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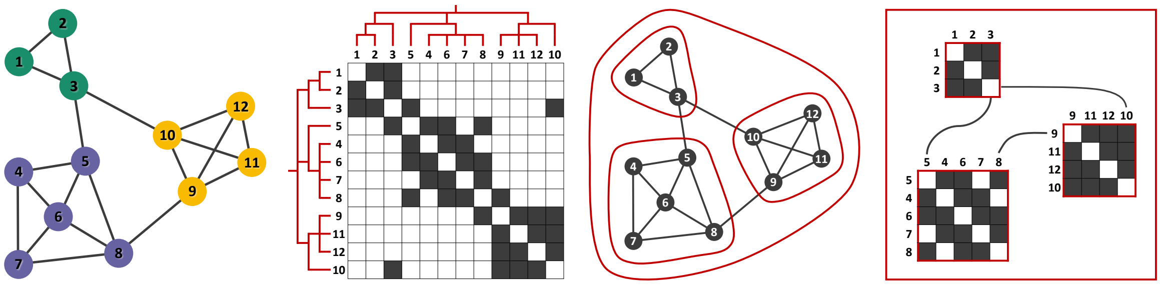
STAR – State of The Art Report

The State of the Art in Visualizing Group Structures in Graphs

Corinna Vehlow, Fabian Beck, and Daniel Weiskopf

VISUS, University of Stuttgart, Germany



(a) Visual node attributes (b) Juxtaposed (c) Superimposed (d) Embedded

Figure 1: *Illustrating examples of the four main categories of visualization techniques to explicitly encode different types of group structures within graph visualizations. (a) Visual node attributes—here color. (b) Juxtaposed—here using an attached approach. (c) Superimposed—here using a contour approach. (d) Embedded—here using a hybrid approach.*

Abstract

Graph visualizations encode relationships between objects. Abstracting the objects into group structures provides an overview of the data. Groups can be disjoint or overlapping, and might be organized hierarchically. However, the underlying graph still needs to be represented for analyzing the data in more depth. This work surveys research in visualizing group structures as part of graph diagrams. A particular focus is the explicit visual encoding of groups, rather than only using graph layout to implicitly indicate groups. We introduce a taxonomy of visualization techniques structuring the field into four main categories: visual node attributes vary properties of the node representation to encode the grouping, juxtaposed approaches use two separate visualizations, superimposed techniques work with two aligned visual layers, and embedded visualizations tightly integrate group and graph representation. We discuss results from evaluations of those techniques as well as main areas of application. Finally, we report future challenges based on interviews we conducted with leading researchers of the field.

Categories and Subject Descriptors (according to ACM CCS): H.5.2 [Information Interfaces and Presentation]: User Interfaces—Graphical user interfaces (GUI)

1. Introduction

Graphs or networks are used to model relationships between objects of any kind. When analyzing these graphs—in particular, if the size of the graph is non-trivial—we, however, do not want to or cannot study each object and each relationship connecting two objects individually. We use visualization to give us a meaningful overview of the graph structure, to highlight central objects, to show similar objects, and to reveal outliers. The ability of a visualization to provide these features largely depends on its efficiency to abstract from individual objects into groups or clusters of objects. For instance, applying a random arrangement of visual rep-

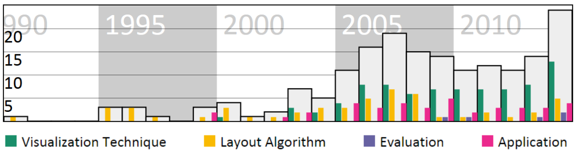


Figure 2: *Number of publications and distribution of paper types from 1991 to 2014 in our literature collection.*

resentatives of objects does not show any of these groups and largely affects the readability of the visualization, for node-link representations [Pur02] as well as for adjacency matrix diagrams [MML07].

Indicating groups in the graph by placing similar objects close to each other implicitly shows some group structures. However, it reduces the potentially multi-dimensional concept of object similarity to a two-dimensional (node-link) or one-dimensional (matrix) layout problem: while similarity implies closeness, closeness does not necessarily imply similarity; or in other words, close objects are perceived as similar although their close placement might only be an artifact of the layout algorithm or dimensionality reduction. Moreover, groups could not just be interpreted as disjoint sets of objects, but might be structured hierarchically, might overlap, or might be fuzzy. Implicit encodings of group structures lack the ability to unambiguously define group structures and to encode more complex concepts of groups.

To overcome these limitations of implicit group encodings, a growing number of visualization approaches have been developed that explicitly indicate which group structures are contained in the graph. These group structures can be either automatically identified by clustering or categorization algorithms, or imported from an external source of information. The means to visualize the structures explicitly are versatile (Figure 1): for instance, the group memberships can be encoded in visual node attributes (Figure 1(a)), they can be shown in a separate view that is dynamically linked to the graph view (Figure 1(b)), the group encoding can be overlaid onto the graph structure (Figure 1(c)), or both graph and group structure can be merged into an embedded representation (Figure 1(d)). Describing the large design space of explicit visual encodings of group structures in graphs and classifying existing visualization technique is the main scope of this survey article.

The literature we collected reveals that already 81 visualization techniques showing group structures in graphs were proposed, most of them in the past decade (Figure 2, green bars). These are accompanied by various papers on graph layout algorithms that highlight group structures, evaluation papers that study the visualization techniques, and application papers that use variants of the techniques in practice (Figure 2, yellow, purple, and pink bars).

Although the body of literature is constantly growing, the design space for explicitly encoding group structures in graphs has not yet been surveyed in detail. Existing reports of state of the art focus on other aspects of graph visualization or subproblems: Herman et al. [HMM00] describe several approaches that use the hierarchical group structure for navigation and abstraction with a focus on the application to graphs. The survey by Brockenauer and Cornelsen [BC01] contains mainly graph layout algorithms to visualize flat or hierarchical disjoint groups in graphs. Von Landesberger et al. [vLKS*11] survey the area of graph and tree visualization in general but only occasionally describe techniques to visually represent groups in graphs. Saket et al. [SSK14] introduce a taxonomy of tasks for group-level graph visualization for disjoint groups. General techniques to visualize sets and group structures are reviewed by Alsallakh et al. [AMA*14], however, without discussing the integration of these techniques into graph visualizations. Beck et al. [BBDW14] survey visualization techniques of graphs that change over time, where in some of them the group structure of the graph is considered. Furthermore, there exist several surveys of general layout algorithms for node-link diagrams [BETT98, DPS02, GFV13]. Elmqvist and Fekete [EF10] provide an overview of how to use a hierarchical group structure of objects for navigation and aggregation in information visualization techniques, such as scatter plots, parallel coordinates, and node-link diagrams.

In this paper, we review the state of the art in visualizing group structures in graphs. We first introduce the area by discussing the background of the visualized data and, in particular, formulate a consistent terminology and data model (Section 2). We define the scope of the survey and describe the applied methodology to collect and analyze the literature (Section 3). As a basis for the techniques that explicitly visualize graphs and groups, we give an overview of implicit layout methods (Section 4). Our main contribution is the classification of explicit visualization techniques into a two-layered taxonomy that we derived from the collected literature (Section 5). We discuss evaluations and applications of the presented techniques (Sections 6 and 7). Based on interviews we conducted with experts of the field, we identify major research challenges that could guide future research (Section 8).

The collected, tagged bibliography is available online[1] in an interactive literature browser. Throughout the paper, we use small icons as visual cues within the text summarizing and augmenting terms, figures, and references; Table 2 also acts as a legend for these icons. For good comparability, all main figures illustrating the discussed visualization techniques show the same data set (i.e., the same graph and the same groups for each type of group structure).

[1] http://go.visus.uni-stuttgart.de/groups-in-graphs

2. Group Structures in Graphs

Group structures occur in different applications of graphs structuring the graph vertices in the form of sets, categories, or hierarchies. In the following, we introduce a data model of group structures in graphs including a taxonomy for the types of group structures. We further discuss origins that the groups can arise from and typical tasks users might want to perform with a visualization of group structures in graphs.

2.1. Data Model

We first introduce a static graph $G = (V, E)$, which consists of a set of vertices V and a set of edges $E \subseteq V \times V$. Groups within graphs, in general, can be defined as a family of sets of vertices $\mathcal{S} = \{S_1, \ldots, S_K\}$, where each $S_k \subseteq V$ and K denotes the number of groups. Groups can be differentiated in several ways (Table 1): they can be disjoint or overlapping, unstructured (flat) or structured (usually, hierarchically).

Table 1: *Taxonomy of group structures including the respective numbers of technique papers in our literature collection.*

Group Structure Taxonomy		Overlap	
		Disjoint	Overlapping
Structure	Flat	18	20
	Hierarchical	42	1

Overlap: In disjoint group structures, for all pairs (S_{k_1}, S_{k_2}), with $k_1 \neq k_2$: $S_{k_1} \cap S_{k_2} = \emptyset$. Overlapping group structures, in contrast, contain at least two sets S_{k_1} and S_{k_2} with $S_{k_1} \cap S_{k_2} \neq \emptyset$. Overlapping groups can be further differentiated into crisp and fuzzy. In crisp overlapping groups, each vertex v_i fully belongs to one or more sets S_k. This belonging can be described, in alternative to the set notation, by a $|V| \times K$ matrix $\mathcal{F}$, where each matrix coefficient $f_{ik} \in \{0, 1\}$ describes if v_i belongs to the k-th set S_k ($f_{ik} = 1$) or not ($f_{ik} = 0$). In contrast, in fuzzy overlapping groups, vertices v_i may belong to different sets S_k to different extent. Here, $f_{ik} \in [0, 1]$ describes to what fraction the vertex v_i belongs to set S_k.

Structure: The groups within the graph might be unstructured, referred to as flat group structures, or structured. While arbitrarily complex group structures are possible, we only focus on hierarchical group structures (also called *compound graph*) because other forms are only rarely used in visualizations showing group structure in graphs. We define a hierarchical group structure as a family of sets $\mathcal{H} = \{H_0, H_1, \ldots, H_L\}$, where each $H_l \in \mathcal{H}$ is a set of other group elements from $\mathcal{H}$ or graph vertices $v_i \in V$. These groups represent the inner elements of a hierarchy where H_0 forms the root element. Hence, for all $H_l \in \mathcal{H}$ where $l = 1, \ldots, L$ (i.e., all groups but the root element), there exists exactly one parent group $H_{l'} \in \mathcal{H}$ ($l' \in \{0, \ldots, L\}$) with $H_l \in H_{l'}$; since also each graph vertex is contained in exactly one group, the same applies to all $v_i \in V$ ($\forall v_i \in V\ \exists!\ l' \in \{0, \ldots, L\} : v_i \in H_{l'}$).

To build a taxonomy of group structures, we consider *overlap* and *structure* as orthogonal concepts. Hence, as listed in Table 1, both can be combined into four categories: disjoint flat, overlapping flat, disjoint hierarchical, and overlapping hierarchical. For the flat approaches, the group structure is modeled by the family of sets $\mathcal{S}$, whereas the hierarchical taxonomy categories require a hierarchical group structure $\mathcal{H}$. In case of disjoint hierarchical groups, the hierarchical structure $\mathcal{H}$ replaces $\mathcal{S}$ because the group elements of the hierarchy also provide an overlap-free grouping on every level of the hierarchy. For overlapping hierarchical groups, in contrast, both $\mathcal{S}$ and $\mathcal{H}$ are required to encode both the overlap of groups and the hierarchy. The numbers in Table 1 show that all categories, but overlapping hierarchical groups, are covered by various visualization techniques, as further discussed below in Section 5.

Graphs can be extended in different directions, for instance, to encode directed or weighted egdes, to allow multiple edges between a pair of vertices (multi-graph), or to embed additional multivariate attributes for vertices and edges. Graphs may also change over time regarding their topology and attributes. With the graph, also the groups and their hierarchical structure might evolve. Since these extensions are unlimited and often orthognal to the encoding of group structures, we do not explicitly reflect them in our data model.

2.2. Origin of Group Structures

Graph and group structures only need to be visualized together when there is a relationship between them, which is either known beforehand or should be retrieved through the visual analysis. Group structures can be based on the graph topology or additional vertex attributes. Without further attributes required, topology-based group structures are commonly extracted using graph clustering methods [For10]. Such methods try to detect groups of vertices, the so-called community structure or clustering, with a high density of edges within the groups but low density of edges between groups. These methods usually result in disjoint flat or hierarchical group structures /, and for some specialized algorithms, crisp or fuzzy overlapping groups /.

When there are other attributes available to describe the graph vertices in a specific application, these can be used as well to derive a group structure. A categorical attribute directly translates into disjoint flat groups; but also overlapping and hierarchical structures might already be encoded explicitly in a set of attributes. If multiple attributes—in particular, numeric ones—should be aggregated, vertices can be grouped based on these multivariate attributes using standard feature-based clustering and classification algorithms [XW05].

2.3. Tasks

Depending on the application and the type of group structure, different tasks are relevant for conducting a visual analysis of group structures in a given graph. Saket et al. [SSK14] introduce a task taxonomy for such group-related graph tasks for disjoint flat groups including *group-only*, *group–node*, *group–link*, and *group–network* tasks. This task taxonomy complements our taxonomy of visualization techniques. In contrast to our taxonomy, the task taxonomy does not yet cover overlapping groups or hierarchical groups. It might need to be extended in the future: In overlapping groups, further tasks arise for vertices belonging to several groups. With respect to *group-only tasks*, among others, the following additional tasks might be relevant: "Which groups overlap?" and "How big is the overlap?" Additional *group–node* tasks for overlapping groups could include "Find bridges between groups" (i.e., identify vertices that are assigned to different groups, therefore connecting them [LPP*06]), "Which vertices are member of only one group?", or for fuzzy groups, "To which extent does a vertex contribute to a group?" In a similar way, the taxonomy could be extended with respect to the other task categories and hierarchical groups. This extension is, however, beyond the scope of this survey, which focuses on the design space of visualization techniques.

3. Scope and Methodology

In order to derive a taxonomy of group structure visualizations, we first defined the scope of the survey, collected relevant publications, and tagged all of them with respect to certain categories to structure them. This section describes the methodology we applied and gives an overview of the collected literature dataset.

3.1. Scope

The scope of our survey is the visualization of group structures within graphs following the data model defined in Section 2.1. We thereby consider only techniques that support the visualization of both the group structure and the graph topology. Techniques that visualize only the groups but not the graph, or vice versa, only the graph were considered out of scope. We further differentiate between implicit and explicit visualization of group structures. There are many layout techniques for node-link representations and vertex sorting algorithms for matrices that can be used to implicitly encode the group structure in the node positions. Such implicit encoding techniques are briefly summarized in Section 4 but are not part of our taxonomy unless the implicit encoding was combined with an explicit encoding. Our taxonomy therefore comprises only publications that use an explicit encoding of the group structure.

3.2. Data Collection and Analysis

To collect relevant publications for this survey, we first started with a selection of publications that we knew from previous research and manually inspected the title of all publications of various information visualization journals and proceedings:

- **Journals**
  - *Computer Graphics Forum*
  - *IEEE Transactions on Visualization and Computer Graphics*
  - *Information Visualization*
  - *Journal of Graph Algorithms and Applications*
- **Conferences**
  - *IEEE Pacific Visualization Symposium (PacificVis)* [2001–2004: *InVis.au*; 2005–2007: *APVIS*]
  - *IEEE Symposium on Information Visualization (InfoVis)* [since 2006 a special issue of *IEEE Transactions on Visualization and Computer Graphics*]
  - *International Conference on Information Visualisation (IV)*
  - *Joint Eurographics–IEEE VGTC Symposium on Visualization (EuroVis)* [1999–2004: *VisSym*; since 2008 a special issue of *Computer Graphics Forum*]
  - *Symposium on Graph Drawing (GD)*

We also looked at the publications cited by relevant papers and work that cited these relevant publications. This way, we could extent our data base step by step to retrieve a possibly complete list of publications relevant to our scope.

This literature was structured using tagging as a main instrument, starting with a list of freely assigned reasonable tags that are iteratively merged, extended, and grouped to categories while working through the literature. For further details, we refer to the survey by Beck et al. [BBDW14], whose tagging process we followed.

3.3. Literature Dataset

To analyze the data, we tagged all publications with respect to several categories starting with the paper type. First, we differentiate papers that use only implicit encoding (tag: *layout_technique*; 54 papers) from papers that use explicit encoding. For the latter, we distinguish *application* (39), *evaluation* (5), and *technique* (81) papers. Moreover, each of the publications is assigned at least one tag for each of the following categories: *graph visualization*, *group overlap*, *group structure*, *graph type*, *evaluation*, and *application*. Table 2 gives an overview of these tags and the number of technique (#T), evaluation (#E), and application (#A) papers for each tag. The main tags for our visualization taxonomy are the tags for the category *group visualization* and further tags to define the subcategories (not part of Table 2). Each explicit visualization paper is assigned to exactly one of the four main *group visualizations*. Only papers that present or evaluate more than one technique are assigned more than one *group visualization* tag if the presented techniques are of different type.

Table 2: *Categories and contained tags with descriptions as well as the number of technique, evaluation, and application papers using an explicit visualization of group structures. All icons used in this survey are added to the respective tags, except for the icon representing coloring approaches, not listed in the table.*

tag (category)	#T	#E	#A	description
	81	5	39	total numbers
graph visualization				graph visualization paradigm
node-link	71	5	37	node-link representation of the graph
matrix	11	2	1	matrix representation of the graph
generic	4		1	being applicable to all graph representations
group overlap				overlap of group
disjoint	60	4	27	no overlap
crisp overlapping	20	1	13	vertices may belong to different groups
fuzzy overlapping	1			vertices may belong to different groups with different extent
group structure				structure type of group
flat	38	4	24	unstructured
hierarchical	43	1	15	groups are hierarchically structured
group visualization				visual representation of groups
visual node attribute	7	2	6	properties of node representation vary
juxtaposed	25	1	4	groups and graph visualized separately
superimposed	29	4	21	use of two aligned visual layers
embedded	21		1	integrate group and graph representation
graph				graph properties
bipartite	2		1	bipartite or semi-bipartite graph
directed	14	1	5	relations are directed
dynamic	14		6	graph changes over time
generic	39	3	18	none of the other graph attributes applies
multi			2	multi-graph
multivariate	14	2	8	graph with multivariate attributes
weighted	9	1	2	edges are weighted
evaluation				type of evaluation
algorithmic	7		3	algorithmically using metrics
case study	43		17	application within application domain
comparison	3	1	1	comparison with other visualization technique
user feedback	4	1	2	collection of user feedback
user study	10	5	2	conducting a study involving users
application				application domain
biology	14		17	visualizing biological data
computer	4	1	1	visualizing computer networks
document	4		3	visualizing documents and text
economy	9		2	visualizing business/ financial/ transport data
media	3	1		visualizing media data
social network	29		12	visualizing social networks (e.g. co-author)
software engineering	18	2	6	visualizing software artefacts
sports	3			visualizing sports-related data

4. Implicit Encodings of Groups

The most common visual representations of graphs are node-link diagrams (i.e., visual nodes connected by graphical links represent vertices and edges) and adjacency matrices (i.e., rows and columns represent vertices; cells are marked if the two respective vertices are connected by an edge). For both techniques, the visual representatives of vertices need to be positioned on the canvas, i.e., laid out or ordered. By placing related or similar vertices next to each other, group structures can be already indicated implictly. Please note that our taxonomy and the scope of the paper does not cover these implicit encodings based on vertex positioning. We only give a brief overview of implicit approaches in this section because they are often combined with explicit encodings of groups and part of some of the discussed visualization techniques. We differentiate between one-dimensional and multi-dimensional layout strategies.

4.1. One-Dimensional Layout

One-dimensional layouts are mainly used for adjacency matrix representations to position vertices along one axis. Groups of vertices that are well connected appear as visual block structures, given that the vertices are ordered appropriately at the matrix axes [MML07, Lii10]. Often, a hierarchical group structure is used to arrange the vertices [EDG*08]; even when using the hierarchical structure, we can still create different sortings by switching the order of children of a hierarchy element. The problem of finding a good sorting can be described as an optimal linear arrangement problem [Hor97]. Some approaches let users interactively build a subjectively satisfying order of rows and columns [Ber11, PDF14] while others solve the sorting problem algorithmically [HF06, MML07]. But also for node-link diagrams, one-dimensional layouts are used, for instance, arranging the nodes on a circle [Hol06] or linear axes [BVB*11].

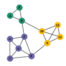
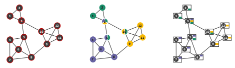
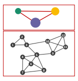
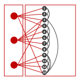
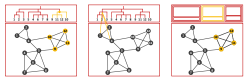
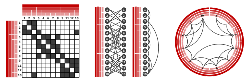
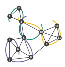
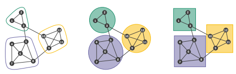
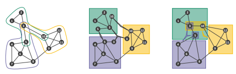
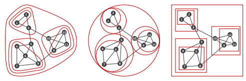
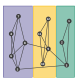
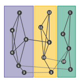
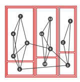
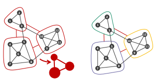
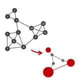
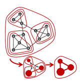
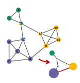
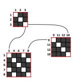
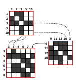
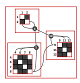
4.2. Multi-Dimensional Layout

In contrast, multi-dimensional layouts are only applicable to node-link diagrams because only node-link diagrams allow the free positioning of nodes in a two- or three-dimensional space. Force-directed layout algorithms, such as the Fruchterman-Reingold method [FR91] or the Kamada-Kawai method [KK89], can reveal groups because connected nodes are positioned close to each other. Force-based approaches have been extended in various ways to further enforce the implicit grouping of nodes for disjoint flat groups [BC01, DKM06, DM14b, Noa07]. In general graph layout algorithms, a generic approach to consider disjoint or overlapping groups / is to use pseudo (dummy) vertices that represent sets of vertices and are connected to all contained vertices [EFN99, EH00, GF11]. For disjoint groups, another method is based on a divide-and-conquer strategy [ACJM03, AMA07b, EF97, FT04]: first, a meta-layout is derived for an aggregated graph with collapsed groups; then, the vertices of each group are laid out independently. For overlapping groups, some approaches apply a sequence of different layout algorithms to first generate a rough layout that is refined in later steps by other algorithms [BALJ06, BCL*07, LDB11, VRW13].

5. Taxonomy of Group Structure Visualizations

There are various visualization techniques that explicitly encode the group structure within the graph visualization. Some of the explicit encodings are based on layouts already implicitly showing group structures. In total, we collected

Table 3: *Visualization techniques classified by our taxonomy of group visualizations and group structures. References are marked with 1^{st} (2^{nd}) if the visualization approach is used as primary (secondary) visual mapping for the type of group structure. Illustrating images are included only for primary visual mappings.*

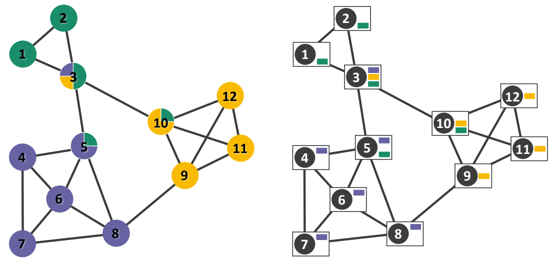
Group Visualization Taxonomy		Group Structure Taxonomy: Disjoint flat	Overlapping flat	Disjoint hierarchical	Overl. hier.
Visual node attributes	Color Section 5.1 Figure 1(a)	 1^{st} [DS13, SKL*14, vHW08] 2^{nd} [BPF14, CDA*14, EHKP14, ET07, GHK10, HGK10, HKV14, SMM13, vdEvW14, VBAW14]	1^{st} [–] 2^{nd} [AHRRC11, BT06, BBT06, DvKSW12, DEKB*14, IMMS09, LQB12, LWC*14, NIST12, HRD10, TLTC05, XDC*13]	1^{st} [–] 2^{nd} [BD05, BD07, KG06, SBG00]	1^{st} [–] 2^{nd} [VRW13]
Visual node attributes	Glyph Section 5.1 Figure 3		 1^{st} [IMMS09, LWC*14, NIST12, TLTC05] 2^{nd} [ST08, XDC*13]		1^{st} [–] 2^{nd} [VRW13]
Juxtaposed	Separate Section 5.2.1 Figures 4(a)-(b)	 1^{st} [SMM13, vdEvW14]	 1^{st} [SJUS08]	 1^{st} [AKY05, AvHK06, CC07]	
Juxtaposed	Attached Section 5.2.2 Figures 4(c)-(e)			 1^{st} [AZ13, BPD11, BBV*12, BD13, BD08, BFBD10, BVB*11, BHW11, BSW13, GF03, GZ11, GBD09, Hol06, HCvW07, NSC05, PvW06, vH03, vHSD09, VBSW13] 2^{nd} [RMF12]	
Superimposed	Line overlay Section 5.3.1 Figure 5(a)		 1^{st} [AHRRC11, XDC*13]		
Superimposed	Contour overlay Section 5.3.2 Figure 5(b)	 1^{st} [BPF14, EHKP14, ET07, GHK10, HGK10, HKV14] 2^{nd} [VBAW14]	 1^{st} [BT06, BBT06, BT09b, DvKSW12, DEKB*14, LQB12, HRD10, ST08]	 1^{st} [BD05, BD07, DGC*05, Hol06, KG06, SBG00] 2^{nd} [NSC05]	
Superimposed	Partitioning Section 5.3.3 Figure 6	 1^{st} [SKB*14, SA06, ZCCB13]	 1^{st} [LSKS10]	 1^{st} [AFH*10, DWS*14, FWD*03, Hol06]	
Embedded	Node-link Section 5.4.1 Figure 7(a)	 1^{st} [CDA*14, SMER06, VBAW14]	 1^{st} [RHR*10, SZPM10]	 1^{st} [ASH14, AMA07a, AMA08, AMA09, AMA11, DM12, DM14a, HN07b, HN07a, RPD09, vHvW04]	 1^{st} [VRW13]
Embedded	Hybrid Section 5.4.2 Figure 7(b)	 1^{st} [HFM07]	 1^{st} [HBF08, MZ11]	 1^{st} [RMF12]	

81 explicit visualization technique papers, which we categorized according to a hierarchical taxonomy that consists of two layers (Table 3). In the first layer, the four main categories of our taxonomy (illustrated in Figure 1) are visual node attributes, juxtaposed visualization, superimposed visualization, and embedded visualization. They are largely disjoint; only some superimposed and embedded visualization approaches use visual node attributes as additional explicit encoding. The second layer further subdivides the categories according to main distinguishing visual features. This section describes all categorized techniques following the hierarchical taxonomy and illustrates them using conceptual sketches.

All techniques were additionally tagged with respect to the type of group structure (see taxonomy of group structures in Section 2.1) that they visualize. The references are therefore marked with the respective icons: flat or hierarchical, disjoint or overlapping. With respect to the type of overlap, by default crisp overlap can be assumed if not indicated otherwise; therefore, only the few fuzzy overlapping groups are marked. Table 3 contrasts both taxonomies by listing all technique papers classified into the respective combination of categories. Few techniques combine two explicit visualization approaches or can be used for different types of group structures; each of these occurs in several cells of the table. Techniques are thereby marked with 1st (2nd) if the approach represents the primary (secondary) visualization approach of this technique. In particular, color is often used as secondary explicit visual mapping of the group structure. In the following, techniques that represent a dynamic graph are additionally marked accordingly. Finally, depending on the underlying graph visualization, each technique is classified as node-link representation, matrix representation, or hybrid.

5.1. Visual Node Attributes

The association of a vertex with one or more groups can be encoded visually by changing the node representation. Although we can easily distinguish no more than about 7 colors [Hea96], color is widely used to convey group information. Each group $S_k \in \mathcal{S}$ is assigned a color and the nodes of the graph (Figure 1(a)) or group representatives (e.g., Figures 5(a), (b.1), and (b.2)) are colored respectively. In total, 30 techniques use visual node attributes, i.e., color (30) and/or glyphs (7), as primary or secondary explicit encoding of the group memberships; all of them are based on node-link diagrams to represent the graph. Most of these approaches combine the group encoding with one of the other explicit visualization approaches—juxtaposed, superimposed, or embedded visualization. Since these other encodings usually dominate the visual appearance, we discuss them in later subsections in detail, but indicate the additional encoding via visual attributes by an icon.



(a) Pie-chart (b) Icon

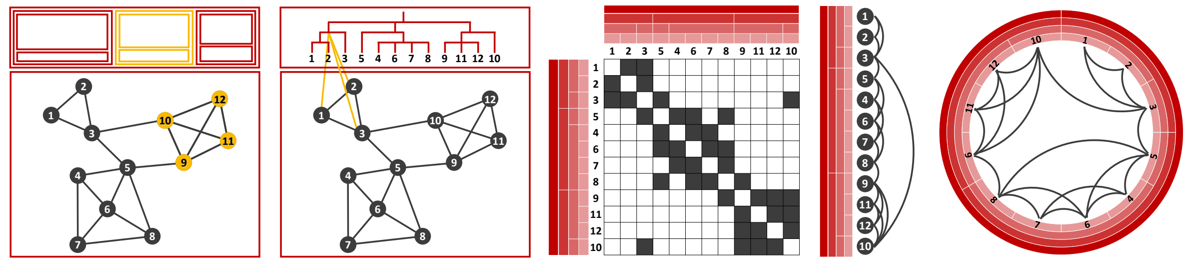
Figure 3: *Visualization of overlapping groups using glyphs and color. (a) Pie-charts encode the fuzzy membership degrees. (b) Icons within the node representatives encode crisp overlapping group memberships.*

We identified 7 techniques that use only color to explicitly visualize group membership [DS13, IMMS09, LWC*14, NIST12, SKL*14, TLTC05, vHW08]. Nodes that belong to only one group are simply colored with respect to that group [DS13] (Figure 1(a)). For flat overlapping groups, nodes are represented using glyphs—"graphical objects designed to convey multiple data values" [War04]. One approach is to represent vertices as pie charts [IMMS09, LWC*14, NIST12, ST08] with sections colored with respect to the groups the vertex belongs to [IMMS09, LWC*14]. For crisp overlapping groups, the sections of the pie charts have equal size [LWC*14, ST08]. In contrast, for fuzzy overlapping groups, they can have different size to encode the fuzzy membership degrees f_{ik} [VRW13] (Figure 3(a)). Another approach for crisp overlapping communities is to represent vertices using boxes that contain icons (Figure 3(b)), such as cross or check marks, in the particular color for all groups they belong to [TLTC05]. Xu et al. [XDC*13] use glyphs to encode the group overlap as well as other metrics by combining different visual channels including intensity of color, hue, size, and shape.

Some techniques optimize the color assignment to maximize either the color differences between neighboring groups [GHK10, HGK10, LQB12] or the color stability between similar groups [HKV14]. Vehlow et al. [VBAW14] developed an approach for dynamic graphs with dynamic groups. Here, each dynamic group—rather than each individual group—is assigned a color to highlight the evolution of groups, where the optimization approach assigns similar hues to similar dynamic groups.

5.2. Juxtaposed Visualization

In juxtaposed visualization approaches, the graph G and the group structure $\mathcal{S}$ are visualized next to each other (Figure 4). We distinguish between separate juxtaposition, where



(a) Separate—brushing and linking (b) Separate—visual links (c) Attached—matrix (d) Attached—node-link (e) Attached—radial

Figure 4: *Juxtaposed visualization of disjoint hierarchical groups. (a) Brushing and linking and (b) visual links are used to highlight associated elements of a subhierarchy. In (c)–(e), the hierarchical group structure visualization is aligned with the graph visualization to allocate leaves of the hierarchy to the respective nodes of the graph.*

both visualization layouts are independent from each other, and attached juxtaposition, where the layouts are aligned, e.g., using the same vertex order. We found 25 technique papers for that category (as primary approach), whereof all but 3 visualize disjoint hierarchically structured groups (; compare to Table 3).

5.2.1. Separate

In separate juxtaposed visualizations, the group structure $\mathcal{S}$ or $\mathcal{H}$ is visualized independently of the graph in different views. Although drawn separately, the juxtaposed visualizations are usually linked by interactions (Figure 4(a)) or visual indicators (Figure 4(b)). In total, we identified 6 separate juxtaposed visualizations—all but one [SJUS08] for disjoint group structures; two for flat and 3 for hierarchical group structures.

Disjoint flat group structures can be visualized using node-link diagrams [vdEvW14]. Nodes represent groups defined interactively based on multivariate attributes; the number of aggregated edges between groups is mapped to the width of the link connecting the group nodes. Sallaberry et al. [SMM13] visualize the evolution of groups using a time-line approach and the graph of a selected time step separate from the group visualization.

Disjoint hierarchical group structures are visualized using tree visualization methods such as axis-parallel [AvHK06] (Figure 4(b)) or radial [CC07] node-link diagrams, or a treemap [AKY05] (Figure 4(a)). Abello et al. [AKY05, AvHK06] link the group structure view with the graph view via brushing and linking. By selecting a subtree in the hierarchical structure H_l, the user can navigate through the graph as only the respective subgraph will be visualized. The ASK-GraphView approach [AvHK06] additionally supports an overview of the complete graph using a matrix representation in a third view. VisLink [CC07] arranges two planes showing the group structure and the graph in 3D space. Visual links connect internal nodes of the hierarchy, i.e., group nodes H_l, with all its vertices $v_i \in H_l$, respectively. Again, the highlighting—here using visual links—is done only on demand via selection, and hence, only for a selected subtree of the hierarchy (Figure 4(b)). Also Schulz et al. [SJUS08] make use of visual links between the groups and the graph vertices. They visualize semi-bipartite graphs, i.e., bipartite graphs with possible edges within the bipartite sets of vertices. In their visualization of semi-bipartite graphs, both vertices and groups are arranged separately on two vertical axes and linked visually by straight links, where arcs are used to visualize relations between the vertices. The sorting of either one of the two axes can be adapted to reduce edge crossings.

5.2.2. Attached

In contrast to separate juxtaposed group visualizations, attached juxtaposed visualizations align the group structure visualization with the graph visualization. In total, we identified 19 attached juxtaposed visualizations (as primary approach), all for disjoint hierarchical group structures. For the alignment, these approaches use the same linear order and position vertices along one axis [AZ13, BPD11, BBV*12, BD13, BVB*11, BHW11, BSW13, GF03, GBD09, NSC05, PvW06, vH03, vHSD09] (Figures 4(c) and 4(d)) or a circle [BD08, BFBD10, GZ11, Hol06, HCvW07, VBSW13] (Figure 4(e)).

One approach to visualizing disjoint hierarchical group structures is to use a layered icicle plot that is attached to a matrix representing the graph [AZ13, BD13, BSW13, GF03, vH03, vHSD09] (Figure 4(c)). The leaves within the icicle plot have to be aligned with the rows and columns of the matrix, i.e., the hierarchical structure is used to generate a linear ordering of the vertices represented in rows and columns. Most of these techniques support an abstraction of the graph based on the hierarchical structure by collapsing and expanding groups to aggregate rows and columns [AZ13, GF03, vH03, vHSD09].

Instead of using a matrix as graph representation, the disjoint hierarchical group structure can also be aligned with a node-link representation of the graph (Figure 4(d)). To be aligned with the hierarchy, the nodes need to be arranged linearly; arcs are usually used instead of straight links to avoid overplotting of nodes and links. The ArcTrees approach [NSC05] combines the linear node-link diagram with a one-dimensional treemap: the arcs are attached to the leaves of the tree visualization. The disjoint hierarchical structure can also be visualized by a node-link diagram or other tree visualizations with a linear leaf order [PvW06]. The TimeArcTrees approach [GBD09] extends these approaches to dynamic graphs. For each time step, the vertices are aligned vertically and directed links are drawn as arcs right (direction is downwards) and left (direction is upwards) of the vertices. An aligned tree node-link diagram attached at the left visualizes the hierarchy. Increasing the scalability of the graph representation, other approaches place the vertices of the graph on two parallel vertical axes and, instead of arcs, straight links between the two axes visually encode directed graph edges [BBV*12, BPD11, BVB*11]. This technique can be used not only for dynamic graphs [BBV*12, BVB*11], but graph comparison as well [BPD11]. To overcome the problem of visual clutter for dense graphs, edge bundling [BPD11] or edge splatting [BVB*11, BBV*12] (i.e., ploting edge density fields) is applied.

The group structure can also be aligned with the graph visualization radially, for instance, by positioning the vertices along a circle circumference and by surrounding the graph visualization with a radial layered icicle plot [GZ11, Hol06, HCvW07] (Figure 4(e)), by drawing the hierarchical structure as an indented hierarchy in the center of a radial graph representation [BHW11], or by drawing the hierarchical structure on top of the graph visualization [BD08]. The edges of the graph are visualized using arcs [GZ11] or bundled edges [Hol06, HCvW07] (Holten [Hol06] presents three explicit visualization techniques and therefore is referenced in three subsections, respectively). Ghou and Zhang [GZ11] furthermore allow an abstraction of the graph by collapsing inner nodes of the tree. For representing dynamic graphs, the graph within the circle needs to be replaced by a sequence of graph $\mathcal{G} := (G_1, \ldots, G_T)$, for instance, arranged in colored pieces of circle rings in TimeRadarTrees [BD08]. Using the TimeSpiderTrees [BFBD10], relations are visually indicated by orientation of shortened links instead of connectedness. In contrast, within the radial layered matrix visualization [VBSW13], edges are represented as color-coded markers in a polar coordinate system.

5.3. Superimposed Visualization

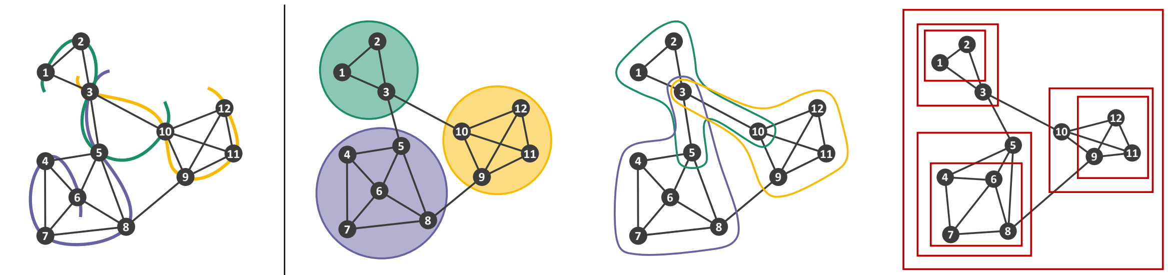
Another method to show the graph and its group structure together is to overlay their representations (Figures 5 and 6). In this case, the visualizations of the two layers cannot be rendered independently but have to be fully aligned in order to create a meaningful superimposition. We identified 29 technique papers that superimpose the group structure onto the graph visualization, where 18 of them use color coding as an additional explicit visual mapping (see also Section 5.1 and Table 3). All of the superimposition techniques are based on two- or three-dimensional node-link diagrams to visualize the graph. We differentiate three main categories of overlays: line overlays (2), contour overlays (20), and partitioning approaches (8).

5.3.1. Line Overlay

When using lines as overlay, for each group $S_k \in \mathcal{S}$, a line of a particular color connects all nodes of that group without interruption [AHRRC11, XDC*13] (Figure 5(a)). The LineSets approach [AHRRC11] draws a smoothly curved line for each group, where the shortest path is computed by an adopted Lin-Kernighan's traveling salesman heuristic. In contrast, in the approach by Xu et al. [XDC*13], for each group S_k, all nodes $v_i \in S_k$ are connected using a spanning-tree-like shape, which is a generalization of the LineSets approach. While LineSets can be applied to any graph layout, the other approach [XDC*13] uses multidimensional scaling (MDS) to arrange similar items close to each other, i.e., combines line overlays with an implicit encoding of groups.

5.3.2. Contour Overlay

Groups can also be visualized within node-link diagrams using closed contours: all nodes v_i within the contour are interpreted as belonging to the enclosed group $S_k \in \mathcal{S}$ or $H_l \in \mathcal{H}$ (Figure 5(b)). Such contours share the characteristics of set diagrams such as Euler diagrams. Contour shapes are versatile, for instance, rectangles [DGC*05, HRD10] (Figure 5(b.3)), circle sections [ET07] or circles [Hol06, KG06] (Figure 5(b.1)), convex hulls [BPF14, ST08], arbitrary two-dimensional curves or splines [BBT06, BD05, BT06, BT09b, DEKB*14, DvKSW12, EHKP14, GHK10, HGK10, HKV14, LQB12] (Figure 5(b.2)), or three-dimensional bubbles [BD07, SBG00]. The GMap approach [GHK10, HGK10, HKV14] creates a map of contours that are adjacent to each other using a Voronoi tessellation. In contrast, the contours within the MapSets [EHKP14] are generated based on non-crossing spanning trees of points belonging to the same cluster. The trees can be grown to contiguous non-overlapping regions that are optimized with respect to their convexity. Also other approaches use such spanning trees but draw the filled contours using texture splatting; a splat is defined as radial function, where the transparency increases with the radius. The eXamine approach [DEKB*14] uses an extended of self-organizing map neuron grid approach to lay out nodes and links but also to draw the contours. The contours within KelpDiagrams [DvKSW12] are generated using a routing algorithm linking elements of the same group



(a) Line overlay in combination with color (b.1) Disjoint flat (b.2) Overlapping flat (b.3) Disjoint hierarchical

(b) Contour overlay in combination with or without color

Figure 5: *Superimposed visualization of the group structure using (a) line or (b) contour overlays; often in combination with . For overlapping groups, also the contours overlap (b.2), whereas for hierarchical group structures, the contours are nested (b.3).*

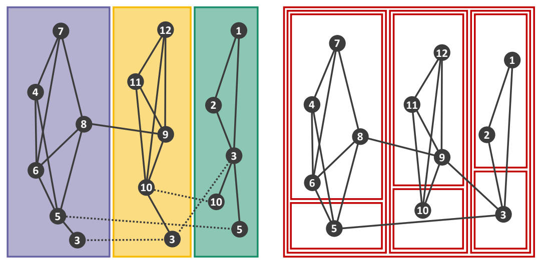
by constructing minimum cost paths over a tangent visibility graph (i.e., a graph including edges that are tangent to the area of linked nodes).

Contours may be used alone [DGC*05, ST08], in combination with texture [BT09b] (i.e., each group S_k is assigned a different texture and the contour is filled respectively), or in combination with color coding (all other approaches). When used in combination with color coding, the contour itself can be colored with respect to the group it surrounds [DEKB*14] (e.g., Figure 5(b.2)) or the contour is filled with that color [BBT06, BD05, BD07, BPF14, BT06, DvKSW12, EHKP14, ET07, GHK10, HGK10, HKV14, HRD10, KG06, LQB12, SBG00] (e.g., Figure 5(b.1)).

Contours are so far used to visualize disjoint flat , overlapping flat , and disjoint hierarchical group structures (Table 3). For disjoint flat group structures , also the contours are disjoint, while the contours representing overlapping group structures intersect. To untangle overlapping contours, Henry Riche and Dwyer [HRD10] introduced two techniques for rectangular contour overlays: a splitting approach (groups with intersections are split up, drawn as non-overlapping rectangular shapes, and linked by lines) and a duplication approach (groups are represented by overlaid rectangles and nodes contained in several groups are duplicated and linked visually). For disjoint hierarchical group structures , the contours or surfaces are nested to visually encode the hierarchical structure [DGC*05, Hol06] (e.g., Figure 5(b.3)). The circle contour approach by Holten [Hol06] visualizes edges between groups by links that are bundled based on the hierarchical structure. Also the ArcTrees [NSC05], although classified as juxtaposed attached visualization, could be considered as well as a contour approach because it uses a contour overlay using rectangles nested in one dimension.

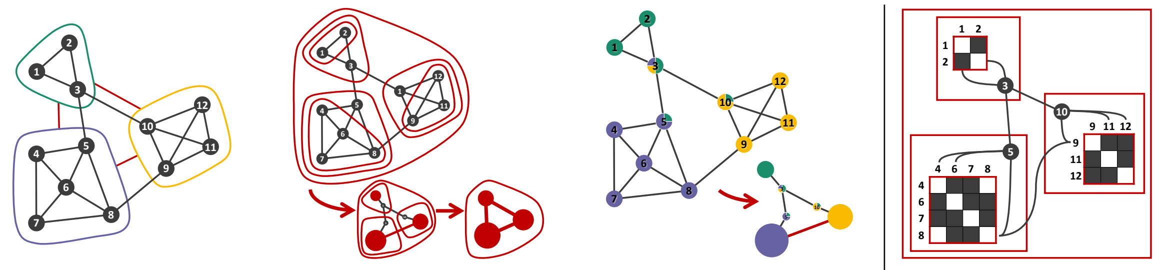
5.3.3. Partitioning

Similar to contour overlays, partitioning indicates group membership by visual enclosing. In contrast to the contour approaches, partitioning is space-filling: the screen space is divided into areas that represent the groups. We identified 8 partitioning approaches, all of them are based on node-link diagrams to represent the graph. For disjoint flat groups , the area of the node-link diagram is partitioned vertically or horizontally into the respective number of areas K—one for each group $S_k \in \mathcal{S}$ [SA06, SKB*14, ZCCB13]; nodes are laid out within the area they belong to (Figure 6). Each area is either surrounded by a rectangular contour [SKB*14, ZCCB13] or colored with respect to the group it presents [SA06] . If groups overlap, the same approach can be used, but nodes that belong to different groups are duplicated [LSKS10] (Figure 6(a)). Beyond what is shown in the figure, the approach by Lex et al. [LSKS10] arranges a two-dimensional area for each group in 3D, like walls of a room, and adds visual links between shared nodes to visualize the overlap. For disjoint hierarchical structures , the screen is partitioned in a space-filling way using a circular icicle plot [AFH*10] or a treemap approach [DWS*14, FWD*03, Hol06] (see Figure 6(b)), where each subsection representing $H_l \in \mathcal{H}$ is surrounded by a contour.



(a) Overlapping flat (b) Disjoint hierarchical

Figure 6: *Superimposed visualization using partitioning of screen space into (a) vertically aligned or (b) nested regions.*



(a.1) Disjoint flat (a.2) Disjoint hierarchical (a.3) Overl. hierarchical (b) Hybrid: node-link & matrix

(a) Node-link-based representation including groups as nodes that can be aggregated

Figure 7: *Embedded visualization of groups: (a) Node-link-based integrated representations, where groups are included as nodes of the graph and can be aggregated. (b) Using a hybrid of a node-link and matrix representation of the graph and groups within the graph.*

5.4. Embedded

The fourth main category of our taxonomy is the embedded visualization of group structures (Figure 7). At a first glance, this category looks similar to the superimposition approach using contours (Section 5.3.2). But in contrast to overlays, groups are modeled as nodes themselves and are integrated into the graph. In total, we identified 21 technique papers, where 17 approaches are based on node-link representations only (Section 5.4.1) and 4 approaches are hybrids of node-link and matrix diagrams (Section 5.4.2).

5.4.1. Node-Link

Using embedded approaches, the groups $S_k \in \mathcal{S}$ or $H_l \in \mathcal{H}$ are drawn as nodes, e.g., using concave shapes (Figure 7(a.1)). Group nodes are connected by visual links if any of their members are related [CDA*14], [HN07b, HN07a]. Besides those aggregated edges, in these approaches, only edges $e \in E$ within each group are visualized in a non-aggregated way.

While these techniques are static with respect to the group structure visualization, the following approaches support interactive aggregation methods: groups or subtrees can be collapsed to visualize only the group node but not the underlying subset of vertices $v_i \in S_k$ and their within-group edges (Figures 7(a.2) and 7(a.3)). In the OntoVis approach [SMER06], each node representing a group S_k is connected to all its members v_i using visual links in addition to links encoding the edges of the graph. An approach to visualize the evolution of groups for dynamic graphs is to draw groups as rectangles on top of flow-like group evolution visualization; between-group edges are aggregated and the subgraphs of individual groups are drawn within the group representations [VBAW14]. Disjoint hierarchical groups can be visualized using nested rectangular [ASH14, DM12, DM14a, RPD09] or circular [AMA07a, AMA08, AMA09, AMA11] (3D: spherical [vHvW04]) group structure representations (Figure 7(a.2)). Reitz et al. [RPD09] use the dynamic hierarchical group structure to control the animation of the dynamic graph visualization and to automatically aggregate subhierarchies that do not change.

The grid-based visualization approach by Rohrschneider et al. [RHR*10] arranges the graph nodes on a regular orthogonal grid, where edges are routed on that grid using a cost minimization technique. Nodes v_i contained in different groups S_k are duplicated. In contrast, Sallaberry et al. [SZPM10] place nodes belonging to at least two groups between the respective group nodes, while vertices v_i that belong to only one group S_k can be aggregated and collapsed into group nodes. The approach by Vehlow et al. [VRW13] for fuzzy overlapping groups is similar: it aggregates vertices v_i hierarchically based on their membership-degrees f_{ik} (Figure 7(a.3)). Van Ham and Van Wijk [vHvW04] collapse groups by default and show only the area underneath a lens in more detail. For all other approaches, aggregation is performed by individually collapsing or expanding group nodes interactively by clicking on group nodes within the node-link diagram [ASH14, DM12, DM14a, RHR*10, SZPM10] or in a separate tree view [AMA07a, AMA08, AMA09, AMA11].

5.4.2. Hybrid: Node-Link and Matrix

We identified 4 approaches that use matrix representations to visualize edges within groups and links for relations between groups [HFM07, HBF08, MZ11, RMF12]. In NodeTrix [HFM07], the adjacency matrices are connected to other matrices using edge bundles that visualize the between-group relations (Figure 7(b)). This approach was extended to visualize overlapping groups by duplicating vertices v_i for each group S_k they belong to [HBF08]. Also the approach by Misue and Zhou [MZ11] allows one to visualize overlaps using node duplication. Here, in addition to the matrices representing groups, a node is drawn for each group and linked to all its members v_i, i.e., to the respective rows or columns of the matrices or to single nodes v_i not contained in any group and hence matrix. The TreeMatrix approach [RMF12] encodes hierarchical structures, where subgraphs H_l are shown as adjacency matrices with an attached hierarchy that is visualized as a node-link diagram or using an icicle plot (see also Section 5.2.2) and can be collapsed interactively.

6. Evaluation

Our collection of publications contains only few evaluation papers that describe extensive user studies (5 in total), but most of the technique papers include some kind of evaluation (see evaluation tags in Table 2). In this section, we summarize the results presented in the 5 evaluation papers as well as insights gained from user studies contained in technique papers that thoroughly evaluate group-related tasks (4 in total).

Contrasting visual node attributes (Section 5.1) and superimposed techniques (Section 5.3), a series of three recent user studies, by now, provides the most systematic evaluation of visualization techniques in the field: Saket et al. [SSKB14] compared a superimposed contour approach (GMap [GHK10]) against the use of color as a visual node attribute (Section 5.1). They investigated node-based, network-based, and group-based tasks. The results of their user study with 36 participants suggest that adding contours does not negatively impact the performance of network-based tasks and the GMap approach outperforms colored nodes with respect to group-based tasks. Jianu et al. [JRHT14] replicated this study and included two more approaches in their online study comprising 800 participants. They evaluated colored nodes, line overlay, and two types of contour overlays—GMap [GHK10] and BubbleSets [CPC09]—based on 10 group and network tasks. With respect to group-related tasks, BubbleSets performs best, followed by lines and the GMap approach, while color appears to be least effective. Line overlays (LineSets) were also compared to contour overlays—again the BubbleSets technique—by Alper et al. [AHRRC11]. They conducted a user study (12 participants) to evaluate the performance on four group-related tasks. Compared to the study by Jianu et al. [JRHT14], they found that LineSets improve the readability of set membership and set intersection tasks—with higher accuracy rates and shorter completion times—compared to the BubbleSets technique. They also did an informal, small-scale eye-tracking study that aimed at understanding some of the effects seen in the quantitative results.

Other evaluations focus solely on superimposed contour approaches (Section 5.3.2): Henry Riche et al. [HRD10] evaluated their Euler diagram technique with respect to its readability considering four group-related tasks and one node-related task. In their study (18 participants), they compared their two rectangular contour overlay techniques—the splitting approach and the node duplication approach (Section 5.3.2)—to a third (non-convex) contour overlay. They found that the duplication approach outperforms the other techniques for two of the group-related tasks, but the splitting approach is preferred by many participants. Using a qualitative evaluation, Byelas an Telea [BT09a] compared algorithmically generated contour overlays to hand-drawn contours to improve the rendering algorithm. The GraphDiaries technique [BPF14] was evaluated based on a user study comparing it to two other approaches for dynamic graphs. The focus of the study lies more on tasks related to the dynamic behavior analyzing groups of added or removed elements.

Some evaluations also take embedded approaches into account (Section 5.4): Archambault et al. [APP10] compared a superimposed contour with an embedded approach, where groups of nodes are replaced by group nodes. They evaluated how this affects the readability, but with respect to tasks focusing on attributes and graph topology rather than group structures. In contrast, Henry et al. [HBF08] evaluated their embedded hybrid approach with respect to four group-related as well as two node-related tasks. Their user study (12 participants) applied different alternatives of duplications of elements in overlapping groups and compared these to an embedded approach without duplication. As a result, they found that duplications improve group-related tasks but sometimes interfere with other graph readability tasks.

Hierarchical group structures in graphs have been evaluated rarely, so far; the same applies to juxtaposed approaches (Section 5.2). There is only one qualitative user evaluation on juxtaposed attached visualizations in the context of hierarchies [ABZD13] comparing a node-link-based [BPD11] and a matrix-based [BD13] approach, but focusing more on tasks for graph comparison.

7. Application

Group structures occur in various application domains of graphs. In total, comprising application, evaluation, and technique papers, the most common application domains for the visualization of group structures are social networks (41 papers), biology (30 papers), and software engineering (25 papers). In this section, we summarize mainly the application papers but occasionally also technique papers with a focus on these areas. Further application domains of group visualizations are economy networks representing business, transport or financial data, computer networks, relations between documents or texts, or relations within media data or sports-related data.

In **biological applications**, graphs are almost exclusively represented as node-link diagrams. In particular in protein-protein-interaction networks and gene correlation networks, disjoint and overlapping flat group structures occur. These mainly result from categorical attributes of the genes or proteins, e.g., from cell compartment and pathway associations or from gene ontology annotations; also clustering is applied to extract motifs, i.e., functional groups of proteins. Commonly, group structures are visualized by visual node attributes [BST03, FGB*07, TvDEF09] and superimposed techniques—including overlaid contours [PLS*13, SXS*12, VHK*13] and partitioning approaches [BMGK08, GFK*14, PK06, SLK*09]. Also attached juxtaposed [SJUS08] and embedded [RHR*10, VRW13] approaches have been applied to biological networks.

In **social networks** such as friendship, communication, collaboration, or co-authorship networks, vertices represent people, while edges encode relationships between them. Groups of vertices therefore identify circles of friends, groups that cooperate, or the like. Social groups, also called communities, may be disjoint but are often modeled more realistically by overlapping groups because people often participate in a multitude of diverse, yet overlapping social communities. So far, social communities have been visualized mainly within node-link diagrams. Similar to the biological domain, the group structure is commonly visualized by visual node attributes (color) [CMF*14, PSK11], superimposed visualization, in particular using line [AHRRC11, XDC*13] or contour overlays [CCC02, DLM14, PS06, SCL*09], or using color and contour overlays in combination [GMT09, HD12, HB05]. Hierarchical group structures in social networks, in contrast, are often visualized in attached juxtaposed views together with static [GZ11] or dynamic graphs [BBV*12, GSZ*11]. Also embedded approaches have been applied to social networks [AMA08, DM14a, HBF08].

In **software engineering**, network visualization is used to analyze program structures and their hierarchical organization, which is usually given by the modularization of the software system. Within software architecture diagrams, also software metrics can be used to define disjoint or overlapping flat group structures [BT09b, TLTC05]. The hierarchical structure of call graphs or other dependency networks is commonly visualized using attached juxtaposed visualizations [BPD11, BD13, PvW07, PvW08, SJSJ05, vH03], superimposed contours [RFG05], or embedded approaches [PGKG08, RMF12]. Overlapping group structures can be visualized using glyphs [TLTC05] and overlaid colored [BT09a] or textured [BT09b] contours.

8. Research Challenges

The taxonomy of techniques shows what has been achieved in the field and reveals possible gaps in the research literature. However, not necessarily, every gap is a good research opportunity and there might be other interesting challenges that are not indicated by gaps in the taxonomy. To provide ideas of worthwhile future research, we discussed research challenges with other researchers who have substantially contributed to the field. We interviewed 7 experts in graph or group visualization face-to-face—on average for about 40 minutes per person. We first showed a preliminary version of our taxonomy of group structure visualizations containing illustrations of existing techniques (similar to Table 3), explained our interpretation of groups and group structures in graphs, and asked them for feedback on terms and definitions—this feedback is already reflected in the terms used in the data model (Section 2.1) and taxonomy of visualization techniques (Section 5). The main purpose of these interviews, however, was to ask for the experts' opinion on open problems and challenges on visualizing group structures in graphs. Besides challenges they named, we also discussed the challenges that we identified beforehand, in case they did not mention them already. Based on the feedback we received within the interviews and some of our ideas, we identified five main challenges—each regarded as relevant by 2 to 5 experts.

8.1. Time-Varying Groups and Comparison

In many application domains, graphs are not static but change over time, i.e., their topology or their attributes change over time. Hence, also the topology-based or node-attribute-based group structures can change over time. Most techniques that have been developed to visualize the evolution of groups, do not visualize the graph topology [FBS06, OMB*07, RTJ*11, RB10]—for this reason, these are not part of our taxonomy. Other approaches focus on the visualization of dynamic graphs but not the temporal evolution of groups; they visualize the group structure aggregated over time. First attempts have been made to visualize both the evolution of groups and the dynamic graph together [SMM13, VBAW14], but these only cover evolving disjoint flat group structures. Related to dynamic graphs is the problem of graph comparison: instead of several graphs in a sequence, an unordered set of graphs is compared. Similarly, the comparison of groups structuring these graphs have not yet been discussed in this context.

8.2. Data Complexity

Instead of having multiple versions of the data, the data itself can get more complex by adding or refining data dimensions. For overlapping groups, for instance, the visualization of fuzzy memberships is challenging, where vertices may belong to different groups with different extent (see Section 2.1). Although the detection of fuzzy overlapping groups has become quite popular in the domain of graph clustering [For10], their visualization was only addressed in one work so far [VRW13]. In many applications, groups need to express a degree of uncertainty that can be modeled as fuzzy groups. Another degree of complexity could be introduced by the topology of the group structure: so far, most of the visualization approaches that were developed for overlapping groups can handle only flat group structures (Table 1). However, also overlapping groups can be organized hierarchically, for example, derived from an ontology, through clustering, or other sources. The complexity of the group structure visualization also increases when multivariate attributes of vertices and edges need to be visualized together with the graph. These attributes could, for instance, explain why certain elements are grouped together or why a pair of groups overlaps.

8.3. Scalability

The data does not need to get more complex, but already visualizing more data elements can be challenging. In graph visualizations, questions of scalability usually relate to the number of vertices and density of edges. Visualizing additional group structures, however, introduces further challenges. For an increasing number of groups, for instance, encoding the groups by colors becomes difficult for more than about 7 groups [Hea96]. There are already some approaches that optimize the color assignment (Section 5.1), but there is still potential to improve and extend these approaches. Also, for larger numbers of groups, coloring approaches probably need to be replaced by other group representations. But even having a constant number of groups, scalability issues could arise from increasing the overlap of groups. For instance, superimposed approaches (Section 5.3) become more and more cluttered through a denser overlay of group structures. Maybe, even new representations need to be found to handle datasets with large overlap of many groups. In hierarchical groups, also the depth of the hierarchy could become a problem of scalability for some visualizations.

8.4. Interaction Technique

One way to address certain issues of scalability is the use of interaction methods such as aggregation, which already is a widely used method—26 of the 81 collected technique papers support aggregation. But some data is lost through this abstraction. The question therefore remains how to aggregate while, at the same time, visually encoding the uncertainty of aggregated groups and the density of edges within these groups. For overlapping groups, aggregation is even more difficult because overlaps either need to be represented explicitly or the overlap is not retrievable for the users. Also, there is a need for advanced interactive (semi-) automatic aggregation methods that guide the user through large datasets or define a good default aggregation. Beyond aggregation, there is also potential in visual analytics approaches that combine data mining methods with the visualization of group structures in graphs into an interactive approach. Clustering and classification algorithms could provide alternative group structures on demand. To update the data in a comprehensible way, the visualization needs to adapt on the fly, which introduces new visualization challenges. Similar updates are required when the users edit the group structures interactively, for instance, by applying set operations to the groups.

8.5. Tasks and Evaluation

In order to choose the right type of group structure visualization for a particular application, we need to be aware of the tasks users want to solve with the help of the visualization. Application-specific tasks can be generalized to abstract data tasks, generalizable to different applications. There was already work done for disjoint flat groups [SSK14], which still needs to be extended to overlapping groups and hierarchical structures (Section 2.3 suggests some specific examples). Also, it is important to study how basic data-related tasks are composed to complex task and which complex tasks are most relevant in specific areas of application. Then, it can be investigated which visualization technique is suitable for which application. Some evaluations have already been conducted (Section 6), but cover the techniques discussed as part of our taxonomy only partially. Advanced evaluation methods to better understand perceptive and cognitive processes such as such eye tracking [KFBW14] have rarely been applied in the field [JRHT14].

9. Conclusions

We presented the state of the art in explicitly visualizing group structures in graphs. Groups are disjoint or overlapping, and might be flat or structured hierarchically. In this survey, we brought together various group visualization techniques for graphs that have been discussed separately, so far. Based on the collected set of publications comprising all these techniques, we derived a taxonomy of visualization techniques consisting of four main categories: *visual node attributes* encode group information in the appearance of a node, *juxtaposed* approaches visualize graph and group structure in separate views, *superimposed* techniques use visual overlays, and *embedded* representations combine the graphs and groups into an integrated visualization. We intersected the visualization taxonomy with a taxonomy of group structures to a lineup showing which visualization has been already used for what type of structure. The comparison hints at opportunities to fill gaps in existing research literature. Based on interviews with experts in the field, we identified important challenges that could guide future research.

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Biography

Corinna Vehlow is PhD student at the VISUS, University of Stuttgart. In 2010, she obtained the Diplom (M.Sc.) degree in computational visualistics from the Otto-von-Guericke University Magdeburg, Germany. Her research interests include information visualization and visual analytics with the focus on graph, set, and uncertainty visualization, often in the context of biological networks.

Fabian Beck is a postdoctoral researcher at VISUS, University of Stuttgart, Germany. In 2013, he obtained his Dr. rer. nat. (PhD) degree in computer science from University of Trier. In his dissertation, he investigated multi-dimensional coupling graph structures of software systems. Most of his research is focused on methods for visualizing and comparing large and dynamic graphs and hierarchies, often in the context of software systems and their evolution.

Daniel Weiskopf is a full professor at VISUS, University of Stuttgart, Germany. He received his Dr. rer. nat. (PhD) degree in physics from the University of Tübingen, Germany (2001), and the Habilitation degree in computer science at the University of Stuttgart, Germany (2005). His research interests include all areas of visualization, visual analytics, GPU methods, perception-oriented computer graphics, and special and general relativity.