Toward an Understanding of Observational Advantages in Information Visualization

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ABSTRACT

Visualizations act as cognitive aids by making reasoning tractable. To choose an appropriate visualization, designers need to know about the cognitive advantages and disadvantages of different visualization techniques. While considerable research has focused on low-level perceptual issues related to visual encodings and judgments, less research has focused on the cognitive operations that are supported by visualization techniques. We conducted a pilot study using mixed methods to uncover properties of some common visualization techniques that allow propositional statements to be directly observed rather than indirectly inferred. We describe the results of our study and discuss potential benefits of this line of research to visualization designers and researchers.

Index Terms: H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous—

1 INTRODUCTION

The main goal of visualization is to amplify cognition. One way in which visualizations do so is by shifting the burden of cognitive processing onto the perceptual system, making reasoning more tractable [4]. However, not all visualizations do so equally or in the same manner. There are many extant visualization techniques, each of which has tradeoffs in the cognitive and perceptual operations it facilitates. Thus some visualization techniques have advantages over others for performing certain tasks. To make appropriate choices when designing visualization tools, designers should be aware of such advantages.

Various features of visualizations influence cognitive and perceptual processing, including the choice of visual encodings, layout, complexity, color, and others. Considerable research has focused on effects of visual elements and encodings on low-level perceptual processes, especially those related to pre-attentive processing and judgments of visual encodings. Less research has focused on cognitive operations that are supported by particular visuo-spatial properties within visualizations [2, 3].

To address this gap, we focus specifically on examining the advantages that various visuo-spatial relationships—also known as *meaning-carrying relationships*—provide for reasoning about propositional statements that are expressed within visualizations. We refer to these as *observational advantages*, based on the theory of Stapleton et al. [5]. We conducted a pilot study using various eye-tracking metrics and semi-structured interviews to characterize the meaning-carrying relationships that exist within four common visualizations. The extension of this research can lead to the development of a catalog of observational advantages of common visualization techniques based on the data and tasks that need to be performed.

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2 OBSERVATIONAL ADVANTAGES

Within a given dataset there are often many propositional statements that can be evaluated. For example, within social network data, the following statements can be proposed: A is connected to B; D is not connected to F; or C is connected to L through F and R. Different visualizations can be used to convey these statements, each of which expresses them via different meaning-carrying relationships. Here a meaning-carrying relationship refers to the visuo-spatial syntax within a visualization that carries semantics and expresses a statement that evaluates to true or false [5].

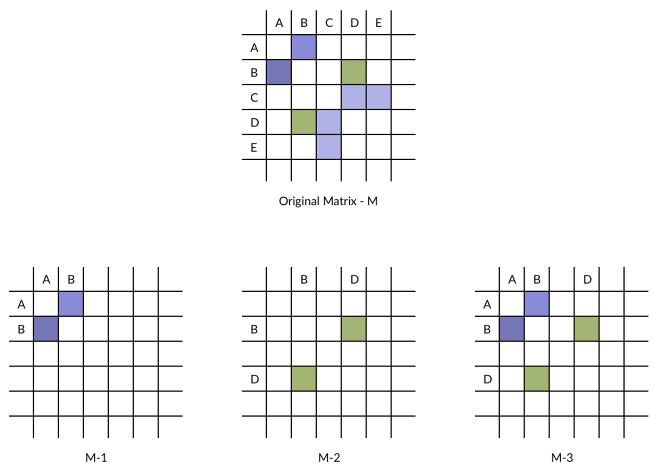

Figure 1: Observing information from an adjacency matrix

When a user makes an *observation*, a meaning-carrying relationship within a visualization is selected and its semantics are evaluated. For example, consider the adjacency matrix in Fig. 1. The original matrix *M* comprises multiple meaning-carrying relationships. An observation may select the visuo-spatial relationships among the labels, lines, and colored squares common to A and B, leading to the meaning-carrying relationship shown in *M-1*. Similarly another observation may select those among B and D, leading to *M-2*. Each of these expresses certain propositional statements through its visuo-spatial properties—i.e., 'A is directly connected to B' and 'B is directly connected to D' respectively. Statements about indirect connections—e.g., 'A is connected to D through B', however, are not directly observable in *M*, and must be *inferred* from information that is directly observable. For example, in *M-3*, the direct connections of A to B and B to D are directly observable, but the indirect connection of A to D is not—thus it must be inferred from the two other observations. This type of required inference results in a higher cognitive load compared to a visualization that allows the statement to be directly observed. Such a visualization is considered to have an *observational advantage* over the adjacency matrix for that particular statement. From this perspective, *observation* requires less cognitive effort than *inference*, as observations can be done perceptually, while inferences cannot–i.e., they must be done 'in the head'. A comprehensive catalog of observational advantages

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of common visualizations for generic tasks could significantly help designers make informed choices when designing visualization tools. In this study, we investigate the meaning-carrying relationships of four common visualization techniques for certain contexts and tasks, and compare them in terms of observational advantages.

3 Experiment

We recruited 7 participants (ages 21 to 35; 2 females, 5 males; all native English speakers). Two pairs of visualization techniques were selected for the study, each to communicate one type of data—either network (node-link diagram and adjacency matrix) or hierarchy (tree and treemap). Each pair had the same underlying data and the same set of statements to evaluate. For the network data there were seven statements, categorized into three main types: (1) direct connection statements (e.g., A is directly connected to B); (2) indirect connection statements (e.g., A is connected to C through others); and (3) statements related to number of connections (e.g., A has more connections than C, but fewer than B). For the hierarchy data there were eight statements, categorized into three main types: (1) kinship relationship statements (e.g., A is a child of B); (2) statements related to number of children (e.g., A has more children than B); and (3) statements related to levels of hierarchy (e.g., A is on a higher level of the hierarchy than B).

We used a mixed-methods approach, employing both qualitative and quantitative methods. Eye-tracking captured patterns of visual attention of subjects as they performed tasks. Measures such as pupil dilation, gaze fixation, and visit count can be used as indicators of task difficulty, fatigue, mental activity, and intense emotion [1]. We also conducted interviews and tracked mouse movements and time spent on task.

3.1 Procedure

Participants were first instructed on how to read each visualization to ensure they understood their syntax and semantics. Subsequently, each participant viewed all visualizations in a randomized sequence. Participants were given each statement in the form of a question, and asked to evaluate it to either true or false based on the visualizations they saw. After the session, participants were interviewed to determine what features (e.g., meaning-carrying relationships) within the visualizations helped them answer the questions.

3.2 Data Analysis

All interviews were coded in an attempt to identify meaning-carrying relationships and observations in participants' responses. Coding was conducted using a grounded theory approach with two coders for inter-coder reliability. All collected pupil size changes from the eye tracker were compared to the established baseline by percentage. Time spent on task and error rates were calculated.

4 Results

Quantitative results from the study are shown in Table 1. For the network data, Task 1, Task 2, and Task 3 represent direct connection statements, indirect connection statements, and statements related to number of connections respectively. For Task 1, the node-link diagram was superior to the matrix both in terms of error rate and time spent on task, but not in terms of pupil size change. For Task 2 and 3, the node-link was superior to the matrix across all metrics.

For the hierarchy data, Task 1, Task 2, and Task 3 represent kinship relationship statements, statements related to number of children, and statements related to levels of hierarchy respectively. For all tasks, the tree was superior to the treemap across all metrics.

During the coding process, the following concepts emerged: *degree*, *connection*, *kinship relationship*, *number* and *level*. These concepts can be divided into two categories: network and hierarchy, where network comprises degree and connection, and hierarchy comprises kinship relationship, number and level.

Table 1: Quantitative Results

Tasks	Visualizations	Change in %	Error rate	Time spent
Task 1	Matrix	+1%	14%	4.71s
	Node-link	+11%	0%	3.43s
Task 2	Matrix	+15%	57%	39.3s
	Node-link	+13%	0%	13.7s
Task 3	Matrix	+17%	25%	46.3s
	Node-link	+12%	14.25%	42.1s
Task 1	Treemap	+15%	3.5%	18.86s
	Tree	+8%	0%	15s
Task 2	Treemap	+23%	43%	25s
	Tree	+15%	0%	12s
Task 3	Treemap	+21%	15%	20.6s
	Tree	+15%	0%	8.3s

5 Discussion and Future Work

Results of the study point to certain benefits of some visualizations over others. For example, quantitative measures indicate that the tree visualization was superior to the treemap for the tasks provided. However, the coded qualitative data did not suggest the advantage was due to true *observational advantages* as described previously, except in the case of indirect relationships in the matrix and node-link. Pupil size changes suggest increases in cognitive load and can potentially point to the *cognitive cost* of various observations that are made with visualizations. For instance, Task 1 for matrix and node-link visualizations saw a greater pupil size change for the node-link—this was likely due to the fact that it is much easier to locate a particular label when it is arranged in the matrix compared to being placed somewhere in the node-link. Deeper analysis of the interview data will help to confirm these hypotheses.

Future work will analyze the collected data more carefully to cross-reference changes in pupil size, recorded behaviors, and interview responses. Subsequently, we plan to expand this study to encompass a larger range of visualizations and more varied tasks. The broad goal of this research is to develop a catalog of observational advantages of common visualization techniques that can help designers with principled design decisions.

References

[1] M. Bradley, L. Miccoli, M. Escrig, and P. Lang. The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology*, 45(4):602–607, 2008. doi: 10.1111/j.1469-8986.2008.00654.x

[2] E. Dimara and A. Bezerianos. The Attraction Effect in Information Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):471–480, 2016. doi: 10.1109/TVCG.2016.2598594

[3] P. Parsons and K. Sedig. Common visualizations: Their cognitive utility. In W. Huang, ed., *Handbook of Human-Centric Visualization*, chap. 27, pp. 671–691. Springer, New York, 2014. doi: 10.1007/978-1-4614-7485-2 27

[4] M. Scaife and Y. Rogers. External cognition: how do graphical representations work? *International Journal of Human-Computer Studies*, 45(2):185–213, 8 1996. doi: 10.1006/ijhc.1996.0048

[5] G. Stapleton, M. Jamnik, and A. Shimojima. What Makes an Effective Representation of Information: A Formal Account of Observational Advantages. *Journal of Logic, Language and Information*, 2017. doi: 10.1007/s10849-017-9250-6