Time-Aligned Edge Plots for Dynamic Graph Visualization

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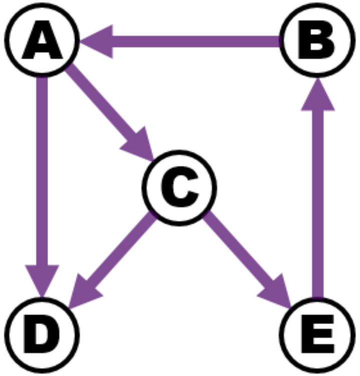
What is a static graph?

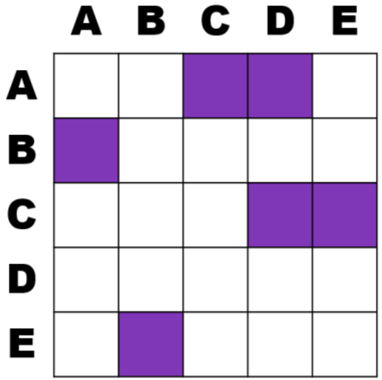
$$G := (V, E),$$

where V is set of vertices and E is set of edges $E \subseteq V \times V$

Graph Visualization



Node-link diagram (NL)



Adjacency Matrix (AM)

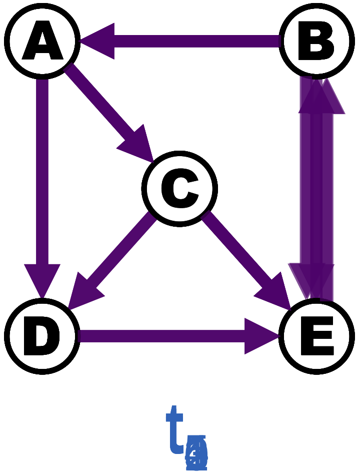
Dynamic Graph

$$\Gamma := (G_0, G_1, \dots, G_{n-1}),$$

where $G_i := (V_i, E_i)$ are static graphs and indices refer to a sequence of time points $\tau := (t_0, t_1, \dots, t_{n-1})$

Dynamic Graph Visualization

- Animation (time-to-time mapping)
  - Intuitive choice
  - But less effective form for analysis

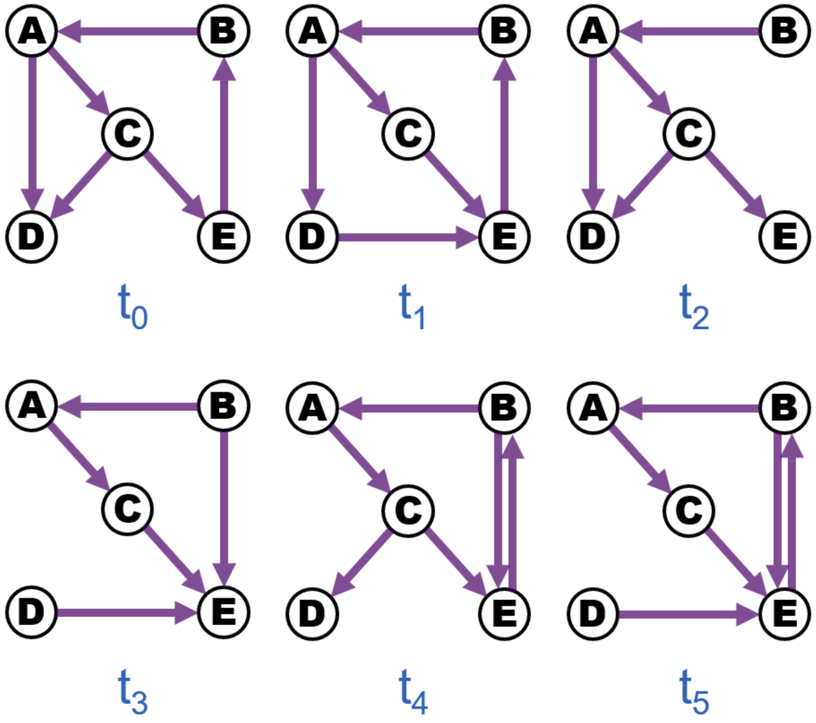


B. Tversky, J. B. Morrison, and M. Betrancourt, “Animation: can it facilitate?” International Journal of Human-Computer Studies, vol. 57, no. 4, pp. 247–262, 2002

G. Robertson, R. Fernandez, D. Fisher, B. Lee, and J. Stasko, “Effectiveness of animation in trend visualization,” IEEE Transactions on Visualization and Computer Graphics, vol. 14, no. 6, pp. 1325–1332, 2008

Dynamic Graph Visualization

- Timeline (time-to-space mapping)
  - Small multiples
  - Not scalable in time



Small Multiples of Node-link diagram (SMNL)

Dynamic Graph Visualization

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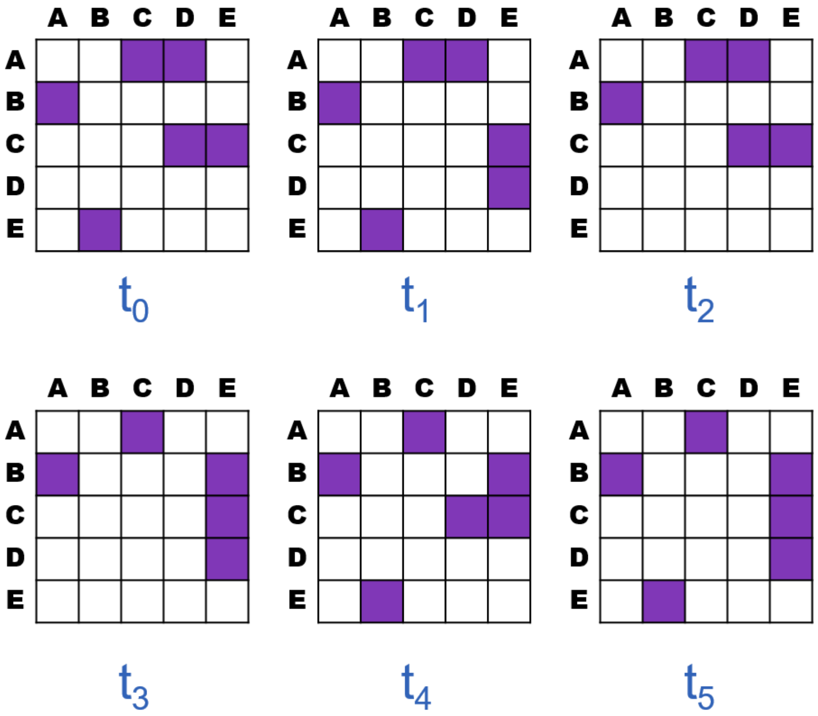


Small Multiples of Adjacency Matrix (SMAM)

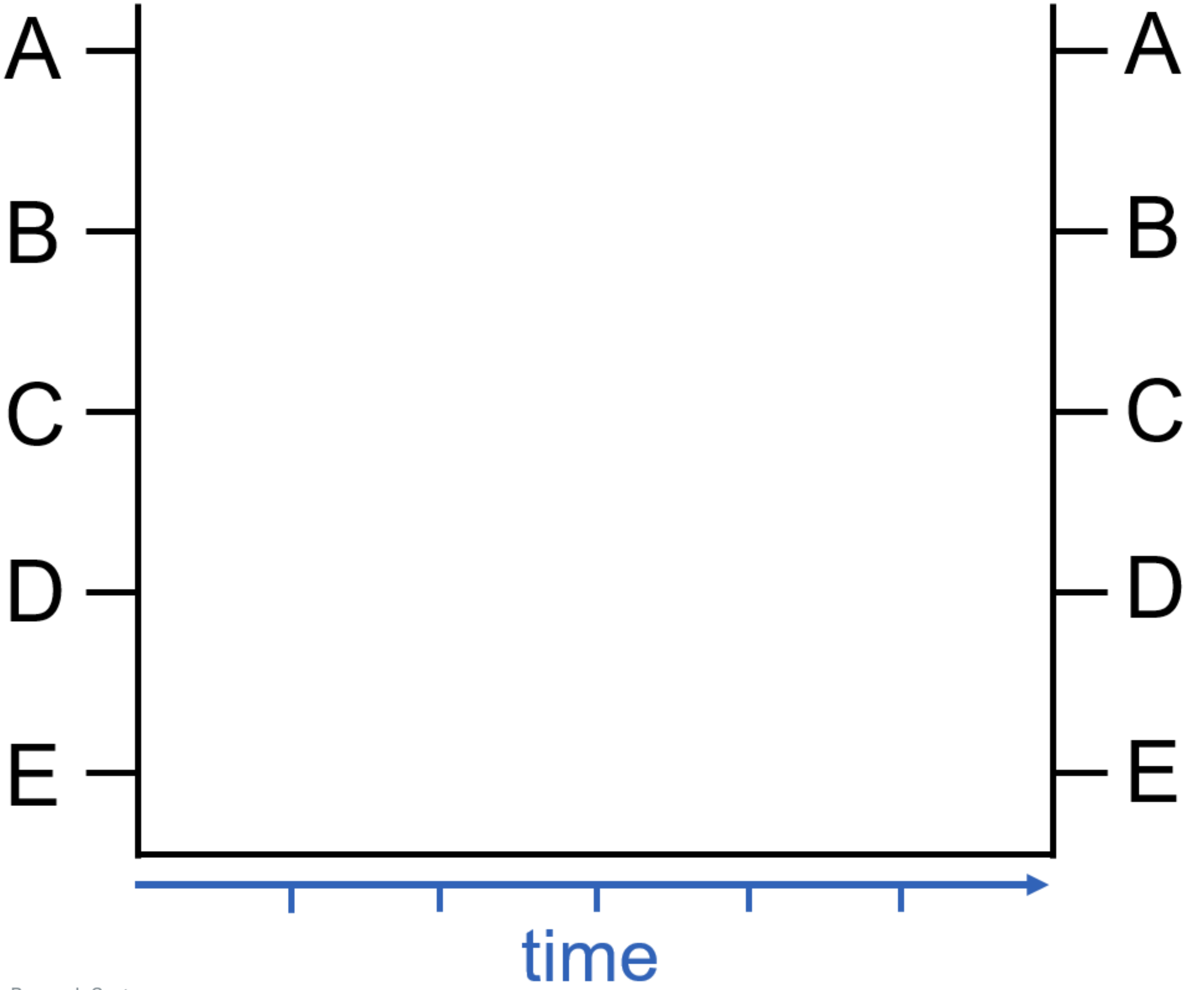
Time-Aligned Edge Plots (TEPs)

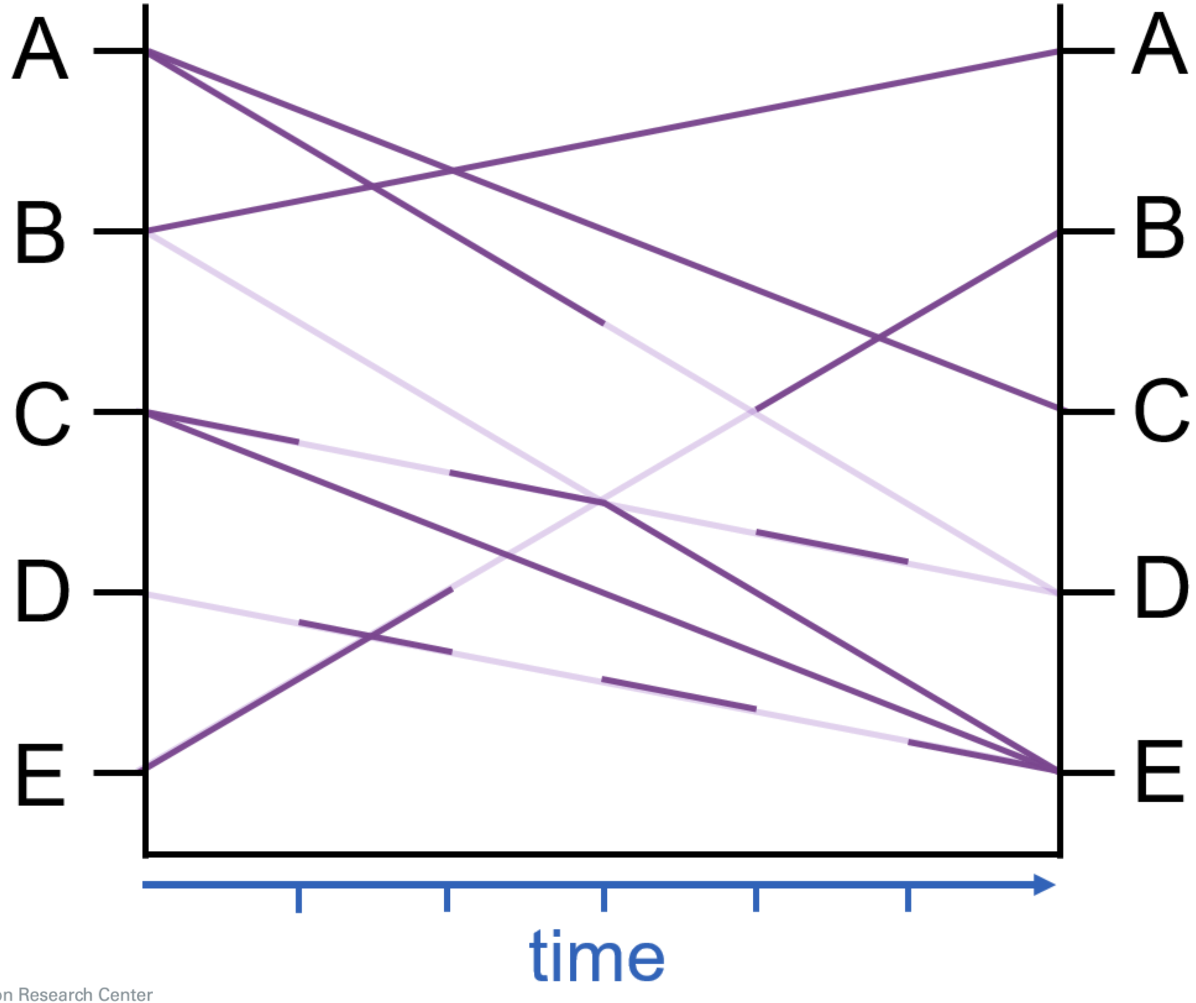
- A representation of dynamic graphs that is scalable in the time and edge dimensions


A
B
C
D
E
A
B
C
D
E


A
B
C
D
E
A
B
C
D
E

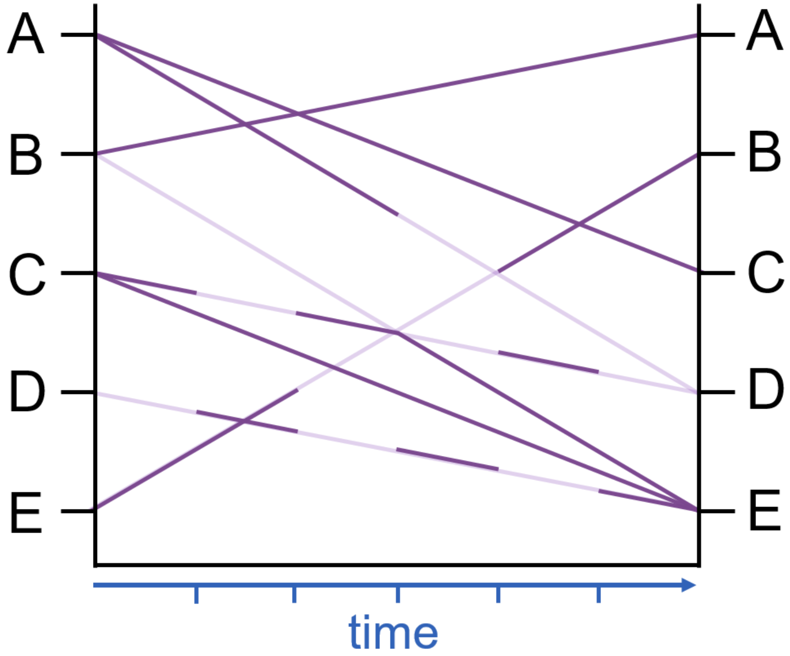

A
B
C
D
E
A
B
C
D
E

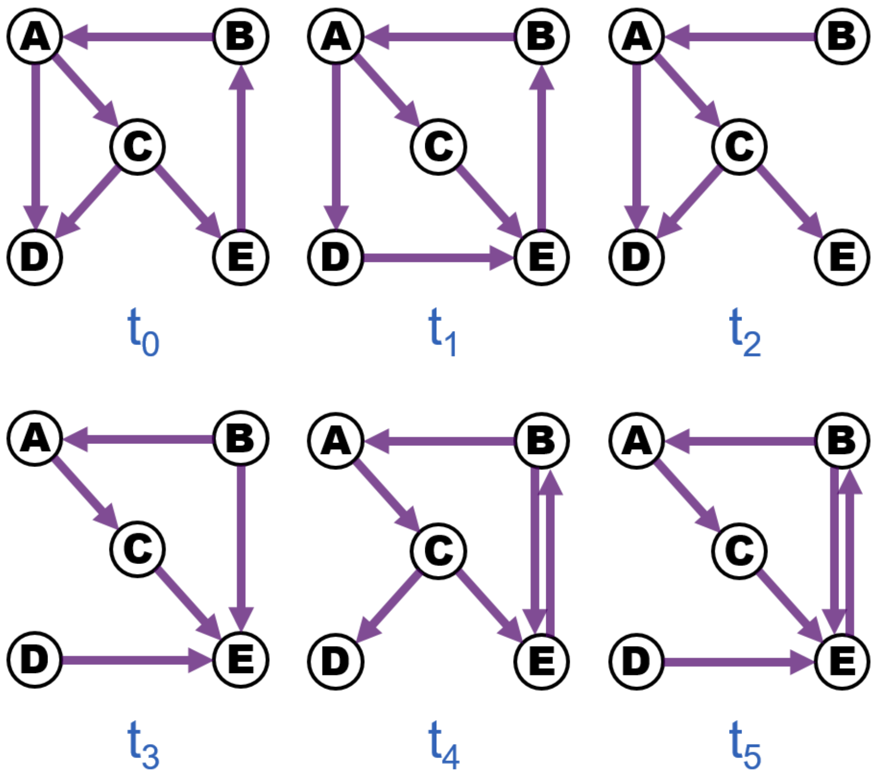

A
B
C
D
E
A
B
C
D
E
time


A
B
C
D
E
A
B
C
D
E
time

Time-Aligned Edge Plots (TEPs)

- We model the dynamic graph as a single super graph $G := (V, E)$
- While edges are dynamically changing over time: $f_e(t)\colon \mathbb{R} \to \mathbb{R}, t \in [t_{min} \dots t_{max}]$





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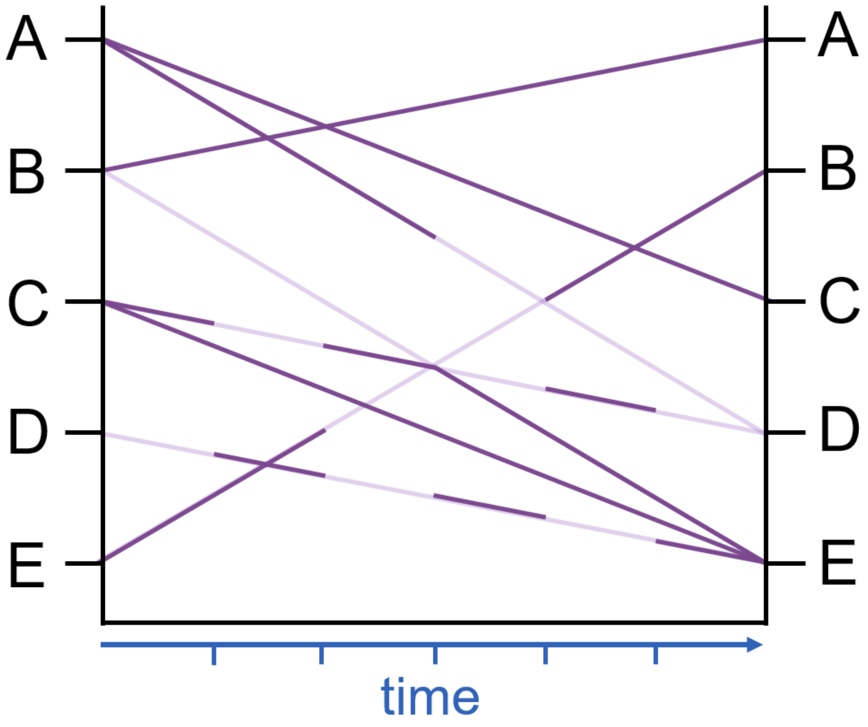
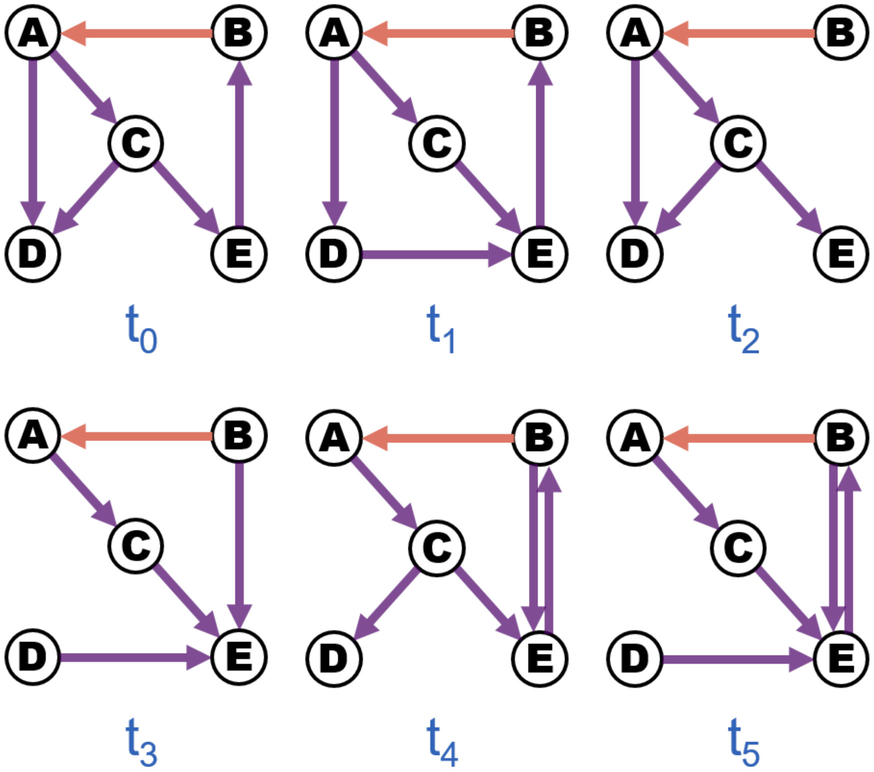


Time-Aligned Edge Plots (TEPs)



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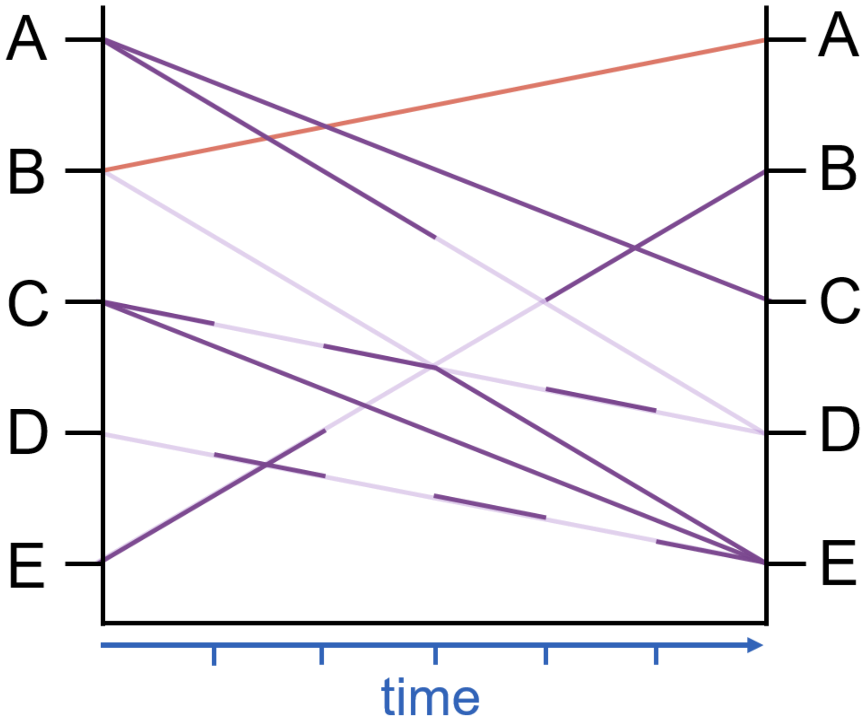

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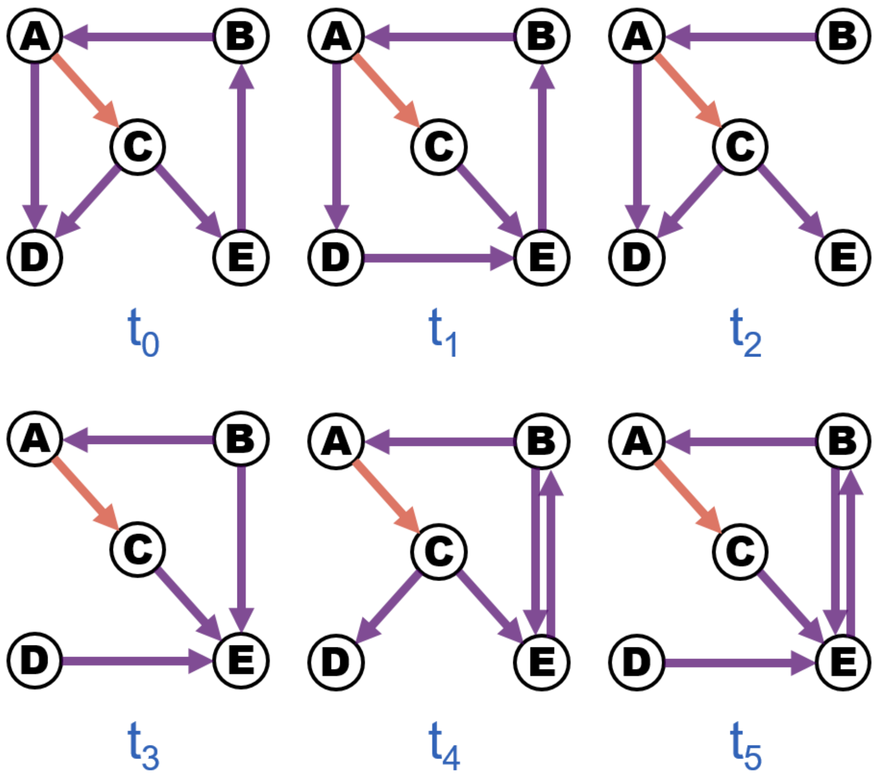

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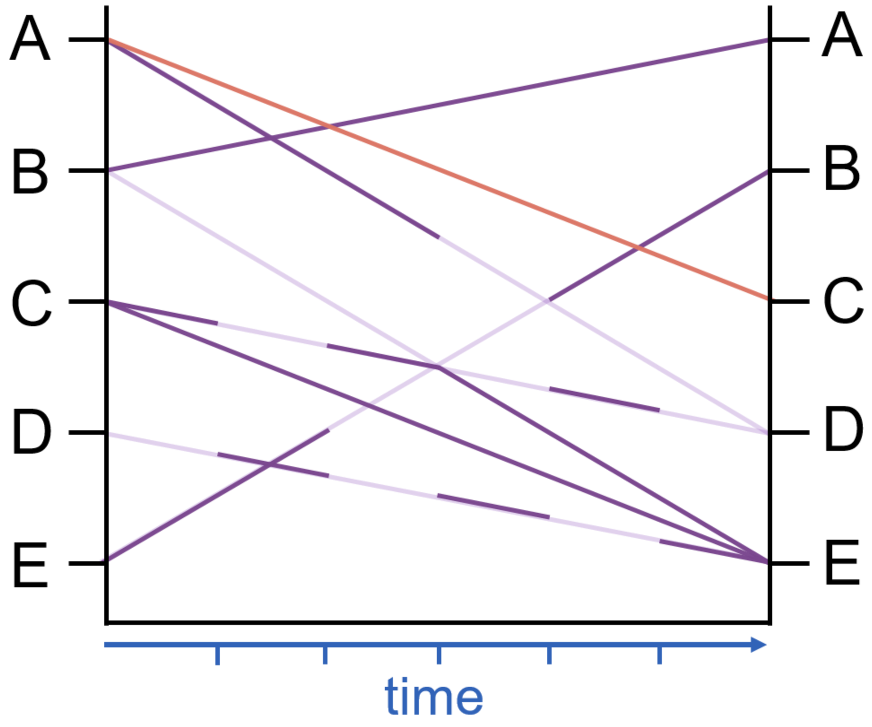

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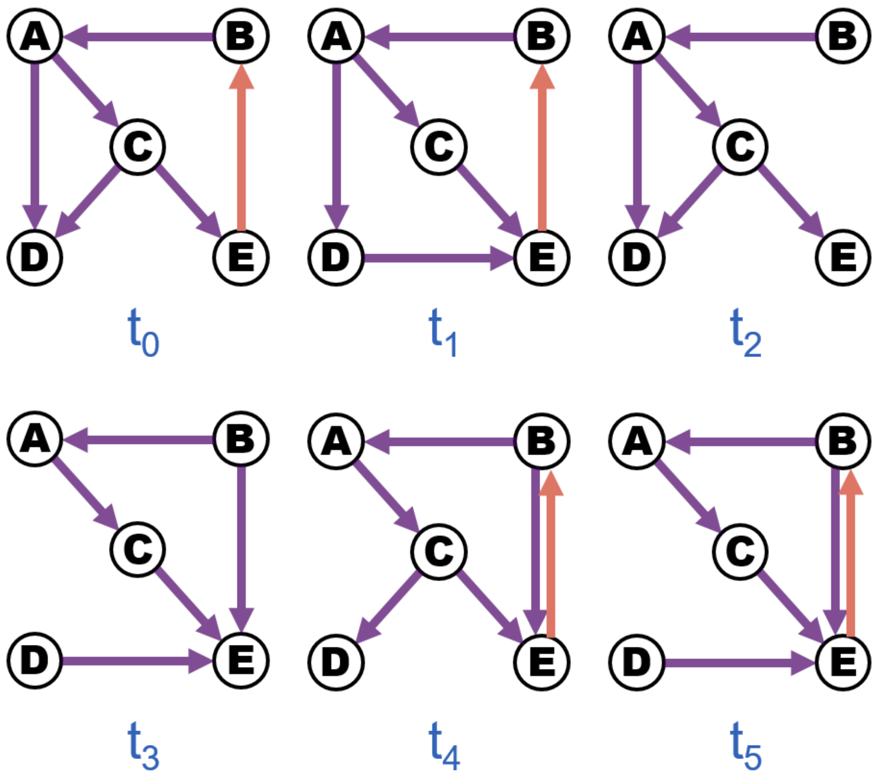

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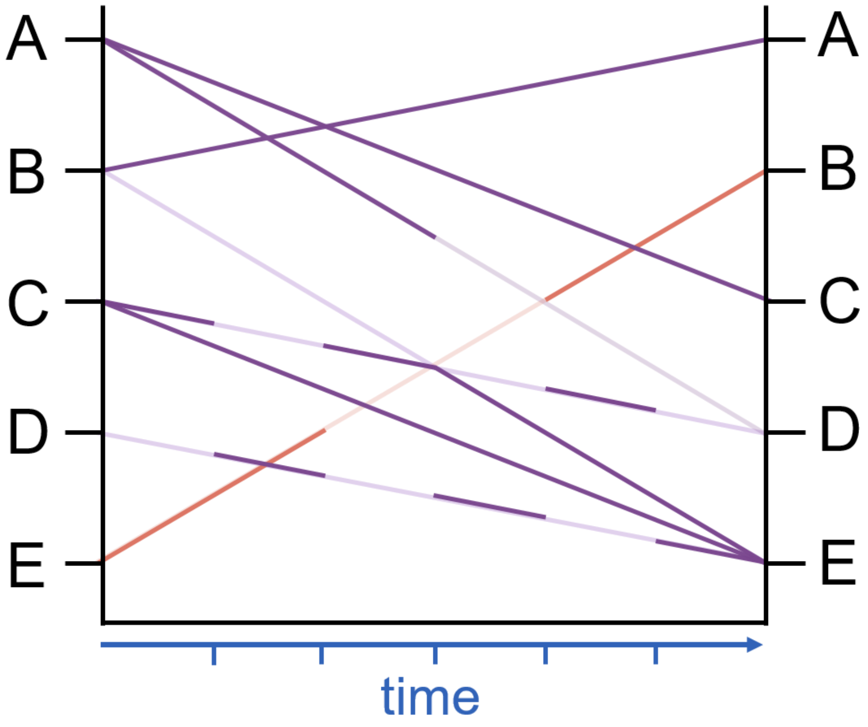

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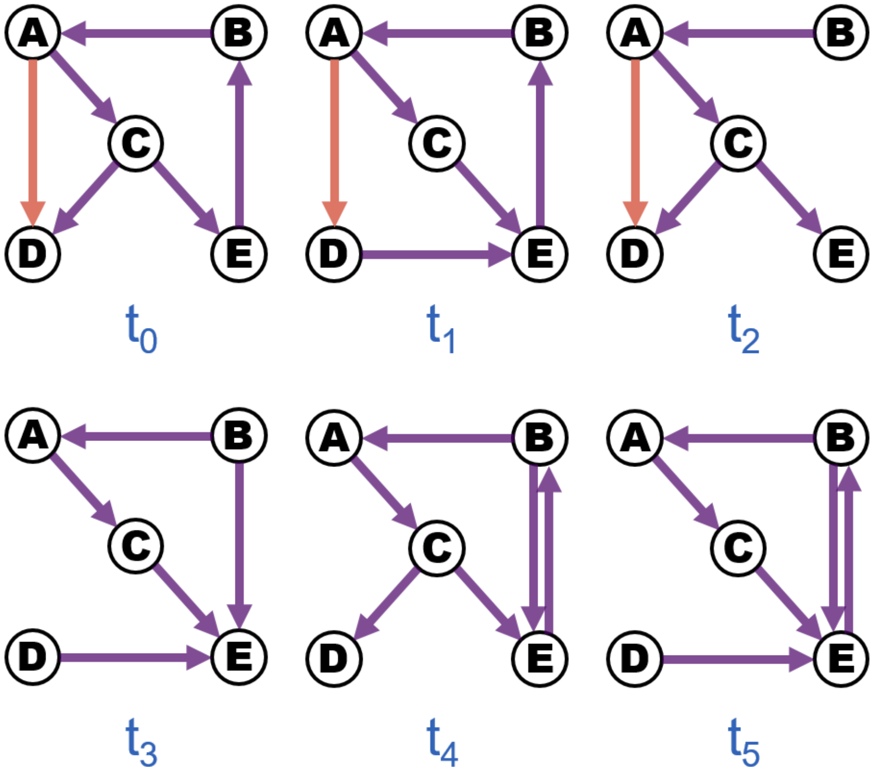

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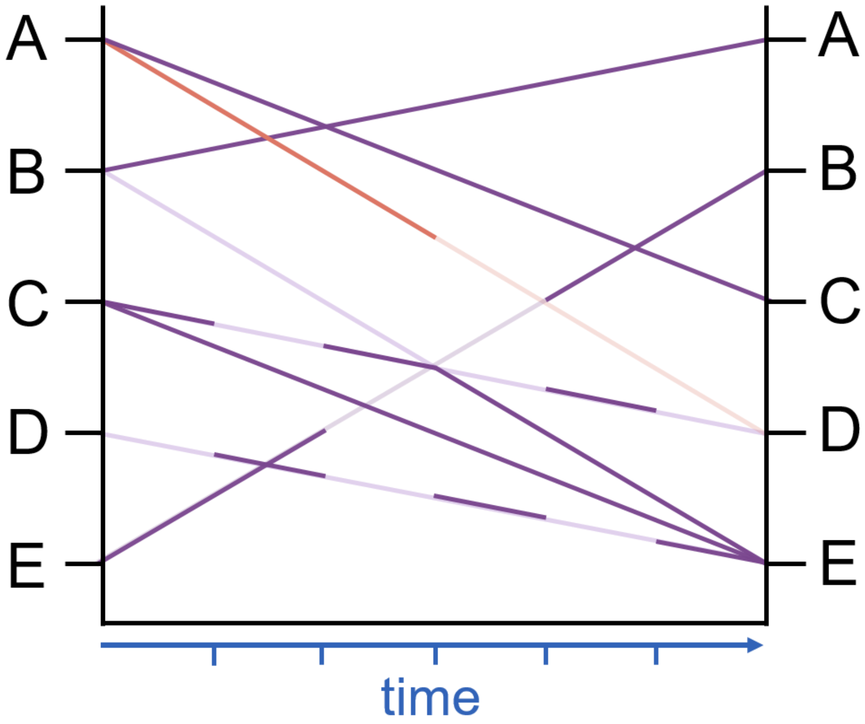

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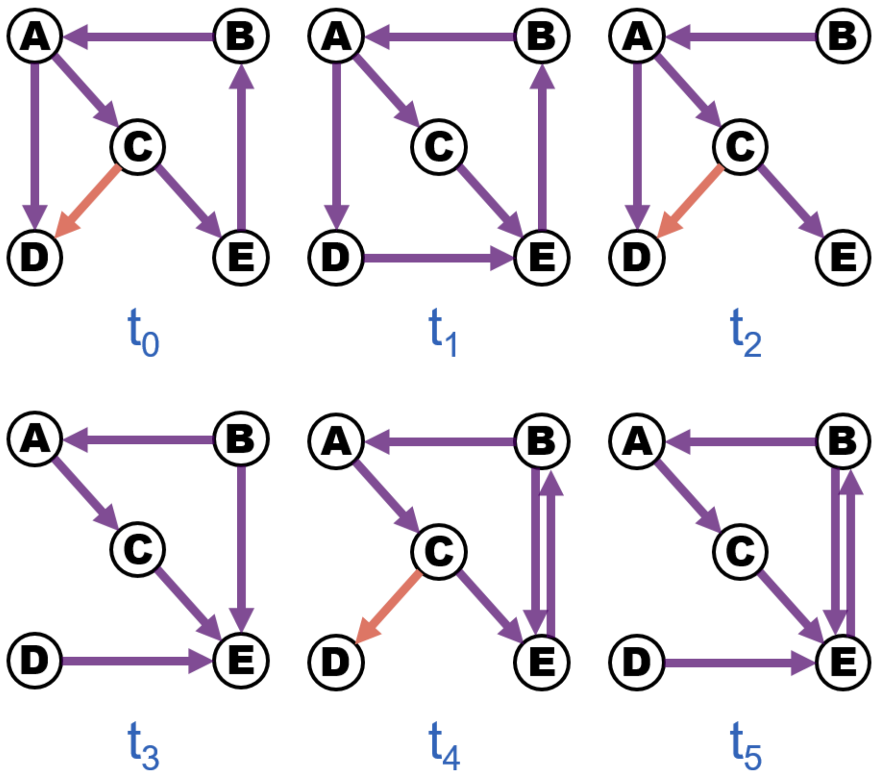

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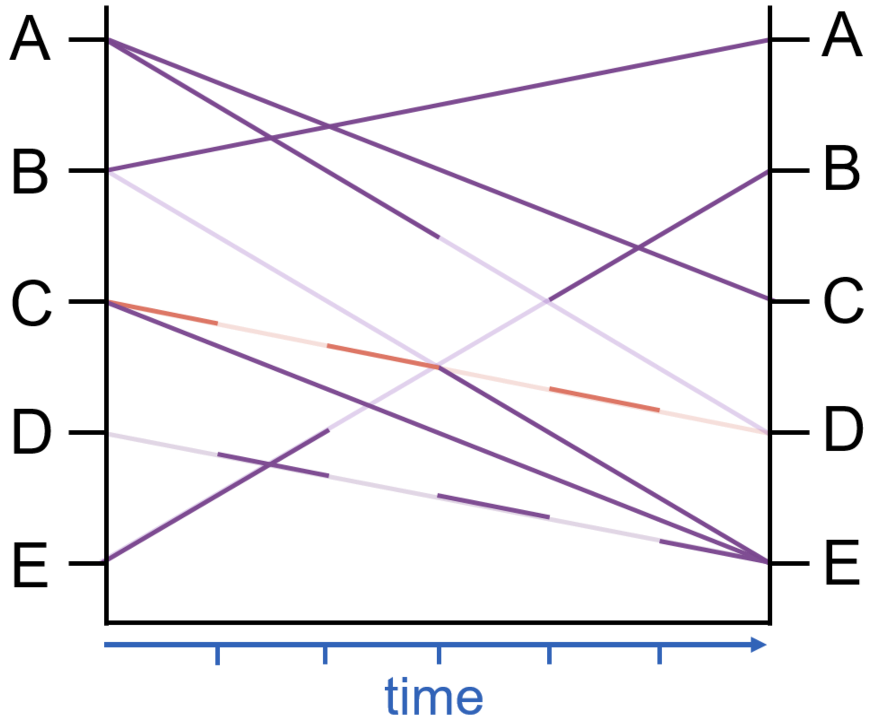

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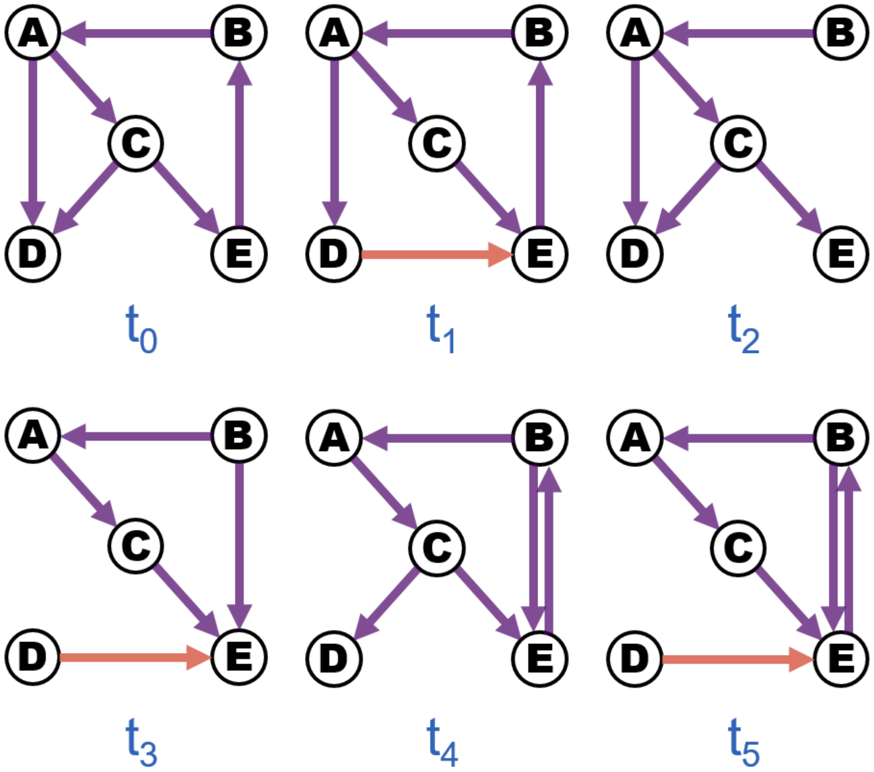

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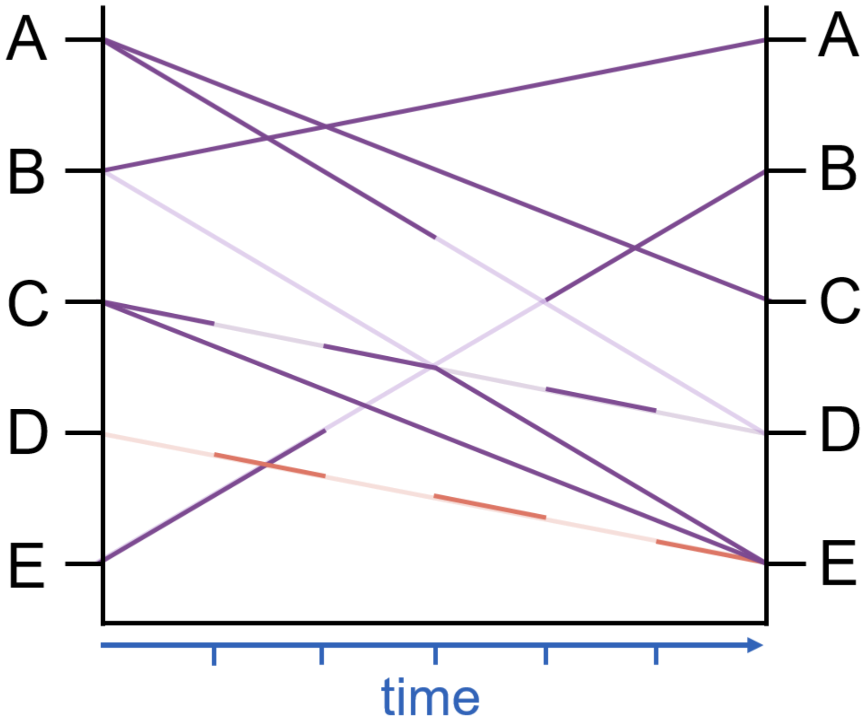

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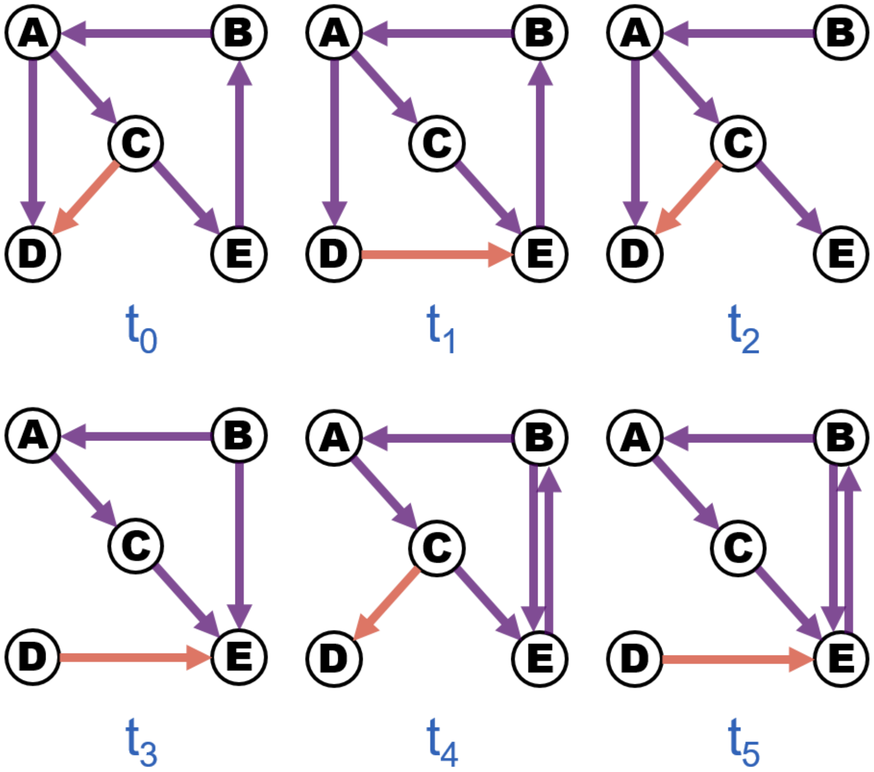

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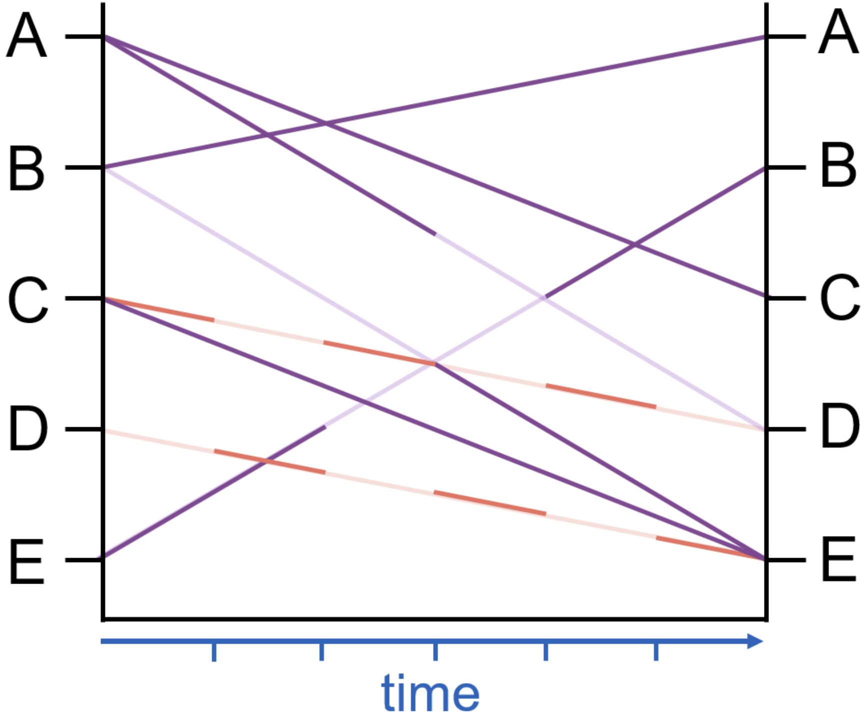
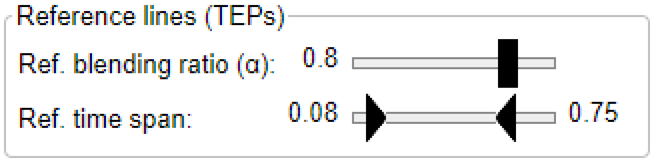


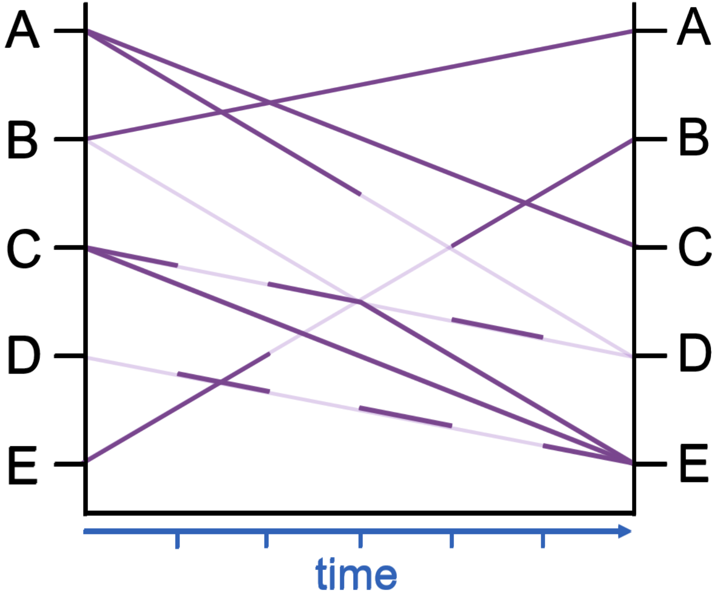
Time-Aligned Edge Plots (TEPs)

Problem 1

- It is hard to follow partially drawn edges

- Work-around
  - Reference Lines + User-adjustable





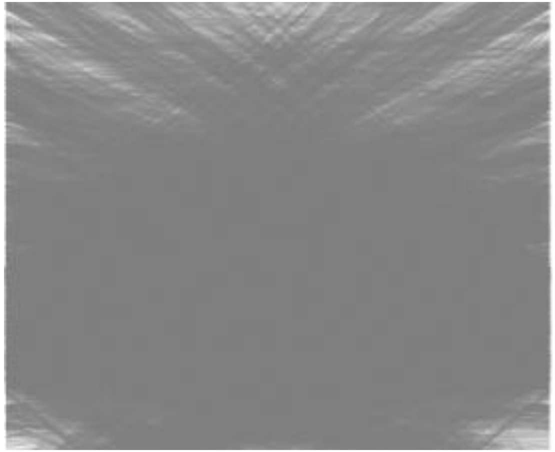
Problem 2

- Placing vertices in 1D vertical line results in a limited space for drawing edges and therefore increase visual clutter

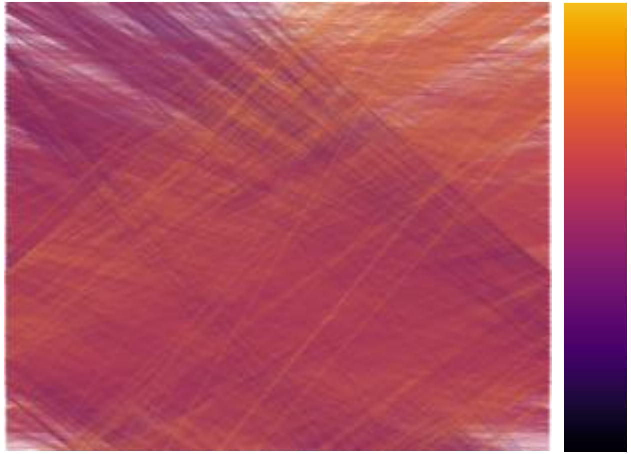
- Work-around
  - Slope Encoding
  - Vertex Ordering

Slope Encoding

Edges are drawn as opaque lines



Edges are blended by applying alpha compositing



Edges are blended, and slope is encoded by color

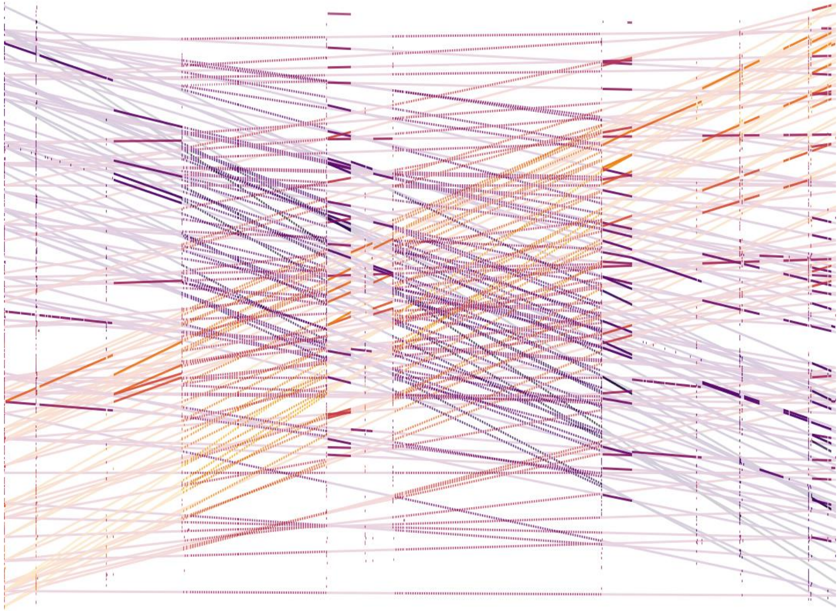
Vertex Ordering

- We combine Hierarchical Clustering (HC) with Simulated Annealing (SA)
- The similarity between two graph vertices v_i and v_j is obtained by calculating the Jaccard coefficient:

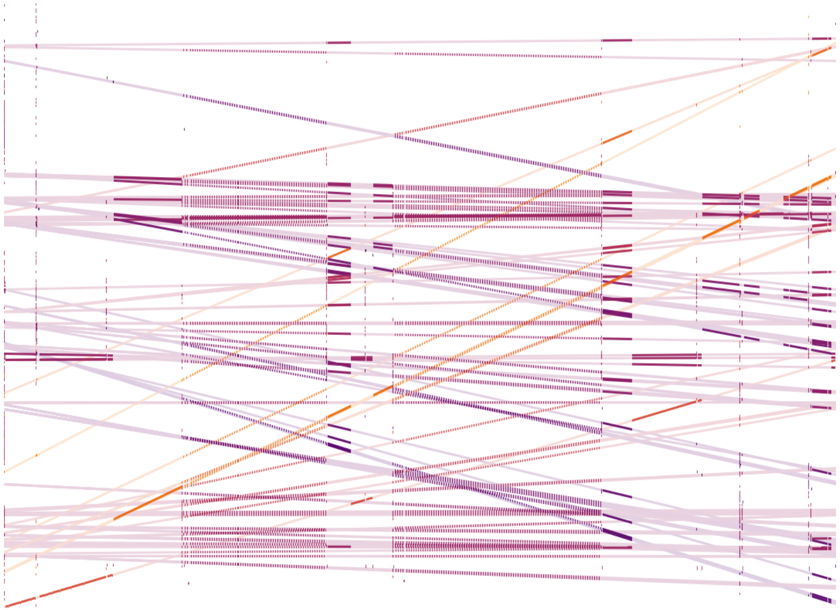
$$J(\bar{V}_i, \bar{V}_j) = \frac{|\bar{V}_i \cap \bar{V}_j|}{|\bar{V}_i \cup \bar{V}_j|} \in [0,1],$$

where $\bar{V}_i$ and $\bar{V}_j$ are the sets of direct neighbors for vertices v_i and v_j, respectively.

Vertex Ordering



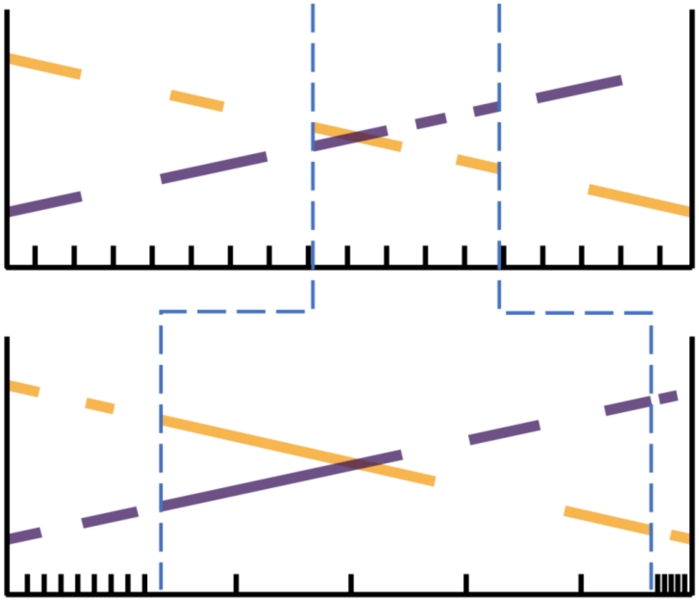
Not ordered



Ordered

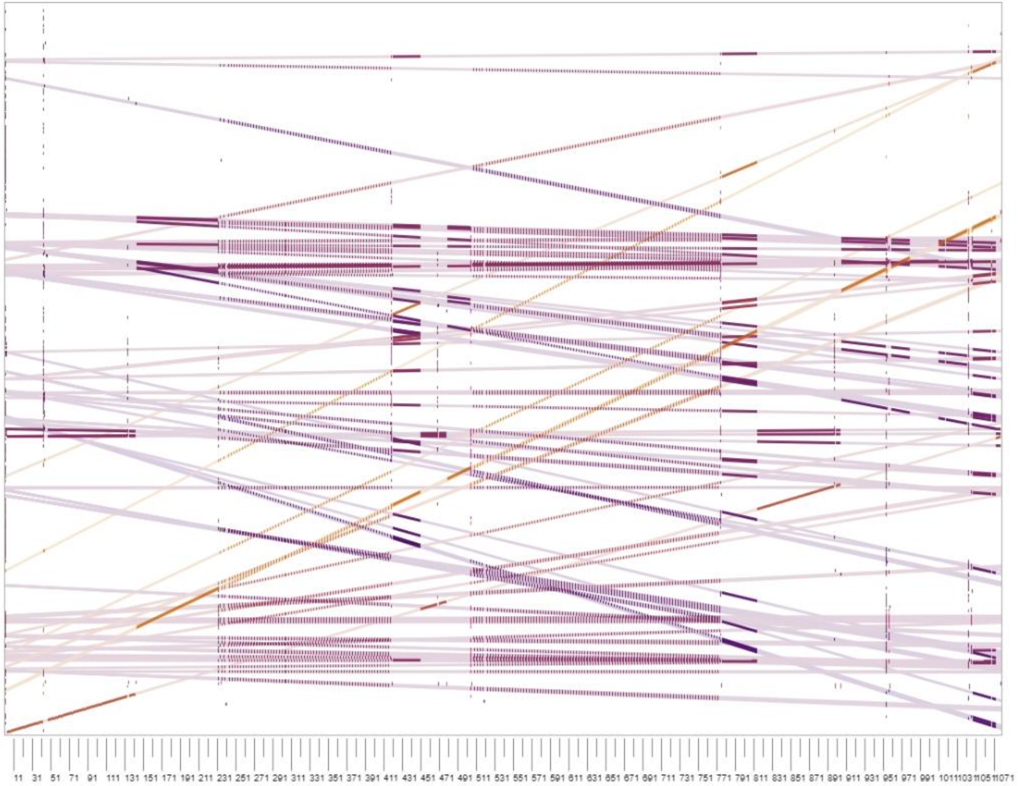
Problem 3

- Outliers may not be visible
- Work-around
  - Zoom Lens



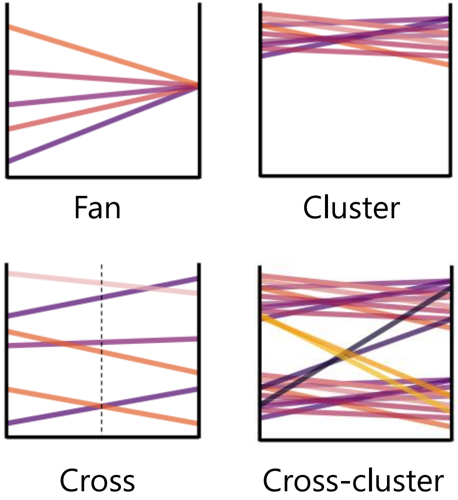
Time-nonlinear Zooming Lens

Zoom Lens

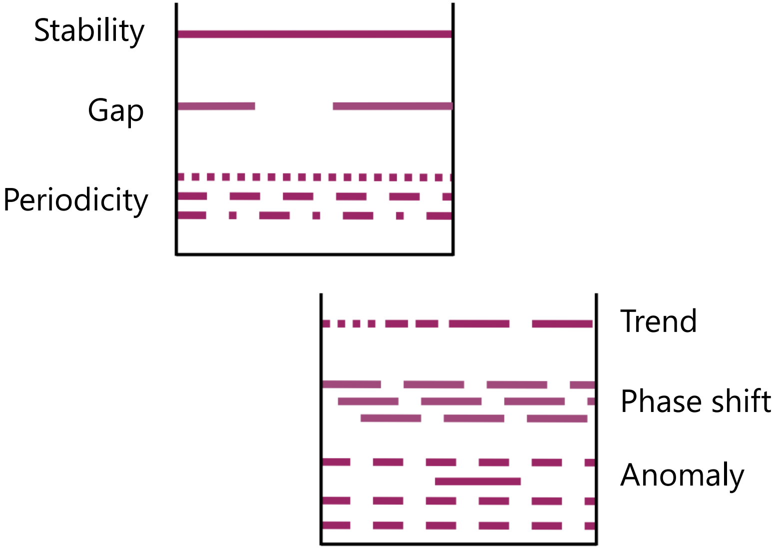

11 31 51 71 91 111 131 151 171 191 211 231 251 271 291 311 331 351 371 391 411 431 451 471 491 511 531 551 571 591 611 631 651 671 691 711 731 751 771 791 811 831 851 871 891 911 931 951 971 991 1011 1031 1051 1071

Visual Patterns

Structural Patterns



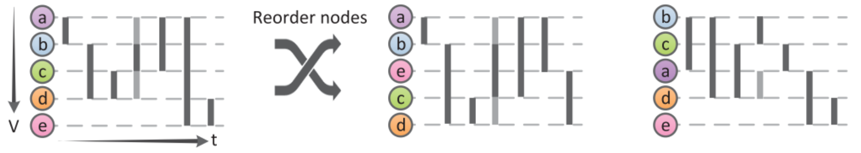
Temporal Patterns



Evaluation

Competitors

Massive Sequence Views (MSVs)



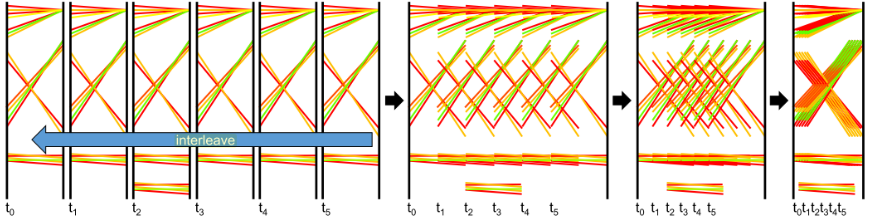
(c) MSV: Lexicographic node order.

(d) Maximal edge length order.

(e) Minimal edge length order.

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

Interleaved Edge Splatting (IES)



M. Burch, M. Hlawatsch, and D. Weiskopf. Visualizing a sequence of a thousand graphs (or even more). Computer Graphics Forum, 36(3):261–271, 2017

Comparison

- **Theoretical and Empirical**
- Real-world and Synthetic data
- Three analysis tasks
- Qualitative Results Inspection (QRI)

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[1]Software call graph dataset (JHotDraw) http://www.jhotdraw.org/

Comparison

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- Real-world[1] and **Synthetic[2]** data
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Comparison

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- **Three analysis tasks[3]**
  - T1: Identifying node addition/removal events
  - T2: Identifying link addition/removal events
  - T3: Identifying temporal patterns (i.e., periodicity, stability, trend, outliers ...etc.)
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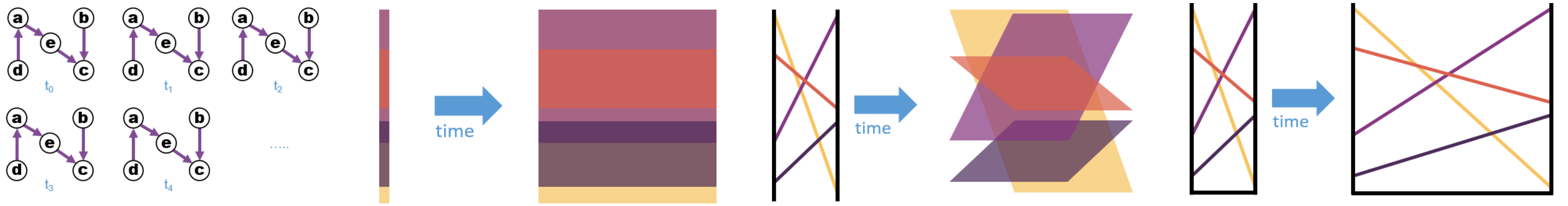
[4]T. Isenberg, P. Isenberg, J. Chen, M. Sedlmair, and T. Mller, “A systematic review on the practice of evaluating visualization,” IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2818–2827,2013

Findings

Findings (1)

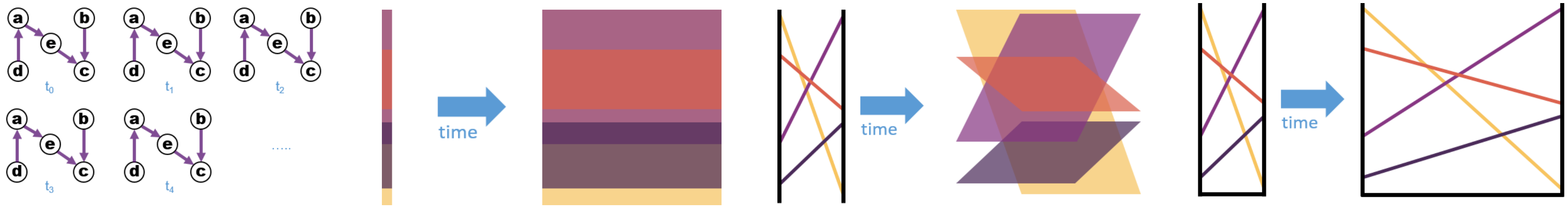
- TEPs, MSVs, as well as, IES are scalable in the time dimension



Small Multiples of NL　　Massive Sequence Views　　Interleaved Edge Splatting　　Time-Aligned Edge Plots

Findings (2)

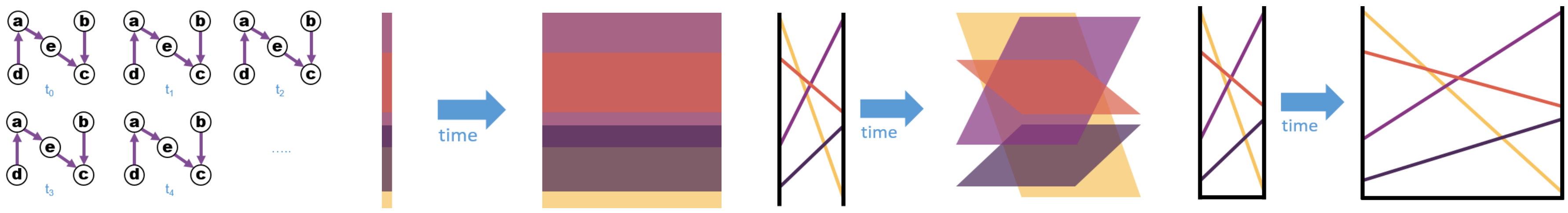
- TEPs, MSVs, as well as, IES are NOT suitable for node-related events



Small Multiples of NL | Massive Sequence Views | Interleaved Edge Splatting | Time-Aligned Edge Plots

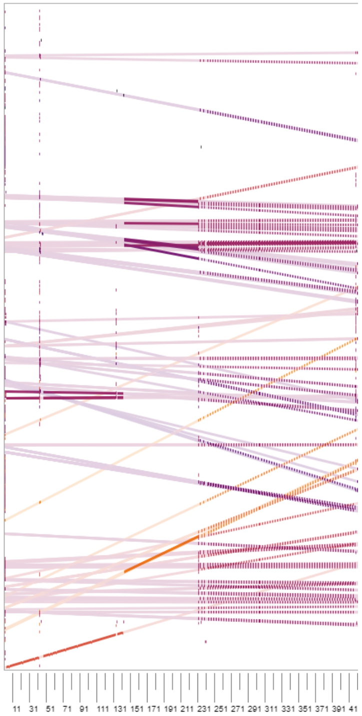
Findings (3)

- TEPs is more scalable in the edge dimension

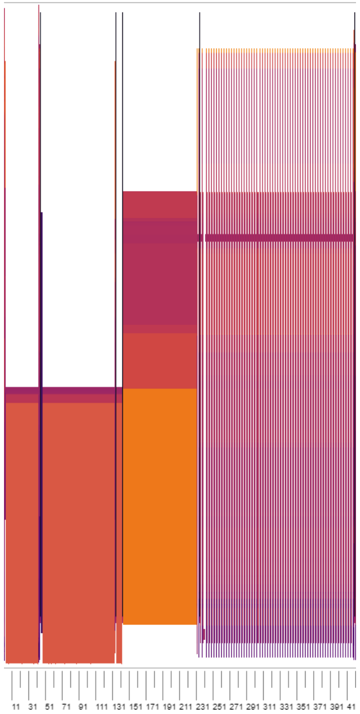


Small Multiples of NL   Massive Sequence Views   Interleaved Edge Splatting   Time-Aligned Edge Plots

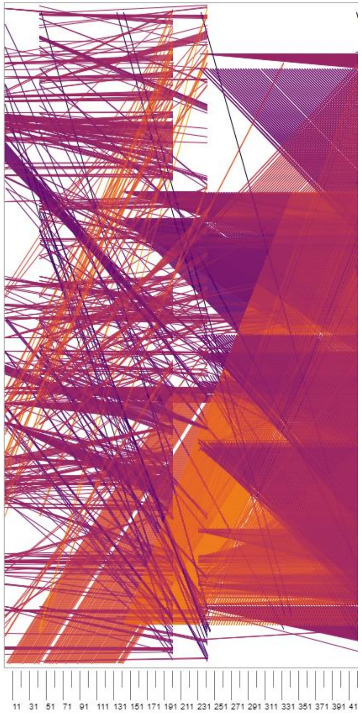
Pixel Overdraw Metric



TEPs: 0.1247



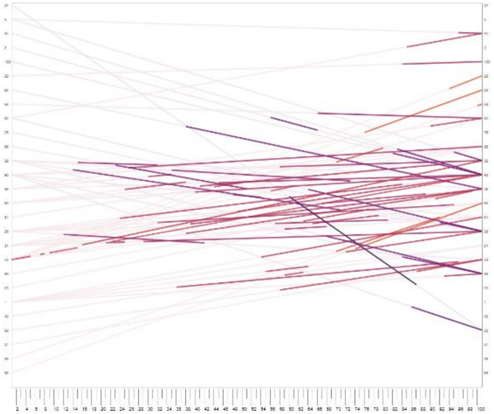
MSVs: 3.3383

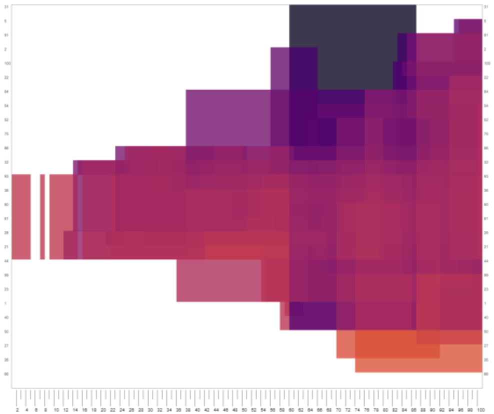


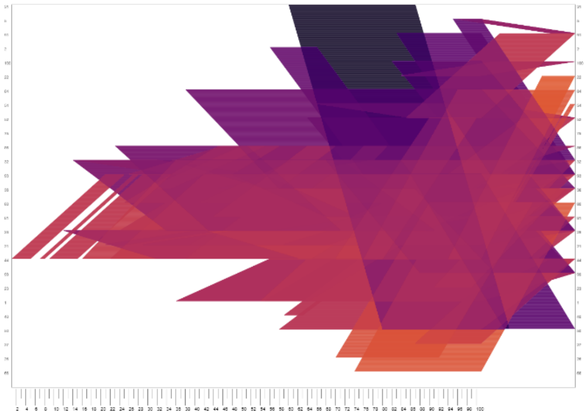
IES: 8.0545

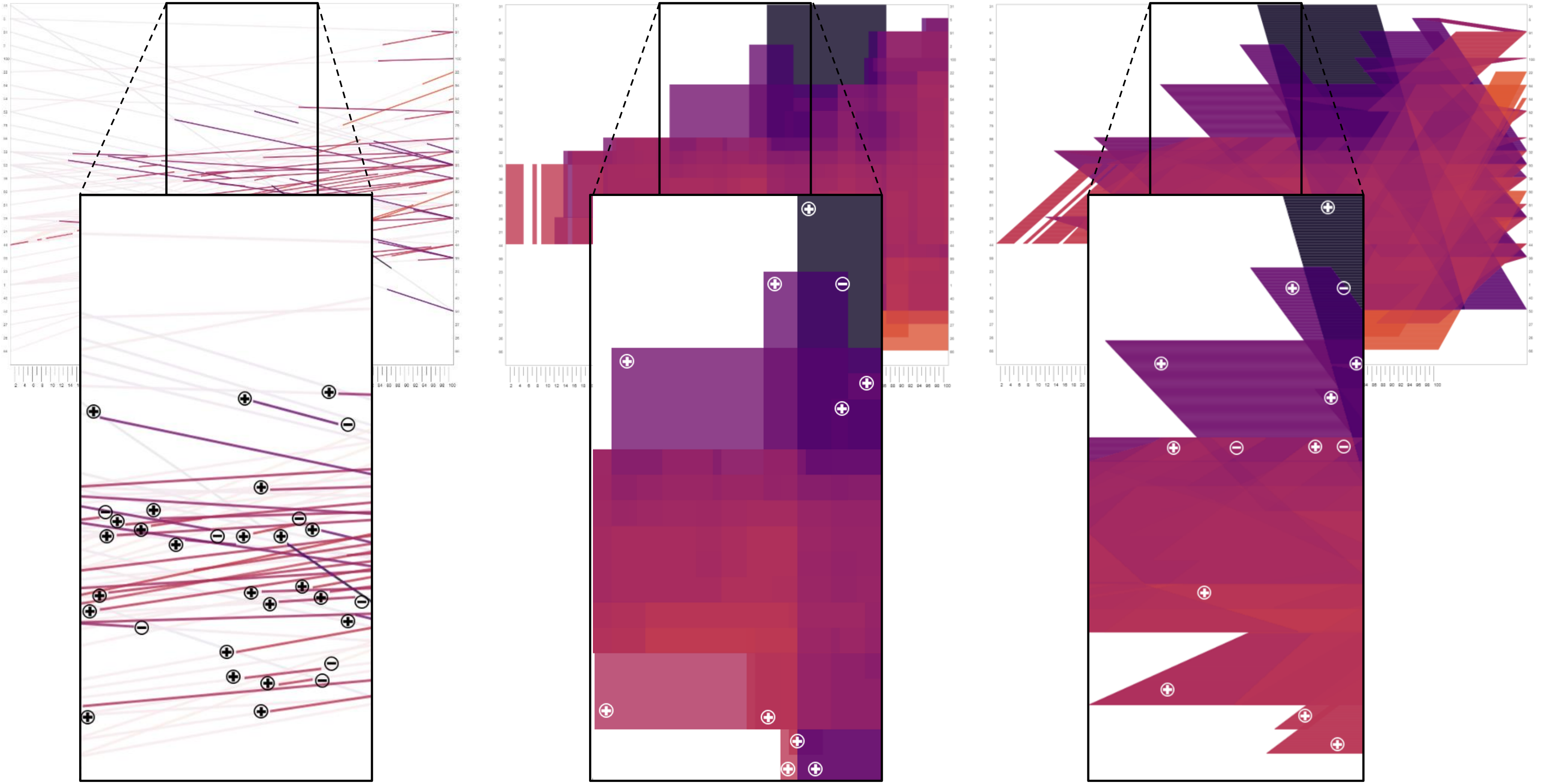
Findings (4)

- TEPs reveal more link events and temporal patterns





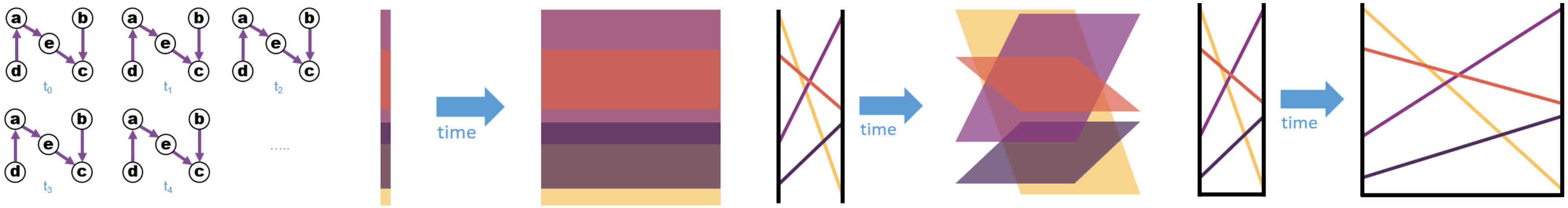




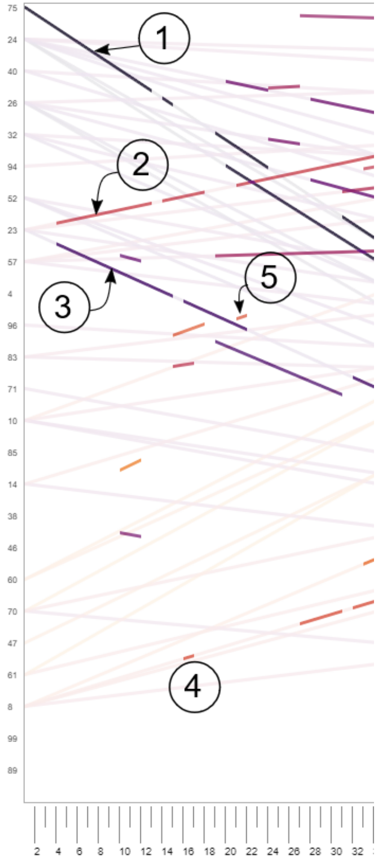
TEPs MSVs IES

Findings (5)

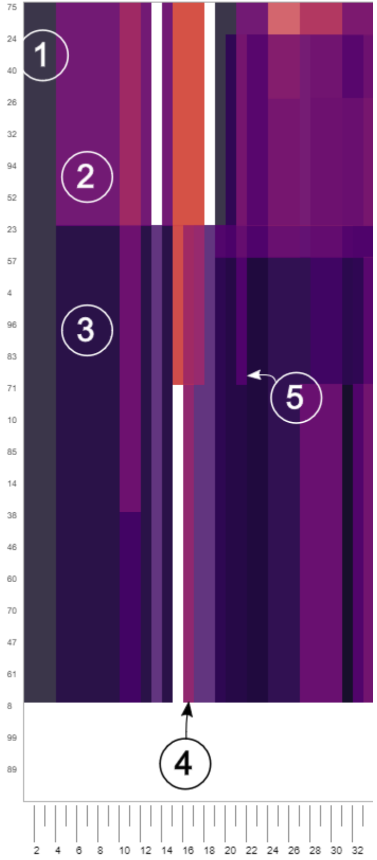
- It is very hard to recognize edges in MSVs due to the lack of slope encoding



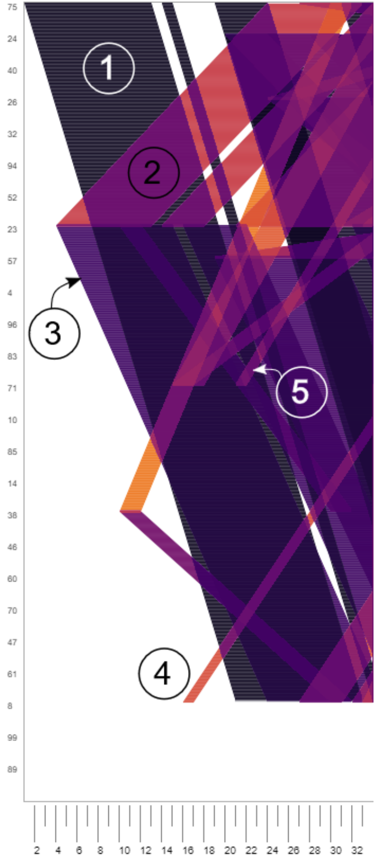
Small Multiples of NL   Massive Sequence Views   Interleaved Edge Splatting   Time-Aligned Edge Plots



TEPs



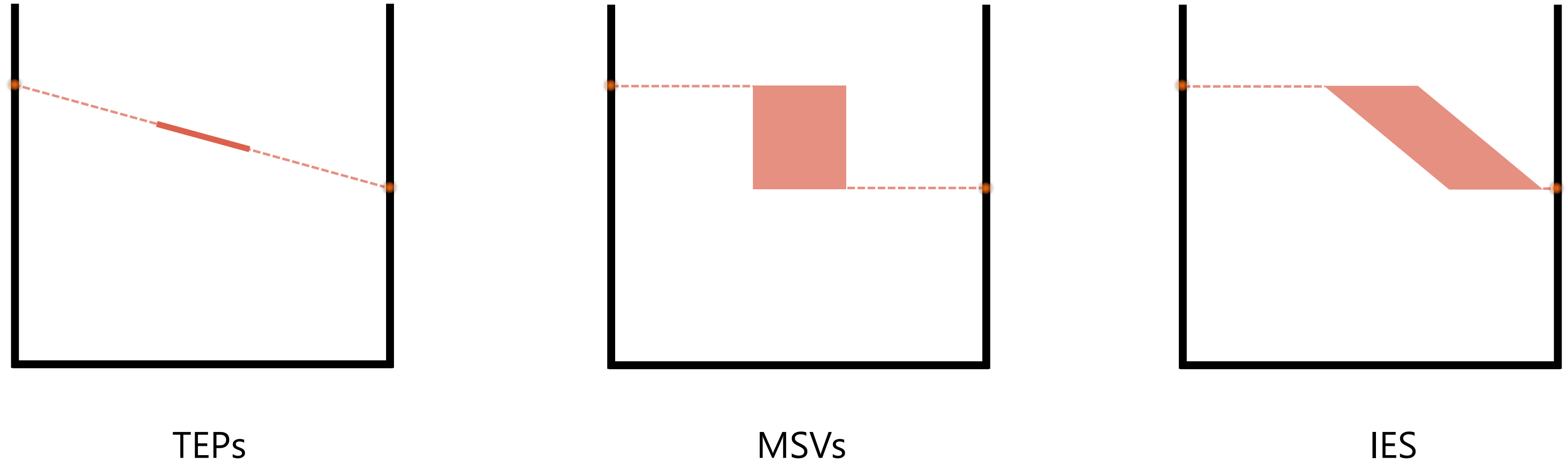
MSVs



IES

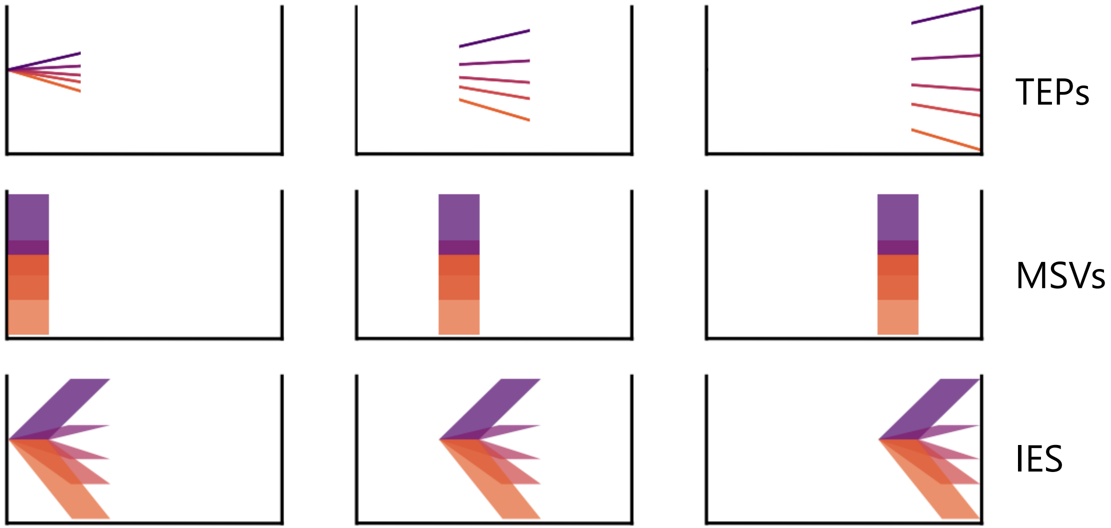
Findings (6)

- Without reference lines, it is hard to identify the source and target nodes in TEPs



Findings (7)

- In TEPs, the shape of the structural patterns changes over time



Fan-out pattern depicted over time

Conclusion

- TEPs: a novel visualization approach that is scalable in the edge and time dimensions
- To amplify the recognition of edges:
  - Drawing Ref. Lines
  - Zoom Lens
  - Vertex Ordering
  - Slope Encoding
- Evaluation is done through a comparative QRI versus MSVs and IES
  - Theoretically and empirically
  - Synthetic and real-world datasets
  - Three analysis tasks
- TEPs reduce the amount of visual clutter significantly allowing us to see more edge events and temporal patterns
- However, it might be difficult to determine the source and target nodes of certain events
- TEPs can serve as an entry point for analyzing networks

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Thank You!

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