Influence of Shape, Density, and Edge Crossings on the Perception of Graph Differences

An Investigation under Time Constraints

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Abstract. The perception of differences between graphs represented as node-link diagrams is an important issue in many disciplines. This paper presents results from a study with 40 participants. The goal of the study was to test whether shape, density, and edge crossings of the graph influence the perception of differences between graphs and the order in which they are perceived. The participants worked under time constraints. Our results indicate that an increase in density lowers the recognition of differences while a newly introduced edge crossing helps to spot a change. Shape did not have a significant influence on the perception of differences.

Keywords: Graph comparison · graph differences · perception.

1 Introduction

Analysts are frequently exposed to the task of visually comparing two similar graphs [1]. In many cases, the differences can be explicitly encoded in the graph structure, e.g., through color-coding of nodes and edges [7]. This, however, is not always possible as visual variables such as color may already be used for encoding other information. In such cases, the observer needs to compare the structure of the graphs visually. Thus, better understanding which factors facilitate or impede the recognition of differences in node-link diagrams can be of great value, e.g., to help create specifically optimized layouts for comparison purposes.

In our previous work [19] we studied which factors influence the perception of changes in directed acyclic graphs (DAGs) and which strategies people adapt to compare them by relying on screen capturing and qualitative content analysis of thinking aloud protocols. As the study was exploratory and relied on people's explanations, no time limit was imposed for comparison. However, time may impact which changes are recognized, which factors contribute to recognition, and how people approach the comparison. Research in cognitive psychology indicates that time constraints result in a more shallow processing of information, more important features are predominantly perceived, and that the accuracy of judgements decreases [17]. Time constraints also impose a higher workload on study participants (e.g., [4, 9]). Time constraints also play an important role in many practical contexts. However, to the best of our knowledge, time constraints have not been investigated systematically in usability research.

Hence we decided to find out whether time constraints also play a role for detecting differences in DAGs. In this paper, building upon our previous results, we thus present a follow-up study focusing on the influence of time on the perception of differences. Our results show that changes to the outer shape (i.e silhouette) of the graph, lower local density, and the introduction of edge crossings help to facilitate the recognition of differences also under time constraints.

2 Related Work

In cognitive psychology, the investigation of similarity perception has been an important topic. The development of categories is based on similarity perception because similar objects are placed into the same category [8]. There are different mathematical models (e.g., multidimensional or featural models) to describe similarity perception. Most models rely on the comparison of distinct features of objects, but it has been noted that similarity is a more complex phenomenon [15].

There is some research in information visualization addressing comparing processes in visualization in general. Gleicher [6] describes common challenges in comparison processes. He assumes that the main challenges are size and complexity of the visualizations being compared. He states that there are different strategies to tackle comparison processes: scan sequentially, select subsets, and summarize. Possible design solutions to support comparison processes include adding statistical/analytical measures or appropriate interaction possibilities.

Investigations concerning the perception of visual features of node-link diagrams mainly concentrate on single graphs and do not address the comparison of such representations. Li et al. [10] investigated which nodes are more salient, focusing on features such as node degree and attributes of the surroundings of a node. Marriott et al. [12] studied the influence of different layout features, including symmetry and collinearity, on the memorability of graphs. Soni et al. [16] studied whether properties like graph density influence the perception of graphs. These studies do not address graph comparison as such, but are still relevant for consideration in the design of graphs that should facilitate comparison processes.

Processes concerning the comparison of node-link diagrams have been investigated much less than the perception of single node-link diagrams. Some research addressed the perception of dynamic graphs. Making sense of dynamic graphs is partly based on comparing a number of time-slices of a node-link diagram. Archambault et al. [2] studied whether difference maps could assist users in such processes. They found out that, overall, difference maps did not help, but were useful to assess the changes in the number of edges. Bridgeman and Tamassia [5] investigated the perception of differences and similarities of graphs. Their results show that similarity perception relies more on the borders or the shape of the graphs, while detection of differences rather focuses on the interior of graphs. In cognitive psychology it is discussed whether object perception is more holistic or analytic. There is some indication that this depends on whether the features of an object depend very much on the context in which they are shown [13]. There are still many open issues in this context.

Ballweg et al. [3] investigated which factors influence similarity perception of small directed acyclic graphs (DAGs). von Landesberger et al. [18] described methodological challenges to be addressed when conducting studies on graph comparison and reported preliminary results on factors influencing the perception of similarity of very small star-shaped node-link diagrams. Wallner et al. [19] studied which factors influence the perception of changes in DAGs. Especially shape of the graph, density of links and nodes, and edge crossings were found to influence the perception of differences. The study presented here is based on this work. To the best of our knowledge, the issue of time constraints has not been investigated extensively in Human-Computer Interaction or cognitive psychology, which both concentrate on measuring reaction time but not the effect of time constraints on the achievement of participants.

3 Study Design

In previous research, Wallner et. al. [19] found that the shape of graphs, their density, and edge crossings influenced the ease with which users were able to identify differences between graphs. This research was conducted without time constraints. For reasons detailed in Section 1 we thus decided to conduct similar research under time constraints. We formulated the following research questions:

R1: Do the variables shape, edge crossings, and local density influence the recognition of differences under time constraints?
R2: Do the variables shape, edge crossings, and local density affect the sequence of perceived differences? When several differences between two graphs exist, are shape changes, for example, detected earlier than other changes?

For comparability with previous studies, we used the same dataset as Wallner et al. [19]. This dataset consists of in total 16 graph pairs. These were originally created by deriving four alterations by adding up to four edges and nodes (incl. an extra edge) to four different base graphs that themselves differed in size (between about 40 - 100 nodes) and structure. In the study the original (base) graph was displayed below the altered version. Figure 1 gives some examples with differences marked in red for representation purposes.[4]

Procedure: For data collection we administered an online survey using LimeSurvey [11] to students at the TU Wien by advertising it in lectures. Informed

[4] For a complete overview of all graph pairs please refer to: https://figshare.com/s/27396e7451506f3e827d

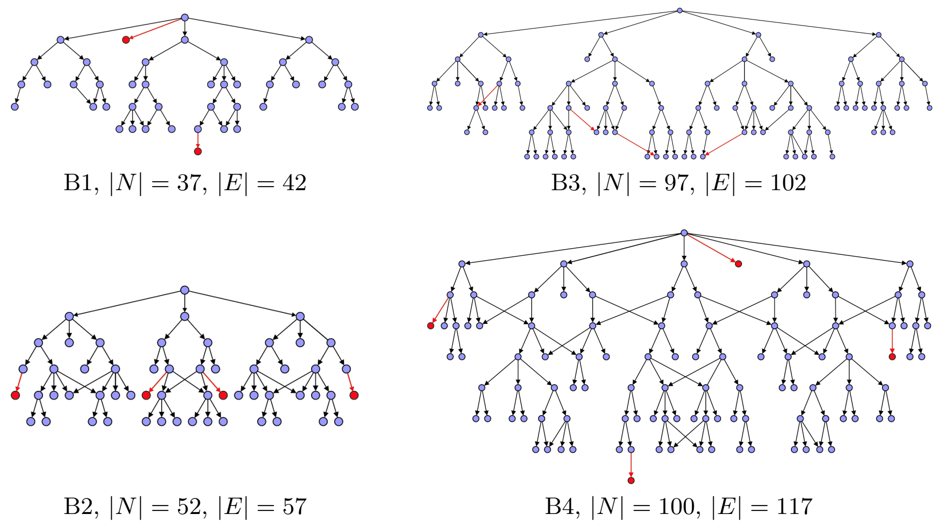

Fig. 1. The four base graphs $B1$ – $B4$ (blue) with the changes of one alternative graph highlighted in red (for representation purposes only). In the study alternative and base graph were displayed below each other.

consent was obtained on the first page of the survey. This was followed by basic demographic questions inquiring about the age, gender, and familiarity with graph visualization. The latter was recorded on a 5-point scale anchored by 1 = very familiar and 5 = very unfamiliar. The main part of the survey consisted of showing the 16 graph pairs in, following Wallner et al. [19], semi-random order. In other words, we counterbalanced the order of graphs while also making sure that graphs with similar changes are not displayed consecutively. For each graph pair, participants had to mark the differences in the upper graph by dragging markers to the respective locations. Once a marker was placed it could not be moved anymore. To allow subjects to familiarize themselves with this interaction we included an example before showing the actual graphs. As we were interested in how salient certain changes are, we imposed a time limit of one minute for each graph pair. Once the participant indicated to have finished marking all differences or the time limit was over, the participants were asked to indicate on 5-point scales how certain they were (1 = very certain, 5 = very uncertain) to have found all differences and how difficult it was (1 = very easy, 5 = very difficult) to find them. Afterward, the survey continued with the next graph pair.

Participants: In total, we received 40 complete responses from 29 males and 11 females. Participants were on average 25 years of age (min = 19, max = 50). Five participants indicated to be very familiar with graph visualization. The majority (24) rated their familiarity with a 2 or 3, and seven with a 4. Only five stated to be very unfamiliar. On average participants needed 21 minutes to complete the survey.

4 Analysis and Results

As the survey only stored the coordinates of the markers, these were exported and mapped to the positions on the graph images on a per-user basis. Through manual inspection of the resulting images these were then compared to the encoded differences. We opted to perform this matching of markers to graph differences manually as sometimes the participants did not exactly place the markers on, for instance, a newly added node. Markers not matching a difference were ignored for the analysis. One graph pair was omitted due the tracked coordinates being erroneous. That is, the following results are based on a total of 11 pairs. If people marked both, the added node and corresponding edge, it was counted only once. We then compiled if and how often a difference was spotted as well as the sequence in which they were marked. Each difference was categorized based on three 'local' factors which were revealed to have an influence on the perception of differences (cf. [19]): 1) shape (*yes/no*), that is, if the newly added node or edge changes the outer hull, i.e. silhouette of the graph. If no, the change was further categorized based on 2) density and 3) edge crossing. Density encoded how dense the graph is in the area of change. It was classified qualitatively into *low*, *medium*, and *high*. *Medium* had approximately twice as much space surrounding the change and *high* roughly twice as much as *medium*. Edge crossing (*yes/no*) encoded if the change introduced a new edge crossing. Responses to the Likert-like scales were treated as ordinal for the analysis.

Averaged certainty and difficult ratings for the four base graphs show a decrease in certainty (c) and an increase in perceived difficulty (d) with increasing graph complexity with B1 ($c = 1.44 \pm 0.68$, $d = 1.64 \pm 0.76$), B2 ($c = 1.81 \pm 0.87$, $d = 2.16 \pm 0.93$), B3 ($c = 2.11 \pm 0.89$, $d = 2.38 \pm 0.84$), and B4 ($c = 2.59 \pm 1.04$, $d = 2.99 \pm 0.92$). Spearman correlations based on the certainty and difficulty ratings of the individual pairs showed significant correlations between certainty and difficulty ($r_s = .717$, $p < .001$) and between the percentage of found differences[5] and difficulty ($r_s = -.230$, $p < .001$) and certainty ($r_s = -.313$, $p < .001$).

A chi-square test to examine if changing the shape influenced the perception of a difference was not significant ($\chi^2(1) = 2.48$, $p = .115$). To assess if density and newly introduced edge crossings influenced the perception of differences we used generalized estimating equations (GEE) with a binary logistic regression model. The encoded differences were treated as a within-subject variable. GEE model estimates are summarized in Table 1(a). No statistically significant interaction effect between density and edge crossing could be observed. The results indicate that an increase in density lowers the recognition of a difference significantly, while a newly introduced edge crossing helps to spot a change.

Since places within sequences of different length are not directly comparable, sequences in which differences were found were analyzed separately for graph pairs encoding two (6 pairs), three (5), and four differences (4). Influence of shape was again assessed using chi-square tests showing a significant influence of shape

[5] Since different graph pairs had a different number of changes we expressed the number of detected differences in terms of percentages instead of raw counts.

Table 1. Results of generalized estimating equations models predicting the effect of edge crossing and density on (a) if a differences is recognized or not and the order in which they are found for graphs with (b) two, (c) three, and (d) four changes (OR = odds ratio, calculated as e^B, B = coefficient, CI = confidence interval).

Predictor	B	OR	95% CI	p	B	OR	95% CI	p
edge crossing								
no			*— reference —*				*— reference —*	
yes	1.438	4.212	[1.807, 2.820]	.001	1.421		[0.540, 2.302]	.002
density								
low			*— reference —*				*— reference —*	
medium	-0.697	0.498	[-1.172, -0.222]	.004	-0.412	0.662	[-0.628, -0.196]	< .001
high	-2.079	0.125	[-2.583, -1.576]	< .001	-1.430	0.239	[-2.237, -0.624]	.001

(a) recognition (b) order, two changes

Predictor	B	OR	95% CI	p	B	OR	95% CI	p
edge crossing								
no			*— reference —*				*— reference —*	
yes	-0.749		[-1.203, -0.294]	.001	-1.810	0.164	[-2.264, -1.356]	< .001
density								
low			*— reference —*				*— reference —*	
medium	0.186	1.204	[-0.157, 0.529]	.288	1.853	6.380	[1.371, 2.336]	< .001
high	1.138	3.120	[0.618, 1.658]	< .001	3.708	40.77	[2.445, 4.972]	< .001

(c) order, three changes (d) order, four changes

changes on how early a difference was marked for graphs with two ($\chi^2(1) = 15.41$, $p < .001$) and four ($\chi^2(3) = 12.86$, $p = .005$) changes but not for graphs with three changes ($\chi^2(2) = 0.535$, $p = .765$). Influence of density and edge crossings were assessed using GEE as above but with ordinal logistic regression models. GEE model estimates for graphs with two, three, and four changes are shown in Table 1(b-d). Interestingly, results for the three and four changes graphs are antipodal to those of graphs with two changes. In case of the former two, increased density is a factor that contributed to changes being recognized later while for graphs with only two changes, increased density surprisingly helped to spot differences early. The same applies to changes introducing edge crossings, in case of three and four changes these helped to recognize a difference before others, while for graphs with two changes it was the other way round.

5 Discussion

In summary, if graphs were perceived as more difficult, participants were less certain to have found all differences. If participants found more differences than they considered the task less difficult. Finding more changes also made participants feel more confident that they really spotted all differences.

If a change affected the shape, i.e. the hull of the graph, then it helped to spot the change before other changes in the majority of cases. However, it also showed not to be a decisive factor if a change is recognized or not. Density and introducing edge crossings, on the other hand, showed to be important if a change is recognized at all when the outer shape is not affected. Our results thus confirm the findings of our qualitative work [19] that introducing an edge crossing helps to locate a difference. While edge crossings have been considered detrimental for graph comprehension (e.g., [14]) it appears that for certain applications such as difference perception purposefully introducing a crossing can also be beneficial. Similarly, higher density areas made it more difficult to actually find a difference and also how early it was recognized, whereas placing changes in low density areas helped to spot them. However, our results also showed the inverse effect in case of graphs with only two changes. This may warrant further investigations but we suspect this to be a result of some of the changes in high density areas also being located near the boundary of the graph and were thus easier to spot.

When interpreting the results of this study it should thus be kept in mind that controlling for all kinds of confounding factors while still maintaining a certain systematic variation across the encoded differences is challenging to achieve in such a complex setting. Results may also change if the time limit is further reduced and/or the graph size increases.

In general, however, our results indicate that the influence of these factors also hold up when comparisons need to be made under time constraints. However, the importance of the outer shape – while still important – appears not to be as pronounced compared to our results without enforced time limit. There is some indication that time constraints generate a less holistic approach of participants, but there are still many open issues to be investigated in future research. Use of eye-tracking technology may shine further light on these issues. Lastly, we should highlight that we relied on a convenience sample and graphs of a certain size and complexity. As such results may not apply equally to other graphs. In future work, we will make use of these findings to inform the development of an algorithm that adjusts the layout specifically for comparison purposes.

6 Conclusions

In the study reported here, we tested how time limits affect the importance of several graph-related properties for the perception of differences in directed acyclic graphs. With respect to RQ1 – the influence of shape, edge crossings, and local density – our results indicate that edge crossings and density significantly impacted the recognition of differences, while the outer shape of the graph did not. In response to RQ2, all three factors, in general, did affect the order in which differences were perceived but the direction (beneficial or detrimental) of their influence was not entirely consistent across graph pairs with different amount of changes. Further work is required to gain more holistic insights on this matter.

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