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Clustering for Stacked Edge Splatting

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Visualization Research Center
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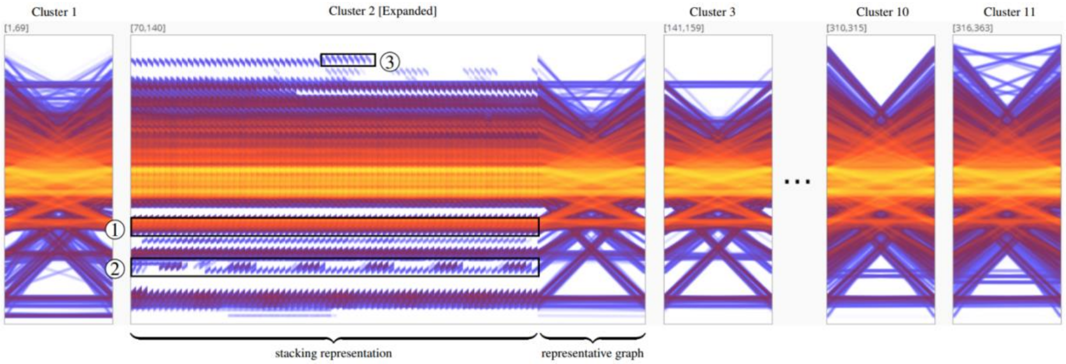
Overview

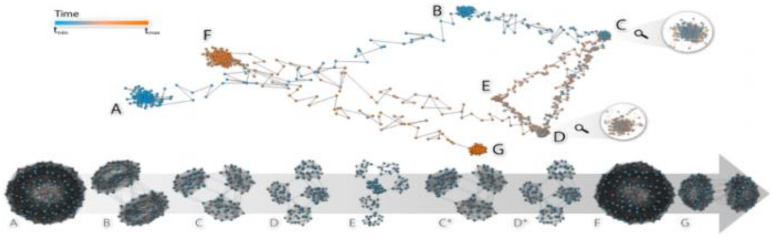
- Dynamic graph data
- Time-scalable overview
  - Temporal patterns
  - Temporal phases
  - Structural information



A dynamic graph visualization depicting the US domestic flight dataset

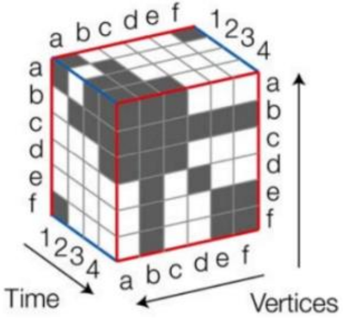
Related Work

- Reducing graphs to points
- Graphs are considered points in high-dimensional space
- Scalability concerns w.r.t. graph size and number of time steps
- Harder to interpret the resulting dimensions

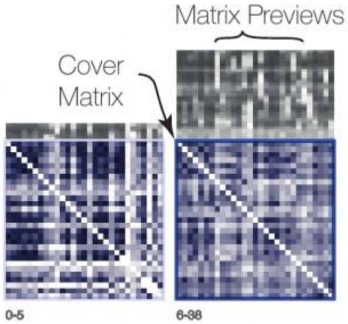


Reducing Snapshots to Points
Van den Elzen et al. [vdEHBvW16]

- Adjacency matrices
- Cubix
- Small MultiPiles
- Hard to use [GFC05] in long and dense dynamic graphs.



Cubix
Bach et al. [BPF14]

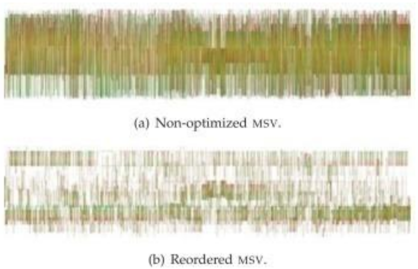


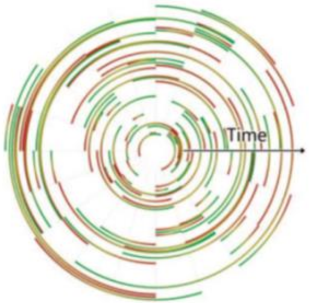
MultiPiles
Bach et al. [BHRD∗15]

[GFC05] GHONIEM M., FEKETE J., CASTAGLIOLA P.: On the readability of graphs using node-link and matrix-based representations: a controlled experiment and statistical analysis. *Information Visualization 4*, 2 (2005), 114–135. 2

Related Work

- Extended Massive Sequence View (MSV)
- Support different clustering and reordering techniques
- Circular MSV needs much screen space & introduces bias
- Temporal clustering not supported

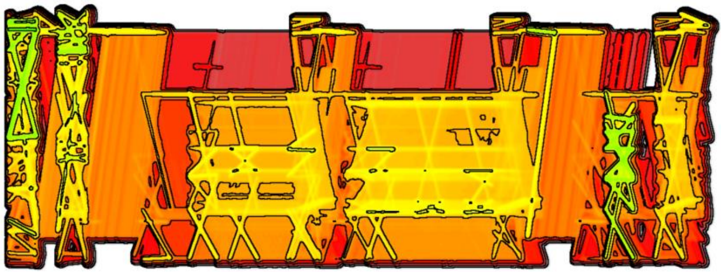




Circular MSV
Van den Elzen et al. [vdEHBvW13]

➢ Visualizing a Sequence of a Thousand Graphs

- Pushing the individual graphs together by an interleaving them
- Time-scalable but suffers from over-drawing problems



Visualizing a Sequence of a Thousand Graphs
Burch et al. [BHW17]

Contributions

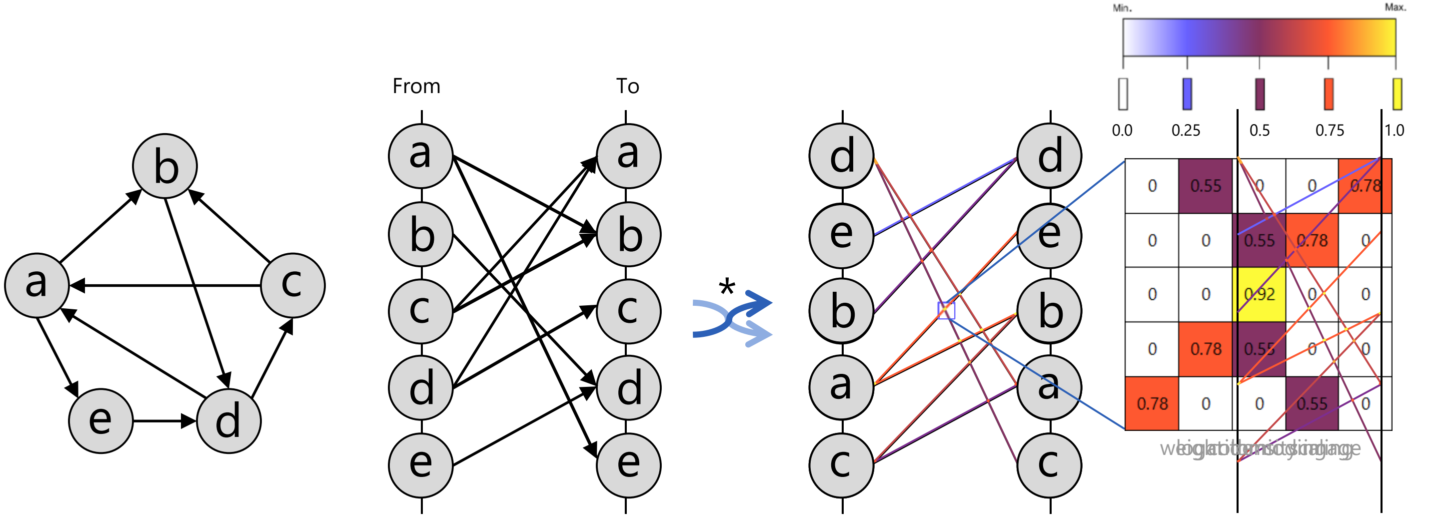
1) Introducing the *stacked edge splatting* representation
   - To avoid the over-drawing problems of the interleaving method -> uncover temporal patterns

2) Applying sequential temporal clustering
   - To identify temporal phases

Visualization Technique

Time	From	To	Weight
1	a	b	5
1	b	d	2
1	d	c	3
1	c	b	4
1	d	a	4
1	c	a	2
1	a	e	6
1	e	d	1
2	…	…	…

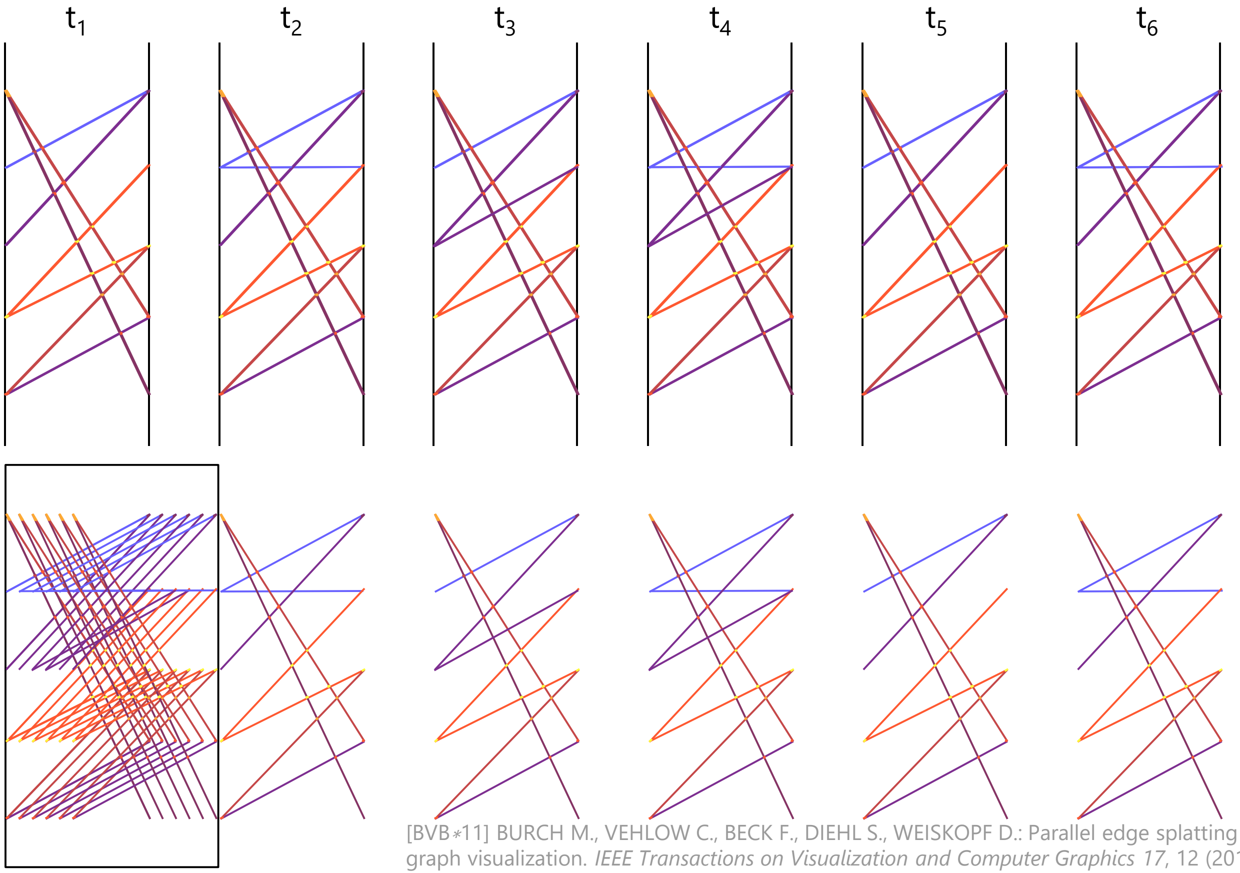
(a) Dataset



(b) Node-link diagram (c) Bipartite graph layout (d) Ordered bipartite graph layout (e) Parallel edge splatting [BVB*11]

* Vertices are hierarchically clustered and then reordered by computing Jaccard similarities

[BVB∗11] BURCH M., VEHLOW C., BECK F., DIEHL S., WEISKOPF D.: Parallel edge splatting for scalable dynamic graph visualization. *IEEE Transactions on Visualization and Computer Graphics 17*, 12 (2011), 2344–2353. 2, 3

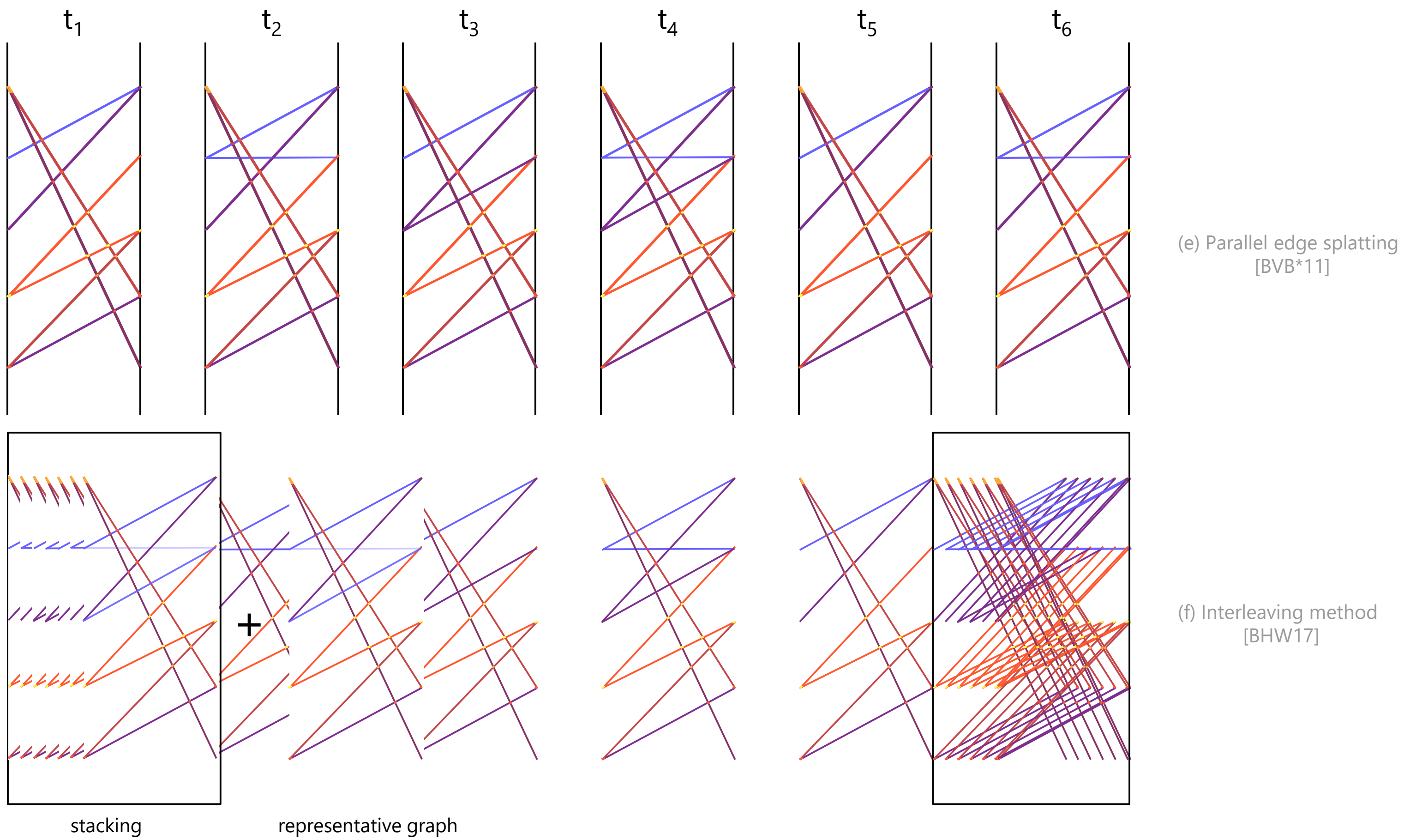


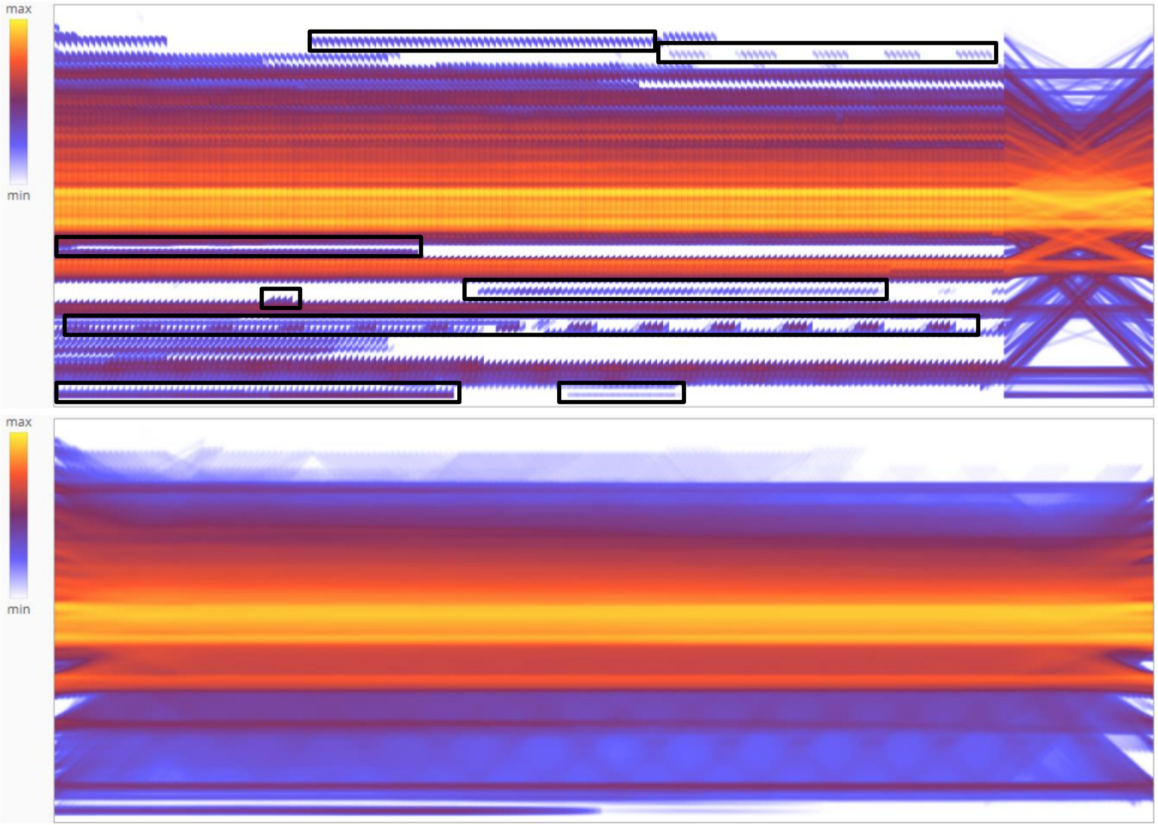
(e) Parallel edge splatting [BVB*11]

(f) Interleaving method [BHW17]

[BVB∗11] BURCH M., VEHLOW C., BECK F., DIEHL S., WEISKOPF D.: Parallel edge splatting for scalable dynamic graph visualization. *IEEE Transactions on Visualization and Computer Graphics 17*, 12 (2011), 2344–2353. 2, 3

[BHW17] BURCH M., HLAWATSCH M., WEISKOPF D.: Visualizing a sequence of a thousand graphs (or even more). *Computer Graphics Forum 36*, 3 (2017), 261–271. 2, 3


t_1
t_2
t_3
t_4
t_5
t_6
(e) Parallel edge splatting
[BVB*11]
(f) Interleaving method
[BHW17]
+
stacking
representative graph



First 159 timepoints of the flight dataset visualized using stacked edge splatting (top) and the interleaving method (bottom). Temporal patterns are more recognizable in the top visualization

Temporal Clustering

- Provides an overview of different temporal phases
- Improves the edge-tracing task
- Clustering is done sequentially by computing the Euclidian distance

d < p

yes / ***no***

t_i is added to the cluster c_j | *a new cluster creates for* t_i

d**:** euclidian distance between ***m*****(*****t*****$_i$)** and ***m*****(*****c*****$_j$)**

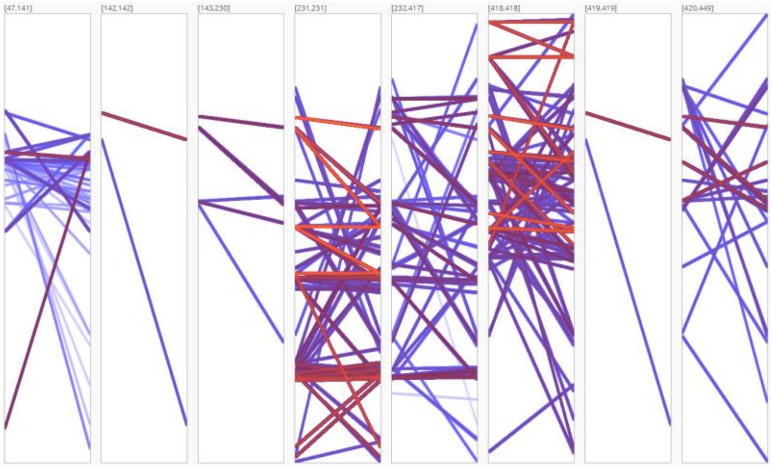
m**(*****t*****$_i$):** adjacency matrix for the current timepoint t_i

m**(*****c*****$_j$):** adjacency matrix for the aggregated timepoint of the current cluster c_j

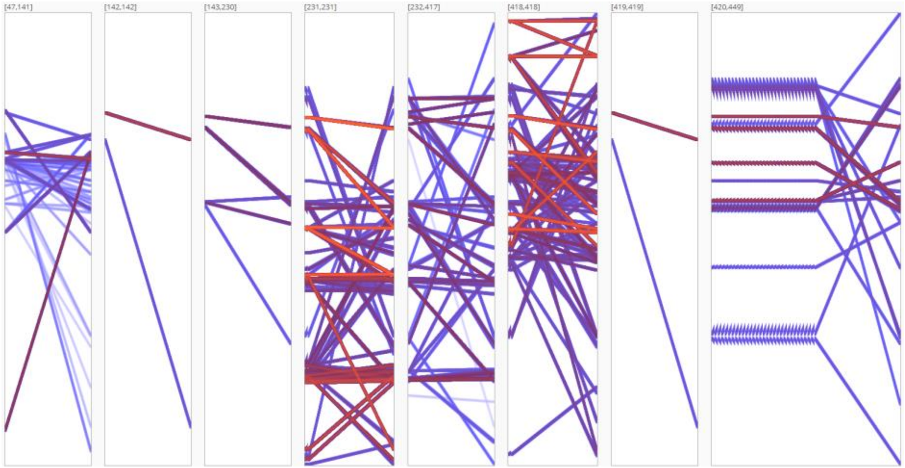
p**:** *given threshold*

Temporal Clustering

- *collapsed view -> structural overview*
- *expanded view -> temporal details*



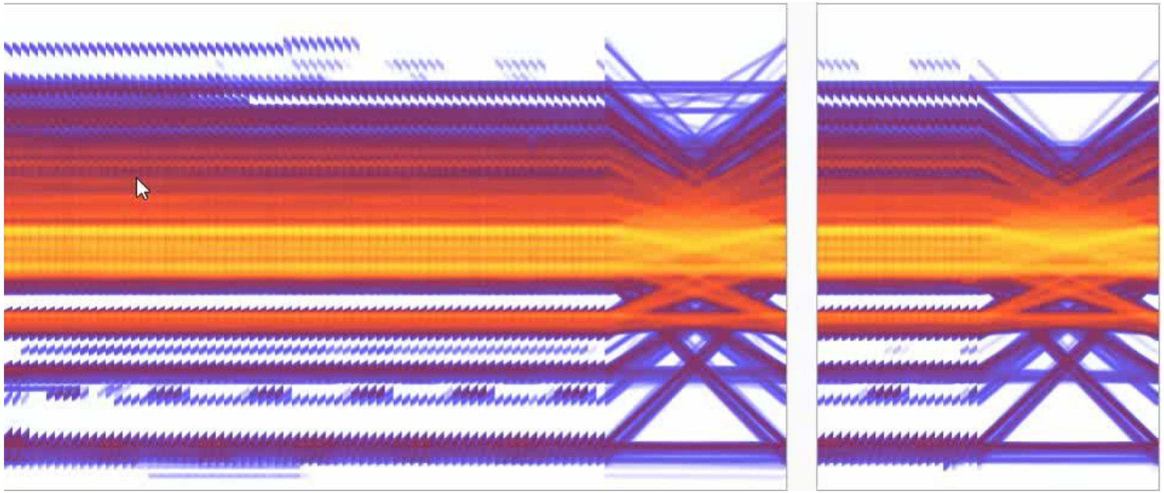
Default view, all clusters are collapsed



The last cluster is expanded

When graphs are very dense

- Timepoint-expanding
- Edge-highlighting



Interaction techniques

Application Example

- US domestic flight traffic dataset [Uni18]
- 30 years starting from October 1st, 1987, to December 31st, 2017
- The data is aggregated on a per-month basis
- 402 vertices (airports)
- ~1 million weighted edges (flight connections)
- 363 timepoints (graphs per month)

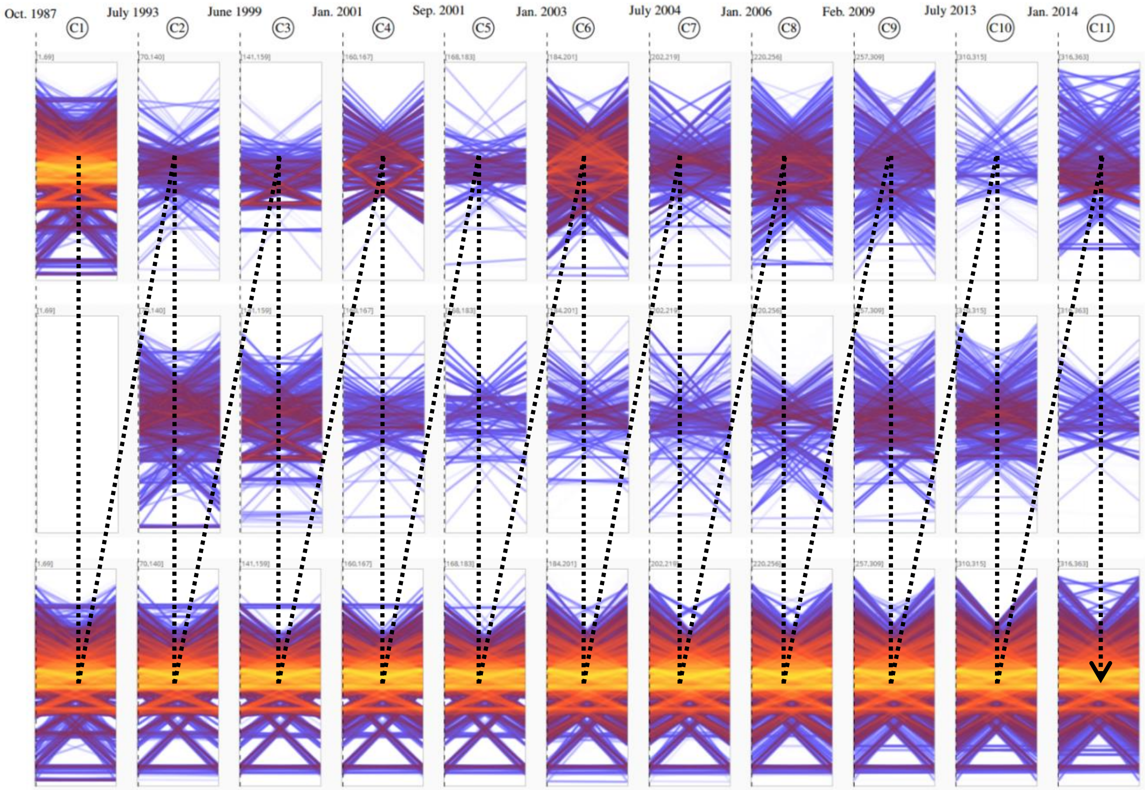
[Uni18] UNITED STATES DEPARTMENT OF TRANSPORTATION: OnTime Performance. https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time, 2018. (Accessed on 03/22/2018). 2, 4

Identifying temporal phases

Clusters’ added links

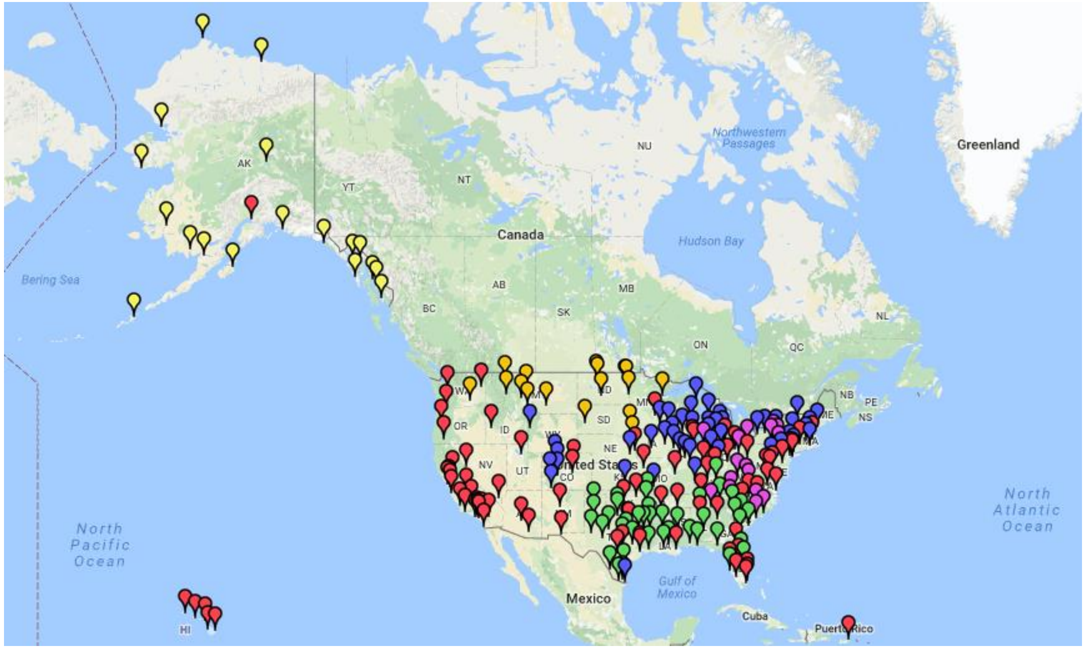
Clusters’ deleted links

Clusters’ representative graphs

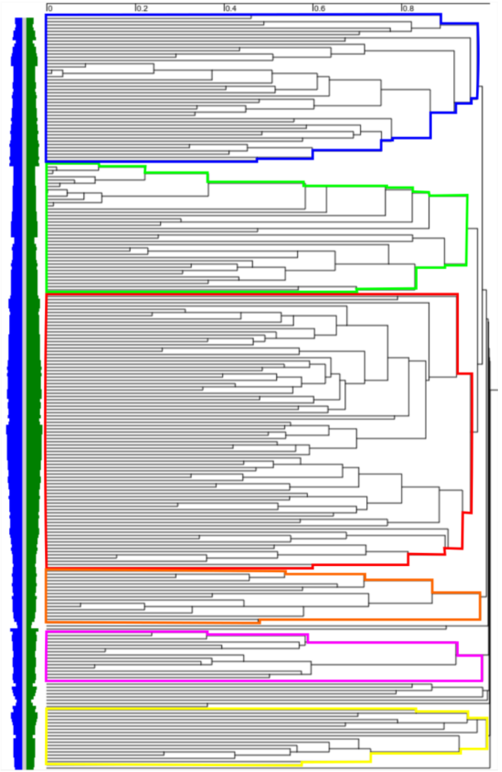


Sequentially clustering the flight dataset at a threshold of 1.1, resulting in 11 clusters

Geographical Context

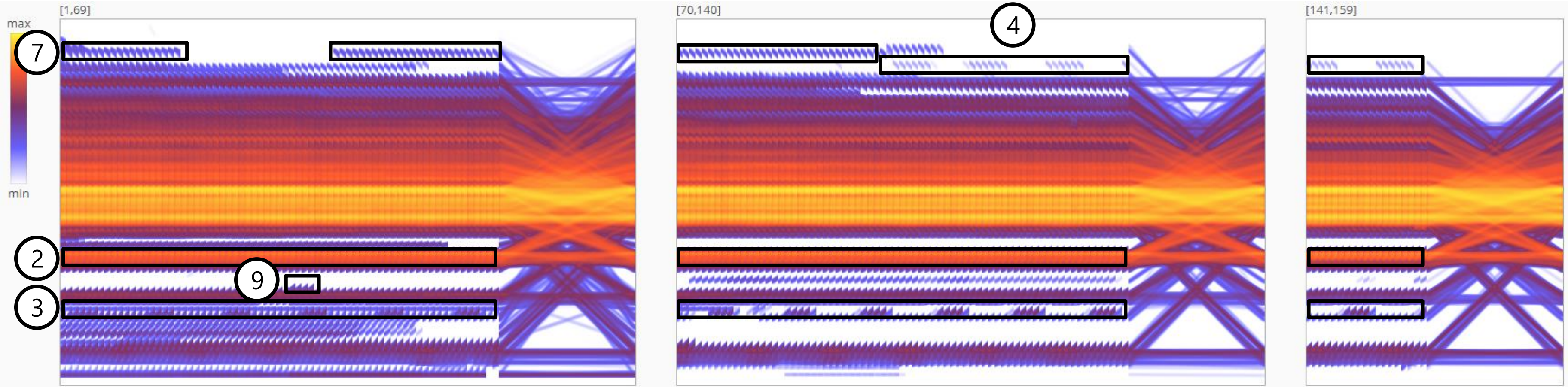


Vertex-clusters visualized on the map of the United States



Dendrogram of the vertex-clusters hierarchies

Identifying temporal patterns



2 Stability

3 4 Periodicity

7 Shift

9 Anomalies

Conclusion

- A time-scalable approach for visualizing dynamic graphs
- The stacking representation
  - To uncover temporal patterns
  - To achieve time-scalability
- Temporal clustering
  - To identify temporal phases
  - To improves the edge-tracing task
- For future work
  - Other heuristics for temporal clustering
  - Further evaluation

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Thanks ☺

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References

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- [BHW17] BURCH M., HLAWATSCH M., WEISKOPF D.: Visualizing a sequence of a thousand graphs (or even more). *Computer Graphics Forum 36*, 3 (2017), 261–271. 2, 3
- [vdEHBvW16] VAN DEN ELZEN S., HOLTEN D., BLAAS J., VAN WIJK J. J.: Reducing snapshots to points: A visual analytics approach to dynamic network exploration. *IEEE Transactions on Visualization and Computer Graphics 22*, 1 (2016), 1–10. 2
- [vdEHBvW13] VAN DEN ELZEN S., HOLTEN D., BLAAS J., VAN WIJK J. J.: Reordering massive sequence views: Enabling temporal and structural analysis of dynamic networks. In *Proceedings of IEEE Pacific Visualization Symposium* (2013), pp. 33–40. 2
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- [BHRD*15] BACH B., HENRY-RICHE N., DWYER T., MADHYASTHA T., FEKETE J.-D., GRABOWSKI T.: Small MultiPiles: piling time to explore temporal patterns in dynamic networks. *Computer Graphics Forum 34*, 3 (2015), 31–40. 4

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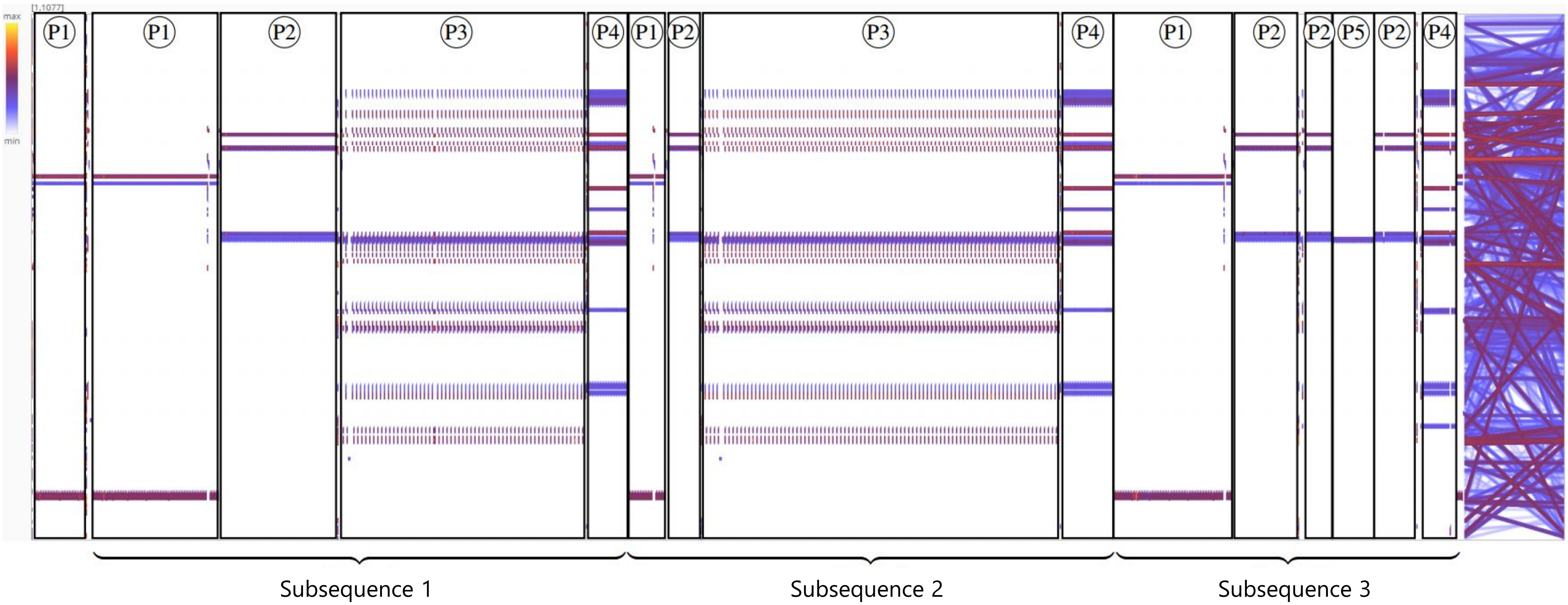
- [BPF14] BACH B., PIETRIGA E., FEKETE J.: Visualizing dynamic networks with matrix cubes. In *Proceedings of Conference on Human Factors in Computing Systems* (2014), pp. 877–886. 2
- [Uni18] UNITED STATES DEPARTMENT OF TRANSPORTATION: OnTime Performance. https://www.transtats.bts.gov/DL_SelectFields.asp?Table_ID=236&DB_Short_Name=On-Time, 2018. (Accessed on 03/22/2018). 2, 4
- [JHo18] JHotDraw Start Page. http://www.jhotdraw.org/, 2018. (Accessed on 03/22/2018). 2, 4

Application Example (2)

- The software call graph dataset [JHo18]
- 787 vertices (software functions)
- 25,906 weighted edges (call relations)
- 1,077 timepoints

[JHo18] JHotDraw Start Page. http://www.jhotdraw.org/, 2018. (Accessed on 03/22/2018). 2, 4

Identifying temporal patterns



Investigating subsequences

P: pattern (cluster)
T: transition (single timepoint)

Subsequence 1 [47 – 449]

Subsequence 2 [450 – 812]

Subsequence 3 [813 – 1071]