Augmented Intelligence with Interactive Voronoi Treemap for Scalable Grouping: a Usage Scenario with Wearable Data

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Abstract

Interactive Voronoi Treemaps have been proposed to support arrangement and grouping tasks of data with snippet image representations. They rely on time-consuming manual actions to group data and cannot display more than a hundred images without occlusion. We propose visualizations designed to manage images visibility, evaluate group homogeneity, and shorten grouping task completion time while keeping control. It is supported by an automatic classifier forming an augmented intelligence system to tackle arrangement and grouping tasks at scale. We propose the usage scenario of a clinician using Interactive Voronoi Treemaps to group wearable data based on sleep visual patterns.

1. Introduction

We aim to develop an Augmented Intelligence system [BCF*19] based on interactive visualization [BABB*21] where humans and machines work in symbiosis to solve challenging problems. Arrangement and grouping (A&G) actions are essential to human intelligence [Kir95]. They can help domain experts explore new data and generate hypotheses about groupings [WN20], or assign data to groups for training automatic classifiers [BZSA18].

Voronoi treemaps [BD05] are static idioms that represent hierarchical quantitative data graphically. Recently, an interactive Voronoi treemap (IVT) was proposed to support A&G tasks of image data for visual analytics, see [AA20, AA21]. However, this approach suffers some limitations regarding scalability. **Spatial and visual scalability challenge (DO1):** A large number of images within a limited screen space, degrades their visual perception due to occlusion or small size, and the capacity to interact by dragging or clicking them (Figure 1). **Time and effort scalability challenge (DO2, DO3):** Moreover, too many images at once makes the A&G task overwhelming, tedious and time consuming, more likely to hinder task completion. Unfortunately, full automation is not desirable in sensitive application domains like health and medicine [RCBT22], and is hardly possible anyway at least for a start. Indeed, grouping images new to the expert users, is an unsupervised task which relies mainly on their subjective expert judgments hence must remain under their control to reflect their mental model; moreover, user-defined labels do not exist yet at the initial stage to train such classifiers, nor well understood features are yet engineered for natural groups to be discovered by clustering and multidimensional projection techniques [WCR*18, NA18]. At last, the high uncertainty of these models when trained on too few data, is likely to undermine user's confidence in the generated arrangements and groups if they are used too early [BABB*21].

We propose to tackle the **spatial and visual (DO1)** scalability with a Focus+Context [BHR99] approach, and to scale down the **time and effort (DO2, DO3)** of interactive A&G intending to preserve trust and control at best, by supporting these tasks with visual interactive learning concepts [BZSA18] and an enriched layout. The resulting interactive treemap visualization made scalable with machine learning forms an augmented intelligence system to support A&G tasks. We present a realistic usage scenario of a clinician analyzing data from wearable sensors [FLAP*19, KSS*22].

2. Related works

Different approaches exist to support A&G of data following principles of direct, fluid and semantic interactions [EMJ*11, End16, DP20]. Users can relocate images or points in multidimensional projection layouts under data similarity constraints [JCC*11, HAF13, JAL*22]. Users can also freely spatialize image-based data to realize A&G that match with their mental model using enriched interactive interfaces [WWI07, LZC*20], or with the Interactive Voronoi Treemap [AA21, AA20] studied in this work. **Spatial and visual scalability** issues have been tackled by using magic lenses [TGK*17], by stacking piles [LZC*20], or by optimizing location to minimize screen space usage [DTSO20]. We follow a Focus+Context approach [BHR99, MMC*19]. We propose a summary representation of the whole dataset with an automatic load balancing of the group areas in the IVT (Focus), and control widgets and bar charts (Context) on a side panel. **Time and effort scalability** problems of A&G tasks have been addressed with automation. A framework for Visual Interactive Labeling [BZSA18] relies on active learning techniques to progressively automatize the

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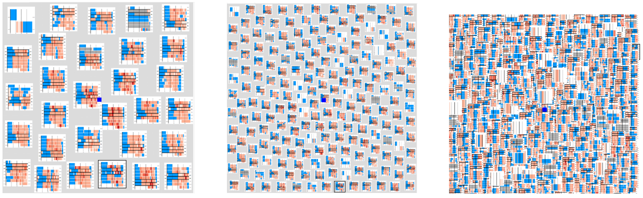
(a) (b) (c)

Figure 1: *Spatial & visual scalability challenge (DO1): (a) Big images are readable but many are not shown; (b) All small size images can fit but none is readable; (c) All images with big size are unreadable due to occlusion and clutter. We opt for showing few big images (a) but adding a contextual view (Figure 2 CDE).*

labeling task. Guiding users is essential for taking group assignment decisions [CGM19]. The layout can be enriched based on multidimensional similarities [NA18] or classifier output probabilities [REHT19, RAL*17] to help users understand automatic decisions. We propose to enrich the IVT layout with color-coded information and spatialization of the classification probabilities.

3. Interactive Voronoi Treemaps

The Interactive Voronoi Treemap (IVT) [AA21, AA20] extends power-diagram-based Voronoi Treemaps [BD05,NB12] with interaction techniques to support A&G tasks. The IVT layout (Figure 2) is made of three nested layers: the main rectangular view is the root cell (A); it is partitioned by *weighted* voronoi cells (power-diagram polygons) representing groups (J,K,L,M); at last, each group contains images centered on the leaf cells of its *unweighted* Voronoi partition. The area of the group cells are dynamically maintained proportional to the number of images they contain. Group cells are first computed using weighted Voronoi mapping [NB12], then Centroidal Voronoi Tesselation (CVT) [DFG99] is applied to get uniform space between images which avoids overlap. Users can interact with IVT. For instance: users can drag an image nearby another one for visual side-by-side comparison (*Arrangement* action); images can be assigned to a group by dragging them within that group cell (*Grouping* action), or can generate a new group by dragging them out of the root cell. Space between images is maintained at all time using CVT. A typical A&G task starts with all images put in a single group with undetermined meaning (Figure 2a A), from which they are progressively pulled out by the user (Figure 2b J,K,L,M) to form as many meaningful groups as needed to eventually represent all the discovered concepts (Figure 4). Those and other interactions have been designed and implemented in `Javascript` with D3, to support A&G tasks [AA21].

4. Design objectives to tackle scalability challenges

DO1: Maintain readable images. Although CVT maximizes distances between images to avoid overlap and clutter, we need to maintain a minimal size for each image to make them readable, which entails the impossibility to display too many of them at once in a finite screen space without occlusion (Figure 1). Hence, not all images can be made visible at a time. Therefore, users need to **DO1$_A$: know the proportion of visible and invisible images in each group** to get a sense of the groups importance and the grouping task completion. Users also need to **DO1$_B$: select which images will be made visible** to interact with.

DO2: Save arrangement time. Grouping relies on arranging images for side-by-side comparison to decide whether an image is an outlier to be removed, or an inlier that contributes to give the group its meaning. However, the invisibility of most of the images in a group (DO1) prevents users to get a faithful overview of its content. Therefore, users need to **DO2$_A$: visualize and easily access the most representative images of each group** and to **DO2$_B$: evaluate their amount of representativity**.

DO3: Save grouping time. Grouping task completion requires that every single image get assigned to a group. However, time and focus are scarce user resources while taking each assignment decision must be under control and responsibility, as it can entail accountability in sensitive application domains [RCBT22]. Therefore, users need to **DO3$_A$: visualize and easily access the most likely images to assign to a group** to operate that assignment faster and focus remaining time on harder decisions. And they need to **DO3$_B$: keep control of the assignment decisions** to feel empowered and take responsibility.

5. Design solutions

DS1: Visibility bar chart and navigation controls

We set a visibility management panel (Figure 2a (C,D,E)). We use a stacked bar chart (C) to display the quantity of visible (bottom segment) and invisible (top segment) images in each group (DO1$_A$). The bottom bar is filled with the solid color of its group cell (A). The top bar gets a lighter tone to express invisibility. A slider (E) controls the amount of visible images. The mouse-wheel sets the size of all images [AA21]. We use pagination to deal with image visibility selection (DO1$_B$). The full set of images in each group is divided into chunks of size the amount of visible images allowed for that group, except for the last chunk, possibly smaller. Each group gets an additional pair of back and forth paging buttons (D) to swap from one chunk to the next. New visible images replace old ones, each being assigned to a specific Voronoi cell, without recomputing the treemap layout. We use a watershed approach to determine the amount of visible images for each group, as if the bars of the barchart were forming a cave to flood with a fixed amount of water trying to reach the same level in each bar (Figure 4 (C$'''$)). The total visibility budget (E) is split in unit tokens to be distributed among the groups. We loop through all groups and assign visibility tokens one at a time until group capacity (number of images they contain) is reached or the budget depleted.

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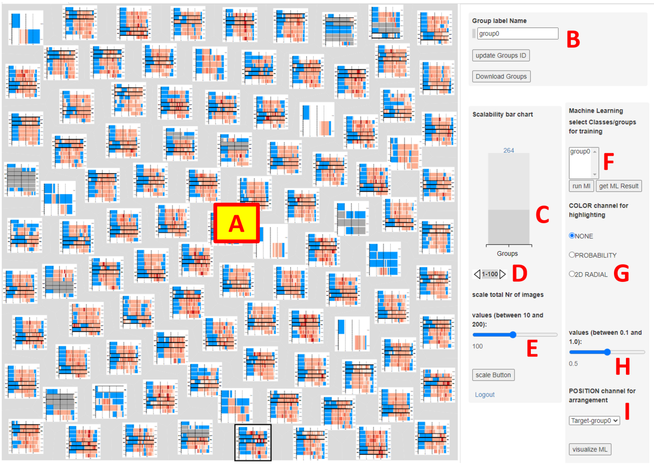
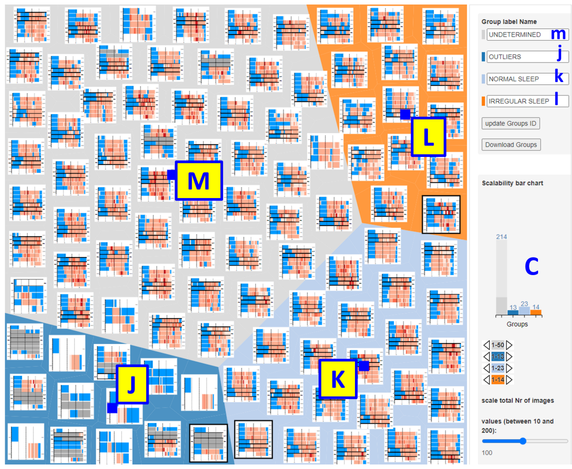
DS2: Own group centrality arrangement and coloring

We compute a centrality measure of each image based on a summary statistic of the data in their group, rank the images, and make visible the most central ones (DO2$_A$)(Figure 3a (J$'$,K$'$,L$'$,M$'$)). Several statistics could be used like the Euclidean distance to the group medoid (mean or median). We use the probability that an image data gets assigned to its group given by a classifier set to predict the probability for each image data to belong to any of the groups. This approach tends to increase the contrast between images most central to each group. We use a multinomial logistic regression model taking as inputs the features of the data associated to each image, and as output a categorical variable representing the group of that

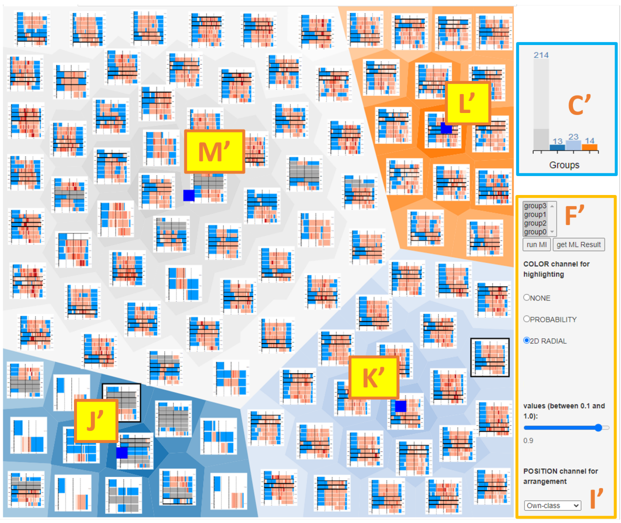


(a) Initial IVT interface

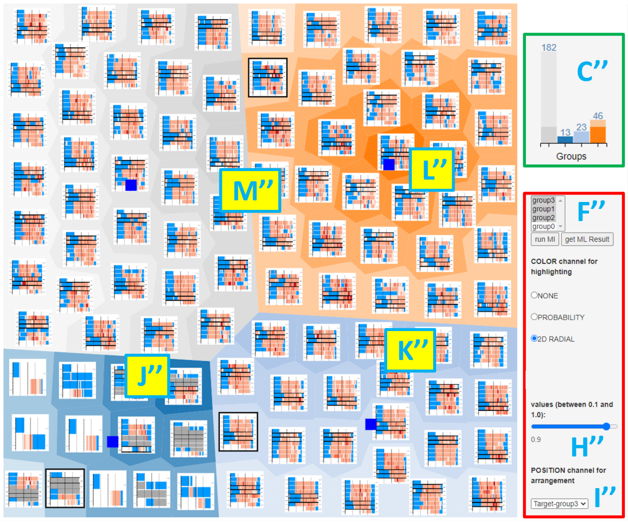


(b) DS1: Visibility bar chart and paging controls

Figure 2: *Design solution for spatial and visual scalability (DO1): (a) The interface is made of four panels: the Interactive Voronoi Treemap panel (A); the group editing panel (B); the visibility panel (**DS1**) containing the visibility barchart (C), paging controls (D), and the visibility budget slider (E); and the machine learning panel (**DS2, DS3**) with the training group selector (F), the color mapping selector (G), the probability threshold slider (H), and the target probability selector (I). (a) The slider E is set to show 100 images. Other 164 invisible images (light grey segment of the visibility bar C) can be accessed by paging D. (b) Three groups have been created by drag-and-drop. The visibility bar chart C shows the amount of visible and invisible images in each group. The user assigned names (j,k,l,m) to groups (J,K,L,M).*



(a) DS2: Own group centrality arrangement and coloring



(b) DS3: Target group predictive arrangement and coloring

Figure 3: *Design solutions for time and effort scalability (DO2 and DO3): (a) **DS2** The concentric color pattern (J',K',L',M') highlights the images most central (dark tone) to each group (I') computed with a multinomial logistic regression classifier (not shown) in the feature space based on* all groups *(F'). (b) **DS3** A single concentric color pattern centered on the target class (orange) (L'',I'') shows the images most likely (dark tone) to be assigned to that group by the classifier trained on* all groups except the undetermined one (grey)*(F''). The images remain in their respective groups but move closer to the target group (J'',K'',M''). The slider H'' is used to automatically transfer images with probability above* 0.9*, into the target group to save time and effort (bar chart before C' and after C'' the move).*

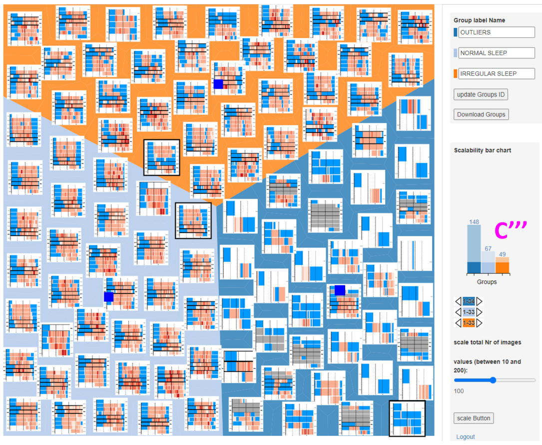


Figure 4: *The Clinician categorized all images in meaningful groups. The amount of visible images is identical for all groups (C''').*

image. It is trained on all groups (F'). We use spatialization and opacity to visualize the most central images with more saliency ($DO2_B$). We rank images by decreasing centrality, then we locate the most central image on the cell closest to the center of gravity of its group cell (J',K',L',M'). We map the remaining images in sequence, along concentric layers around the first one, over the Voronoi adjacency network. All free (visible) cells are allotted in each group independently. The opacity of the cells only depends on the concentric layers and aims to reinforce the perception of the spatial encoding. Using exact centrality values for opacity encoding would bring more confusion with an unnecessary level of details, blurring the concentric arrangement of the images.

DS3: Target group predictive arrangement and coloring

We compute a group assignment prediction measure for each image data based on a classifier to determine which of them should be visible ($DO3_A$) (Figure 3b). We use the same multinomial logistic regression model as for group centrality-based arrangement (DS2) except it is trained on all but the undetermined group (M''), because the images in that group need to be categorized by the classifier and this group has no specific meaning. A menu allows selecting the target group of the prediction (I''). Again, we use spatialization and opacity to visualize the images with a graphical saliency reflecting their assignment probability to the target group ($DO3_B$). We follow the same centrality-based approach for mapping the images. But we rank them by their decreasing probability of being assigned to the target group, and we pick the center of gravity of the target group cell as the unique root of the concentric layout. Finally, we propagate the concentric layers across the adjacency network of all Voronoi cells disregarding the groups boundaries. We map images in sequence, along these layers, but do so group by group, filling all free slots in one group by the images of that group. We do the same in all groups: images within the target groups are arranged the same way as for centrality-based approach; in other groups, images with the highest probability gather closer to the target group's boundary making easier their drag-and-drop assignment into that group. All free (visible) cells are allotted in each group independently. The opacity of the cells only depends on the concentric layers centered on the target group, and aims to reinforce the spatial encoding for the same reason as in DS2. A slider (H'') controls the minimum probability level to reach before allowing automatic assignment of the images to the target group. The lower the level, the larger the number of images automatically pushed into the target group. Once the slider value is set, all images with high enough probability are assigned to the target group, and the above steps are conducted to reflect this assignment in the layout. This causes images close but outside the target group (J'',K'',M''), to move first, letting free space on the opposite side of their provenance group cell to let enter images of that group invisible so far.

6. Usage scenario with wearable data

Amna is a clinician analyzing images representing wearable data from 264 patients recorded over a week. Each data is a tuple of feature values like the *average duration of vigorous physical activity across all week-end days*, or the *average sleep duration* or *number of naps*. Each image depicts these data over a full week with one horizontal line per day segmented in consecutive blocks. Block lengths code for the duration and color codes for the intensity of the physical activity (orange and red) or sleep and naps (blue). Amna aims to explore sleep patterns appearing as blue vertical alignments across days in the image data, and discover meaningful groups of patients. We simulated realistic patterns by adding noise to real data that we cannot disclose publicly. Letters refer to figures 2, 3, and 4.

Amna sets the visibility slider (E) to 100 to get readable images. She sees that half of the total are visible (Dark grey C). She pages through all images (D) to get an overview (*DS*1). She starts grouping images by similarity of sleep patterns. After 10 minutes, she created three groups (J,K,L) that she named: Outliers (dark blue)(j), Normal sleep (light blue)(k), and Irregular sleep (orange)(l). The bar chart C shows her progression, with the light blue group containing most of the images grouped so far. Then, she uses *own-group centrality* to check groups' homogeneity (*DS*2) (F',I'). It makes outliers more visible in the center of the grey group (M'), that she will assign to the Outlier group (J'). Once groups are big enough, she switches to the *target-group predictor* option (*DS*3) (F'',H'',I''). She selects the Irregular sleep group (L'') as a target, and run the model training and prediction (F''). The images gathering at the boundary of the Irregular sleep group (J'',K'',M'') are more likely to belong to it. She sets the probability threshold H'' to 0.9 to force the automatic assignment of the most likely ones. Visibility bars are updated C'' accordingly. She proceeds until the Undetermined group M'' gets empty (Figure 4).

7. Conclusion and future work

We presented the design of an augmented intelligence systems to support arrangement and grouping tasks at scale for exploratory data analysis. Its trustworthiness relies on ensuring all data are assigned to groups as users desire. Beyond the possibility to manually assign images and to check group's content at any time, we need to indicate the confidence level of the automatic classifier. We plan to run a quantitative user study as part of the QNRF Qatar Diabetes Prevention Program NPRP11C-0115-180010, to evaluate thoroughly the usefulness and usability of this tool for clinicians, and its benefits in terms of time, effort, and trustworthiness.

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