The Effect of Graph Layout on the Perception of Graph Properties

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Abstract

The way in which a graph is described visually is crucial for the understanding and analysis of its structure. In this study we explore how different drawing layouts affect our perception of the graph's properties. We study the perception of connectedness, tree-ness and density using four different layouts: the Circular, Grid, Planar and Spring layouts. Results show that some layouts are better than others when we need to decide whether a graph is a tree or is connected. More sophisticated algorithms, like Planar and Spring, facilitate our perception, while Circular and Grid layouts lead to performance not better than chance. However, when perceiving the density of a graph, no layout was found to be better than the others.

CCS Concepts

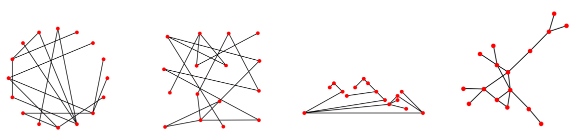
• ***Human-centered computing*** → ***Graph drawings; Empirical studies in visualization;*** • ***Computing methodologies*** → ***Perception;***

1. Introduction

We are surrounded by graphs such as social networks, which need to be understood and analyzed. According to Newman [New18], the visualization of a graph is the first step for analyzing its structure, since it allows us to instantly see important features of the graph. There are many graph drawing algorithms that generate such visual representations [Tam13, BETT98]. These algorithms have specific constraints (e.g. using only straight lines) and also try to optimize some visual characteristics (or aesthetics) [Pur02] of the drawing that are found to affect the human perception of the graph [BRSG07, Pur97, PCJ95, WPCM02]. Our aim is to study the ability of humans to extract information from graph drawings regarding specific properties of the depicted graph. We are particularly interested in how the drawing of the graphs affects our perception of the graph's properties.

2. Related Work

For many computational problems on graphs, the availability of additional geometric information about the input often simplifies the task at hand. Planar graphs can be coloured with four colours in polynomial time [AH76], solving the travelling salesman problem in Euclidean settings is easier than in the general case [Aro96], problems on unit disk graphs are easier if the graph is given along with a geometric embedding [DDK*15]. Studies on humans are more recent. Previous investigation focused on the perception of graph visualizations mostly in terms of their aesthetics, usability and readability. Although there is a great amount of studies on the perception of node-link diagrams (see [YAD*18] for a survey of empirical studies), there is not much research on how humans extract information about *specific graph properties*. Recently, Soni et al. published 'the *first experiment* designed to model humans' ability to perceptually discriminate graph properties' [SLH*18].



(a) Circular (b) Grid (c) Planar (d) Spring

Figure 1: *Exemplar stimuli (a) Circular (non-target graph, Connectivity) (b) Grid (non-target graph, Tree) task (c) Planar (target graph, Connectivity) (d) Spring (target graph, Density).*

Our study extends the work of Soni et al. by investigating the perception of properties of smaller graphs. Studies on visual perception suggest that there are two independent mechanisms involved when perceiving stimuli of low versus high density [ATCB15], and hence they need to be studied separately. While Soni et al. used graphs of order 100 for their experiments, we focus on smaller graphs of 16 nodes each, which we expect to be perceived as structures of relations, rather than as a global texture.

3. Method

The aim of this study is to provide some insight on how the different drawing layouts might affect the perception of specific graph

DOI: 10.2312/evs.20201039

properties of small graphs. Previous user studies in the field allowed participants unlimited time to process the graph drawings and measured the reaction time and accuracy as dependent variables. In this study we are trying to identify the basic perceptual mechanisms and hence we have chosen to limit the presentation time to 3000 milliseconds per trial. The relatively small information content of our stimuli allowed us to run quite fine-grained tests. We implemented the two-alternative forced choice (2AFC) methodology, in which we present two alternative images, only one of which contains the target graph, and participants need to select the graph with the desired property. After testing different variations of small graphs of 12 to 20 nodes on this very short presentation time, we fixed the order of our graphs to 16 nodes. We also restricted our study to the class of planar graphs, in order to use a planar layout and examine the effect of edge crossings.
We used two of the layouts used in Soni et al., namely the Force Directed (or Spring) and the Circular, and we also included the Circular and Grid layouts (Figure 1), these two being simple to implement benchmarks. We studied the properties of connectedness, being a tree and density, using three experimental tasks, one for each property (see Table 1). We chose the properties such that the tasks are relatively easy to perform in such short presentation time and easy to explain to non-expert users. To avoid carry-over effects, we counterbalanced task order by applying a Latin square design. Participants were randomly assigned to one of the three experimental conditions of task order (group A, B, or C).
We have taken into account the methodological challenges of the empirical studies on graph drawings perception [vLPW*17, HEH08]. During our experimental design, specific consideration was given to the generation of the images, taking into account any confounding variables. We rigorously designed the properties of the graphs and their drawings. We also controlled the previous knowledge of participants regarding graphs. Finally, we used a mixed design of both quantitative and qualitative methods, by using a questionnaire between the different parts of our experiment. All materials of this study are available online as an OSF project [KBZ20].

Task	**Graph Properties**	
Connectivity: select the graph that is connected	$n = m = 16$. Forced to be planar. Always a non-tree, because $m > 15$.	
	Target: Forced to be connected.	Non-target: The disjoint union of two connected graphs of $n' = m' = 8$.
Tree: select the graph that is a tree	$n = 16$. Forced to be planar. Always connected.	
	Target: A tree $G1$ ($m = n - 1 = 15$, connected)	Non-target: $G1$ plus an extra edge ($m = 16$, connected, has one cycle)
Density: select the graph with the more edges	$n = 16$. Forced to be planar & connected. Always a non-tree, because $m > 15$.	
	Target: $G1$ with $m = 16$	Non-target: $G1$ plus two extra edges ($m = 18$)

Table 1: *Properties of graphs used for each task, where n is the number of nodes and m the number of edges.*

3.1. Participants

Twenty-four first-year Psychology students (5 males, aged 18-26) took part in the study and were evenly distributed across the three experimental conditions of task order (groups A, B, C). They all reported a normal or corrected-to-normal vision and no previous knowledge about graphs. The experiment passed the local ethics committee approval (PSYC-5698). One of the participants had very low score (29%) for the Tree task and we decided to exclude the corresponding data for this task.

3.2. Apparatus and Procedure

Participants were tested individually in a quiet darkened room and head position was stabilized with a chin rest in a fixed distance of 57 cm from a 15.6" laptop monitor with a 60 Hz refresh rate and a 1920×1080 monitor resolution. The experiment comprised three parts, one for each property. For each part, participants read relevant instructions describing the graph property and then the experimenter verbally explained the property and provided eight example drawings. Then they performed a training session of 16 trials, during which auditory feedback was provided. Following the training, participants provided feedback on how confident they were about their understanding of the property. In cases of low confidence self-reports, the experimenter provided additional information. After ensuring that all was sufficiently explained, participants proceeded to the actual experiment. At the end of each task they answered two open-ended questions regarding their strategies (see section 3.4). The above procedure was repeated three times, one for each task. The total length of the experiment was 30 to 40 minutes for each individual.

3.3. Stimuli

3.3.1. Graph Generation.

All stimuli were drawings of planar graphs of 16 nodes. For each task we generated a pool of two hundred graphs half of which had the desired property (target graphs) and the other half did not (non-target graphs). Because all three properties of the study are related to each other, we tried to limit any effects from confounding variables by fixing as many properties as possible. Table 1 gives a summary of the way we generated the graphs and their properties. For Connectivity, we assume that the task becomes trivial when we have isolated nodes in the graph. To avoid such cases, we restrict the class of non-connected graphs to those of 2 connected components, with 8 nodes each. We force the two components to be of the same order, because otherwise the task becomes trivial again (e.g., a 2-node component forms a line). For the Tree task, we decided to restrict the non-trees class to connected uni-cyclic graphs to keep connectivity across target and non-target graphs fixed, while minimizing the difference of density between the two.

3.3.2. Graph Drawing.

After generating the graphs, we used four algorithms for drawing them. This resulted in a pool of eight hundred graph drawings for each task. The Circular and Grid layouts acted more as baseline layouts, in the sense that the correspondence node to point in space was independent of the abstract graph: nodes were randomly allocated to the pre-selected positions in the plane. On the contrary, for both the Planar and the Spring layouts, we used more sophisticated algorithms and hence the topology of resulting drawings was highly dependent on the graphs. Next we briefly describe each of the drawing algorithms.

Circular Layout: Nodes positions were assigned to regularly placed points on the circumference of a circle of radius $r = 1.0$. The placement is arbitrary, and the algorithm does not try to minimize edge crossings or any other quality metric.

Grid Layout: Each node was originally assigned to a point of a 4×4 grid in an arbitrary setting. The grid's points were on $S \times S$, where $S = \{-0.9, -0.3, 0.3, 0.9\}$. To avoid collinear edges, we then adjusted the node coordinates by a random value in $[-0.13, 0.13]$.

Planar Layout: We used a planar drawing based on the algorithm of Chrobak and Payne [CP95], which gives a straight-line drawing of a planar graph of n nodes on a $(2n-4) \times (n-2)$ grid.
For the non-target graph of the Connectivity task, we observed that when the nodes list was ordered by component, the algorithm would draw the two components as two distinct shapes. Hence, to avoid making the task trivial, we shuffled the nodes ordering so that the two components appear more arbitrary placed in the final drawing.

Spring Layout: Nodes positions were defined using the force-directed algorithm by Fruchterman-Reingold [FR91].

We chose to draw graphs as similarly as possible between target and non-target drawings, so as to keep constant any other features of the drawing that might affect perception (such as edge lengths, crossing numbers or angles). For example, for the Tree task, we arbitrarily set the node positions for the target graph G1, and keep them fixed for the non-target graph G2. This way we ensured that the drawings of G1 and G2 of the same layout would only differ by one edge. However, this could only work for the Circular and Grid layouts. For the Planar and Spring layouts, where nodes positions depend on the graph, this approach would possibly lead to drawings that do not obey the properties of the layout (e.g. for the Planar layout, adding an extra edge could create edge crossings). Hence, for those layouts we draw target and non-target graphs independently.

3.3.3. Image Generation.

After assigning positions to the graph's nodes, we generated images where each node was represented by a red dot of fixed size, and each link by a black line (Figure 1). Drawings were saved as png files of 180 dpi and 1080x720 pixels. All drawings were positioned on the center of the image and all graph's elements were always enclosed inside a disc of fixed radius $r = 1.5$. We also made sure that all drawings were occupying a relatively equivalent area of the image.

3.4. Experimental Design and Materials

For designing the experiment we used Python 3.6 with networkx version 2.4 [HSSC08] and PsychoPy version 3 [PGS*19]. Each trial started with a fixation cross displayed at the centre of the screen for 1500 msec, after which the two graph drawings appeared, one on the left and one on the right side of the screen. For each trial both images were of the same layout, but only one of the two graphs had the related property (target graph). The placement of the target graph was balanced with respect to its position. Each pair of images was briefly presented for 3000 msec, after which a prompt screen appeared. The screen remained visible until a valid keyboard response was provided and the procedure continued with the next trial.
We prepared an instructions document to explain the graph properties and provide example drawings of target and non-target graphs of all four layouts. We also prepared a questionnaire that was used throughout the experiment. The first part was about basic demographic information and there were three more identical parts, one for each task of the experiment. Each part had a pre-task self report question on a four-level Likert scale, about participants' confidence level on understanding the graph property. This was to ensure that they had the necessary understanding of the task. There were also two post-task open-ended questions regarding their strategy and any specific feature of the drawing that they might have found useful. This was to gain some deeper understanding on the perceptual mechanisms, and to identify any possible features of the stimuli that could act as confounding variables.

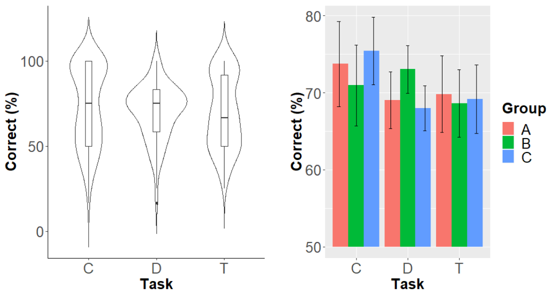
4. Results

4.1. Questionnaire Results

Participants were in most cases highly (33.2%) to very highly (64%) confident about their understanding of the concept before each task. In the two cases where low confidence was reported, the experimenter made sure that everything was sufficiently clear before running the experiment. The above results show that participants, although they were unfamiliar with graphs and their properties, gained a clear idea about the concepts and the task before performing the experiment.

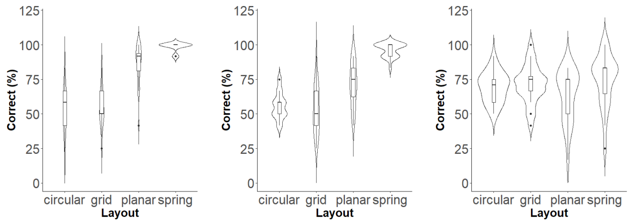
4.2. Experimental Results

The above was also evident by participants' performance. To check whether their scores were better than random answering, we performed a one-sample t-test with a 99% confidence interval. The mean % correct score of each task was found to be significantly different than chance in all cases ($t(95) = 9.75, p < 0.001$ for the Connectivity task, $t(95) = 11.96, p < 0.001$ for the Density task, and $t(91) = 8.66, p < 0.001$ for the Tree task).
We also conducted a two-way mixed-design 3×3 ANOVA for the task and group factors. The results show that there was no significant main effect of the task ($F(2,40) = 2.77, p > 0.05$), nor of the group factor ($F(2,20) = 1.57, p > 0.05$). Hence, all tasks were equally difficult and the task order had no effect on performance (Figure 2). In the following sections we are further exploring the effect of layout on the performance for each of the three tasks separately (Figure 3).



(a) (b)

Figure 2: *(a) Violin plot of overall performance for each task, (b) bar chart of overall performance for each task, per task order.*



(a) Connectivity (b) Tree (c) Density

Figure 3: *Violin plots for performance (% correct) per layout, for each task.*

Connectivity: The layout was found to have a significant main effect ($F(3,69) = 69.51, p < 0.001$), with post-hoc pairwise t-tests revealing significant differences among all pairs of layouts ($p \leq 0.0083$), except for the Grid - Circular pair ($t(23) = 0.41, p = 0.69$). Moreover, when testing performance against chance, we found the Grid and Circular layouts to be not significantly different than random answering.

Tree: Results are similar to the Connectivity task. There was a significant main effect of the layout ($F(3,66) = 60.19, p < 0.001$), with post-hoc pairwise t-tests revealing significant differences among all pairs of layouts ($p \leq 0.0083$), except for the Grid - Circular pair ($t(22) = -0.53, p = 0.61$), which were also found to be not significantly different than chance.

Density: The layout had no significant main effect ($F(3,69) = 2.42, p = 0.07$), indicating that there were no differences in performance between any pair of layouts. Moreover, performance was relatively high and significantly higher than chance for all layouts.

5. Discussion

Connectivity: The Spring layout clearly facilitated the perception of connectivity, by increasing the distance between nodes of distinct components. This is consistent with the results of van Ham and Rogowitz [vHR08]. Using graphs of similar order to our study (16 nodes, 8 nodes in each cluster), they found that the Spring algorithm was a good approximation for simulating the human produced drawings in terms of separating the two clusters and placing the nodes in space. Moreover, participants had the tendency to create a convex hull around the nodes of each cluster, in a similar way as the Spring layout does. We argue that the distance between the two components is a good predictor of performance for this task. The closer the two components are, the harder the task becomes. This is probably why the Planar layout, in which the two components were distinguishable but not far from each other, did not produce as good results as the Spring one. On the other hand, both the Circular and Grid layouts resulted in performance not better than chance. These layouts, because of the random assignment of nodes to positions, not only failed on placing the two components far from each other, but also produced drawings in which the two components intersected. We claim that in such cases, the crossing number between edges of the two components could be another good predictor of performance.

Tree: Since our graphs were always connected for this task, the existence of cycles was the only criterion that guided participants to identify non-trees. This was also evident from the questionnaire, where the majority of them mentioned 'loops' or 'closed areas' as the feature of the drawing that they found useful for performing the task. We argue that this is why the Spring layout clearly facilitated the perception of trees. For the Circular and Grid layouts, the cycles of the abstract graph were not always visually prominent, because of the large number of edge crossings which made the drawings conveying misleading information regarding the existence of cycles. This resulted to performance not significantly better than chance. However, crossing number is not necessarily the only predictor of performance in this task, since the Spring layout outperformed the Planar. This was because the Spring layout clearly demonstrated the existence of the cycle in the target graphs and drew non-target graphs in a 'string' form. Moreover, Spring produced planar embeddings in most of the cases (93% of target and 81% of non-target graphs). The Planar layout on the other hand, missing this force-directed background, was not as facilitating. Although it avoided misleading closed areas, it usually created 'almost closed' areas by placing non-adjacent nodes close to each other. This could lead to faulty perceiving cycles in cases of trees.

Density: For this task, although all layouts resulted in performance better than chance, none of them was found to be significantly better than the others. This fact, which is also consistent with the findings of Soni et al. [SLH*18] on larger graphs and through different experiments, seems to suggest that alternative layout methods might be more useful.

6. Conclusions

In this study we examined the effect of particular layouts for the perception of specific graph properties. For some of these, such as recognizing trees or connectedness, we argue that the more sophisticated drawing algorithms can facilitate the task. However, this is not always the case. None of the layouts considered seem to be particularly good at recognizing the densest of two small graphs. In such cases it would be worth examining alternative layouts or trying to relate particular features of the layout considered and the way these might affect human perception.

References

[AH76] APPEL K., HAKEN W.: Every planar map is four colorable. *American Mathematical Society Bulletin 82*, 5 (1976), 711–712. 1

[Aro96] ARORA S.: Polynomial time approximation scheme for euclidean tsp and other geometric problems. In *Proceedings of the 37th Annual Symposium on Foundations of Computer Science* (1996), IEEE, pp. 2–12. 1

[ATCB15] ANOBILE G., TURI M., CICCHINI G. M., BURR D. C.: Mechanisms for perception of numerosity or texture-density are governed by crowding-like effects. *Journal of Vision 15*, 5 (2015), 4–4. 1

[BETT98] BATTISTA G. D., EADES P., TAMASSIA R., TOLLIS I. G.: *Graph drawing: algorithms for the visualization of graphs*. Prentice Hall PTR, 1998. 1

[BRSG07] BENNETT C., RYALL J., SPALTEHOLZ L., GOOCH A.: The aesthetics of graph visualization. *Computational aesthetics 2007* (2007), 57–64. 1

[CP95] CHROBAK M., PAYNE T. H.: A linear-time algorithm for drawing a planar graph on a grid. *Information Processing Letters 54*, 4 (1995), 241–246. 3

[DDK*15] DAS G. K., DE M., KOLAY S., NANDY S. C., SUR-KOLAY S.: Approximation algorithms for maximum independent set of a unit disk graph. *Inf. Process. Lett. 115*, 3 (2015), 439–446. 1

[FR91] FRUCHTERMAN T. M., REINGOLD E. M.: Graph drawing by force-directed placement. *Software: Practice and experience 21*, 11 (1991), 1129–1164. 3

[HEH08] HUANG W., EADES P., HONG S.-H.: Beyond time and error: a cognitive approach to the evaluation of graph drawings. In *Proceedings of the 2008 Workshop on BEyond time and errors: novel evaLuation methods for Information Visualization* (2008), pp. 1–8. 2

[HSSC08] HAGBERG A., SWART P., S CHULT D.: *Exploring network structure, dynamics, and function using NetworkX*. Tech. rep., Los Alamos National Lab.(LANL), Los Alamos, NM (United States), 2008. 3

[KBZ20] KYPRIDEMOU E., BERTAMINI M., ZITO M.: Graph layout and perception of graph properties, Feb 2020. URL: `https://osf.io/g3jsx`. 2

[New18] NEWMAN M.: *Networks*. Oxford university press, 2018. 1

[PCJ95] PURCHASE H. C., COHEN R. F., JAMES M.: Validating graph drawing aesthetics. In *International Symposium on Graph Drawing* (1995), Springer, pp. 435–446. 1

[PGS*19] PEIRCE J., GRAY J. R., SIMPSON S., MACASKILL M., HÖCHENBERGER R., SOGO H., KASTMAN E., LINDELØV J. K.: Psychopy2: Experiments in behavior made easy. *Behavior research methods 51*, 1 (2019), 195–203. 3

[Pur97] PURCHASE H.: Which aesthetic has the greatest effect on human understanding? In *International Symposium on Graph Drawing* (1997), Springer, pp. 248–261. 1

[Pur02] PURCHASE H. C.: Metrics for graph drawing aesthetics. *Journal of Visual Languages & Computing 13*, 5 (2002), 501–516. 1

[SLH*18] SONI U., LU Y., HANSEN B., PURCHASE H. C., KOBOUROV S., MACIEJEWSKI R.: The perception of graph properties in graph layouts. In *Computer Graphics Forum* (2018), vol. 37, Wiley Online Library, pp. 169–181. 1, 4

[Tam13] TAMASSIA R.: *Handbook of graph drawing and visualization*. Chapman and Hall/CRC, 2013. 1

[vHR08] VAN HAM F., ROGOWITZ B.: Perceptual organization in user-generated graph layouts. *IEEE Transactions on Visualization and Computer Graphics 14*, 6 (2008), 1333–1339. 4

[vLPW*17] VON LANDESBERGER T., POHL M., WALLNER G., DISTLER M., BALLWEG K.: Investigating graph similarity perception: A preliminary study and methodological challenges. In *VISIGRAPP (3: IVAPP)* (2017), pp. 241–250. 2

[WPCM02] WARE C., PURCHASE H., COLPOYS L., MCGILL M.: Cognitive measurements of graph aesthetics. *Information visualization 1*, 2 (2002), 103–110. 1

[YAD*18] YOGHOURDJIAN V., ARCHAMBAULT D., DIEHL S., DWYER T., KLEIN K., PURCHASE H. C., WU H.-Y.: Exploring the limits of complexity: A survey of empirical studies on graph visualisation. *Visual Informatics 2*, 4 (2018), 264–282. 1