Visualizing Group Structure in Compound Graphs: The Current State, Lessons Learned, and Outstanding Opportunities

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Abstract: Compound graphs are common across domains, from social science to biochemical pathway studies, and their visualization is important to both their exploration and analysis. However, effectively visualizing a compound graph's topology and group structure requires careful consideration, as evident by the many different approaches to this particular problem. To better understand the current advancements in compound graph visualization, we have consolidated and streamlined existing surveys' taxonomies. More specifically, we aim to disentangle the visual relationship between graph topology and group structure from the visual encoding used to visualize its group structure in order to identify interesting *gaps in the literature*. In so doing, we are able to enumerate a number of *lessons learned* and gain a better understanding of the outstanding *research opportunities* and *practical implications* across domains.

1 INTRODUCTION

Compound graph data, their visualization, and analysis are common across many different fields: from social networks (Federico et al., 2011), to biochemical pathways (Partl et al., 2013), to business analytics (Adomavicius and Bockstedt, 2008) and transportation logistics (Mesa-Arango and Ukkusuri, 2015). In social network analysis, for example, researchers are interested in understanding a person's role across social groups. Here, compound graphs can be used to model individuals as nodes and their relationships as edges, as well as their place in various types of groups, such as circles of friends, roles within a workplace, or associations with organizations. For another example, in the context of biological pathways, domain experts are interested in understanding the mechanistic relationships between individual and groups of genes and metabolites, in order to understand the biochemical underpinnings of disease or cell function. No matter their application area, compound graphs are a useful framework for probing and understanding networks whose nodes also share group-level relationships.

However, compound graphs are challenging to visualize, as researchers are interested in understanding such graphs on both a topological and a group level for increasingly large datasets. Thus, any visualization of compound graphs must tackle the challenge born of trying to balance the visual communication of both entity topology and group structure. Various visualization approaches and systems have been put forth in literature, each tackling this challenge differently: Some forgo interactivity in the interest of scalability (De Domenico et al., 2015), others aim to combine the two using summarization or linked views (Dunne and Shneiderman, 2013), while others yet build upon domain-specific visual conventions to better serve a particular user group (Lex et al., 2010).

While existing reviews have taxonomically summarized these various visualization approaches for compound (Vehlow et al., 2015), multivariate (Nobre et al., 2019), multilayered (McGee et al., 2019), and dynamic (Beck et al., 2014) graphs, we note that none

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had classified compound graph visualization strategies along the more abstract axes of general (comparative) visualization (Kim et al., 2017). We argue that doing so allows for a more general understanding of literature gaps and the identification of new, interesting research opportunities.

In this position paper, we identify and discuss lessons learned and novel research opportunities within the context of group structure visualization in compound graphs. To better understand the current state-of-the-art, we draw upon existing taxonomies developed in recent surveys, namely i) (Vehlow et al., 2015), (Beck et al., 2014), (Nobre et al., 2019), and (McGee et al., 2019)'s reports on (particular types of) compound graphs, ii) (Alsallakh et al., 2016)'s survey on set-typed data, and finally iii) in order to position compound graph visualization within a comparison-oriented framework, (Kim et al., 2017)'s report on comparative strategies. These reviews were selected as, based on their impact on the field, we believe them to be authoritative and representative. These state-of-the-art reports and their taxonomies share notable overlap and all shed light on various facets of the group structure visualization challenge in compound graphs. We argue, however, that none, by themselves, provide a complete view of the current opportunities. Instead of providing a meta-review, here, we consolidate and extend these taxonomies to provide a comprehensive overview of the topic. This is to aid us in identifying both major lessons learned from past research in the field as well as open challenges across compound graph visualization domains not yet discussed by these aforementioned reports.

Specifically, we identify three core axes along which to categorize literature, namely

1. the *visual relationship* between group and topological information, inspired by (Kim et al., 2017),
2. the *visual encoding* chosen for the graph's group structure, inspired by (Alsallakh et al., 2016),
3. the kind of *group-level relationships* admitted by the approach in question, as investigated by (Vehlow et al., 2015).

We collect 167 references, partially based on the bibliographies of existing reviews, and place them within our taxonomy. Based on our findings, we identify gaps in the literature, outstanding challenges, and lessons that can be useful for domain researchers. We also identify several novel research opportunities.

2 RELATED WORK

2.1 Compound Graph Visualization

Dynamic Graphs. Dynamic graphs describe the evolution of entities and their relationships over time. (Beck et al., 2014) survey and taxonomically classify current approaches to the visualization of such graphs. They identify three families of approaches, namely i) *animation*, i.e. the mapping of time to time, as seen in the work of (Ma et al., 2015), ii) *timelines*, i.e. the mapping of time to space, exemplified by *MatrixFlow* (Perer and Sun, 2012), and iii) *hybrid* approaches that combine the two, such as *Small Multiples* (Bach et al., 2015). While these families of approaches can indeed be utilized for general compound graph visualization, their work naturally does not discuss this in much detail. Nonetheless, they identify a large set of relevant techniques, approaches, and applications of dynamic graph visualization, and a number of their findings are mirrored in more general surveys (Vehlow et al., 2015; McGee et al., 2019).

Multilayer Graphs. Multilayer networks are a general framework describing various group-level relationships of both edges and nodes (Kivelä et al., 2014). (McGee et al., 2019) survey the state-of-the-art of visualizing such networks. They classify papers collected based on the visualization method: i) *1D representations*, e.g. circular (Bothorel et al., 2013) or axis-based (Krzywinski et al., 2012) approaches, ii) *2, 2.5, and 3D node-link diagrams* which often use color (Archambault et al., 2007b) or linked views (Renoust et al., 2015) to communicate group structure, iii) *matrix-based visualizations*, such as *Termite* (Chuang et al., 2012) or *MuxVis* (De Domenico et al., 2015), iv) *hybrid* approaches, such as the matrix/node-link diagram *NodeTrix* (Henry et al., 2007), and v) *summary* approaches, such as *Graph Thumbnails* (Yoghourdjian et al., 2018).

Multivariate Graphs. Multivariate graphs are collections of nodes and edges with additional data attached to them, such as group-level associations. Here, (Nobre et al., 2019) classify existing multivariate graph techniques along their view-, layout-, data-operations, and layouts. While they do not specifically address the visualization of group-level information, a number of their taxonomy categories are mirrored by other surveys discussed here. Most notably they discuss three types of view operations; juxtaposed, integrated, and overloaded. Nonetheless, their recent publication contains a number of papers featured in other state-of-the-art reports that are worth classifying in our own taxonomy.

Compound Graphs. Finally, (Vehlow et al., 2015) survey approaches to the visual communication of group structure of compound graphs. They ultimately identify four meta-categories to describe different approaches with which to visualize such group structures, namely i) *visual node attributes*, i.e. the encoding of group structure in the form of glyphs or color in the compound graph's embedding, exemplified by *TopicPanorama* (Wang et al., 2016) and *NetworkAnalyst* (Xia et al., 2015), respectively, ii) *juxtaposition*, i.e. the separate visualizing group structure in either a linked view or attached to the graph's embedding, as seen in the works of (Burch et al., 2013) and (Zhou et al., 2015), respectively, iii) *superimposition*, i.e. the overlaying of group structure atop the graph's embedding using regions or lines, such as *Kelp Diagrams* (Dinkla et al., 2012) and *LineSets* (Paduano and Forbes, 2015), respectively, iv) *embedding*, i.e. the drawing of a separate graph with which to communicate group structure relations, using, for example, hypernode summarization (Chaturvedi et al., 2014) or hybrid graph embeddings (Henry et al., 2007; Angori et al., 2019).

Summary. All four of these categorizations, while useful, are complementary to each other, and all, to some extent or another, conflate i) the *visual relationship* between topological and group-level information, i.e. how a graph's group structure is visualized relative to the topology's visualization, and ii) the group structure's chosen *visual encoding*, i.e. how a graph's group structure, not its topology, is visually represented. Subsequently, we aim to build upon, unify, and extend them to produce a novel perspective on the current state of compound graph visualization.

2.2 Visualizing Group Structure

(Alsallakh et al., 2016) study different strategies for visualizing group-level information for sets and their elements. While this taxonomy was not developed with compound graphs in mind, there is notable overlap with, and opportunities for extending, the aforementioned compound graph visualization taxonomies (Section 2.1). They identify six types of visualization strategies with which to encode group structure, namely i) *Euler/Venn* diagrams that represent each set as a closed curve and intersections as the overlap between them, ii) *Overlays*, which, given some embedding of each element as a point in 2D (or 3D) space, overlay set-membership using (colored) glyphs, lines, or region overlays, iii) *node-link diagrams* that represent each set and element as a node and draw bipartite edges between to communicate set-element-membership, iv) *matrices* which place either elements and sets along rows and columns to communicate identity, or will place sets/elements along both rows and columns to communicate similarity, v) *aggregation-based representations* that do not visualize all elements, but instead only show the number of elements per set in order to provide an effective overview of larger datasets, vi) *scatter plots*, a special type of aggregation, which embeds each set as a single point in 2D or 3D space as a function of some similarity metric or data attribute.

2.3 Comparative Visualization

Lastly, (Kim et al., 2017) describe four different approaches to comparative visualization of 3D and 4D spatial data. While not complete on their own, we argue that these abstract classes of comparative visualization can be meaningfully mapped to group-structure visualization approaches in compound graphs. More specifically, we argue that the compound graph visualization problem can be understood as a comparison of graph topology on the one hand and group structure on the other. Four classes of approaches to comparative visualization are identified. *Juxtaposition* describes the side-by-side visualization of objects to be compared. *Superimposition* describes overlaying the objects to be compared. *Interchangeability* describes the interactive or animated scrubbing through objects. Finally, *explicit visualization* is the visualization of some derived (summary) quantity instead of the objects directly.

3 PAPER COLLECTION

In order to obtain a representative set of papers and applications, key references selected from the bibliographies of four relevant state-of-the-art reports, (Nobre et al., 2019), (McGee et al., 2019), (Vehlow et al., 2015), and (Beck et al., 2014) were consolidated. Interestingly, despite the relatedness of the topics, we note little overlap in general between these four reviews, with the possible exception of (Beck et al., 2014) and (Vehlow et al., 2015) (Figure 1. It should, however, be noted that the inclusion of references from existing works may introduce a certain bias to our literature review. Thus, in order to include more recent papers not present in these aforementioned works, we additionally manually curated an additional set of references from relevant venues,

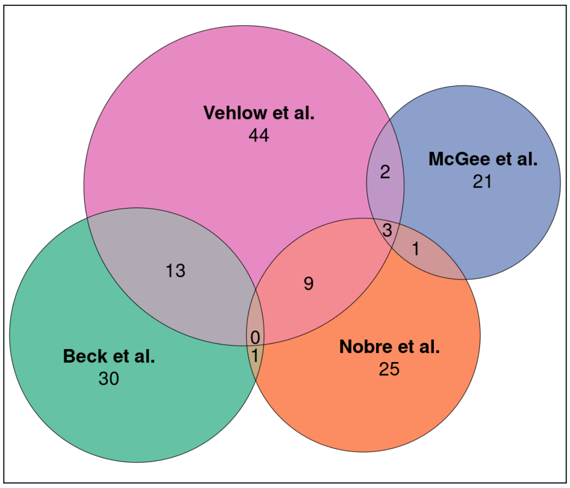

Figure 1: Sources and overlap of the selected papers collected from (Beck et al., 2014), (Nobre et al., 2019), (Vehlow et al., 2015), and (McGee et al., 2019) illustrated as an area-proportional Euler diagram. Among other goals, we aim to unify their collected references in addition to extending this collection of literature.

such as *IEEE TVCG*, *Computer Graphics Forum*, *PacificVis*, *Graph Drawing and Network Visualization*, and *Information Visualization*. In total, 167 papers were collected and subsequently manually categorized based on their visual relationship (Section 4.1), visual encoding (Section 4.2), group structure (Section 4.3), as well as their application area. The final set of papers and their categorization have been made publicly available on GitHub.

4 THE CURRENT STATE

Drawing upon these taxonomies, we propose to categorize papers along three main "axes", namely i) the chosen *visual relationship* between groups and their elements, ii) the selected *visual encoding* with which to communicate the graph's group structure itself, and iii) the *group structure* of the data.

4.1 Visual Relationships

A compound graph's visual relationship describes how a graph's group structure is visualized relative to its topology - Figure 2. Here, combining (Kim et al., 2017) and (Vehlow et al., 2015)'s taxonomies, we identify five possible visual relationships.

Separate. Defined by (Vehlow et al., 2015) as "*Partitioned*", a *separate* visual relationship, describes the visualization of group structure in a separate (possibly linked) view, such that the graph's global topology and group structure can be investigated independently. Such representations are especially useful if the graph's group structure is too complex to visualize atop or within its topological embedding. Consider, for example, the tree attached to a node-link diagram seen in *ASK-GraphView* (Abello et al., 2006).

Juxtaposed. Equivalently found in (Vehlow et al., 2015)'s taxonomy under "*Superimposed / Partitioned*", a *juxtaposed* visual relationship (Kim et al., 2017) describes the side-by-side visualization of each group's subgraph's embedding in separate, possibly linked, views. Such representations are beneficial when a set of topologically similar graphs are to be compared side-by-side. For example, *Entourage* (Lex et al., 2013) opts to visualize different pathways side-by-side in a juxtaposed manner.

Embedded. Defined as "*Superimposed*" by (Kim et al., 2017) and "*Visual Node Attribute*" as well as "*Superimposed / Overlay*" by (Vehlow et al., 2015), an *embedded* visual relationship defines the simultaneous visualization of graph topology and group structure in a single view, be it through color or region overlays or an explicit axis. Such representations can be useful, especially in explorative analysis endeavors, where one must first locate areas of simultaneous topological or group-structural interest. *TopicPanorama* (Wang et al., 2016), for example, visualizes group assignments as embedded glyphs.

Interchangeable. Not explicitly found in (Vehlow et al., 2015), an *interchangeable* visual relationship (Kim et al., 2017) describes the visualization of each group's subgraph as a separate "slice" in a pile of linearly arranged slices that are traversed interactively, or automatically, using animation. Similar to juxtaposed representations, such visual relationships lend themselves well to immediate comparisons of pairs of subgraphs, especially when a compound graph's group structure can be linearly arranged, e.g. time slices in dynamic graphs. Consider, for example, the small multiples of adjacency matrices presented in the work of (Bach et al., 2015).

Explicit. Defined by (Vehlow et al., 2015) as "*Embedded*", an *explicit* visual relationship (Kim et al., 2017) describes the visualization of some computed characteristic, such as differences or averages or similarity, in order to provide a simpler summary visualization. These representations are especially useful for highly complex or large compound graphs, where

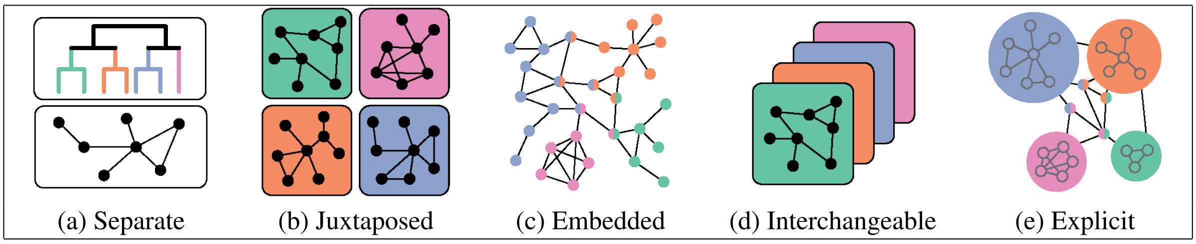

Figure 2: Examples showcasing the five identified visual relationships between group-level and topological encodings. **(a) Separate** relationships describe the visualization of group structure independently of any (topological) embedding of the compound graph. **(b) Juxtaposed** relationships place each group's subgraph side-by-side, allowing for straightforward comparisons between them. **(c) Embedded** relationships embed group-level information within/atop a compound graph's drawing. If a particular node forms an intersection between two groups, its glyph is accordingly colored. **(d) Interchangeable** relationships only visualize one group's subgraph's topology at a time but allow for a user to scrub through them linearly. **(e) Explicit** relationships, rather than displaying all topological and group-level relationships, visualize only a composite of the two.

the simultaneous visualization of group structure and topology (in a single view) is not feasible or useful. For example, (Sallaberry et al., 2010) opt to visualize each group and their intersections as hypernodes and regular nodes, respectively.

4.2 Visual Encoding

The visual encoding describes here how a graph's group structure—not its topology—is visually represented, i.e. how set membership, intersections, and exclusions are visually communicated to the user, as seen in Figure 3. Drawing primarily from (Vehlow et al., 2015) and (Alsallakh et al., 2016) we identify and define eight approaches with which to visually communicate nodes' group associations.

Node Attribute. Described as "*Overlays*" by Alsallakh et al. (Alsallakh et al., 2016), *node attributes* (Vehlow et al., 2015) are characteristics, here group membership(s), of a compound graph's elements, which can be utilized to alter the visual attributes of each node during the embedding of the graph. *Color* is arguably the most common such node attribute with which to communicate group/set/cluster membership as it is simple to implement and understand. Similarly, *shapes* can also be used. Lastly, *glyphs* are useful for more complex element-set-memberships and relationships, as they can, for example, express such relationships as pie charts instead of simple shapes or colors, as seen in *TopicPanorama* (Wang et al., 2016). In general, node attributes are a non-invasive, if limited, approach to visually communicating group memberships and relations without affecting the graph's topological embedding.

Overlay. Given some embedding of elements in 2D, *overlays*, described by (Vehlow et al., 2015) as "*Line/Region-based overlays*", add visual information atop elements/nodes to communicate set membership. This commonly takes the form of a *hulls/regions* overlaid atop grouped vertices (Alsallakh et al., 2016), as seen in (Partl et al., 2013)'s *enRoute*. A key disadvantage of region-based overlays is the ambiguity that can arise from overlapping, but non-intersecting, contiguous regions (Alper et al., 2011). *Line* overlays avoid such ambiguity by encoding group membership to line-node-intersections, as seen in (Alper et al., 2011)'s *LineSets*. Lines, however, can require a lot of "ink" when connecting vertices close to each other, resulting in more visual clutter than a simple region. In an effort to leverage the advantages of both, *hybrid* overlays combine both regions and lines, as exemplified by (Meulemans et al., 2013)'s *KelpFusion*. In general, overlays can be an effective means of communicating (disjoint) vertex-group membership, though they struggle to effectively communicate denser or more complex group-level relationships.

Bipartite Node-Link Diagram. Thus far, group-level relationships have not affected the topological embedding, thereby communicating topological relationships clearly at the potential cost of group-level clarity. Here, *(bipartite) node-link diagrams* (Alsallakh et al., 2016; Vehlow et al., 2015) represent both groups and their elements as different vertices in the same embedding, and visualize their associations as bipartite edges connecting them. The produced node-link diagram thus has two types of edges: topological edges connecting element vertices to each other, and bipartite edges connecting group and element edges. This can allow group-level clustering to be more apparent as the group structure now directly affects the embeddings seen in (Bigelow et al., 2019)'s *Origraph*.

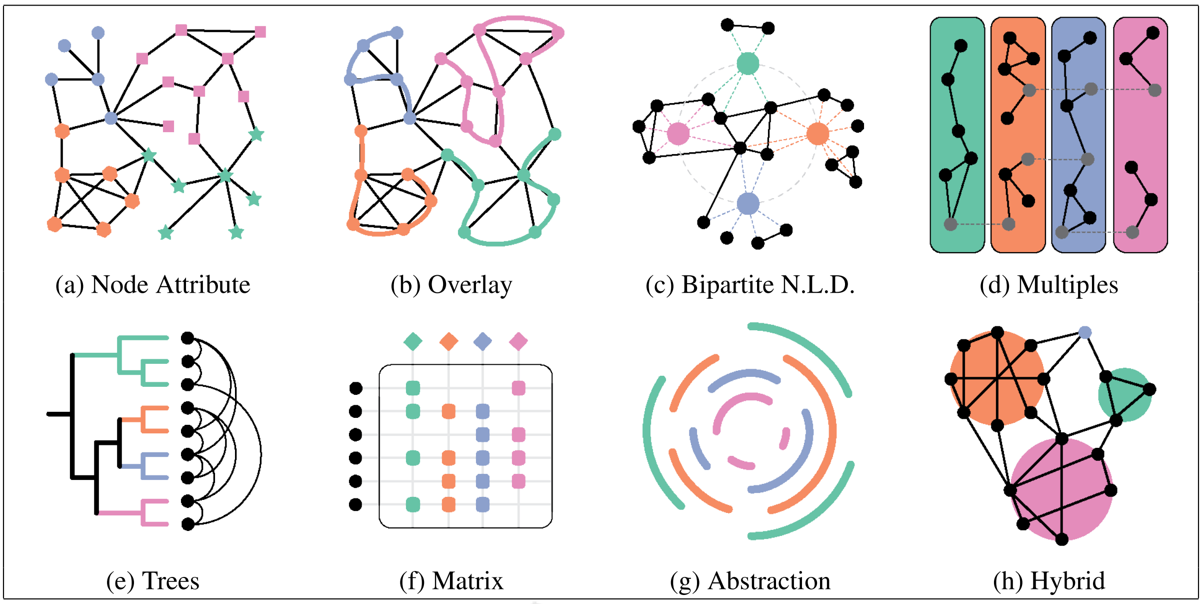

Figure 3: Examples of the eight identified visual encodings of group structure. **(a) Node-Attribute** encodings simply visualize nodes' group memberships using those nodes' color and/or shape. **(b) Overlay** encodings visualize group membership as regions or lines atop the nodes in the graph embedding. **(c) Bipartite node-link diagram** encodings visualize groups as additional nodes within the graph's embedding. Group membership is communicated using bipartite edges connecting group nodes to topological nodes. **(d) Multiples** encodings visualize each group's subgraph separately in its own "tile". **(e) Tree** encodings communicate (hierarchical) group structure between entities, visualized as leaf nodes, as hierarchical nodes whose edges indicate super/sub-set relationship between them. **(f)** Identity **matrix** encodings communicate set membership tabularly where if a node (row) pertains to a group (column), the respective cell is filled. **(g) Abstraction** encodings provide an overview of groups' cardinalities and their relationships by abstracting away the individual elements that make up said group. Intersections are communicated through angular overlap between lines. Finally, **(h) hybrid** encodings combine any of the above encoding types, e.g. a combination of multiples with node-link diagrams.

Multiple. Instead of visualizing group information within, atop, or next to a graph's embedding, *multiples*, described as "*Partitioning*" by (Vehlow et al., 2015), visualize each group's topology separately. Here, each such subgraph is displayed in its own "tile", arranged most commonly either in a juxtaposed or interchangeable manner. Juxtaposed multiples, such as (Bach et al., 2015)'s *Small MultiPiles*. allow for a straightforward side-by-side comparison of subgraphs. Interchangeable multiples require (animated) transitions from one tile to the next, as seen in (Bach et al., 2014a)'s *Graph Diaries*. On the one hand, multiples allow for a clear visualization of each group's subgraph's topology and its element-group memberships. On the other, however, the visual communication of group-level intersections in non-disjoint graphs is complicated, as vertices that map to multiple groups must be duplicated; once per tile.

Tree. *Trees* are prevalent in the visualization of disjoint, hierarchical group structures. Elements are represented as the tree's leaves and the various levels of the tree represent the various (hierarchically related) sets. Edges encode set-element membership as well as set-set hierarchies. Most commonly, trees are visualized in separate views, e.g. (Abello et al., 2006)'s *ASK-Graph*. as visualizing topological edges between the tree's leaf nodes can be visually difficult. For example, (Telea and Auber, 2008)'s *Code-Flows* addresses this challenge by visualizing topological relationships as a bipartite graph and duplicating the group's hierarchical tree structure along each bi-partition.

Matrix. *Matrices* (Alsallakh et al., 2016) can communicate set membership and relationships tabularly in one of two ways. On the one hand, an identity matrix arranges elements and sets along its rows and columns, respectively, and "fills" a corresponding matrix cell if an element maps to that particular set. Intersections are communicated by a specific row (element) mapping to multiple columns (sets) — e.g. (Chuang et al., 2012)'s *Termite*. On the other hand, a similarity matrix places either sets or elements along both rows and columns and fills each cell with some measure of similarity, thereby communicating set or element relationships, but being unable to communicate element-set-membership on its own.

Abstraction. *Abstraction*-based techniques, described by (Alsallakh et al., 2016) as "*Aggregation*", opt to visualize not all sets, elements, and their relationships, but instead provide an overview of one, at the expense of the others. Here, given the scope of the paper, we define abstraction-based techniques as techniques that abstract away element information in favor of more clearly communicating group-level information. Quite naturally, this fairly broad category can encompass many different approaches; from the relatively simple *Linear Diagram* (Rodgers et al., 2015) to the much more complex *Graph Thumbnail* (Yoghourdjian et al., 2018).

Hybrid. Finally, *hybrid* approaches (Vehlow et al., 2015) combine the aforenoted representations in unique ways, exemplified by (Henry et al., 2007)'s fusion of node-link diagrams and matrices - *NodeTrix*, or (Angori et al., 2019)'s combination of chord and node-link diagrams - *ChordLink*.

4.3 Group Structure

Lastly, continuing the work of (Vehlow et al., 2015), we categorize collected techniques based on the type of group structure they are designed to visualize. While they focused on distinguishing not only *hierarchical* from *flat* and *disjoint* from *overlapping* group structures, these authors additionally noted *crisp* from *fuzzy* groupings. Given the scope of our work, we omit the latter from our own categorization of literature. Thus, for each combination of visual encoding and visual relationship, we count the total number of approaches that apply to each considered type of data in order to identify potential gaps (Figure 4).

5 LESSONS LEARNED

Following our taxonomy of visual encoding and visual relationships described in Sections 4.2 and 4.1, we classify the collected corpus accordingly, the results of which are presented in Figure 5.

Foregone Conclusions. Somewhat unsurprisingly, many combinations of visual encodings pair (almost) exclusively with certain visual relationships (Figure 5). Most notably, overlays and node attributes, by definition, are embedded encodings, visualized within the graph topological embedding. Thus, the 39 overlay and 22 node-attribute techniques map exclusively to the embedded relationship category. Similarly, multiples, if presented in 2D, would most commonly only be visualized either interchangeably or juxtaposed to each other, or separately from some other topological representation.

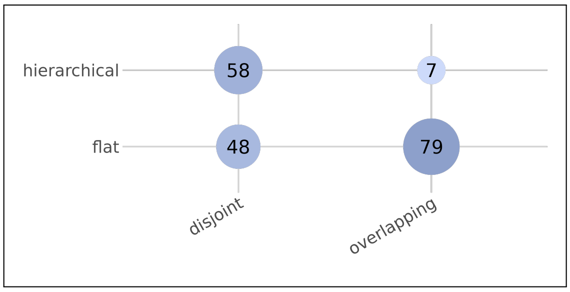

Figure 4: Group structures compatible with the visualization approaches collected from the selected papersp. Circle area and color intensity encode the number of papers and techniques that map to a particular combination of group structure and "overlappedness". The exact number of papers is displayed at the center of each circle in black. Papers could map to more than one such combination of categories.

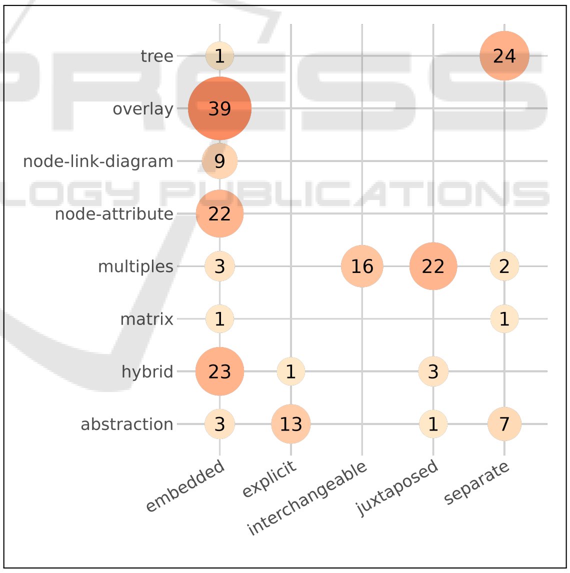

Figure 5: Co-occurence of visual encodings and visual relationships of the selected papers. Circle area and color intensity encode the number of papers and techniques that map to a particular combination of encoding and relationship. The exact number of papers is displayed at the center of each circle in black. Some papers featured multiple visual encodings and/or relationships and were thus mapped to more than one combination of such categories.

Everyday Embedded. Of the 167 papers collected, the majority (98 references) featured an embedded relationship between graph topology and group structure (Figure 5). Most commonly, these papers represented their graph's group structure using overlay, node-attribute, or hybrid techniques. Overlays and node-attributes appear to be especially popular when the graph's topology is of greater importance than its group structure, as they do not alter the topology representation. For completeness, however, it should be noted that several *region-based overlays* specifically, such as *Polyptychon* (Daniel et al., 2014) and *H-BLOB* (Sprenger et al., 2000), are algorithmically incorporated during the (spring-)embedding of the graph and thus do affect the graph's visualization. Their popularity seems to also be connected to their conceptual simplicity and ease of implementation.

Embedded relationships were used for all group structures, though primarily for *flat* ones. 37 papers were applied to *disjoint/flat* group structures, such as the region-based overlay *MapSets* (Efrat et al., 2014) or the hybrid technique *ChordLink* (Angori et al., 2019), and 36 papers mapped to *overlapping/flat* group structures, as seen in (Dinkla et al., 2014)'s hybrid tool *eXamine* or (Vehlow et al., 2013)'s node-attribute approach.

This combination of *embedded* encoding and *flat* groupings is perhaps unsurprising, as the use of node attributes or overlays —the two most common embedded encoding techniques— do not straightforwardly allow for the encoding of hierarchical relationships on their own. Additionally, as discussed in Section 4.2, *embedded* approaches' ability to visually communicate overlap between more complex groups is also somewhat limited. Thus, most combinations of *embedded* encoding and *overlapping* groupings limit themselves to fairly simple cases, i.e. either few groups or few intersections.

However, *embedded* approaches were also utilized for hierarchical relationships, though primarily disjoint ones, with 24 instances of *disjoint/hierarchical* and 4 *overlapping/hierarchical*. *Disjoint/Hierarchical* relationships mostly focus on visualizing a single layer of the hierarchy within the compound graph's embedding while visualizing the full hierarchy in a separate (linked) view, as seen in *OntoTrix* (Bach et al., 2013), *HybridVis* (Bach et al., 2013), or *TreeMatrix* (Rufiange et al., 2012).

Lastly, for the few *overlapping-hierchical embedded* visualizations, (Wang et al., 2016) and (Nakazawa et al., 2012) opted to visualize one layer at a time and communicate overlap using colored glyphs while the complete hierarchy was visualized separately, while (Jusufi et al., 2013) opted to visualize group-entity associations as a node-link diagram.

Seeing the Forest for the Trees. *Tree*-style encodings were applied predominantly to *disjoint/hierarchical* group structures with 21 instances thereof, while all other group structures featured 2 instances each. Here, tree representations of group structure are most commonly visualized separately from the graph's topology: of these 21 *disjoint/hierarchical* group structures, 20 were visualized separately (Figure 5). This can be attributed to the visual complexity that such trees introduce on their own, i.e. a whole set of nodes and edges representing set relationships between groups in addition to topological ones between entities. By visualizing topology and group structure separately, equal weight can be given to both without one affecting the other which allows for such complex, hierarchical relationships to be visualized more easily.

Indeed, looking at techniques intended for larger networks, such as (Abello et al., 2006)'s *ASK-GraphView* or (Abello et al., 2005)'s combination of fisheye views and treemaps, the graph's hierarchical group structure becomes complex enough to require a separate view. For simpler hierarchies and smaller graphs, a separate tree representation has been combined with abstracted graph embeddings, such as (Archambault et al., 2007a)'s *Grouse* framework. Combining topological and group node-link diagrams in a single integrated view is possible as well (Pretorius and Van Wijk, 2006). However, even in the examples given, understanding the graph's topology and group structure is challenging.

This Is Getting Out of Hand: Now There Are Multiples of Them! Multiples are a reasonably popular approach for representing group structures, as they allow for each group's subgraph to be embedded (partially) independently of other groups' topologies. With 37 counts, they are primarily used for the visualization of *overlapping/flat* group structure, though they are also applied to 6 *disjoint/flat* groupings. Of these 37 *overlapping/flat* applications, 14 visualized these multiples *interchangeably*, such as (Erten et al., 2004)'s *GraphAEL*, and 19 *juxtaposed* (Federico et al., 2011) (Figure 5). Especially for dynamic graphs, the use of interchangeable multiples, akin to the mapping of time to time (Beck et al., 2014), is a popular choice, with 12 of the 14 interchangeable papers using the visualization of dynamic graphs (Ma et al., 2015; Rufiange and Melançon, 2014).

If the comparison of two or more graphs is of interest, the juxtaposition of subgraphs as multiples allows for a clear and uncluttered view of their differences, as seen in the works of (Yoghourdjian et al., 2018), (Bach et al., 2015), and (Behrisch et al., 2014).

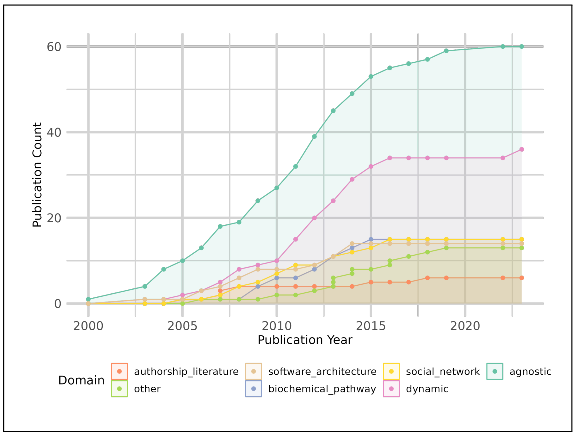

Figure 6: Cumulative number of the selected papers mapped to application area across time. Papers could map to multiple such application areas.

However, multiples can also be valuable in providing users with a small "thumbnail" representation of a subgraph to aid in exploration (Al-Awami et al., 2014; Barsky et al., 2008).

Lastly, beyond such 2D arrangements, 3 papers opted to present multiples in *embedded* relationships. Here, multiples are presented in 3D "cubes", formed by arranging them independently as seen in *Matrix-Cubes* (Bach et al., 2014b), or arranging them in a juxtaposed manner as seen in *Caleydo* (Lex et al., 2010).

6 OUTSTANDING OPPORTUNITIES

Enter the Matrix. Adjacency matrices are used to visually communicate graph topology, which is expected given their advantages over common node-link diagrams (Ghoniem et al., 2004). Surprisingly matrices, despite being a straightforward and scalable method for the visualization of group structure, are hardly used (Figure 5). Though, it should also be mentioned that some hybrid techniques, most notably *NodeTrix* (Henry et al., 2007) and *Anchord+Matrix Diagrams* (Misue and Zhou, 2011), combine topological adjacency matrices and node-link diagrams to communicate topology and structure simultaneously. This has also been noted by (Nobre et al., 2019) within the context of multivariate graphs, (Beck et al., 2014) within the context of dynamic graphs, as well as (Alsallakh et al., 2016) within the context of set-typed data visualization. We also see ample opportunity to reap the benefits of (interactive) matrix visualization for the communication of compound graph group structures, as they are *simple to implement* and *understand*.

Putting Some Node-Link Diagrams in Your Node-Link Diagrams. Somewhat surprisingly, *bipartite node-link diagrams* are infrequently used to communicate group structure, be it embedded or separately (Figure 5). Similar to trees (Section 5), it is possible that the additional complexity introduced by a second set of nodes for groups and edges, representing group memberships, simply makes them unsuitable for graphs with more complex topologies. Indeed, as seen in the works of (Bigelow et al., 2019), (Ahmed et al., 2007) and (Pienta et al., 2018), the graphs studied are relatively small and simple. Moreover, color and/or shape are necessary to distinguish between topological and group nodes, further adding visual complexity. Nonetheless, this particular gap strikes us as worth investigating with scalable, and presumably interactive, bipartite node-link diagrams that combine topology and group structure in a single embedding. Specifically, for more clustered group structures, this could potentially allow for very clear visual distinctions between nodes that map to exclusively one group, and those that map to multiple.

Looking for Group. Mirroring the finding of (Vehlow et al., 2015) *Disjoint/Flat* and *Disjoint/Hierarchical* are well represented with 48 and 58 papers, respectively, and the *Overlapping/Flat* category is the most represented with 79 entries. Interestingly, only 7 of the collected papers were applied to *Overlapping/Hierarchical* group structure (Figure 4). Most such papers opted to visualize only two or three group hierarchies at a time, usually separately, and link these to the graph's topology using either color (Wang et al., 2016) or edges (Daniel et al., 2014). Since overlapping, hierarchical groupings are common in ontologies and clusterings (Vehlow et al., 2015), we see a great opportunity to tackle the challenges that such group structures present in the context of compound graphs, such as how to concurrently visualize different levels of the overlapping hierarchies, or how to best visualize each node's mapping to multiple categories of different hierarchies.

Yeah, It's a Hybrid. 16 hybrid visualization techniques (defined as any combination of visual encodings) were found in our paper set (Figure 5). Interestingly, however, all collected hybrid techniques combine specifically node-link diagrams with other visualization encodings, such as i) matrices (Henry et al., 2007; Misue and Zhou, 2011; Bach et al., 2013), ii) treemaps (Balzer and Deussen, 2005), iii) bounded node-link diagram embeddings (Vehlow et al., 2013; Chaturvedi et al., 2014), and iv) chord diagrams (Angori et al., 2022). However, node-link diagrams are known to suffer from certain visual aesthetic limitations that can make them difficult to read when applied naively to larger and complex graphs, such as node/node occlusions, heterogeneous node density, edge crossings, or incident edge angles. Here, we see an opportunity for interesting and novel hybrid visualization strategies with which to communicate the group structure of compound graphs that go beyond node-link diagrams, thereby potentially opening the door for more visually scalable approaches.

Brave New Worlds. Certain application domains are notably more represented than others in the paper set collected (Figure 6). More specifically, domain-agnostic techniques and dynamic graphs appear to far outnumber all others. Application areas, such as authorship and citation networks, appear not to have been studied as extensively or recently. Often, as seen in biochemical application areas, a particular application area is constrained by the visual conventions of the domain and/or the (perceived) visual literacy of its users (Lex et al., 2010; Partl et al., 2013). This points, at least in our estimation, to an opportunity to revisit such domains, to identify potentially unanswered challenges.

7 CONCLUSION & FUTURE WORK

We have surveyed literature based on both an independent collection of references, and the existing works of (Nobre et al., 2019), (McGee et al., 2019), (Beck et al., 2014), and (Vehlow et al., 2015). The collected corpus of application and technique papers were then categorized within a comprehensive taxonomy that, inspired by the works of (Kim et al., 2017) and (Alsallakh et al., 2016), disentangles the visual relationship between the graph's topology and group structure, as well as the chosen visual encoding of the graph's group structure, respectively. Based on this classification of literature, several lessons and outstanding research opportunities were identified: i) the under-utilization of identity and similarity matrices, ii) the under-representation of bipartite node-link diagrams, iii) the under-studied visualization of *Overlapping/Hierarchical* data sources, iv) the over-representation of node-link diagram-based hybrid visualization approaches, and v) the under-studied of certain application domains. A future elaboration of this paper in the shape of a formal state-of-the-art report should aim for a completely independent, large-scale collection of literature, and/or the collection of additional authoritative reviews to avoid any possible bias in the collected corpus of literature to, in turn, draw potentially broader and more general conclusions.

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