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

Ala Abuthawabeh*
Amman Arab University

Michael Aupetit†
Qatar Computing Research Institute,
Hamad Bin Khalifa University

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 the researcher has identified and validated typical cases, 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 is 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 tesselation 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].

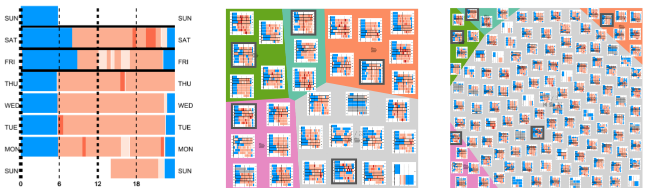
3 Structure and interactions

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 1bc), 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 all selected images 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-end-drop, line-selection and lasso-selection to teleport multiple images at once in another group. Groups can be merged by stitching adjacent groups

*e-mail: a.abuthawabeh@aau.edu.jo
†e-mail: maupetit@hbku.edu.qa (Corresponding author)



(a) Wearable data (b) Low density (c) High density

Figure 1: (a) A typical image of sleep/nap (blue) and activity (orange-red) wearable data encoded as a bar chart. (b,c) Visual scalability is resolved using treemap arrangement of the images and groups rather than a rigid snap-to-grid. When only a part of a group is visible, paging controls are available (Figure 2IJK).

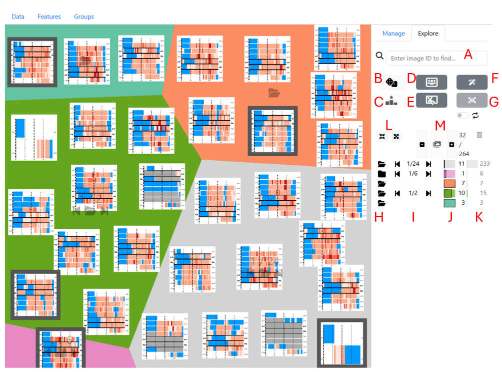
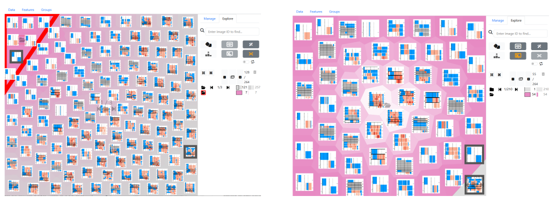


Figure 2: The Explore panel of the Groups tab allows navigation and support for automatic arrangement to identify and create groups.



(a) (b)

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 to clean up the outlier group (pink). We ran the show-outliers action (E) to show the images the least in that group (near the center). In both cases, the automatic arrangement eases the selection, which is still controlled by the user (with scroll-wheel, individual click, line or lasso), as well as the decision to move the selected images to the target (a) or another group (b).

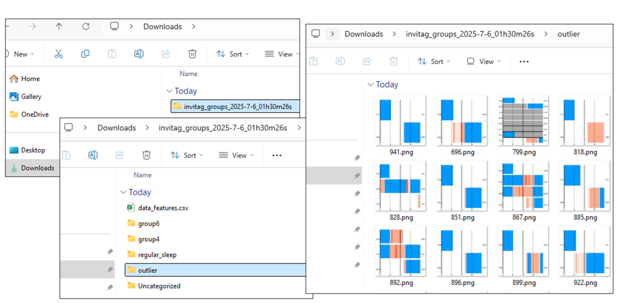


Figure 4: Group hierarchy and data can be downloaded as a zipped CSV file and image folders to ease re-use and further analysis.

with a zigzag line on their common boundary, or by dragging and dropping a group handle over the handle of the other group.

The side panel also has a Manage group tab to rename or delete entire groups and download grouped images as a ZIP. The ZIP contains images organized into folders with their respective group names and a data feature CSV file. The output CSV file is identical to the input CSV file but with additional columns `group_name` and `group_color` to enable statistical analysis of the groups or training of machine learning models, and to re-use 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 1bc). 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 a few seed images and double-clicking in the background to generate one group for each seed image. The automatic clusterize option (F) uses K-means in the data feature space to help discover 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). The show-outliers action (E) can be used to clean up the group (Figure 3b).

Once the analyst has finalized the groups, they can be downloaded for further analysis or usage (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` [6] 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 tesselation and power diagrams [9].

`InViTAG` is a `Flask` application [3] using `Python` and the `Scikit-learn` module [5] on the server-side, for classification (Multinomial logistic regression for multi-class and Mahalanobis metric for single class rankings (D,E,G)) and clustering (K-means (F)). It uses `Javascript` modules on the front-end like `d3.js` [2] and `Weighted Voronoi` [1] with additional custom logic to realize the novel interactive Voronoi treemap component. It embeds the `LineUp.js` [19, 4] interface for feature analysis of the created groups in the Features tab.

5 Future Work

`InViTAG` is publicly available for grouping 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 benefits and limitations of our design.

Acknowledgments

This contribution was made possible by NPRP11C-0115-180010/NPRP11C-30752-SP-32 Grant from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

References

[1] D3.js Weighted Voronoi Treemap API reference. https://github.com/Kcnarf/d3-voronoi-map. Accessed: 2020-04-08. 2

[2] D3.js, Accessed [2025-07-01]. https://d3js.org/. 2

[3] Flask framework, Accessed [2025-07-01]. https://flask.palletsprojects.com/. 2

[4] Line-Up, Accessed [2025-07-01]. https://lineup.js.org/. 2

[5] scikit-learn, Accessed [2025-07-01]. https://scikit-learn.org/. 2

[6] Tropy, Accessed [2025-07-01]. https://tropy.org/. 2

[7] Y. Abdelaal, M. Aupetit, A. Baggag, M. Bashir, and D. Al-Thani. How much wearable data is enough for the utility and trust of augmented artificial intelligence systems? A scenario-based interview with medical professionals. *Int. J. Hum. Comput. Interact.*, 41(12):7684–7710, 2025. doi: 10.1080/10447318.2024.2400388 1

[8] A. Abuthawabeh and M. Aupetit. A force-directed power diagram approach for interactive voronoi treemaps. In A. Kerren, C. Garth, and G. E. Marai, eds., *EuroVis 2020, Norrköping, Sweden, May 25-29, 2020 [online only]*, pp. 109–113. Eurographics Association, 2020. doi: 10.2312/evs.20201057 1

[9] A. Abuthawabeh and M. Aupetit. Toward an Interactive Voronoi Treemap for Manual Arrangement and Grouping. In M. Agus, C. Garth, and A. Kerren, eds., *EuroVis 2021 - Short Papers*, pp. 97–101. The Eurographics Association, 2021. doi: 10.2312/evs.20211062 1, 2

[10] A. Abuthawabeh, A. Baggag, and M. Aupetit. Augmented intelligence with interactive voronoi treemap for scalable grouping: a usage scenario with wearable data. In M. Agus, W. Aigner, and T. Höllt, eds., *24th Eurographics Conference on Visualization, EuroVis 2022 - Short Papers, Rome, Italy, June 13-17, 2022*, pp. 43–47. Eurographics Association, 2022. doi: 10.2312/EVS.20221091 1

[11] M. Aupetit, L. Fernández-Luque, M. Singh, and J. Srivastava. Visualization of wearable data and biometrics for analysis and recommendations in childhood obesity. In P. D. Bamidis, S. T. Konstantinidis, and P. P. Rodrigues, eds., *30th IEEE International Symposium on Computer-Based Medical Systems, CBMS 2017, Thessaloniki, Greece, June 22-24, 2017*, pp. 678–679. IEEE Computer Society, 2017. doi: 10.1109/CBMS.2017.120 1

[12] M. Aupetit, M. Sedlmair, M. M. Abbas, A. Baggag, and H. Bensmail. Toward perception-based evaluation of clustering techniques for visual analytics. In *30th IEEE Visualization Conference, IEEE VIS 2019 - Short Papers, Vancouver, BC, Canada, October 20-25, 2019*, pp. 141–145. IEEE, 2019. doi: 10.1109/VISUAL.2019.8933620 1

[13] E. Beauxis-Aussalet, M. Behrisch, R. Borgo, D. H. Chau, C. Collins, D. Ebert, M. El-Assady, A. Endert, D. A. Keim, J. Kohlhammer, D. Oelke, J. Peltonen, M. Riveiro, T. Schreck, H. Strobelt, and J. J. van Wijk. The role of interactive visualization in fostering trust in ai. *IEEE Computer Graphics and Applications*, 41(6):7–12, 2021. doi: 10.1109/MCG.2021.3107875 1

[14] J. Bernard, M. Zeppelzauer, M. Sedlmair, and W. Aigner. VIAL: a unified process for visual interactive labeling. *The Visual Computer*, 34(9):1189–1207, 2018. doi: 10.1007/s00371-018-1500-3 1

[15] S. Bonakala, M. Aupetit, H. Bensmail, and F. El-Mellouhi. A human-in-the-loop approach for visual clustering of overlapping materials science data. *Digital Discovery*, 3:502–513, 2024. doi: 10.1039/D3DD00179B 1

[16] S. Broschert, T. Coughlin, M. Ferraris, F. Flammini, J. G. Florido, A. C. Gonzalez, P. Henz, D. de Kerckhove, R. Rosen, R. Saracco, A. R. Singh, A. Vitillo, and M. S. Yousif. Symbiotic autonomous systems : White paper iii. 2019. 1

[17] L. Fernandez-Luque, M. Aupetit, J. Palotti, M. Singh, A. Fadlelbari, A. Baggag, K. Khowaja, and D. Al-Thani. *Health Lifestyle Data-Driven Applications Using Pervasive Computing*, pp. 115–126. Springer International Publishing, Cham, 2019. doi: 10.1007/978-3-030-06109-8_10 1

[18] L. Fernández-Luque, M. Singh, F. Ofli, Y. Mejova, I. Weber, M. Aupetit, S. K. Jreige, A. K. Elmagarmid, J. Srivastava, and M. Ahmedna. Implementing 360° quantified self for childhood obesity: feasibility study and experiences from a weight loss camp in qatar. *BMC Medical Informatics Decis. Mak.*, 17(1):37:1–37:13, 2017. doi: 10.1186/S12911-017-0432-6 1

[19] S. Gratzl, A. Lex, N. Gehlenborg, H. Pfister, and M. Streit. Lineup: Visual analysis of multi-attribute rankings. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2277–2286, 2013. doi: 10.1109/TVCG.2013.173 1, 2

[20] H. Jeon, M. Aupetit, D. Shin, A. Cho, S. Park, and J. Seo. Measuring the validity of clustering validation datasets. *IEEE Trans. Pattern Anal. Mach. Intell.*, 47(6):5045–5058, 2025. doi: 10.1109/TPAMI.2025.3548011 1

[21] K. Khowaja, W. W. Syed, M. Singh, S. Taheri, O. Chagoury, D. Al-Thani, and M. Aupetit. A participatory design approach to develop visualization of wearable actigraphy data for health care professionals: Case study in qatar. *JMIR Hum Factors*, 9(2):e25880, Apr 2022. doi: 10.2196/25880 1

[22] D. Kirsh. The intelligent use of space. *Artif. Intell.*, 73(1-2):31–68, 1995. 1

[23] F. Lekschas, X. Zhou, W. Chen, N. Gehlenborg, B. Bach, and H. Pfister. A generic framework and library for exploration of small multiples through interactive piling. *IEEE Transactions on Visualization and Computer Graphics*, (01):1–1, oct 2020. doi: 10.1109/TVCG.2020.3028948 2

[24] L. G. Nonato and M. Aupetit. Multidimensional projection for visual analytics: Linking techniques with distortions, tasks, and layout enrichment. *IEEE Trans. on Visualization & Computer Graphics*, 2018. doi: 10.1109/TVCG.2018.2846735 1

[25] I. Perez-Pozuelo, B. Zhai, J. R. M. Palotti, R. Mall, M. Aupetit, J. M. Garcia-Gomez, S. Taheri, Y. Guan, and L. Fernández-Luque. The future of sleep health: a data-driven revolution in sleep science and medicine. *npj Digit. Medicine*, 3, 2020. doi: 10.1038/S41746-020-0244-4 1

[26] C. T. Rueden, J. Schindelin, M. C. Hiner, B. E. DeZonia, A. E. Walter, E. T. Arena, and K. W. Eliceiri. Imagej2: Imagej for the next generation of scientific image data. *BMC Bioinformatics*, 18(1):529, Nov 2017. doi: 10.1186/s12859-017-1934-z 2

[27] D. Sacha, A. Stoffel, F. Stoffel, B. C. Kwon, G. Ellis, and D. A. Keim. Knowledge generation model for visual analytics. *IEEE Trans. on Vis. & Comp. Graph.*, 20(12):1604–1613, 2014. 1

[28] S. Vahdati, B. Khosravi, E. Mahmoudi, K. Zhang, P. Rouzrokh, S. Faghani, M. Moassefi, A. Tahmasebi, K. P. Andriole, P. Chang, K. Farahani, M. G. Flores, L. Folio, S. Houshmand, M. L. Giger, J. W. Gichoya, and B. J. Erickson. A guideline for Open-Source tools to make medical imaging data ready for artificial intelligence applications: A society of imaging informatics in medicine (SIIM) survey. *J Imaging Inform Med*, 37(5):2015–2024, Apr. 2024. 1, 2

[29] J. Wenskovitch and C. North. An examination of grouping and spatial organization tasks for high-dimensional data exploration. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–1, 2020. doi: 10.1109/TVCG.2020.3028890 1