Back to the Graphs: A Collection of Datasets and Quality Criteria for Temporal Networks Layout and Visualization

Velitchko Filipov[1] Alessio Arleo[1] Tatiana von Landesberger[2] Daniel Archambault[3]

Problem Statement:

As the dynamic network visualization discipline evolves, different time abstractions are introduced:

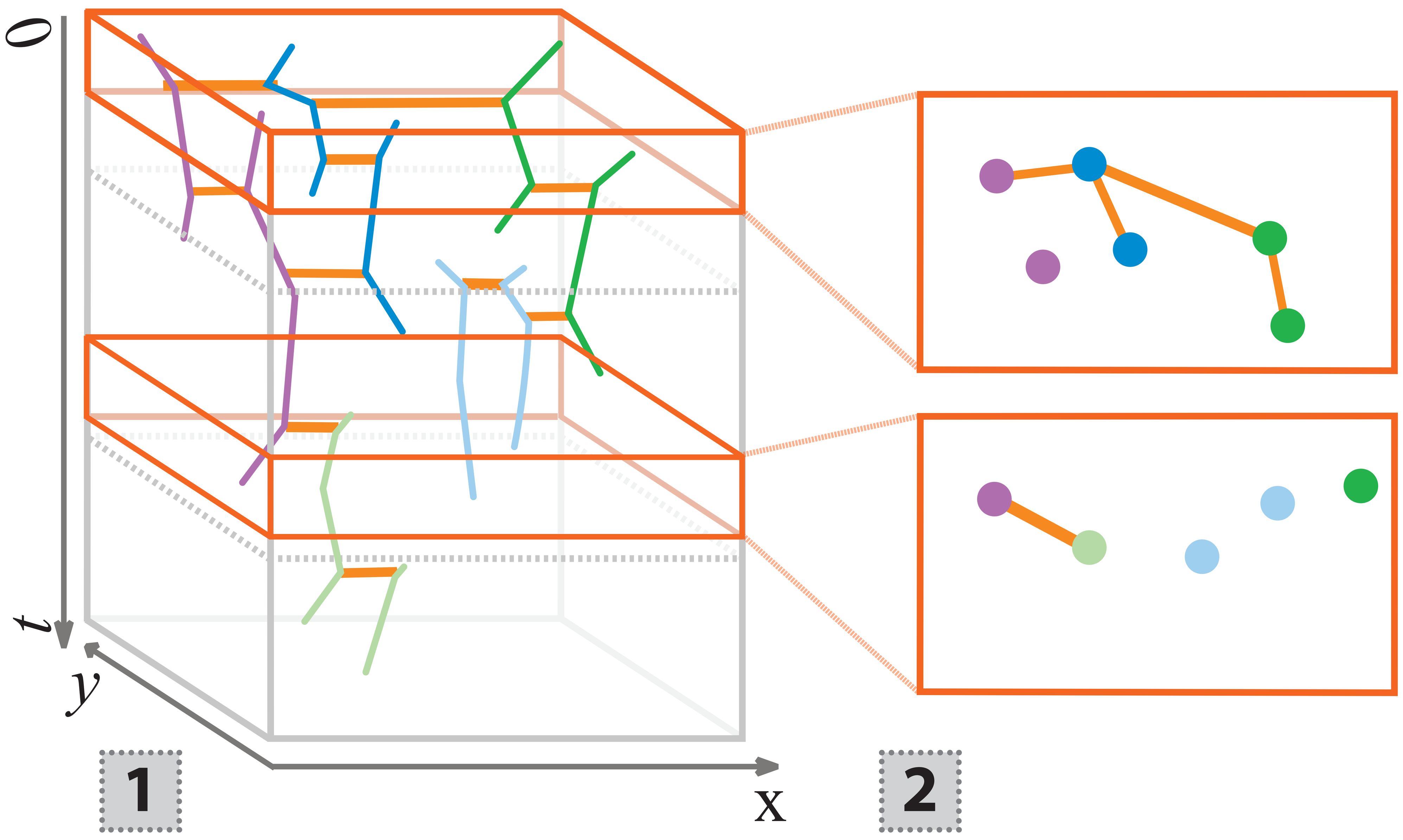
[1] Temporal Networks model the dynamics of nodes and edges (e.g., addition/deletion) as events with real time coordinates and duration.

[2] Timesliced Networks model snapshots of the graph at equally spaced, discrete moments in time (the timeslices)

Quality criteria and benchmark datasets are lacking to enable comparative evaluations of different dynamic network visualization techniques.

We propose quality criteria for evaluating timesliced and temporal dynamic graph layouts.

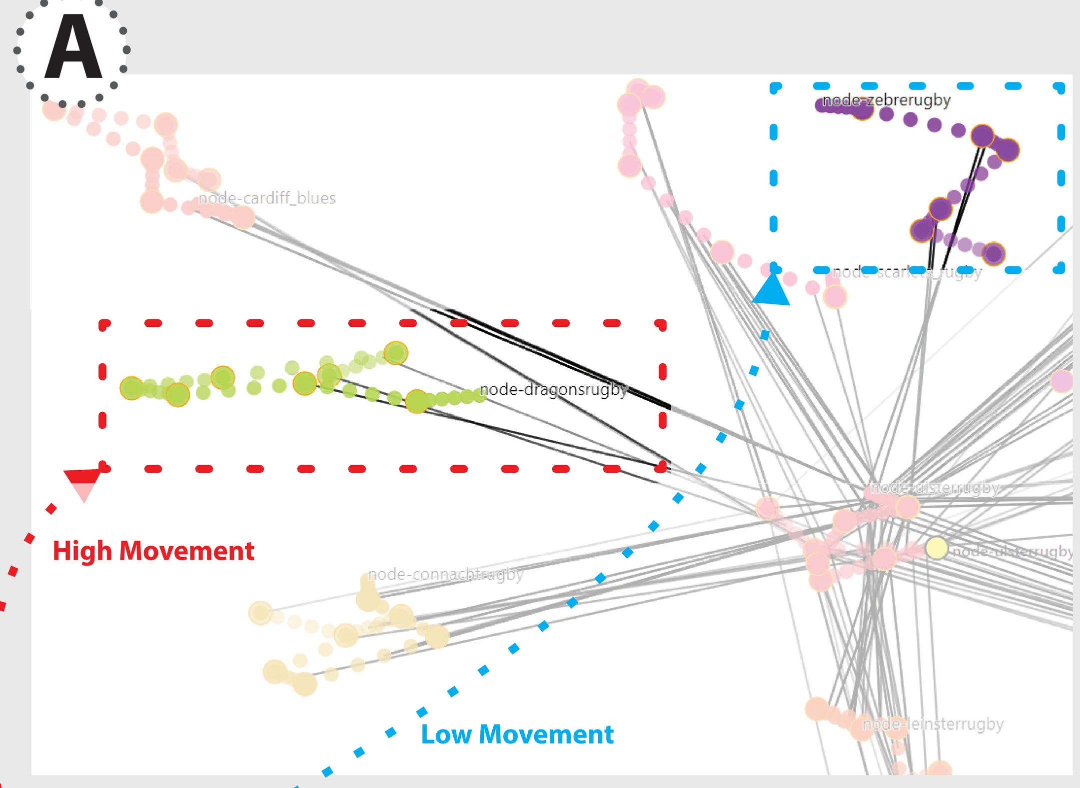
We also present real world datasets included as benchmark sets for future researchers to use in their evaluations.



Quality Criteria:

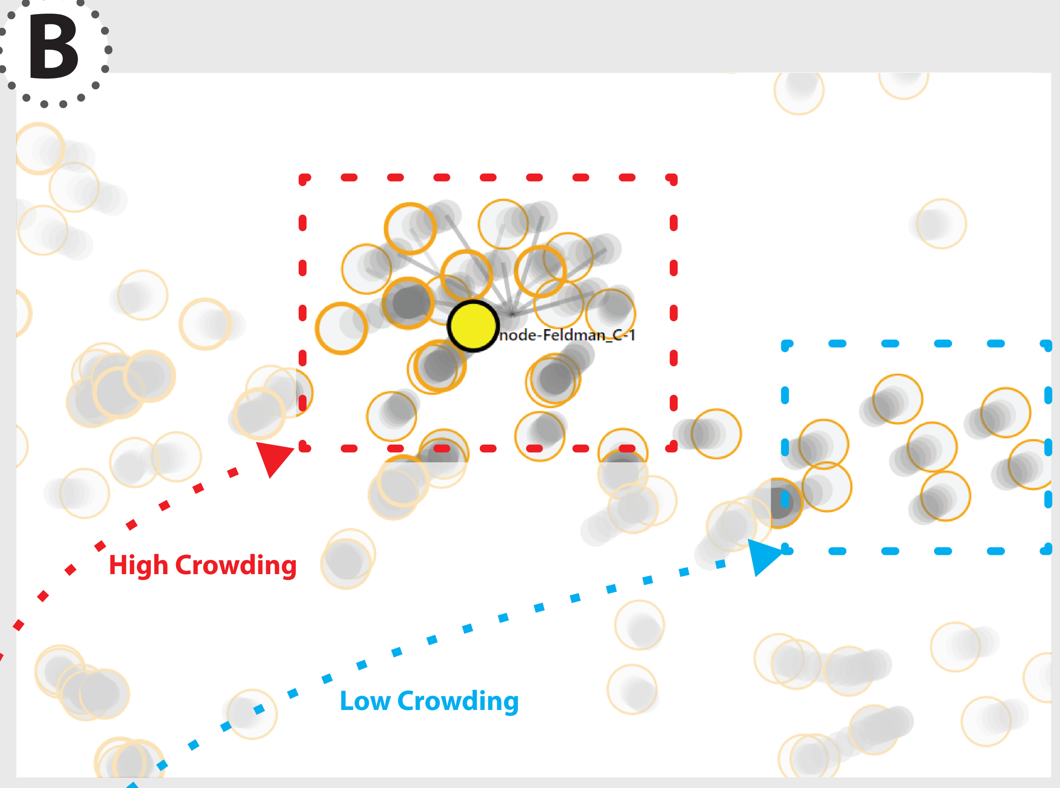
Figures by Velitchko Filipov, Davide Ceneda, Daniel Archambault, and Alessio Arleo "TimeLighting: Guidance-enhanced Exploration of 2D Projections of Temporal Graphs" Proceedings of 2023 International Symposium on Graph Drawing and Network Visualization

A



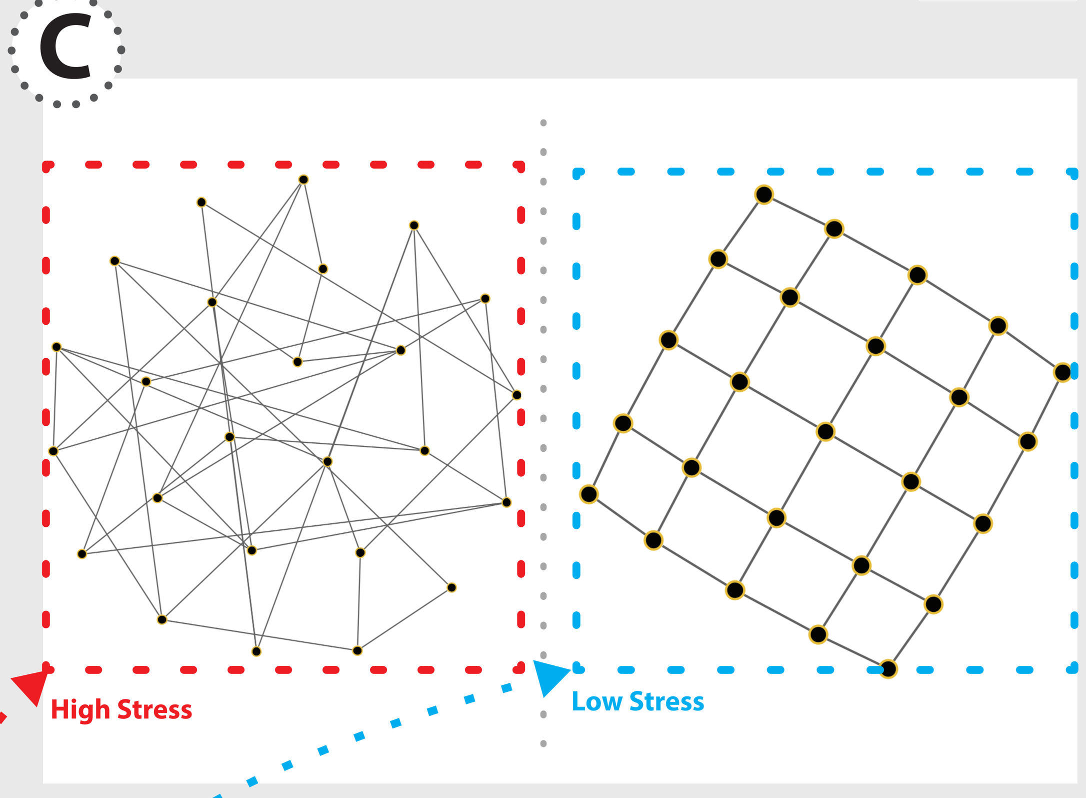
(A) Node Movement tracks the average distance traveled by a node during the graph's evolution. This metric is related to layout stability which is required to support the cognitive map of the viewer.

B



(B) Crowding counts the times a node passes close to another one during the evolution. This means that nodes could be confused.
Low crowding means that nodes are easily distinguishable.
High crowding indicates that it could be hard to follow the node through network's evolution.

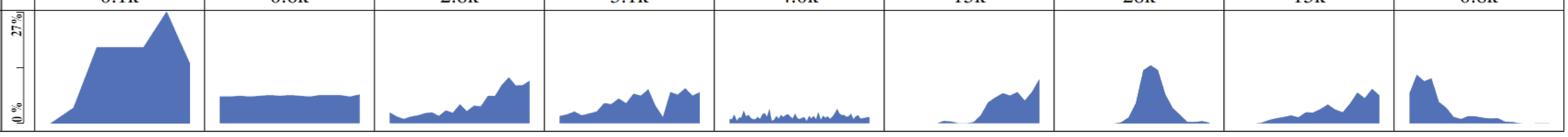
C



(C) Stress measures the difference between the Euclidean and graph theoretic distance in the drawing.
It has been used to evaluate dynamic graph drawings. We identify two methods for computing stress:
(i) Timesliced Stress and
(ii) Continuous Stress.

Datasets:

Dataset Name	Van Debunt	Newcomb	InfoVis	Rugby	Pride	MOOC	RM	MSG	RAMP
Reference	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Dataset Type	Timesliced	Timesliced	Timesliced	Event-based	Event-based	Event-based	Event-based	Event-based	Event-based
# of Events	0.1k	0.6k	2.8k	3.1k	4.0k	15k	28k	15k	0.8k
Events Distribution									



References:

[1] G. G. Van De Bunt, M. A. Van Duijn, and T. A. Snijders. Friendship Networks Through Time: An Actor-Oriented Dynamic Statistical Network Model . Computational & Mathematical Organization Theory, 5(2):167–192, 1999. doi: 10.1023/A:1009683123448

[2] T. M. Newcomb. The acquaintance process as a prototype of human interaction., pp. 259–261.

[3] P. Isenberg, F. Heimerl, S. Koch, T. Isenberg, P. Xu, C. Stolper, M. Sedlmair, J. Chen, T. M oller, and J. Stasko. vispubdata.org: A Metadata Collection about IEEE Visualization (VIS) Publications . IEEE Transactions on Visualization and Computer Graphics, 23, 2017. doi: 10.1109/TVCG.2016.2615308

[4] P. Simonetto, D. Archambault, and S. Kobourov. Event-Based Dynamic Graph Visualisation. IEEE Transactions on Visualization and Computer Graphics, 26(7):2373–2386, 2020.

[5] S. Grayson, K. Wade, G. Meaney, and D. Greene. The Sense and Sensibility of Different Sliding Windows in Constructing Co-occurrence Networks from Literature . In Computational History and Data-Driven Humanities, pp. 65–77, 2016.

[6] S. Kumar, X. Zhang, and J. Leskovec. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, p. 1269–1278, 2019. doi: 10.1145/3292500.3330895 1961. doi: 10.1037/13156-015

[7] N. Eagle and A. (Sandy) Pentland. Reality mining: sensing complex social systems. Personal and Ubiquitous Computing, 10(4):255–268, 2006. doi: 10.1007/s00779-005-0046-3

[8] P. Panzarasa, T. Opsahl, and K. M. Carley. Patterns and dynamics of users' behavior and interaction: Network analysis of an online community . Journal of the American Society for Information Science and Technology, 60(5):911–932, 2009. doi: 10.1002/asi.21015

[9] S. Mohr, L. Matthews, S. Brett, V. Mano, J. Nonweiler, R. Takahashi, and E. Townsend. Contact-tracing-model. See https://github.com/ScottishCovidResponse/Contact-Tracing-Model, 2020.

1 TU WIEN CVAST
2 University of Cologne
3 Newcastle University