Edge-stacked Timelines for Visualizing Dynamic Weighted Digraphs

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Abstract: We investigate the problem of visually encoding time-varying weighted digraphs to provide an overview about dynamic graphs. Starting from a rough overview of dynamic relational data an analyst can subsequently explore the data in more detail to gain further insights. To reach this goal we first map the graph vertices in the graph sequence to a common horizontal axis. Edges between vertices are represented as stacked horizontal and color-coded links starting and ending at their corresponding start and end vertex positions. The direction of each edge is indicated by placing it either above or below the horizontal vertex line. We attach a vertically aligned timeline to each link to show the weight evolution for those links. The order of the vertices and stacked edges is important for the readability of the visualization. We support interactive reordering and sorting in the vertex, edge, and timeline representations. The usefulness of our edge-stacked timelines is illustrated in a case study showing dynamic call graph data from software development.

1 INTRODUCTION

The visual encoding of dynamic graphs is challenging (Beck et al., 2014a) compared to the visualization of static graphs. Using node-link diagrams in a two-dimensional layout as well as matrix representations either in a time-to-time (animation) or time-to-space mapping either leads to cognitive efforts due to the preservation of the viewer's mental map or to visual scalability problems due to showing a number of graphs in a small multiples or stacked fashion. This gets even more challenging when the focus is on finding time-varying patterns among the edge weights.

We introduce a novel dynamic graph visualization that avoids explicit link crossings and supports the preservation of a viewer's mental map. To achieve these goals we use a time-to-space mapping of the graph sequence by visually encoding the vertices occuring in the graph sequence to a horizontal centered line to equidistant positions. The edges are placed in a vertex-aligned manner as color coded parallel and stacked straight links each starting and ending at their corresponding vertex positions. The time-varying weights of each edge are displayed by stacked and link-aligned timelines to the left hand side without overlap of the graph view.

This technique provides an overview for a time-varying weighted digraph with an additional hierarchical vertex organization. As a second step the technique supports interactively zooming into any rectangular region in the graph view. Filtering in the vertex, edge, and time dimensions can be used to further reduce the vast amounts of displayed data. Finally, details-on-demand features are also integrated which might be used to display a selected graph in another representation (Shneiderman, 1996).

The technique supports two ordering techniques for the vertices or the edges: Interactive reordering of vertices is applied to reduce link lengths as also proposed in the work of (van den Elzen et al., 2013) and edge stacking ordering to put edges close to each other that are required to find graph structures. In combination, these ordering strategies can reveal common trends among edge groups between hierarchically organized vertex groups.

2 RELATED WORK

Dynamic graph visualization has become a growing discipline due to many application domains (Beck et al., 2014a). Several aesthetic graph drawing criteria (Beck et al., 2009, 2013) play a crucial role in order to make first static diagrams readable and aesthetically pleasing and second, allow to visually analyze the dynamics of the graph. For the dynamics, criteria such as dynamic stability leading to a preservation of a viewer's mental map (Archambault et al.,

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2011; Purchase et al., 2007) are of special interest to reduce the cognitive efforts for a viewer when making comparisons among the single graphs in a sequence.

There are two lines of research: Graph animation (Diehl and Görg, 2002; Frishman and Tal, 2007), on the one hand, has become an approach to visually map the dynamic graph data. But when the graphs become dense, the node-link metaphor which is mainly used for displaying animated graph sequences, suffers from visual clutter (Rosenholtz et al., 2007) making even a single diagram hard to read. For animation, sophisticated layout algorithms are needed which focus on producing aesthetically pleasing diagrams on the one hand but also follow rules such as dynamic stability. Even when many of these design principles are followed in an animated diagram it still remains hard to analyze the data for temporal patterns and to apply interactive features as well as a hierarchical organization of the vertices if one exists (Burch et al., 2010; Beck et al., 2014b).

In our design we are more in favour of a non-animated diagram for showing the graph evolution over time. Such non-animated time-to-space approaches are for example the parallel edge splatting technique (Burch et al., 2011) that uses a small multiples representation by mapping the graphs in a sequence to side-by-side vertical stripes similar to parallel coordinates. Although, this is a useful idea, by making a graph artificially bipartite and by mapping the vertices to one-dimensional vertical lines, the probability of link crossings increases.

In our approach, instead, we apply a more clutter-free visualization strategy by stacking the links and the aligned timelines for the edges. In this technique, links are not crossing each other. Moreover, the graphs are not made artificially bipartite which introduces additional representatives (as also in adjacency matrix visualizations) making path-related tasks in a graph difficult to solve. Another concept apart from using small multiples is by directly integrating the graphs in a stacked manner into one static diagram by using aligned planes (Brandes and Corman, 2003).

Also matrix representations have been introduced for dynamic graph visualization where each cell of the matrix includes some timeline showing the evolution of a single edge, for instance, based on pixel representations (Stein et al., 2010), line angles (Brandes and Nick, 2011), or bar charts (Burch et al., 2013). Also radial matrix-based approaches have been designed (Burch and Diehl, 2008; Vehlow et al., 2013) which suffer from visual scalability problems for vertices and edges. Moreover, visual comparisons over time are difficult to solve due to the mapping to circular shapes.

Our novel technique is in some way related to the approach proposed by (van den Elzen et al., 2013) which is based on the Massive Sequence Views (MSV) introduced by (Jerding and Stasko, 1995, 1998) as Execution Mural and later adapted to software visualization by (Cornelissen et al., 2007; Holten et al., 2007). Van den Elzen et al. investigate the ordering problem of vertices as well as the optimal linear arrangement problem (OLA) (Garey and Johnson, 1979) with the goal to make the diagrams more readable and understandable. This algorithmic strategy focuses on trends, countertrends, and anomalies in the graph dynamics but also on static graph patterns such as community or star patterns.

3 DATA MODEL

We model a directed weighted graph as $G = (V, E_A)$ where $V := \{v_1, \ldots, v_n\}$ denotes the finite set of $n \in \mathbb{N}$ vertices and $E_A \subseteq V \times V := \{e_1, \ldots, e_m\}$ the finite set of $m \in \mathbb{N}$ directed adjacency edges. Each edge $e_j \in E_A$, $1 \leq j \leq m$ is attached by a weight $w(e_j)$ where $w : E \longrightarrow \mathbb{R}$ denotes a weight function giving each edge a specific real-valued number.

A dynamic graph Γ of length $k \in \mathbb{N}$ is denoted as a sequence of single graphs $\Gamma := \{G_1, \ldots, G_k\}$ where each graph G_i, $1 \leq i \leq k$ is a static directed and weighted graph in the sense described above with a vertex set V_i and an edge set E_{A_i}.

The hierarchical organization among the graph vertices is modeled as another graph, i.e. a hierarchy, $H = (\bigcup_{i=1}^{k} V_i, E_I)$. The hierarchical organization is hence composed of the set of all vertices occuring in the graph sequence and another set of relations, the inclusion edges E_I expressing parent-child relationships among the hierarchy vertices. It may be noted that E_A and E_I are disjoint sets, i.e. $E_A \cap E_I = \emptyset$.

3.1 Vertex and Edge Ordering

Our novel visualization technique places graph vertices equidistantly on a one-dimensional line. For this, all vertices from the set $\mathcal{V} := \bigcup_{i=1}^{k} V_i$ are taken into account, i.e. all vertices that occur in all graphs in the sequence. If a hierarchy H exists among the vertices $\mathcal{V}$ this must be maintained when laying out the graph vertices, i.e. the hierarchical organization must also be mapped to a one-dimensional line.

The traversal of the graph vertices plays a deciding role for the edges E_A. The Optimal Linear Arrangement Problem (Garey and Johnson, 1979) which is NP-hard can be algorithmically solved by a heuristics as also described in the work of (van den Elzen et al.,

2013) when reordering Massive Sequence Views but we additionally have to deal with a hierarchical organization of the vertices which makes the problem even harder.

In our work we do not focus on an effective and efficient automatic reordering of the graph vertices focusing on the reduction of link lengths or the sum of overlaps since our novel contribution is more on showing a dynamic weighted graph with explicit timelines attached to the graph links in an edge-aligned manner. Moreover, the graph edges should be aligned to their corresponding timeline to better explore the time-series weights for dynamic patterns as described in the work of (Burch and Weiskopf, 2011).

Also the ordering of the edges E_A, i.e. the stacking order, plays an important role when discovering temporal trends. The vertical order of the edges directly influences the order of the timelines in the same way. This again helps to find groups of similar time-varying patterns and can directly be explored for matching a group of relations coming from similar subhierarchies and targeting to other or the same subhierarchies. For the edge order we achieve more freeness than in the approach of (van den Elzen et al., 2013) because in their work the edge stacking dimension is fixed since it is used as time axis. The edge ordering also plays a deciding role when detecting graph patterns such as star patterns, clusters, or graph symmetries. For this reason we support several edge stacking strategies in our technique which are described in more detail in Section 4.1 such as ordering by shortest edges, oldest edges, youngest edges, edges with the smallest start vertex index, edges with the shortest path through a given hierarchy and the like.

3.2 Data Aggregation

We live in a data-driven era, i.e. datasets become larger and larger due to the progress in hardware technologies. The growing of datasets has also an impact on dynamic graph data. Todays dynamic graph visualization techniques must keep up with the flood of relations. Graphs can grow in either the vertex, edge, or time dimension. Also additional attributes such as edge weights or a hierarchical organization among the graph vertices is present in many scenarios which is also of interest for a graph analyst.

As (Tufte, 1992) puts it "Above all else show the data", we follow a similar concept in our approach. We display as much of the graph data in a compressed and aggregated way. This means we display as many vertices, edges, and time steps as are given in a dataset. Since we have a limited display capacity this data should be aggregated in an effective and efficient way in all three dimensions.

Generally, spatially neigbored vertices must be represented in a single pixel when the screen resolution is not large enough to display all of them separately. The same holds for neighbored links as well as timelines. To achieve a good overview of the dynamic graph data in all three dimensions, aggregation in both horizontal and vertical direction is required.

To this end we support simple aggregation techniques that take either the sum, the average, or the maximum of the edge weights into account. The aggregated weights are displayed as color-coded pixels. Moreover, the color coding can be displayed linearly or logarithmically.

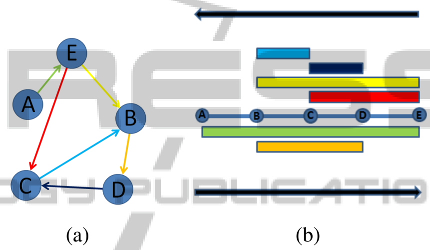


Figure 1: A weighted and directed graph: (a) Standard node-link representation with color-coded links and arrow heads. (b) Edge-stacked visualization of the same static graph as in (a) but with color-coded stacked lines.

4 VISUALIZATION TECHNIQUE

Our novel visualization technique has to deal with three data dimensions as well as additional attached and inherent data. The contribution of this work is that the vertex, edge, and time dimension of a dynamic graph should be displayable in a scalable way. Time-varying edge weights, structural graph properties, symmetries, the direction of the edges, or the hierarchical organization of the graph vertices will also be visually encoded in the diagram. Apart from using a time-to-space mapping for the dynamic data also visual clutter should be reduced, i.e. the static diagram should not suffer from link crossings as typically occuring in node-link diagrams. Runtime complexities should be reduced allowing an interactive visualization technique. This is problematic for graph animation when generating stable graph layouts.

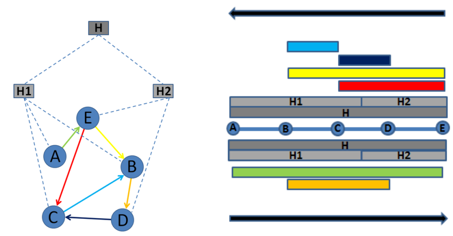
Another advantage, in particular compared to matrix visualizations, is the fact that only one representative element is displayed for each graph vertex which makes path-related tasks easier to solve. Moreover, both absolute as well as relative time can be displayed in the aligned and stacked time axes which allows comparisons between time intervals, also on different time axis granularities.

4.1 Static Graph Visualization

We first show how a static directed and weighted graph is visualized as an edge-stacked visualization. First the vertices of a graph are mapped equidistantly to a horizontal line. The edges are mapped as parallel stacked lines (or rectangles) where the horizontal positions of the start and target vertices indicate the line ends. Depending on the direction of an edge, the corresponding line is placed either above or below the horizontal separation line. Self-edges are displayed on both sides to give a correct impression on the symmetries in a graph. Color coding is used to visually map the edge weights of a static graph. Also categorical edge attributes instead of quantitative weights might be visually encoded by color.

Figure 1 (a) illustrates a weighted directed graph consisting of five vertices and six edges. The directed links are color-coded to demonstrate different weights in a graph. The mapping of this static graph to an edge-stacked visualization is shown in Figure 1 (b).

The hierarchical organization among the graph vertices (if one exists) is displayed as a layered icicle plot (Kruskal and Landwehr, 1983) oriented to the top and to the bottom. This hierarchical organization can be used to collapse or expand subhierarchies. Moreover, if it is present in the dataset it allows to derive graph patterns between subhierarchies and also on different levels of hierarchical granularity.



(a) (b)

Figure 2: A weighted and directed graph with an additional hierarchical organization of the vertices: (a) Standard node-link diagram with hierarchy indicated by dashed lines. (b) Edge-stacked visualization with attached layered icicle plot to display the hierarchy.

Figure 2 (a) illustrates a static weighted and directed graph with an additional hierarchical organization of the graph vertices. This is indicated by the dashed lines showing a small hierarchy H consisting of subhierarchies $H1$ (leaf vertices A, B, and C) and $H2$ (leaf vertices D and E). Figure 2 (b) visualizes this static graph with an additional hierarchy as an edge-stacked representation.

It may be noted that the reordering of the vertices, i.e. a traversal of the hierarchy does not influence the order of the stacked edges. It can have an impact on single line lengths and the sum of line lengths as well as their overlap. The reduction of this overlap is refered to as the Optimal Linear Arrangement Problem (OLA) which is NP-hard.

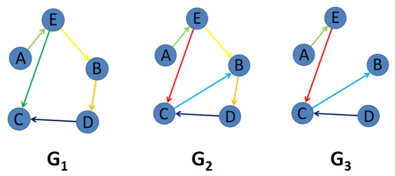
Based on a given vertex order we apply different strategies for the graph edge stacking as ordering by shortest edges, by oldest edges, by youngest edges, by edges with the smallest start vertex indices, by the shortest path through a given hierarchy, or by edges of graph-theoretic problem solutions.

4.2 Time Mapping

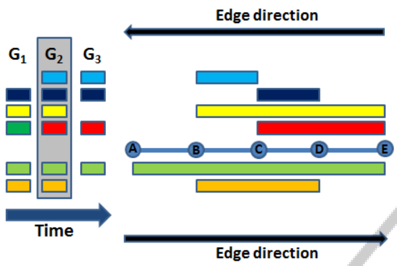
A dynamic graph $\Gamma := \{G_1, \ldots, G_k\}$ consists of a sequence of k static graphs. One solution to display the graph sequence would be a small multiples representation which shows each graph of the sequence in the visualization technique described above in Section 4.1. Following this concept would lead to visual scalability issues and problems when comparing the evolution of weights of longer sequences.

In our approach we apply a different visualization strategy. We integrate the graph sequence into a static diagram by displaying all graph vertices and edges occuring in the sequence as an edge-stacked visualization. Moreover, each edge is attached by an aligned timeline on the left hand side to indicate the evolution of its weight over time. Doing this supports not only to explore the graph for structural properties but also for time-varying patterns on different levels of hierarchical as well as temporal granularity.

Moreover, single graphs or longer subsequences can be selected which has an influence on the color coding of the stacked edges. If only one graph is selected, all edges in the edge-stacked visualization occuring in this selected graph are color coded by the same color as used for the weights in this graph. If more than one graph is selected we color code all edges occuring in at least one of the graphs. If the same edge occurs in more than one selected graph we support edge weight aggregation by either showing the maximum, minimum, average, or sum of the weights in the color coding. The edges in the edge-stacked visualization which are not occuring in selected graphs are displayed as grayed out lines. This helps to provide context information and to support mental map preservation when a viewer wants to click through the graph sequence one-by-one in order to analyze the graph sequence for changes (see for example Figures 5 (a) to (f)).



(a)



(b)

Figure 3: A sequence of three weighted digraphs is shown: (a) As a side-by-side representation of traditional node-link diagrams. (b) As an edge-stacked timeline visualization.

Figure 3 (a) illustrates a sequence of three directed and weighted graphs as node-link diagrams with color coded links. The edge-stacked timeline visualization with graph G_2 selected for this dynamic graph is represented in Figure 3 (b). We can easily recognize that there are two edges which show a constant behavior, i.e. the edge starting at vertex D and ending at vertex C has always the same color (dark blue). Also the edge starting at vertex A and ending at vertex E shows a constant behavior (green color). Also weight changes over time can be found for example for the edge from E to C which changes from green to red color over time. If edges are added or deleted over time this can be recognized by inspecting the gaps in the timeline view.

Following all these design principles leads to a representation of dynamic weighted digraphs without showing any explicit link crossing in the resulting dynamic graph diagram. Sorting algorithms and aggregation techniques can further be used to achieve a more pattern-indicating visualization. For example, clusters among the vertices might be of interest meaning a reordering of the horizontal vertex positions. Dynamic patterns might also be of interest meaning the vertical stacking order of the links (attached by timelines) must be reordered. It may be noted that any reordering will not introduce any link crossings which is typically the case for traditional layout algorithms in two-dimensional layouts for static graphs due to aesthetic graph drawing criteria.

We show the dynamic graph data in a static (time-to-space) mapping which allows to integrate several interaction techniques to explore the dynamic graph data in the vertex, edge, and time dimensions. The most prominent ones are zooming and distortion, filtering, brushing and linking, region expansion and collapse, vertex and edge orderings, solutions to graph-theoretic problems, a difference functionality for graph directions, and computation of differences or commonalities between subsequent graphs.

5 DYNAMIC CALL RELATIONS

We inspect dynamic graph data from the open source software project PMD which supports the analysis of source code implemented in the JAVA programming language. With PMD one is able to find inefficient code structures like local variables not used during program execution, package imports occuring several times, or empty try/catch blocks. The graph to be analyzed contains 1,851 vertices, 28,748 edges and 7 timesteps which are the revisions for this project.

The edge-stacked timeline visualization for the complete dataset is represented in Figure 4 in which graph G_1 is selected from the sequence. For the edge stacking we use the shortest edge stacking strategy, i.e. the shorter an edge the closer it is placed to the horizontal separation line. We use a vegetation color scale, mapping low values to blue color and high values to red. Values in-between are mapped to green to yellow color, see Figure 4.

From this diagram we can make interesting observations: If we inspect all relations in the edge-stacked view (color coded and grayed out edges) we see graph structures which refer to call clusters. This insight can be derived from the short stacked edges (blocks) which express call relations inside a directory. Only a fraction of the edges are very long, crossing the complete horizontal display area. In general, the longer edges refer to calls between functions located far away in the hierarchy. Such inter-package calls might be problematic for software engineering.

In Figure 4 graph G_1 is selected and only the edges are color coded in the edge-stacked view which are present in G_1. Here we can detect two clusters located to the left and to the right and also some longer edges to the top (and to the bottom due to symmetries) which connect elements from both clusters. Hovering over the hierarchy shows that the leftmost cluster is caused by relations from the *ast* and *cpd* directories whereas the rightmost cluster contains calls of *swingui* and *rules* directories.

Looking at Figures 5 (a) to (f) one can see that the clusters with the short edges persist for the first five revisions, whereas the cluster with the longer edges persists over the complete time interval.

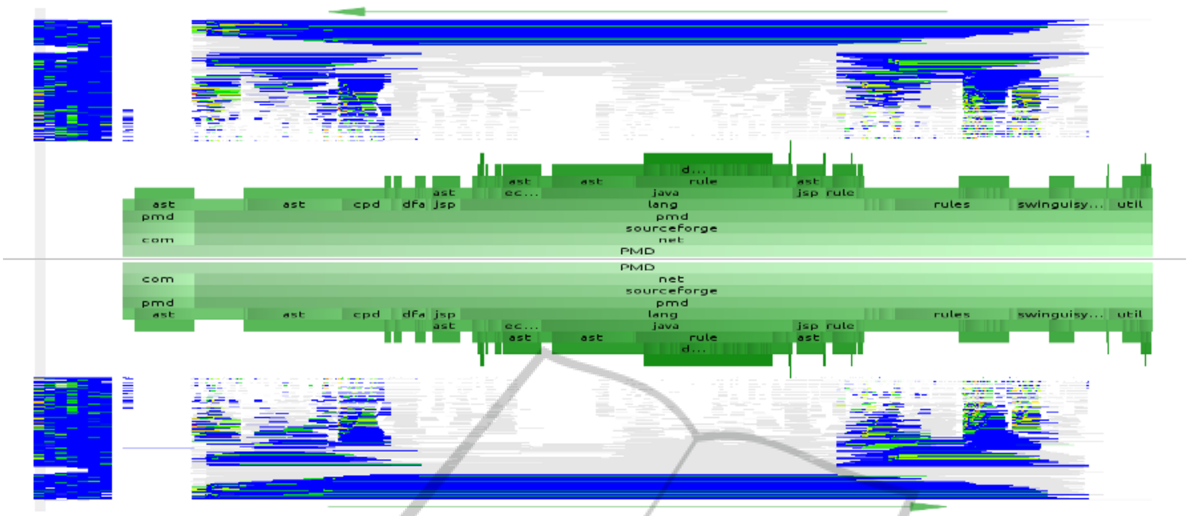


Figure 4: The dynamic call relations of the PMD Open Source software project. 1,851 vertices, 28,748 weighted edges, and 7 timesteps are displayed. In this example graph G_1 is selected and the links are color coded as in G_1. All other existing relations in the graph sequence are grayed out to provide context information.

Applying interaction techniques uncovers that the methods of the subdirectories *java*, *dfa*, *jsp*, *ecmascript*, *ast*, and *cpp* as well as several methods of the directory *sourceforge/pmd/lang* are not related to any other method during the first five time steps.

6 LIMITATIONS

Although we proposed a scalable visualization technique for dynamic weighted digraphs we are aware of the fact that there are also several limitations of our approach. Also various improvements might be added to the existing technique, some of them have been described in the paper.

Visual scalability is achieved by data aggregation which means that several data points are summarized into one single data point. By this operation insights are lost which might be important to derive other not apparent visual patterns and consequently, patterns in the data. For this reason, we allow several aggregation techniques which can be switched on users' demand.

Pattern detection can be difficult if the vertex, edge, or timeline order strategy is not suitable for the dataset under exploration. To mitigate this situation we provide several ordering techniques which must also be tested for their suitability.

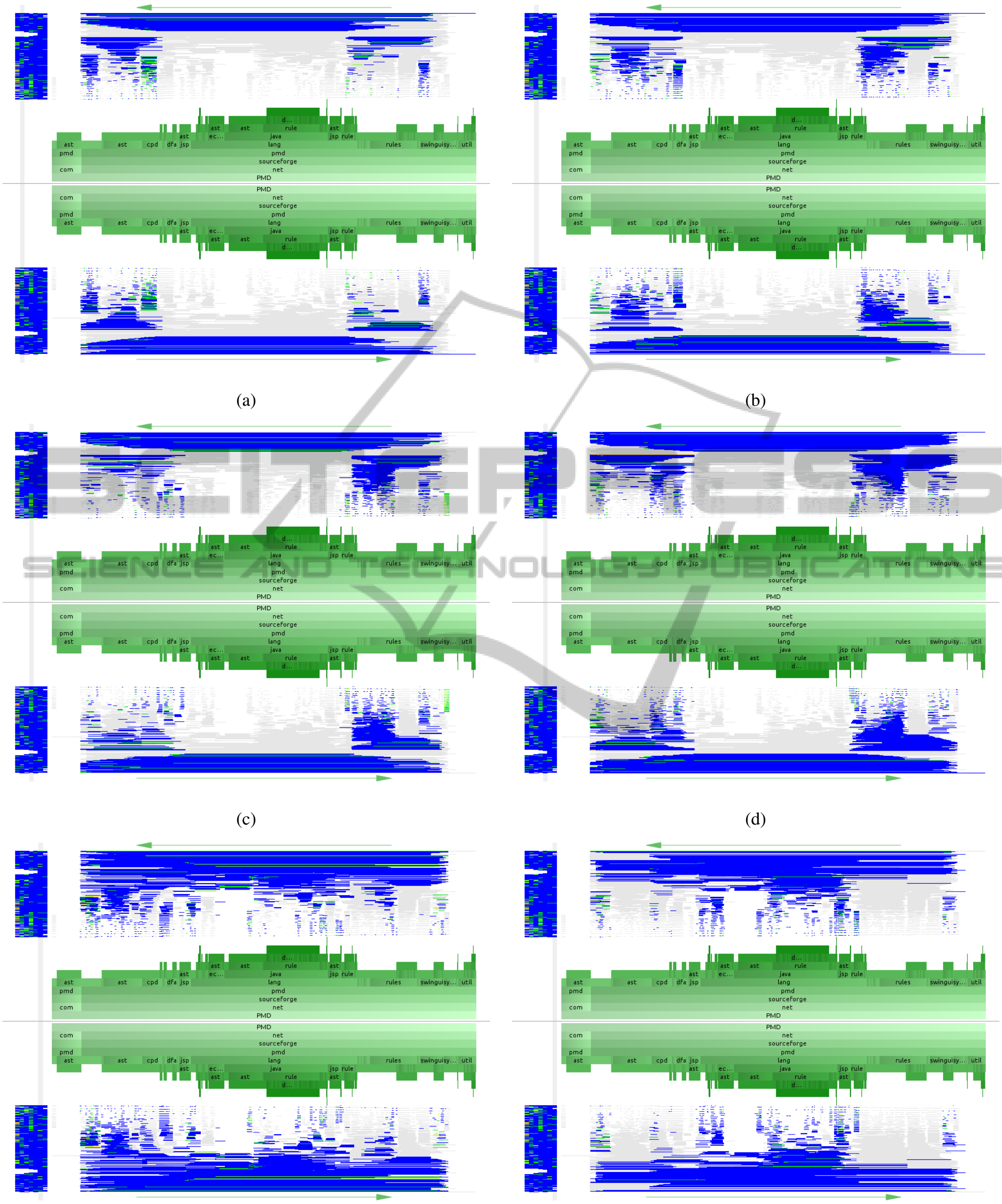
The network topology is not derivable that easily as in node-link diagrams in the two-dimensional space. In our work we plot the vertices to a one-dimensional horizontal line to only use one representative element for each vertex but clusters and outliers may be harder to identify.

Also the computational scalability plays a deciding role in our work. As sophisticated layout algorithms must be applied in traditional node-link diagrams also in our edge-stacked timelines visualization, reordering techniques should be applied to make the diagrams more readable. But the reordering is also proved to be an NP-hard problem.

7 CONCLUSION

In this paper we introduced a visualization technique for dynamic weighted and directed graphs based on edge-stacked timelines. The approach is able to display graphs with many vertices, edges, and long time sequences by using an aggregated pixel-based representation. Interaction techniques for vertex and edge ordering are proposed and tested for suitability. By using our technique we were able to detect time-varying patterns in real-world graph data for both the evolution of edge weights and the structural properties of the graph. Apart from inspecting the static diagram, which already shows several visual patterns and serves as an overview, our visualization tool supports interaction techniques also for finding graph-specific properties.

Since this visualization is designed to be scalable for large graphs, limitations for path-related tasks can be regarded as a drawback which can be solved by interaction techniques. A better exploration of single graphs is focus of future work. Additional graph views in form of traditional node-link diagrams or adjacency matrices might be integrated combined by



(a) (b) (c) (d) (e) (f)

Figure 5: Call graphs G_2 to G_7 of the PMD project displayed as edge-stacked timeline visualizations in a side-by-side small multiples representation. In each of the figures, one graph is selected and the occuring edges are color coded accordingly.

brushing and linking features to give an analyst a way to inspect the data from different perspectives. A user study should be conducted with the goal to find out if our novel visualization technique can keep up with existing dynamic graph visualizations.

REFERENCES

Archambault, D., Purchase, H., and Pinaud, B. (2011). Animation, small multiples, and the effect of mental map preservation in dynamic graphs. *IEEE Transactions on Visualization and Computer Graphics*, 17(4):539–552.

Beck, F., Burch, M., and Diehl, S. (2009). Towards an aesthetic dimensions framework for dynamic graph visualisations. In *Proceedings of International Conference on Information Visualisation (IV)*, pages 592–597.

Beck, F., Burch, M., and Diehl, S. (2013). Matching application requirements with dynamic graph visualization profiles. In *Proceedings of International Conference on Information Visualisation (IV)*, pages 12–18.

Beck, F., Burch, M., Diehl, S., and Weiskopf, D. (2014a). The state of the art in visualizing dynamic graphs. In *EuroVis State-of-the-Art Reports*, EuroVis STAR.

Beck, F., Burch, M., Munz, T., Silvestro, L. D., and Weiskopf, D. (2014b). Generalized Pythagoras trees for visualizing hierarchies. In *Proceedings of the International Conference on Information Visualization Theory and Applications*, pages 17–28.

Brandes, U. and Corman, S. R. (2003). Visual unrolling of network evolution and the analysis of dynamic discourse. *Information Visualization*, 2(1):40–50.

Brandes, U. and Nick, B. (2011). Asymmetric relations in longitudinal social networks. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2283–2290.

Burch, M. and Diehl, S. (2008). TimeRadarTrees: Visualizing dynamic compound digraphs. *Computer Graphics Forum*, 27(3):823–830.

Burch, M., Raschke, M., and Weiskopf, D. (2010). Indented Pixel Tree Plots. In *Proceedings of the International Symposium on Advances in Visual Computing*, pages 338–349.

Burch, M., Schmidt, B., and Weiskopf, D. (2013). A matrix-based visualization for exploring dynamic compound digraphs. In *Proceedings of International Conference on Information Visualisation (IV)*, pages 66–73.

Burch, M., Vehlow, C., Beck, F., Diehl, S., and Weiskopf, D. (2011). Parallel edge splatting for scalable dynamic graph visualization. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2344–2353.

Burch, M. and Weiskopf, D. (2011). Visualizing dynamic quantitative data in hierarchies - TimeEdgeTrees: Attaching dynamic weights to tree edges. In *Proceedings of the International Conference on Information Visualization Theory and Applications*, pages 177–186.

Cornelissen, B., Holten, D., Zaidman, A., Moonen, L., van Wijk, J. J., and van Deursen, A. (2007). Understanding execution traces using massive sequence and circular bundle views. In *Proceedings of International Conference on Program Comprehension*, pages 49–58.

Diehl, S. and Görg, C. (2002). Graphs, they are changing. In *Proceedings of Graph Drawing*, pages 23–30.

Frishman, Y. and Tal, A. (2007). Online dynamic graph drawing. In *Proceedings of EuroVis*, pages 75–82.

Garey, M. R. and Johnson, D. S. (1979). *Computers and Intractability: A Guide to the Theory of NP-Completeness*. W. H. Freeman.

Holten, D., Cornelissen, B., and van Wijk, J. J. (2007). Trace visualization using hierarchical edge bundles and massive sequence views. In *Proceedings of VISSOFT*, pages 47–54.

Jerding, D. F. and Stasko, J. T. (1995). The information mural: a technique for displaying and navigating large information spaces. In *Proceedings of INFOVIS*, pages 43–50.

Jerding, D. F. and Stasko, J. T. (1998). The information mural: A technique for displaying and navigating large information spaces. *IEEE Transactions on Visualization and Computer Graphics*, 4(3):257–271.

Kruskal, J. and Landwehr, J. (1983). Icicle plots: Better displays for hierarchical clustering. *American Statistician*, 37(2):162–168.

Purchase, H. C., Hoggan, E., and Görg, C. (2007). How important is the "mental map"? – An empirical investigation of a dynamic graph layout algorithm. In *Proceedings of Graph Drawing*, pages 184–195.

Rosenholtz, R., Li, Y., and Nakano, L. (2007). Measuring visual clutter. *Journal of Vision*, 7(2):1–22.

Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings of the IEEE Symposium on Visual Languages*, pages 336–343.

Stein, K., Wegener, R., and Schlieder, C. (2010). Pixel-oriented visualization of change in social networks. In *Proceedings of the International Conference on Advances in Social Networks Analysis and Mining*, pages 233–240.

Tufte, E. R. (1992). *The visual display of quantitative information*. Graphics Press.

van den Elzen, S., Holten, D., Blaas, J., and van Wijk, J. (2013). Reordering massive sequence views: Enabling temporal and structural analysis of dynamic networks. In *Proceedings of IEEE Pacific Visualization Symposium*, pages 33–40.

Vehlow, C., Burch, M., Schmauder, H., and Weiskopf, D. (2013). Radial layered matrix visualization of dynamic graphs. In *Proceedings of International Conference on Information Visualisation*, pages 51–58.