Penta: Towards Visualizing Compound Graphs as Set-Typed Data

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Abstract: Compound graphs are graphs whose nodes, in addition to topological connections, share group-level relationships. The need to incorporate both topological and group-level relationships makes them inherently challenging to visualize, especially for large data. We present *Penta*, a prototypical dashboard that, by combining elements of compound graph and set visualization, provides a complete view of both types of relationships. To this end, we employ five linked views that provide insight into a compound graph's i) *global and set-local topology* using both hypernode and traditional node-link diagrams, respectively, ii) *set and entity-level relationship and identity* using similarity matrices linked by a bipartite node-link diagram, as well as iii) *node-centric topology* across sets visualized as a layered node-link diagram. We demonstrate the workflow and advantages of *Penta* in three small-scale case studies, using character co-occurrence networks as well as biochemical pathway data. While still a prototype, the proposed dashboard shows promise in facilitating a complete visual exploration of the topology and group-level relationships present in compound graphs, simultaneously.

1 INTRODUCTION

A clustered or compound graph is a graph whose nodes, in addition to topological connections, share group-level relationships (Vehlow et al., 2015b). In the context of social networks, for example, nodes may represent individual people, edges (different types of) relationships between them, and groups circles of friends. Given their general utility and applicability, compound graphs, their visualization, and their analysis are common across many different domains: from social sciences (Humayoun et al., 2016), through biochemistry (Paduano and Forbes, 2015) and neurology (Al-Awami et al., 2014), to transportation logistics (Ducruet, 2017). Subsequently, various visualization approaches and systems have been put forth to tackle the visualization of compound graphs differently: some of these forgo interactivity in the interest of scalability (Xia et al., 2015), others combine the two using summarization techniques (Paduano and Forbes, 2015) or linked views (Al-Awami et al., 2014), while others yet build upon domain-specific visual conventions to better serve a particular user group (Humayoun et al., 2016). Ultimately, all these approaches address the challenge of simultaneously visualizing graph topology and group structure.

A compound graph's group structure can be conceptualized as a collection of sets; their elements formed by the graph's nodes, and their intersections by nodes present in two or more groups (Pezzotti et al., 2018). When visualizing or analyzing sets, we are interested in understanding their relations, such as containment, exclusions, or intersections, to better understand the role or importance of their elements (Alsallakh et al., 2016). However, even when the underlying data is not a graph, such set-typed data can become challenging to visualize. Depending on the complexity and size of the data, such visualizations often require the use of abstraction (Rodgers et al., 2015) or summarization (Lamy and Tsopra, 2020) to remain legible. Domain-specific applications may additionally require the interactive visualization of meta-data attached to sets' and their elements (Lex and Gehlenborg, 2014). Many different families of techniques and tools have been developed to tackle these challenges, both for generic set-typed and application-area-specific data (Alsallakh et al., 2016). However, few—if any—of these techniques can be applied to compound graphs, and fewer still scale to large datasets, common in modern biochemical and social network analysis.

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In this paper, we present *Penta*, a prototype dashboard for the visualization of non-hierarchical, non-disjoint compound graphs as set-typed data. With this prototypical implementation, we aim to address several outstanding gaps in the fields of both set visualization (Alsallakh et al., 2016) and compound graph visualization (Vehlow et al., 2015b; Ehlers et al., 2024a), by combing multiple linked views, (similarity) matrix visualizations, and ego network representations. More specifically, the contribution of *Penta*'s linked views is that they provide insight into i) the group's global and local topology using both hypernode and traditional node-link diagrams, respectively, ii) set and vertex-centric relationship and identity using similarity matrices linked by a bipartite node-link diagram, as well as iii) node-centric topology across sets visualized as a layered node-link diagram.

2 RELATED WORK

As *Penta*'s five linked views draw from conventions of compound graph visualizations, matrix-based set-visualization, as well as ego-network visualization, we here discuss the state-of-the-art of each.

Compound Graph Visualization. Compound graphs have been visualized in a multitude of ways (Ehlers et al., 2024a; Vehlow et al., 2015b), using node attributes, overlays, bipartite node-link diagrams, multiples, trees, matrices, abstractions, and hybrid techniques. The most common way of visualizing group-level memberships in compound graphs, node attributes take the form of, for example, colors (Vehlow et al., 2015a) or glyphs (Wang et al., 2016). Overlay techniques add group-level associations atop a graph's embedding, using, for example, regions (Partl et al., 2013), lines (Alper et al., 2011), or combinations of the two (Meulemans et al., 2013). Less common than either overlays or node attributes, bipartite node-link diagrams represent both nodes and groups as (different types) of vertices with topological and group-level-association edges connecting them (Bigelow et al., 2019). Multiples opt to visualize each group's subgraph separately, as seen in Bach et al.'s *Small Multiples* (Bach et al., 2015) or *Graph Diaries* (Bach et al., 2014). Trees, commonly visualized alongside a compound graph's topology, visualize elements, i.e. vertices, as the leaves of the tree and their (hierarchical) set-element relationships as edges (Abello et al., 2006). (Biadjacency) matrices, also visualized separately from a compound graph's topology, depict vertex-group memberships tabularly where each row corresponds to a vertex and each group to a column (Chuang et al., 2012). Abstractions do not visualize all sets, elements, and their relationships but provide a view into one by abstracting away the others. This broad category can unsurprisingly include many different types of approaches (Rodgers et al., 2015; Yoghourdjian et al., 2018) Finally, hybrid techniques combine any of these aforementioned techniques to visualize group membership and topology simultaneously (Angori et al., 2019; Henry et al., 2007).

Matrices for Set-Typed Data. While several examples of set visualization and their elements as *biadjacency*-based matrices can be found in the literature (Sadana et al., 2014; Lex et al., 2014), *similarity*-based matrix representations are less common. We could only identify two examples for the explicit purpose of similarity-matrix-based set visualization. First, Liu et. al's *Similarity Lattice* (Xu Liu et al., 2005) represents sets' pairwise *Completeness* and *Intensity* similarity as a non-symmetric similarity matrix. Second, *Intervene* (Khan and Mathelier, 2017) features similarity-based matrix representations alongside more conventional biadjacency-based ones. As also discussed in reviews of both compound graph visualization (Vehlow et al., 2015b; Ehlers et al., 2024a) and set visualization (Alsallakh et al., 2016), the use of (similarity) matrices is a novel avenue with which to communicate group and entity-level relationships in both sets and compound graphs.

Ego Network Visualizations. Ego network representations visualize graph topology relative to some selected node of interest—the so-called "*ego*" (Ehlers et al., 2024b). Ego networks may be used to simplify the visualization of a graph's topology, by only visualizing those nodes and edges of immediate importance to the selected ego. Examples of node-centric visualizations of larger graphs can be found across several domains (Ehlers et al., 2024b). Here, we are particularly interested in the use of layered (tree-like) node-link diagrammatic representations, as they promise an intuitive and orderly view into the intrinsically layered topology of ego networks. Such layered representations align nodes along "layers" representing the distance from the selected ego (Sayers, 2004). While not related to ego networks directly, similar ideas of edge scaling and distance-based node embedding can be found in the visualization of phylogenetic trees (Shank et al., 2018), evolutionary graphs (Miller et al., 2011), or synaptic/brain graphs (Al-Awami et al., 2014). To the best of our knowledge, such ego network visualizations have not yet found application in compound graph visualization.

3 THE FIVE FACETS OF PENTA

Visualizing compound graphs is challenging, as one needs to visually communicate both graph topology and group-level relationships simultaneously. Specifically, supporting the following aspects is necessary:

1. viewing all groups' **global topology**,
2. investigating the particular **set-relative topology** of selected groups,
3. understanding the **similarities of all groups and nodes** relative to each other,
4. viewing all selected **set-element mappings**, and
5. investigating the **node-relative topology** of the graph, i.e. topology relative to a selected ego.

To integrate the aforementioned channels of information, we propose the prototypical web-based *Penta* dashboard, which aims to visualize different facets of a compound graph's group structure and topology in five linked views. Users are expected to upload their compound graph's topology and group-level associations they wish to investigate to *Penta*, within which they then interactively filter and explore their dataset. This may entail selecting entities or sets within its multiple linked views or looking them up based on their unique identifiers. More specifically, in accordance with Shneiderman's (Shneiderman, 1996) mantra of "*Overview First, [...] filter, then details on demand*" the dashboard aims to funnel users from a *global view of topology*, through the *topology* and *similarity of selected sets*, to the immediate *topology of a particular node*. Interactive selections of vertices and sets in any of these five views are reflected in all other views through brushing and linking (Buja et al., 1991). *Penta*, available on GitHub, was developed in `Svelte` using `D3.js` (Bostock et al., 2011).

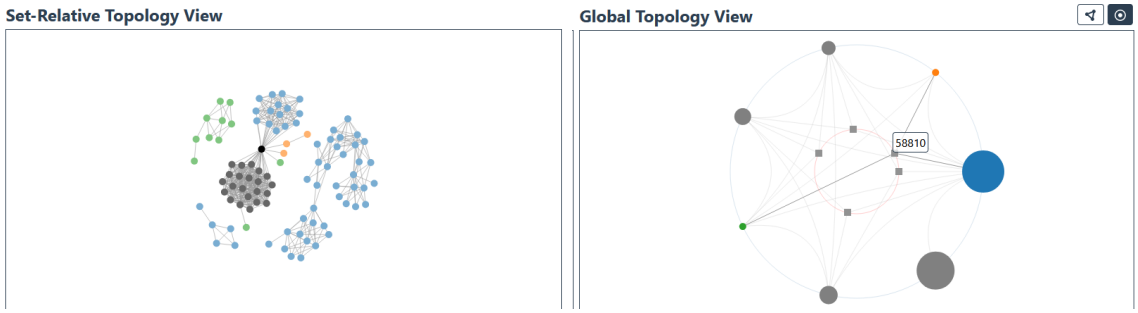
Global Topology. For some compound graph $G(V,E,S)$ let V denote its total set of elements/nodes, E its total set of edges, and S its elements' non-hierarchical, non-disjoint group structure. For a set $s \in S$, node-set pairs (v_a,s) and (v_b,s) in V_G are connected by edges $E_G \subseteq V_G \times V_G$, where $V_G \subseteq V \times S$. Here, the input graph's global topology can be either represented as a force-directed or (as presented here) a radial node-link diagram (Figure 1b). As straight-line node-link diagrams do not tend to produce aesthetically pleasing or readable results for graphs of larger sizes and greater complexity (Ehlers et al., 2023), we do not visualize nodes $v \in V$ and their edges $e \in E$ directly. Instead, each set of nodes V_G is visualized as its own circular hypernode (Terje Bjørke et al., 2010). Hovering over such hypernodes reveals their labels. To communicate which groups of nodes are present across sets, groups of nodes that form intersections between sets of nodes are represented by separate, square hypernodes (Figure 1b). Hypernodes' sizes encode the cardinality of their sets or intersections, i.e. the more elements a set contains, the larger the set's corresponding hypernode.

In the particular example shown in Figure 1b, seven groups, representing seven *Mus musculus* KEGG pathways, are depicted—one circular node per group. The size of each node represents the number of genes (nodes) in each pathway. Between these seven groups, there are five unique intersections, represented by five square nodes. One particular intersection, consisting only of a single node with identifier *58810* is highlighted. Said node is the intersection between the three selected, i.e. colored, groups, indicated by the edges connecting the intersection's square node to the three groups' circular nodes.

Set-Relative Topology. From the aforementioned global topological view, hypernodes can be selected, thereby adding their elements, i.e. vertices, to the set-relative topological view. This is represented as a straight-line node-link diagram (Figure 1a), laid out using `D3.js`'s particle-based force-directed algorithm (Bostock et al., 2011). Each added group of nodes is color-coded, using an appropriate *ColorBrewer* color palette (Harrower and Brewer, 2003) used consistently across all views. To ensure colors remain visually distinct from each other (Healey, 1996), users can only select up to ten such groups simultaneously. We highlight intersections between two or more groups by color-coding them in black. Hovering over any individual node reveals its label and highlights its corresponding hypernode in the global topological view, as well as its location in the (to-be-discussed) element-similarity matrix in a similar way.

In the example shown in Figure 1a, three of the seven aforementioned *Mus musculus* KEGG pathways have been selected, one colored green, the other blue, and the final one orange. Nodes that form an intersection between any two of the three selected pathways are colored dark grey. The selected node *58810*, which forms an intersection between all three selected pathways, is colored black.

Set and Vertex Similarity. To navigate both sets and elements, we propose the use of two interactive similarity matrices—one depicting *set similarity* and the other representing *vertex similarity* (Figure 2c). Unlike identity matrix representations, which may necessitate panning and scrolling to navigate owing to potential asymmetries, a square, symmetric similarity matrix offers a clearer overview of all sets or ele-



(a) (b)

Figure 1: The **(b) global topology view** for seven KEGG mouse (*MMU*) pathways (groups) and their intersections. The **(a) set-relative topology** of a selection of three sets from the global topological view, colored in blue, orange, and green in both views. A notable intersection between these three selected is the entity (vertex) with identifier *58810* which is highlighted in black on the (a).

ments simultaneously. Moreover, matrix representations offer overall greater visual clarity and flexibility over many other approaches for set and element visualization (Alsallakh et al., 2016). This conceptual flexibility includes the **straightforward use of different similarity measures** with which to understand groups and elements relationships (Vijaymeena and Kavitha, 2016). Here, for any two sets $A, B \in S$, their similarities are computed using the Jaccard distance $J(A,B) = (|A \cap B|)/(|A \cup B|)$, chosen for its conceptual simplicity and its applicability to both set and topological node similarity. To quantify element similarity, the same conceptual approach based on the Jaccard distance is used: for any two vertices/elements $a, b \in V$, we can define their "sets" as $A = q(a)$ and $B = q(b)$, where $q(x)$, for an element $x \in V$, can take different forms. We make use of a topological set definition: $q(x) = \{v : \forall v \in V, \{x,v\} \in E\}$, i.e. we simply define a node's set as its immediate neighborhood. In both cases, the similarity is encoded using a luminance colormap, i.e. white indicating low and black high similarity. Moreover, a selected set's rows and columns are indicated using colored lines. Additionally, **matrices can be flexibly reordered** based on selected criteria to facilitate the detection of novel or unexpected relationships between entities (Mueller et al., 2007). Here, as a proof of concept, we allow the user to reorder both set and element similarity matrices by either i) a random ordering for the identification of unexpected relationships, or ii) an attribute-based ordering that organizes entities by their lexicographic order, or iii) an agglomerative, hierarchical clustering-based order to identify clusters of interest (Kaufman and Rousseeuw, 1990).

In the example shown in Figure 2c, the set-similarity matrix represents the character similarities among the first four books of the Harry Potter series (Ravi, 2024). Each set, i.e. book, is represented by one of the four rows and columns of the matrix, ordered lexicographically. Each cell represents the Jaccard distance between two sets. The darker a cell, the more similar the two sets are. Instead of space-consuming conventional labels, colored lines indicate the identity of each row and column. Here, books two and three have been selected from the global topological view (Figure 2a). The vertex-similarity matrix (Figure 2c), shows the similarity between nodes (characters) as a function of their immediate neighborhood, i.e. the more neighbors two nodes have in common, the more similar they are. Each row and column corresponds to a particular character, and each cell to the similarity between two nodes. Again, similarity is mapped to cell brightness.

Set-Node Connection Graph. The previously discussed similarity matrix representations allow for an in-depth exploration of within-set and within-element relationships. However, they do not visualize the set membership of elements or the mapping of sets to elements (Pezzotti et al., 2018). To link the aforementioned similarity views, we visually exploit the bipartite relationship between them and visualize said relationship as a "*Connection Graph*" (Figure 2c). For matrices, drawing (curved) edges between their rows (or columns) is conceptually fairly straightforward, as they already form a one-dimensional projection of their elements (Misue and Zhou, 2011). More specifically, given a single selected set S, its projection point is connected to all its elements' ($x \in S$) projection points by curved edges. Alternatively, given a single selected element x, its projection point is connected to all sets of which it is a member, i.e. $\{s : \forall s \in S, x \in s\}$. Edge and label colors utilize the same color palette as in the global and set topology views.

In this particular example (Figure 2c), the connection graph shows the mapping of Harry Potter books

(sets) to the characters of the series (nodes), and vice-versa. For each book's character, curved edges are drawn between the books' and the character's row in their respective similarity matrices. The color of the curved line corresponds to the color of the set, as depicted in both the global and set-relative topological views (Figures 2a and 2b). If a node, i.e. character, maps to multiple sets (books), multiple such lines will be drawn, connecting the one node to multiple sets.

Node Relative Topology. While the global and set-local topological views of the graph provide a good starting point for exploring particular sets and their elements, they are insufficient in understanding a node's connectivity across all sets. To amend this, we employ a vertex-centric representation of topology for a particular selected entity, i.e. an ego network where the selected vertex forms the "*ego*" (Ehlers et al., 2024b). This ego network is generated from the graph's global topology based on a selected ego node of interest and a user-specified maximum exploration depth. More specifically, *Penta* employs a breadth-first search algorithm to traverse the graph from the ego node, through its neighbors, its neighbors' neighbors, and so on, up to the specified depth, thereby constructing a tree(-like) data structure that encapsulates the shortest possible paths to all reachable nodes. This tree is visualized as a layered node-link diagram (Figure 3c). Its layers, i.e. nodes, are sorted by their inverse weighted edge distance to the ego, i.e. the greater the edge weight between any two nodes, the closer they will be visualized in the tree. This also allows for *Penta* to sort a node's neighbors based on this edge weight, i.e. the closest neighbor appears at the top of its branch, and the furthest at the bottom.

In the example of Figure 3, a co-occurrence network of *Star Wars* characters across the first six movies is shown. The depicted ego network displays the node-relative topology of one selected character, namely *R2-D2*, depicted in the top left of Figure 3c. The layered node-link diagram shows a character's connections across all sets in the dataset. The more a character interacted with *R2-D2*, i.e. the larger their co-occurrence edge weight, the higher up in the layered node-link diagram it appears, i.e. *Anakin* interacted more with *R2-D2* than *Qui-Gon*, who interacted more than *Luke*. The same ordering system applies to each layer of this layered node-link diagram. The ordering is reinforced by scaling each edge's horizontal length based on edge weight, i.e the more two characters interact, the larger their edge weight, and the closer they appear in the horizontal space.

4 USE CASES

In order to demonstrate the potential utility of *Penta*, three small-scale usage scenarios are presented.

Scenario 1: Noticing Notable Nodes. In order to demonstrate the utility of both the global and set-local topological view, consider a *Mus musculus* example dataset, in which each node represents a gene, each edge a gene-gene interaction, and groups of genes represent KEGG pathways in mice (Kanehisa and Goto, 2000). For seven such pathways, their global topology is visualized as a hypernode-link diagram (Figure 1b). Here, three pathways of particular interest, *mmu0010*, *mmu00053* and *mmu00040*, colored in blue, green, and orange, respectively, are selected in the global topological view, their vertices visualized in the corresponding set-local topology view (Figure 1a). From the global topology view, we can immediately discern the relative sizes of these three sets, i.e. *mmu0010* (blue) is larger than any other pathway in the dataset, indicated by the area encoding of the nodes. Moreover, we can immediately see how all our datasets intersect and the cardinalities of these intersections. More specifically, a particular intersection between the three pathways of interest is revealed to be a single node, namely *58810*. The importance of this particular node across the selected pathways is also made immediately apparent in the set-relative local topological view (Figure 1a), where said node not only forms an intersection between these three pathways but also a bridge between two large clusters of nodes. Among those, one forms an intersection of its own between two selected pathways (colored in grey). The combined use of these two views—hypernode and traditional node-link diagrams—has enabled an intuitive and speedy overview of the pathway's global and local topology and facilitated the identification of a notable node.

Scenario 2: Such Similarity, Much Wow. In order to demonstrate the utility of set and node-similarity matrix views, consider a Harry Potter character co-occurrence network (Ravi, 2024), in which each node represents a character, each weighted edge the number of interactions two characters shared, and each group one of the first four books of the series. In order to determine the similarities between books two and three, colored orange and red respectively, the two groups' hypernodes have been selected from the global topological view (Figure 2a) and their nodes and connections added to the local topological view (Figure 2b), as discussed previously. This view already sheds some view into the strong overlap in char-

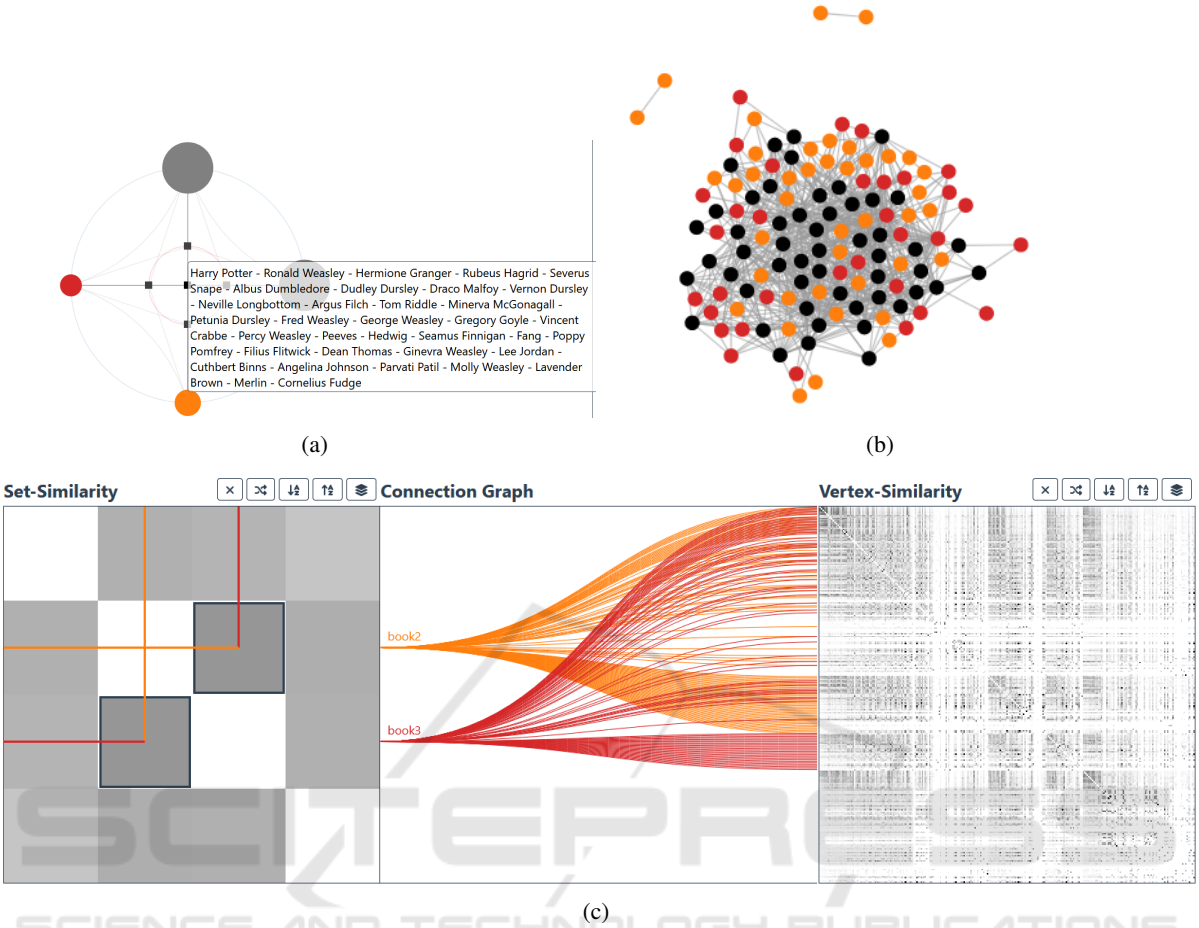
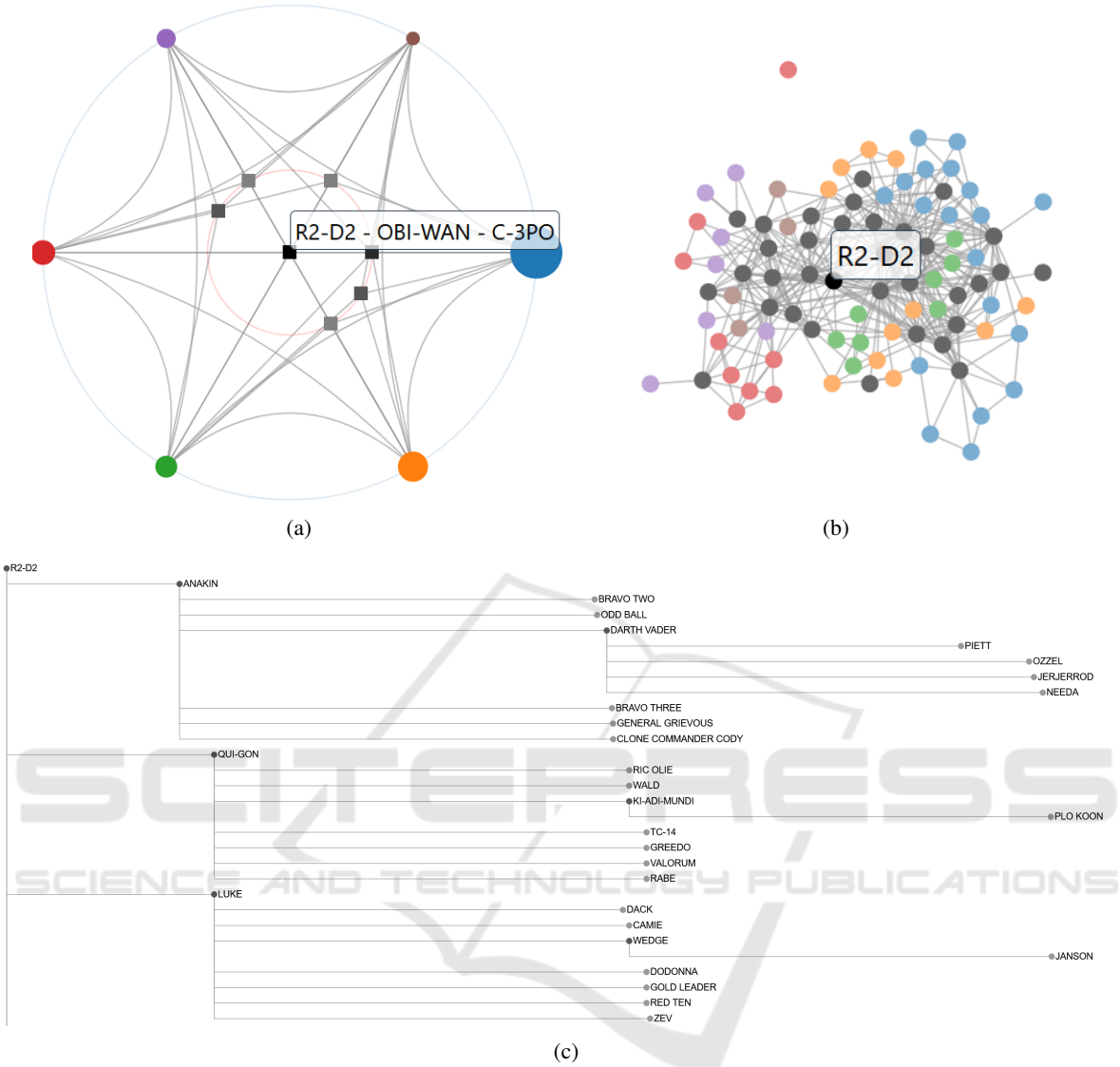


Figure 2: Visualizing Character Interactions Across *Harry Potter* Books. **(a) Global Topology View:** Overview of character interactions across the first four books, highlighting recurring characters. **(b) Local Topology View:** Dense inter-character connections between books two and three. **(c) Set and Vertex-Similarity Analysis:** Consistent level of recurring characters and interactions between books.

acters between the two books, given the many (black) nodes that form intersections between the two books. However, viewing the set-similarity matrix (Figure 2c), the darker gray color of books two and three's similarity, immediately communicates that these two books share the greatest set of characters across the first four published books. Following the connection graph and viewing the vertex similarity matrix, one can immediately note three interesting blocks of characters, namely i) those that strongly co-occur across books two and three, ii) those that primarily co-occur in book two, and iii) those that primarily co-occur in book three Figure 2c). The interactive dashboard now allows for individual inspection of character-character similarity scores. The set and vertex similarity matrices allow us to quickly identify subsets of nodes of potential interest for follow-up study.

Scenario 3: Me! Me! Me! Me! Here, to explore the utility of the ego network, consider a co-occurrence network of Star Wars characters across the first six movies, in which each node represents a character, each weighted edge the number of interactions two characters shared, and each group one of the six movies (Gabasova, 2024). Here, given some prior exploration of groups and their connectivity, a user has identified a particular node of interest, namely *R2-D2*, as this particular character forms an intersection across all six groups (Figure 3a). As the local topological view (Figure 3b) is too dense to make out said character's immediate neighborhood, a user can utilize the vertex-relative ego network view (Figure 3c. Here, the selected ego, here *R2-D2*, forms the root node of the layered tree representation in the top left. From a simple cursory look, a user can immediately identify the ego's closest neighbors, here *Anakin*, *Qui-Gon*, and *Luke*, thanks to the vertical ordering of the



(a) (b)

(c)

Figure 3: Analyzing the *Star Wars* Character Network. **(a) Global Topology View:** Comprehensive visual map of the Star Wars character network, highlighting key characters across all movies. **(b) Local Topology View:** View into the dense interrelationships of characters across the first six movies. **(c) Ego-Network of R2-D2:** Central role and extensive connections of R2-D2 within the Star Wars narrative.

ego's neighbors by edge weight, i.e. *R2-D2*'s closest neighbors are located at the top of the tree. Moreover, thanks to the horizontal ordering of nodes based on cumulative proximity to the ego, one can additionally notice that, while *Piett* and *Ozzel* are both a hop-distance of three away from *R2-D2*, *Piett* is closer once edge weights are factored in. This node-relative topological view facilitated by the ego network allows for an in-depth look at the selected ego's (immediate) neighborhood in an intuitive and fast manner.

5 SUMMARY AND TAKE-AWAY

The prototypical *Penta* dashboard offers a holistic approach to visualizing compound graph data, enabling users to analyze both topological and group-level relationships across multiple datasets. Through our three case studies, *Penta* demonstrates its ability to highlight both global and local graph structures effectively. For example, in the first scenario, *Penta* allows users to quickly identify key intersections and pathways, such as important genes within

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biological networks. The second scenario showcases *Penta*'s utility in visualizing co-occurrence networks, revealing shared character groups across Harry Potter books. Lastly, the third scenario focuses on individual nodes within a Star Wars network, where users can explore character relationships based on interaction frequency. Overall, *Penta*'s prototypical implementation already promises to be a valuable tool for researchers looking to interpret compound graph relationships in larger datasets.

6 CONCLUSION AND FUTURE WORK

In this paper, we have presented the prototypical implementation of *Penta*, a novel approach to the holistic visualization of compound graph data. We further demonstrated the use and effectiveness of our tool on three use case scenarios, which indicate *Penta*'s utility in making sense of a compound graph's topology, both on a local and global level, as well as group structure. In future work, we hope to i) implement additional similarity measures with which to view set and vertex relationships(Vijaymeena and Kavitha, 2016), ii) implement additional clustering algorithms with which to sort similarity matrices (Koutrouli et al., 2020), iii) allow for the integration of node and edge attribute data to go beyond purely topological analyses, and iv) improve the scalability of multiple views through, for example, latent variable space scatter plots (Pezzotti et al., 2018).

REFERENCES

Abello, J., van Ham, F., and Krishnan, N. (2006). ASK-GraphView: A Large Scale Graph Visualization System. *IEEE Transactions on Visualization and Computer Graphics*, 12(5):669–676. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Al-Awami, A. K., Beyer, J., Strobelt, H., Kasthuri, N., Lichtman, J. W., Pfister, H., and Hadwiger, M. (2014). NeuroLines: A Subway Map Metaphor for Visualizing Nanoscale Neuronal Connectivity. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2369–2378.

Alper, B., Riche, N., Ramos, G., and Czerwinski, M. (2011). Design Study of LineSets, a Novel Set Visualization Technique. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2259–2267. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Alsallakh, B., Micallef, L., Aigner, W., Hauser, H., Miksch, S., and Rodgers, P. (2016). The State-of-the-Art of Set Visualization. *Computer Graphics Forum*, 35(1):234–260.

Angori, L., Didimo, W., Montecchiani, F., Pagliuca, D., and Tappini, A. (2019). ChordLink: A New Hybrid Visualization Model. In *Graph Drawing and Network Visualization: 27th International Symposium, GD 2019, Prague, Czech Republic, September 17–20, 2019, Proceedings*, pages 276–290, Berlin, Heidelberg. Springer-Verlag.

Bach, B., Henry-Riche, N., Dwyer, T., Madhyastha, T., Fekete, J.-D., and Grabowski, T. (2015). Small MultiPiles: Piling Time to Explore Temporal Patterns in Dynamic Networks. *Computer Graphics Forum*, 34(3):31–40.

Bach, B., Pietriga, E., and Fekete, J.-D. (2014). GraphDiaries: Animated Transitions andTemporal Navigation for Dynamic Networks. *IEEE Transactions on Visualization and Computer Graphics*, 20(5):740–754.

Bigelow, A., Nobre, C., Meyer, M., and Lex, A. (2019). Origraph: Interactive Network Wrangling. In *2019 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 81–92.

Bostock, M., Ogievetsky, V., and Heer, J. (2011). D³ Data-Driven Documents. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2301–2309. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Buja, A., McDonald, J., Michalak, J., and Stuetzle, W. (1991). Interactive data visualization using focusing and linking. In *Proceeding Visualization '91*, pages 156–163.

Chuang, J., Manning, C. D., and Heer, J. (2012). Termite: visualization techniques for assessing textual topic models. In *Proceedings of the International Working Conference on Advanced Visual Interfaces*, AVI '12, pages 74–77, New York, NY, USA. Association for Computing Machinery.

Ducruet, C. (2017). Multilayer dynamics of complex spatial networks: The case of global maritime flows (1977–2008). *Journal of Transport Geography*, 60:47–58.

Ehlers, H., Marin, D., Wu, H.-Y., and Raidou, R. (2024a). Visualizing Group Structure in Compound Graphs: The Current State, Lessons Learned, and Outstanding Opportunities. pages 697–708.

Ehlers, H., Pahr, D., Filipov, V., Wu, H.-Y., and Raidou, R. G. (2024b). Me! Me! Me! Me! A study and comparison of ego network representations. *Computers & Graphics*, 125:104123.

Ehlers, H., Villedieu, A., Raidou, R. G., and Wu, H.-Y. (2023). Improving readability of static, straight-line graph drawings: A first look at edge crossing resolution through iterative vertex splitting. *Computers & Graphics*, 116:448–463.

Gabasova, E. (2024). evelinag/StarWars-social-network. original-date: 2015-12-15T00:33:54Z.

Harrower, M. and Brewer, C. A. (2003). ColorBrewer.org: An Online Tool for Selecting Colour Schemes for Maps. *The Cartographic Journal*, 40(1):27–37.

Healey, C. (1996). Choosing effective colours for data visualization. In *Proceedings of Seventh Annual IEEE Visualization '96*, pages 263–270.

Henry, N., Fekete, J.-D., and McGuffin, M. J. (2007). NodeTrix: a Hybrid Visualization of Social Networks. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1302–1309.

Humayoun, S. R., Ezaiza, H., AlTarawneh, R., and Ebert, A. (2016). Social-Circles Exploration through Interactive Multi-Layered Chord Layout. In *Proceedings of the International Working Conference on Advanced Visual Interfaces*, AVI '16, pages 314–315, New York, NY, USA. Association for Computing Machinery.

Kanehisa, M. and Goto, S. (2000). KEGG: Kyoto Encyclopedia of Genes and Genomes. *Nucleic Acids Research*, 28(1):27–30.

Kaufman, L. and Rousseeuw, P. (1990). Agglomerative Nesting (Program AGNES). In *Finding Groups in Data*, Wiley Series in Probability and Statistics, pages 199–252. John Wiley & Sons, Ltd.

Khan, A. and Mathelier, A. (2017). Intervene: a tool for intersection and visualization of multiple gene or genomic region sets. Pages: 109728 Section: New Results.

Koutrouli, M., Karatzas, E., Paez-Espino, D., and Pavlopoulos, G. A. (2020). A Guide to Conquer the Biological Network Era Using Graph Theory. *Frontiers in Bioengineering and Biotechnology*, 8:34.

Lamy, J.-B. and Tsopra, R. (2020). RainBio: Proportional Visualization of Large Sets in Biology. *IEEE Transactions on Visualization and Computer Graphics*, 26(11):3285–3298. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Lex, A. and Gehlenborg, N. (2014). Sets and intersections. *Nature Methods*, 11(8):779–779.

Lex, A., Gehlenborg, N., Strobelt, H., Vuillemot, R., and Pfister, H. (2014). UpSet: Visualization of Intersecting Sets. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1983–1992. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Meulemans, W., Riche, N. H., Speckmann, B., Alper, B., and Dwyer, T. (2013). KelpFusion: A Hybrid Set Visualization Technique. *IEEE Transactions on Visualization and Computer Graphics*, 19(11):1846–1858. Conference Name: IEEE Transactions on Visualization and Computer Graphics.

Miller, R., Mozhayskiy, V., Tagkopoulos, L., and Ma, K.-L. (2011). EVEVis: A multi-scale visualization system for dense evolutionary data. In *2011 IEEE Symposium on Biological Data Visualization (BioVis).*, pages 143–150.

Misue, K. and Zhou, Q. (2011). Drawing Semi-bipartite Graphs in Anchor+Matrix Style. In *2011 15th International Conference on Information Visualisation*, pages 26–31. ISSN: 2375-0138.

Mueller, C., Martin, B., and Lumsdaine, A. (2007). A comparison of vertex ordering algorithms for large graph visualization. In *2007 6th International Asia-Pacific Symposium on Visualization*, pages 141–148.

Paduano, F. and Forbes, A. G. (2015). Extended LineSets: a visualization technique for the interactive inspection of biological pathways. *BMC Proceedings*, 9(6):S4.

Partl, C., Lex, A., Streit, M., Kalkofen, D., Kashofer, K., and Schmalstieg, D. (2013). enRoute: dynamic path extraction from biological pathway maps for exploring heterogeneous experimental datasets. *BMC Bioinformatics*, 14(19):S3.

Pezzotti, N., Fekete, J.-D., Höllt, T., Lelieveldt, B. P., Eisemann, E., and Vilanova, A. (2018). Multiscale Visualization and Exploration of Large Bipartite Graphs. *Computer Graphics Forum*, 37(3):549–560.

Ravi, N. (2024). nikhil-ravi/harry-potter-interactions. original-date: 2023-11-05T01:37:30Z.

Rodgers, P., Stapleton, G., and Chapman, P. (2015). Visualizing Sets with Linear Diagrams. *ACM Transactions on Computer-Human Interaction*, 22(6):27:1–27:39.

Sadana, R., Major, T., Dove, A., and Stasko, J. (2014). OnSet: A Visualization Technique for Large-scale Binary Set Data. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1993–2002.

Sayers, C. (2004). Node-centric RDF Graph Visualization.

Shank, S. D., Weaver, S., and Kosakovsky Pond, S. L. (2018). phylotree.js - a JavaScript library for application development and interactive data visualization in phylogenetics. *BMC Bioinformatics*, 19(1):276.

Shneiderman, B. (1996). The eyes have it: a task by data type taxonomy for information visualizations. In *Proceedings 1996 IEEE Symposium on Visual Languages*, pages 336–343. ISSN: 1049-2615.

Terje Bjørke, J., Nilsen, S., and Varga, M. (2010). Visualization of network structure by the application of hypernodes. *International Journal of Approximate Reasoning*, 51(3):275–293.

Vehlow, C., Beck, F., Auwärter, P., and Weiskopf, D. (2015a). Visualizing the Evolution of Communities in Dynamic Graphs. *Computer Graphics Forum*, 34(1):277–288.

Vehlow, C., Beck, F., and Weiskopf, D. (2015b). The State of the Art in Visualizing Group Structures in Graphs. *Eurographics Conference on Visualization (EuroVis) - STARs*, page 20 pages.

Vijaymeena, M. and Kavitha, K. (2016). A Survey on Similarity Measures in Text Mining. *Machine Learning and Applications: An International Journal*, 3(1):19–28.

Wang, X., Liu, S., Liu, J., Chen, J., Zhu, J., and Guo, B. (2016). TopicPanorama: A Full Picture of Relevant Topics. *IEEE Transactions on Visualization and Computer Graphics*, 22(12):2508–2521.

Xia, J., Gill, E. E., and Hancock, R. E. W. (2015). NetworkAnalyst for statistical, visual and network-based meta-analysis of gene expression data. *Nature Protocols*, 10(6):823–844.

Xu Liu, Ming Luo, and Ben Shneiderman (2005). Visualization of Sets.

Yoghourdjian, V., Dwyer, T., Klein, K., Marriott, K., and Wybrow, M. (2018). Graph Thumbnails: Identifying and Comparing Multiple Graphs at a Glance. *IEEE Transactions on Visualization and Computer Graphics*, 24(12):3081–3095.