Approach to Automated Storytelling Using Geospatial-Temporal Polygons

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I. Methodology

A. Change Analysis Predicates

Our change predicates are derived from the Aconcagua Framework [6]. We consider c is a spatial cluster polygon from the batch timed t_i and m is another spatial cluster polygon from a batch timed t_{i+x}, with x indicating a time increase. We denote cluster intersection as $\cap$ and union as $\cup$. $Area(x)$ denotes the area covered by the polygon x, upto a desired level of accuracy.

- $Agreement(c, m) = (area(c \cap m))/(area(c \cup m))$
- $Containment(c, m) = (area(c \cap m))/(area(m))$
- $Overlap(s, p) = area(s \cap (p_1 \cap \ldots \cap p_m))/area(s)$

The change function $Agreement(c, m)$ is a measure of similarity. $Containment(c, m)$ measures whether individual polygons coincide. To measure concurrence between one polygon and a set of polygons, we use the $Overlap(s, p)$ functions. Here $p_1, ..., p_m$ are spatial clusters from a batch b, and s is a cluster from a different batch b'. Other basic functions include $Centroid(x)$, which indicates the Centorid of a polygon as defined as:

$C_x = \frac{1}{6A} \sum_{i=0}^{N-1} (x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)$
$C_y = \frac{1}{6A} \sum_{i=0}^{N-1} (y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i)$

where $x_N = x_0$ and A = the area of the polygon. We also use a simple Manhattan distance function $Distance(c, m)$ which is tuned to the required georeferenced accuracy.

We use all these functions to defined these seven change predicates:

1) $S - Continuing(c, m) \leftrightarrow Agreement(c, m) \geq 0.8$
2) $B - Continuing(c, b) \leftrightarrow Overlap(c, b) \geq 0.8$
3) $Growing(c, m) \leftrightarrow Containment(c, m) \geq 0.9$
4) $Shrinking(c, m) \leftrightarrow Growing(m, c)$
5) $Disappearing(c) \leftrightarrow \exists i(belong - to(c, i)$
6) $Novel(c) \leftrightarrow \exists i(belong - to(c, i) and (i = 1 or not(B - Continuing(c, i - 1))$
7) $Shifting \leftrightarrow \frac{\sum_{i=1}^{N} Distance(Centroid(c), Centroid(m))}{N}$

B. Interestingness Functions

In order to tell a coherent spatio-temporal data story from the change analysis output, we propose using an interestingness function for this task.[11]

We choose a set of change polygons SCP. It not only contains those polygons but also their associated characteristics. For example, a SCP could contain a set of spatial clusters represented by polygons, their average drought score, total area of each polygon, centroid coordinates of each polygon and other summaries for each spatial cluster (polyogn). We define the function as:

$$f : SCP \ \rightarrow \ [0 \, , \infty)$$

We define a threshold ω, which ensures that a narrative will only be generated an object $p \in SCP$ such that $f(p) \geq \omega$. Sample parameters for ω include

- $Max\left(\frac{area(Polygon\ P_i)}{\sum_1^i area(Polygon\ P_i)}\right)$
- $Max\,(Percentage\ Change\ in\ Polygon)$
- Largest shift in polygon centroids

The threshold parameters need to be finely tuned so as to not exclude those polygons who fall through exceptions. Once we have a suitable selection of polygons and chose a threshold value, we can create a summary narrative based on that.

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