Visualization Support to Interactive Cluster Analysis

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Abstract. We demonstrate interactive visual embedding of partition-based clustering of multidimensional data using methods from the open-source machine learning library Weka. According to the visual analytics paradigm, knowledge is gradually built and refined by a human analyst through iterative application of clustering with different parameter settings and to different data subsets. To show clustering results to the analyst, cluster membership is typically represented by color coding. Our tools support the color consistency between different steps of the process. We shall demonstrate two-way clustering of spatial time series, in which clustering will be applied to places and to time steps.

1 Introduction

Our system V-Analytics [1] enables analytical workflows involving partition-based clustering by methods from an open-source library Weka [2] combined with interactive visualizations for effective human-computer data analysis and knowledge building. According to the visual analytics paradigm, knowledge is built and refined gradually by iterative application of analytical techniques, such as clustering, with different parameter settings and to different data subsets. A typical approach to visualizing clustering results is representing cluster membership on various data displays by color-coding [3-5]. To properly support a process involving iterative clustering, the colors assigned to the clusters need to be consistent between different steps. We have designed special color assignment techniques that keep the color consistency.

When data are stored in a table, clustering can be applied to the table rows or to the columns [6]. Spatial time series, i.e., attribute values referring to different spatial locations and time steps, can be represented in a table with the rows corresponding to the locations and columns to the time steps. Two-way clustering groups the locations based on the similarity of the local temporal variations of the attribute values and the time steps based on the similarity of the spatial situations, i.e., the distributions of the attribute values over the set of locations [5].

2 Interactive Two-way Cluster Analysis of Spatial Time Series

To support iterative data analysis and knowledge building with the use of clustering, V-Analytics provides the following functionality:

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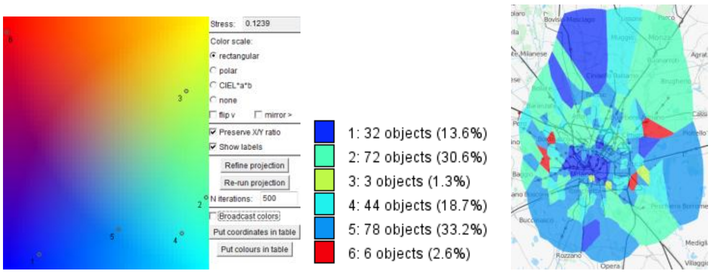

Stress: 0.1239

Color scale:

● rectangular

○ polar

○ CIEL*a*b

○ none

□ flip v □ mirror >

☑ Preserve X/Y ratio

☑ Show labels

N iterations: 500

□ Broadcast colors

Fig. 1. Left: a projection of cluster centers onto a color plane; right: the spatial distribution of the cluster membership; center: a legend showing cluster colors and sizes.

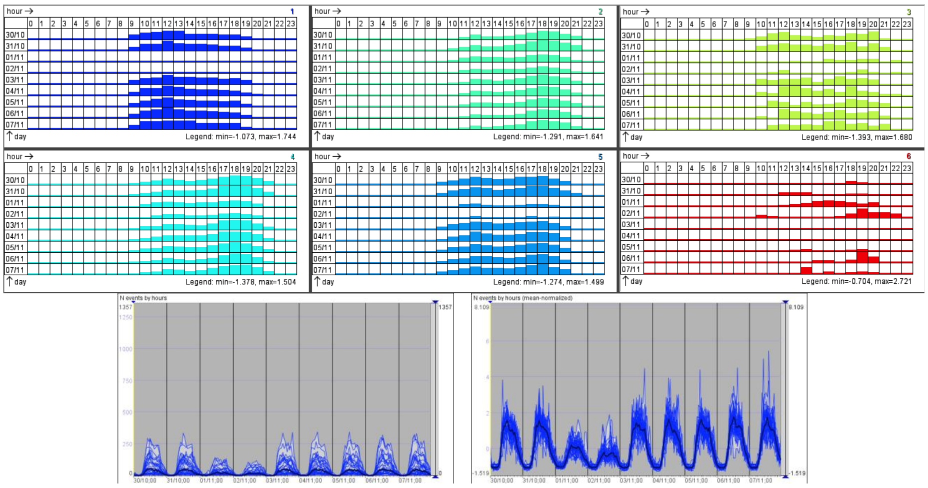

Fig. 2. Top: the 2D time histograms (9 days x 24 hours) correspond to different clusters; the bars in the cells represent the cluster means. Bottom: the time graphs show the variations of the absolute (left) and transformed (right) values for cluster 1.

- Colors are assigned to clusters based on Sammon's projection [7] of cluster centers (provided by the clustering algorithm or computed) onto a plane with continuous background coloring. This ensures that close clusters receive similar colors.
- After data re-clustering with different parameter settings, the projection of the new cluster centers is aligned with the previous projection, aiming at minimizing the distances between the positions of the corresponding clusters in the two projections. In this way, corresponding clusters receive similar colors, which makes the clusters traceable throughout the analysis process.
- Interactive techniques support progressive clustering [8], in which further clustering steps are applied to selected clusters obtained in previous steps. This allows controlled refinement of the clustering results and, on this basis, refinement of the analyst's knowledge.

This functionality is generic, i.e., applicable to various types of data and diverse partition-based clustering methods. We shall demonstrate it on an example of spatial time series obtained by spatio-temporal aggregation of records about mobile phone calls made in Milan (Italy) during 9 days by 235 spatial regions and 216 hourly time steps. To focus on the temporal variation patterns rather than purely quantitative differences between the call counts in different regions, we transform the original absolute values to the region-based z-scores. As a clustering method, we shall apply k-means.

Figures 1 and 2 show an example of partitioning the set of regions into 6 clusters based on the similarity of the region-associated temporal variations of the transformed call counts. Figure 1 shows the projection of the cluster centers onto a color plane, the colors assigned to the clusters on the basis of the projection, and a map with the regions colored according to their cluster membership. To see and compare the temporal variation patterns corresponding to the different clusters, we use temporal displays shown in Fig. 2. In the upper part, there are 2D time histograms with the rows corresponding to the days, columns to the hours of a day, and colored bars in the cells representing the average values for the clusters. Each histogram corresponds to one cluster, the bars being painted in the color of this cluster. The histograms demonstrate prominent daily and weekly periodic patterns and clearly show the pattern differences between the clusters. In the lower part of Fig. 2, the original and transformed time series from one of the clusters are shown on time graphs.

We iteratively increase the number of clusters and observe the impacts. In this example, the major clusters mostly keep unchanged, but several singletons emerge. They consist of regions with unusual time series, for example, having peaks of call counts at times of some public events. Hence, in this example, we have found four major common patterns of the temporal variation of the calling activities (clusters 1, 2, 4, and 5) and several more specific patterns.

Next, we consider the same data set from a different perspective by clustering the table columns (i.e., the hourly time intervals) according to the similarity of the distributions of the attribute values over the set of regions. We start with five clusters, the centers of which are projected on a color plane in Fig. 3 (upper left). On the upper right, there is a calendar display with the rows corresponding to the days, columns to the hours of a day, and cells colored according to the cluster membership of the corresponding time intervals. A prominent periodic pattern can be seen. The upper two rows correspond to Thursday and Friday, rows 3 and 4 to the weekend, and the following rows to five week days from Monday to Friday. In the center of Fig. 3, the spatial distributions of the calling activities corresponding to the five time clusters are shown on maps. The shades of blue and red represent, respectively, values below and above the means.

The observed temporal periodicity corresponds to our background knowledge about human activities. The pattern is preserved with increasing the number of clusters. Thus, the lower part of Fig. 3 shows the result for ten clusters. The temporal pattern has been refined while preserving the same main features as for five clusters.

To conclude, V-Analytics supports cluster analysis by providing immediate visual feedback allowing the analyst to interpret clusters, assess their similarity, identify major patterns and separate outliers, and understand the impact of clustering method parameters.

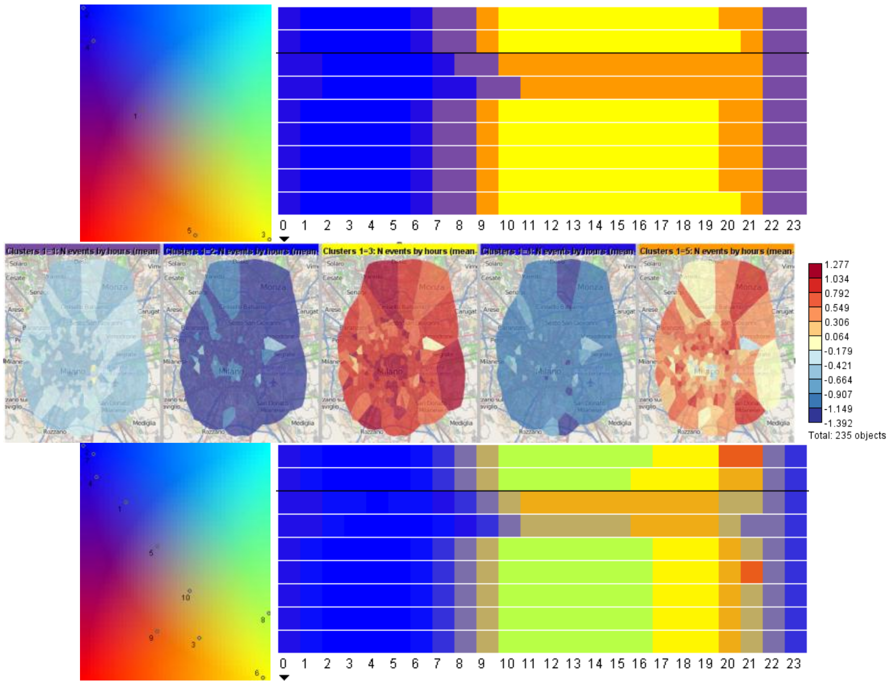

Fig. 3. Clustering of the hourly time intervals according to the spatial distributions of the calling activities. Top: projection and calendar displays for 5 clusters; center: the spatial distributions corresponding to the clusters; bottom: projection and calendar displays for 10 clusters.

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