Towards an Aesthetic Dimensions Framework for Dynamic Graph Visualisations

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Abstract

Most research on the readability of graph visualisation focuses on node-link diagrams of static graphs. But in many applications graphs are not static, but change over time, or graphs are too dense to be drawn as node-link diagrams. In this paper we look at dynamic graph visualisations: We translate the general goal of graph visualisation—to convey the underlying information of a graph—into aesthetic dimensions that are applicable in practice. These aesthetic dimensions help to design, compare, and evaluate dynamic graph visualisations.

1 Introduction

While the aesthetics of node-link representations of static graphs have been studied a lot [1], those of alternative visual representations, as well as those of visual representation of dynamic graphs have received little attention. The quality of visual representations of graphs in form of node-link diagrams has been widely assessed by how good they meet certain, mostly geometrical requirements often called *aesthetic criteria* in the literature. These include the minimisation of the number of edge crossings or the reduction of overlap of nodes and links. The goal of these criteria is to improve the "aesthetics" of the visual representation. Empirical studies [9, 8] have tried to validate or rank these criteria by how good users could solve given tasks based on different visual representations of graphs. In essence, these studies reduce aesthetics to usability, or more precisely readability.

In this paper, we discuss and classify different representations of graphs (Section 2) and different approaches to visualise the dynamics of graphs (Section 3). In Section 4 we formulate general aesthetic criteria for graph visualisations, propose aesthetic criteria for visual representations of dynamic graphs and discuss three dimensions of scalability that are relevant for visualising dynamic graphs. To illustrate the usefulness of the proposed criteria, we apply them to discuss the benefits and drawbacks of three recently developed graph visualisation techniques in Section 5. Finally, Section 6 presents some concluding remarks.

2 Visualising Graphs

Graphs are a method to formally model relations between objects. In graph theory the objects of a graph are called vertices whereas the relations between pairs of objects are called edges. In this section we will discuss three widely used techniques to represent graph structures. All three approaches visualise the same kind of data—weighted directed graphs—but they differ in the visual elements and layout principles used. Figure 2 presents a small graph in the three different representations as an example.

Node-Link Each vertex of the graph is represented by a single visual element (node). Relations between vertices are displayed as lines connecting their visual representations (links). If the relation is not symmetric, arrow heads indicate the direction of the relation. If the relation is associated with a weight, the corresponding link can be coloured with respect to a given colour scheme.

Matrix A second approach to visualise a graph is to map the weighted edges to a matrix. The vertices appear twice in such a matrix. A vertex is represented vertically by a column and horizontally by a row. The appearance of a cell of the matrix indicates the existence of a certain edge: This edge connects the vertices represented by the row and column intersecting at this cell.

List A slightly different approach to visualise a graph structure is to show for each vertex a visual representation of the list of all related vertices. As a result, a vertex is represented multiple times, once as an entire list and possibly once as a member of each list.

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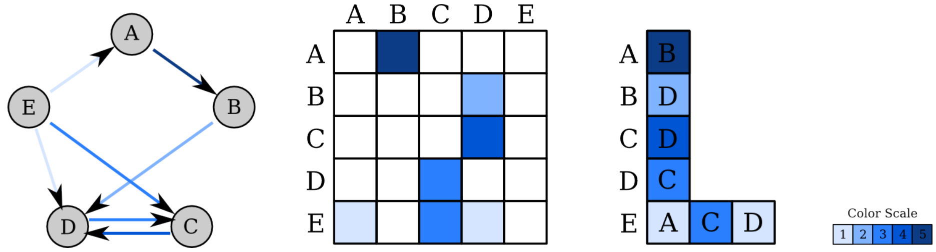

Figure 1. Node-link, matrix and list representation of the a small graph that consists of five vertices and seven edges.

3 Visualising Dynamic Graphs

A graph structure that changes over time is called a *dynamic graph*. Orthogonal to the introduced visual representations, the following visualisation techniques render this additional dimension visual.

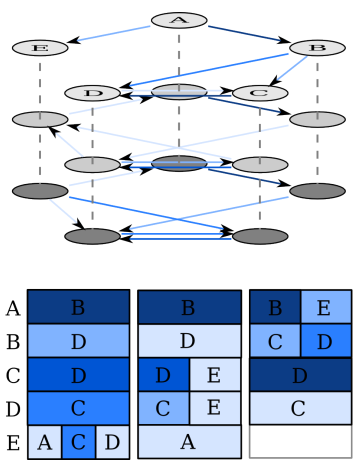

Figure 2. Aligned node-link and list representation of a dynamic graph consisting of three subsequent graphs.

Sequence Dynamic graphs are often shown as a sequence of single images put next to each other as in a comic strip.

Animation An animation is a sequence of images which are shown one after another. Each image represents one of the graphs or an intermediate step of a smooth transition from one graph to the next.

Alignment Another approach is to connect the diagrams of the subsequent graphs more closely by integrating them into a single diagram and aligning multiple visual representatives of the same vertex or edge over the entire sequence of graphs.

For example, to integrate a sequence of node-link diagrams into a single image, a common approach is to stack the sequence of node-link diagrams on top of each other such that the nodes representing the same vertex are vertically aligned. For list representations the alignment is straightforward. Figure 3 shows examples of such aligned dynamic graph visualisations.

An alternative way to visualise dynamic graphs is to aggregate all graphs into a single non-dynamic graph. Since such an aggregation loses most of the dynamic information, this case is out of scope for this paper.

4 Aesthetic Dimensions

The main goal of graph visualisation is on the one hand to provide easy to access detail information and on the other hand to uncover general regularities and anomalies of the graph structure. This includes that the user is able to detect and read information like edge weights, adjacency of vertices, paths, as well as, clusters of vertices, outliers, trends, symmetries and patterns. A dynamic graph visualisation that meets these two general design goals is considered readable, or in other words, aesthetic.

In this section we translate the unspecific term *aesthetic* into a set of specific criteria that are directly applicable to arbitrary dynamic graph visualisations. These criteria aspire to be independent and exhaustive as far as possible. We consider them as aesthetic dimensions of dynamic graph visualisations. They are arranged in three groups: general criteria, dynamic criteria, and scalability criteria.

4.1 General Aesthetic Criteria

For node-link representations various aesthetic criteria [9, 8, 12] have been investigated, including minimisation of drawing area, edge length, number of edge crossings and edge bends, reduction of overlap, as well as the maximisation of angles between outgoing edges, crossing edges or in edge bends.

Some of these criteria also apply directly to matrix and list representations. For example, in a matrix visualisation a coloured pixel suffices to represent a weighted edge. Thus, the drawing area required can be considered as minimal for dense graphs. Other criteria do not apply directly: In matrix visualisations there exist no edge crossings because cells of a matrix do not overlap. Thus, by crystallising the gist of the criteria we identified the following generalised aesthetic criteria that apply to all three kinds of graph representations:

GAC1: Reduce visual clutter *Visual clutter is the state in which excess visual elements or their disorganisation lead to a degradation of performance at some task [10].*

In particular for node-link diagrams visual clutter overly increases when the graphs become more dense. Matrices have many benefits when visualising very dense graphs [6]. Visual clutter that is caused in the node-link approach by lots of edge crossings is here reduced to a minimum.

GAC2: Reduce spatial aliases *Visual elements that might be mistaken one for the other due to their placement are called spatial aliases.*

Spatial aliases can occur if similar visual elements representing different objects are put too close to each other. In matrix representations of larger data set, this easily happens when the user cannot distinguish two adjacent rows or columns. In node-link diagrams spatial aliases may also appear, for instance, if two edges cross at a small angle.

GAC3: Spatial matching of multiple representatives *Multiple visual representatives of the same underlying object that are spatially spread have to be matched to extract the information.*

For example, in matrix representations path tracking is difficult due to unconnected multiple representatives of vertices. The user has to switch from rows to columns and columns to rows to follow edges.

GAC4: Maximise compactness *A graph visualisation is compact if it uses space (and time) efficiently for displaying the graph information.*

Matrix visualisations can be scaled down such that a cell is shown by a single pixel on the screen and are still readable to some extent. The matrix visualisation is compact for dense graphs. In contrast, node-link diagrams need more space to draw edges. Edge length minimisation aims to increase compactness of the diagrams.

4.2 Dynamic Aesthetic Criteria

When it comes to visualise the dynamics of a graph, additional aesthetic criteria come into play. The user should be able to follow trends easily, that is to say, the development of edge weights, missing edges, or temporal patterns should be visible.

DAC1: Preserving the mental map *The term* mental map *refers to the abstract structural information a user forms by looking at the layout of a graph [7].*

The mental map facilitates navigation in the graph or comparison of it and other graphs. In the context of dynamic graph drawing, changes to this map should be minimal. The same property is sometimes also called *dynamic stability*.

DAC2: Reducing the cognitive load *The cognitive load refers to the amount of information the user has to keep in his working memory to read the visualisation.*

To track what is going on in an animation or to compare different graphs in a sequence or aligned representation, the user has to keep some of the information in his or her working memory. A visualisation is of no use if the required amount of information exceeds the capacity of the working memory or if it demands too much attention such that the working memory is not refreshed. In particular, for animations the cognitive load is a major problem, because at each moment, we see only a single image and have to rely on our working memory to remember what happened before. Our use of the term *cognitive load* is motivated by the concept of *extraneous cognitive load* in learning theory [11].

DAC3: Minimising temporal aliases *Visual elements that might be mistaken one for the other due to their placement in time/on a time axis are called temporal aliases.*

To detect changes in animations, a correspondence between visual elements in subsequent pictures has to be established. The illusion of backward-spinning wagon wheels in Western movies demonstrates that it is possible that the mind matches the wrong elements. If the visual properties like position or shape of the visual elements representing the same object in subsequent graphs differ considerably, the user may not be able to realise that these visual elements actually represent the same object. This is not only possible in animations, but might also be a problem if the entire graph sequence is concurrently displayed.

4.3 Aesthetic Scalability Criteria

In general, scalability addresses the question whether a tool is able to handle a growing data set or, more specifically in the context of this paper, whether a visualisation is still readable for larger data sets. Since dynamic graphs are able to grow on different dimensions, their aesthetic scalability has to be discussed separately for each dimension.

SC1: Scalability in number of vertices *For increasing numbers of vertices the readability of the visualisation is preserved.*

It is not realistic to assume that while increasing the number of vertices, no edges are added to the graph. Thus, a practical assumption for discussing the scalability in number of vertices is that the density of the graph stays at a constant level.

SC2: Scalability in number of edges *For increasing numbers of edges the readability of the visualisation is preserved.*

Increasing the number of edges—thus, increasing the density of the graph—the node-link and list representation are growing while the space consumption of a matrix representation stays the same. The matrix representation, however, already needs quadratic space for sparse graphs.

SC3: Scalability in number of graphs *For increasing numbers of graphs the readability of the visualisation is preserved.*

The dynamic aspect adds a third dimension to the discussion of scalability: the number of subsequent graphs. At first glance, animated dynamic graphs are infinitely extensible in their number of graphs. Nevertheless, this does not result in a good scalability because watching the animation the user is just able to remember a few of the previous graphs. Thus, animations do only scale up to a very small number of graphs but are independent from the sizes (number of vertices and edges) of the single graphs.

4.4 Discussion

At best, all these aesthetic criteria are fulfilled concurrently by a dynamic graph visualisation. But in practise some of the criteria are indirectly in conflict. For instance, usually the scalability in number of graphs (SC3) can be traded for the scalability in number of vertices or edges (SC1 and SC2). Thus, the choice of a visualisation method should be based on the criteria that are most important for the particular application without ignoring the trade-offs.

To satisfy a certain criterion, the parameters of the visualisation can be adapted. For example, for node-link representations almost arbitrary node positions and edge routes can be chosen. In contrast, for matrix visualisations rows and columns can only be reordered. Thus, depending on the type of visualisation the degrees of freedom are different.

Moreover, the visual representations can be extended by interaction features. The user might browse through the graph, request details on demand, or customise the visualisation to his or her requirements. In particular, interaction features are able to compensate shortcomings with respect to some of the criteria. For example, brushing can mitigate the problem of multiple representatives (GAC3). It would be interesting for future work to investigate how interactions might support particular aesthetic dimensions and what further dimensions are needed for assessing interactions (for example, based on the general dimensions introduced by the Cognitive Dimensions Framework [4]).

5 Case Study

The introduced aesthetic dimensions can be used for various purposes, for example,

- to formulate design goals of a novel dynamic graph visualisation
- to classify and compare existing dynamic graph visualisations in qualitative evaluations
- to identify promising hypotheses for quantitative evaluations

This case study picks up the second use case. It compares three recently developed dynamic graph visualisations: TimeRadarTrees [2], TimeArcTrees [5], and Foresighted Layout with Tolerance [3]. Although such a case study does not replace an quantitative evaluation, it provides a standardised qualitative assessment scheme that helps to identify the pros and cons of the visualisations and can be used for formative evaluations. Like the following assessment, such ratings are, however, subjective to some extent.

The following list describes the assessed techniques in terms of the classification scheme for dynamic graph visualisations introduced in Sections 2 and 3.

TimeRadarTrees (TRT) *An aligned dynamic graph visualisation based on a combined matrix-list representation (Figure 5).*

TRT uses a radial layout where vertices are represented by circle sectors of the inner circle. The representation is aligned—it depicts each graph from the sequence of graphs as a ring of the inner circle. The edge representation is a mixture of a matrix and a list representation:

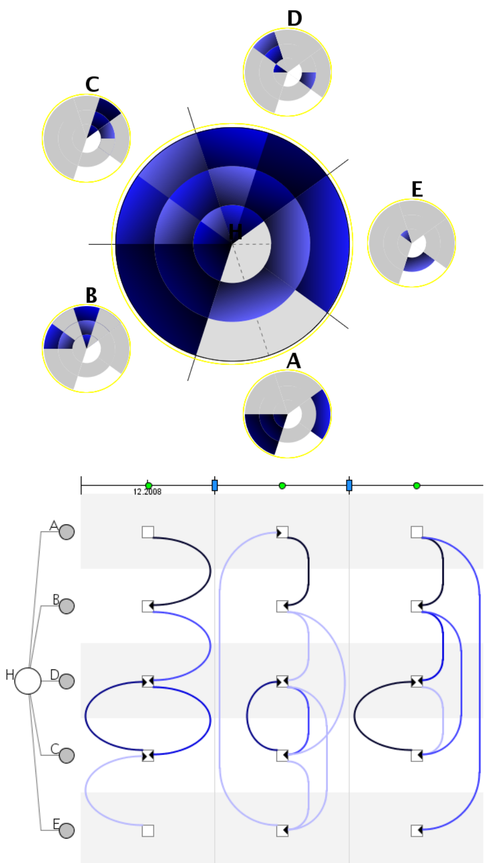

Figure 3. TimeRadarTrees (top) and TimeArcTrees (bottom) visualisation showing the same dynamic graph that was already presented in Figure 3.

Incoming edges are coloured blocks in the inner circle (a list representation without adjacency information). Outgoing edges are coloured blocks in the outer circles at the same position of the associated incoming edge (a distributed matrix representation).

TimeArcTrees (TAT) *An aligned dynamic graph visualisation based on a node-link representation (Figure 5).*

To visualise a dynamic graph, TAT draws a sequence of node-link diagrams from left to right such that each node is placed in a particular row (aligned representation). A specialised algorithm, that aims to reduce visual clutter, draws edges as links at the left and right hand side of the nodes.

Foresighted Layout with Tolerance (FLT) *An animated dynamic graph visualisation based on a node-link representation.*

FLT is an offline approach to compute animated node-link diagrams. It tries to minimise the changes of the layouts of subsequent graphs without sacrificing quality of each individual layout. There are many other approaches to produce animated node-link diagrams. Here, FLT serves as a concrete representative of this group—it would be questionable to generalise all possible approaches.

	TRT	TAT	FLT
GAC1: Reduce visual clutter	+	-	o
GAC2: Reduce spatial aliases	-	o	+
GAC3: Spatial matching of multiple representatives	-	+	+
GAC4: Maximise compactness	+	-	-
DAC1: Preserving the mental map	+	+	o
DAC2: Reducing the cognitive load	+	+	-
DAC3: Reducing temporal aliases	+	+	-
SC1: Scalability in number of vertices	o	-	+
SC2: Scalability in number of edges	+	-	o
SC3: Scalability in number of graphs	+	o	-

Table 1. Summarised comparison of the three dynamic graph visualisations based on the aesthetic dimensions.

Next, we discuss these three visualisations based on the aesthetic dimensions. Table 5 summarises the results of the comparison. Please note that the ratings (+ *good*, o *moderate*, - *bad*) are based on relative rankings of the three approaches.

First, the general aesthetic criteria (Section 4.1) just consider static graphs. In TRT visual clutter is reduced (GAC1) because visual elements do not overlap. But this also leads to hard to match multiple representatives (GAC3) of edges which are distributed over several circles. The compactness (GAC4) is high because edge representations just need at least a few pixels to be drawn. The compact representation, however, is prone to spatial aliases (GAC2), especially in the cramped circle center. In contrast, TAT and FLT—both based on node-link diagrams—show nearly inverse qualities: They produce visual clutter through edge crossings (GAC1) and are not as compact (GAC4) as TRT because links are not as space-efficient. But there are no multiple representations of vertices or edges (GAC3), and spatial aliases (GAC2) only might appear for a few edges (e.g., if they are draw nearly parallel). Comparing TAT and FLT, TAT is heavily restricted in the positioning of nodes. Thus, it is not possible to optimise the graph layout as far as in FLT. The result is a better rating for FLT for visual clutter (GAC1) and spatial aliases (GAC2).

For the general aesthetic criteria, the FLT approach performs well. The following discussion about dynamic aesthetic criteria, however, shows that the representation of time in FLT is a main drawback of this visualisation. While it is hard for the user of an animated node-link representation to preserve his or her mental map (DAC1), the whole graph is concurrently visible in TRT and TAT, that is to say, the mental map is always refreshable. Since TRT and TAT are aligned representations, the user's cognitive load (DAC2) is low and temporal aliases (DAC3) are improbable. In contrast, the animated representation of FLT challenges the user much more with respect to these two criteria. FLT, like some other animated node-link approaches, however, uses a special layout algorithm that strives to preserve the mental map (DAC1).

Finally the scalability aspects complete the assessment. Due to its high compactness, TRT has a good scalability in number of edges and graphs (SC2 and SC3). Only the scalability in number vertices (SC1) is not as high because the vertex representation as circle sectors needs some space to be readable. For TAT this problem is even worse. Furthermore, TAT is far less compact which leads to a poor rating concerning number of edges (SC2) and a moderate rating concerning number of graphs (SC3). Since in FLT the nodes can be scattered all around the drawing area, it performs best with respect to the number of vertices (SC1) and at least better than TAT with respect to the number of edges (SC2). Although FLT is theoretically unrestricted in number of graphs (SC3), we ranked this scalability criterion last because the user is only able to remember a few of the previously shown graphs. Analysis over longer time periods are nearly impossible with such an animated representation.

All in all, this case study provides a clear picture of the differences and similarities of the assessed visualisations. While TRT and TAT support analyses in time, FLT might be preferred when the dynamic aspect is not so important. The main difference between TRT and TAT is on the one hand the totally different behaviour for the general aesthetic criteria and on the other hand the better scalability of TRT. In practise, the right trade-off between all aesthetic criteria has to be found for a particular application.

6 Conclusions

In this paper we briefly discussed dynamic graph visualisation with the help of a general classification scheme. We introduced aesthetic dimensions for these visualisations consisting of three criteria groups: general and dynamic aesthetic criteria, as well as scalability criteria. The case study showed the usefulness of these criteria by comparing three recently developed dynamic graph visualisations. Differences and similarities clearly emerged on the different dimensions. We consider the aesthetic criteria a major step towards an aesthetic dimensions framework to design, compare, and evaluate dynamic graph visualisations.

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