

A Novel Ordering Strategy for 1D Pixel Visualization for Dynamic Networks

Bachelor Project Data Analysis and Visualization

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Project Timeline

Introduction



■ First Dashboard

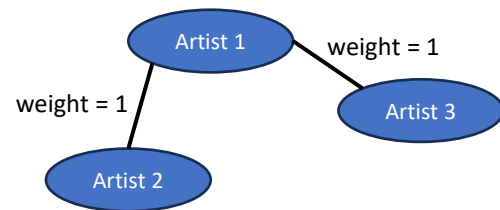
■ Internship at University of Alberta, Canada

■ Decision to switch to Design Study

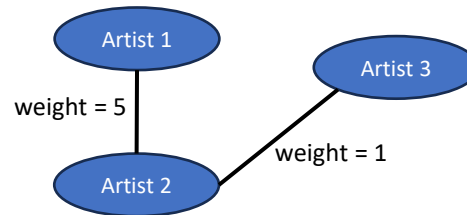
Dynamic Network in Modern Exhibition Data

Introduction

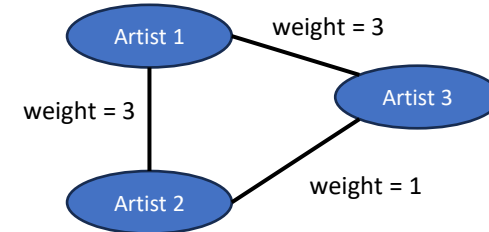
- Artists
- Exhibitions
- Both combined: dynamic network of co-exhibiting artists



t = 1905



t = 1906



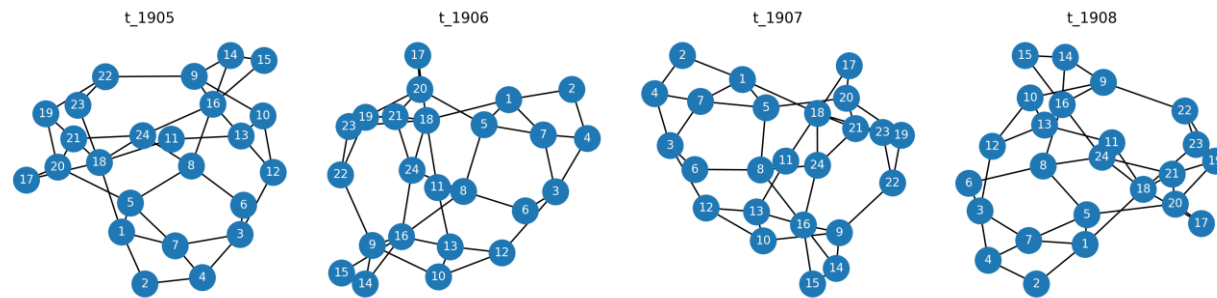
t = 1907

Goal: effectively analyze structural changes in that dynamic network

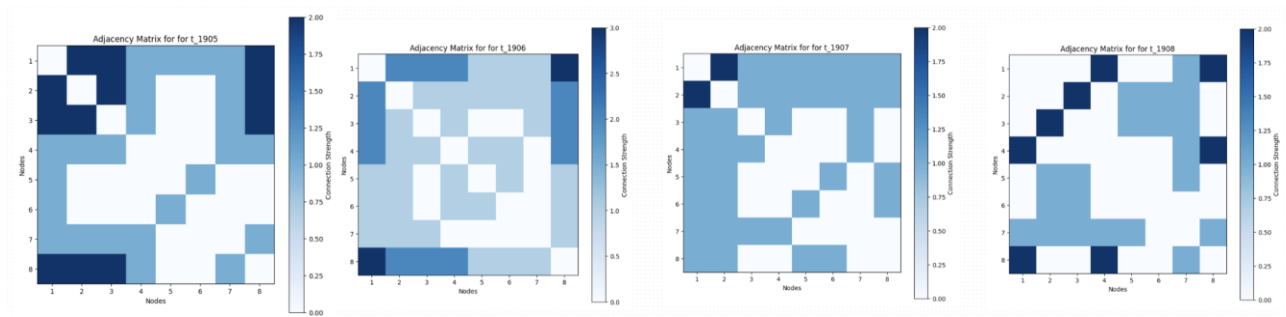
Different Dynamic Network Visualization Techniques

Motivation

- Node-Link Diagrams



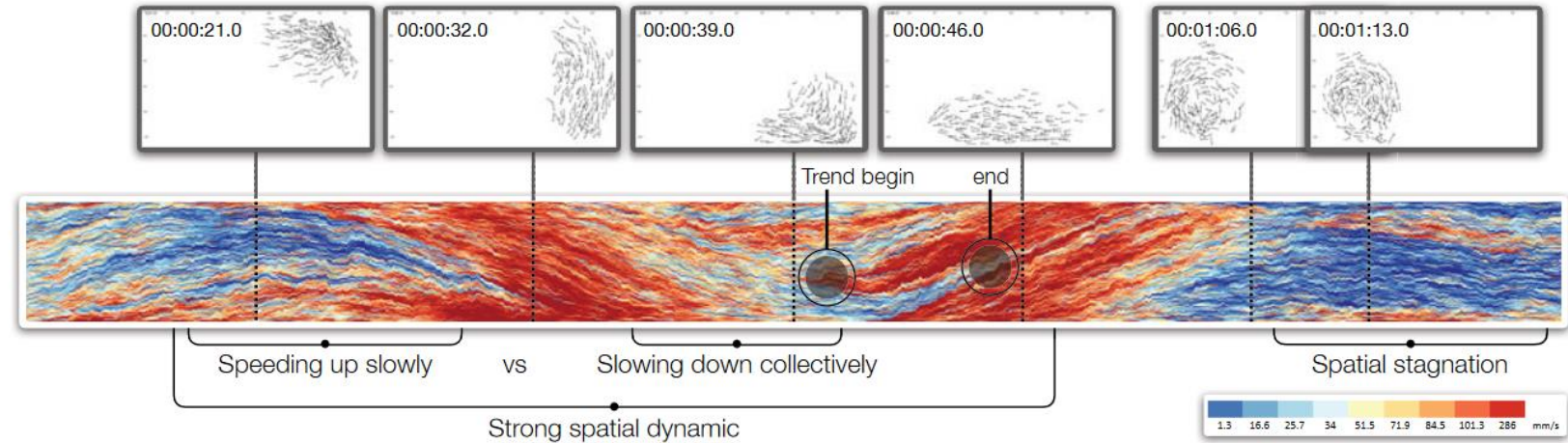
- Adjacency Matrices



Pixel Visualization – Related Work

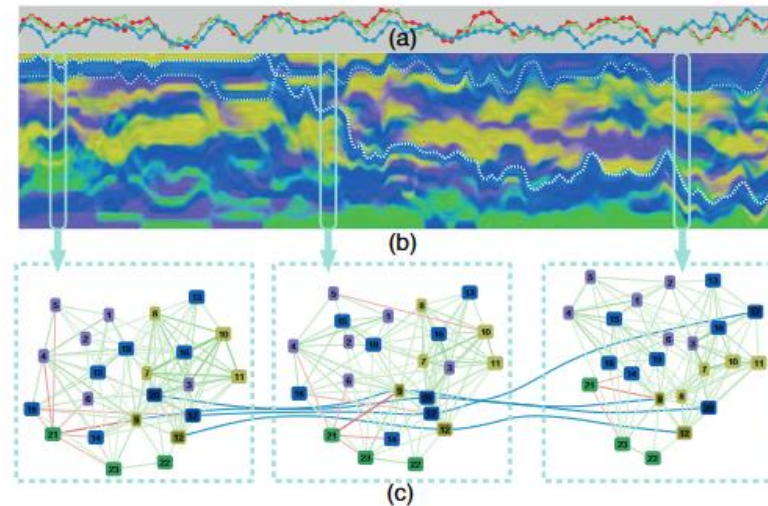
Motivation

- MotionRugs



Buchmüller et al., 2019. MotionRugs: Visualizing Collective Trends in Space and Time.

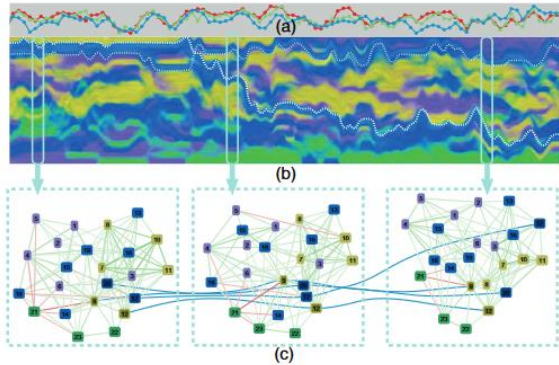
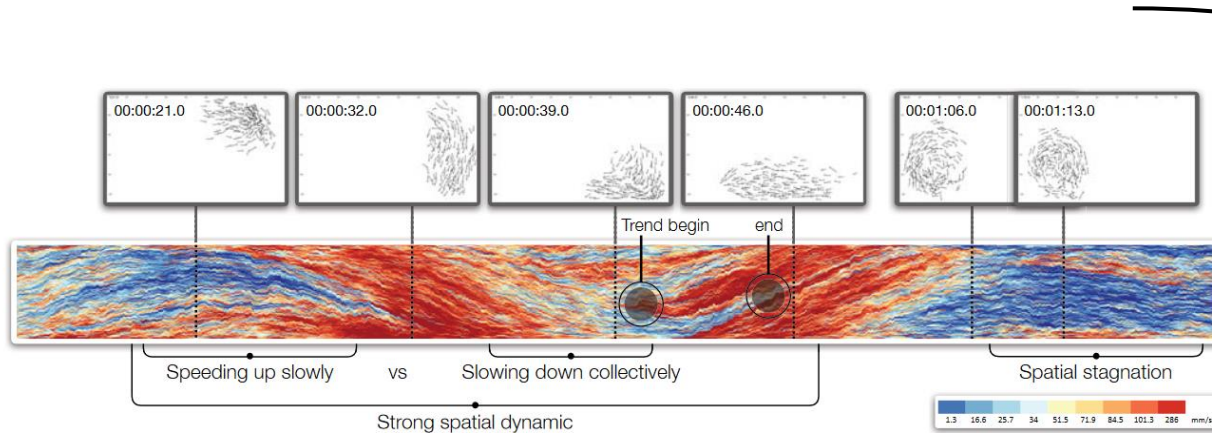
- GraphFlow



Cui et al., 2014. Let It Flow: A Static Method for Exploring Dynamic Graphs.

NetworkRugs - 1D Pixel Displays for Dynamic Networks

Motivation



Network Rugs
= compact visualization of
network changes over time

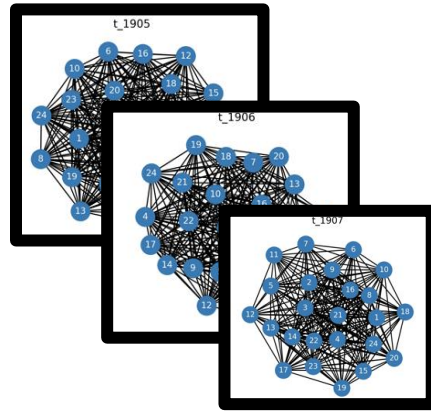
The NetworkRug Technique

Approach

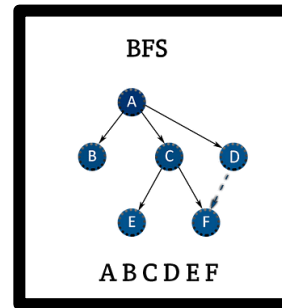
```
data > {} data.json > ...  
1  
2 "t_1905": {  
3   "nodes": [  
4     {  
5       "id": 1,  
6       "name": "Artist 1",  
7       "num_exhibitions": 1  
8     },  
9     {  
10      "id": 5,  
11      "name": "Artist 5",  
12      "num_exhibitions": 1  
13    }  
14  ],  
15  "links": [  
16    {  
17      "source": 1,  
18      "target": 5,  
19      "weight": 1  
20    }  
21  ]  
22 }  
23 }
```

Data

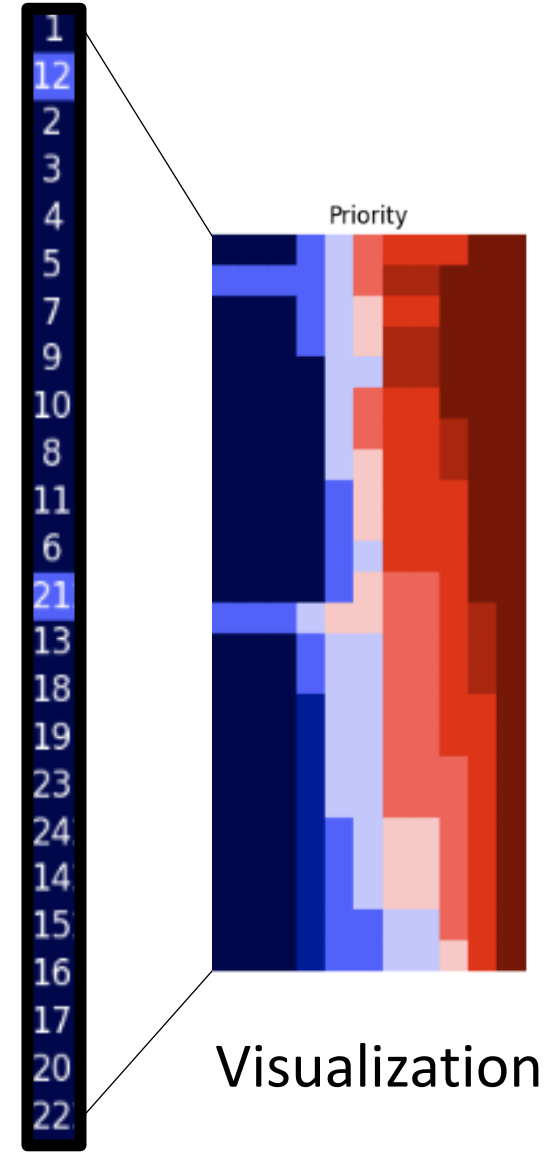
①



Graph Data



1D Ordering

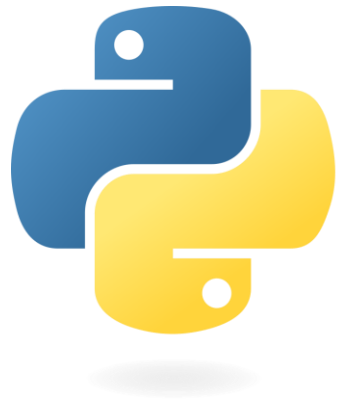


Visualization

① apply graph data structure to each time frame

Project Environment and Tools

Data Structure

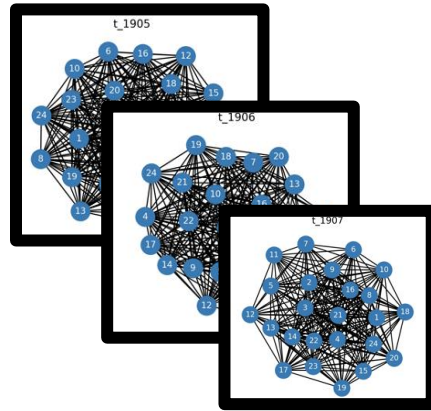


The NetworkRug Technique

Approach

```
data > {} datajson > ...  
1  
2 "t_1985": {  
3   "nodes": [  
4     {  
5       "id": 1,  
6       "name": "Artist 1",  
7       "num_exhibitions": 1  
8     },  
9     {  
10      "id": 5,  
11      "name": "Artist 5",  
12      "num_exhibitions": 1  
13    }  
14  ],  
15  "links": [  
16    {  
17      "source": 1,  
18      "target": 5,  
19      "weight": 1  
20    }  
21  ]  
22 }  
23 }
```

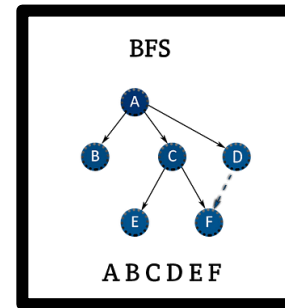
Data



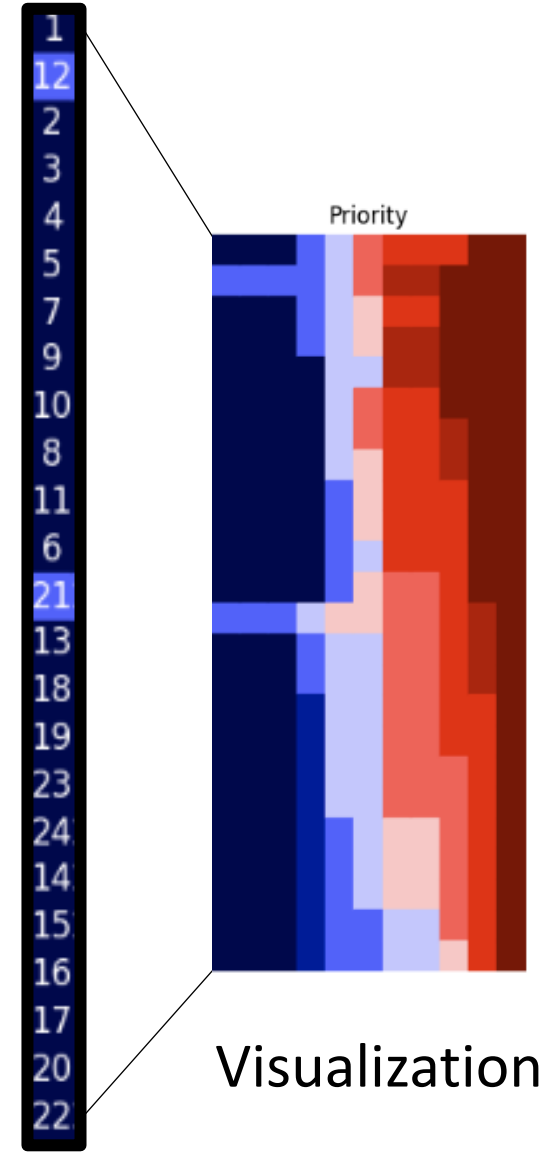
Graph Data



②



1D Ordering



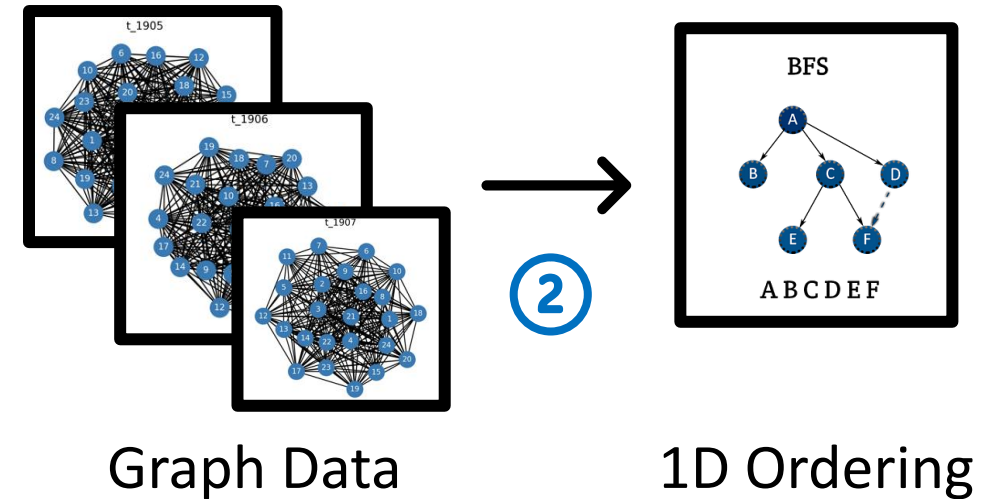
Visualization

② apply ordering strategy per time frame

Overview: Ordering Strategies

Ordering Strategies

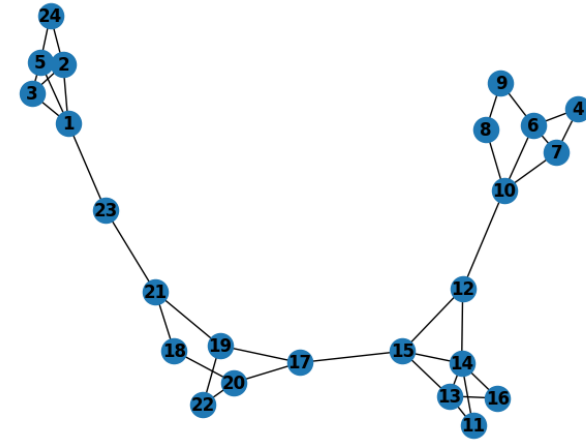
- Goals:
 - Prioritize highly connected nodes
 - Ensure locality
 - Minimize redundant processing
- Different approaches:
 - Community detection-based
 - Linear metrics-based
 - Traversal-based



Community Detection-Based Ordering

Ordering Strategies

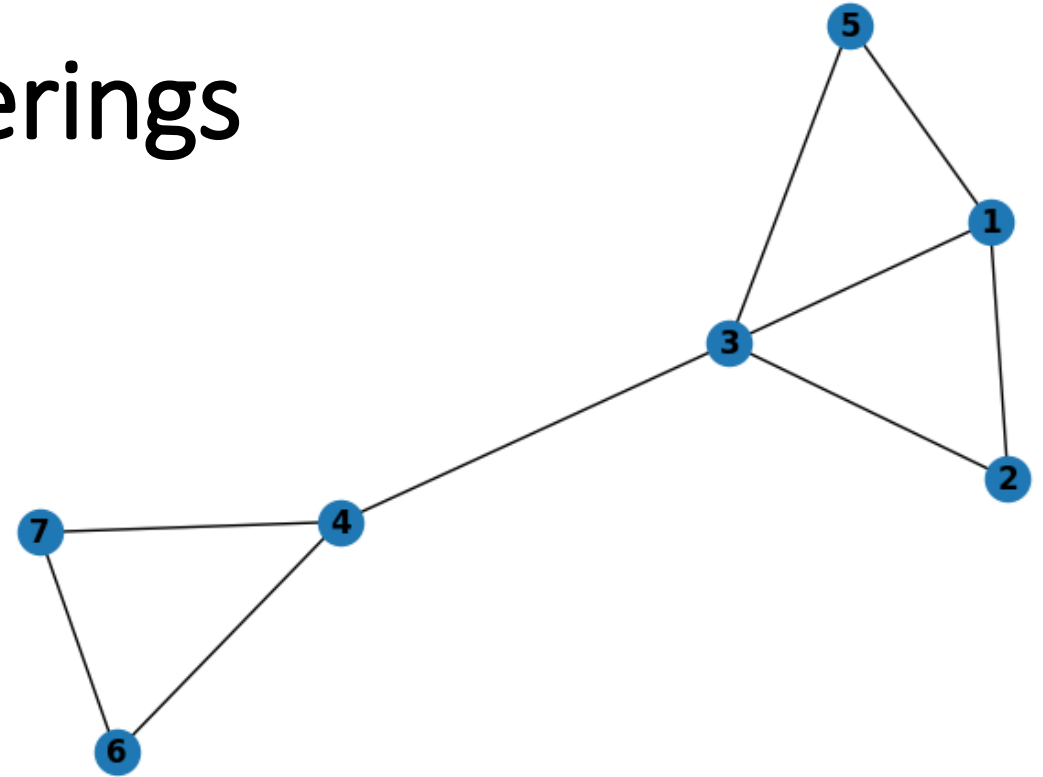
- community detection algorithm to find node groupings
 - Orders nodes by community membership
 - Ensures nodes in same community are grouped together
 - Problems:
 - Non-deterministic, detected communities can be different
 - Produces non-overlapping communities
 - Enforces groups too much, not flexible enough to see change
-
- [1, 2, 3, 5, 24, 17, 18, 19, 20, 21, 22, 23, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]
 - [1, 2, 3, 5, 24, 4, 6, 7, 8, 9, 10, 17, 18, 19, 20, 21, 22, 23, 11, 12, 13, 14, 15, 16]



Linear Metrics-Based Orderings

Ordering Strategies

- Makes usage of graph metrics of a node
 - Degree/ Degree centrality
 - Eigenvector centrality
 - Closeness centrality
 - Betweenness centrality
- Orders nodes based on their value
 - Tie-Breaking Criterion: ID
- degree [3, 1, 4, 2, 5, 6, 7]
- closeness [3, 4, 1, 2, 5, 6, 7]
- betweenness [3, 4, 1, 2, 5, 6, 7]
- eigenvector [3, 1, 2, 5, 4, 6, 7]

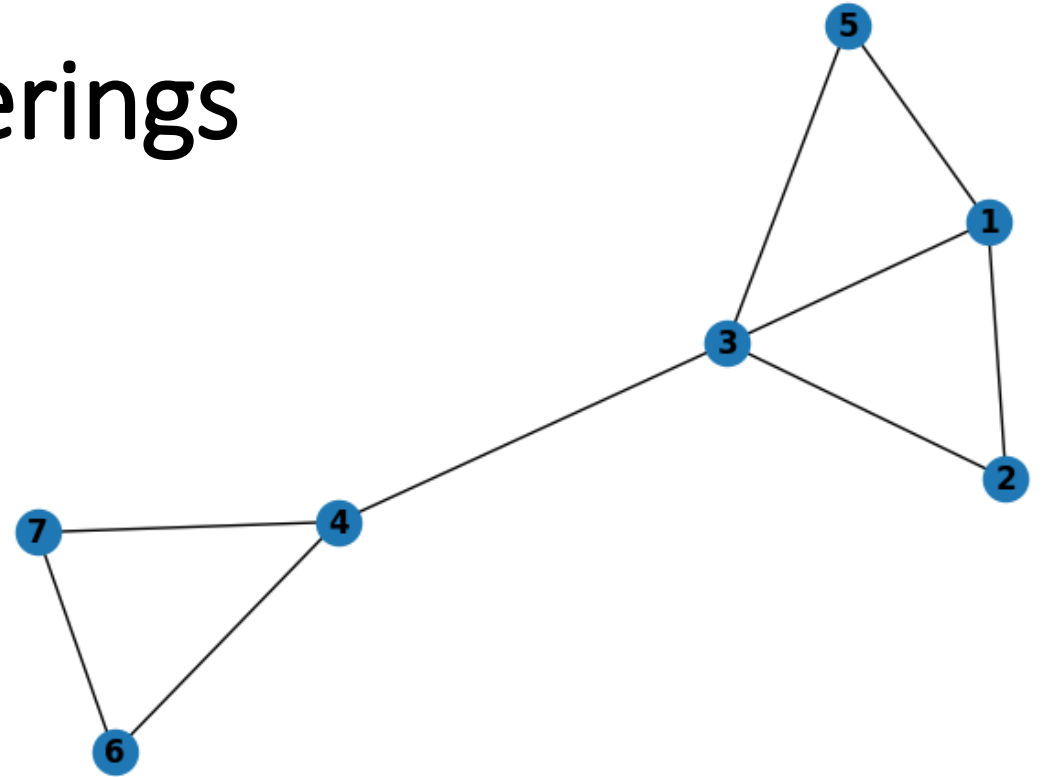


Node	Betweenness	Degree	Degree Centrality	Eigenvector
1	0.033	3	0.5	0.47
2	0.0	2	0.333	0.371
3	0.633	4	0.667	0.56
5	0.0	2	0.333	0.371
4	0.533	3	0.5	0.34
6	0.0	2	0.333	0.192
7	0.0	2	0.333	0.192

Linear Metrics-Based Orderings

Ordering Strategies

- Makes usage of graph metrics of a node
 - Degree/ Degree centrality
 - Eigenvector centrality
 - Closeness centrality
 - Betweenness centrality
- Orders nodes based on their score
 - Tie-Breaking Criterion: ID
- Problems:
 - Breaks up connections between nodes, no locality
 - but possibly good for certain tasks, e.g. to identify most influential artists



Ordering Strategies

-

[1, 2, 3, 5, 24, 23, 21, 18, 20, 17, 15, 12, 10, 6, 4, 7, 9, 8, 14, 11, 13, 16, 19, 22]

Ordering Strategies

-

weight: [1, 2, 3, 5, 23, 24, 21, 18, 19, 20, 17, 22, 15, 12, 13, 14, 10, 11, 16, 6, 7, 8, 4, 9]

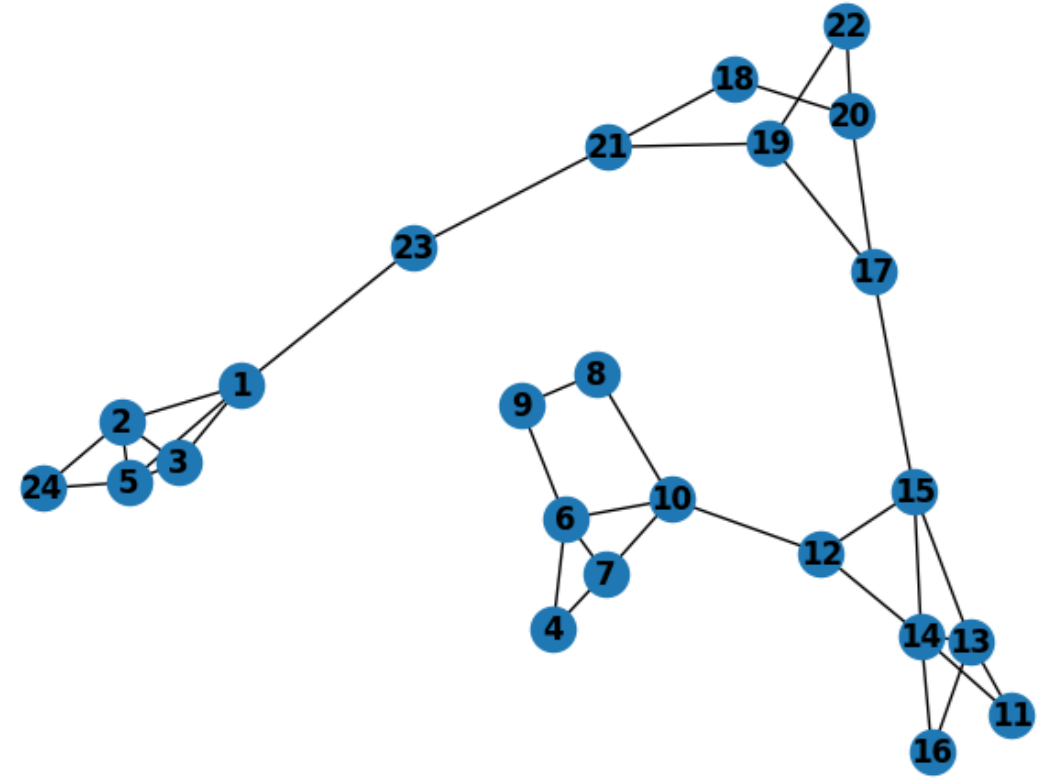
priority:[1, 2, 5, 3, 24, 23, 21, 19, 17, 15, 14, 13, 12, 11, 16, 10, 6, 7, 4, 20, 8, 9, 18, 22]

priority:[1, 2, 5, 3, 24, 23, 21, 19, 17, 15, 14, 13, 12, 11, 16, 10, 6, 7, 4, 20, 8, 9, 18, 22]

Traversal Based-Orderings

Ordering Strategies

- Explores node relationships based on traversal
- Problems:
 - need to specify Start node
 - Artifacts

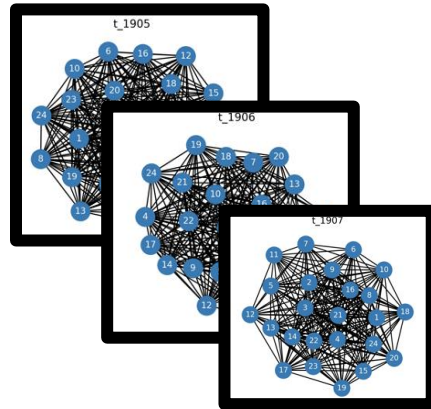


The NetworkRug Technique

Approach

```
data > {} data.json > ...  
1  
2 "t_1905": {  
3   "nodes": [  
4     {  
5       "id": 1,  
6       "name": "Artist 1",  
7       "num_exhibitions": 1  
8     },  
9     {  
10      "id": 5,  
11      "name": "Artist 5",  
12      "num_exhibitions": 1  
13    }  
14  ],  
15  "links": [  
16    {  
17      "source": 1,  
18      "target": 5,  
19      "weight": 1  
20    }  
21  ]  
22 }  
23 }
```

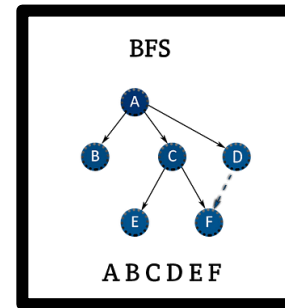
Data



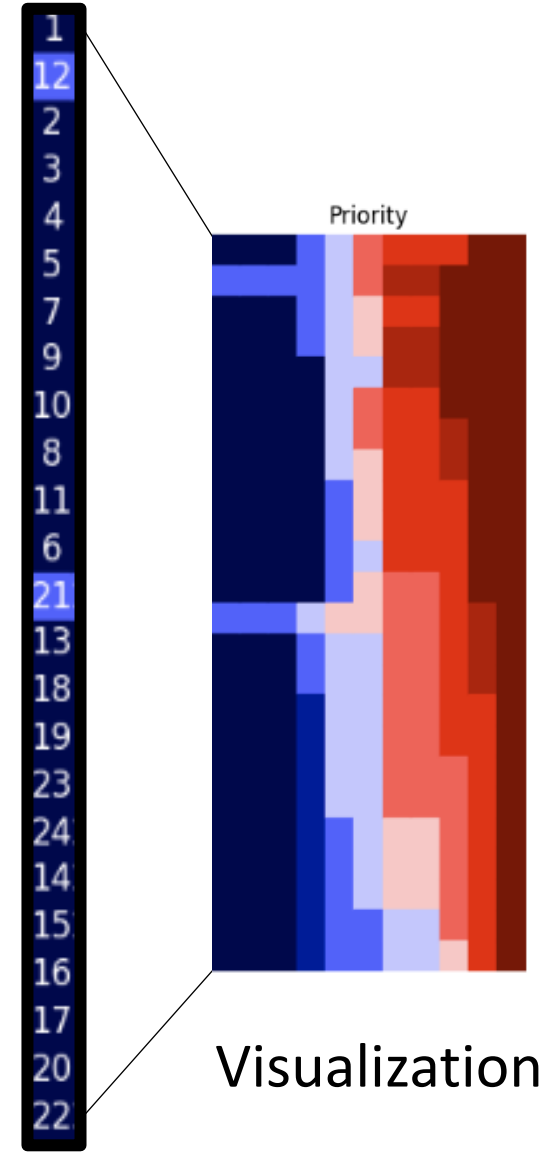
Graph Data



③



1D Ordering



③

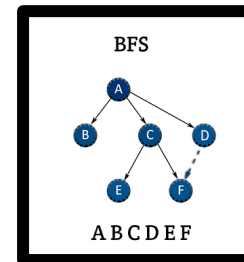
sequential alignment of the slices on temporal axis and visualization

Layout Decisions

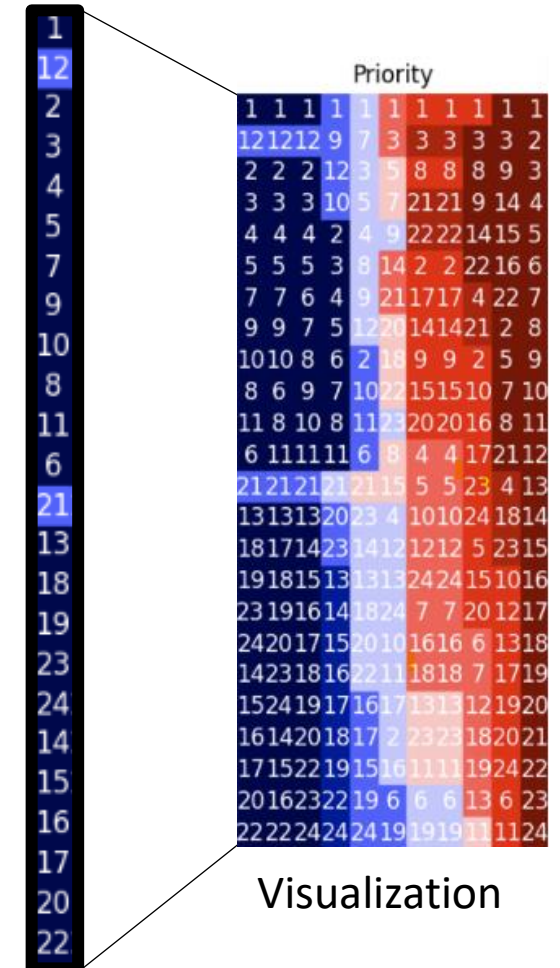
Visualization

- How do we map the ordering to the visualization?

[1, 12, 2, 3, 4, 5, 7, 9, 10, 8, 11, 6, 21, 13, 18, 19, 23, 24, 14, 15, 16, 17, 20, 22]



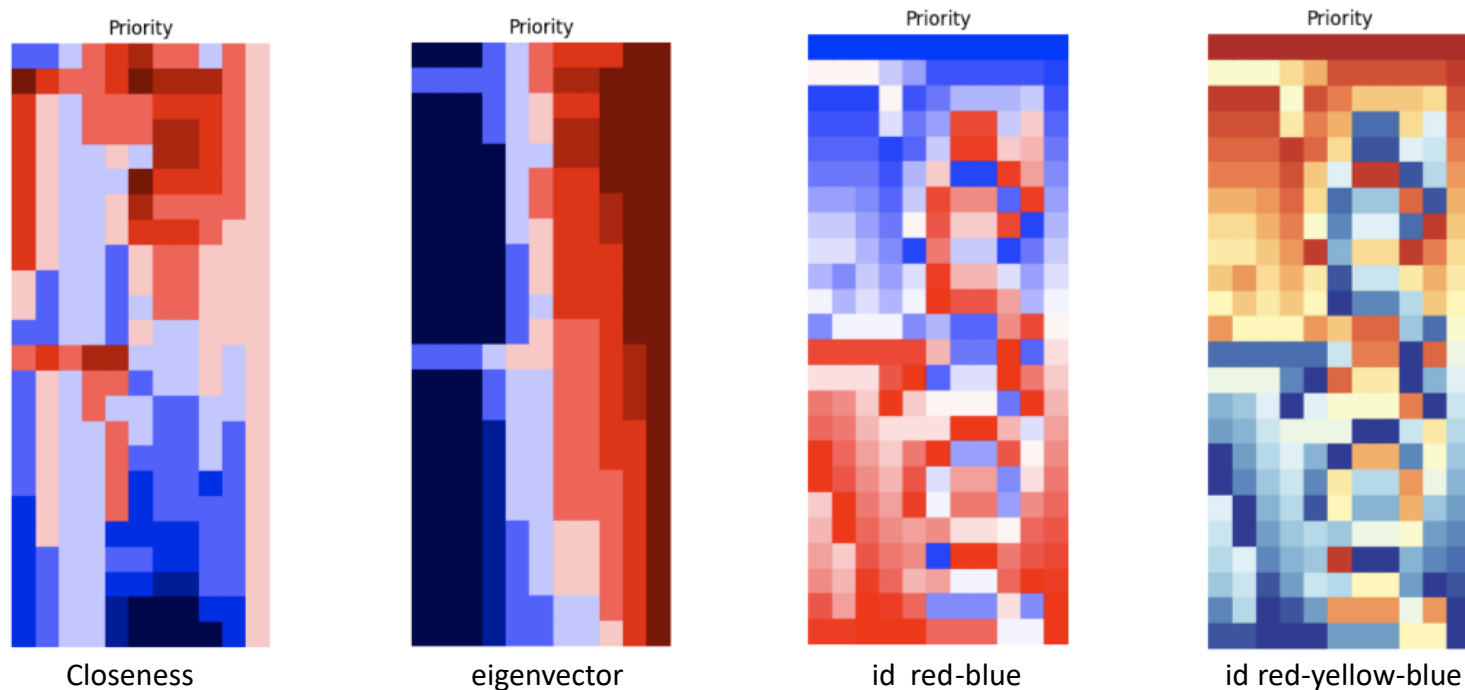
1D Ordering

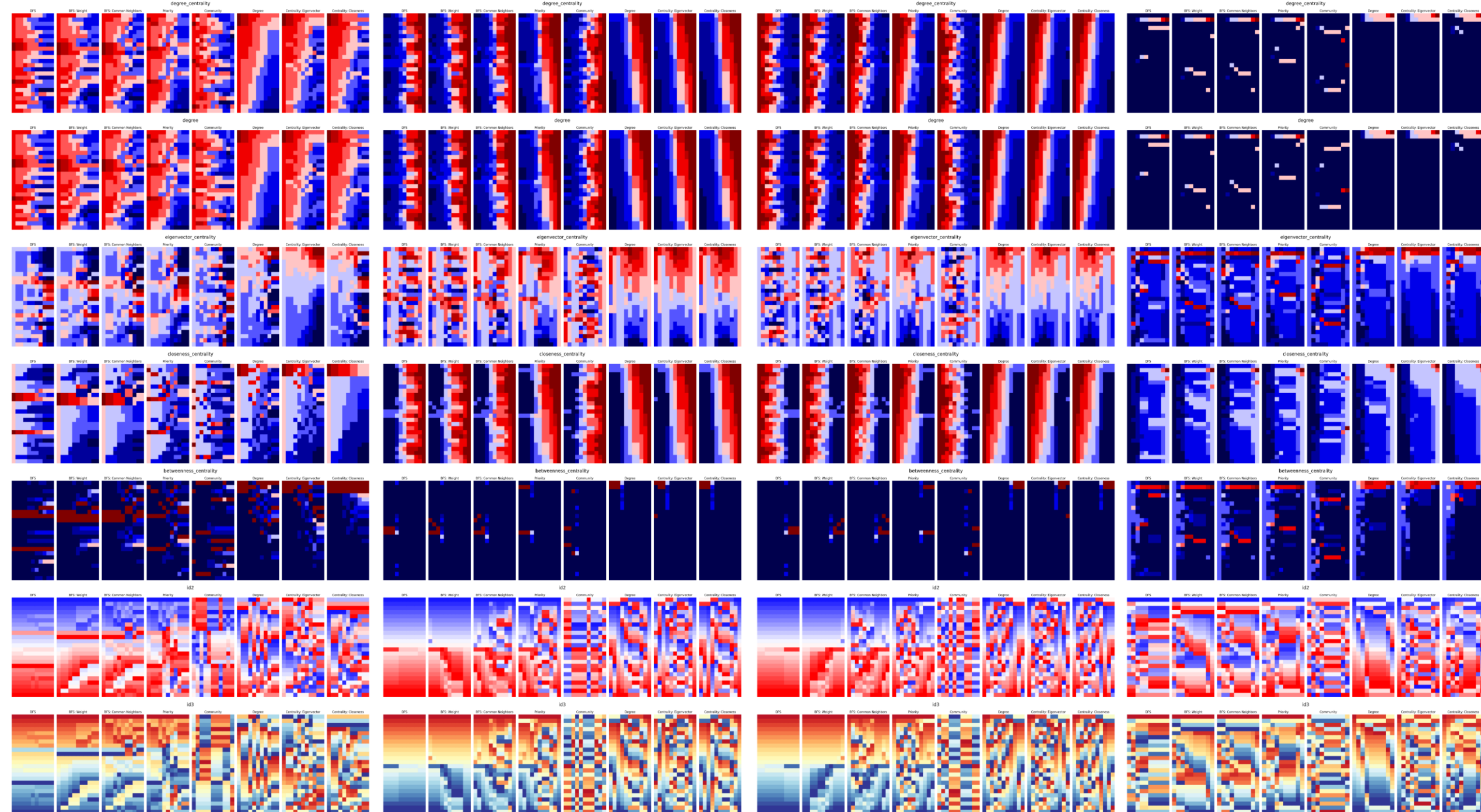


Color Encoding

Visualization

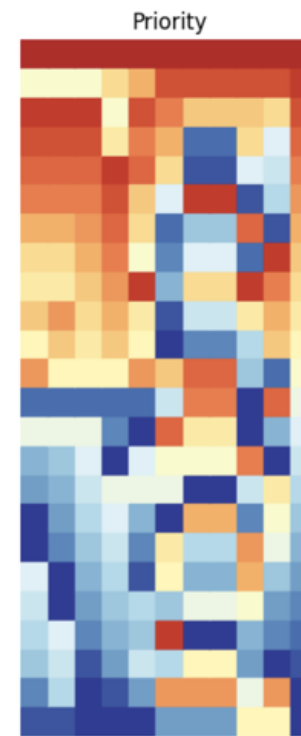
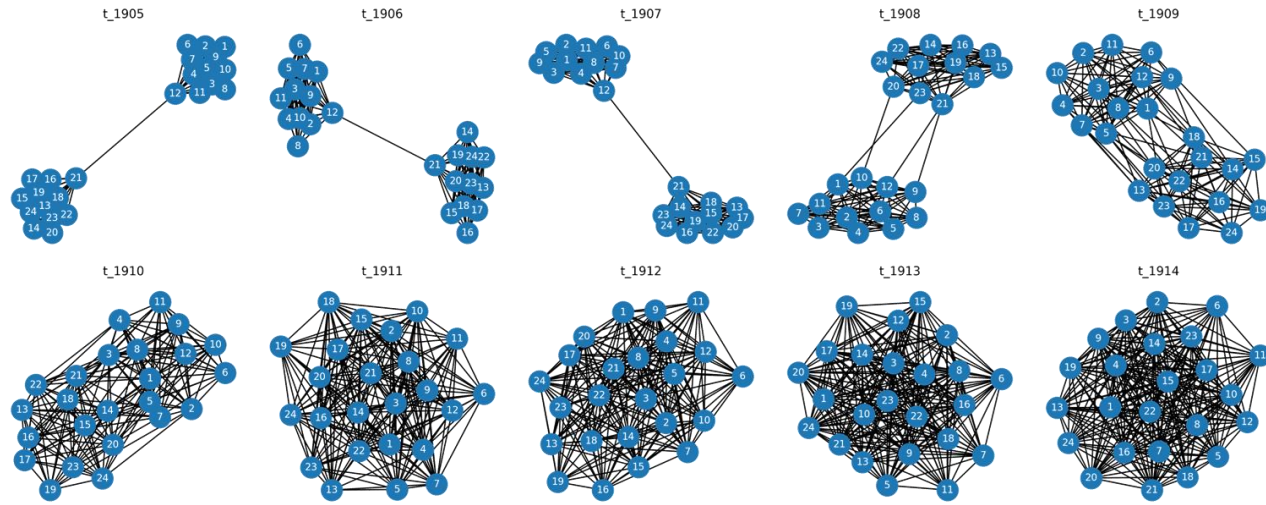
- each pixel represents one artist in one time frame
- coloring by different features, using different colormaps improves ability to identify and distinguish patterns



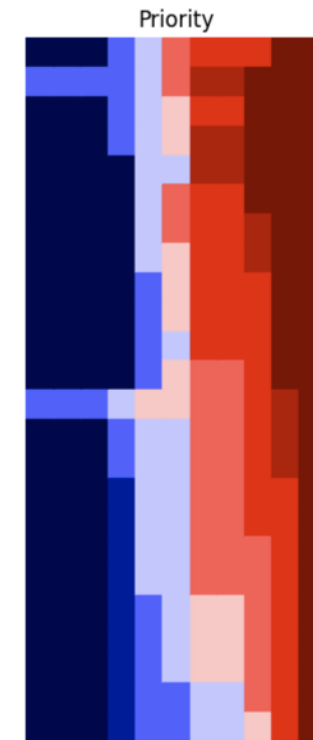


Results: Merge and Split

Evaluation



ID coloring



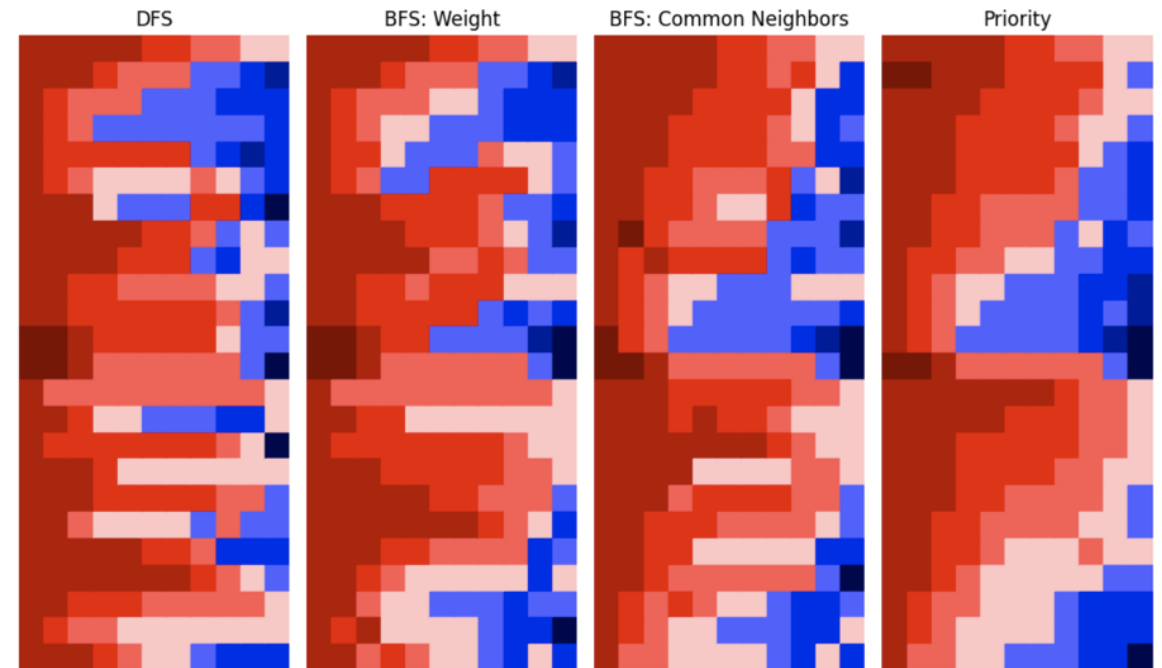
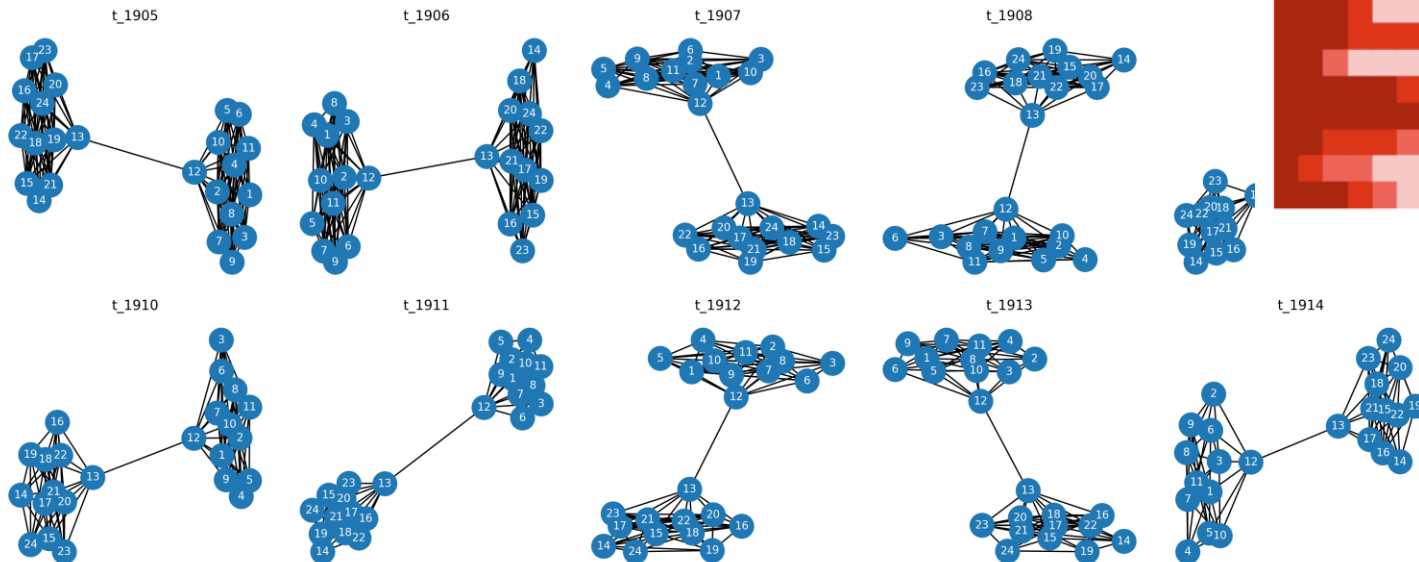
closeness coloring



split

Result: Two Groups

Evaluation



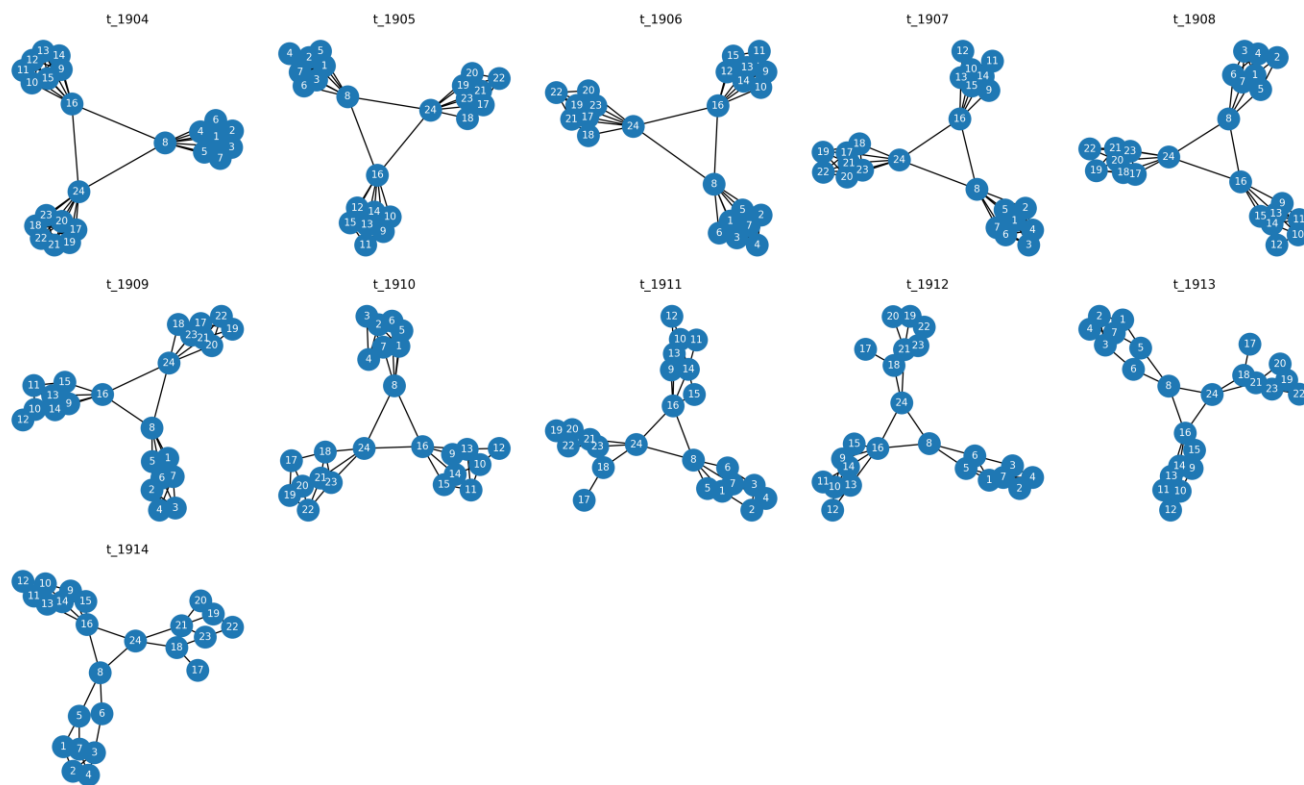
degree coloring



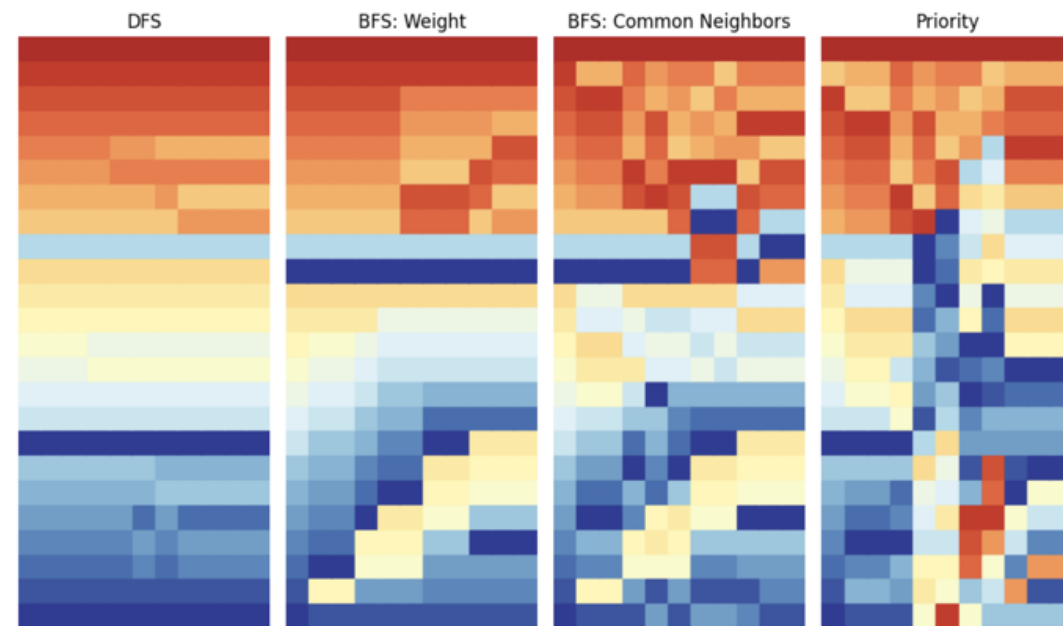
closeness coloring

Results: Three Groups

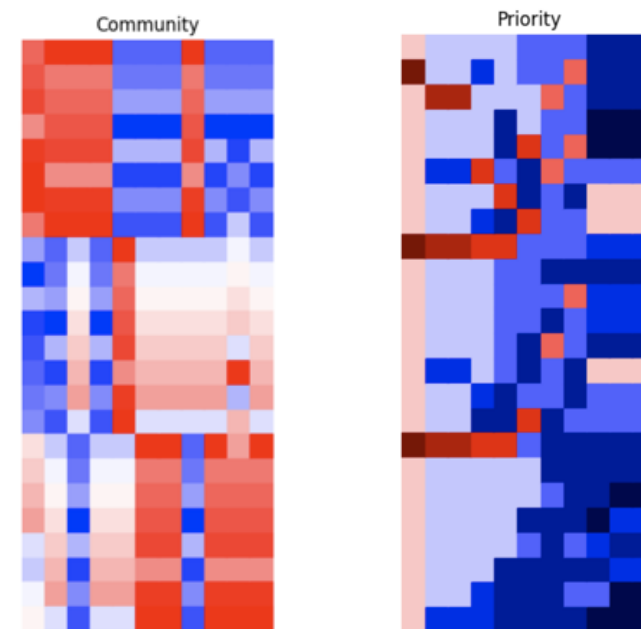
Evaluation



Three Groups



ID coloring

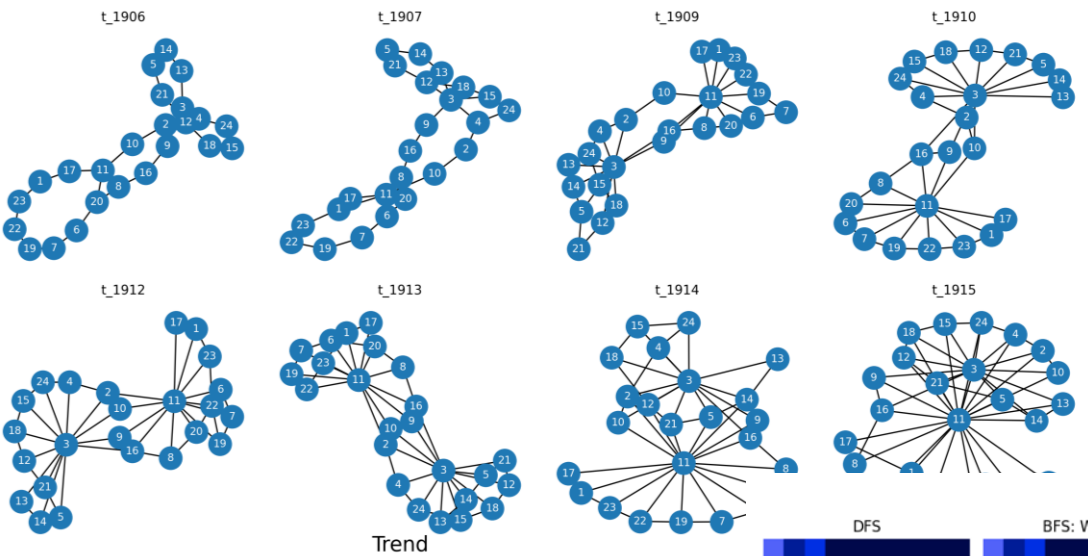


ID coloring

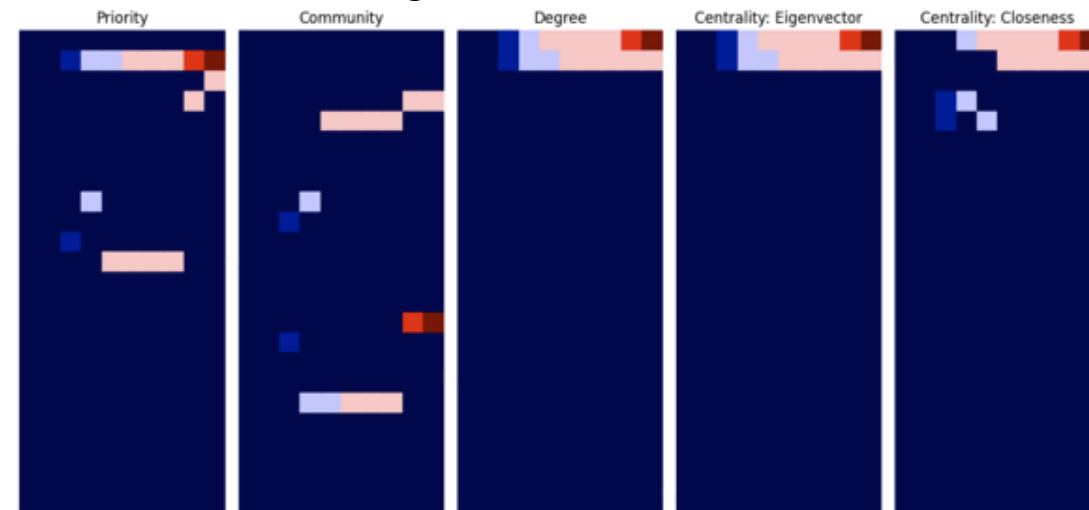
closeness coloring

Results: Trend

Evaluation

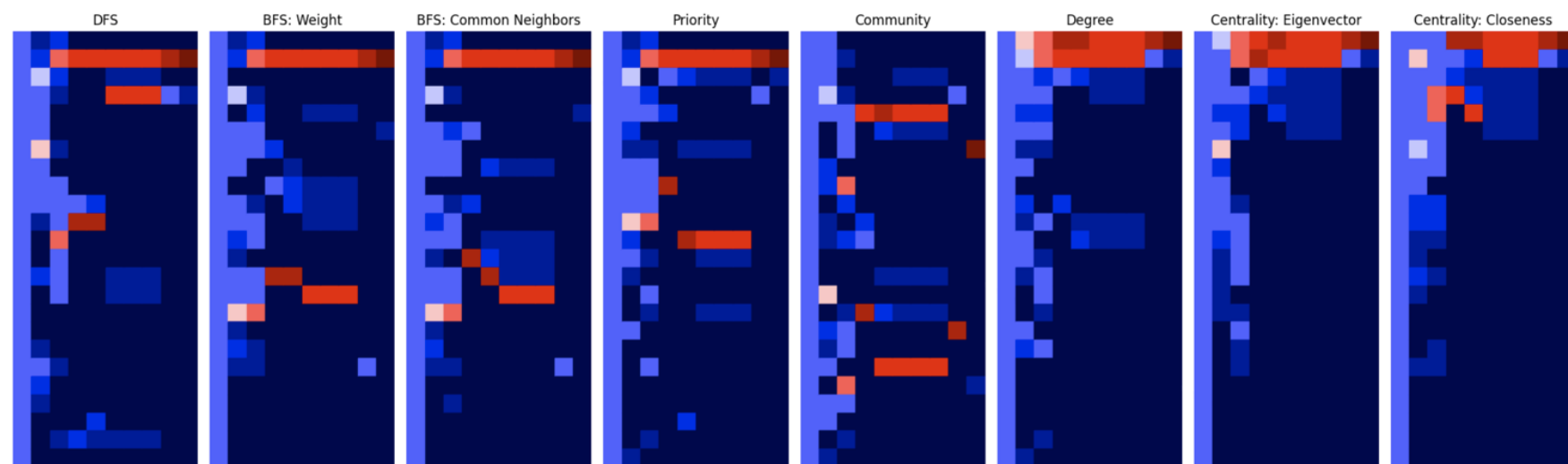


degree coloring



coloring

betweenness centrality



Limitations

Conclusion

- Visual outcome highly sensitive to ordering strategy
- ID has no semantic meaning
- Validation only on artificial dataset
- High degree/ same exhibition not necessarily meaningful

Outlook to Bachelor Thesis

Conclusion

- Needs to be tested on much bigger datasets
- Edge Weights
- Delay Effect
- Network Embedding/Projection as Ordering Strategy

Conclusion

Conclusion

- This is a novel approach
- We introduce one way to solve it – still experimental
- Choice of ordering strategy is key
- Closeness coloring + priority ordering most promising

References

- [1] Juri Buchmüller, Dominik Jackle, Eren Cakmak, Ulrik Brandes, and Daniel A. Keim. MotionRugs: Visualizing Collective Trends in Space and Time. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):76–86, January 2019.
- [2] Juri F. Buchmüller, Udo Schlegel, Eren Cakmak, Daniel A. Keim, and Evanthia Dimara. SpatialRugs: A compact visualization of space and time for analyzing collective movement data. *Computers & Graphics*, 101, December 2021.
- [3] Weiwei Cui, Xiting Wang, Shixia Liu, Nathalie H. Riche, Tara M. Madhyastha, Kwan Liu Ma, and Baining Guo. Let It Flow: A Static Method for Exploring Dynamic Graphs. In *2014 IEEE Pacific Visualization Symposium*, pages 121–128, Yokohama, March 2014. IEEE.
- [4] Nicola Pedreschi, Christophe Bernard, Wesley Clawson, Pascale Quilichini, Alain Barrat, and Demian Battaglia. Dynamic core-periphery structure of information sharing networks in entorhinal cortex and hippocampus. *Network Neuroscience*, 4(3):946–975, January 2020.
- [5] Marie Stolk. GroupRugs: Visualizing Group Motion.
- [6] Jules Wulms, Juri Buchmüller, Wouter Meulemans, Kevin Verbeek, and Bettina Speckmann. Stable Visual Summaries for Trajectory Collections. In *2021 IEEE 14th Pacific Visualization Symposium (PacificVis)*, pages 61–70, Tianjin, China, April 2021. IEEE.

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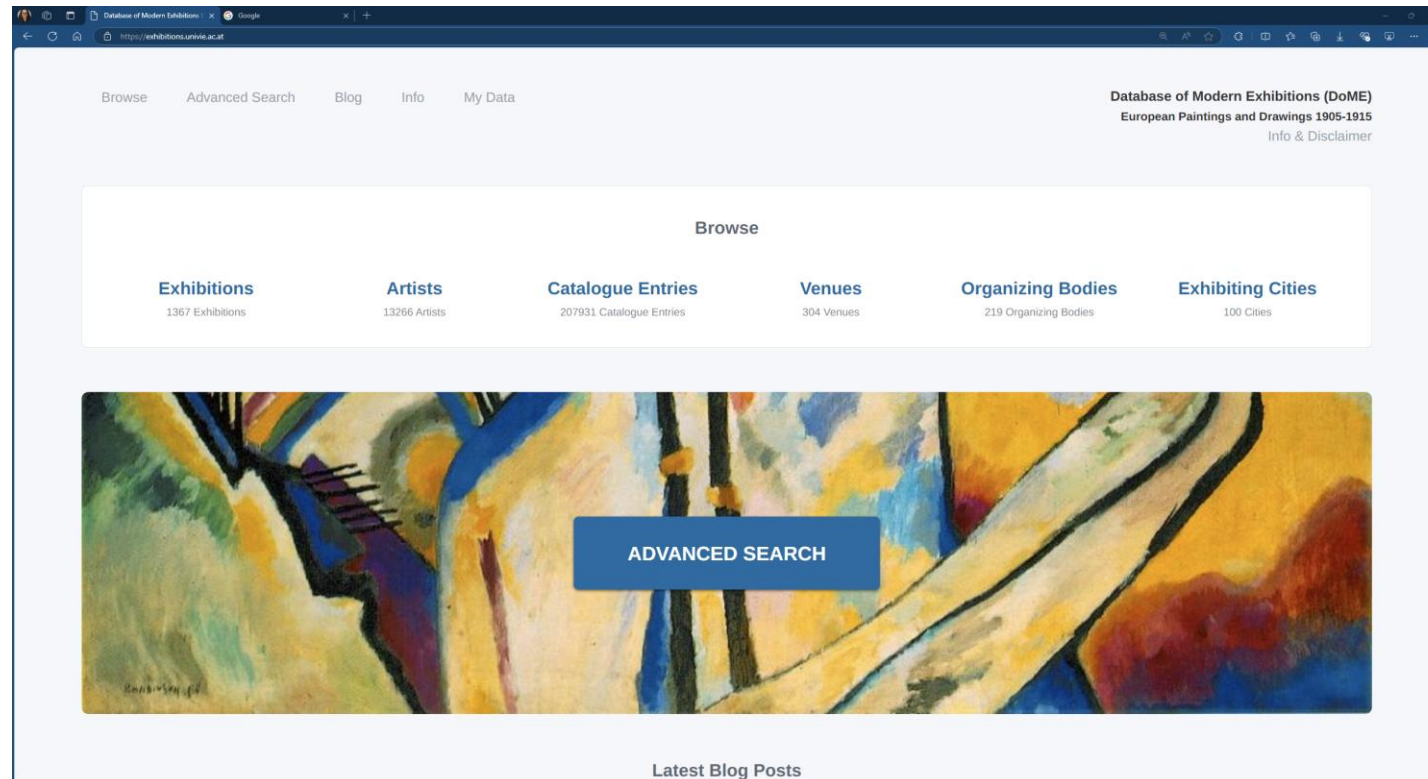
Faculty of Science

University of Konstanz, Germany, 2025-01-20

Project Idea

Introduction

- Database of Modern Exhibitions (DoME) – University of Vienna
<https://exhibitions.univie.ac.at/>



Design Phase

Introduction

