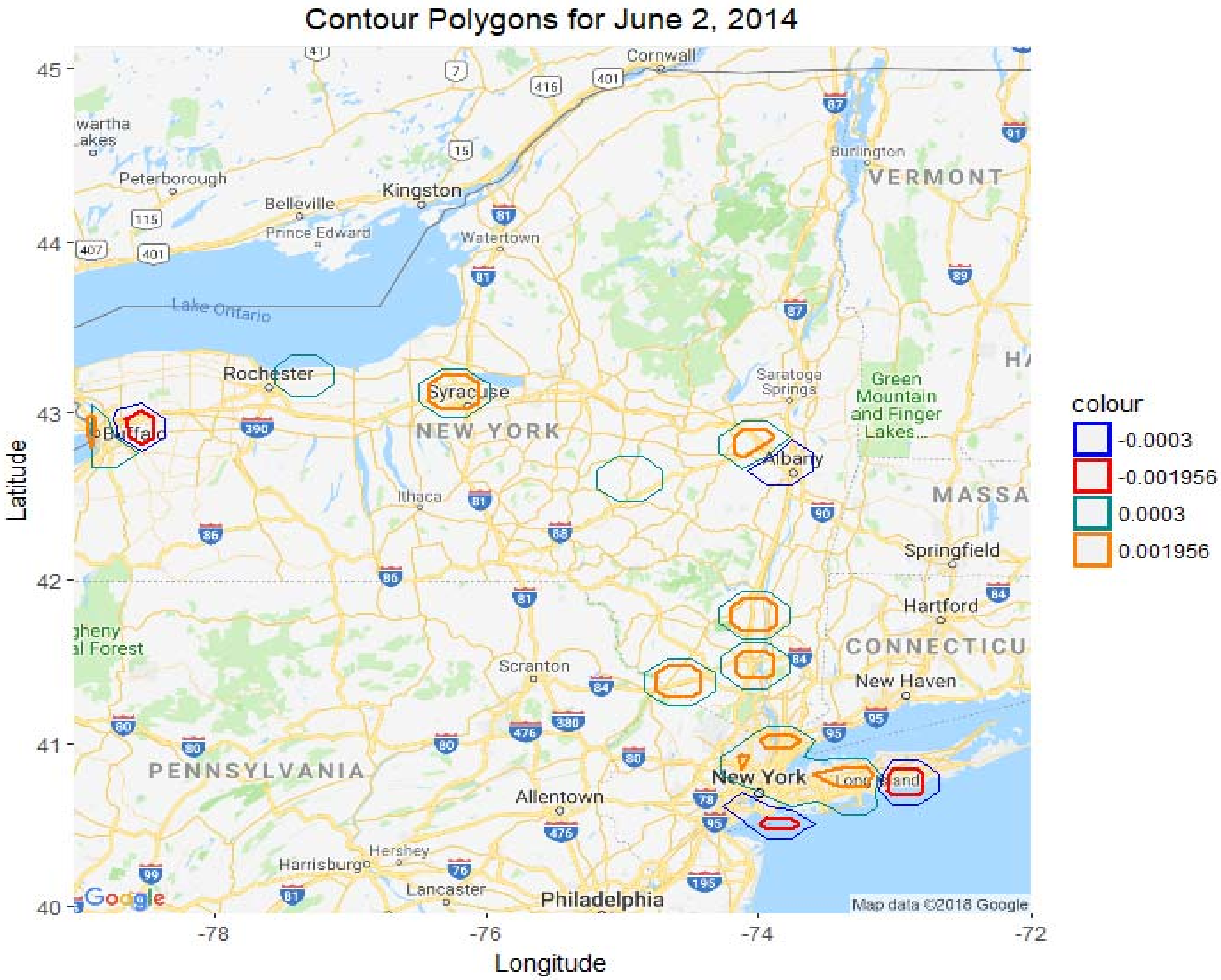

Fig. 4: Spatial Clusters for June 2, 2014

particular type t between a spatial cluster s and a batch b are also supported. One example is a continuing relationship between a spatial cluster s belonging to a batch f with the spatial cluster s' belonging to another batch f'. Finally, unary predicates can be defined to record change; for example, a spatial cluster belonging to batch i might disappear in the subsequent batch $i+1$.

Next, we introduce three change functions that are particularly useful for defining change predicates. Let c be a spatial cluster polygon in batch i and m a spatial cluster polygon in batch i', different form i. The operators $\cap$ and $\cup$ denote cluster intersection and union; $area(p)$ is the area covered by polygon p. In this case, agreement between c and m can be computed as follows:

$$Agreement(c,m) = \frac{area(c \cap m)}{area(c \cup m)} \tag{4}$$

Agreement measures how similar two polygons c and m are. In addition to agreement, the degree of containment between two polygons is defined as follows:

$$Containment(c,m) = \frac{area(c \cap m)}{area(m)} \tag{5}$$

Basically, containment measures the degree to which a polygon c is contained in another polygon m; the function returns numbers in [0,1]

Finally, we can measure overlap between a spatial cluster s, and the set of spatial clusters belonging to a different batch, as follows:

Let $p_1, \ldots, p_m$ be the spatial clusters polygons of batch f and we assume p is the polygon of cluster s belongs to the batch $f^{`}(\neq f)$; then the function Overlap between $p$ and $f^{`}$ is defined as follows:

$$Overlap(p, f) = \frac{area(p \cap (p_1 \cup ..... \cup p_m))}{area(p)} \qquad (6)$$

For example if $Overlap(p, f) = 0.8$ this means that 80% of the area of the spatial cluster p is covered by the spatial clusters belonging to batch f.

Agreement, containment, and overlap can be utilized to define change predicates. Below we define six popular change predicates:

1) S-Continuing (c,m) $\Leftrightarrow$ Agreement (c,m) ≥ 0.8
2) B-Continuing(c,b) $\Leftrightarrow$ Overlap (c,b) ≥ 0.8
3) Growing(c,m) $\Leftrightarrow$ Containment (c,m) ≥ 0.9 and $\frac{area(m)}{area(c)} > 1.15$
4) Shrinking(c,m) $\Leftrightarrow$ Growing (m,c)
5) Disappearing(c) $\Leftrightarrow \exists$ i (belong-to(c,i) and (i=r or not(B-Continuing(c,i+1))
6) Novel (c) $\Leftrightarrow \exists$ i (belong-to(c,i) and (i=1 or not(B-Continuing(c,i-1))

In the above definition we assume that batches are numbered $1, \ldots, r$, with r being the number of the last batch. A spatial cluster s continues as cluster $s^{‘}$ in the next batch if the agreement between the two cluster polygons is 80% or more. Shrinking and growing measures define regions whose sizes become smaller or larger and the area covered by the smaller clusters is mostly covered by the larger cluster.

In general, to monitor change we define a set of unary change Predicate C, such as Disappearing and Novel spatial clusters, a set of inter cluster change predicates CC, such as S-Continuing, Growing, and Shrinking and a set of cluster-batch change predicates CB, such as B-Continuing. Then using the sets *C, CC and CB* as an input we create change relationships and ultimately create the Change Graph; The pseudo-code of the algorithm that adds edges to the change graph is given below:

The algorithm starts by checking all the spatial clusters in all batches if they satisfy any change predicates belonging to the three sets. For example when a S-Continuing predicate is processed, we find all the pairs $(s, s^{‘})$ with $s^{‘}$ belonging to different batches and for which S-Continuing$(s, s^{‘}) = true$ predicate is true. Next, we add an edge labeled ‘S-Contnuing’ to the Change Database for each pair identified in the last step. As a result of this process, we will obtain the relationship instances that will be inserted the Change Graph.

In particular, the change analysis process will add new relations of type T between pairs of clusters-belonging to different batches-and between spatial cluster-batch pairs. For example, if the spatial cluster s remains identical in all k batches an S-Continuing relationship will be stored for all pairs of those clusters. If a spatial cluster s grows in a large spatial clusters $s^{‘}$ in the batch a relationship $growing(s, s^{‘})$ will be added to the database. Finally, if a cluster s belonging to batch 1 continues to exist for all the subsequent batches a relationship B-Continuing(s, r) will be added to the database for $r = 2, .., k$ where k is the number of the last batch.

ALGORITHM 1

Pseudo-code of the Change Graph Generation Algorithm

for all spatial clusters s in all batches $1, ..., r$ **do**
  for all $P \in C$ **do**
    if $P(s) = true$ **then**
      Record that that unary predicate $P(s)$ is true in the Change Graph
    end if
  end for
  for all $P \in CC$ **do**
    Assuming that s is in batch i, find all pairs $(s, s^{‘})$ with $s^{‘}$ belonging to batch $i^{‘}$ different from i for which $P(s, s^{‘}) = true$
    Add edge $P(s, s^{‘})$ to the Change Graph for each pair found in the previous step
  end for
  for all $P \in CC$ **do**
    Assuming that s is in batch I, find all pairs $(s, i^{‘})$ with $i^{‘}$ being a batch different from i different from i for which $P(s, i^{‘}) = true$
    Add edge $P(s, i^{‘})$ to the Change Graph for each pair found in the previous step
  end for
end for

In summary, the change analysis component can be viewed to generate a Change Graph whose nodes represent spatial clusters that are annotated by specific change predicate edges that capture different types of change:

- Unary predicates that describe properties of spatial clusters
- Binary predicates that capture relationships between spatial clusters
- Binary predicates that capture relationships between spatial cluster and batches

B. ST-Storytelling Component

As a result of the change analysis step, we will obtain a very detailed Change Graph that stores emotion clusters and “interesting” changes that occurred or did not occur with respect those emotion clusters. However, to tell a spatial-temporal story, the Change Graph needs to be aggregated, summarized and potentially mined. As there are many different story-types one might tell, the system we are currently developing supports different story types, and the user of the ST-Storytelling component is expected to select a story type and also input user preferences; based on this input an animation with an associated narrative will be generated; Possible story-types include:

1) Spatial Cluster focused: The rise and fall of spatial clusters
2) Extreme Cases; Where are the happiest/unhappiest regions in space over an observation period?
3) Extreme Cases: Time intervals of High/Low Happiness

4) Drill Down with Topic Discovery: Why is Kentucky so happy and Oklahoma so unhappy?
5) Building Blocks: Which regions show significant amounts of emotional stability?
6) Chaos Theory: What are the regions with the most emotional change?
7) Where are the losers and winners—which regions happiness did significantly improve/decrease over the observation period?
8) Where are the ones who don't care: Low Emotion Regions?
9) Outliers: Which emotion regions evolved significantly differently from the rest of the pack?

For example, if the first story-type is chosen, the user is expected to select a spatial cluster, and then a story is generated for this particular cluster; for example, if the user select a positive emotion cluster s from the first batch, by retrieving the edges B-Continuing change predicate in the Change Graph, we might observe that the spatial cluster continued to exist in batches 2-6 then disappeared in batches 7-12, reoccurred as a negative emotion cluster in batch 13, that then grow further in "final batch" batch 14, using the growing relationship. Quite different analysis functions will be used when other story-types are selected by the user. If story type 2 is chosen we would compute spatial clusters with high positive and negative emotion values first, and then use story-type one as a sub-function to tell a story for each spatial cluster that was identified in the first step.

V. Conclusion

In this paper, we introduced a novel sentiment analysis framework that creates positive and negative emotion spatial clusters and summarizes the change of emotions in time. It introduces a novel, generic spatio-temporal data analysis and storytelling framework and its architecture that goes for beyond concerning what other frameworks have to offer. To obtain positive and negative emotion spatial clusters a novel density estimation, called emotion-weighted density estimation, was introduced which transforms a spatial tweet dataset into a continuous function and our framework employs contouring algorithms that operate on this continuous function to identify positive and negative emotion regions. Finally, the paper introduced a novel, generic change analysis framework. Using this framework unary and binary change predicate is defined and matched against the identified spatial clusters, and a Change Graph is created that records the change relationships for those spatial clusters for which a match occurred.

Future work includes the implementation of the ST-Storytelling Component. We would also like to perform a thorough experimental evaluation of the framework. We also hope to convince the United Nations to use our framework for their annual Happiness Report, adding more depth to their analysis by summarizing spatial, temporal, and spatio-temporal variation of happiness in the world. Finally, as our approach is very generic in nature, it can be easily applied to mail-based and questionnaire-based happiness analysis.

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