

Navigating the Zoo of Visualization Techniques

Abdulhaq Adetunji Salako*

Christian Tominski†

University of Rostock
Institute of Visual and Analytic Computing
Rostock, Germany

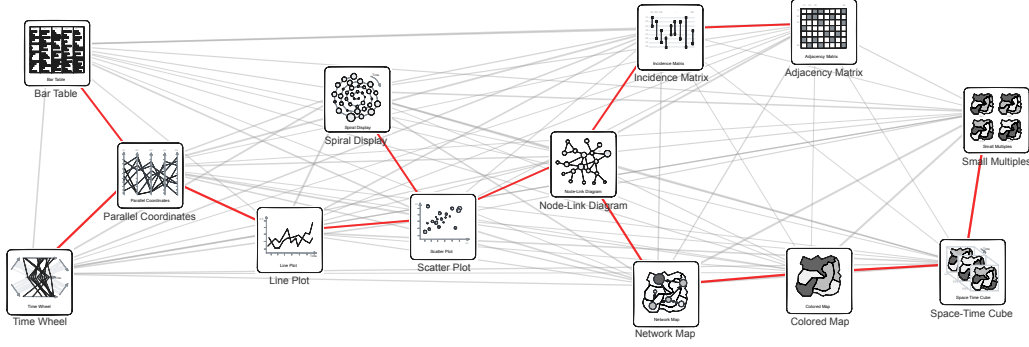


Figure 1: Minimum spanning tree illustrating the strongest expert-driven similarity between visualization techniques.

ABSTRACT

The space of visualization techniques remains challenging to navigate despite numerous surveys categorizing the existing works. What could help is a better understanding of the similarities of visualization techniques. We explore this open research question from two angles: (1) a model-driven approach that is based on signatures of visualization techniques and (2) an expert-driven study capturing the intuitive similarity assessment from visualization experts. Both approaches give us similarity scores that can be used to extract a minimum spanning tree as a pathway through the zoo of visualization techniques. For this preliminary work, we considered a set of 13 basic and advanced visualizations for different types of data.

Index Terms: Similarity, visualization techniques, data facets.

1 INTRODUCTION

The visualization community has created a large number of visualization techniques. Surveys document the wide variety of existing techniques, sometimes listing hundreds of works. This variety is both a curse and a blessing. A blessing, because there are solutions for many different types of data, analysis tasks, and application scenarios. A curse, because it can be difficult to find a suitable technique for a specific problem, and in general, to navigate the space of visualization techniques. How are visualization techniques related through commonalities and differentiated by peculiarities? What are pathways through the space of visualization techniques? Are there central techniques that are shared for several pathways?

To answer these questions, we need to better understand the similarity of visualization techniques. Yet, similarity is not easy to capture and might involve various aspects [1]. Techniques can be similar in how they look, work, or what kind of data they visualize. Existing surveys try to group techniques using structured categories, but they are typically limited to specific visualization aspects. A better understanding of similarity could make it easier to find and learn suitable techniques, and navigate the visualization space.

Table 1: Visualization techniques and their signatures.

Vis. Technique	Signature
Bar Table BT	$D_A M_A C_P C_L C_C R_A O_L L_S$
Scatter Plot SP	$D_A M_P C_P C_A C_C R_S O_L L_D$
Parallel Coordinates PC	$D_A M_L C_P C_C R_A O_P L_D$
Line Plot LP	$D_T D_A M_P M_L C_P C_C R_O O_L L_D$
Spiral Display SD	$D_T D_A M_A C_P C_C R_O O_R L_S$
Time Wheel TW	$D_T D_A M_L C_P C_C R_O O_R L_D$
Colored Map CM	$D_S D_A M_A C_P C_C C_S R_S O_L L_S$
Small Multiples SM	$D_T D_S M_P M_L M_A C_P R_A O_L O_P O_R L_S$
Space-Time Cube STC	$D_T D_S M_A C_P C_C C_S R_O O_L L_S$
Network Map NM	$D_S D_R M_P M_L M_A C_P C_A C_C C_S R_S R_O O_L L_S$
Node-Link Diagram NLD	$D_R D_A M_P M_L C_P C_A C_C R_S O_L L_D$
Adjacency Matrix AM	$D_R D_A M_A C_P C_C R_A O_L L_S$
Incidence Matrix IM	$D_R D_A M_L C_P C_A C_C R_A O_L O_P L_D$

To this end, we conducted two studies: (1) a model-driven study and (2) an expert-driven study, to investigate the similarity of 13 representative visualization techniques covering four data facets: time (T), space (S), multivariate attributes (A), and structural relationships (R). The obtained similarity scores allow us to extract a minimum spanning tree to define pathways between techniques. For more details, we also refer to a slightly longer report in [4].

2 MODEL-DRIVEN & EXPERT-DRIVEN APPROACHES

We applied two complementary approaches. The model-driven approach aims to capture visualization similarity more formally, while the expert-driven approach aims to capture ad-hoc intuitive human similarity judgments.

Model-driven approach We categorized each visualization technique using Munzner’s design space [2], focusing on key properties such as data facets D , visual marks M , encoding channels C , spatial regions R , orientation O , and layout L . Based on this categorization, we defined a string signature for each technique as a structured sequence of categorical tokens that captures these core design elements.

*e-mail: abdulhaq.salako@uni-rostock.de

†e-mail: christian.tominski@uni-rostock.de

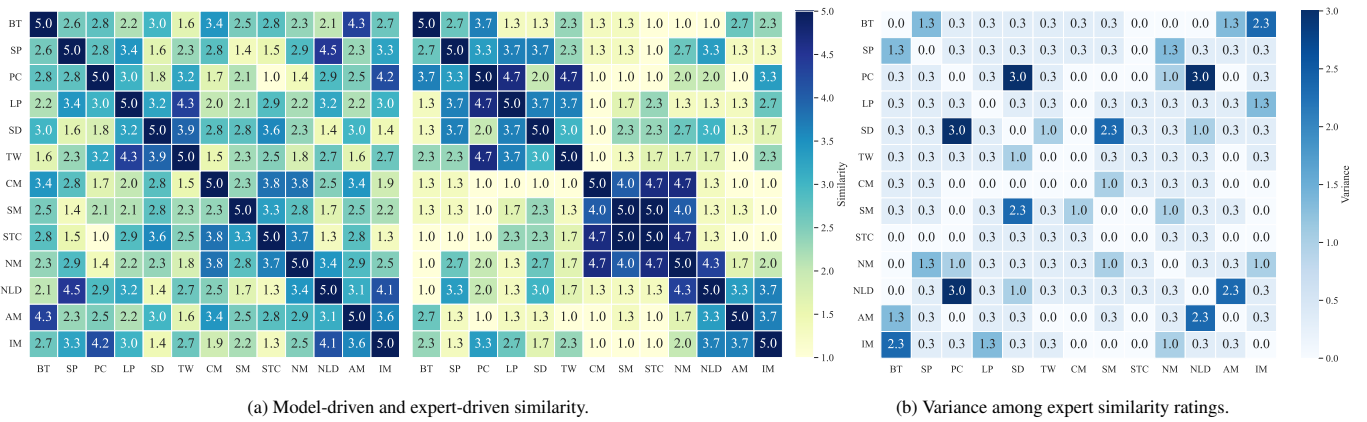


Figure 2: Heatmap of model-driven and expert-driven similarity scores and variance of similarity ratings.

Our 13 visualizations and their signatures are listed in Tab. 1, and small thumbnails can be seen in Fig. 1. For example, the signature for the Line Plot technique is $D_T D_A M_P M_L C_P C_C R_O L L D$, capturing its key design features: time and attribute data, point and line marks, position and color channels, ordered region, rectilinear axis, and dense layout. Based on such signatures, we can estimate technique similarity by computing pairwise similarity scores between signatures. To this end, we use the Jaro-Winkler string similarity metric, which allows us to measure how closely techniques align in their design structure, even when their signatures differ in length.

The similarity scores (scaled to 1.0 – 5.0 for easier comparison) are presented in Fig. 2a (left). Techniques sharing data facets (e.g., Node-Link Diagram, Adjacency Matrix, Incidence Matrix) tend to score higher. However, shared visual features such as mark type or layout also strongly influence similarity. For instance, Adjacency Matrix is structurally similar to Colored Map and Bar Table due to area-based, space-filling layouts, despite differing in data type.

It should be noted that our signature approach is of course a compromise that aims to balance the modeling effort and the expressiveness of the obtained signatures. Moreover, certain parts of the signature are not necessarily unique per technique. Scatter Plots, for example, could also use shape as an additional visual channel to visualize another categorical attribute.

Expert-driven approach In this approach, we asked three visualization experts to rate the similarity of all 78 unique pairs from our set of 13 visualization techniques. We asked for their ad-hoc intuitive impression without prescribing any specific interpretation of the notion of similarity. Further, the techniques were presented as sketch-style images (see Fig. 1), allowing experts to focus on general concept and visual appearance, rather than implementation details. Each pair was rated on a 5-point Likert scale (from highly dissimilar to highly similar), resulting in 234 similarity scores. At random intervals, we also collected qualitative comments about what experts found most similar or different.

We analyzed average similarity and variance to understand expert-perceived similarity and agreement. The heatmap in Fig. 2a (right) reveals notable patterns of similarity. Some technique pairs, like Spiral Display vs. Scatter Plot (score 3.7), were seen as visually similar due to shared use of orientation and area marks. Parallel Coordinates and Time Wheel received the highest score (4.7), both using line marks despite different layouts.

As shown in Fig. 2b, low variance appeared mostly among basic techniques, indicating consistent expert judgments. Higher variance occurred in complex cases, such as Node-Link Diagram vs. Parallel Coordinates, where different experts probably focused on different features like shape or visual patterns.

3 NAVIGATING PATHS OF SIMILARITY

So, what can we do with the similarity scores? Consider designing a course teaching visualization techniques. You would want to start teaching a central technique and then continue with techniques that are similar to the already taught ones so that knowledge about one technique can be easily transferred to another by analogy [3].

Using the similarity scores, we can construct a minimum spanning tree (MST) to reveal how visualization techniques are structurally connected. We applied Kruskal’s algorithm to generate the MST, where edges represent the strongest similarity links. This structure offers a way to navigate the space of visualization techniques through their closest neighbors.

Fig. 1 shows the MST (in red) based on expert similarity. Its structure is shaped by shared visual encodings and layout properties. We can see that Node-Link Diagram is a central technique and has Network Map, Incidence Matrix, and Scatter Plot as neighbors, which would be good candidates for teaching by analogy. The MST highlights how the experts assess the underlying design relationships across data facets and visualization types.

A similar MST can also be constructed based on the model-driven similarity scores [4]. It is not exactly the same as for the expert-driven similarity scores, and it is left for future work to validate and fine-tune the results to arrive at a more definite navigation structure through the visualization zoo.

4 CONCLUSION

Our work provides initial insights into the similarity of visualization techniques by combining data facets, visual and structural properties, and expert intuition. Preliminary results reveal interesting relationships and pathways among visualization techniques.

Main limitations of our work are the small number of techniques, the low model complexity, and the small number of experts. Future work should also explore further aspects of similarity, including analysis tasks, interactivity, and visualization literacy.

REFERENCES

- [1] Y. Kim, K. Wongsuphasawat, J. Hullman, and J. Heer. GraphScape: A Model for Automated Reasoning about Visualization Similarity and Sequencing. In *CHI*. ACM, 2017. doi: 10.1145/3025453.3025866 1
- [2] T. Munzner. *Visualization Analysis and Design*. A.K. Peters visualization series. A K Peters, 2014. doi: 10.1201/b17511 1
- [3] P. Ruchikachorn and K. Mueller. Learning Visualizations by Analogy: Promoting Visual Literacy through Visualization Morphing. *TVCG*, 21(9), 2015. doi: 10.1109/TVCG.2015.2413786 2
- [4] A. A. Salako and C. Tominski. Toward Understanding Similarity of Visualization Techniques. Technical Report arXiv:2506.17032 [cs.HC], CoRR, 2025. doi: 10.48550/arXiv.2506.17032 1, 2