Aconcagua: A Novel Spatio-temporal Emotion Change Analysis Framework

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ABSTRACT

In this paper, we introduce Aconcagua, a novel spatio-temporal emotion change analysis framework. Our current research uses Twitter tweets as the knowledge source for emotion analysis. The inputs for the emotion mapping and change analysis system, we are currently developing, are the location and time of the tweets and their corresponding emotion assessment score falling in the range [-1, +1], with +1 representing a very positive emotion and -1 representing a very negative emotion. We start by identifying spatial clusters that capture positive and negative emotion regions for batches of the dataset with each batch corresponding to a specific time interval, e.g. a single day. These obtained spatial clusters and their statistical summaries are then used as the input for Aconcagua which monitors change of emotions with respect to a set of unary and binary change predicates that are evaluated with respect to the set of spatial clusters; as the result of this process an emotion change graph is obtained whose nodes are spatial clusters and whose edges capture different types of temporal relationships between spatial clusters. An implementation of the change monitoring process is discussed which operates on top of a relational database and uses SQL queries to specify change predicates. To obtain more aggregated change summaries and ultimately change stories, the change graph further must be mined and summarized based on what aspects of change the analyst is interested in. To support such capabilities, our approach supports several types of change analysis templates called story types. We demo our approach using tweets collected in the state of New York in June 2014.

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CCS CONCEPTS

• Information systems → Geographic information systems; Clustering.

KEYWORDS

Sentiment Analysis, Tweet Emotion Mapping, Spatial Clustering, Emotion Change Analysis, Spatio-temporal Data Analysis, Spatio-Temporal Data Storytelling.

1 INTRODUCTION

The rapid proliferation of microblogging websites has resulted in significant interest in using this existing source to develop social science knowledge. Twitter as an example has evolved to become a great tool for various kinds 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. Most recent research regarding Twitter analysis has concentrated on sentiment analysis, which categorizes tweets as positive, negative or neutral. The majority of the existing approaches focuses on the lexical contents of a tweet, parsing the tweet and try to measure the emotion [1, 2].

Spatio-temporal change analysis of emotions is possible thanks to the fact that tweets are time-stamped, and location information is included in tweets and user profiles. Many change detection techniques have been developed in the literature. Lu et al. group change detection methods into several categories: algebra, transformation, classification, advanced models, geographical information system approach, visual analysis and other approaches [3]. A high-performance remote sensing method called Comprehensive Change Detection Method (CCDM) [4] integrates spectral-based change detection algorithms including a Multi-Index Integrated Change Analysis (MIICA) model and a novel change model called Zone, which extracts change information from two Landsat image pairs to update the National Land Cover Database to circa. Im et al. [5] introduce a change detection model based on Neighborhood Correlation Image (NCI) analysis and decision tree classification. Computing the piecewise correlation between two data sets provides valuable information regarding the location and numeric change value derived using contextual information within the specified neighborhood. Ridd et al. [6] propose a Chi square transformation for change detection in an urban environment. Minu and Shetty [7] analyze the effectiveness of various image change detection algorithms, such as Image Differencing, Image Ratioing, Change Vector Analysis (CVA), Tasseled Cap Transformation (TCT) and Principal Component Analysis (PCA).

However, all the algorithms we reviewed so far rely on image analysis techniques for change detection. There are other types of change detection techniques available in the literature as well. Spiliopoulou et al. [9] propose a framework called MONIC for detecting and tracking change in clusters. Lin and Chen [10] introduce a new test framework for spatio-temporal surveillance based on the Exponentially Weighted Moving Average (EWMA) technique. This EWMA-based test statistic that applies the weighting technique to both temporal and spatial axes can be used to detect emerging clusters with mean shifts in spatiotemporal data.

Our work also relates to emotion analysis. Misue and Taguchi [8] propose a methodology to represent spatial distributions of complex emotions expressed as multivariate from a large group of people, called emotion-weather maps. The emotions are divided into eight categories. Larsen et al. [11] introduce the "We Feel" system for analyzing global and regional variations in emotional expression through Twitter, and for reporting the results of validation against a known pattern of variation in mood. Emotional words were classified into six primary emotions categories with 25 subgroups of secondary emotions. "We Feel" provides an interactive map which allows an area of interest to be selected from the global, continental, or country zone level and visualizes time series and circumflex models of emotional tweet counts, refined by geography, time interval, and emotion of interest. However, the "We Feel" system does not analyze emotion change over time.

In this paper, we focus on measuring and summarizing the well-being of large populations in space and how their happiness evolves over time. A novel spatio-temporal data analysis framework called Aconcagua will be introduced in this paper to facilitate emotion change analysis and change storytelling. Compared with the approaches in [3-7], which are based on image analysis techniques, Aconcagua focuses on analyzing the evolution of spatial emotion clusters. To the best of our knowledge, Aconcagua is the first emotion change analysis framework that analyzes, summarizes and animates how spatial clusters describing areas of 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.

The main contributions of this paper include:

- It introduces an emotion mapping and change analysis framework and its architecture.
- It discusses a novel, generic change analysis framework called Aconcagua that monitors and summarizes the evolution of positive and negative emotion regions.

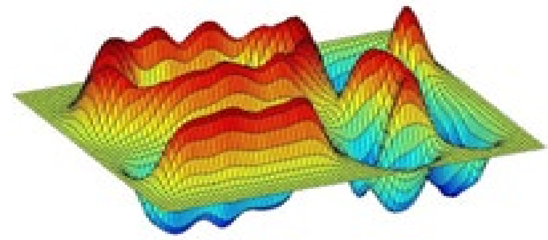

Figure 2: Example of an Emotion-Weighted Density Function.

- The design and the unique implementation of the change monitoring component are discussed.
- It briefly introduces a novel approach called *change storytelling* and briefly discusses how we plan to provide such capabilities within Aconcagua.

The remainder of the paper is organized as follows. In section 2, we introduce the architecture of the proposed Emotion Mapping and Change Analysis system. Section 3 describes a novel, quite generic emotion change monitoring framework. Section 4 discusses how the data collected by the change monitoring framework can be used to support particular change story types. Finally, section 5 summarizes our contributions and identifies areas of future work.

2 SYSTEM ARCHITECTURE FOR SPATIO-TEMPORAL EMOTION ANALYSIS

In this section, we describe the architecture of an integrated framework for tweet emotion mapping, change analysis and storytelling. Figure 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. We use VADER Sentiment Analysis Tool [12] to assign an emotional score to each tweet. Next, 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 [13] to transform each batch into a continuous function which takes positive and negative values as displayed in Figure 2. The obtained values are proportional to the degree of happiness/unhappiness at a measuring point. Next, a contour-based spatial clustering algorithm ST-DCONTOUR [14][16] 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. To give an example, Figure 3 depicts the spatial clustering results we obtained for tweets in New York State that were posted on June 9, 2014. In the figure, red polygons depict high negative emotion clusters, blue polygons depict medium negative emotion clusters, orange polygons depict high positive emotion clusters, and green polygons depict medium positive emotion clusters. As we can see, overall there are more positive emotion regions, specifically in the bottom right of the

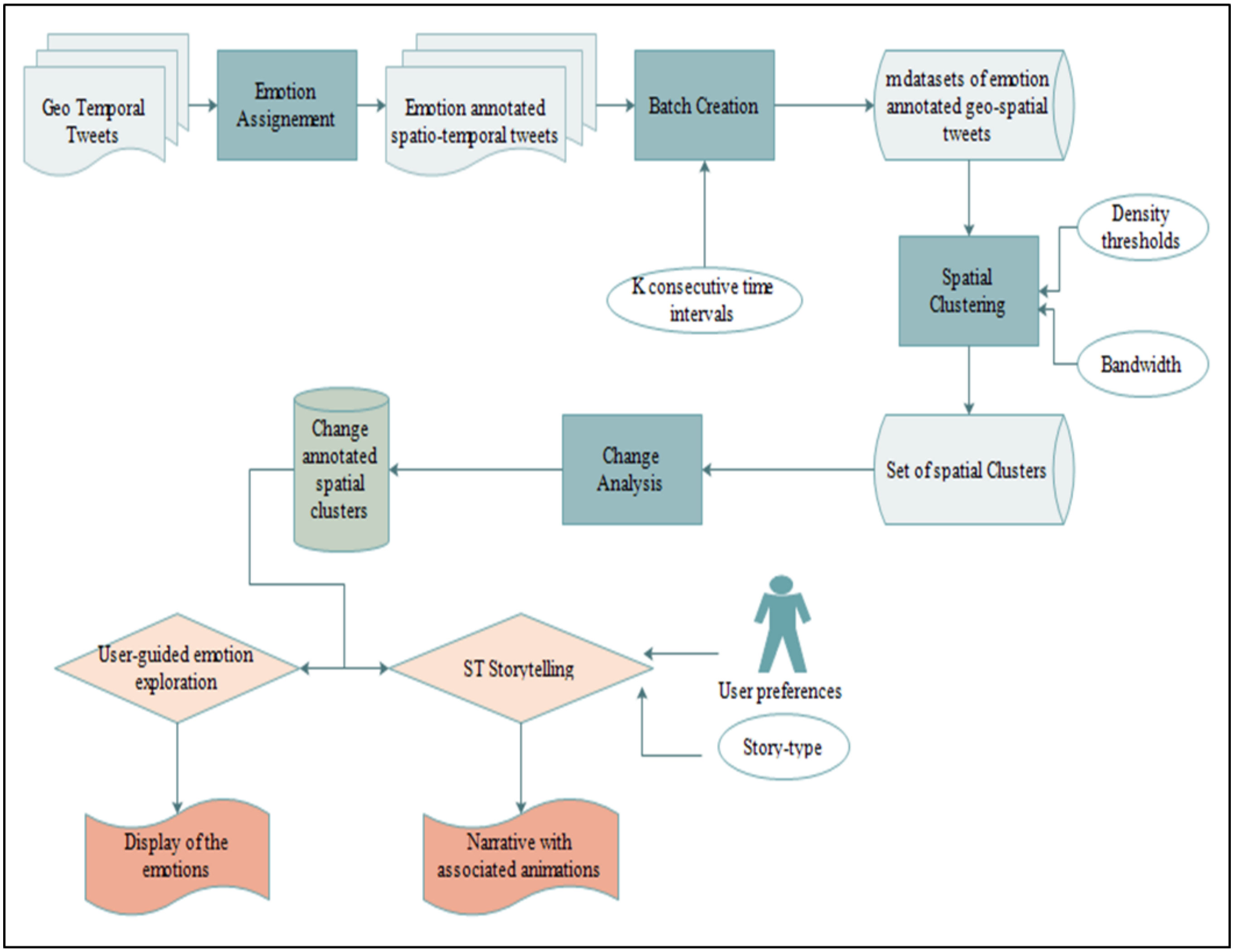

Figure 1: Architecture of the Emotion Mapping and Change Analysis Framework.

figure covering the New York City and the Long Island area. However, two negative emotion clusters occur on the boundary of New York City positive emotion cluster.

Next, a generic change monitoring framework is employed to summarize how positive and negative emotion regions evolve over time. Change of emotions is analyzed with respect to a set of unary and binary change predicates that are evaluated with respect to the set of spatial clusters which were obtained as the result of the spatial clustering step. An emotion change graph is constructed whose nodes are spatial clusters and whose edges capture different temporal relationships between spatial clusters.

Finally, to obtain aggregated change summaries, our approach supports different types of change analysis templates, called story types, and change narrative with animations is then created based on the chosen story type by aggregating, summarizing and mining the change graph. Moreover, the architecture contains a user-guided emotion exploration component that allows users to explore data by navigating through at three levels: the emotion-weighted density function, the spatial clusters and the change graph.

The remainder of the paper discusses the design and the implementation of the change monitoring component, and briefly discusses our approach how we plan to create change summaries and narrative from the output of the change monitoring component.

3 THE CHANGE MONITORING COMPONENT

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. Our particular approach provides a change monitoring framework that will be described in this section. It creates a change graph that captures the changes in spatial emotion clusters and a change summarization framework that, based on change story types, creates specific change summaries based on change graph; our change summarization approach will be discussed in Section 4.

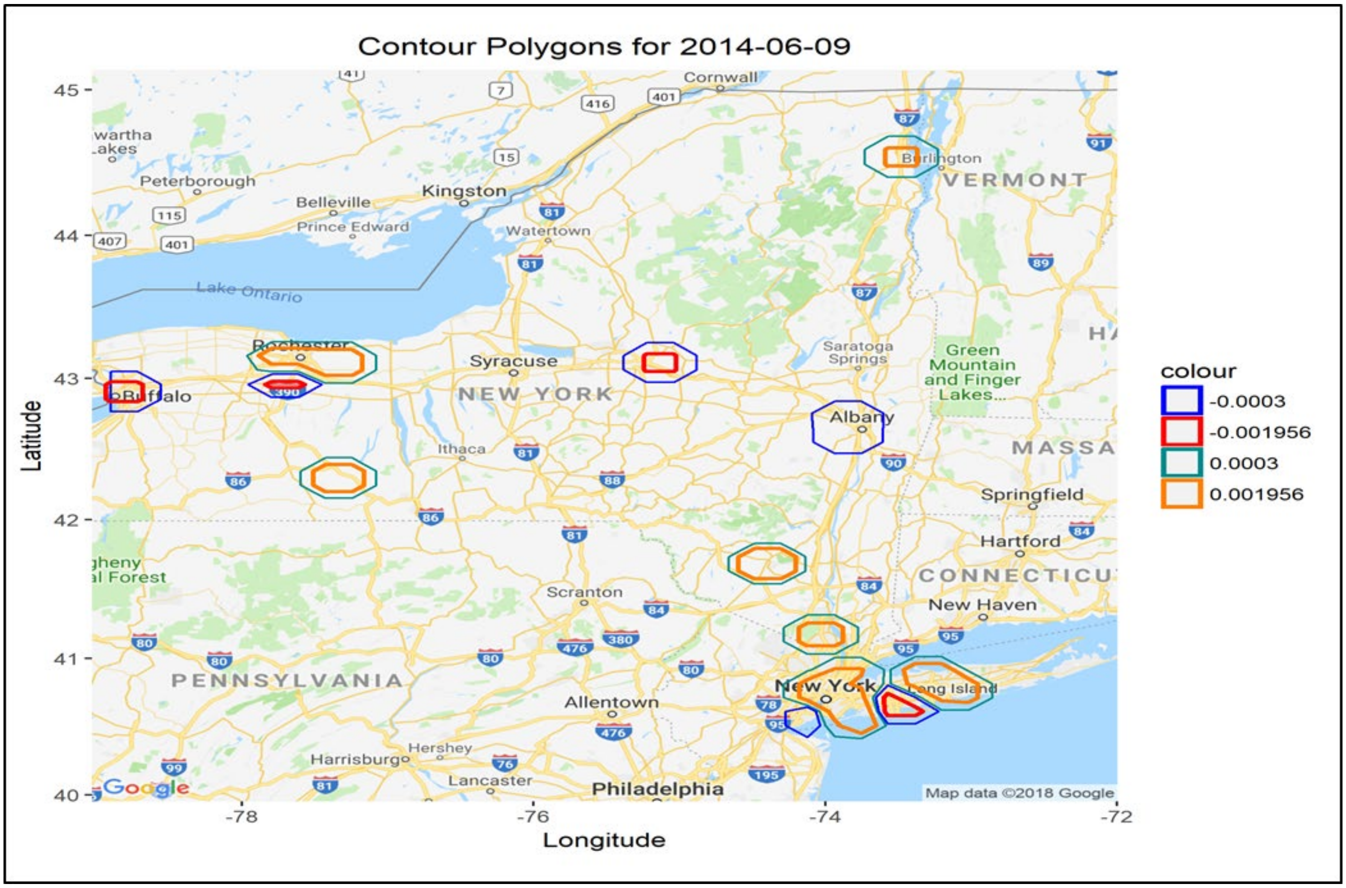

Figure 3: Spatial clusters for June 9, 2014.

Our particular Aconcagua framework monitors change by comparing sets of polygons which represent spatial clusters for a particular time window/batch—as shown in Figure 3—that have been created with the methods we described in [1]. After identifying spatial clusters that capture positive and negative emotion regions for different batches, the obtained spatial clusters and their statistical summaries—a scope polygon that captures the location of the spatial cluster, average emotion value, an emotion standard deviation, and a density threshold—are the input for the change analysis component. Each spatial cluster belongs to a single batch. Change of emotions is then analyzed with respect to a set of unary and binary change predicates that are evaluated with respect to the set of spatial clusters, and an emotion change graph is constructed whose nodes are spatial clusters and whose edges capture temporal relationships between spatial clusters.

Emotion change monitoring is conducted by analyzing particular relationships between polygons associated with batches. This is done by introducing a set of change predicates that refer to spatial clusters and their average emotion values belonging to different batches. 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 a database. In general, the output of the change monitoring is a graph that represents the spatial clusters that occurred in various batches as nodes, and whose edges are labeled, representing the type 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 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 frame f with the spatial cluster s' belonging to another frame 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 from i. The operators '∩' and '∪' denote cluster intersection and union; area (p) is the area covered by polygon p. In this case, the agreement between c and m can be computed as follows:

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

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:

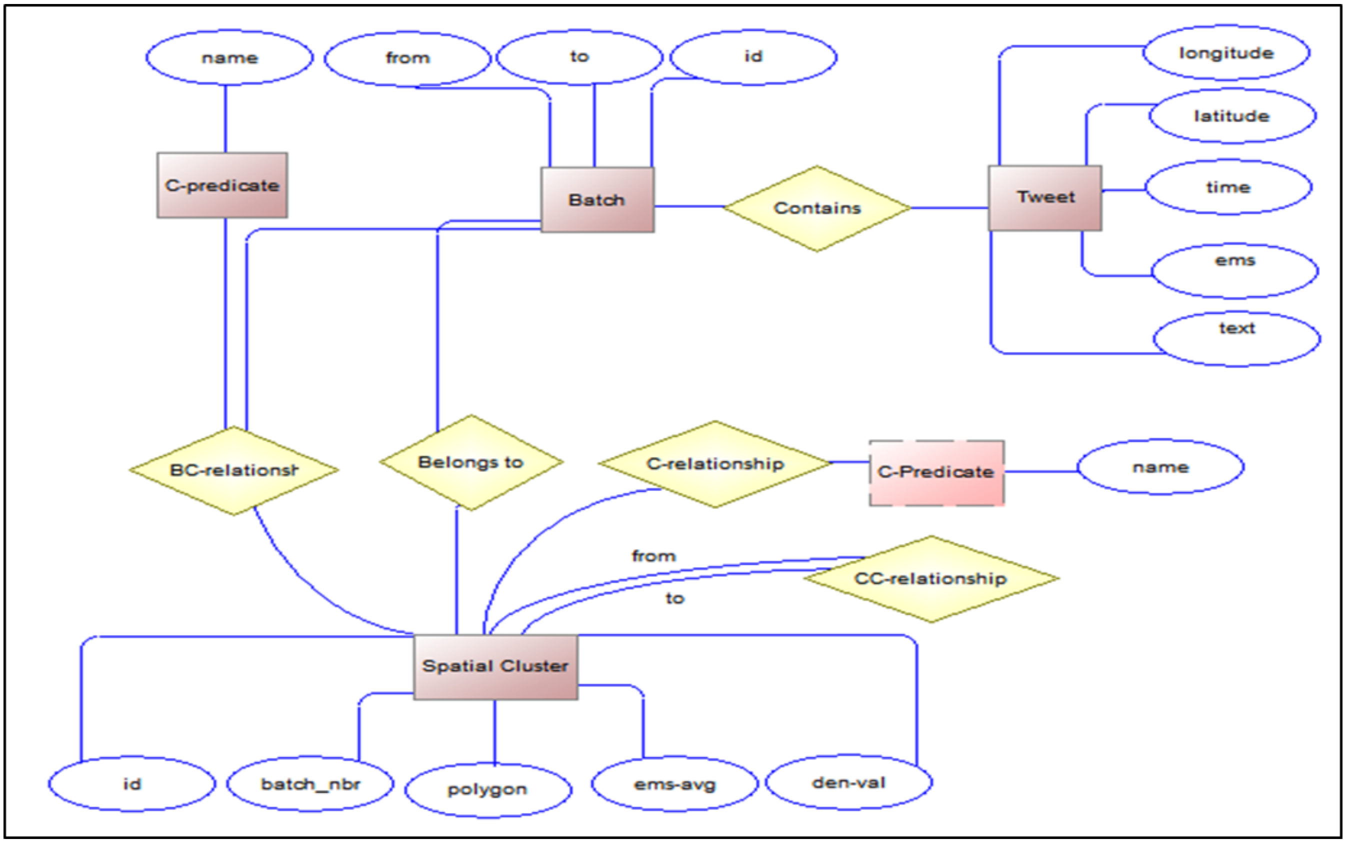

Figure 4: **ER-Diagram for the Database Generated by the Spatial Clustering Followed by the Change Analysis Step**.

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

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 frame f and we assume p is the polygon of cluster s belongs to the frame f'(!=f):

$$Overlap(p,f) = area(p \cap (p_1 \cup \ldots \cup p_m))/area(p)$$

For example, if overlap(p,f)=0.8 this means that 80% of the area of the spatial cluster s 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:

a. S-Continuing (c,m) ↔ Agreement (c,m) ≥ 0.8
b. B-Continuing(c,b) ↔ Overlap (c,b) ≥ 0.8
c. Growing(c,m) ↔ Containment (c,m)≥0.9 and area(m)/area(c)>1.15
d. Shrinking(c,m) ↔ Growing (m,c)
e. Disappearing(c) ↔ ∃i (belong-to(c,i) and (i=r or not (B-Continuing(c,i+1)).
f. Novel (c) ↔ ∃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… 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 clusters.

Our implementation relies on database technology and uses the PostGIS DBMS; PostGIS is a spatial database extender for PostgreSQL object-relational database. It adds support for geographic objects allowing location queries to be run in SQL such as extra types (geometry, geography, raster and others), functions/predicates (Union, Intersection…) and indexes that apply to those types which were useful for our Aconcagua framework. Moreover, we use SQL stored procedures for defining change functions to facilitate the specification of change predicates; for example, the functions Agreement, Containment and Overlap we introduced earlier, are implemented as SQL stored procedures; consequently, those functions can be used when defining complex change predicates.

In general, we define a set of unary change predicate C, such as Disappearing and Novel, 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. In general, our implementation monitors change as follows: first, the spatial cluster component inserts its results into the relational database. As a result of this process, spatial cluster instances that are described by a unique cluster number names id, its polygon, the density threshold that was used to obtain the polygon, the average emotion value of the tweets that belong to the spatial cluster, the batch number that the spatial cluster belongs are inserted into the database. Furthermore, information about the batch such as batch number, and the time interval associated with the batch are inserted into the database. Next, the change predicates in C, CC, CB will be instantiated and the obtained change relationships will be recorded in the relational database. We will describe how this is done in the next paragraphs.

We use SQL-queries to specify change predicates; that is, the files C, CC, and CB contain entries ‘<change predicate name>=<SQL-query>’. In particular, the SQL queries, if executed on the content of the relational database containing the results of the spatial clustering process will return tuples that will be inserted into tables called BC-relationship, C-relationship, and CC-relationship, respectively. In particular, the SQL-queries in file C compute sets of spatial clusters, the SQL-queries in the file CC compute pairs of spatial clusters, and the SQL-queries in file BC compute sets of pairs of the form (b,s) where b is a batch and s is a spatial cluster.

We will explain next how this change monitoring process works for the ‘S-Continuing’ change predicate. We assume that the relational database contains the following tables:

Spatial_Cluster(id,B#,polygon,ems-avg,den-val)
CC-Relationship(from, to, c-predicate)

In the tables, the attributes id, from, and to refer to spatial clusters using the unique spatial cluster number, and c-predicate stores the name of a change predicate, such as ‘Shrinking’ and B# refers to a batch using its batch number. Using this approach, the ‘S-Continuing’ change predicate would be specified as follows:

```
S-Continuing= SELECT S1.id, S2.id
FROM Spatial_Cluster S1, Spatial_Cluster S2
WHERE S1.B#<>S2.B# AND
area(intersection(S1.polygon,S2.polygon))
/area(union(S1.polygon,S2,polygon))>0.8
```

The above query computes all pairs of spatial clusters belonging to different batches whose polygon overlap is 80% or more. All SQL queries in the CC file are executed and the obtained queries results are then used to construct tuples that are inserted into the CC-Relationship relation. For example, if the SQL query associated with the S-Continuing change predicate returns {(22, 41), (29,444)} indicating that spatial clusters 22 and 41 and spatial clusters 29 and 44 are in an S-Continuing relationship; next, using the query results’2 tuples (22, 41,’S-Continuing’) and (29, 444,’S-Continuing’) will be inserted into the CC-Relationship table. The other change predicates in the CC file, and the predicates in the C and BC files will be processed in the same way, instantiating other change relationships.

Conceptually, the change monitoring component can be viewed to generate a change graph whose nodes represent spatial clusters that are annotated by specific change predicates 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.

4 CREATING CHANGE SUMMARIES BASED ON STORY TYPES

4.1 Change story-types

As we discussed in the previous section, as the results of the change monitoring step, we will obtain a very detailed database that stores emotion clusters, their properties, batches and particular types of changes that occurred with respect to those positive and negative emotion clusters. However, in order to create summaries and to tell spatial-temporal change stories, the result of the change monitoring step needs to be aggregated, summarized and potentially mined. As there are many different types of stories one might tell, the system we are currently developing supports different change story types, and the user of the Change Summarization component is expected to select a story type and also input user preferences; based on this input a change summary and an animation with an associated narrative will be generated—as depicted in Figure 1. Change story-types we plan to support include:

1. Spatial Region Focused: The rise and fall of spatial emotion clusters in South Texas.
2. Extreme Cases: Regions with very strong positive and negative emotions and how they changed over time.
3. Change Summaries: Which regions showed the highest emotional stability with respect to positive and negative emotions?
4. Which regions showed the most significant increase of positive/negative emotions over time?
5. Summary of Emotion Flip-Floppers: regions that switched from showing positive emotions to negative emotions and vice versa.
6. Outliers: Which region’s emotion evolved differently, compared to how other regions evolved?

Different analysis methods will be applied to the change monitoring results based on the selected story type. However, in most cases the user is not interested to obtain a change summary for the whole observation area but rather for a significantly smaller region, e.g. Long Island. Moreover, the user might want to exclude certain spatial clusters from the change summary that are not ‘interesting’, such as very small spatial clusters, positive and negative emotion clusters, negative emotion clusters with emotion

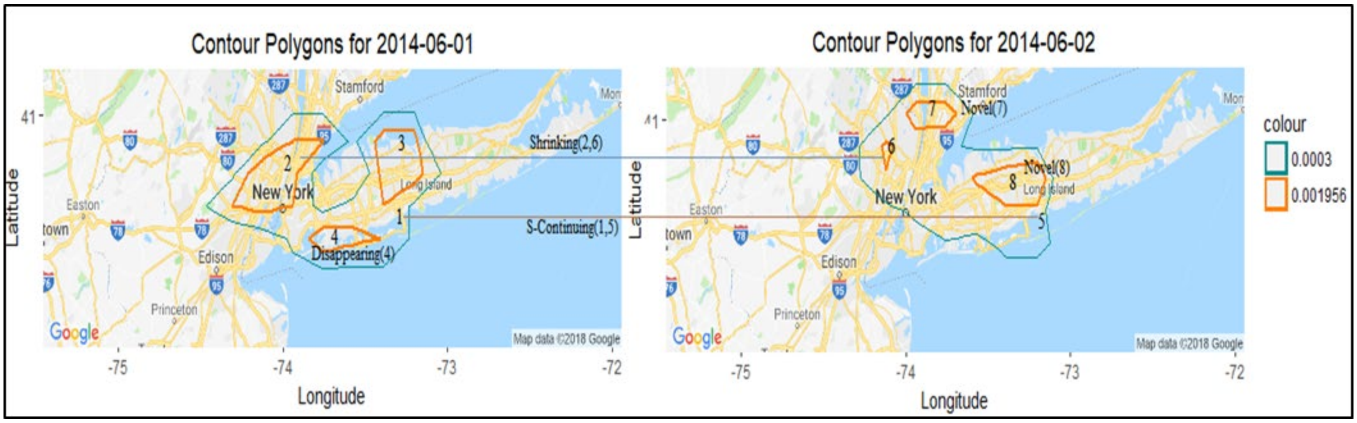

Figure 5: Positive Emotion Clusters in the New York City/Long Island Area on June 1 - 2, 2014.

values too close to zero. Therefore, after the user selects a change story-type she is asked to provide the following:

a. A region of interest—change summaries will be only generated for spatial clusters that belong to the region of interest. Regions of interest are specified using bounding rectangles.
b. A spatial cluster interestingness function[1] i including an interestingness threshold θ.
c. Other user preference parameters that are specific to the chosen change-story type.

Based on the first two user inputs, the generated change summary will exclude discussion of spatial clusters s, which are not in the region of interest and whose interestingness i(s) ≤θ; that is, change summarization will only be performed for 'interesting' spatial clusters that are inside the region of interest.

4.2 Example: Creating Change Summaries and Narrative for Story Type1

We will illustrate how change stories will be generated from the results of the change monitoring process as an example that involves positive emotion clusters that have been displayed in Figure 5. Looking at Figure 5, as far as June 1 is concerned, we see a green positive emotion cluster (#1) which contains 3 orange sub-clusters with higher positive emotions (numbered 2-4 from west to east). As far as June 2 is concerned, we see a green positive emotion cluster which covers a similar area (#5) and which also contains 3 orange sub-clusters (numbered 6-8 from west to east). the change monitoring process that we described in Section 3[2]:

S-Continuing(1,5),Shrinking(2,6),Novel(7),Novel(8), Disappearing(2),Disappearing(3), Disappearing(4).

From this information the following change story could be created and presented to the user in conjunction with Figure 5: "*We observe that medium-positive emotion spatial cluster 1 that covers Long Island and New York City continues on June 2*[3] *as cluster 5; cluster 1 contains more intense positive emotion sub-clusters 2-4. Cluster 2 shrinks significantly when it becomes cluster 6 on June 2; clusters 2-4 disappear on June 2, and two novel, more intense emotion clusters 7 and 8 appear June 2 that are contained in cluster 5.*"
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.

5 CONCLUSION

In this paper, we introduced an emotion mapping and change analysis system, then we introduced a novel spatio-temporal emotion change analysis framework named Aconcagua to monitor and summarize the change of positive and negative emotions over time and space.

In particular, Aconcagua extracts complex change patterns by comparing interesting regions that have been obtained by using contour clustering for different batches. A set of unary and binary change predicates are evaluated with respect to the set of spatial clusters in batches uncovering the temporal variations in happiness. Next, an emotion change graph whose nodes are the spatial clusters and whose edges capture the temporal relationships of different types between spatial clusters is constructed. The proposed change monitoring framework employs SQL queries to specify change predicates and its architecture is quite generic in the sense that new change predicates can be added to the system without having to change anything else in the implementation of the change monitoring component. Finally, we introduced change storytelling—a novel approach for change analysis—and discussed

[1] We support simple predefined interestingness functions, such as the size of the spatial clusters, but also allow the definition of new, more complex interestingness functions; e.g. we could define an interestingness function i for which a positive emotion cluster in batch i is only interesting if it overlaps with a negative emotion cluster in batch i+1. Such an interestingness function would create summaries only for flip-flopping positive emotion clusters.

[2] Remark: Cluster 6 is not novel as its area is covered by cluster 2 on for the batch of the day before: June 1.

[3] Although the area of coverage of cluster 1 and 5 is somewhat different there is still an agreement of 81% between the two clusters.

an example how our approach creates a change story from change monitoring data.

Future work includes finalizing the design and implementing the change summarization component. Moreover, we intend to provide a navigational capability to the user so that she can navigate through the emotion weighted density function, the spatial clusters and the change graph. We also plan to perform a thorough experimental evaluation of the whole emotion and change analysis framework. Finally, we will try to convince the United Nations to use our framework for their annual Happiness Report [15], adding more depth to their analysis by summarizing spatial, temporal, and spatio-temporal variation of happiness in the world.

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