Paul Rosen
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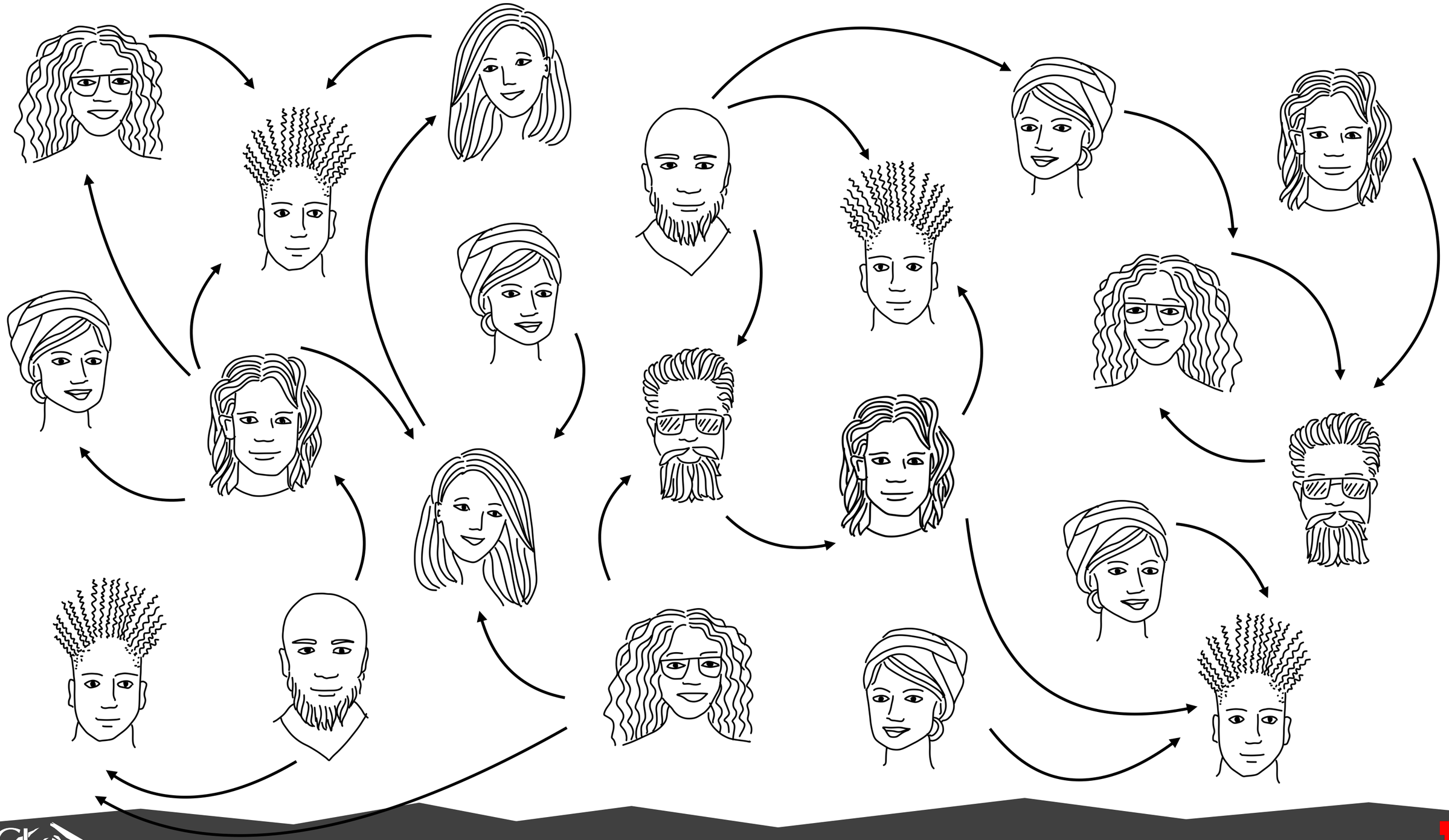
@paulrosenphd
https://cspaul.com

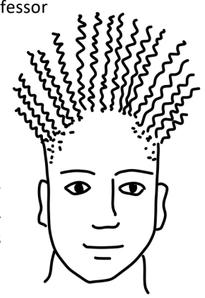
Visualization for Data Science
DS-4630 / CS-5630 / CS-6630

Visualizing Multivariate Networks

Based on an IEEE VIS Tutorial held by Carolina Notre, Marc Streit, and Alexander Lex



Carol
29 years old
Assistant Professor
3.4 GPA
300K Twitter Followers



Levi
32 years old
Nurse
3.1 GPA
10K Twitter Followers

Maya
33 years old
Pediatrician
4.0 GPA
3M Twitter Followers

Adam
27 years old
PhD student
3.9 GPA
3K Twitter Followers

Carol
29 years old
Assistant Professor
3.4 GPA
300K Twitter Followers

Scott
38 years old
Divorce Lawyer
3.3 GPA
32K Twitter Followers

Maya **33** years old
Pediatrician
4.0 GPA
3M Twitter Followers

Sue
23 years old
College student
3.7 GPA
340 Twitter Followers

Scott
38 years old
Divorce Lawyer
3.3 GPA
32K Twitter Followers

Adam
28 years old
PhD student
3.9 GPA
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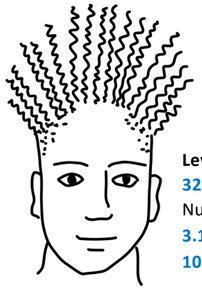

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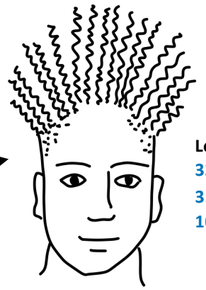


Levi
32 years old Nurse
3.1 GPA
10K Twitter Followers

Multivariate Network

- Network Topology + Node and Edge Attributes
- Visualization is a tradeoff between Topology and Attributes
  - Choosing efficient encodings for one aspect often interferes with the ability to effectively visualize the other.

EUROVIS 2019
R. S. Laramee, S. Oeltze, and M. Sedlmair
(Guest Editors)

Volume 38 (2019), Number 3
STAR – State of The Art Report

The State of the Art in Visualizing Multivariate Networks

C. Nobre[1], M. Meyer[1], M. Streit[2], and A. Lex[1]

[1]University of Utah, Utah, USA
[2]Johannes Kepler University Linz, Austria

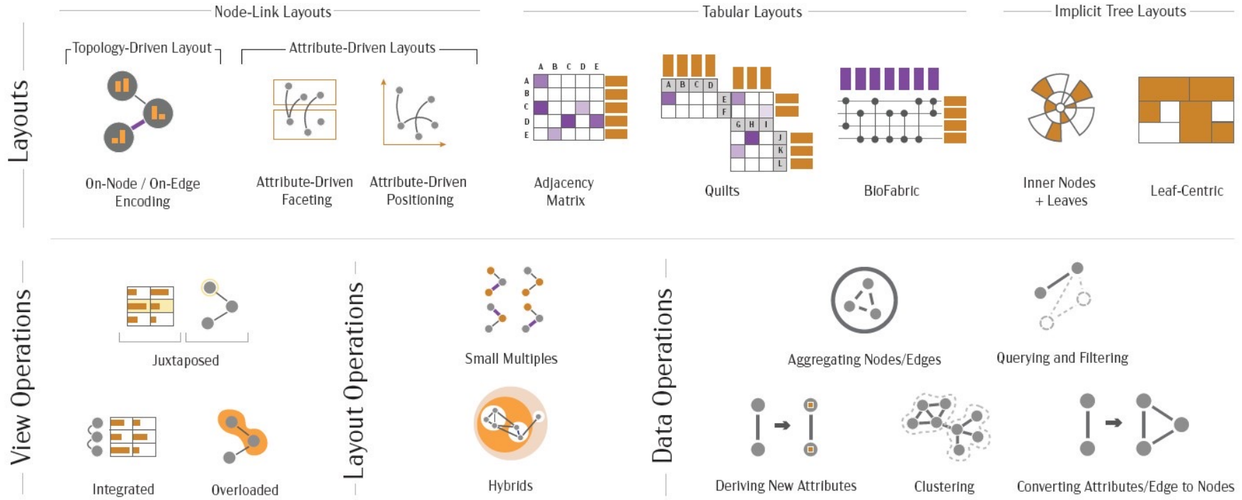


Figure 1: *A typology of operations and layouts used in multivariate network visualization.* ***Layouts*** *describe the fundamental choices for encoding multivariate networks.* ***View Operations*** *capture how topology and attribute focused visualizations can be combined.* ***Layout Operations*** *are applied to basic layouts to create specific visualization techniques.* ***Data Operations*** *are used to transform a network or derive attributes before visualizations. The colors reflect node attributes (orange), edge attributes (purple), and topology (grey).*

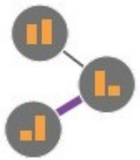
Abstract

Multivariate networks are made up of nodes and their relationships (links), but also data about those nodes and links as attributes. Most real-world networks are associated with several attributes, and many analysis tasks depend on analyzing both, relationships and attributes. Visualization of multivariate networks, however, is challenging, especially when both the topology of the network and the attributes need to be considered concurrently. In this state-of-the-art report, we analyze current practices and classify techniques along four axes: layouts, view operations, layout operations, and data operations. We also provide an analysis of tasks specific to multivariate networks and give recommendations for which technique to use in which scenario. Finally, we survey application areas and evaluation methodologies.

Layouts

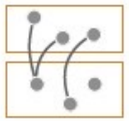
Node-Link Layouts

Topology-Driven Layout



On-Node / On-Edge Encoding

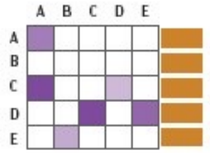
Attribute-Driven Layouts



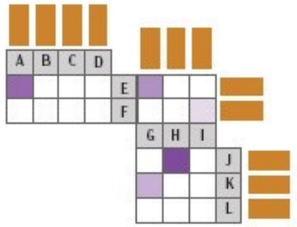
Attribute-Driven Faceting

Attribute-Driven Positioning

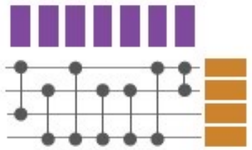
Tabular Layouts



Adjacency Matrix



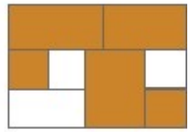
Quilts



BioFabric

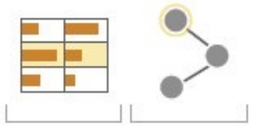
Implicit Tree Layouts

Inner Nodes + Leaves



Leaf-Centric

View Operations



Juxtaposed

Integrated

Overloaded

Layout Operations

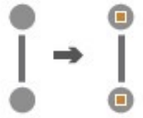
Small Multiples

Hybrids

Data Operations

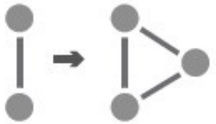
Aggregating Nodes/Edges

Querying and Filtering



Deriving New Attributes

Clustering

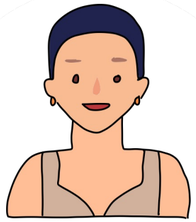


Converting Attributes/Edge to Nodes

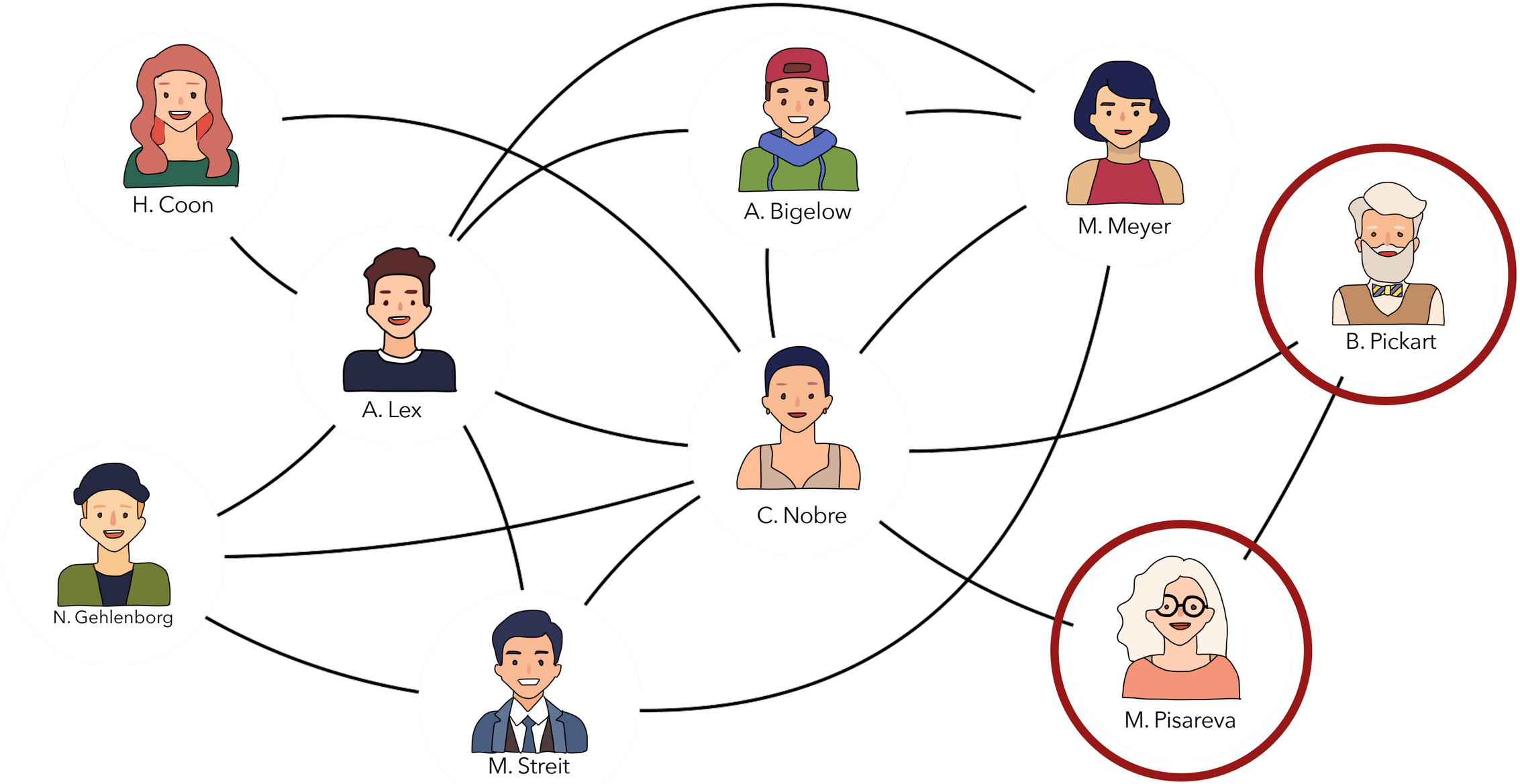
Multivariate Network Tasks

How is a multivariate network task different than a regular graph task?

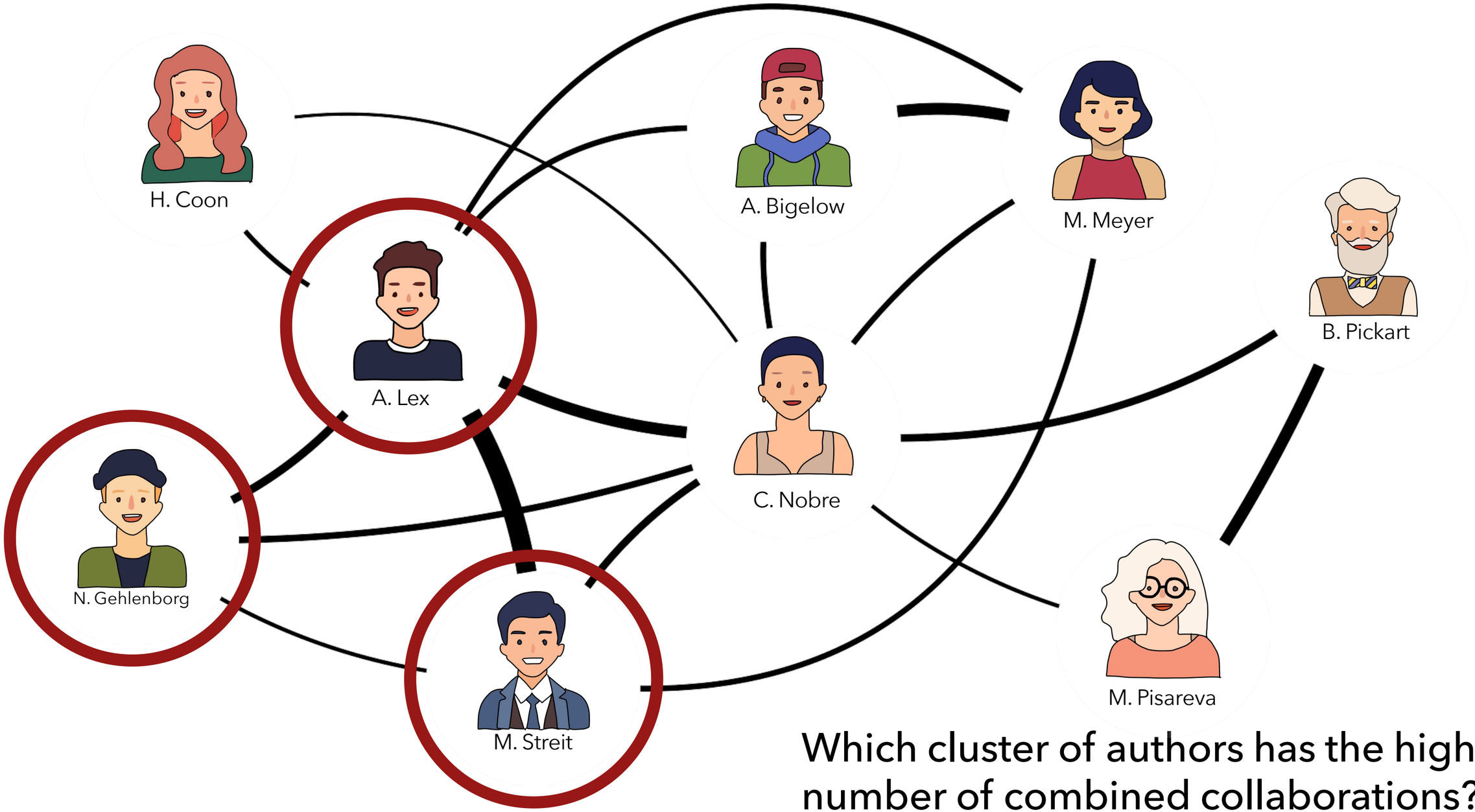
- Rely on both the topology of the network and the attributes of the nodes and edges



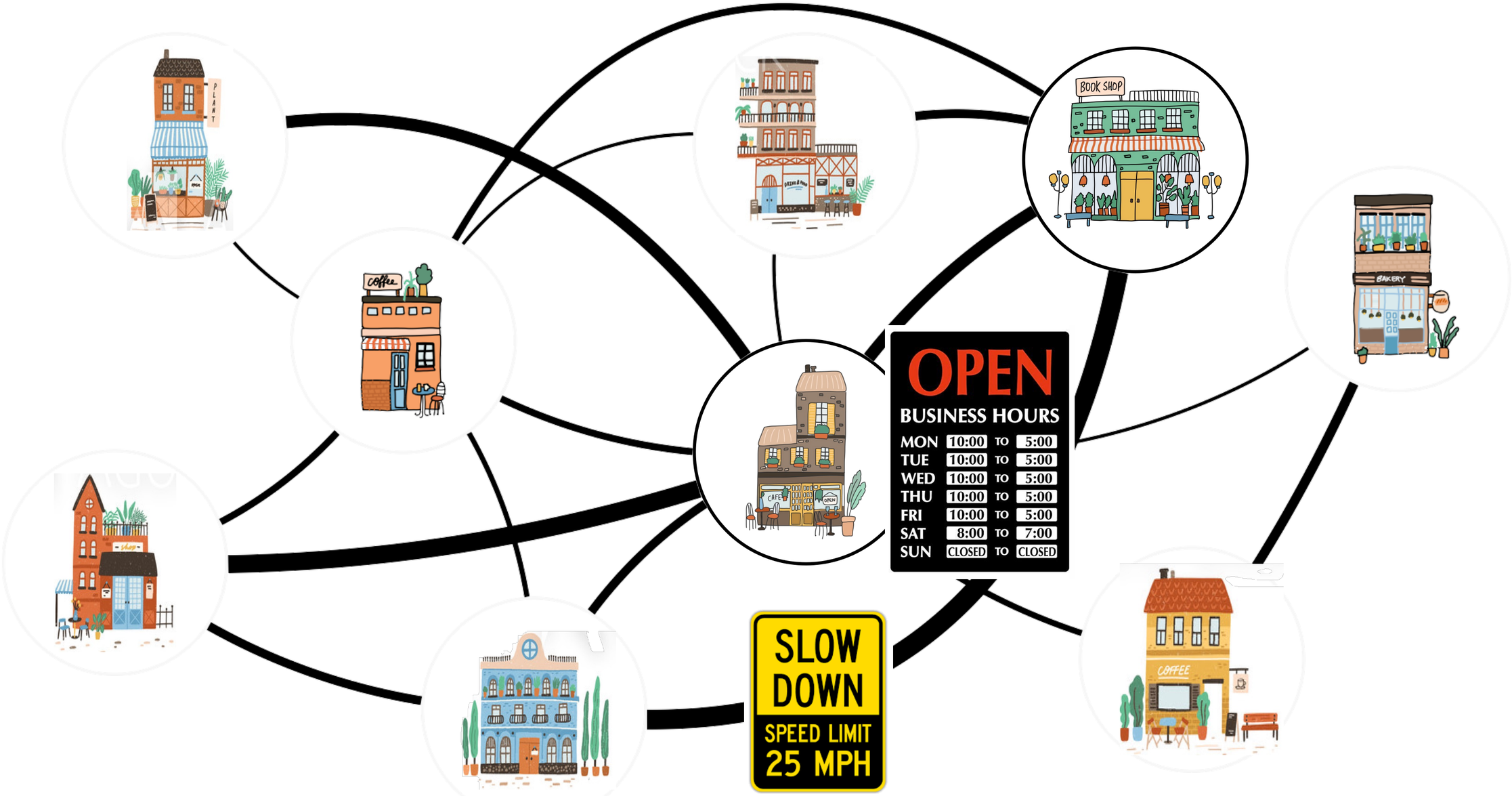
C. Nobre



How many of my collaborators are from the oceanography field?



Which cluster of authors has the highest number of combined collaborations?



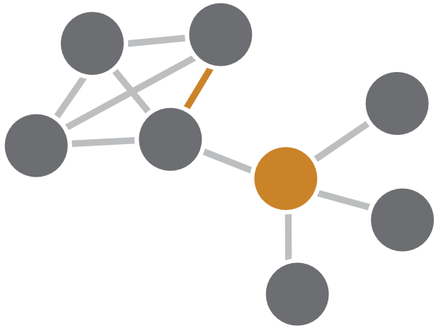
What is an efficient way I can complete all my errands?

- How many of my collaborators are in the oceanography field?
- Which cluster has the highest number of collaborations?
- What is the fastest route to get all my errands done?

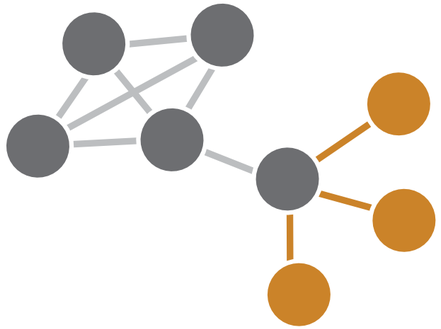
Tasks that rely on the **topology** of the network and the **attributes** of the nodes and edges

MVNV tasks are applied to topological structures

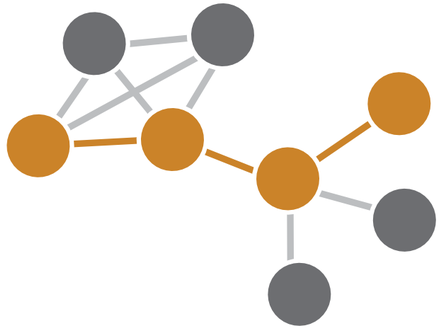
Single Node/Edge



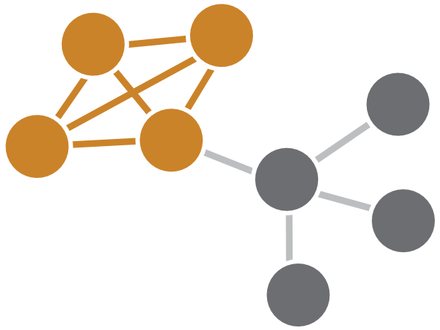
Node Neighbors



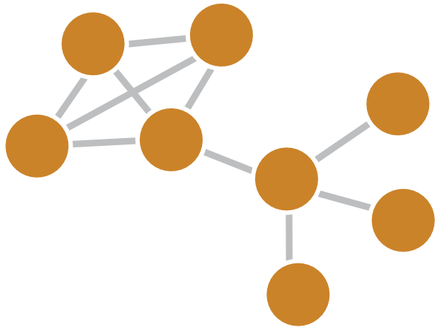
Path



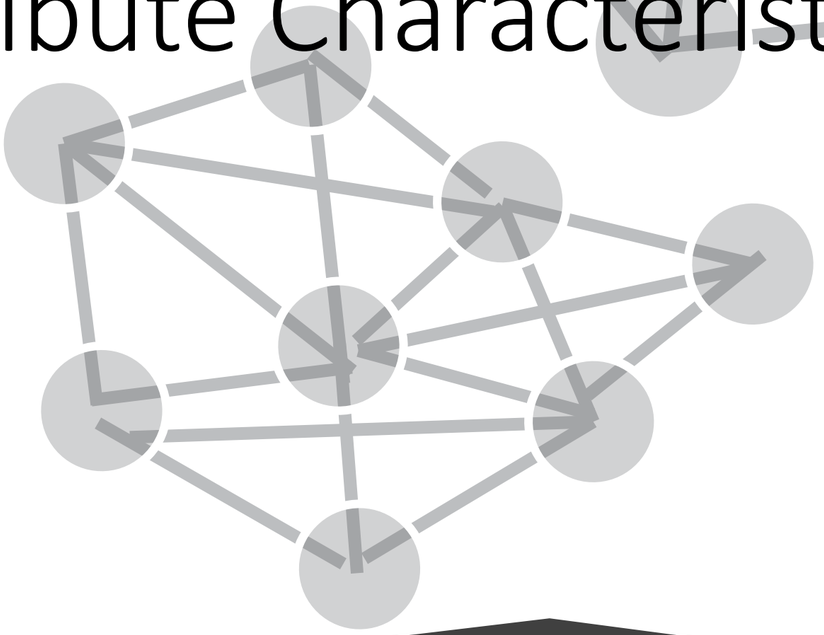
Cluster



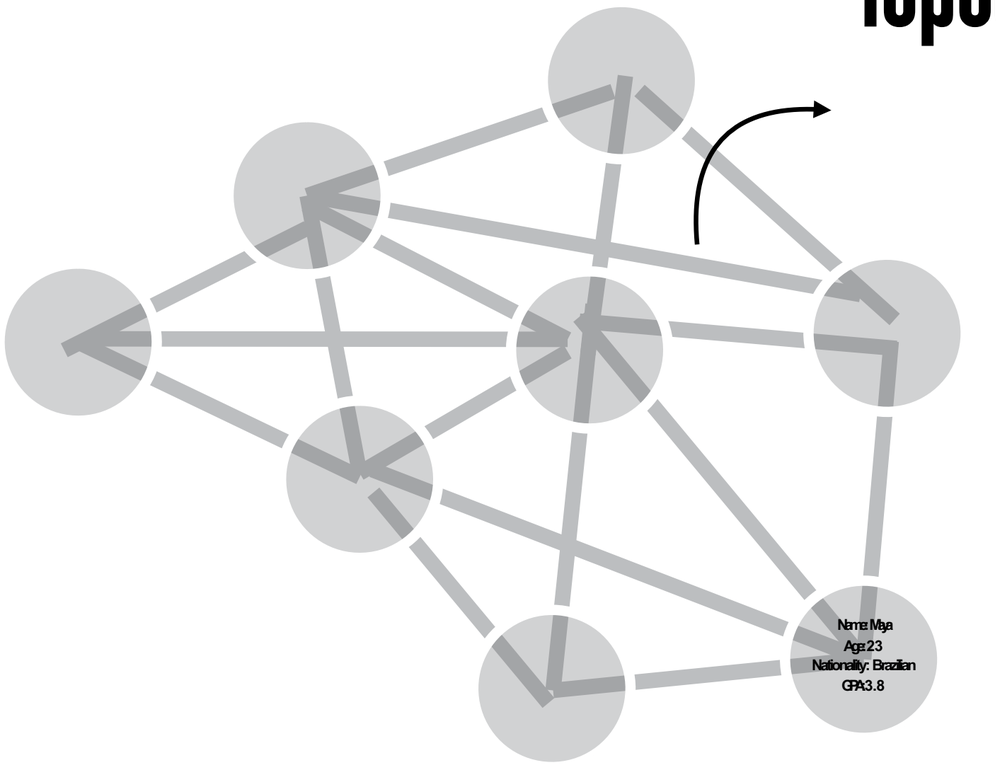
Network/Subnetwork

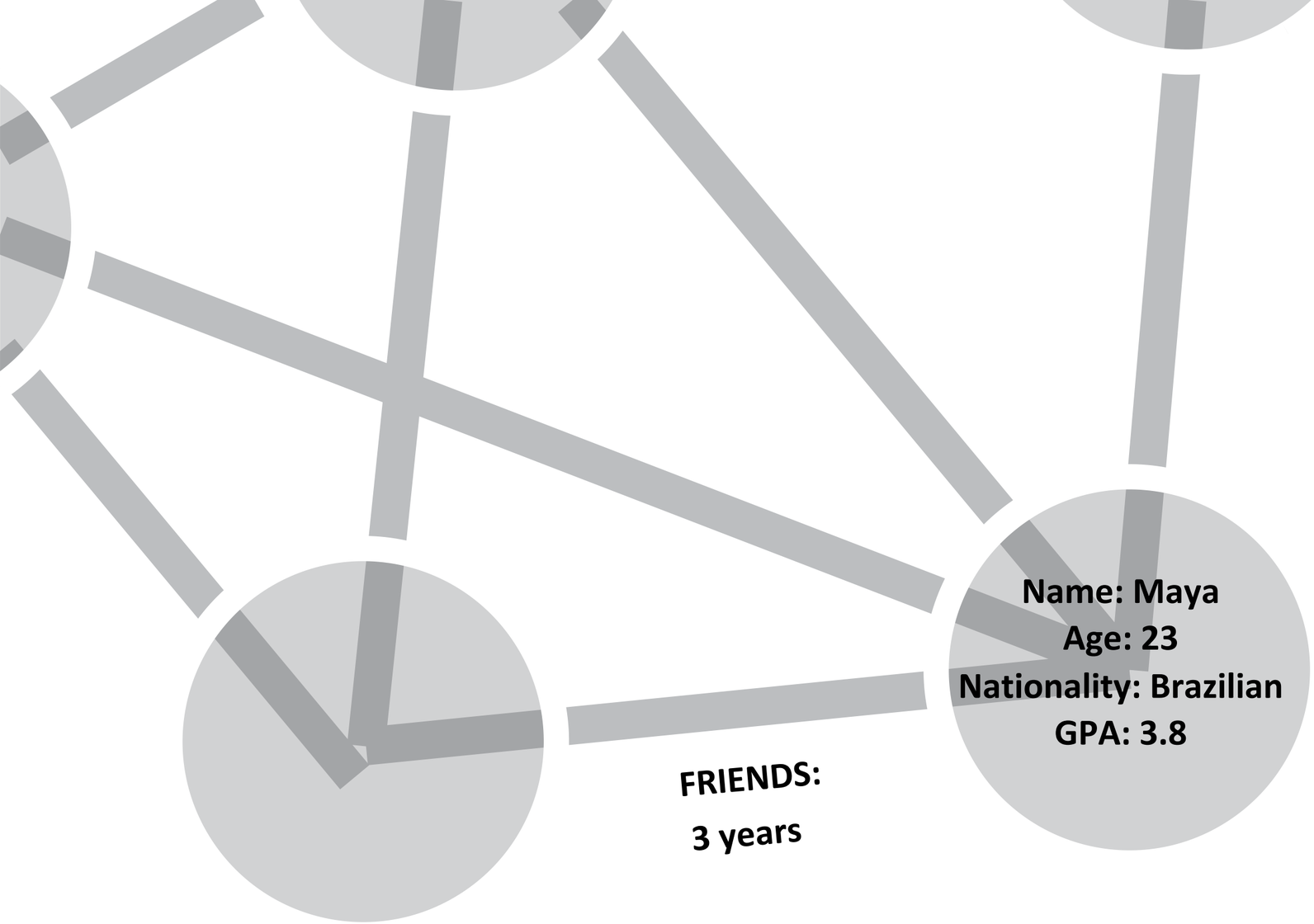


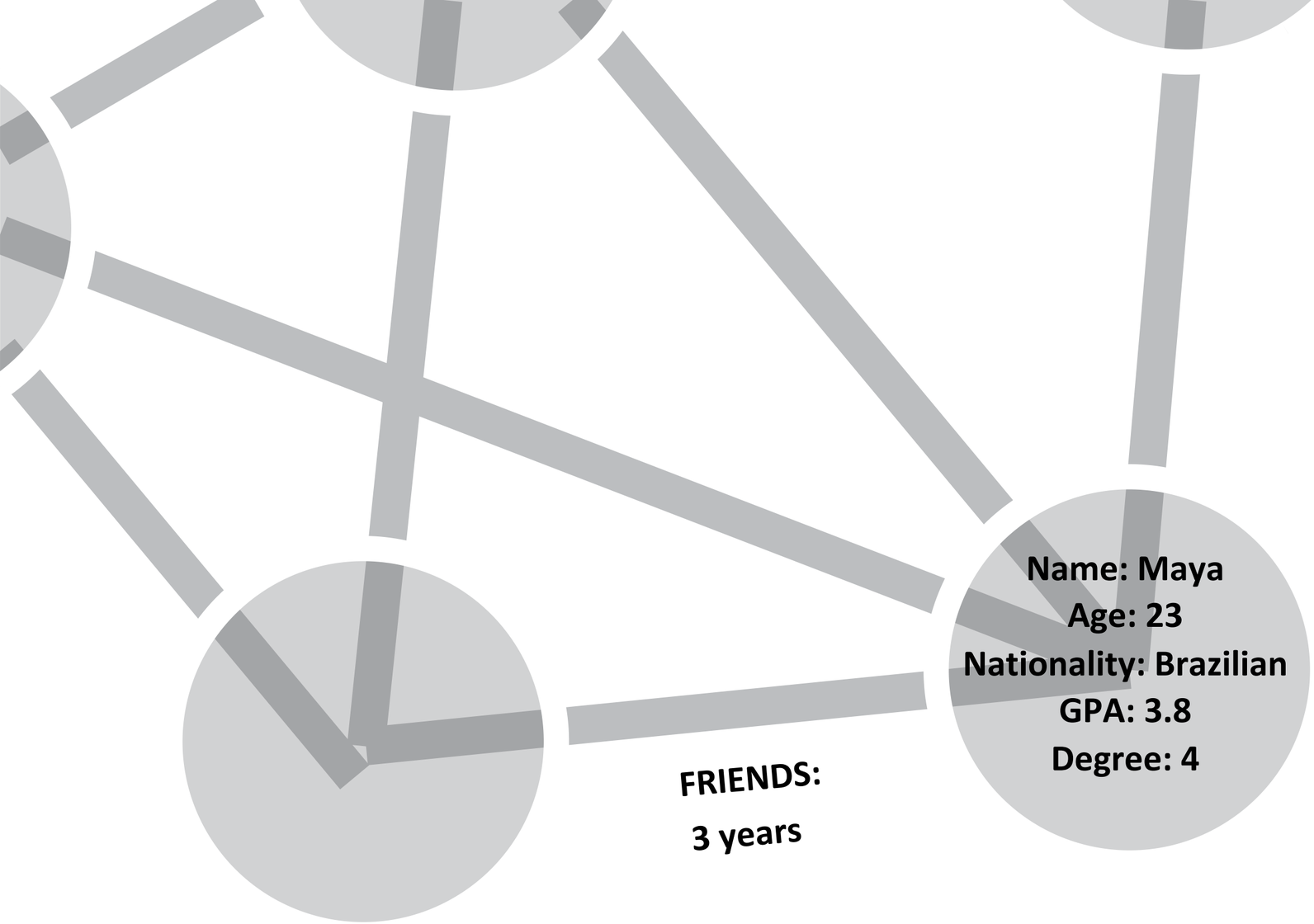
Network and Attribute Characteristics

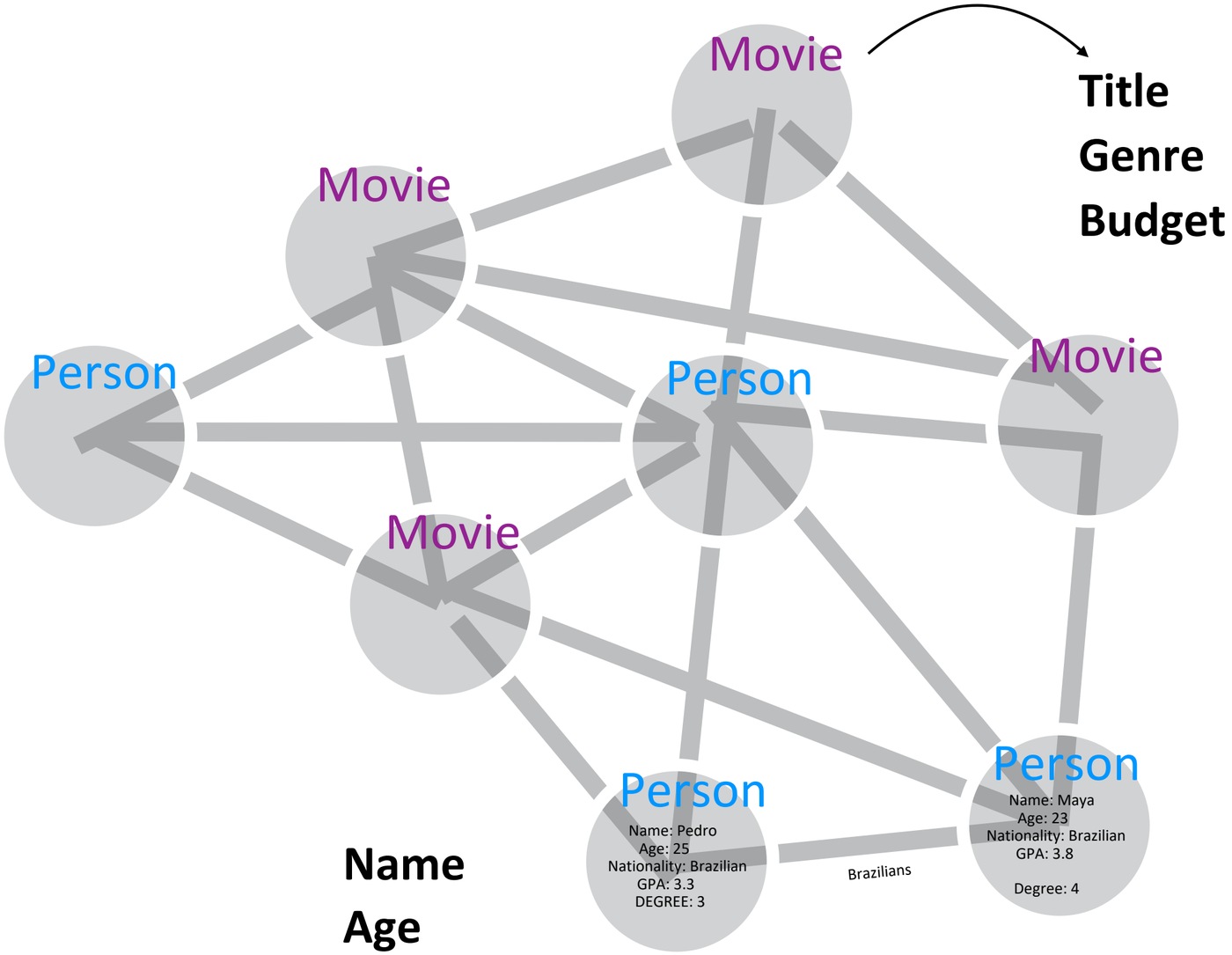


Topology

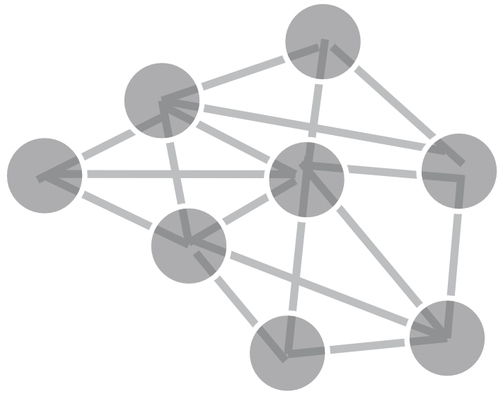



Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
FRIENDS:
3 years


Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
FRIENDS:
3 years


Movie
Movie
Person
Person
Movie
Movie
Person
Name: Pedro
Age: 25
Nationality: Brazilian
GPA: 3.3
DEGREE: 3
Brazilians
Person
Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
Title
Genre
Budget
Name
Age
Nationality
GPA

Network Size



Small
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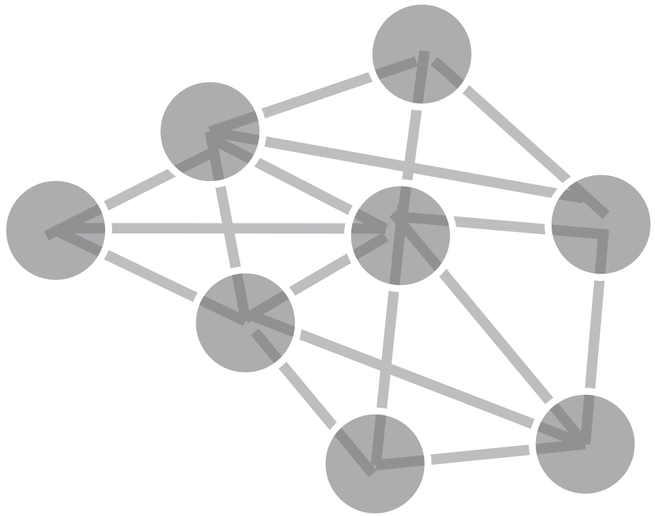
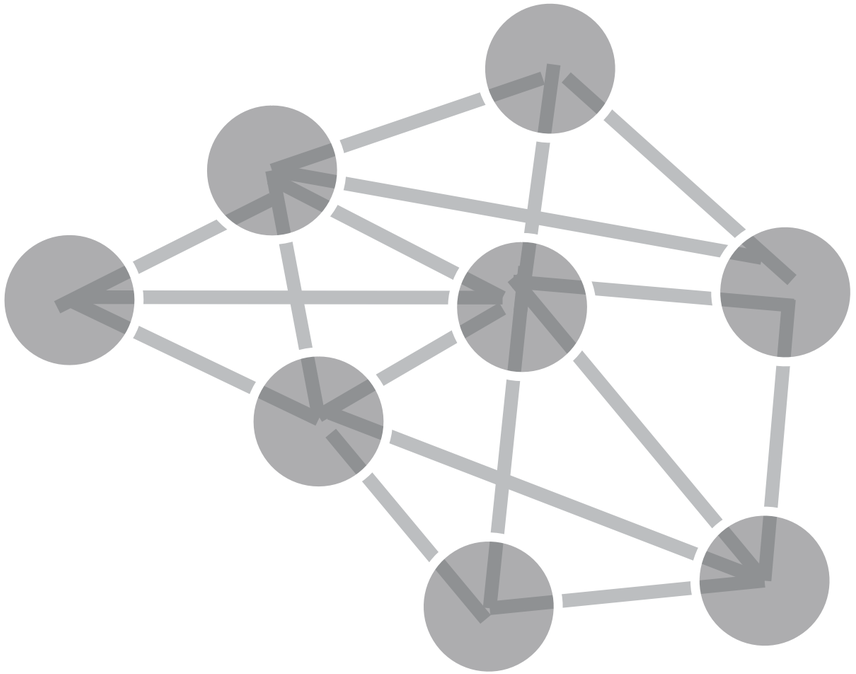
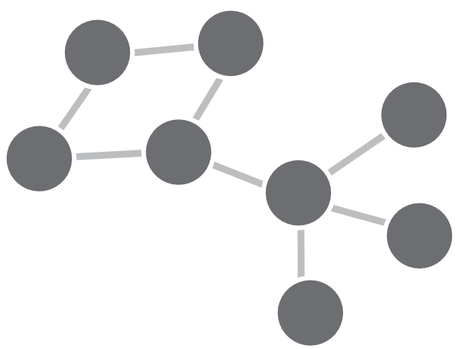


Medium
100–1000

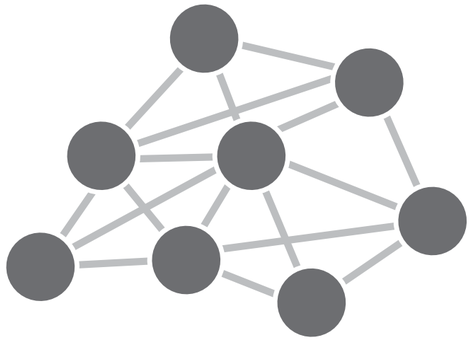


Large
>1000

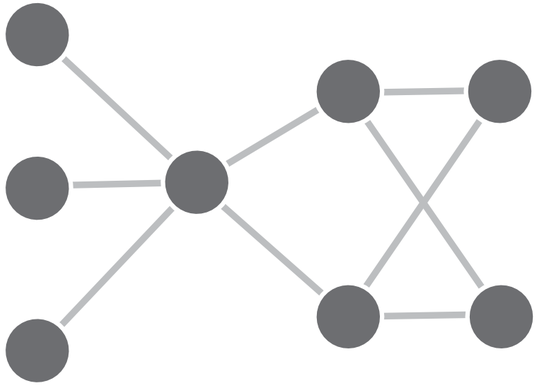
Network Types



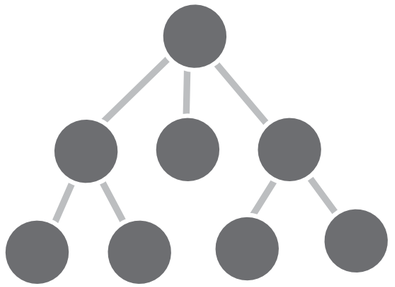
Sparse



Dense

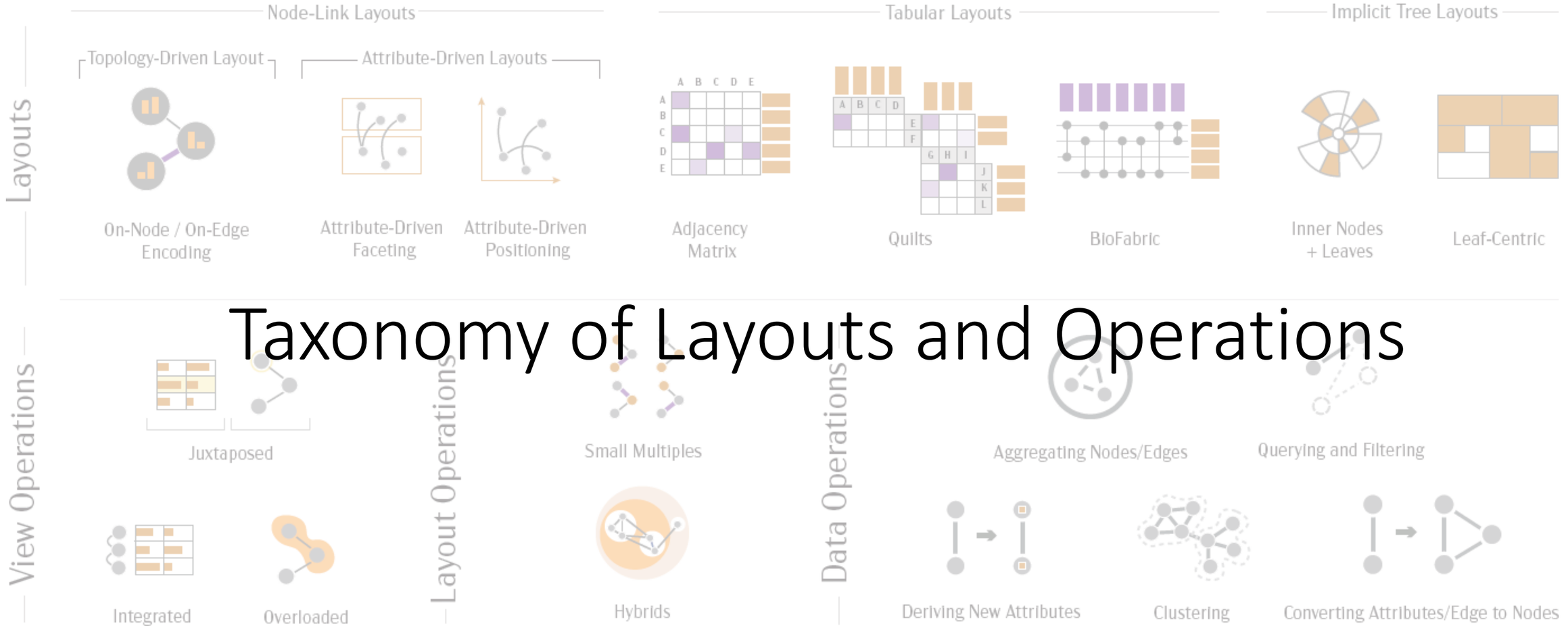


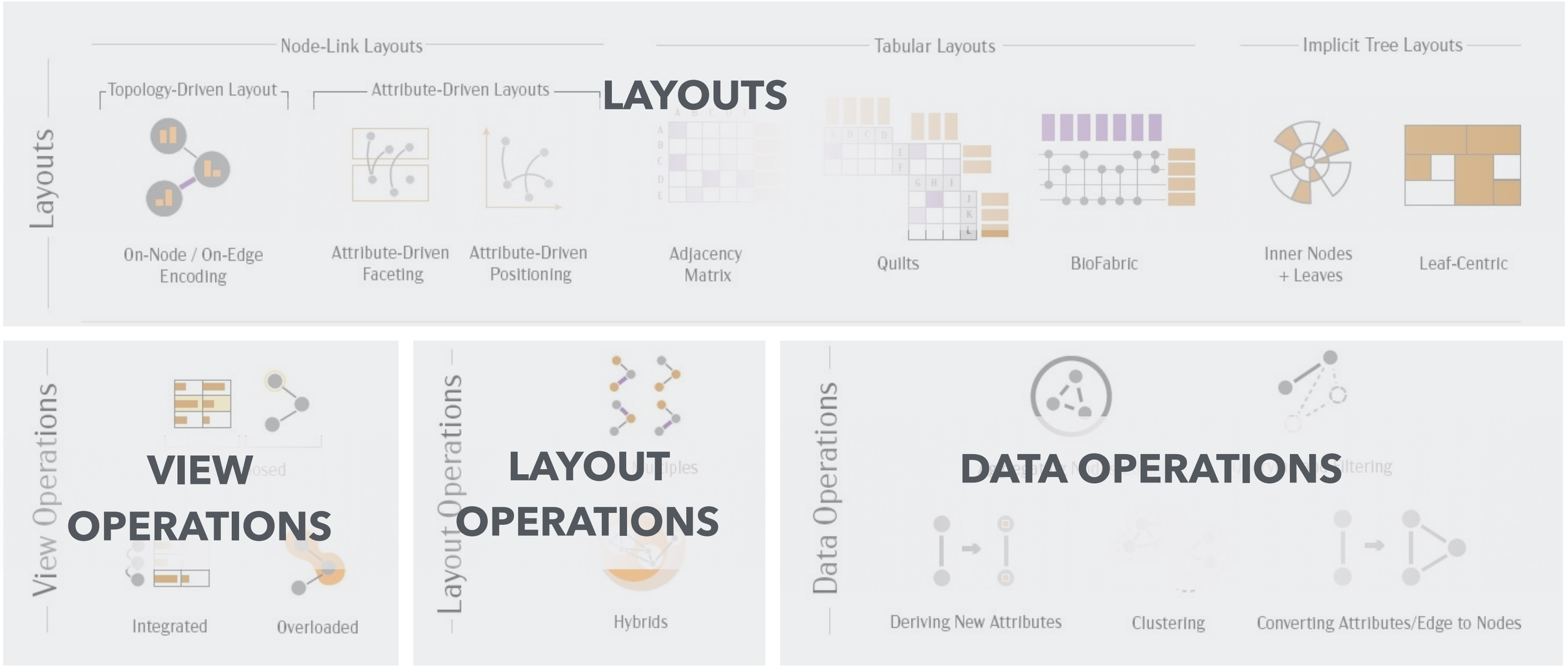
Layered



Trees

Taxonomy of Layouts and Operations




Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
Tabular Layouts
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LAYOUTS
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Attribute-Driven Positioning
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Converting Attributes/Edge to Nodes

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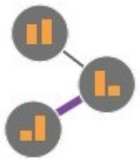
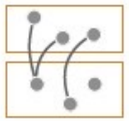
Node-Link Layouts

Topology-Driven Layout



On-Node / On-Edge Encoding

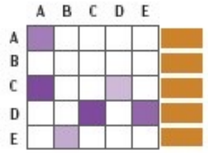
Attribute-Driven Layouts



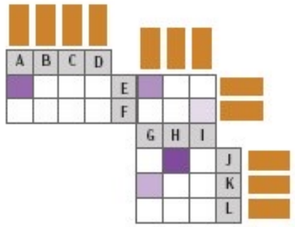
Attribute-Driven Faceting

Attribute-Driven Positioning

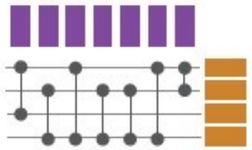
Tabular Layouts



Adjacency Matrix



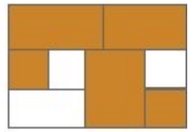
Quilts



BioFabric

Implicit Tree Layouts

Inner Nodes + Leaves



Leaf-Centric

View Operations

Juxtaposed

Integrated

Overloaded

Layout Operations

Small Multiples

Hybrids

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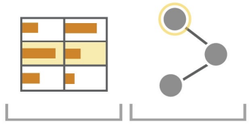


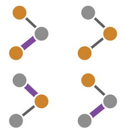
Juxtaposed

Integrated

Overloaded

Separate Views for Topology and Attributes

Layout Operations



Small Multiples

Hybrids

Multiple layouts for Topology or Attributes

Data Operations

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Implicit Tree Layouts

Inner Nodes + Leaves

Leaf-Centric

View Operations

Juxtaposed

Integrated

Overloaded

Layout Operations

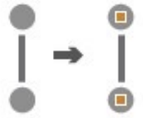
Small Multiples

Hybrids

Data Operations

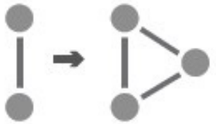
Aggregating Nodes/Edges

Querying and Filtering



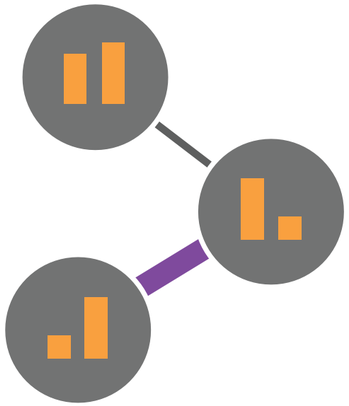
Deriving New Attributes

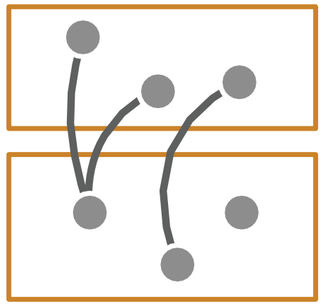
Clustering

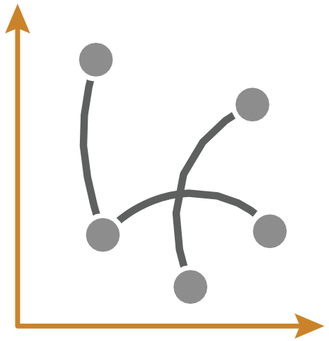


Converting Attributes/Edge to Nodes

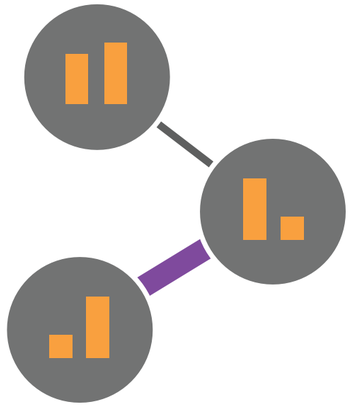
Node-Link Layouts





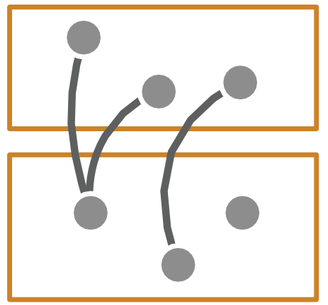


Topology Driven Layout

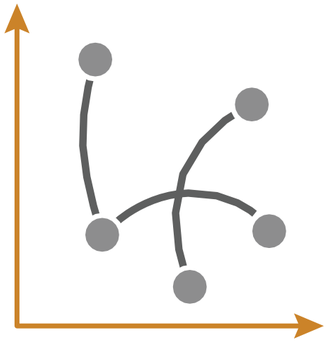


On-Node / On-Edge Encoding

Attribute Driven Layouts

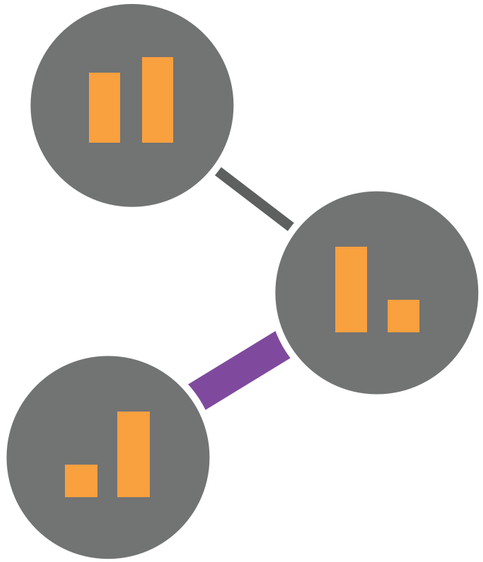


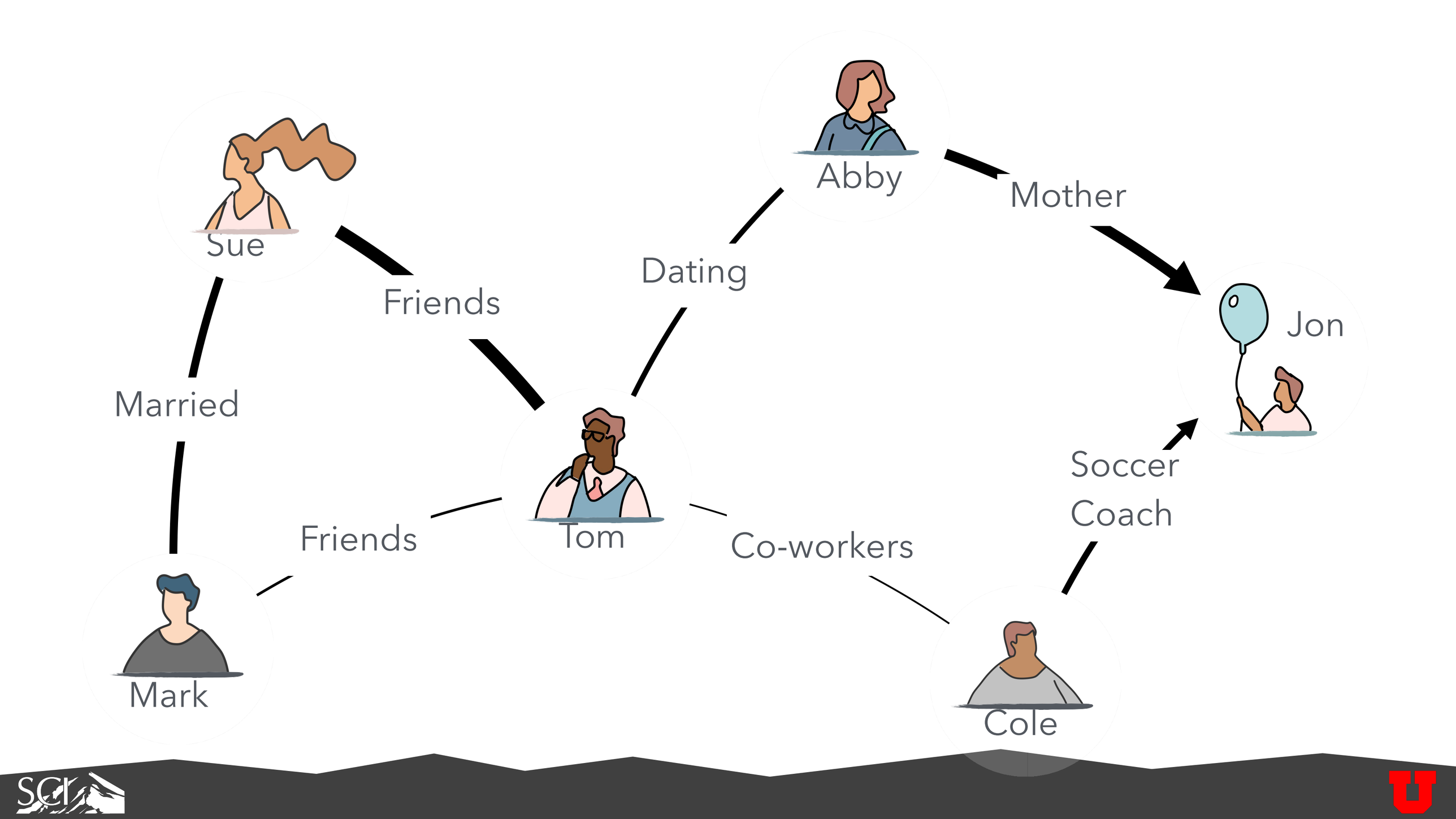
Attribute-Driven Faceting



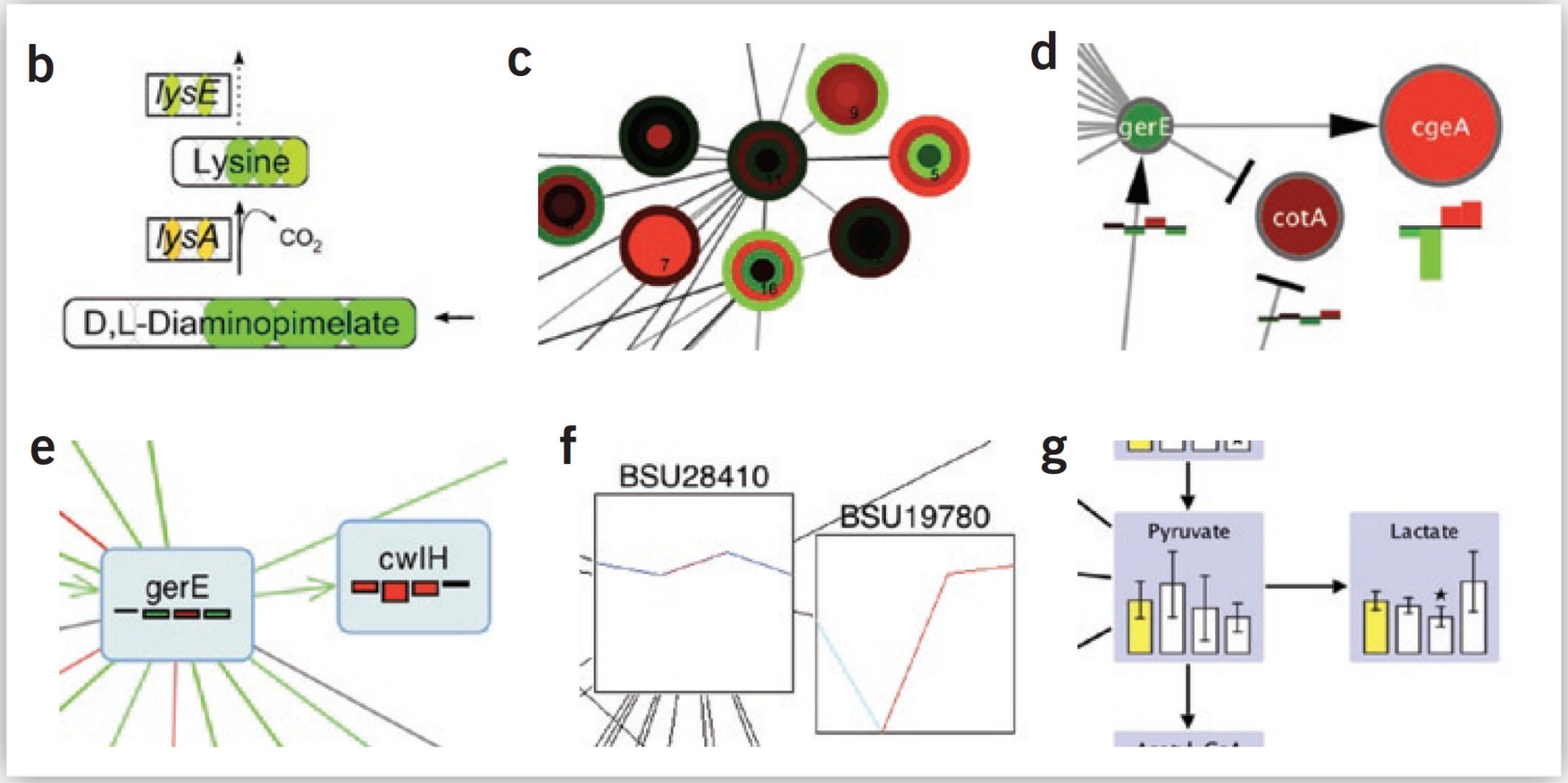
Attribute-Driven Positioning

On-Node / On-Edge Encoding



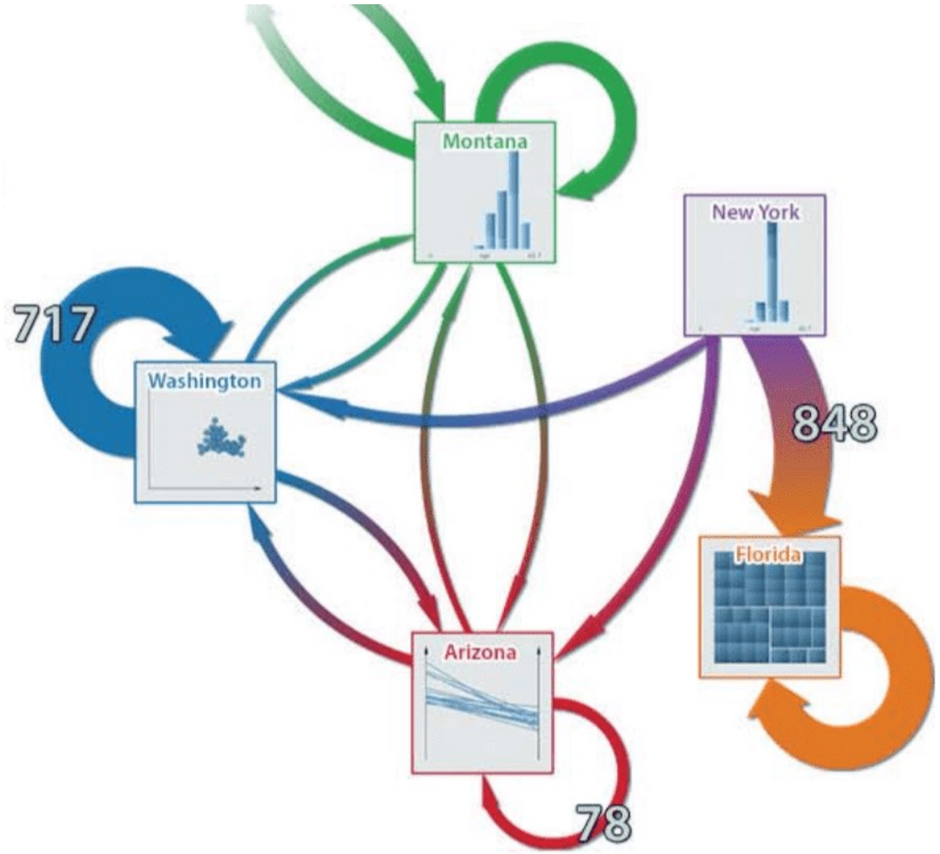

Sue
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole

On-Node / On-Edge Encoding

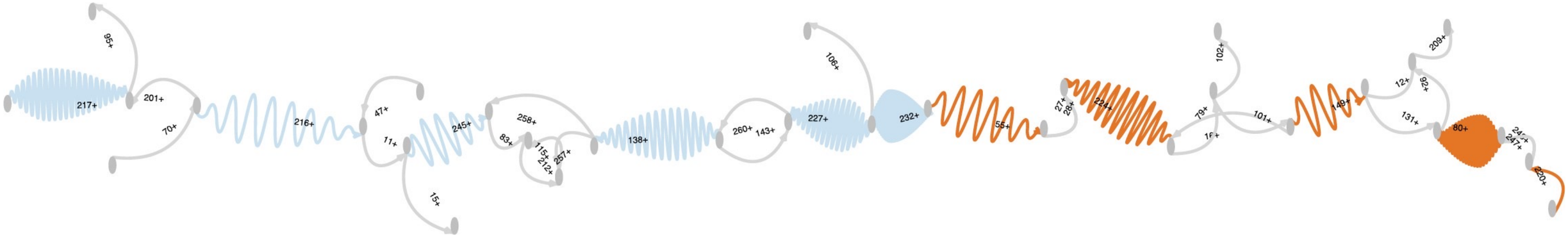


Gehlenborg et al. 2010

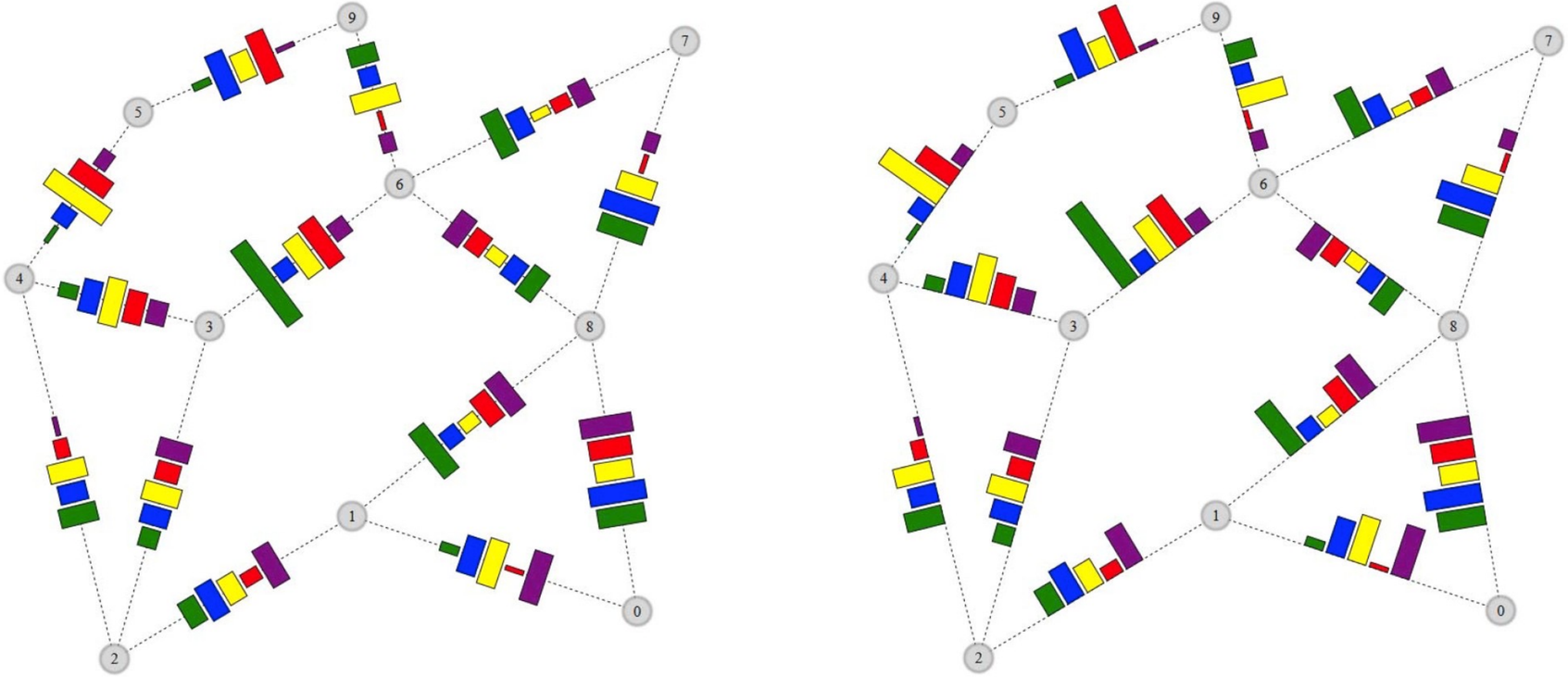
On-Node / On-Edge Encoding

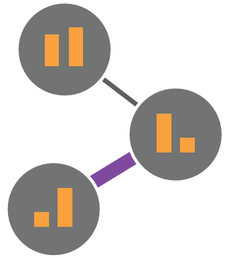


On-Node / On-Edge Encoding



On-Node / On-Edge Encoding





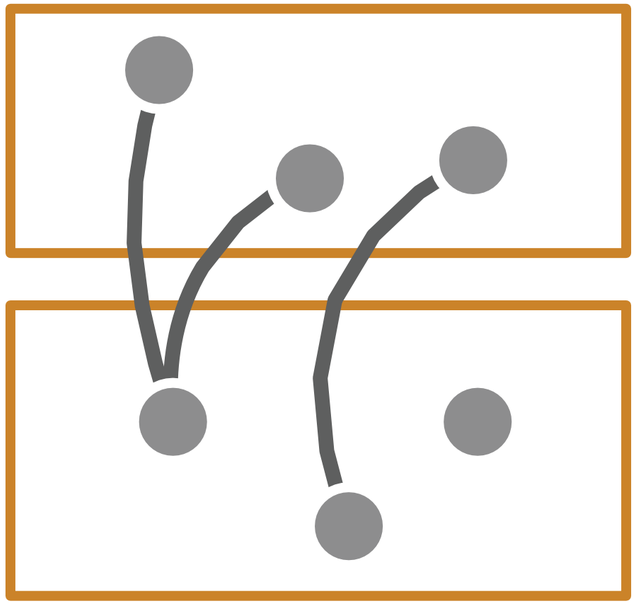
On-Node / On-Edge Encoding

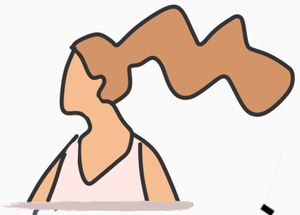
Is easily understood by most users
Works well for all types of networks

Scalability.
Node size leaves little space to encode attributes.

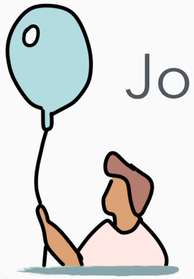
Recommended for small networks when only a few (usually under five) attributes on the nodes are shown, or in combination with a zooming/filtering strategy

Attribute-Driven Faceting





Sue

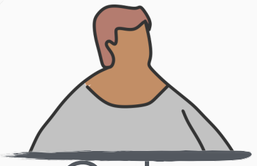


Jon

Mark

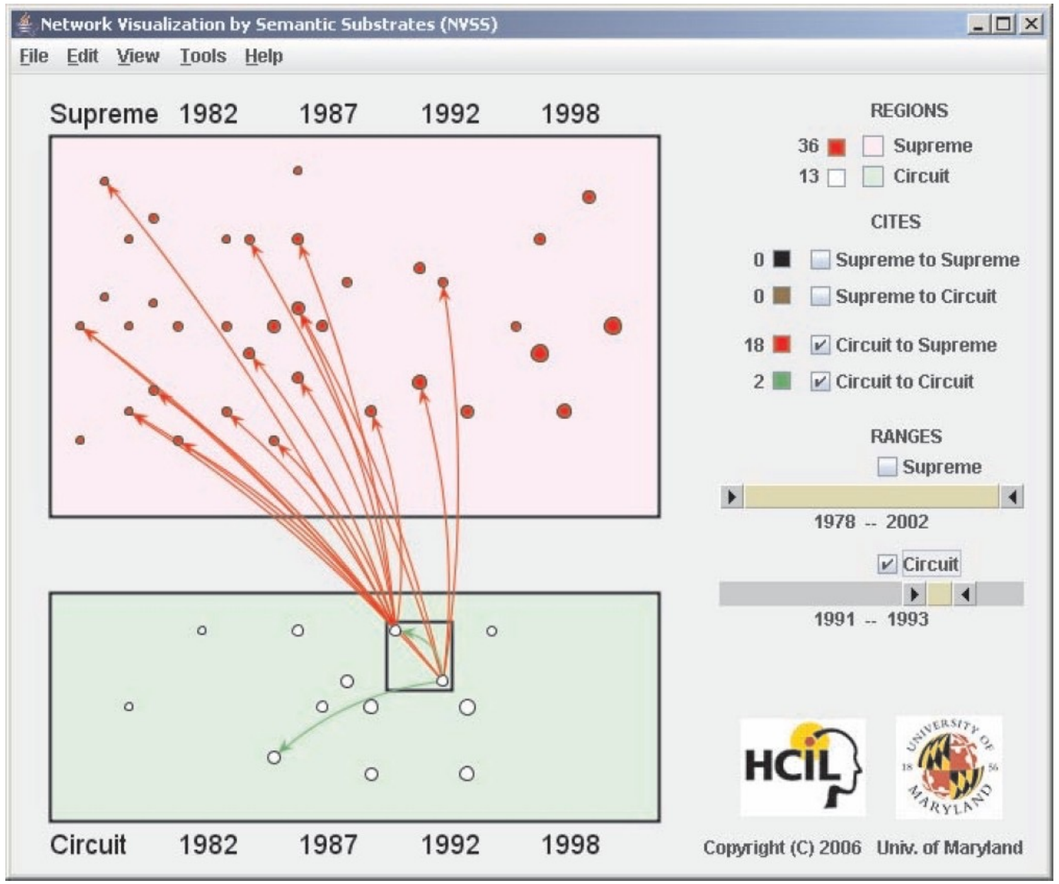
Tom

Abby



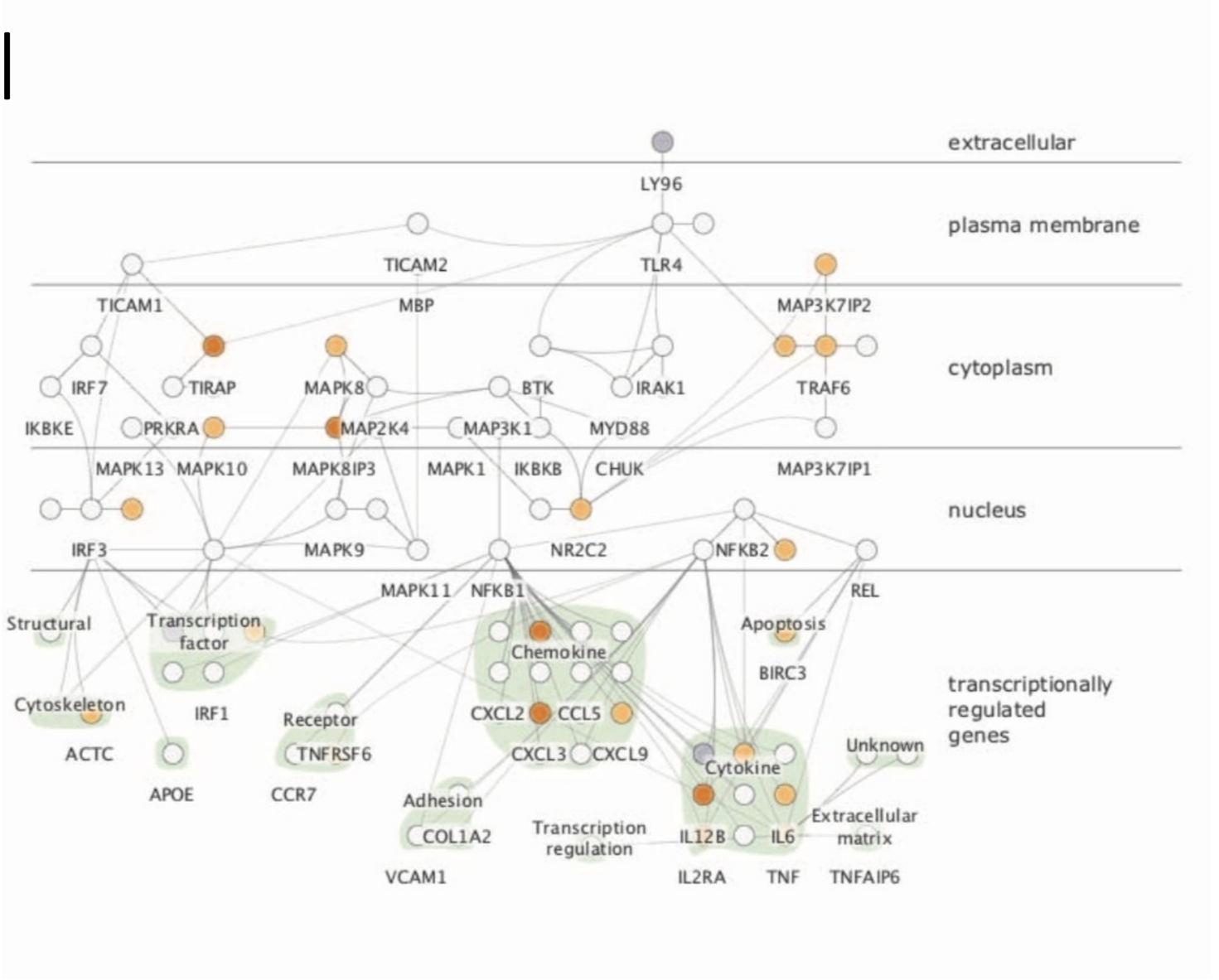
Cole

Semantic Substrates

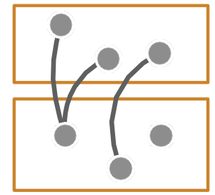


Shneiderman and Aris, 2006

Cerebral



Barskey et al. 2008



Attribute-Driven Faceting

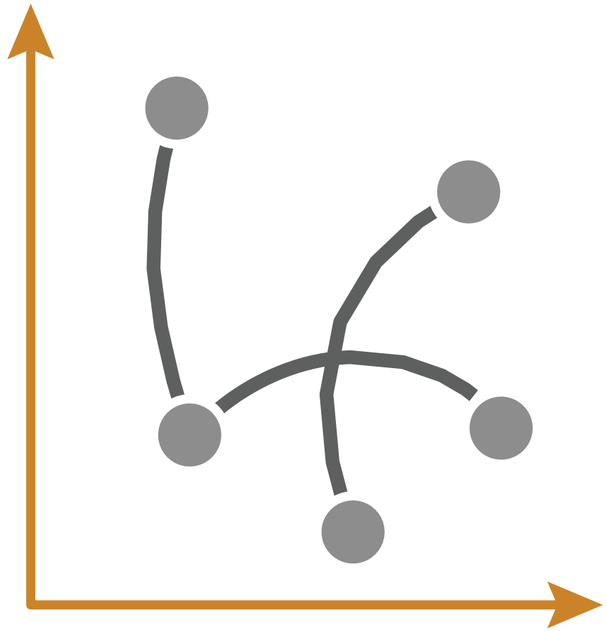
Well suited for networks with different node types or with an important categorical or set-like attribute.

Less scalable with respect to the number of nodes and network density than node-link layouts.

Neighborhoods, paths, and clusters are not easily visible if they span different facets.

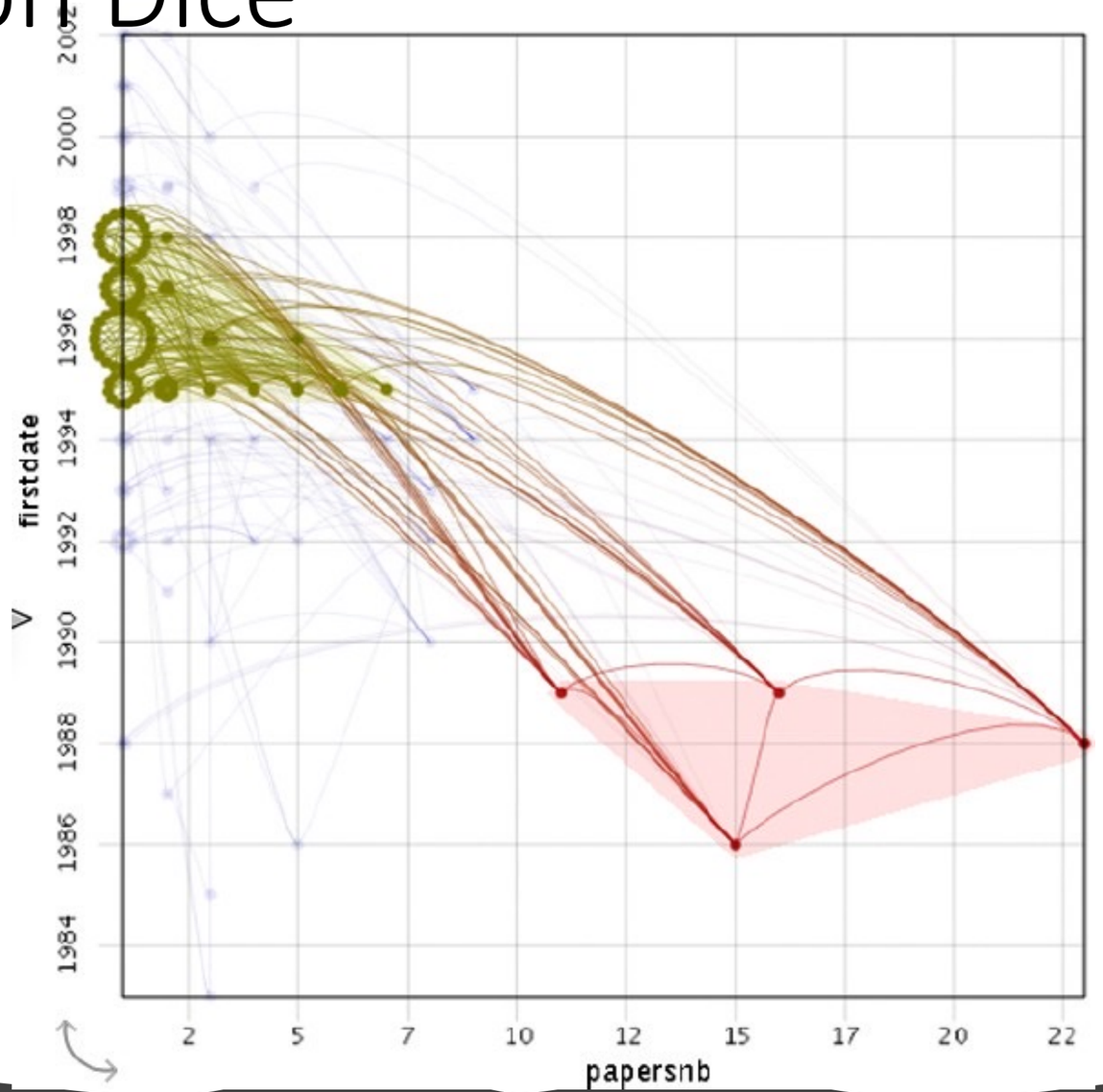
Recommended for networks where nodes can be separated into groups easily and where these groups are central to the analysis

Attribute-Driven Positioning



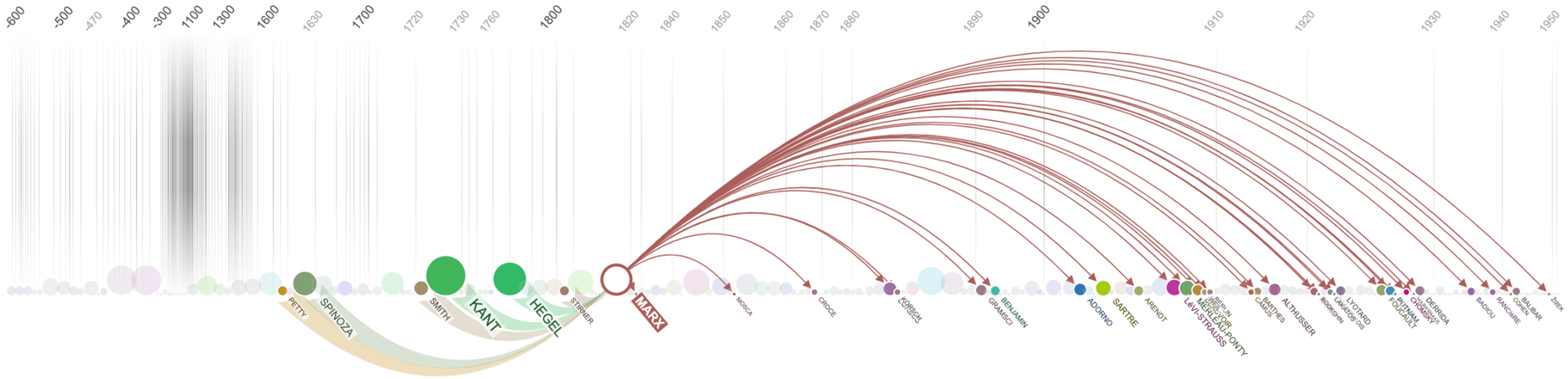

ANCHORAGE
VANCOUVER
EDMONTON
SEATTLE
PORTLAND
SAN FRANCISCO
DENVER
MINNEAPOLIS / ST. PAUL
CHICAGO
KANSAS CITY
TORONTO
DALLAS
CLEVELAND
MONTREAL
BALTIMORE
HALIFAX
WASHINGTON D.C.
BOSTON
PHILADELPHIA
NEW YORK
JFK & NEWARK
TAMPA BAY
ORLANDO
ICELAND
HELSINKI
STOCKHOLM
OSLO
GOTHENBURG
BERGEN
COPENHAGEN
BILLUND
BERLIN
HAMBURG
FRANKFURT
MUNICH
AMSTERDAM
GLASGOW
BRUSSELS
ZURICH
MANCHESTER
MILAN
DUBLIN
LONDON
HEATHROW
& GATWICK
PARIS
ORLY & CDG
GENEVA
MADRID

Graph Dice

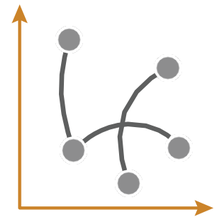


Bezerianos et al. 2010

Edge Map



Dork et al. 2011



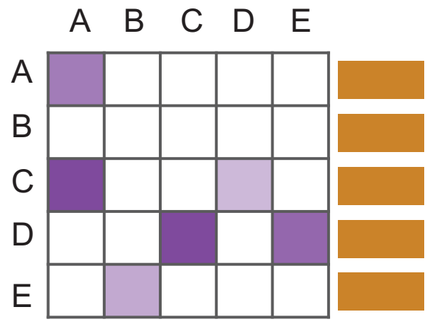
Attribute-Driven Positioning

Well suited for quantitative attributes

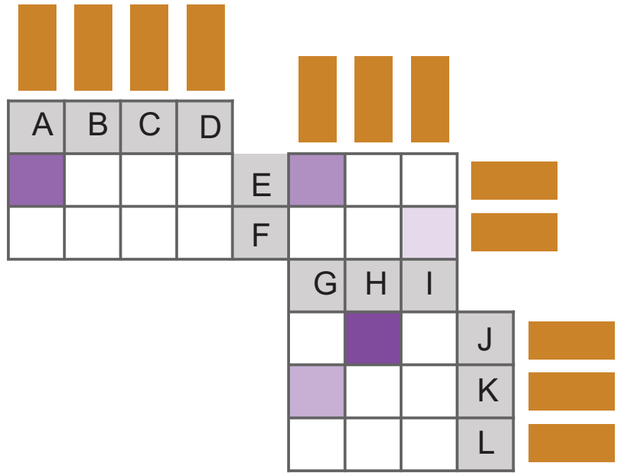
Does not lend itself well to visualizing the topology of the network.

Recommended for smaller, sparse networks where relationships between node attributes are paramount to the analysis task, and topological features only provide context

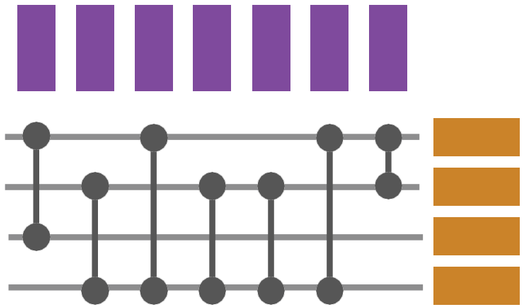
Tabular Layouts



Adjacency Matrix

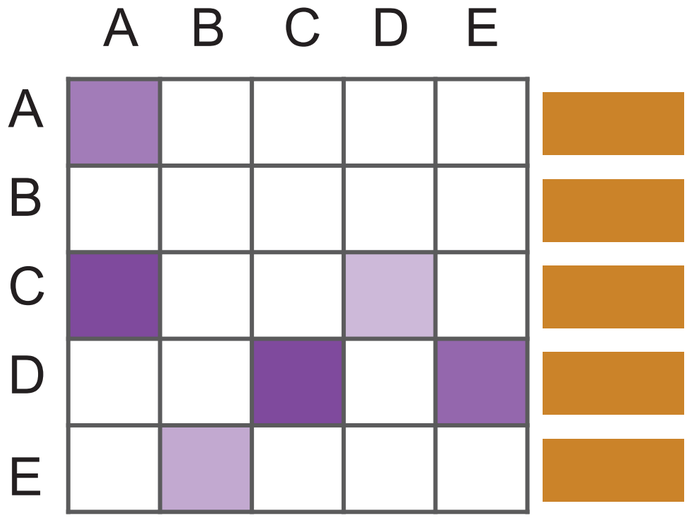


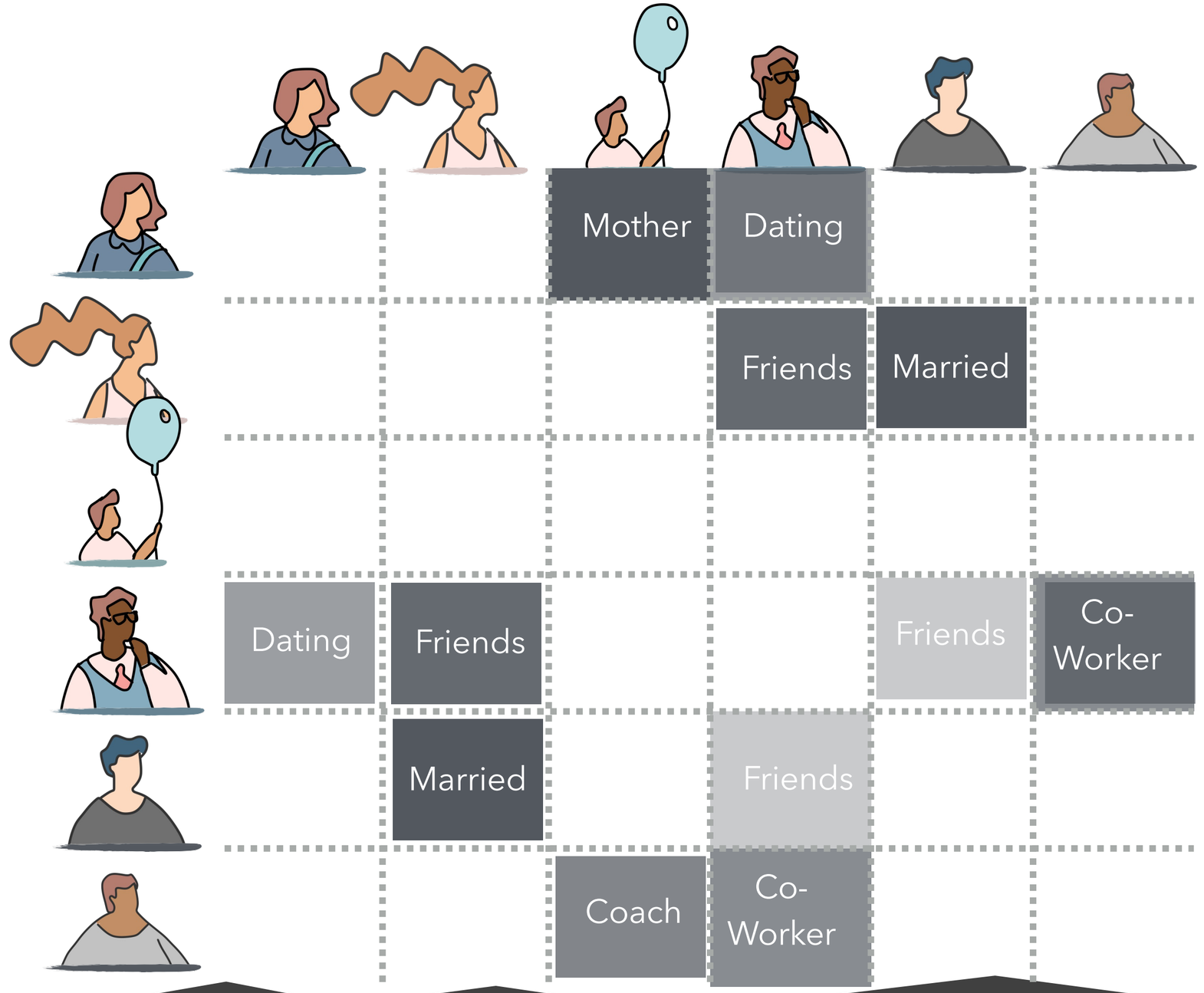
Quilts



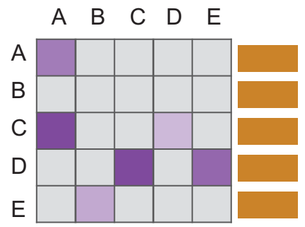
BioFabric

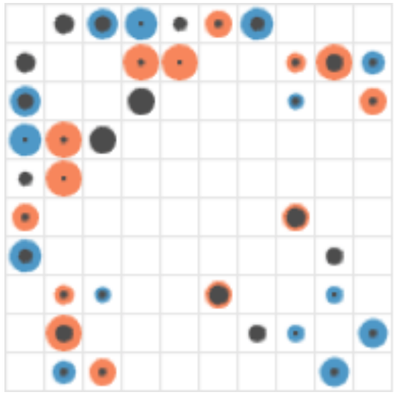
Adjacency Matrix

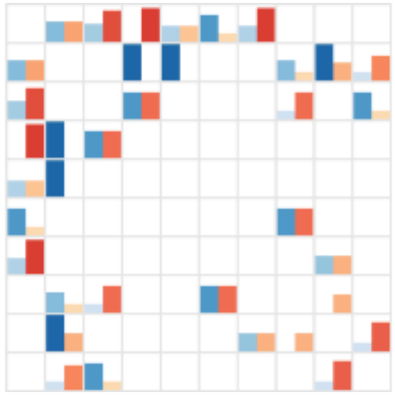


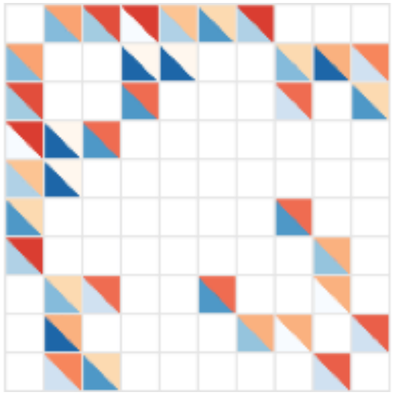

Mother
Dating
Friends
Married
Dating
Friends
Friends
Co-
Worker
Married
Friends
Coach
Co-
Worker

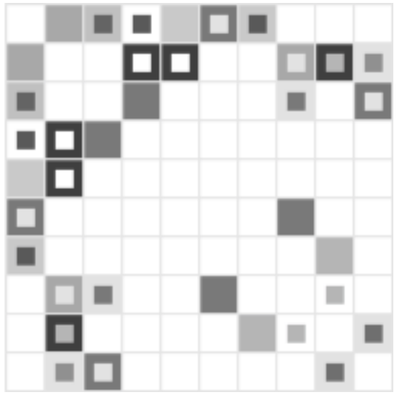
Adjacency Matrix



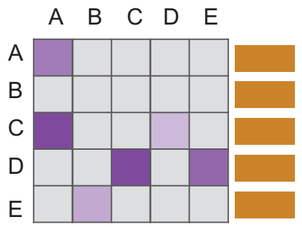


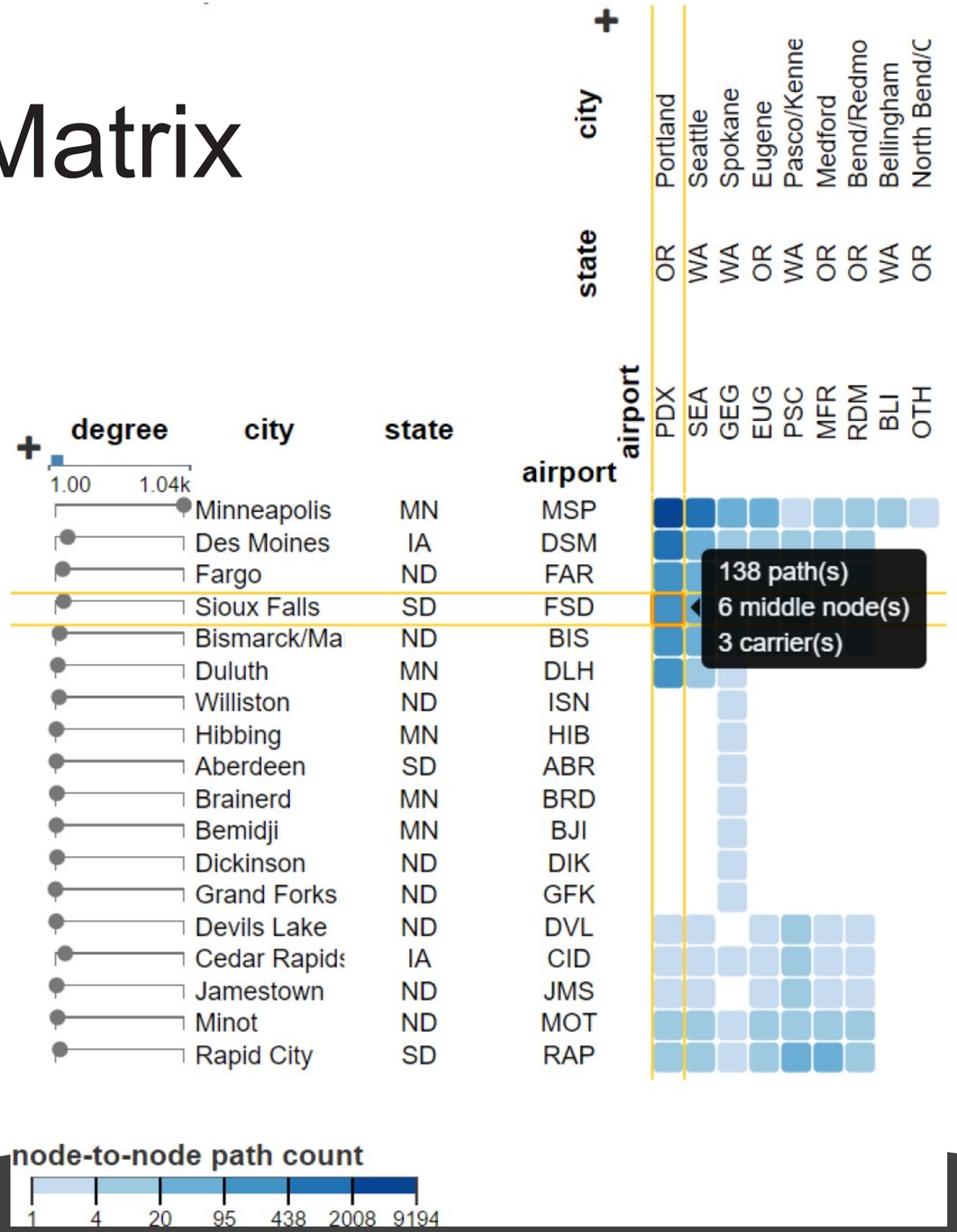




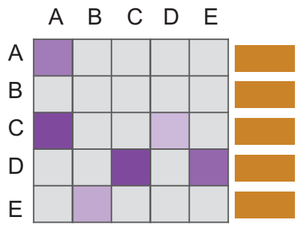


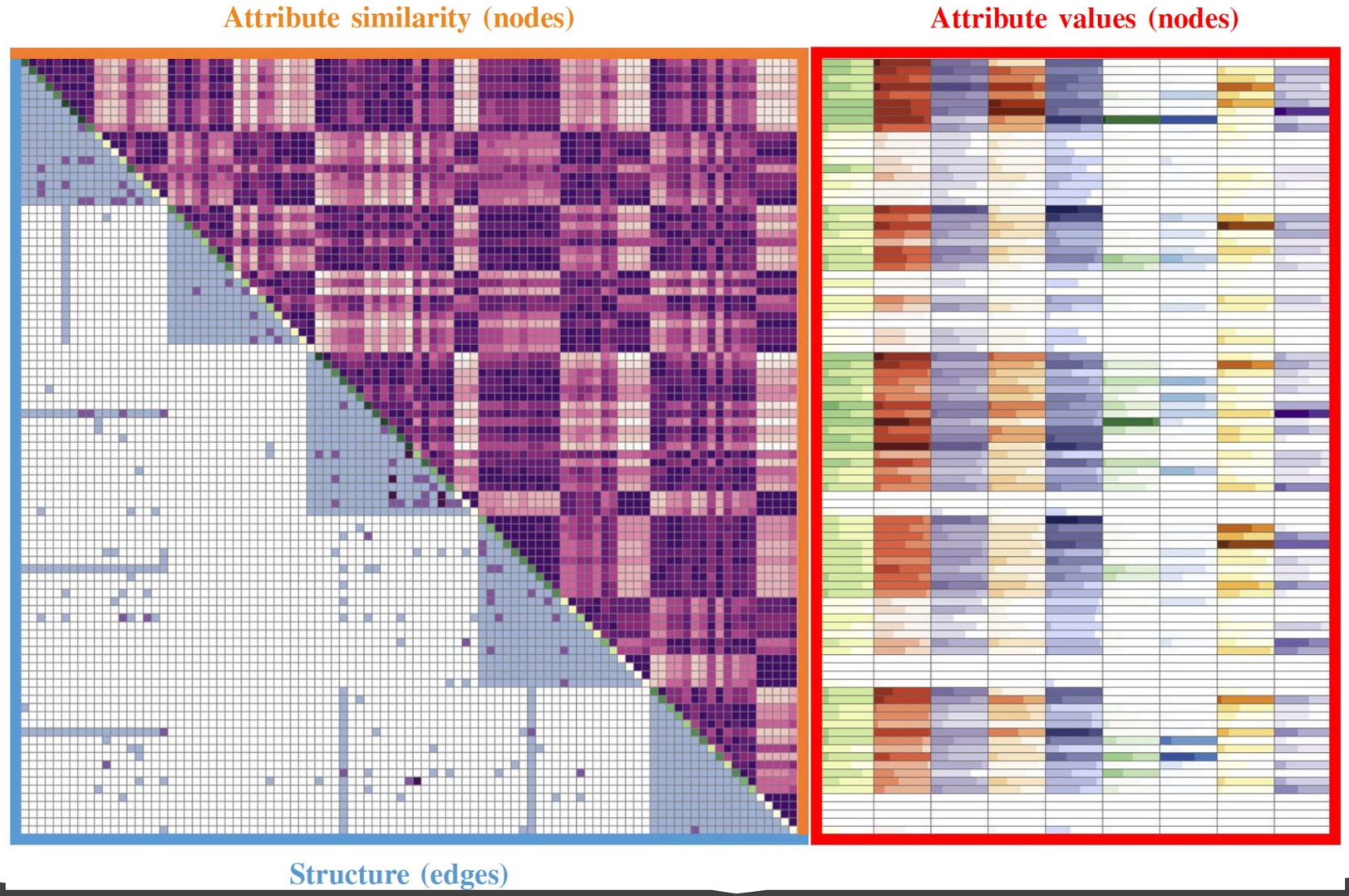
Adjacency Matrix



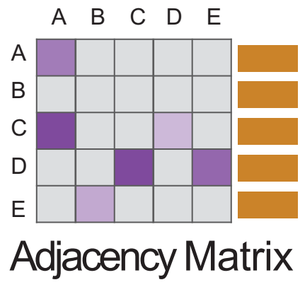


Adjacency Matrix





Berger et al, 2019



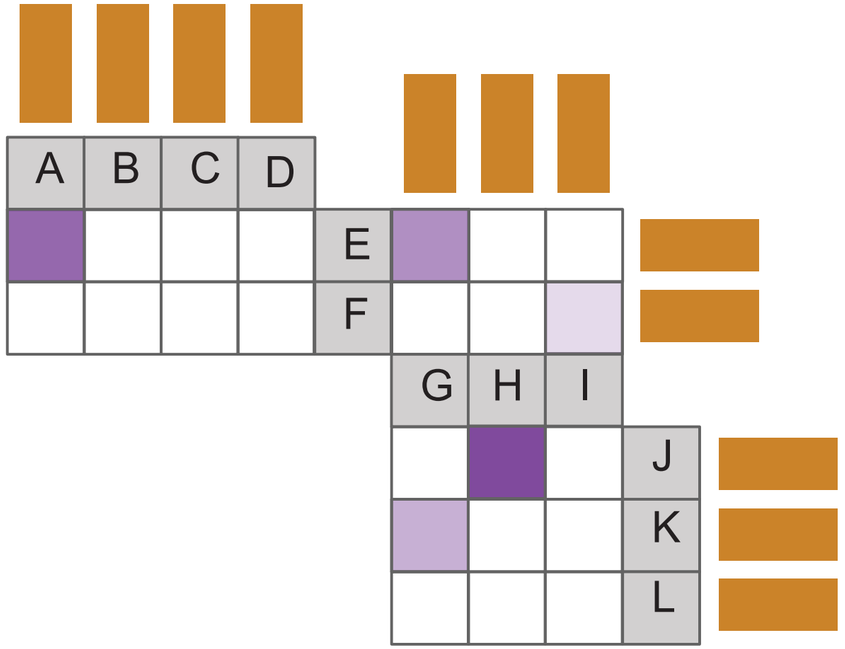
Ideal for dense and completely connected networks

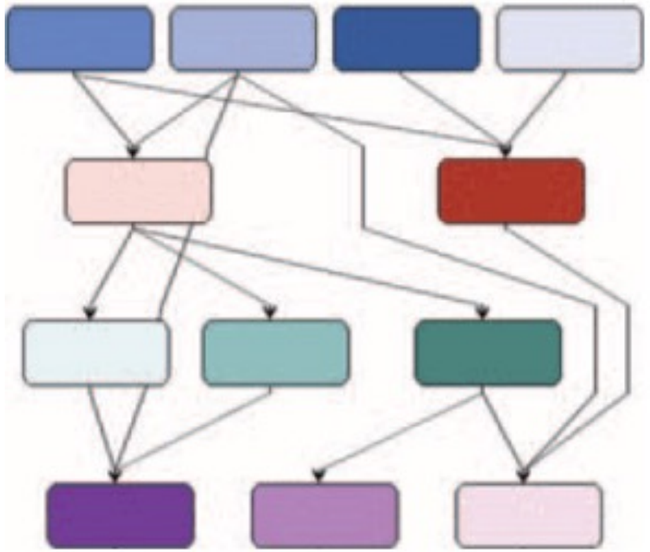
Requires quadratic space with respect to the number of nodes.

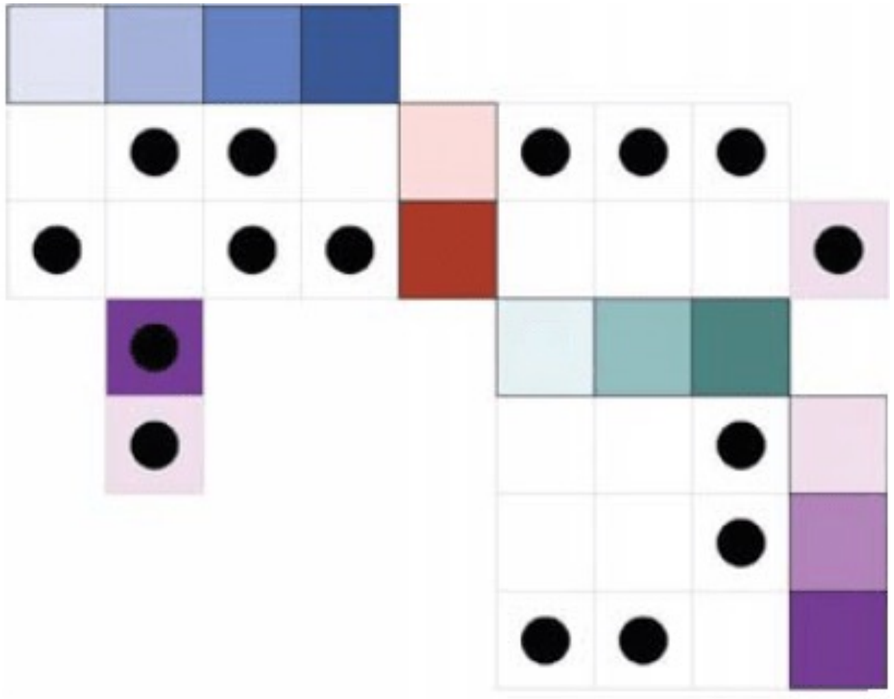
Complexity of choosing the right reordering algorithm

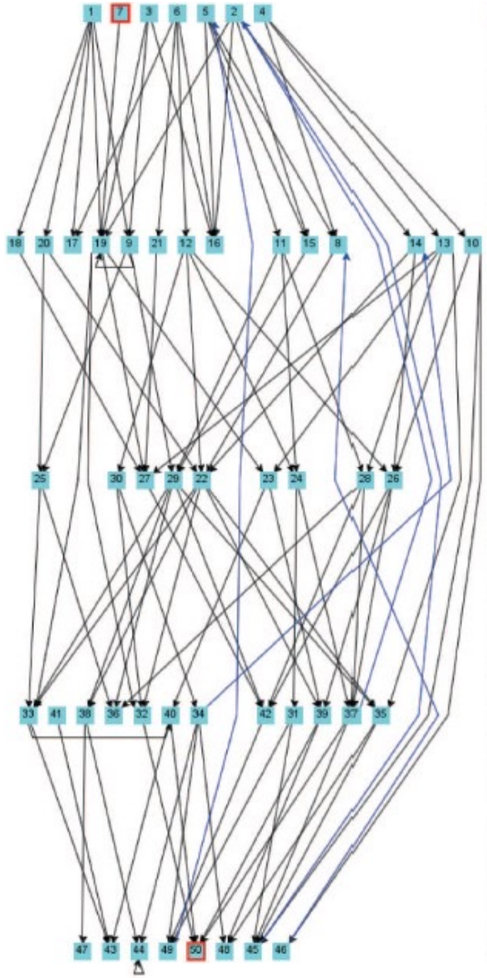
Recommended for smaller, complex and dense networks with rich node and/or edge attributes, for all tasks except for those involving paths

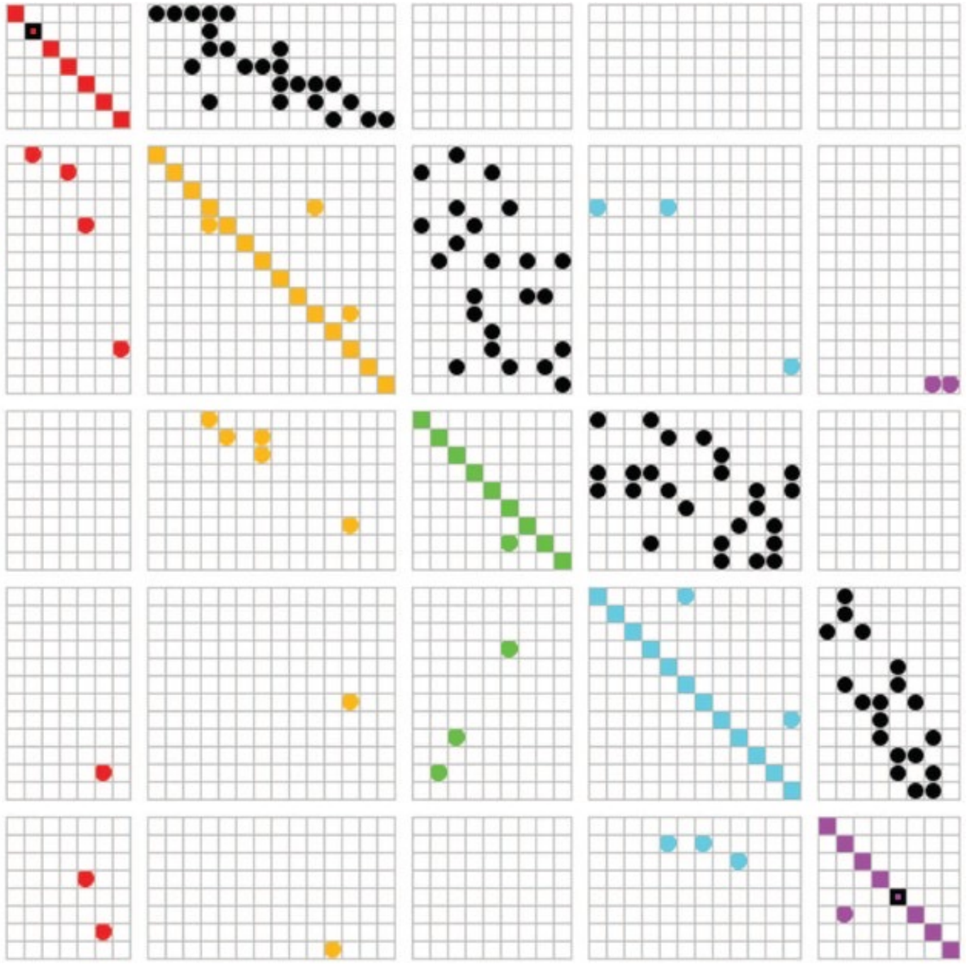
Quilts

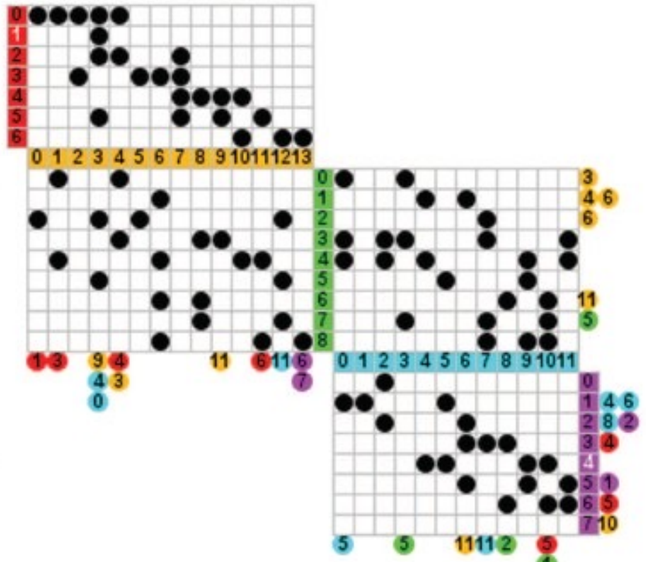


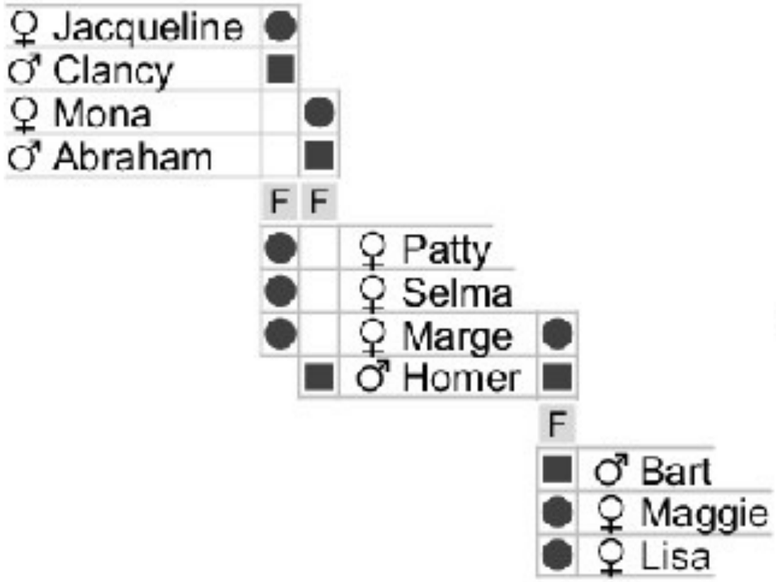


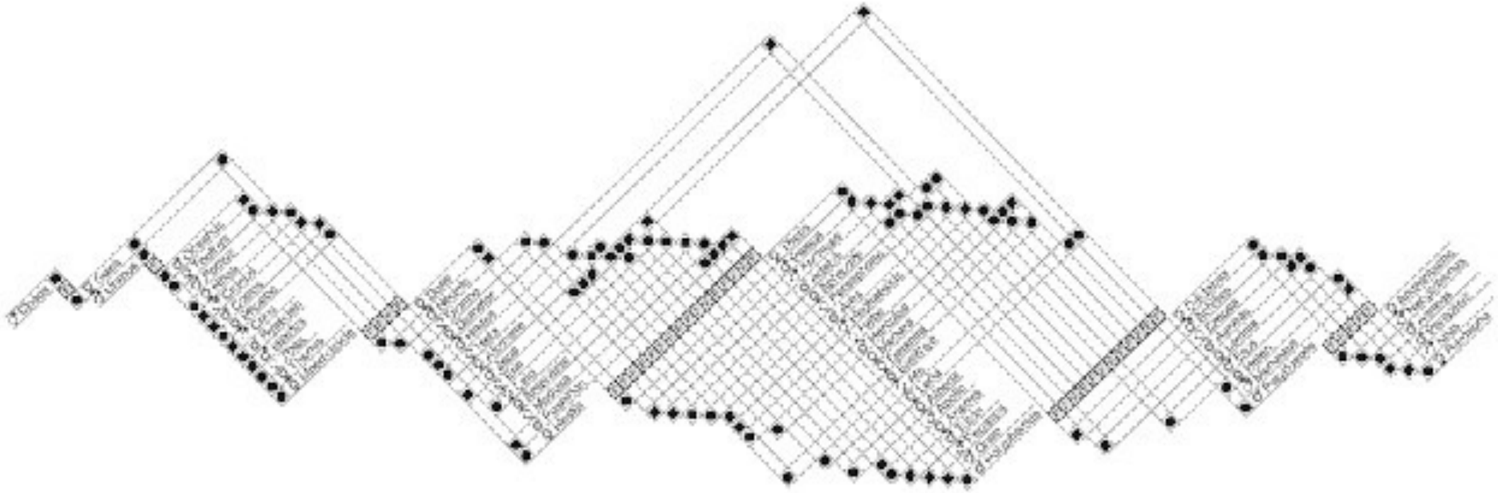









♀ Jacqueline
♂ Clancy
♀ Mona
♂ Abraham
F F
♀ Patty
♀ Selma
♀ Marge
♂ Homer
F
♂ Bart
♀ Maggie
♀ Lisa

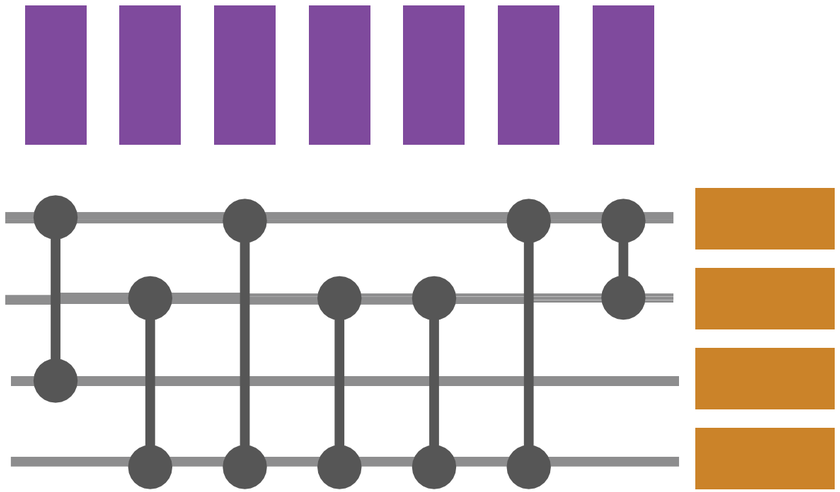


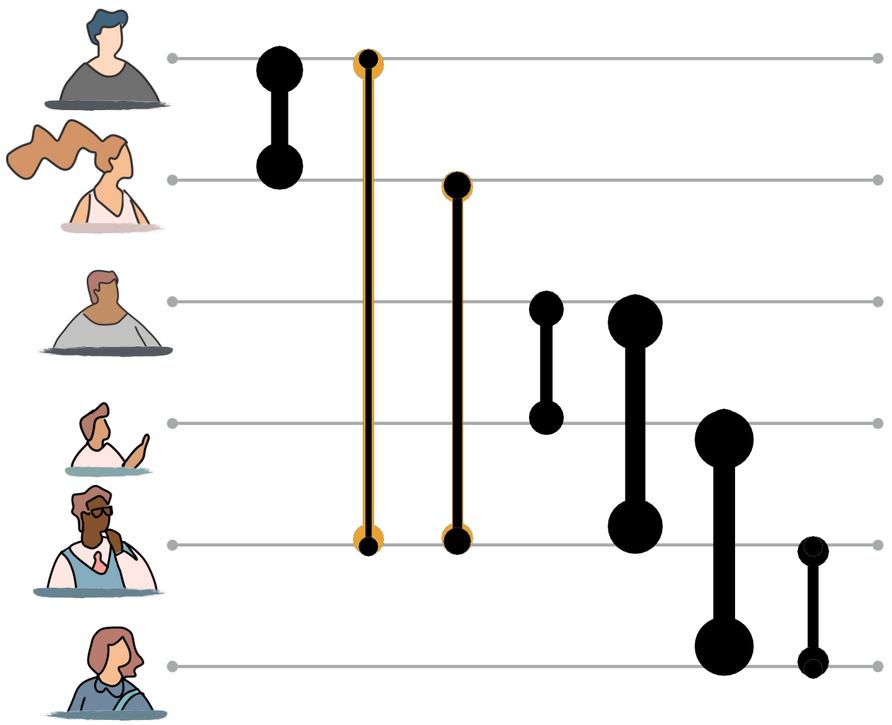
Well suited for layered networks

Links between nonconsecutive layers can be problematic to integrate and non-intuitive

Recommended for layered or k-partite networks with limited skiplinks.

BioFabric

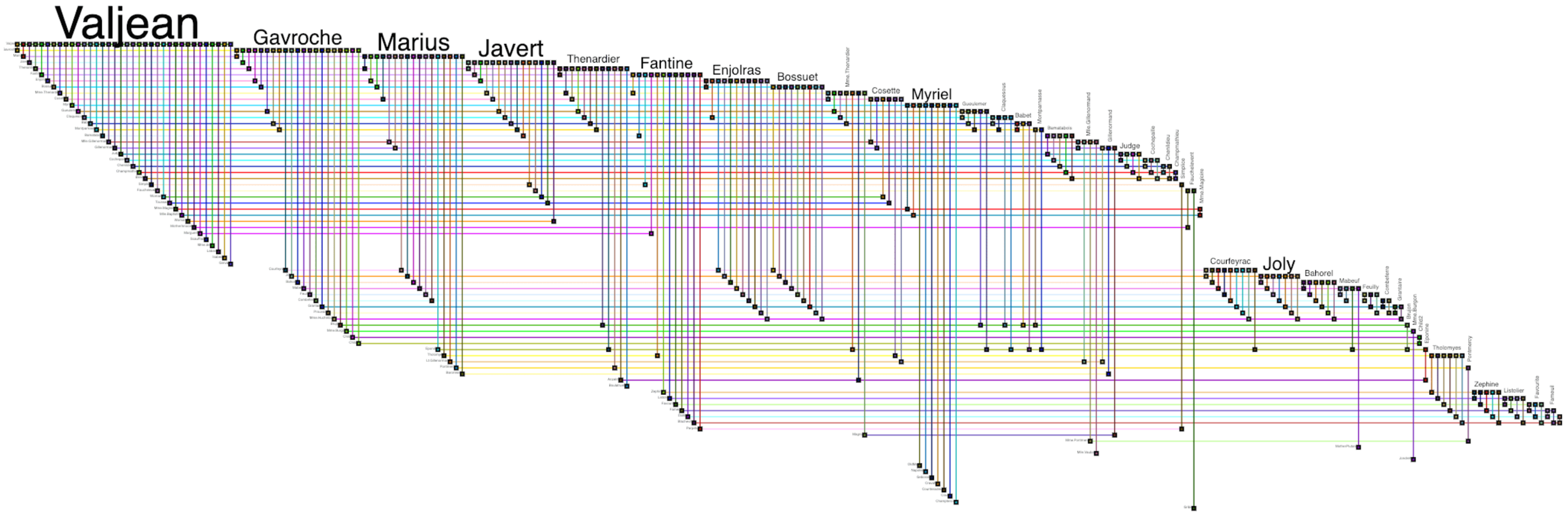




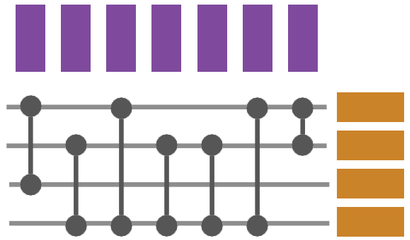
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

Relationship	Years
Married	4
Friends	3
Friends	8
Soccer Coach	2
Co-workers	3
Mother / Son	12
Dating	4

BioFabric



Longabaugh, 2012



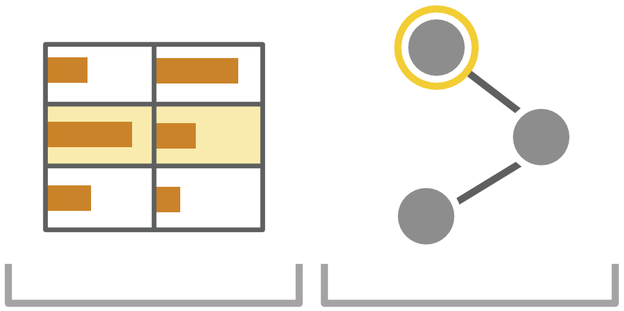
BioFabric

Can be used to visualize rich edge attributes and node attributes at the same time

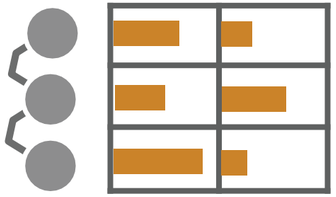
More difficult to discover neighbors and clusters in Biofabric compared to matrices.

Recommended for small, sparse networks with many nodes and rich edge attributes

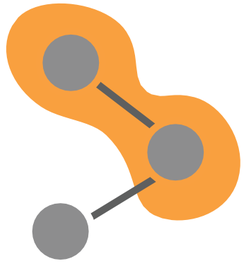
View Operations



Juxtaposed

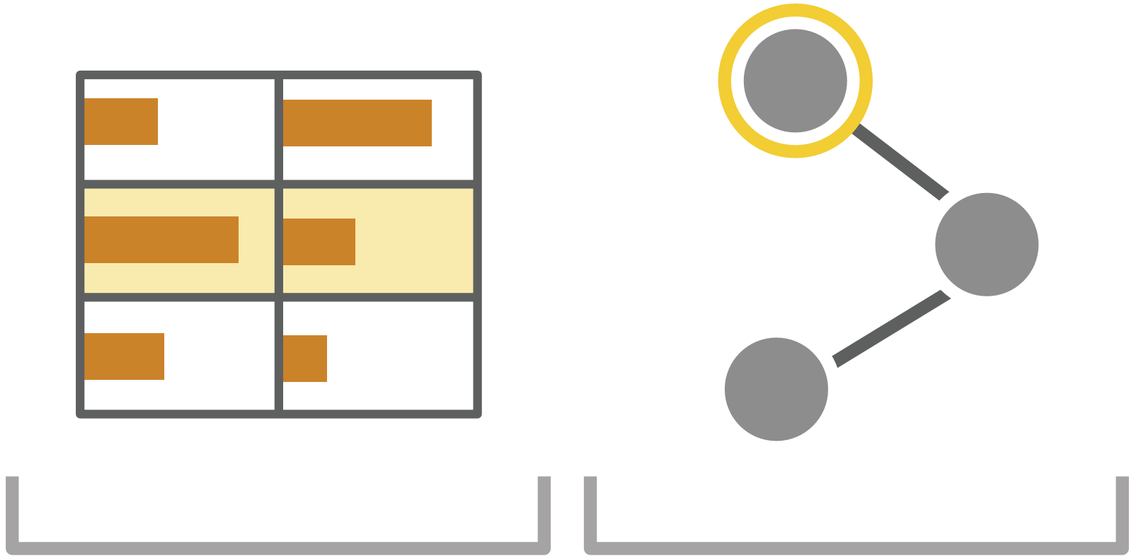


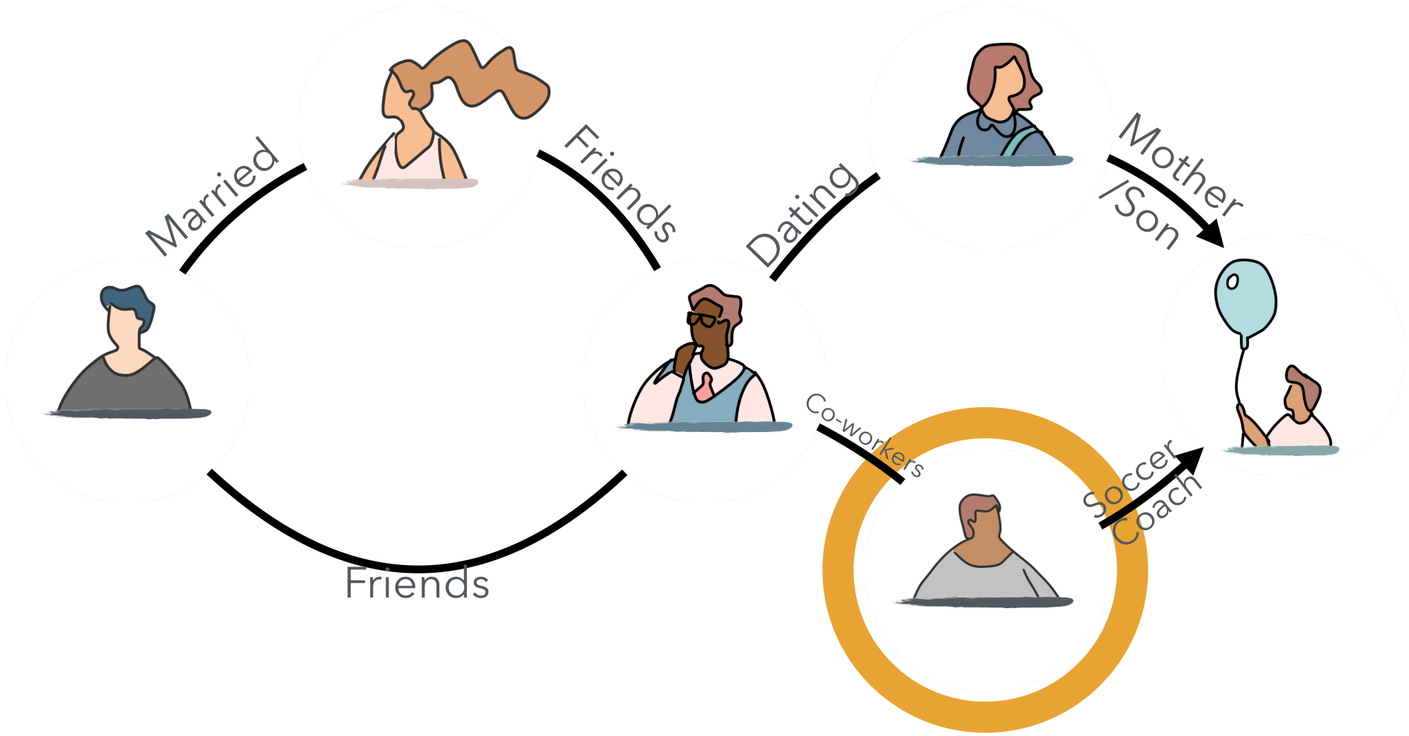
Integrated



Overloaded

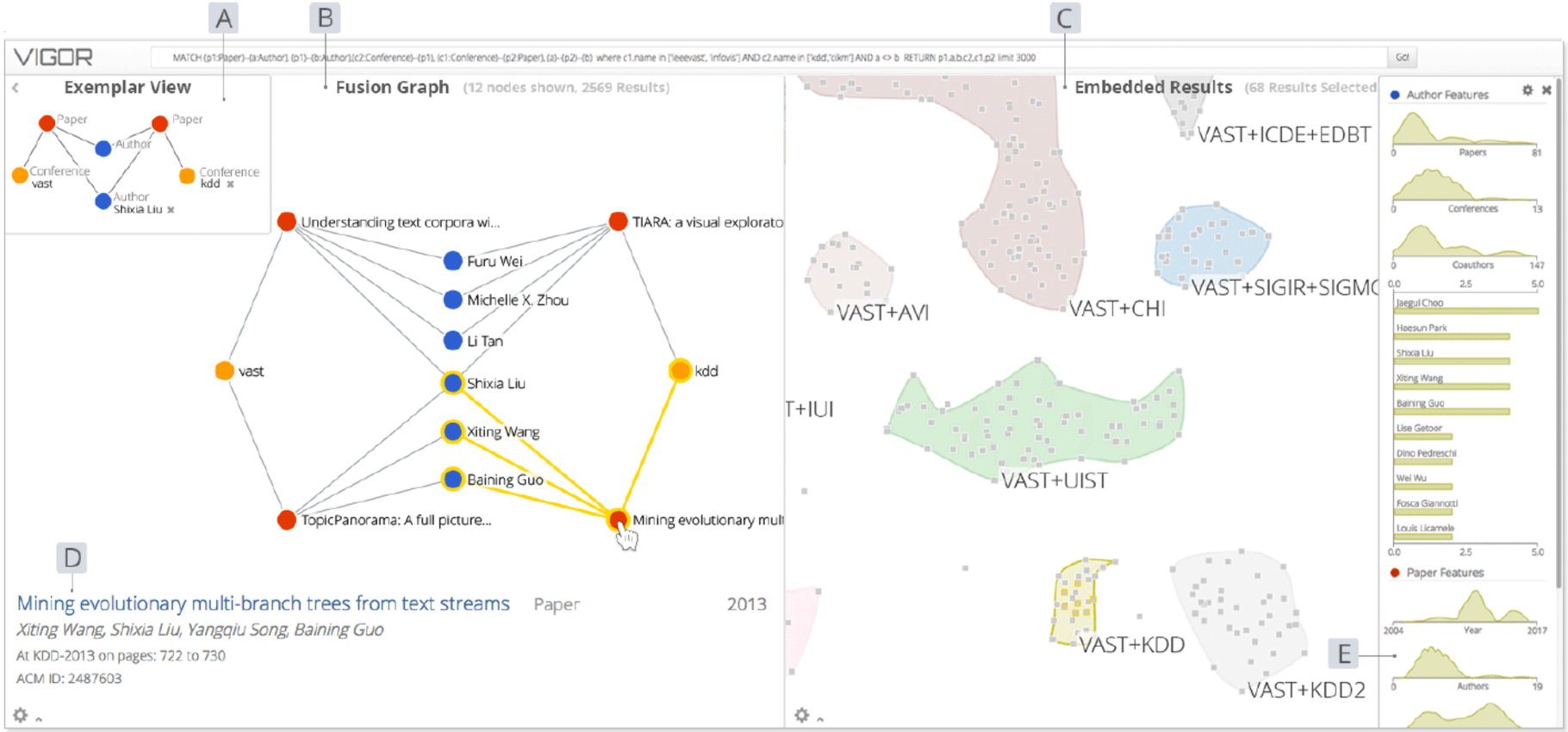
Juxtaposed





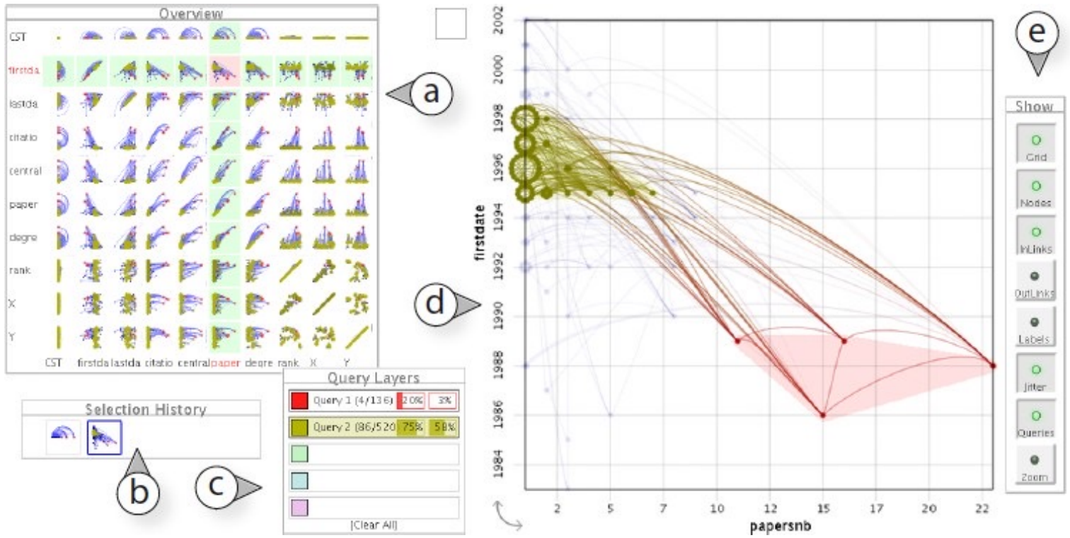
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

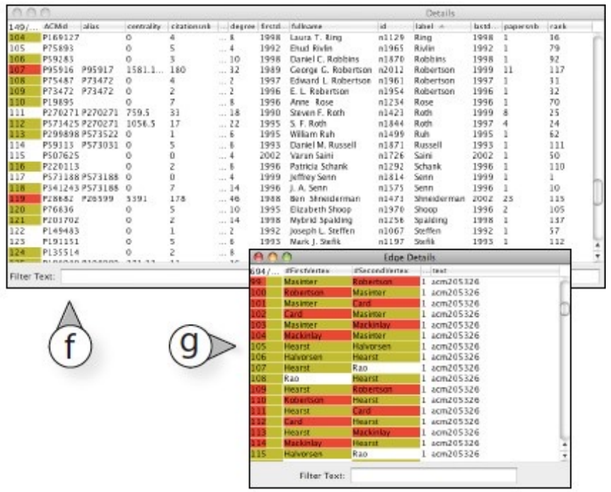
VIGOR



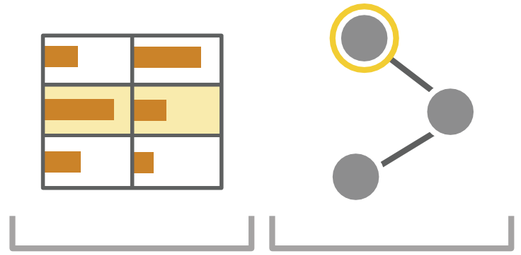
Pienta et al. 2018

Graph Dice


Overview
CST
firstdate
lastdate
citatio
central
paper
degree
rank
X
Y
a
b
c
d
e
Selection History
Query Layers
Query 1 (4/136) 20% 3%
Query 2 (86/520) 75% 58%
[Clear All]
firstdate
papersnb
Show
Grid
Nodes
InLinks
OutLinks
Labels
Jitter
Queries
Zoom


Details
Filter Text:
Edge Details
Filter Text:
f
g

Independent views can optimize for topology and attribute independently.

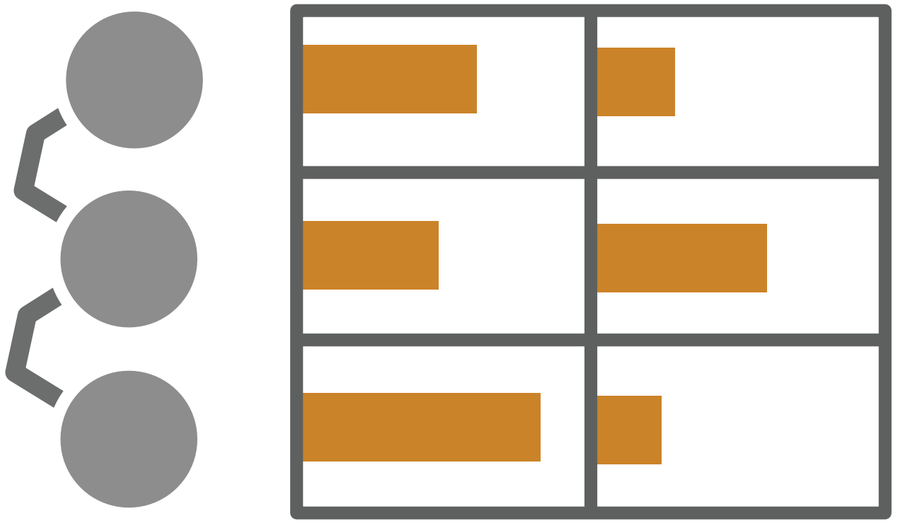


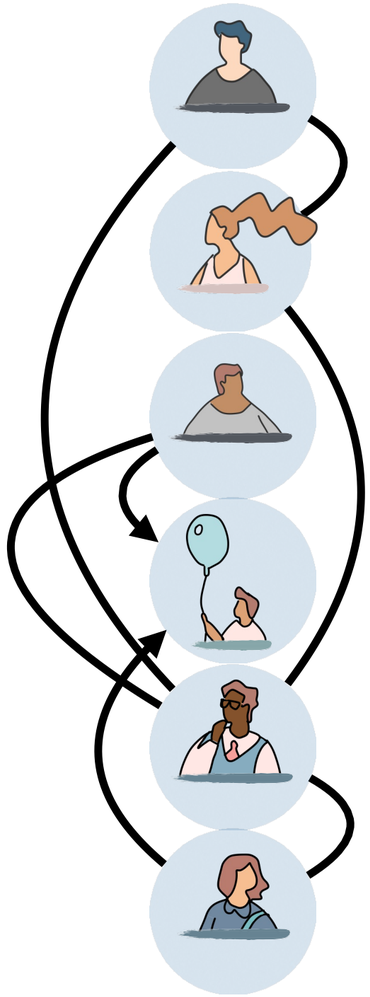
Juxtaposed

Not great for tasks on topological structures beyond a single node or edge.

Recommended for large networks and/or very large numbers or heterogeneous types of node and link attributes

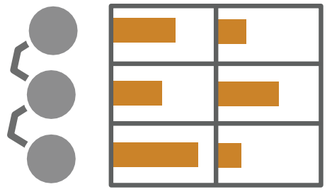
Integrated

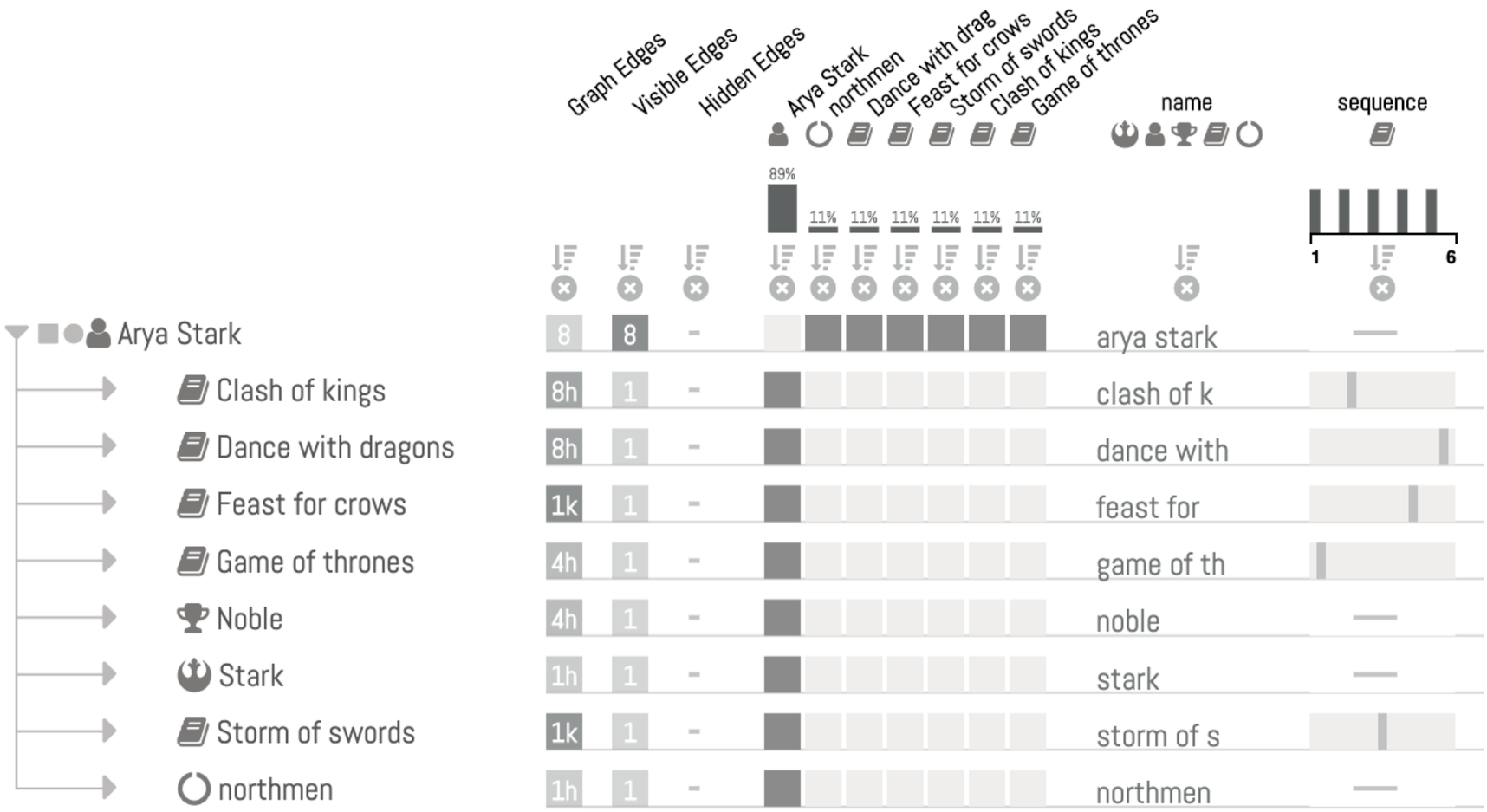




Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

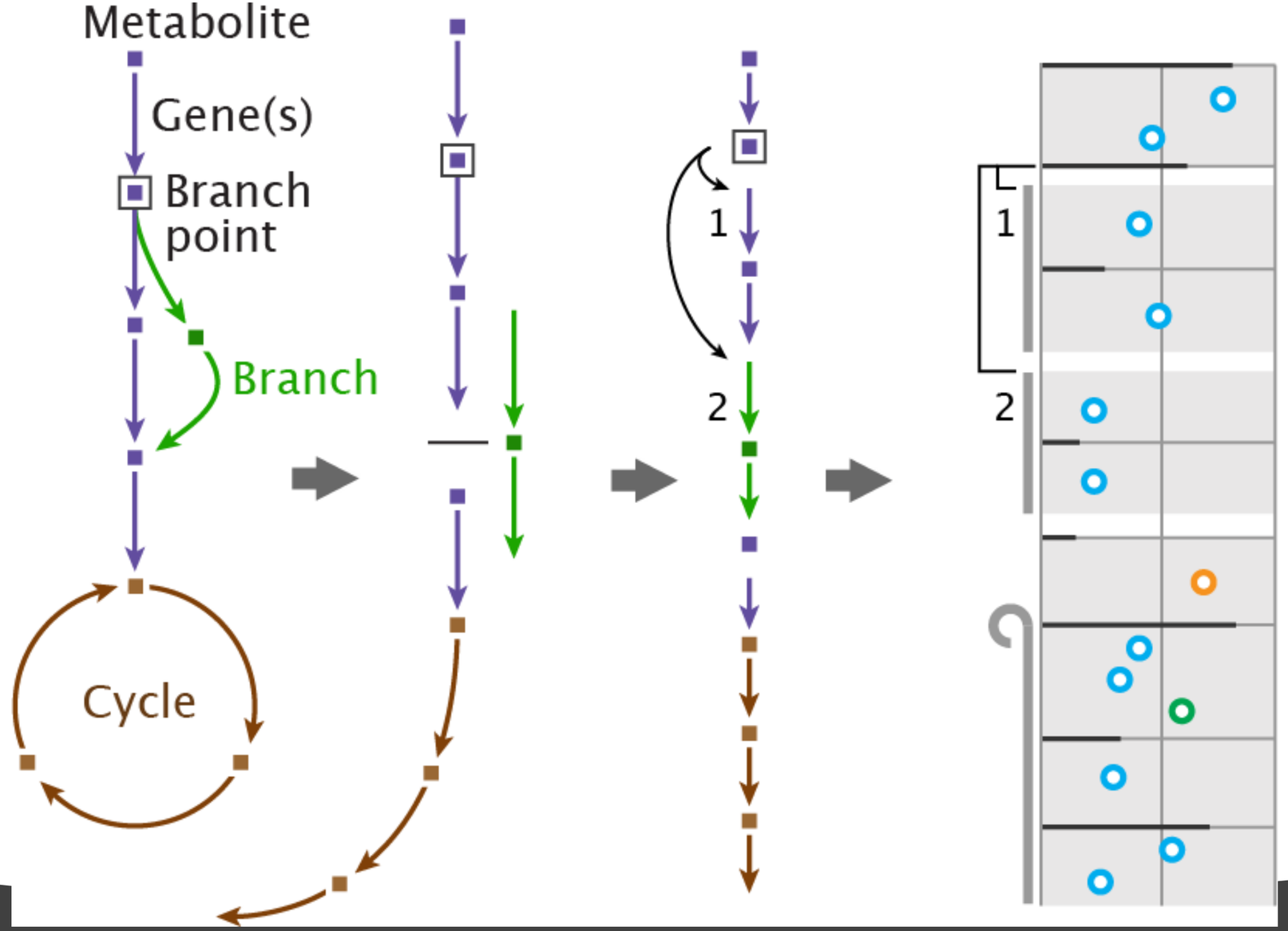
Juniper



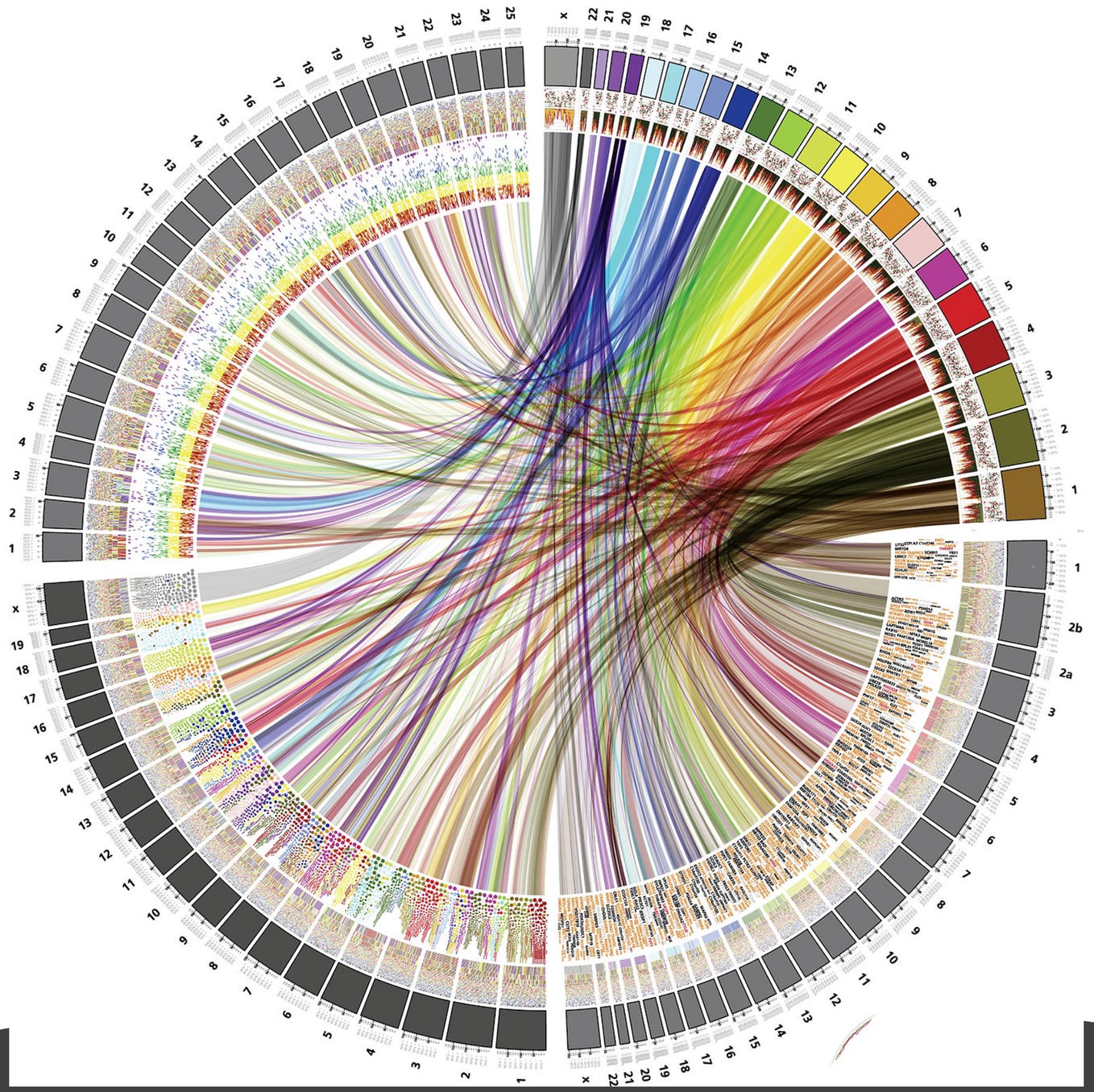


Nobre et al. 2018

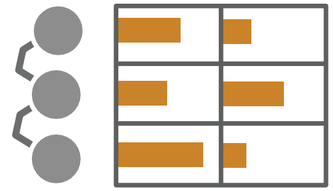
Pathline



Circos



Krzywinski et al. 2009



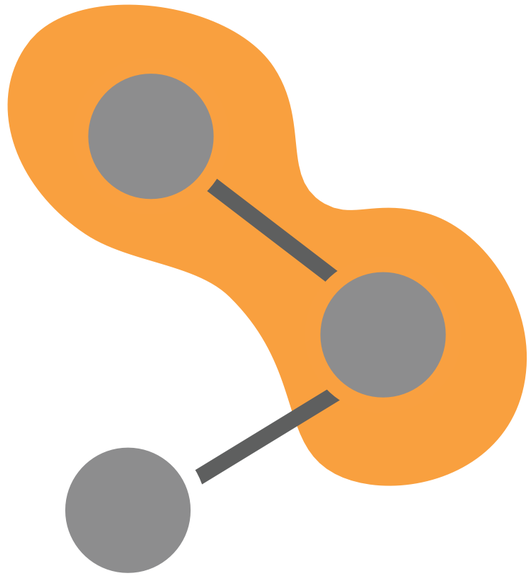
Integrated

good at integrating attributes with topology, if the topology can be represented in a linear layout.

Not suitable for networks that can not be sensibly linearized.

Recommended for networks with several, heterogenous, node attributes and well suited for tasks on single nodes, neighbors, and paths

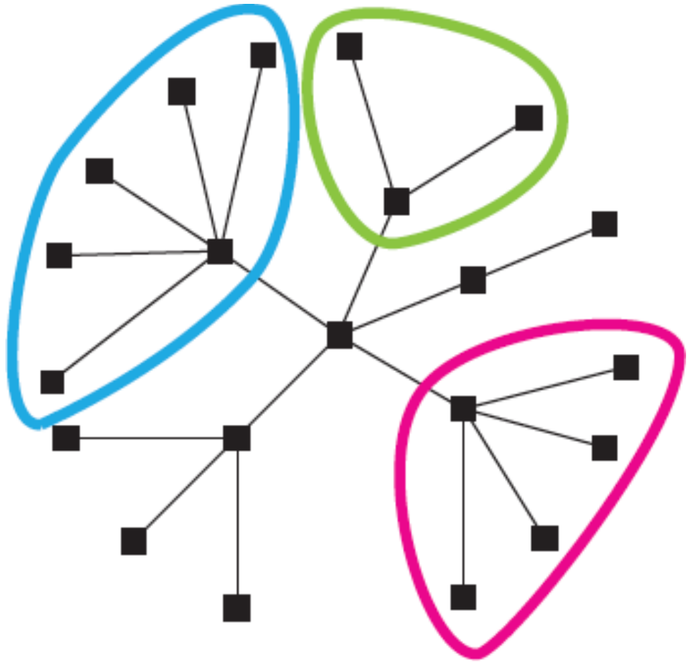
Overloaded

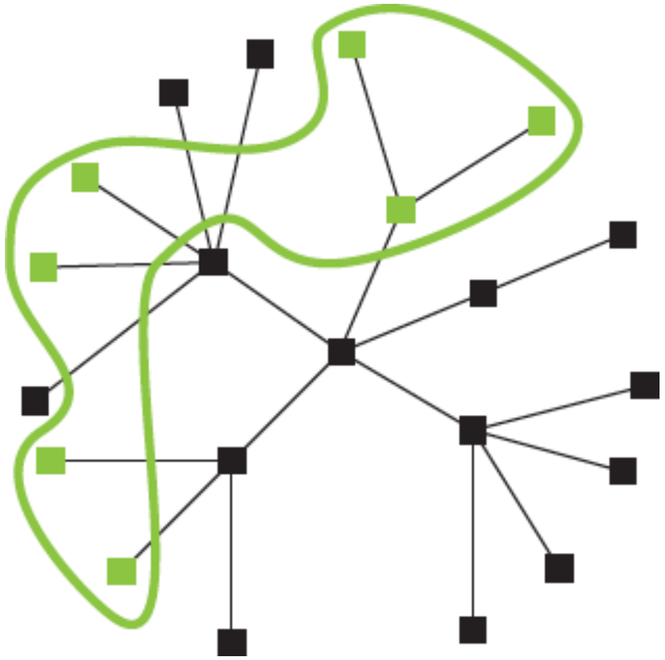


GMaps

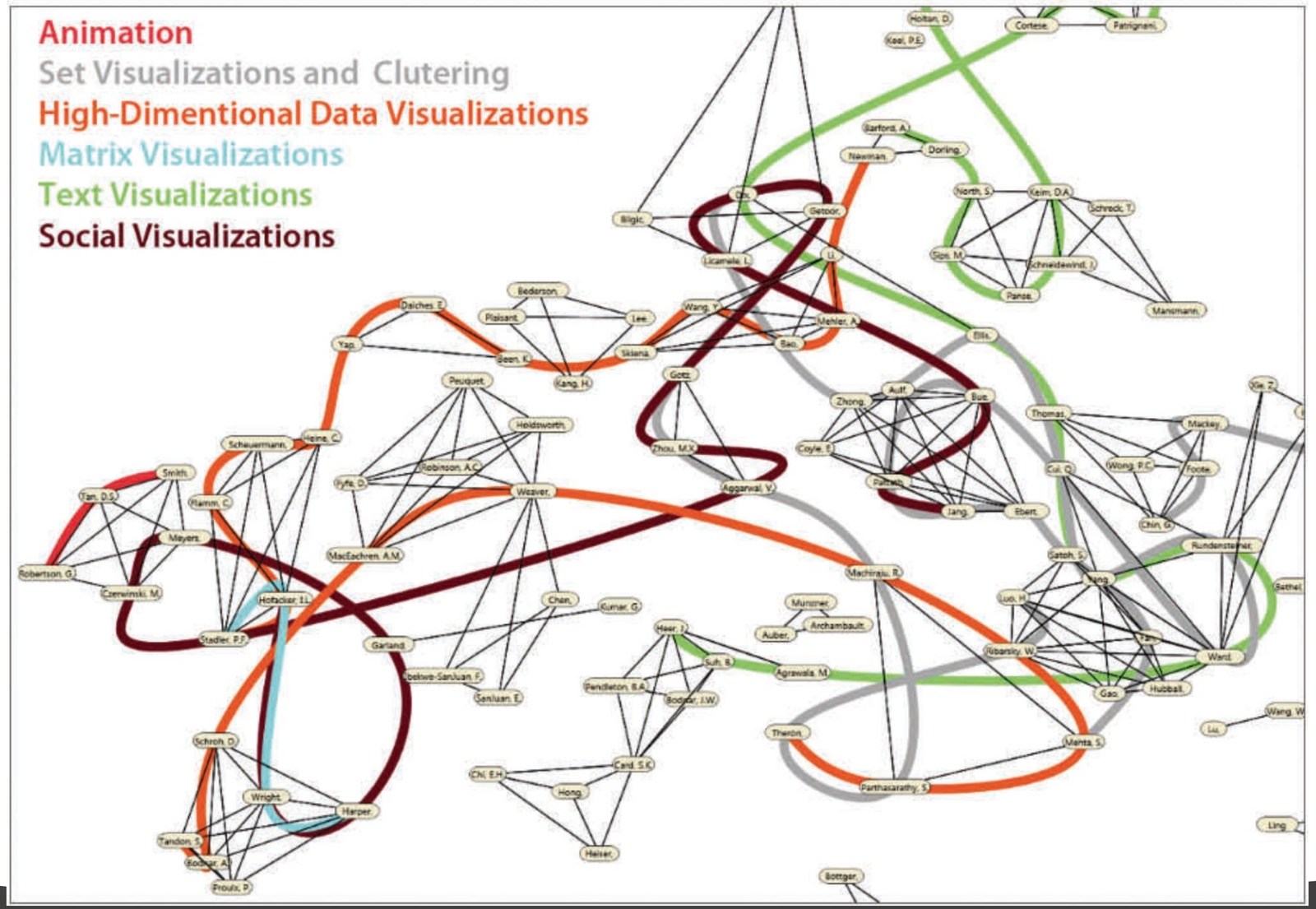
Gansner et al. 2010

Bubble Sets



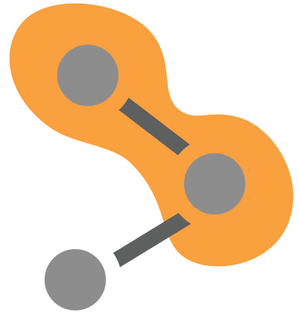


LineSets



Alper et al. 2011

good at displaying sets and clusters

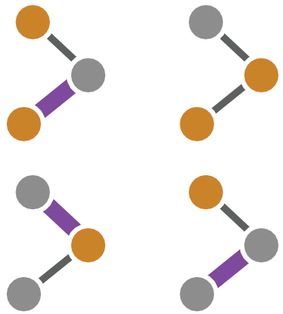


Overloaded

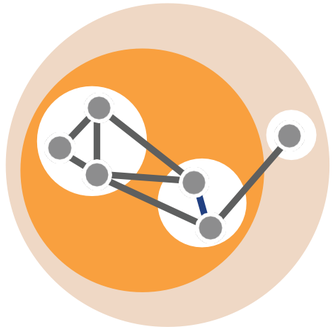
Not suitable for displaying more than one or two attributes at a time.

Recommended for recommend overloading for the particular use case of visualizing set-memberships or clusters on top of node-link diagrams

Layout Operations

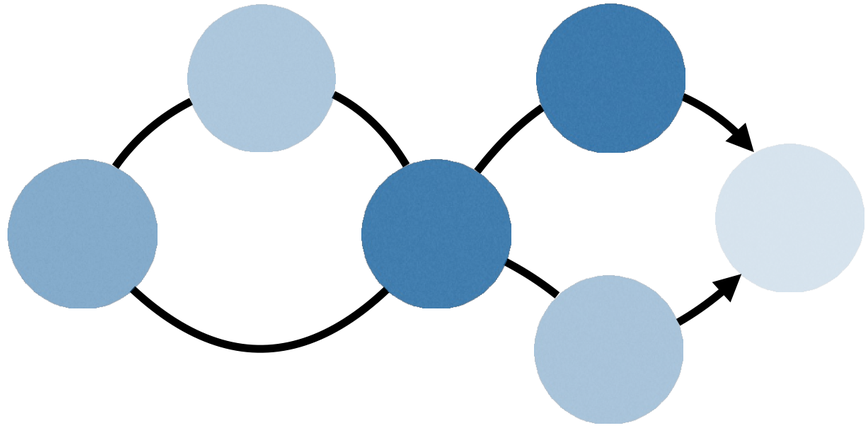


Small Multiples

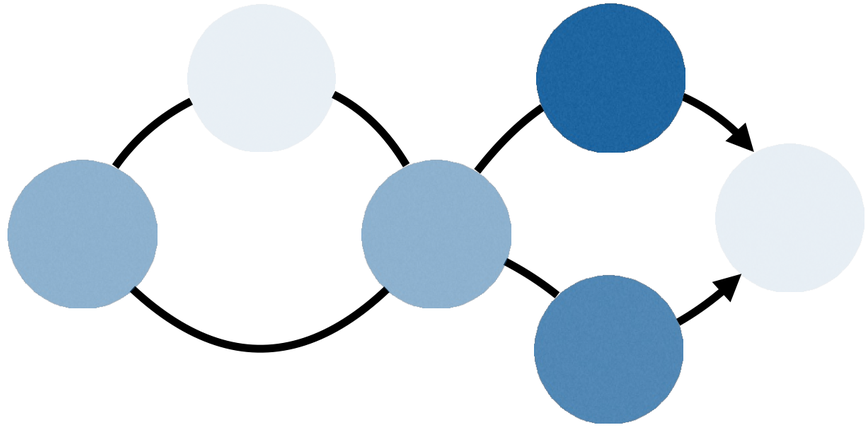


Hybrids

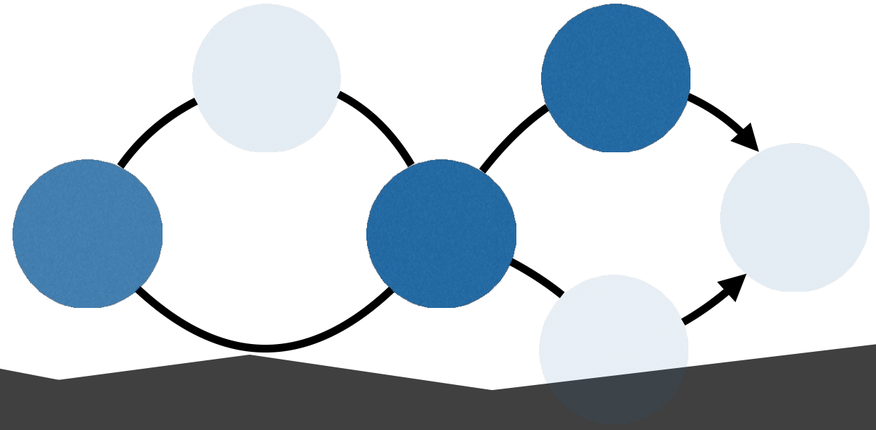
Day 1



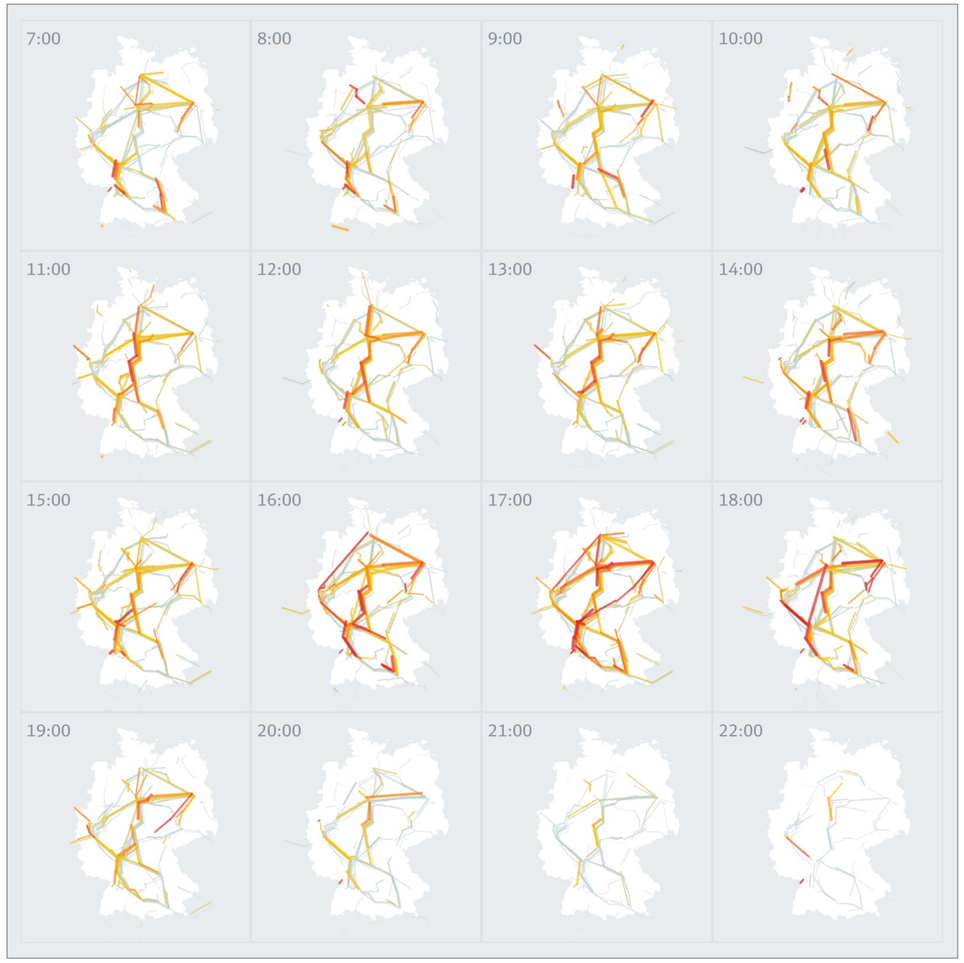
Day 2



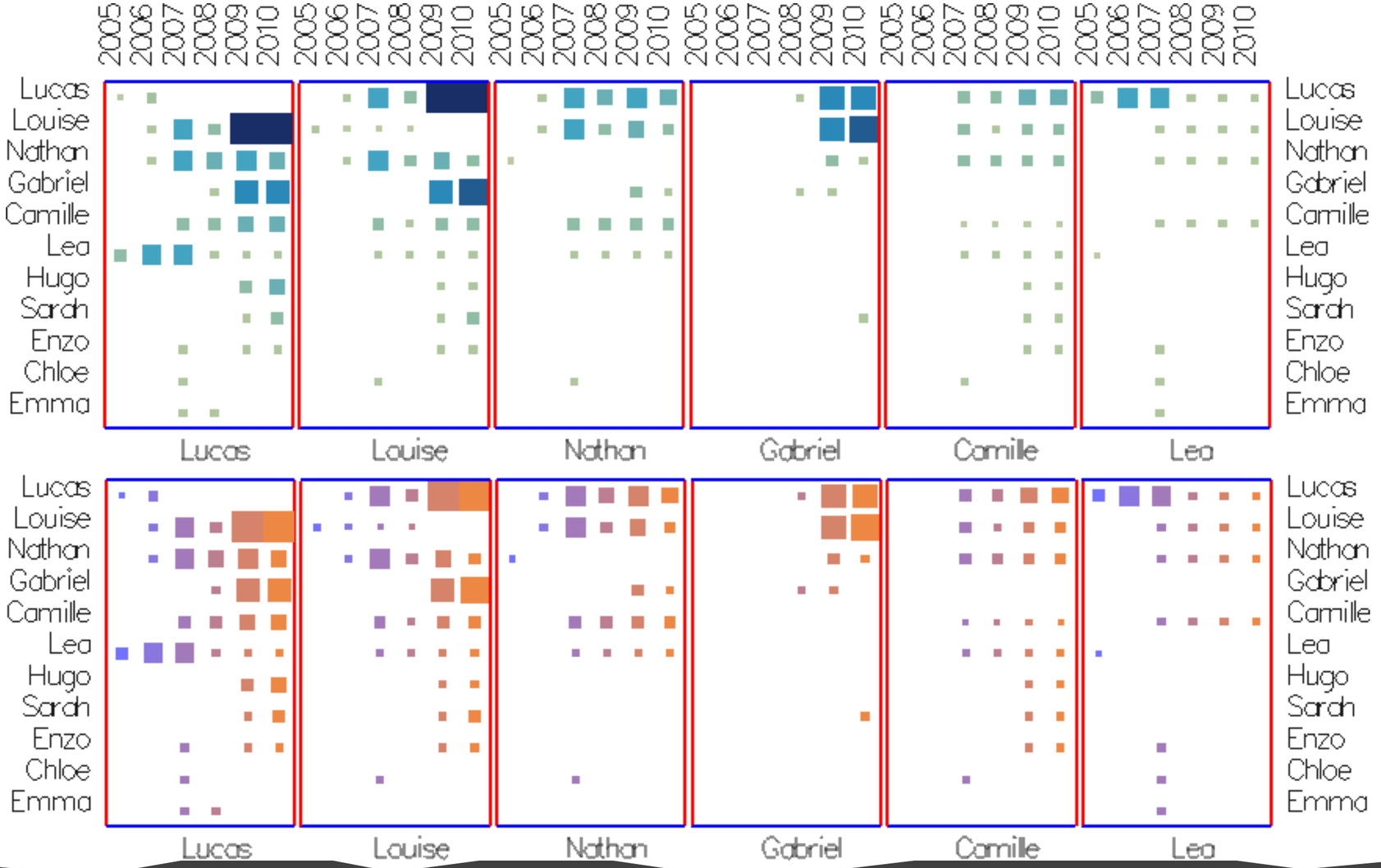
Day 3



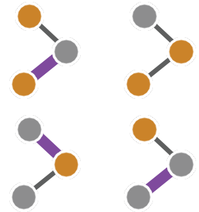
Peakspotting



Small Multiples



Common layout facilitates attribute comparisons in specific topological features



Small Multiples

Not ideal for large networks, or tasks on clusters

Recommended for small networks where the tasks are focused on attribute comparison

More at http://vdl.sci.utah.edu/mvnv/