BlossomNet: Visualizing Influence and Community Evolution with Floral Glyphs in Large Person-Centric Knowledge Graphs

VAST 2025 Design Challenge

Sundas Qaiser[1], Jieqiong Zhao[2], Nabin Khanal[1], Qi Yang[1], Sizheng Cailean Chen[3], Helena Jiuru Liu[3], Hannah Yanhua Zong[1], Yingjie Victor Chen[1], and Cheryl Zhenyu Qian[1]

[1] Purdue University, [2] Augusta University, [3] West Lafayette Junior Senior High School

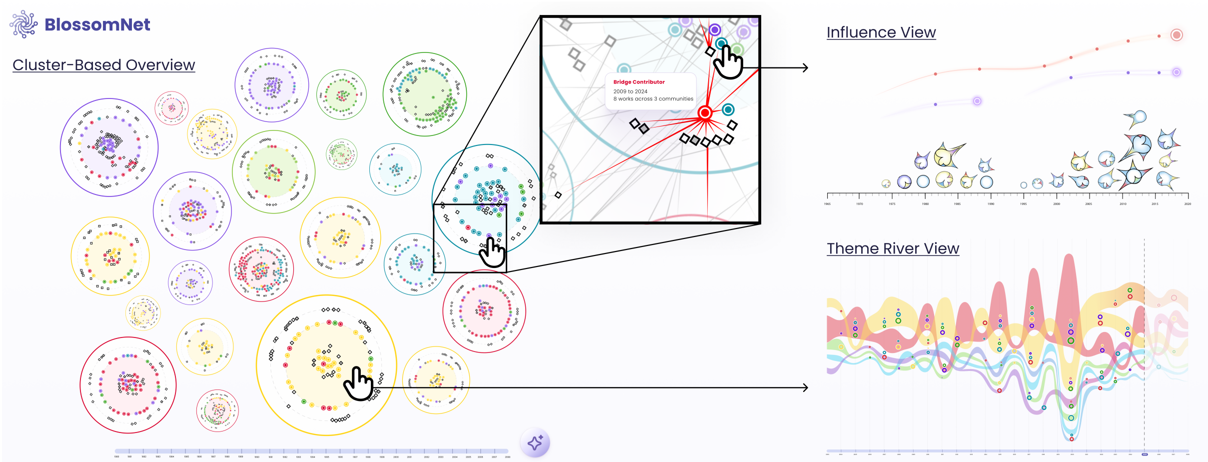

Figure 1: *BlossomNet* integrates three coordinated views to support structural, semantic, and temporal exploration of person-centric knowledge graphs. The left Cluster-based Overview presents a node-link diagram with reduced visual clutter by aggregating nodes into communities. Each community is shown with a three-layer representation separating contributions within and between communities. The top right Influence View encodes individual influence using floral glyphs, where each petal represents a semantic dimension. Above the floral glyphs, trajectory arcs trace an individual's temporal growth throughout their career. The bottom right Theme River view illustrates community membership dynamics, visualizing how individuals migrate across communities over time.

Abstract

Knowledge graphs encode semantic relationships among entities and are an emerging technique in text analysis. Yet their complexity hampers the analysis of relationships in graphs with thousands of nodes. We design *BlossomNet*, a conceptual visual analytics system for community, temporal, and influence analysis of large knowledge graphs. *BlossomNet* integrates three coordinated views: (1) a Cluster-based Overview that reveals community structure, (2) a Theme River View that traces thematic change and migration, and (3) an Influence View that uses floral glyphs and arcs to depict influence and growth. *BlossomNet* contributes a design framework for visual exploration of complex, person-centric social and semantic networks, with applications in domains where lineage, trend formation, and influence pathways are central.

Index Terms: Influence analysis, temporal visualization, large-scale knowledge graph, community detection.

1 Introduction

Large-scale knowledge graphs (KGs) are applied across domains ranging from research ecosystems to creative industries, where entity relationships reveal collaboration, influence, and contribution. KGs typically integrate diverse entities such as people, organizations, and events, calling for tools that balance readability with structural and temporal complexity. *BlossomNet* is designed to make such relationships interpretable, focusing on influence-based ecosystems at scales of up to tens of thousands of sparsely connected nodes (demonstrated with VAST 2025 MC1 KGs). Readability is achieved through community detection, spatial organization, and adaptive detail control.

Our design approach is grounded in situation awareness theory, which conceptualizes analysis in three stages: perception (rapid detection of salient features), comprehension (interpreting features in context), and projection (anticipating evolution). *BlossomNet* supports these stages through three coordinated views: an overview for pattern discovery, detailed views for relationship explanation, and a temporal view for forecasting and trend exploration (Figure 1). By combining information visualization principles with interaction design practices, *BlossomNet* uses expressive and coherent visual encoding to reduce cognitive load, maintain mental map, and enable both macro- and micro-level analysis.

2 System Design

2.1 Cluster-Based Overview

The overview depicts KGs as concentric clusters, where groups of related entities are identified via a community detection algorithm (e.g., Louvain). To reduce visual clutter both between and within clusters, we adopt a hierarchical display strategy. Within each cluster, a Kamada–Kawai layout produces compact, rounded shapes, while a force-directed layout ensures clear separation across clusters. More specifically, each cluster is organized using a three-layer concentric layout: (1) the inner circle contains nodes with edges only inside the cluster, arranged using the Kamada–Kawai method; (2) bridge nodes, those with both intra- and inter-community con-

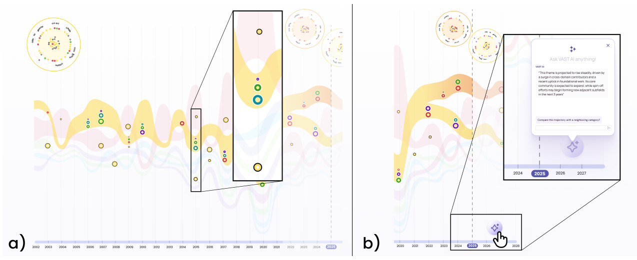

Figure 2: Theme River View: (a) Selecting a cluster highlights its theme, and migration bubbles show entity flow between communities in a given year; (b) AI-assisted query reveals projected trends.

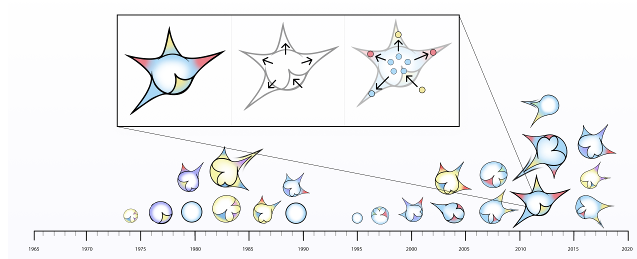

Figure 3: Semantic floral glyphs: petal angles encodes relationship types, lengths represent magnitudes, and colors indicate categories. Outward petals depict a node's influence on others, while inward petals indicate influence received from others.

nections, are repositioned to the cluster periphery; and (3) nodes connected exclusively to bridges are placed around them to preserve structural clarity. Entities are clustered by collaborative outputs, with cluster colors indicating overall dominance and node colors encoding specific categories (e.g., genre of songs, research field of publications). Additional encoding includes shape for entity type, size for importance, tapered edges that reveal directionality [3], and a temporal filter that highlights active communities by selection. This three-layer design reduces visual clutter, as well as reflects the role and contribution of each node within its community. Guided by Gestalt principles of proximity and similarity, the combined encodings support rapid recognition of hubs, bridges, and outliers, supporting both broad pattern discovery and targeted analysis.

2.2 Theme River View

Temporal analysis is supported by a customized sorted theme river view, emphasizing migration patterns among communities. It shows cluster evolution (splits, merges, growth, fades) and inflow/outflow movement between categories of artworks (Figure 2a). Each stream represents a category or theme of artworks, with thickness indicating activity level. Migration bubbles convey group movement; where bubble radius reflects magnitude and color denotes source category, making major shifts immediately visible. Selecting a cluster highlights its categorical stream playing a temporal animation from the earliest point to present, extending into an AI-generated future prediction (Figure 2b). Predictions appear as translucent extensions, based on historical trends, showing structural and connectivity changes over time.

2.3 Influence View

Selecting a node in the overview opens the influence view, which introduces a semantic "flower" glyph to encode relationships (Figure 3). Fixed petal angles map to relationship types, with inward petals for received and outward for exerted influence. Petal length shows magnitude, glyph color indicates category, and petal gradients show the category of the influencer or influencee. Designed to overcome edge clutter in dense networks, the glyph embeds relationship data directly into the node shape, enabling rapid interpretation without expanding into a local subgraph. Glyphs follow the timeline of the selected node's contributions, forming a visual fingerprint of its relational history. Arcs trace trajectories with dots marking collaborations, enabling quick identification of recurring partnerships or enduring influence. Our choice of radial layout was informed by insights from a previous design challenge [1].

3 Cognitive and Design Principles

BlossomNet applies perceptual science, cognitive theory, and professional design practice to improve comprehension:

- **Visualization Mantra:** "Overview first, zoom and filter, then details on demand" [2] guides the layout of three views, moving from the Clustered-based Overview to focused filters and detailed temporal or influence views.
- **Visual Hierarchy:** High-contrast highlights draw attention to selected clusters or streams, while muted context stays legible. Level-of-detail controls prevent clutter, revealing labels and edges when needed.
- **Gestalt Psychology:** Principles of proximity, similarity, and continuity shape cluster layouts, bridge placement, and edge routing, enabling network structure to be read holistically. This further orients users by making the graph scannable, aiding navigation even in large KGs.
- **Affordances and Pre-attentive Encoding:** Encodings such as floral glyph petal length, angle, and hue support rapid recognition. System-wide color schemes separate categories and expose cross-category influence, while consistent brushing and linking interactions ensure ease of navigation.

4 Workflow and Use Scenarios

Analysis often starts in the overview, where hub, bridge, and community nodes are visible. The AI assistant interprets plain-language queries, retrieving and highlighting patterns. Clicking a cluster reveals its temporal stream to track changes and review AI predictions; selecting a node opens Influence View to inspect relationships driving said changes. Example scenarios include tracing stylistic influence that precedes collaboration, confirmed through glyphs and temporal migration, or tracking split–merge narratives as small clusters grow and merge into larger communities.

5 Conclusion

BlossomNet combines a structured Cluster-based Overview, a contextual Theme River View, and a semantic Influence View into a coordinated, perception-aware analytics environment. Grounded in cognitive principles and visualization practices, it lowers the barrier for novices while preserving analytic rigor for experts. Designed for influence, lineage, and trend analysis in person-centric KGs, its adaptable framework extends to domains from social networks to business structures and other complex relational systems.

References

[1] C. Guo, J. Zhao, L. Ding, T. Zhang, W. Deng, P. Owusu Attah, X. Guo, X. T. Nguyen, Y. Ju, Z. C. Qian, and Y. V. Chen. ConstellationBuilder: A high-level situational awareness and team assembly interface for cybersecurity events. In *Proceedings of the IEEE Conference on Visual Analytics Science and Technology*, p. 2 pages, Oct. 2020. 2

[2] B. Shneiderman. The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings of IEEE Symposium on Visual Languages*, pp. 336–343, sep 1996. doi: 10.1109/VL.1996.545307 2

[3] J. Zhao, M. Karimzadeh, H. Xu, A. Malik, S. Afzal, G. Wang, N. Elmqvist, and D. S. Ebert. Route Packing: Geospatially-accurate visualization of route networks. In *Proceedings of the Hawaii International Conference on System Sciences*, pp. 1370–1379, Jan. 2020. doi: 10.24251/HICSS.2020.168 2