

InViTAG: a web application for AI-assisted exploration and grouping of health images and data

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ABSTRACT

In health and clinical research, as in many other scientific domains, important discoveries stem from carefully exploring hundreds of cases, sifting through their graphical representations or images. Once typical cases have been identified and validated by the researcher, artificial intelligence, statistics, and machine learning tools can be leveraged to classify the remaining cases at scale. InViTAG is a web application designed to support exactly this initial exploratory phase, where machines can barely help. We present the main features of this system and a use case where it helps discover categories of sleep and activity patterns in wearable data.

Index Terms: Interactive Voronoi Treemap.

1 INTRODUCTION

An essential step before using data images in machine learning pipelines is data and image curation [28]. It consists in enhancing image quality using computer vision techniques, highlighting, identifying, and annotating regions of interest, and enriching image data with expert knowledge. Part of this data preparation relies on identifying and grouping data into meaningful categories that will serve the training of supervised classifiers [14].

A critical part of the categorization process are arrangement and grouping (A&G) actions, which are key [22, 13] for domain experts to build trust and knowledge[27] while exploring new data and generating hypotheses about groupings.

Human-machine hybrid approaches have been proposed in the Visualization community to support these tasks [14, 29, 15].

We propose an Augmented Intelligence system [16] using interactive visualization called InViTAG, which stands for interactive Voronoi treemaps for arrangement and grouping. The design rationale of this tool has been presented in more details in previous publications [8, 9, 10]. While InViTAG is still a prototype, we make it publicly available to serve the scientific community and to collect feedback on the related GitHub page. The system can be used on the following website:

<https://invitag-health.qcri.org/>.

Comments are welcome using the GitHub page:

<https://github.com/michaelaupetit/invitag>

In the sequel, we remind the main design rationale and present the features of this system.

2 CONTEXT AND DESIGN RATIONALE

This system was initially designed to support a clinician-researcher studying the physical activity and sleep of 264 patients suffering various degrees of obesity and diabetes [17, 25, 18]. They were equipped with wearable sensors capturing their level of physical activity every minute during one week, which was encoded for each

patient as a bar chart (Figure 1a)) with sleep (blue), sedentary, moderate, and vigorous (orange to red) segments.

The clinician needed to visualize each patient’s data to allow the visual discovery and categorization of activity and sleep patterns that were likely unknown by the clinician and the health community at large given the novelty of the technology at that time [7, 18, 11, 21].

This process typically resorts to exploratory data analysis tools like dimensionality reduction [24] to convert multivariate measurements into scatterplots, or clustering techniques [12, 29, 20] to create groups automatically. In contrast to this mostly automatic approach, we opted for an interactive visual approach more able to capture the early stages of the analytic process where the external knowledge and intuition used by the analyst are crucial to determine patterns of interest. The system would record this knowledge-in-the-making through the initial category seeds visually identified and manually grouped, and learn from them the features’ importance, and the multidimensional metrics to use for further automation and assistance.

As this initial stage is fully manual and visual, grouping images requires optimizing space to avoid clutter and overlap while keeping individual images readable. It also requires optimizing time and interactions to reduce the burden of manual and visual exploration and to ease the discovery of interesting patterns and populate the corresponding groups [10].

We pick the Voronoi treemap idiom for its expressiveness to arrange images and groups in a nearly regular layout using centroidal Voronoi tessellation and power diagrams [8, 9], while maximizing the use of space.

We use statistical techniques to scale the categorization process by exploiting the initial groups the analyst forms with only a few images with clustering and classification techniques [10].

3 STRUCTURE AND INTERACTIONS

A video demo is available at: <https://github.com/michaelaupetit/invitag>

InViTAG interface comprises Data, Features, and Groups tabs. The user starts from the Data tab, uploading a set of images and a csv file containing numerical features for each image. Then the user can proceed with the Features or the Groups tab. The Features tab uses the LineUp interface[19] for feature-based exploration. Any instance selection in that interface is reflected in the Groups tab. Group creation, exploration, and management are operated in the Groups tab, the main component of InViTAG.

In the Groups tab (Figure 2), a Voronoi treemap is used to avoid occlusion (Figure 1bcd), fixing the number of visible images on the screen to a tunable portion of the total amount, and allowing paging navigation to access all the data in each group independently (H,I,J,K). A side panel (Figure 2A-M) enables access to image exploration: search by image ID (A), random arrangement (B), push selection to the first page (C), highlight of inliers (D) or outliers (E), automatic clusterization (F) and classification magnet (G). Groups can be split using single image drag-and-drop, line-selection and lasso-selection to teleport multiple images at once in another group. Groups can be merged by stitching adjacent groups with a zigzag

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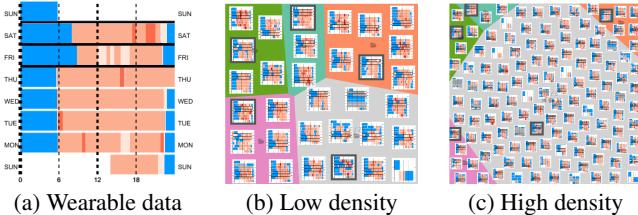


Figure 1: (a) A typical image of sleep/nap (blue) and activity (orange-red) wearable data encoded as a bar chart. (b,c,d) Visual scalability is resolved using treemap arrangement of the images and groups rather than a rigid snap-to-grid. When only a part of group is visible, paging controls are available



Figure 2: The Explore panel of the Groups tab allow navigation and support for automatic arrangement to identify and create groups.

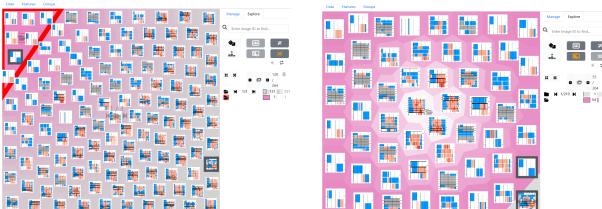


Figure 3: (a) A few images with outlying patterns are grouped (pink) and targeted (red border) by the magnet action (G) to ease filling the group with similar images. (b) We collapsed the Uncategorized group (grey) to maximize the use of space and clean up the outlier group (pink). We ran the show-outliers action (E) to show the images belonging to the least to that group (near the center) and ease their move to another group.

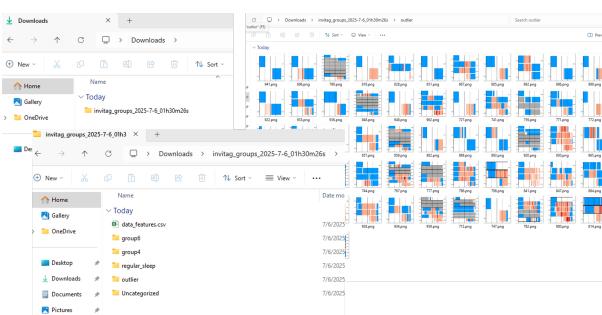


Figure 4: Group structure and data can be downloaded to ease reuse and further analysis.

line on their common boundary, or drag-and-drop a group handle to one of the other group.

The side panel also has a group management tab to rename, delete and download grouped images as a zip containing images organized into folders with their respective group names, and a data feature CSV file with additional group column to enable statistical analysis of the groups or train machine learning models, and a color (hexadecimal code) column to match the colors in other visualizations of the same data.

InViTAG implements the following interactions (Figure 2):

- Direct global image resizing (with mouse over the background and scroll-wheel) or controlling the number of visible images (M) (Figure 1bcd). Single image zooming with mouse over the image and scroll-wheel. Navigation by paging using arrows in the side panel (I) or at the center of each group (by clicking or with scroll-wheel)
- Side-by-side comparison by drag-and-drop of single images. Group creation by drag and drop of a single image outside the main frame. Adding image to a group by drag-and-drop into the polygonal cell of that group.
- Seeding groups by selecting few seed images and double-click generate one group for each seed image. The automatic clusterize option (F) use K-means in the data feature space to help discovering groups.
- Once groups are populated with a few images, automatic classification can be used (G) to show the most similar images from other groups (Figure 3a) or the show-outliers action (E) to clean up the group (Figure 3b).

Once the analyst has finalized the groups. They can be downloaded for further analysis or use (Figure 4).

4 RELATED SYSTEMS AND TECHNICAL CHARACTERISTICS

Existing systems used in data science are enhanced file managers making easier organizing scientific image like Tropy [5] to explore, annotate, and group images. Other tools help researchers annotate and enhance image quality, an essential step before using data in machine learning pipelines [28]. For instance, ImageJ [26] is an open source library to run image analysis and processing to enhance image quality and search region of interest and patterns within images using computer vision techniques. Closer to InViTAG is the Piling.js [23] javascript library which focuses on arrangement and grouping of images based on a piling metaphor. InViTAG implements some aspect of piling but enriches it with many interactions to create groups semi-automatically, and replace the snap-to-grid layout with a more flexible and expressive centroidal Voronoi tessellation and power diagrams [9].

InViTAG is a Flask application [3] using Python and the Scikit-learn module [4] on the server-side, for classification (Multinomial logistic regression for multi-class and Mahalanobis metric for single class rankings) and clustering (K-means). It uses Javascript modules on the front-end like d3.js[2] and [1] with additional custom logic to realize the main interactive Voronoi treemap component, and embeds the LineUp [19, 6] interface for feature analysis of the created groups.

5 FUTURE WORK

InViTAG is publicly available for trying up to 500 images. Comments and feedback are welcome by using the GitHub project page.

We plan to run studies with end-users to thoroughly evaluate the usefulness and usability of this tool and the benefit of our design.

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