An interactive web-based geovisual analytics platform for co-clustering spatio-temporal data¹

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Abstract

Clustering methods are useful in analyzing patterns from big spatio-temporal data. However, previous studies typically rely on traditional clustering methods to explore spatial or temporal patterns. Co-clustering methods allow the concurrent analysis of spatial and temporal patterns by identifying location- and timestamp-clusters at the same time. By combining co-clustering with coordinated multiple views (CMV) in an interactive geovisual analytics platform, we facilitate the exploratory co-clustering analysis of spatio-temporal data and the results. Further enhanced by Web 2.0 standards, our geovisual analytics platform ease the access to co-clustering analysis from any web browser. More specifically, our platform allows users to upload data and to visually explore it using interactive CMV to help the selection of co-clustering parameters. Our platform also allows users to run co-clustering and to visually and interactively explore the results. To illustrate the use of our platform, we analyze Dutch annual average temperature for 28 stations from 1992 to 2011. Results show that our platform not only helps to get a better understanding of the dataset but also to choose the co-clustering parameters. Our platform helps to interpret the co-clustering results too, and it supports the extraction and exploration of complex patterns buried in the data. In the era of big data, our web-based platform enables the exploration of concurrent spatio-temporal patterns from large datasets by combining both computer power and human interpretative capabilities.

Keywords: web-based; geovisual analytics; interactive coordinated multiple views; clustering analysis; spatio-temporal pattern

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1 Introduction

Thanks to the advancement in data collection technologies, the amount of spatio-temporal data have dramatically increased, and the extraction of knowledge from these data becomes a challenge [1, 2]. As one of data mining tasks, clustering methods are very useful in analyzing patterns and further extracting the underlying knowledge. Most previous studies on clustering analysis of spatio-temporal data reply on one-way clustering, also called traditional clustering (Figure 1), which analyzes the data from spatial or temporal aspect separately. Specifically, spatial clustering groups locations in the data into clusters with similar values of the attribute(s) along all timestamps (Figure 1b) whereas temporal clustering groups timestamps into clusters with similar value along all locations (Figure 1c)[3, 4]. However, such clustering analysis only consider the space- or time-varying behavior of the data [5].

Figure 1: A simulated dataset (a) for spatial clustering (b), temporal clustering (c) and co-clustering (d) analysis of spatio-temporal data

Unlike traditional clustering, co-clustering concurrently groups locations to location-clusters and timestamps to timestamp-clusters and identifies co-clusters where values of the attribute(s) are similar along both locations and timestamps (Figure 1d). As such, co-clustering analysis considers both space and time-varying behavior in the data. Having been used in various fields [6-8], co-clustering methods attract

40 attentions in geo-field recently [9-11], where Bregman block average co-clustering algorithm with I-
41 divergence (BBAC_I) is used for the exploration of patterns along both space and time dimensions.

42 However, one common issue for clustering/co-clustering analysis is the selection of parameters, e.g.
43 number of clusters [12, 13]. These parameters are often predefined by trial and error, expert knowledge or
44 by considering the characteristics of the dataset at hand and/or the application. An exploratory analysis of
45 spatio-temporal data helps to “get acquainted with the data” and to decide on the most suitable parameters
46 for a given problem [14]. This analysis is often steered by user’s interactions and visual analysis of the
47 resulting clusters [15].

48 Various geovisualizations have been used to visually analyze the clustering results in spatio-temporal
49 data. For instance, Wu, Zurita-Milla [3] applied the geographical maps to represent the spatial distribution
50 of spatial clusters in weather data. van den Elzen and van Wijk [16] used small multiples to visually
51 explore clusters in winter holiday accommodations. Storme, Derudder [17] applied cluster heatmaps to
52 visually analyze the complex patterns of interactions between producer services firms and world cities.

53 As a core functionality of visual analytics, the Coordinated Multiple Views (CMV) provides various
54 linked geovisualizations for different aspects of spatio-temporal data to help its exploration [18]. By
55 integrating CMV, human interactions and computational methods, e.g. clustering/co-clustering, into
56 interactive visual interfaces, geovisual analytics enables an iterative and exploratory analysis with human
57 involved [19]. For instance, Guo and Jiang [20] presented an interactive geovisual analytics approach by
58 integrating multivariate geographical map, parallel coordinates plot (PCP) and self-organizing map to
59 analyze complex crime patterns. Tatiana, Felix [21] developed a geovisual analytics platform by
60 integrating flow map, calendar map and a spatial graph clustering algorithm to analyze movement data.
61 However, previous studies on developing geovisual analytics approaches only used traditional clustering
62 methods for analyzing spatio-temporal data.

The introduction of Web 2.0 standards enables users to access complex analytical tools and facilitates the analysis of spatio-temporal data for especially non-experts [22, 23]. Now with any web browser, users can explore their data using computational methods and visualizations [24]. For example, Sun, Li [25] proposed an interactive web-based geovisual analytics system using statistical analysis and multiple views for climate studies. Liao, Peng [26] developed a web-based geovisual analytics system with CMV to analyze air quality data. However, until now no web-based geovisual analytics platform has been developed for co-clustering spatio-temporal data.

Thus, in this paper, we follow the work of [9] and build an interactive web-based geovisual analytics platform with BBAC_I, which provides users with easy access to the iterative, visual and exploratory co-clustering analysis of spatio-temporal data. The structure of this paper is as follows. The co-clustering algorithm (BBAC_I) is explained in section 2 while the developed platform is described in section 3. Then the use of the platform is demonstrated using a case study in section 4, followed by discussion in section 5 and conclusion in section 6.

2 Bregman block average co-clustering algorithm with I-divergence (BBAC_I)

BBAC_I allows the analysis of any 2-D data matrix with positive real values. Many spatio-temporal datasets can be organized as a co-occurrence matrix O_{LT} between the location and the timestamp variables that take values across m locations and n timestamps. Correspondingly, the co-clustered spatio-temporal data matrix can be represented as the matrix $O_{\hat{L}\hat{T}}$, which contains the location- and timestamp-cluster variables that take values across k location- and h timestamp-clusters. Rooted in information theory where the mutual information is defined as the quantity of shared information between variables [27], BBAC_I measures the loss of mutual information between O_{LT} and $O_{\hat{L}\hat{T}}$ with information divergence (I-divergence), and minimizes this loss to obtain the optimal co-clustering results. In the following we summarize the main 5 steps of this process (Figure 2) and elaborate on its technical implementation:

Figure 2: The process of BBAC_I

- (1) Step 1: Perform a random initialization of the clusters. This step is implemented in two operations:
  - (i) Randomly map m locations to k location-clusters and construct a binary $m \times k$ matrix, R , to indicate location-cluster membership;
  - (ii) Randomly map n timestamps to h timestamp-clusters and construct a binary $n \times h$ matrix, C , to indicate timestamp-cluster membership.
- (2) Step 2: Compute the loss of mutual information between O_{LT} and $O_{\hat{L}\hat{T}}$. This step is implemented in three operations:
  - (i) First calculate the co-clustered matrix $O_{\hat{L}\hat{T}}$ using O_{LT} , the R , and C binary matrices produced in previous step:

$$O_{\hat{L}\hat{T}} = R^T O_{LT} C \quad (1)$$

Where R^T is the transpose of R .

(ii) Then calculate the approximation matrix $A_{\hat{L}\hat{T}}$ using $O_{\hat{L}\hat{T}}$, R and C . This steps is needed because $O_{\hat{L}\hat{T}}$ ($k \times h$) is of different size than O_{LT} ($m \times n$). Hence, $A_{\hat{L}\hat{T}}$ approximates $O_{\hat{L}\hat{T}}$ but has the same size as O_{LT} :

$$A_{\hat{L}\hat{T}} = R O_{\hat{L}\hat{T}} C^T \quad (2)$$

Where C^T is the transpose of C . During this operation, BBAC_I preserves the averages of each co-cluster (hence the name block average) along both locations and timestamps.

(iii) Calculate the loss in mutual information between $A_{\hat{L}\hat{T}}$ and O_{LT} with I-divergence, which is the objective function of BBAC_I:

$$f_{obj} = D_I(O_{LT} \parallel A_{\hat{L}\hat{T}}) \quad (3)$$

Where $D_I(\cdot \parallel \cdot)$ is the I-divergence among two matrices.

(3) Step 3: Decompose the objective function. Equation (3) can be decomposed to that of rows/locations and columns/timestamps [27]. This step is implemented in two operations.

(i) The objective function is decomposed into the I-divergence related to locations and location-clusters:

$$f_{obj-rows} = D_I(O_{LT} \parallel A_{\hat{L}\hat{T}}) \quad (4)$$

Which produces a distance matrix of locations/location-clusters with size $m \times k$, indicating the I-divergence metrics of assigning each of m locations to k location-clusters.

(ii) The objective function is decomposed into the I-divergence related to timestamps and timestamp-clusters:

$$f_{obj-columns} = D_I(O_{LT} \parallel A_{L\hat{T}}) \quad (5)$$

Which produces a distance matrix of timestamps/timestamp-clusters with size $n \times h$, indicating the I-divergence metrics of assigning each of n locations to h location-clusters.

(4) Step 4: Update cluster assignment. Following step 3, this step is also implemented in two operations.

(i) Assign new location-clusters. For each of m locations, choose the i^{th} location-cluster which has the minimum I-divergence metric in the distance matrix of locations/location-clusters:

$$i = \arg \min_{i \in \{1, \dots, k\}} D_I(O_{LT} \parallel A_{L\hat{T}}) \quad (6)$$

Then update R for the new location-cluster assignment.

(ii) Assign new timestamp-clusters. For each of n timestamps, choose the j^{th} timestamp-cluster which has the minimum I-divergence metric in the distance matrix of timestamps/timestamp-clusters:

$$j = \arg \min_{j \in \{1, \dots, h\}} D_I(O_{LT} \parallel A_{L\hat{T}}) \quad (7)$$

Then update C for the new timestamp-cluster assignment.

(5) Step 5: Re-compute the loss of mutual information with equation (3) using the updated R and C matrices. If the change of the objective function in two successive iterations is smaller than a predefined threshold, the updated R and C matrices are regarded as the optimal clustering. The final co-clustering result is the co-clustered matrix with the same size as the original matrix but each element is the value of co-cluster it belongs to. Else repeat steps 2 to 5.

After each iteration the objective function decreases monotonically [6], thus BBAC_I can achieve a local convergence. Nevertheless, to optimize the likelihood of achieving a global convergence, the above process is repeated with various initial random mapping (outer iterations). The initialization leading to a smaller loss of mutual information is chosen as the final one. For detailed explanation of BBAC_I we refer the readers to the work of [9] and Banerjee, Dhillon [6].

3 The web-based geovisual analytics platform

To facilitate the interactive exploration, our web-based platform consists of a front-end graphical user interface (GUI) and a back-end server (left of Figure 3). Being mainly responsible for the visual exploration, the GUI includes Load data, Co-clustering parameters and Interactive coordinated multiple views (CMV). While the server side is responsible for the implementation of BBAC_I.

Figure 3: The framework of the interactive web-based geovisual analytics platform (left) and the workflow for analyzing spatio-temporal data (right) where solid arrows relate with loaded data while dashed arrows with co-clustering results

The workflow for co-clustering spatio-temporal data (right of Figure 3) using the platform starts with letting users upload their own data, both attribute (.csv) and map data (.geojson), which is displayed instantly using CMV. Then they can explore it interactively, which helps to choose the co-clustering parameters (numbers of location-cluster, timestamp-clusters, outer iterations and inner iterations). After

parameters are selected, GUI will send request to the server with the uploaded data and chosen parameters to ask for being processed with the co-clustering algorithm. When receiving request from the client side (GUI), the server side processes the data using BBAC_I with chosen parameters and afterwards sends the co-clustering results back to GUI for display. Then users can examine the results by visually exploring them. They can also choose different sets of parameters and redo the co-clustering analysis until satisfactory co-clustering results are obtained. As such, this platform can promote users' interactions by allowing them to explore the uploaded data and then discuss their findings on their own.

3.1 Coordinated multiple views (CMV)

To visualize different aspects of the uploaded data as well as the co-clustering results, the CMV are used, which includes the geographical map, linear timeline, heatmap, small multiples and of them the last one is especially for the co-clustering results.

3.1.1 Geographical map

The geographical map is any map from the map data provided by the user. The map is used to visualize the spatial aspects of the original data and co-clustering results. For both cases, it is colored to show the spatial variations of the attribute's value.

The selection of a suitable color scheme is essential. Take the temperature data for example, typically the diverging color scheme <RedYellowBlue> is selected to represent low temperatures with blue and high ones with red [28]. The platform allows users to choose one from a series of diverging and sequential color schemes, which is used for all visualizations.

3.1.2 Linear timeline

The linear timeline is used to visualize the temporal aspects of the original data and the co-clustering results which are related to linear timestamps (e.g. years). For both cases, the linear timeline arranges all timestamps sequentially. For the original data, the event of each timestamp is the value of the attribute and the linear timeline shows the temporal variations of the original data. Whereas for co-clustering results, the event of each timestamp indicates

which timestamp-cluster it belongs to, with timestamp-clusters arranged in y-axis with increasing attribute's value from the first to the last. As such, the liner timeline shows the temporal patterns in the co-clustering results. A toggle button allows users to switch between the two cases for further exploration.

3.1.3 Heatmap

Heatmap uses a range of colors to visualize individual values in a data matrix [29]. The heatmap is used here to visualize the attribute aspects of both the original data and the co-clustering results. For the former, the heatmap offers an overview of the whole original dataset by arranging timestamps and locations in the x- and y-axis from the first to last and coloring each record according to its value of the attribute. For the latter, by preserving the axes arrangement but coloring individual records with co-clustered values, the heatmap provides a straightforward view of the co-clustered matrix in the co-clustering results. After the co-clustering process, a toggle button allows users to switch back and forth to make comparisons between the original data matrix and the co-clustered one. Besides, two buttons (<select observe area> and <clear>) allows users to select regions and time intervals of their interest to reveal spatio-temporal patterns in the co-clustering results.

3.1.4 Small multiples

Map-based small multiples are a set of adjacent geographical maps to represent changes in relation to timestamps [30]. The small multiples is used here to visualize the co-clustering results. Similar as the above, each map in the small multiples is any map provided by the user. Each map is for each of timestamp-clusters, in which location-clusters are represented with bold boundaries. By this means, the small multiples visualize spatio-temporal co-clusters.

3.2 Interactions using CMV

To help users gain more insights into both their original data and the co-clustering results, visualizations in CMV are further integrated with the user interactions, e.g. hover-based brushing and linking. That is, a selection made by hover in one visualization will result in changes in other visualizations automatically. Such exploration is facilitated by using spatio-temporal co-clustering analysis related tasks [31].

3.2.1 Exploration of the user's uploaded data

For the exploration of the original data (the user's uploaded data), questions for tasks related to the co-clustering analysis focus on spatial, temporal and attribute dimensions respectively. These questions can be answered by user interactions among the geographical map, timeline and heatmap.

The formulated question focusing on the spatial dimension can be 'what is the temporal variation of the attribute in a specified location and which locations have similar variations with a specified location?' To answer it, the user can hover over the specified location in the geographical map, with itself highlighted in the map, the temporal variation of the attribute in this location will be displayed in the timeline and also all the records related to that location will be highlighted in the heatmap. By hovering over other locations in the map, the user can identify locations with similar temporal variations.

The question focusing on the temporal dimension can be 'what is the spatial variation of the attribute in a specified timestamp and which timestamps have similar variations with a specified timestamp?' It can be answered by hovering over the specified timestamp in the timeline, which will result in its highlighting, the changes of colors in the map to show the spatial variations of the attribute's value in that timestamp and also the highlighted records related to that timestamp. Similarly, hovering over other timestamps will help to identify those with similar spatial variations.

The question focusing on the attribute dimension can be 'what is the attribute in the specified location and timestamp?' It can be answered by hovering over the individual record

in the heatmap specified by a location and a timestamp. With this record highlighted in the heatmap, the spatial location and timestamp of it will be highlighted in the map and timeline separately. As such, these interactions enable users to visually explore their data in detail to get a better understanding and further help them choose the co-clustering parameters.

3.2.2 Exploration of co-clustering results

For the exploration of the co-clustering results, questions for tasks related to the co-clustering analysis focus on the individual co-clusters and spatio-temporal patterns respectively, each of them containing subtasks focusing on spatial & temporal as well as attribute aspect. These questions can be answered by the interactions among the geographical map, timeline, heatmap and small multiples.

Questions focusing on individual co-clusters. The question focusing on the spatial & temporal aspect of individual co-clusters can be ‘what is the co-cluster with the specified location and timestamp and what other locations and timestamps are also in that co-cluster?’ It can be answered by first hovering over the map, then the timeline and finally the small multiples. When the specified location in the map is hovered over, the corresponding location-cluster will be highlighted in the map and also the small multiples. Then hovering over the specified timestamp in the timeline will highlight the corresponding timestamp-cluster in the timeline and also the small multiples. The co-cluster for the specified location and timestamp is the intersection of both highlights in the small multiples. Finally, by hovering over the identified co-cluster in the small multiples, the highlighted locations and timestamps in the map and timeline are the ones in the same co-cluster for the specified location and timestamp.

The question focusing on the attribute aspect of individual co-clusters can be ‘what are locations and timestamps in a specified co-cluster (e.g. co-cluster with the highest attribute value)?’ To answer it, the user can observe and hover over the specified co-cluster in the small multiples. By observing each co-cluster in the small multiples, the user can identify the

specified one, e.g. with the highest attribute value. Then by hovering over the co-clusters, with itself highlighted in the small multiples, the user can find the locations and timestamps that belonging to this co-cluster highlighted in the map and timeline separately.

Questions focusing on spatio-temporal patterns. Questions for spatio-temporal patterns are more complex and need more interactions to complete the tasks. The formulated question focusing on the spatial & temporal aspect of spatio-temporal patterns can be ‘what are the patterns in specified regions and time intervals?’ It can be answered by interacting with the heatmap and observing the map and timeline. To select the specified regions, the user can click the labels of two locations in the y-axis of the heatmap, the clicked labels enlarged first and then back to normal to indicate the selection. Similarly, the user can select the specified time intervals by clicking the labels of two timestamps in the x-axis. After the selection, the user can click the <select observe area> button and will see a rectangle appear in the heatmap with the selected regions and intervals. These selections are also highlighted in the map and timeline separately to help users double-check selections and users can always clear the selections using the button <clear> and redo the selection. Finally by observing the records within the rectangle, the user can observe the patterns of the attribute in the specified regions and time intervals.

The question focusing on the attribute aspect of spatio-temporal patterns can be ‘where and when has the specified patterns (e.g. with decreasing value of the attribute)?’ It can be answered by observing, hovering and also doing the selection in the heatmap. By directly observing the variations of the attribute’s value in the heatmap for the co-clustering results, the user can identify regions and intervals with specified patterns. In the cases that patterns are too complicated, i.e. cannot be directly identified by observation, the user can also hover over the heatmap, which shows the detailed information of the hovered record, e.g. value, to help the identification of the specified patterns. Then by selecting these regions and intervals of interest through clicking the two locations and timestamps in the axes of the heatmap, the

user can identify the corresponding regions (where) and time intervals (when) highlighted in the map and timeline respectively. Moreover, if there are several regions and intervals with the specified patterns, the user can always repeat clicking buttons for selecting and clearing to record all of them. As such, these interactions enable users to visually explore the co-clustering results to examine if the results are satisfactory for their specific objective and dataset at hand.

3.3 Implementation

We used open-source technologies to build this web-based platform. Hosted on a web server set up using Python², the server side of the platform was developed in R for its rich libraries while the client side was implemented using Data-Driven Documents³ (D3) for its powerful capabilities of visualizations. For the connections between the server and client sides, we used the `jug` library of R⁴ to set up a simple REST API in the server to accept POST requests from the client. Then it was also used to send back RESPONSE to the client side after the co-clustering processing. Finally, it is important to mention that all codes from both client and server sides of this platform are to be made open-source in GitHub.

4 Case study and results

4.1 Case study dataset

Located in the northwest of Europe (bottom right of Figure 4), the Netherlands borders with the North Sea in the west and north where the weather is more influenced by moderate maritime climate while in the south and east it is bordered by Belgium and Germany more influenced by continental climate. As a result, the temperatures in these areas are different in this country despite of its relatively small territory (ab. 41,500 km²).

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² <https://www.python.org/>

³ <https://d3js.org/>

⁴ <http://bart6114.github.io/jug/>

Figure 4: The Thiessen polygon map of 28 Dutch weather stations

More specifically, we use annual average temperature from 1992 to 2011 (20 years) at 28 weather stations, which are available from the Royal Netherlands Meteorological Institute⁵. A Thiessen polygon map was used to show the area under each station's influence (Figure 4).

4.2 Visual exploration of the Dutch annual average temperature dataset

After we upload the temperatures and Dutch Thiessen polygon map data, the platform provides both overview and details of the dataset, which helps users choose the parameters for BBAC_I, e.g. numbers of station- and year-clusters. For this temperature dataset, the color scheme <RedYellowBlue> is selected.

As showed in Figure 5, the platform provides an overview of the temperature dataset in its default view, i.e. before user interactions. The heatmap shows low temperature values in the year 1993, 1996 and 2010. Besides, it shows strange low values in 1998 at station 278 and 1999 at 267.

⁵ www.knmi.nl

Figure 5: Overview of the Dutch yearly temperature dataset

By interacting with these linked visualizations, we can explore more details of the temperature dataset using co-clustering related tasks and questions. Example of questions for the spatial task can be ‘what is the temporal variation of temperature in station 290 (Twente) and which stations have similar variations in temperature?’ To answer it, the user can hover over this station in the map and will see the similar increasing temperature over the study period and low temperatures in 1996 and 2010. With prior knowledge about the dataset (different temperatures in the southwest and northeast), the user can hover over other stations in the northeast to observe similar variations. These linked views, facilitating the selection of the number of station-clusters, suggest 4 as a reasonable number to indicate the transition of temperatures in the Netherlands.

Example of questions for the temporal task can be ‘what is the spatial variation of temperature in 1996 and which years have similar variations in temperature?’ It can be answered by hovering over 1996 in the timeline, the user will see the low temperature values over the whole study area in the map but still with increasing temperatures from southwest to northeast (left of Figure 6). By hovering over other years, the user will identify that 2010 has similar observations whereas 1993 is different in that only stations in the northeast have low temperatures

(right of Figure 6). Thus, these observations suggest that years 1996 and 2010 should be in different year-clusters with 1993. Besides, these views suggest 2 other year-clusters with very high temperatures, e.g. 2006 and 2007 and with high ones, e.g. 2003 and 2004 (timelines and heatmaps in Figures 4, 5 and 6). Therefore, the number of year-clusters is suggested as 4 and this number also complies with human's common sense of temperatures for dividing years into “cold”, “cool”, “warm” and “hot” ones.

Figure 6: Detailed information of the dataset, 1996 (left) and 1993 (right) as examples

Figure 7: Detailed information of the dataset, the temperature in station “Stavoren” in 1999 as an example

Example of questions for the attribute task can be ‘what is the temperature value in 1999 at station 267 (Stavoren)?’ To answer it, the user can hover over the temperature record in the

heatmap for the station “Stavoren” in 1999 and detailed information, e.g. the temperature value etc. with the station and the year is highlighted in the map and timeline separately (Figure 7). As such, interactions with these views can help users to know more about this strange value or outlier in the dataset. Then users can make their own decisions for the next step, e.g. delete the outlier and re-upload or continue with the analysis. It is worth to mention that BBAC_I is insensitive to outliers [9] and therefore the user can continue the co-clustering analysis.

4.3 Visual exploration of the co-clustering results

With the numbers of station- and year-clusters suggested both as 4 in previous session and the number of inner and outer iterations as 1000 and 500 in previous study [9], the users can choose co-clustering parameters and click the co-clustering button in the interface. The co-clustering results of the temperature dataset are then displayed in the CMV (Figure 8).

Figure 8: Co-clustering results of Dutch yearly temperature dataset

Interactions with CMV can help users to further explore the co-clustering results of the temperature dataset using related tasks and questions. The example question for the spatial & temporal aspect of individual co-clusters can be ‘what is the co-cluster for station 280 (Eelde) in 1996 and which other stations and years are in the same co-cluster?’ To answer it, the user can hover over the station 280 (Eelde) in the map and will see all stations belonging to station-

cluster1 highlighted in the geographical map as well as all maps in the small multiples. Station-cluster1 is in the northeast of the Netherlands with the lowest temperature over the whole country. Then the user can hover over 1996 in the timeline and see the highlighted first map in the small multiples for the year-cluster1 with the lowest temperature among all maps. Thus, the station 280 (Eelde) and 1996 belongs to the co-cluster which locates in the northeast of the country in the first map of small multiples with the lowest temperature. Finally, when the user hovers over this co-cluster, all stations and years that belong to this co-cluster will be highlighted in the geographical map and timeline respectively and the user can see other stations and years that are in the same co-cluster as the station 280 (Eelde) and 1996 (Figure 9).

Figure 9: Interactions to explore the spatial & temporal aspect of individual co-clusters, station 280 (Eelde) in 1996 as an example

The example question for the attribute aspect of individual co-clusters can be ‘what are stations and years in the co-cluster with the highest temperatures?’ It can be answered by first observing all maps in the small multiples and identifying the co-cluster in the southwest of the country in the 4th map as the one with the highest temperature. Then by hovering over this co-cluster, the user can see the stations and years belonging to this co-cluster highlighted in the map and timeline separately.

Figure 10: Interactions to explore the spatial & temporal aspect of patterns in the co-clustering results, southwest half of the Netherlands from 1992 to 2000 as an example

The example question for the spatial & temporal aspect of spatio-temporal patterns can be ‘what are the temperature patterns in the southwest half of the Netherlands (including stations De Kooy, Schiphol, De Bilt, Volkel, Arcen and other stations of southwestwards) from 1992 to 2000?’ To answer it, the user can click the station IDs 235 (De Kooy) and 310 (Vlissingen) in the y-axis of the heatmap to specify the southwest half region and also years 1992 and 2000 in the x-axis to specify the time period. Then after clicking the <select observe area> button, the user can observe that the temperatures within in the rectangle have a general increasing trend from regions in the center, i.e. nearby station De Kooy in earlier years, i.e. around 1992 to regions in the southwest, i.e. nearby station Vlissingen in recent years, i.e. around 2000 (Figure 10). Even with the general increasing trend, the user can also observe the decreasing temperature from station De Bilt (260) to station Herwijnen (356) in this period. Besides, the user can observe a decreasing trend of temperature from 1992 to 1993 and a sharp decreasing trend from 1995 to 1996 in the whole region.

The example question for the attribute aspect of spatio-temporal patterns can be ‘where and when has occurred the most increasing temperatures?’ To answer it, the user can first observe the heatmap to identify 2010-2011 as the period with the most increasing temperatures. Then for the regions, the user can hover over stations with different values of co-clusters to examine the regions with the most increasing temperatures: stations 275, 235 and stations 356, 370, in which the temperature increased 1.1°C in sum in the period 2010-2011 from the former (e.g. 275) to the latter (e.g. 235). To see spatial and temporal distribution of the regions and intervals, the user can select the first set of stations and periods, in which two stations are not neighbored and cannot be seen as regions and therefore is meaningless to answer the question. Then the user can select the second set of stations and periods and will see that the region of stations 356, 370 has the most increasing temperatures from 2010 to 2011.

5 Discussion

After the first use of co-clustering in the geo-field, this topic attracted the attention of geographers and the co-clustering methods have been applied in climatology, phenology and disease detection etc. [9-11, 32]. For instance, Wu, Zurita-Milla [9] applied a co-clustering algorithm to analyze Dutch weather patterns. Ullah, Daud [11] used a co-clustering algorithm to detect disease occurrences and Andreo, Izquierdo-Verdiguier [32] applied the algorithm to identify potential spatial and temporal concurrence of favorable conditions for West Nile virus outbreaks. The increasing number of applications of co-clustering in the geo-field require an easily accessed platform with geovisual analytics functionality to facilitate the analysis of spatio-temporal data, especially for non-experts. Compared with the aforementioned studies, our web-based platform offers users a way to perform a visual and exploratory co-clustering analysis with any web browser. Besides, interactions using CMV can help users to select suitable sets of co-clustering parameters and can also facilitate the further interpretation of co-clustering results. For instance, compared with the study of Wu, Zurita-Milla [9] which analyzed the same dataset

using the same co-clustering algorithm and (geo)visualizations as in this study, our interactive platform allows a better understanding of the data and co-clustering parameters (as illustrated in section 4.2).

Moreover, it is also important to mention that our platform is generic and has a strong potential to facilitate the analysis of spatio-temporal patterns in various other fields because it allows users to upload their own dataset. Take the analysis of population migration for example. [33] identified the natural communities/regions to represent the migration flows patterns by clustering locations to regions. We argue that since migration flows change over time, an interactive co-clustering analysis would reveal more underlying flow patterns that spread over both regions and time periods. Our platform can also be used to analyze both spatial and temporal behavior of public transportation passengers. Instead of separately clustering passengers based on their temporal activities and then presenting spatial characterization of clusters [34], our co-clustering method is capable of grouping passengers based on both their spatial and temporal activities and then providing spatio-temporal characterization. This platform also facilitates the pattern analysis by letting the user select a suitable color scheme for the uploaded dataset from various available ones.

Besides geo-field, our web-based geovisual analytics platform could be useful for analyzing and revealing more insights from data in other fields. Many studies have developed visual analytics platforms using co-clustering methods in different fields, especially gene expression. For example, Heinrich, Seifert [35] presented an interactive visual analytics platform based on heatmap and PCP to select co-clusters in gene expression data. Fiaux, Sun [36] presented a visual analytics tool using data mining algorithms and preview pane to analyze co-clusters in textual datasets. Besides, Wu and Kasif [37] and Zhou, Ma [38] developed interactive web-based platforms for co-clustering gene expression data to which users have easy access with any web browser. Compared with these platforms, our geovisual analytics platform not only provides the heatmap that is typically used for displaying co-clustering results. It also provides several other geovisualizations that could be helpful in revealing insights from the data as well as their co-clustering results. Take gene expression data for example, the linear timeline could be used to arrange all

expressions (conditions) in x-axis and their values in the data or cluster membership in the co-clustering results in the y-axis. By this means, it helps users to get a better understanding of variations of conditions or condition-clusters and thus gain more insights into both the original data and co-clustering results.

6 Conclusion

Following the work of [9] who introduced a co-clustering algorithm (BBAC_I) to geo-field, here we present an interactive web-based geovisual analytics platform for the exploratory co-clustering analysis of spatio-temporal data. With easy access in any web browser, the platform allows users to visually and interactively explore their spatio-temporal data as well as the co-clustering results. More specifically, consisting of a front-end GUI and back-end server, this platform allows users to upload data and explore it using interactive coordinated multiple views (CMV), then choose parameters and implement the co-clustering algorithm, and finally explore the co-clustering results.

To illustrate our developed platform, we explored Dutch yearly temperature dataset for 28 stations and 20 years. Co-clustering related tasks and questions are used to facilitate the exploration in a systematic way. Compared with previous studies on co-clustering spatio-temporal data, interactions using CMV in the platform helps the selection of the most suitable set of co-clustering parameters of uploaded data and facilitates the further interpretation of co-clustering results. Besides, our platform could be helpful in pattern analysis for both geo-field and other different fields by integrating both the heatmap and several other geovisualizations. Thus, easily accessed with any web browser enhanced by Web 2.0 standards, our geovisual analytics platform enables the exploration of concurrent spatio-temporal patterns from large amounts of spatio-temporal data by combining both computer power and human interpretative capabilities.

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Computer Code Availability

The link of the GitHub repository for the source code used to develop the platform in this paper is https://github.com/XWU-UT/Clustering_D3platform. We promise to make the repository public upon the acceptance of the manuscript.