THE STATE OF THE ART IN
VISUALIZING MULTIVARIATE NETWORKS

CAROLINA NOBRE, MIRIAH MEYER, MARC STREIT, ALEXANDER LEX

visualization design lab
THE UNIVERSITY OF UTAH
JOHANNES KEPLER UNIVERSITY LINZ


teacher
friends
competitors
friends
siblings
ex-boyfriend
coworkers
parent-child
siblings
friends
married
Photo by Rob Curran


Name: Samuel
Age: 41
Job: Nurse
Name: Julia
Age: 34
Job: Vet
Name: Ellen
Age: 31
Job: Actress
Name: Gordon
Age: 54
Job: Chef
Name: Roger
Age: 51
Job: Doctor
Name: Camille
Age: 42
Job: Teacher
Photo by Rob Curran

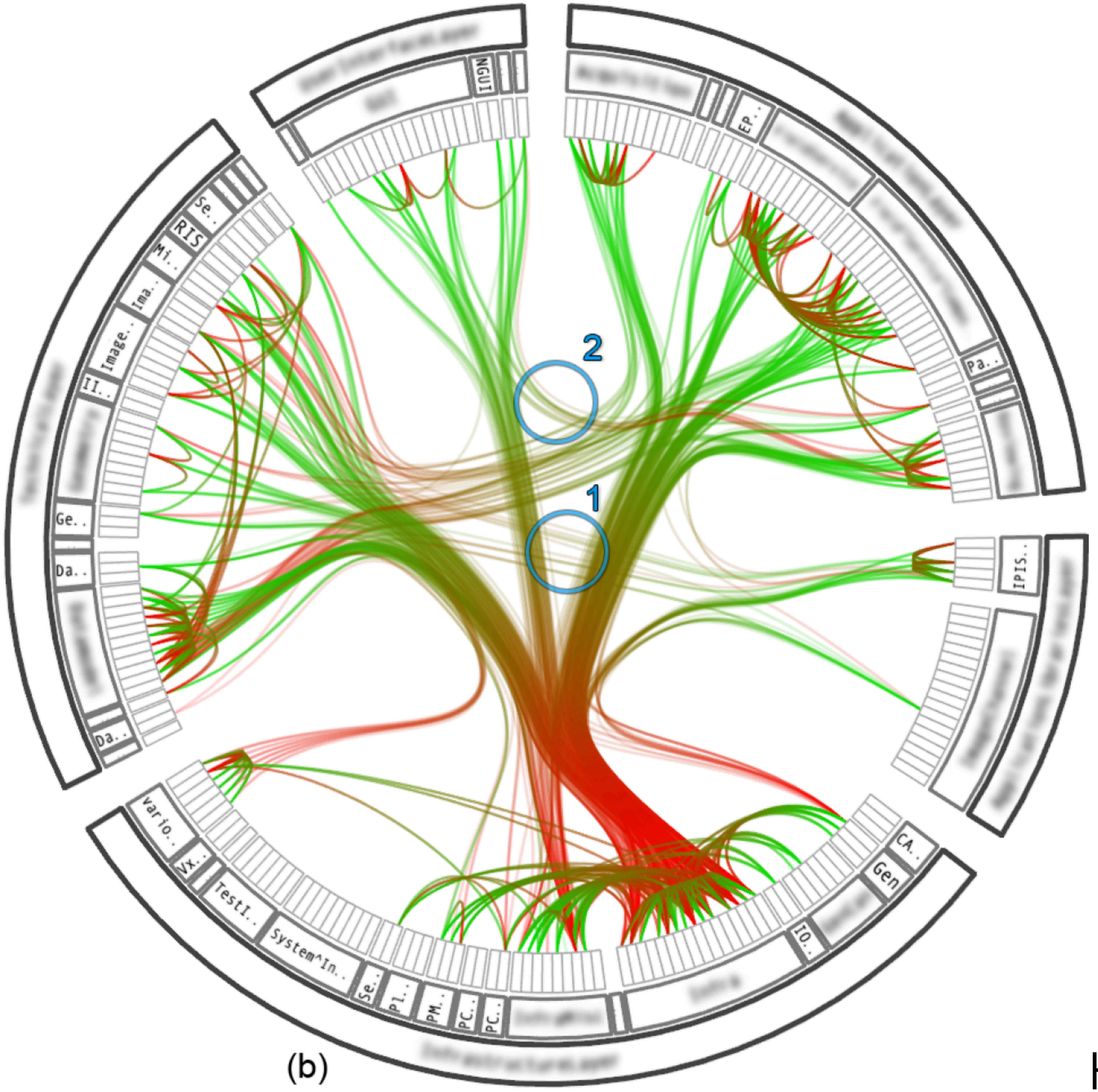
A MULTIVARIATE NETWORK IS

NETWORK TOPOLOGY +

NODE AND EDGE ATTRIBUTES


LiVEJOURNAL
foursquare
Insta
YouTube
vimeo
facebook
Blogger
my
flickr
Behance
twitter
instagram
tumblr.
Like

Glyoxy-
late
cycle
OXALYL-CoA
DECARBOXY-
LASE
OXALATE
DECARBOXY-
LASE
OXALATE-CoA-TRANS
FERRE-
DIOXIN
(red)
FERRE-
DIOXIN
(ox.)
2-OXO-GLUTARATE SYNTHASE
Deficient
in hyper-
oxaluria I
PYRUVATE
ALANINE-
GLYOXYLATE
TRANS-
AMINASE
OXALYL-CoA
OXALATE
CoA-SH
PyrP
L-ALA-
NINE
TOSE,
EROL
NADPH
+H+
NADP+
CoA-SH
GLYOXY-
LATE
DEHYDRO-
GENASE
(ACY-
LATING)
FMNH2 · E
(S)-2-HY-
DROXY ACID
DEHYDRO-
GENASE
FMN · E
O2
H2O2
ThPP
HOOC−C−OH
CH2
CH2
COOH
NAD+
NADH+H+
GLYOXYLATE
REDUCTASE
GLYOXYLATE
NH3
H2O2
D-AMINO
ACID
OXIDASE
O2
H2O
FAD
ThPP
Mg++
YCOLATE
(S)-2-HYDROXY-
ACID OXIDASE
FMN · E
FMNH2 · E
LUORO-
ITRATE
GLYCINE
TRANSAMINASE
PyrP
L-GLUT-
2-OXO-
GLUTARATE
COOH
DEHY
NADH+
CO2
H2O
CoA-SH
SH
E ·



(b)

Holten and Wijk, 2009

CONTRIBUTIONS

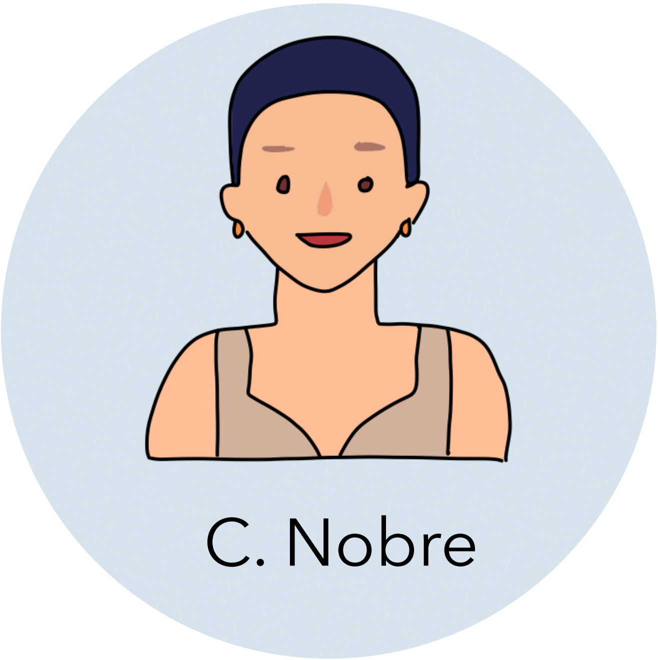
- Multivariate Network Task Taxonomy
- Typology of Multivariate Network Visualization Techniques
- Guidelines/Recommendations for Visualizing MVNs
- Summary of Application Areas
- Evaluations

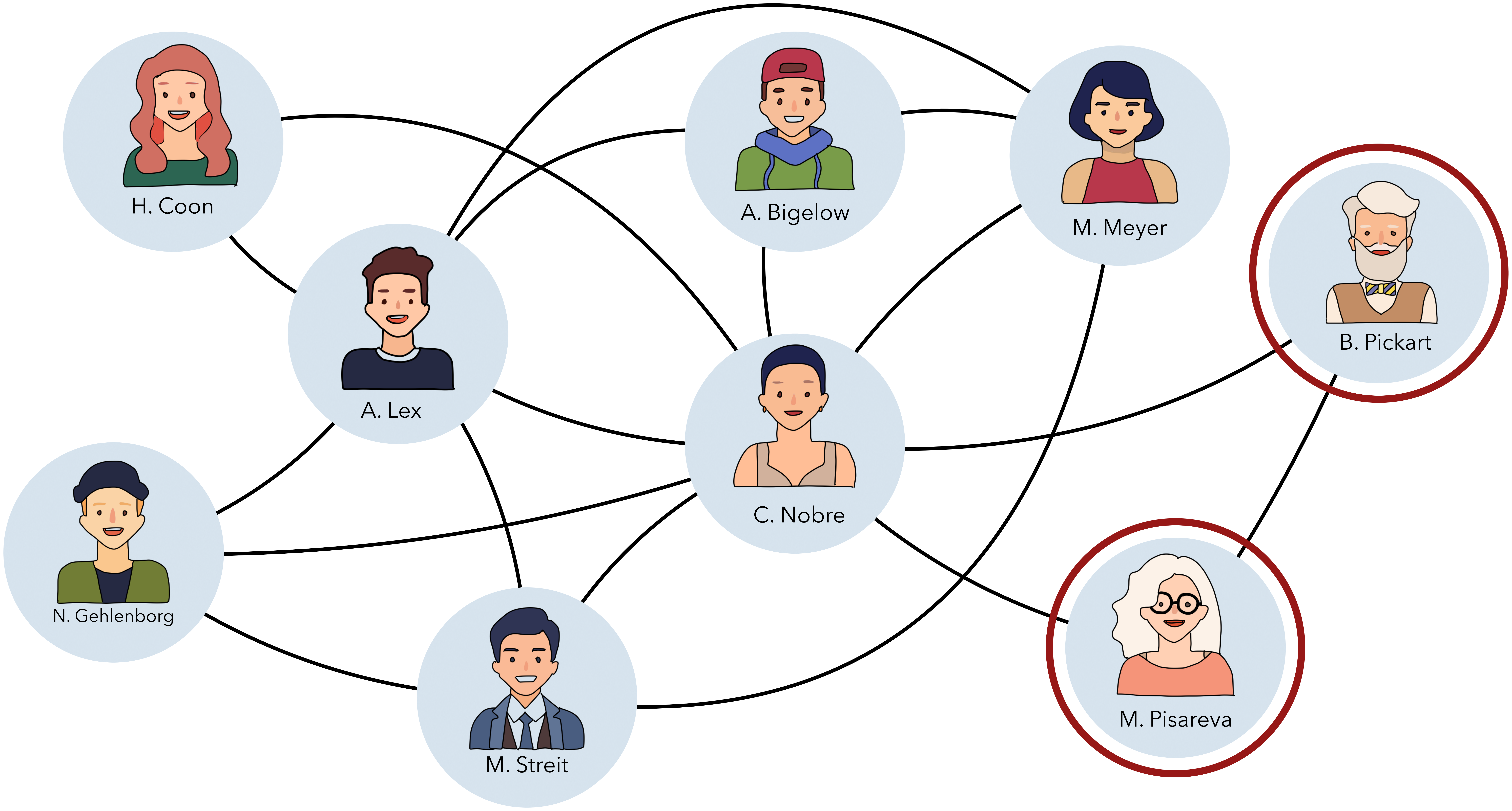
CONTRIBUTIONS

- Multivariate Network Task Taxonomy
- Typology of Multivariate Network Visualization Techniques
- Guidelines/Recommendations for Visualizing MVNs
- Summary of Application Areas
- Evaluations

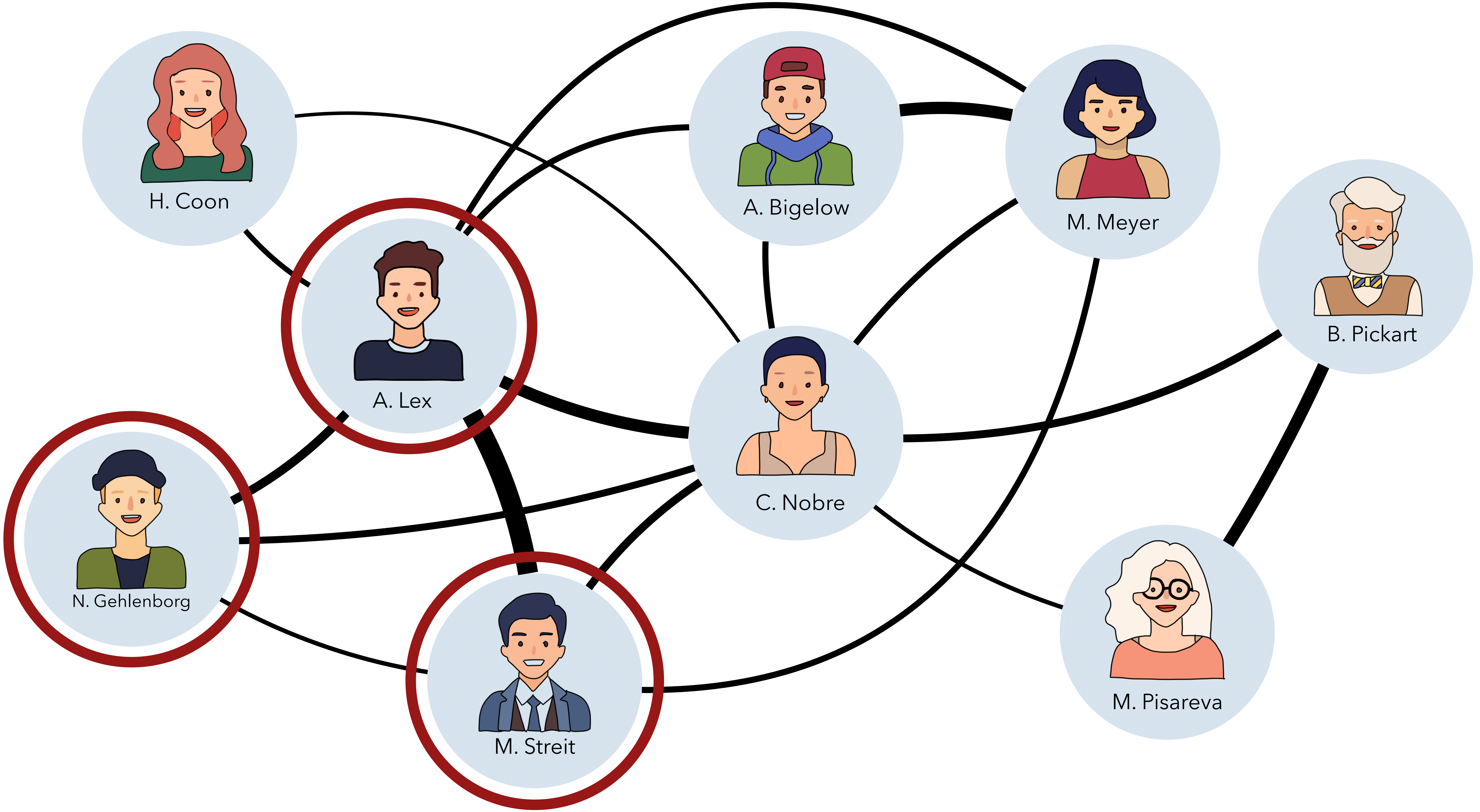
How is an MVN task different than a regular graph task?

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

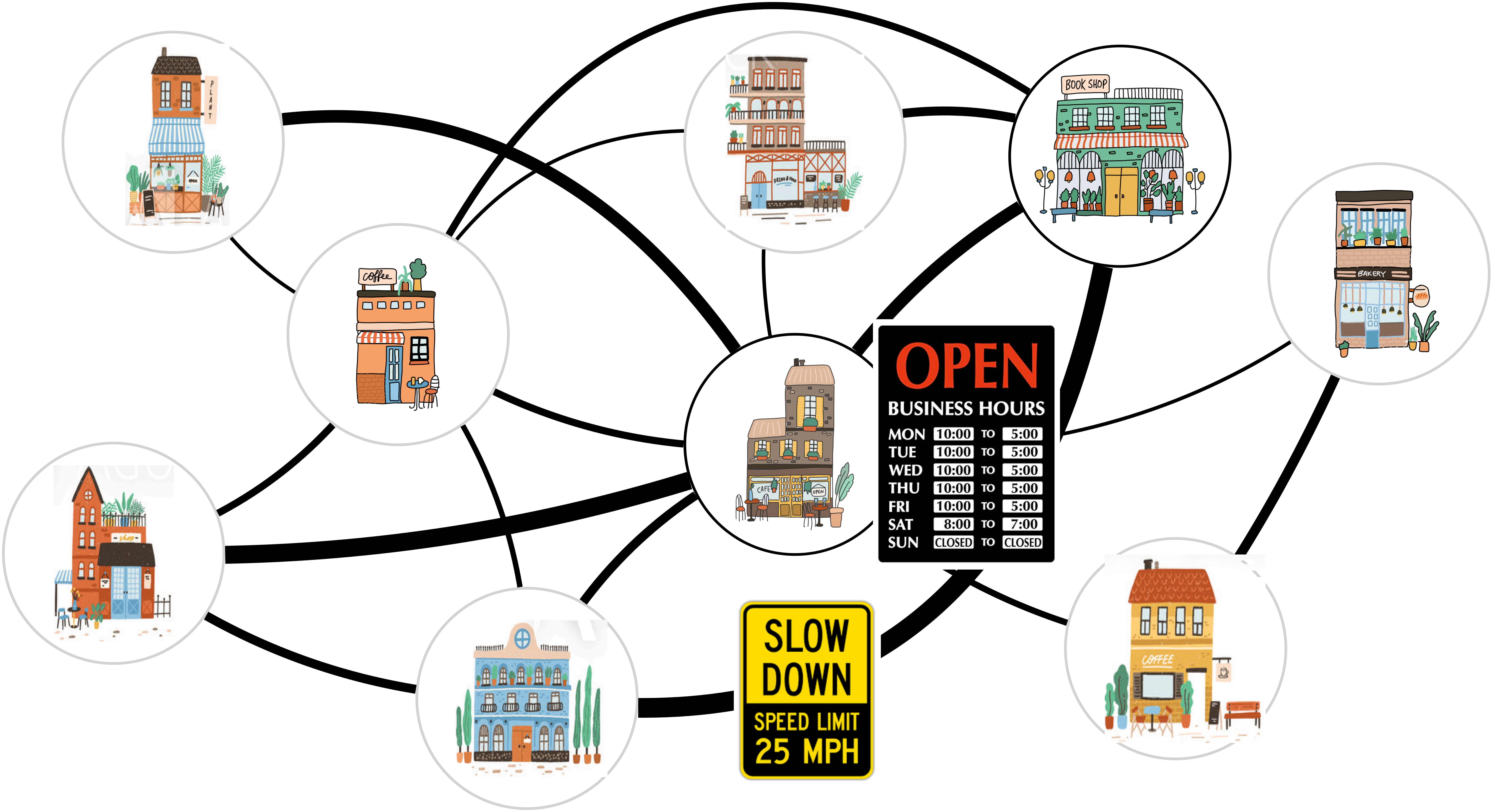

C. Nobre



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

Task Taxonomy for Graph Visualization

Bongshin Lee, Catherine Plaisant,
Cynthia Sims Parr
Human-Computer Interaction Lab
University of Maryland,
College Park, MD 20742, USA
+1-301-405-7445
{bongshin, plaisant, csparr}@cs.umd.edu

Jean-Daniel Fekete,
Nathalie Henry
INRIA Futurs/LRI Bat. 490
Université Paris-Sud,
91405 ORSAY, France
+33-1-69153460
Jean-Daniel.Fekete@inria.fr, nhenry@lri.fr

ABSTRACT
Our goal is to define a list of tasks for graph visualization that has enough detail and specificity to be useful to: 1) designers who want to improve their system and 2) to evaluators who want to compare graph visualization systems. In this paper, we suggest a list of tasks we believe are commonly encountered while analyzing graph data. We define graph specific objects and demonstrate how all complex tasks could be seen as a series of low-level tasks performed on those objects. We believe that our taxonomy, associated with benchmark datasets and specific tasks, would help evaluators generalize results collected through a series of controlled experiments.

Categories and Subject Descriptors
H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *Graphical user interfaces (GUI), Evaluation/methodology*.

General Terms
Design, Experimentation, Human Factors.

Keywords
Task Taxonomy, Graph Visualization, evaluation

1. INTRODUCTION
Despite a long history of graph visualization research, only a few graph visualization systems have actually been tested with real users. Furthermore, the tasks that were used in these studies have been highly domain-specific. To improve the evaluation of information visualization systems, it is important to have

user studies of graph visualization techniques and extracted the tasks used in those studies.

After making those two lists, we considered the set of low-level Visual Analytics tasks proposed by Amar *et al*. [2]. These tasks were extracted from a corpus of questions about tabular data. We realized that our tasks all seem to be compound tasks made up of Amar *et al*'s primitive tasks applied to the graph objects. When some tasks could not be represented with those tasks and objects, we added either an object or a low-level task. In this paper, we demonstrate how all complex tasks could be seen as a series of low-level tasks performed on those objects.

2. GRAPH-SPECIFIC OBJECTS
A graph consists of two types of primitive elements, nodes and links. A subgraph of a graph G is a graph whose nodes and links are subsets of G. There are several meaningful subgraphs such as connected components.

2.1 Nodes
Nodes by nature have an attribute degree that is the number of links incident to that node. In a directed graph, nodes have two types of degrees according to the direction; indegree and outdegree. For practical use, nodes also have a special "label" attribute. They often have application-dependent attributes as well. In network analysis, there are various measures used to determine the centrality, or relative importance, of a node within the graph (for example, the importance of a person within a social network). Measures of centrality include betweenness and closeness. There is also a special kind of node called an articulation point, whose removal disconnects a graph.

2.2 Links

5

Tasks for Multivariate Network Analysis

A. Johannes Pretorius, Helen C. Purchase, and John T. Stasko

In Chap. 1, a multivariate network was defined as having two important characteristics. First, nodes are connected to each other via links; there is topological structure. Second, being multivariate, nodes and links have attributes associated with them, with these attributes having a value.

In this chapter, we describe tasks associated with multivariate networks. We consider a task to be an activity that a user wishes to accomplish by interacting with a visual representation of a multivariate network. This implies that there is user intent [13], and that the network has been presented visually. At the highest level, this intent is usually described as the goal of obtaining *insight* about the data being studied [6].

Pragmatically, the notion of gaining insight from visualizations can be described as one or more very high-level tasks. As Amar and Stasko put it, tasks that "real people want to accomplish" [3]. These include:

- Make complex decisions, especially under uncertainty;
- Learn a domain;
- Identify the nature of trends;
- Predict the future;
- Identify the domain parameters;
- Discover correlative models;

An MVN task can be expressed as a combination of **two fundamental tasks**, as applied to different topological structures of a network.

Analyze the topology for given attributes

[TgA]

Identify, characterize or compare topological structures that have certain attributes

Example: Which of **my collaborators** have **a background in CS**?

Analyze the attributes for a given topological structure [AgT]

Identify, characterize, or compare the attributes of a given topological structure

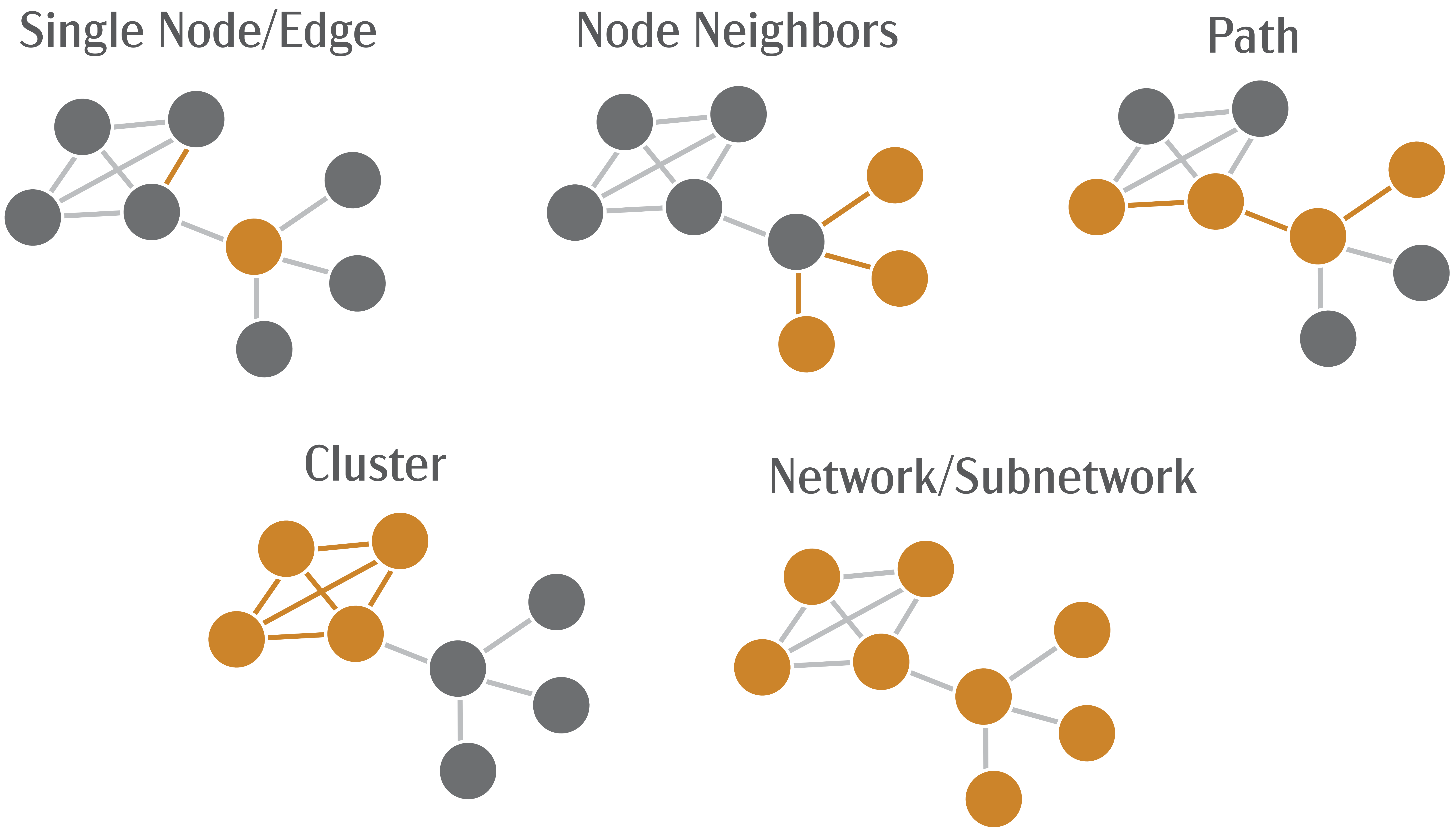
Example: What is the **average age** of **my collaborators**?

What is the average number of publications of my collaborators from Oceanography?

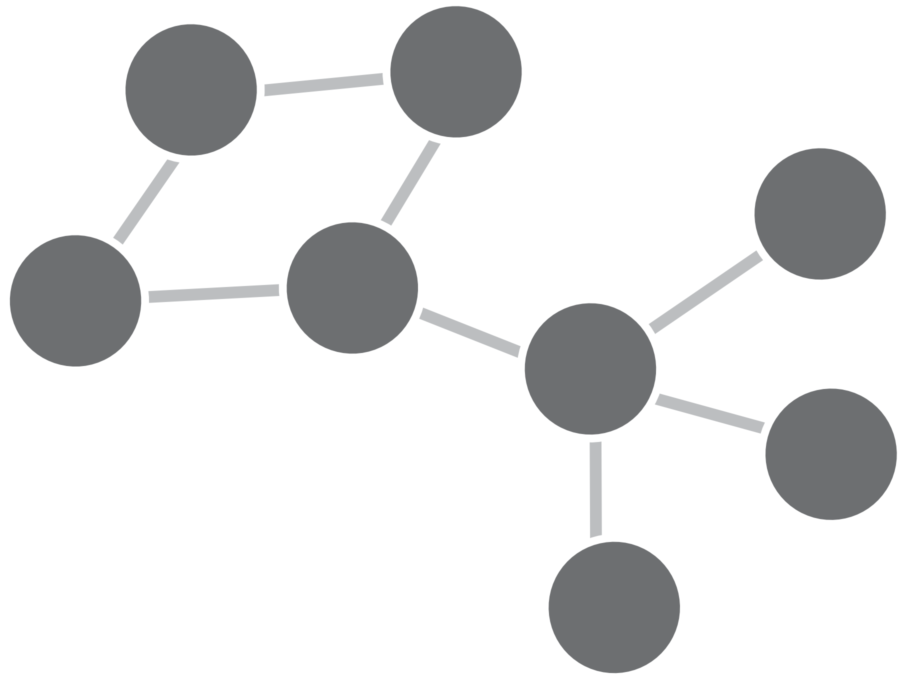
(1) Find the **node** with the **label 'Carolina'** - TgA

(2) Find the **subset of Carolina's neighbors** that are of type **Oceanography** - TgA

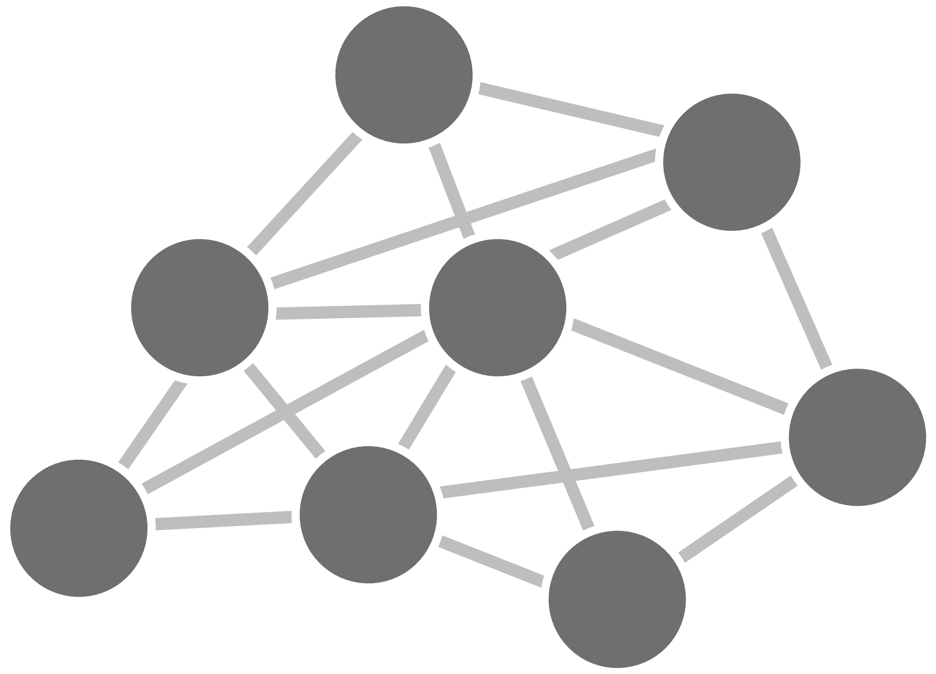
(3) Compute the **average no. of publications** for **those neighbors** - AgT



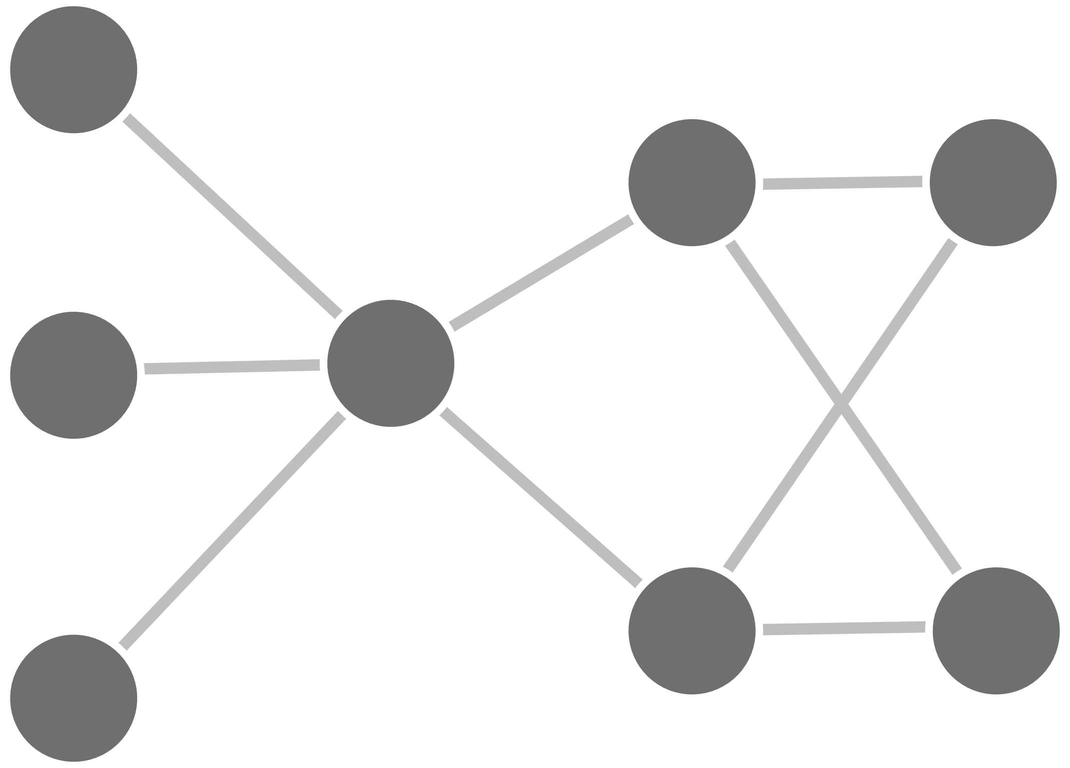
TgA and AgT tasks are applied to topological structures



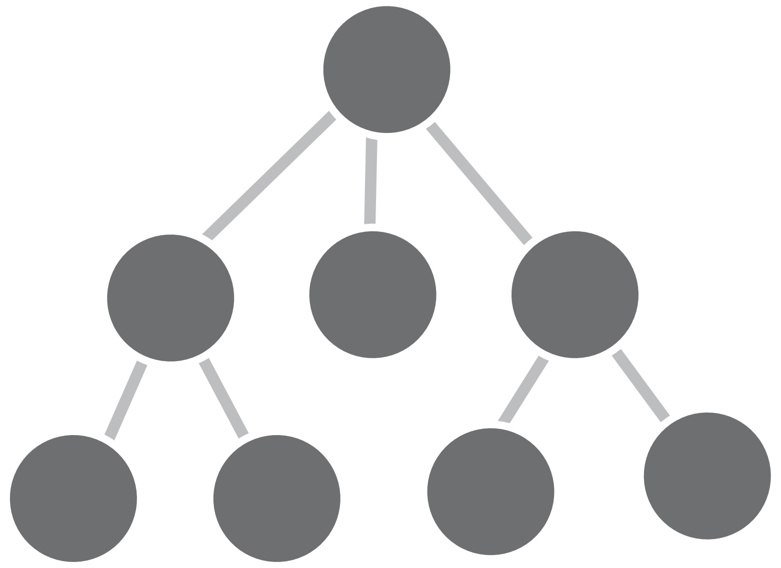
Sparse



Dense



Layered



Trees

We distinguish between the following network types

Group	Technique	Size: Small <100 nodes)	Size: Medium (<1,000)	Size: Large (>1,000 nodes)	Type: Complex (sparse)	Type: Complex (dense)	Type: Layered/K-Partite	Type: Trees	Node Attributes: Few (<5)	Node Attributes: Several (≥5)	Node Attributes: Homog. (1 type)	Node Attributes: Hetero. (>1 type)	Edge Attributes: Few (<3)	Edge Attributes: Several (≥3)	Edge Attributes: Homog. (1 type)	Edge Attributes: Hetero. (>1 type)	Topolog. Structures: Single node/edge	Topolog. Structures: Neighbors	Topolog. Structures: Paths	Topolog. Structures: Clusters	Topolog. Structures: Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
Node-Link Layouts	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
Node-Link Layouts	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
Tabular Layouts	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
Tabular Layouts	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
Implicit	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
View Operations	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
View Operations	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

		Size			Type				Node Attributes				Edge Attributes				Topolog. Structures				
		Small <100 nodes)	Medium (<1,000)	Large (>1,000 nodes)	Complex (sparse)	Complex (dense)	Layered/K-Partite	Trees	Few (<5)	Several (≥5)	Homog. (1 type)	Hetero. (>1 type)	Few (<3)	Several (≥3)	Homog. (1 type)	Hetero. (>1 type)	Single node/edge	Neighbors	Paths	Clusters	Entire/sub network
Node-Link Layouts	On-node/edge encoding	3	2	1	3	1	3	3	2	1	3	2	2	1	3	1	3	3	2	2	2
	Attr.-driven faceting	3	1	1	3	1	3	1	3	1	3	3	2	1	2	1	3	2	1	1	1
	Attr.-driven positioning	3	1	1	3	1	1	1	3	1	3	1	2	1	2	1	3	2	1	1	2
Tabular Layouts	Adjacency matrix	3	1	1	2	3	2	1	2	3	3	2	3	2	3	2	3	3	1	3	2
	Quilts	3	1	1	3	1	3	3	3	3	3	3	3	3	3	2	3	3	2	2	2
	BioFabric	3	1	1	3	3	2	1	3	3	3	3	3	3	3	3	3	1	1	1	2
Implicit	Inner nodes & leaves	3	2	1	0	0	0	3	3	1	3	1	0	0	0	0	3	3	3	0	3
	Leaves	3	2	2	0	0	0	3	3	1	3	1	0	0	0	0	3	2	1	0	3
View Operations	Juxtaposed	3	2	1	3	1	3	3	3	3	3	3	3	3	3	3	2	1	1	2	2
	Integrated	3	2	1	3	1	3	3	3	3	3	3	2	2	3	3	3	3	3	1	2
	Overloaded	3	2	1	3	1	3	3	3	1	3	1	1	1	1	1	3	3	2	3	2

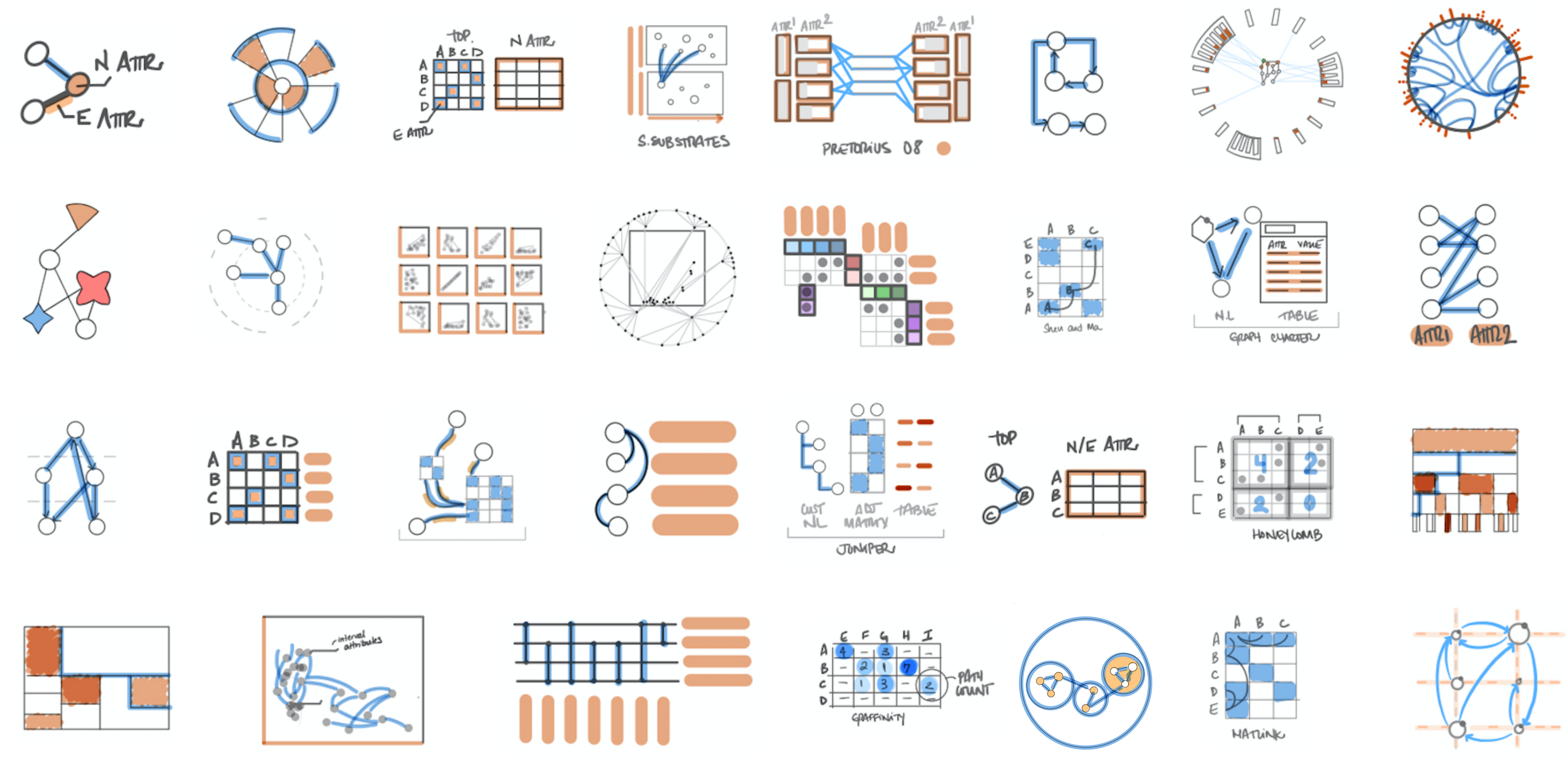
0 Does *not* support

1 Supports poorly

2 Supports

3 Optimized for

SURVEYED 205 PAPERS FROM 1991 – 2018

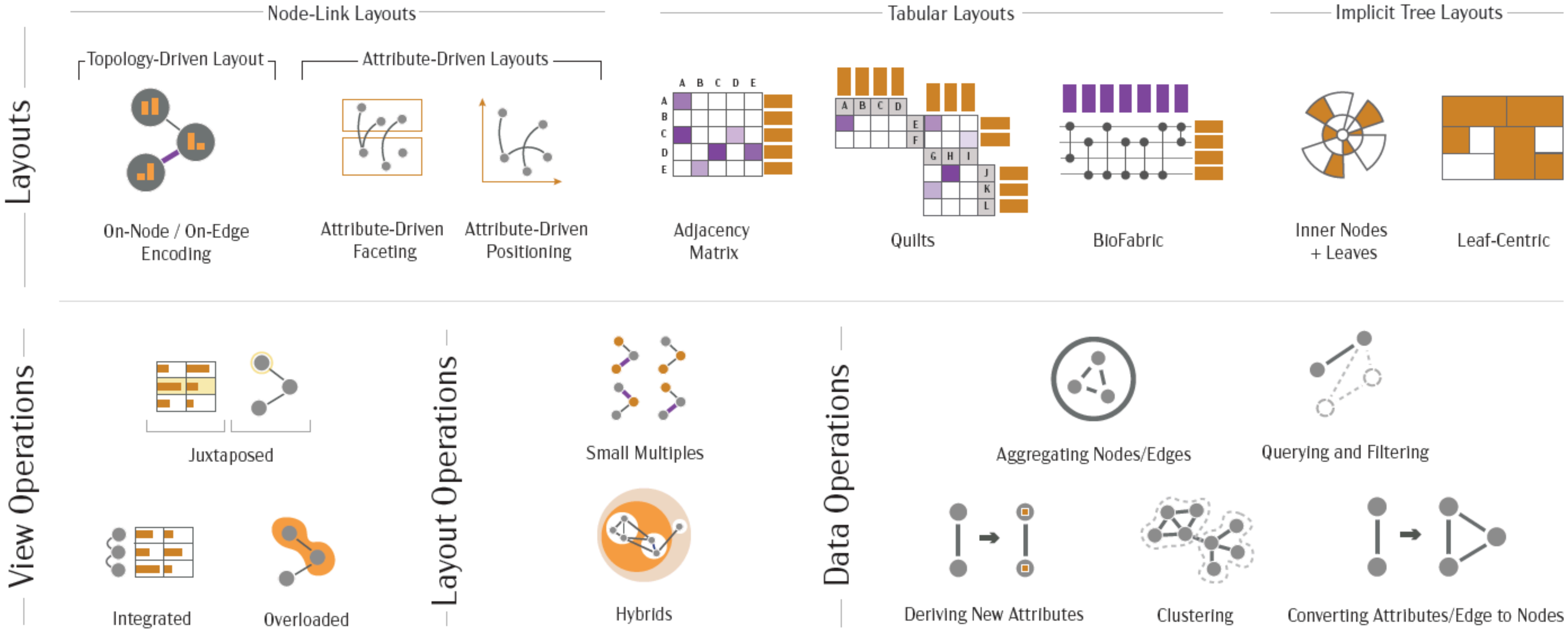


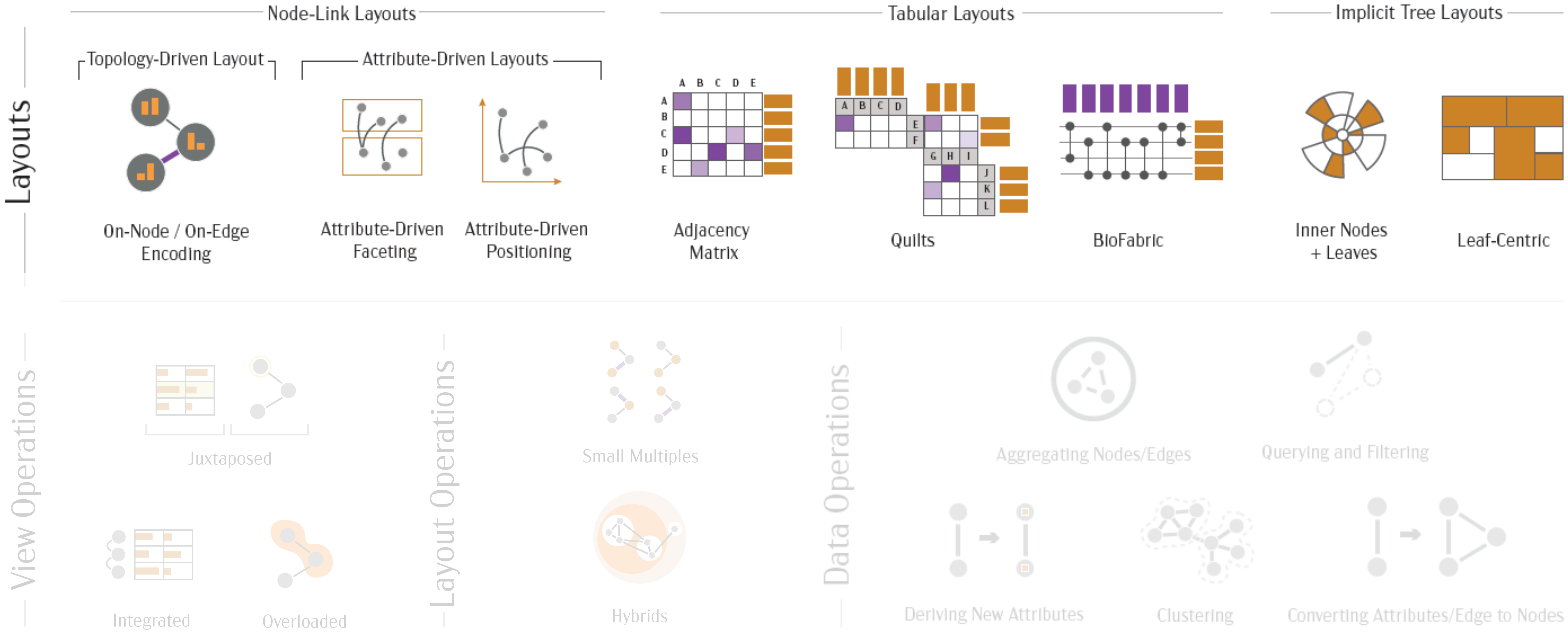
N ATTR
E ATTR
TOP.
A B C D
N ATTR
E ATTR
S. SUBSTRATES
ATTR1 ATTR2
ATTR2 ATTR1
PRETORIUS 08
A B C
E D C B A
Shen and Ma
ATTR VALUE
N.L
TABLE
GRAPH CHARTER
ATTR1
ATTR2
A B C D
CUST N.L
ADJ MATRIX
TABLE
JUMPER
TOP
N/E ATTR
A B C
A B C D E
HONEYCOMB
interval attributes
E F G H I
A B C D
GRAFFINITY
PATH COUNT
A B C
A B C D E
MATLINK


NODE LINK
N ATTR
E ATTR
interval attributes
S.SUBSTRATES
ATTR1 ATTR2
PRETORIUS 08
TABULAR
Shen and Ma
MATLINK
HONEYCOMB
PATH COUNT
GRAFFINITY
MCV
NL
TABLE
GRAPH CHARTER
TOP
N/E ATTR
CUST NL
ADJ MATRIX
JUMPER
N ATTR
E ATTR
HYBRIDS
SMALL MULTIPLES
IMPLICIT

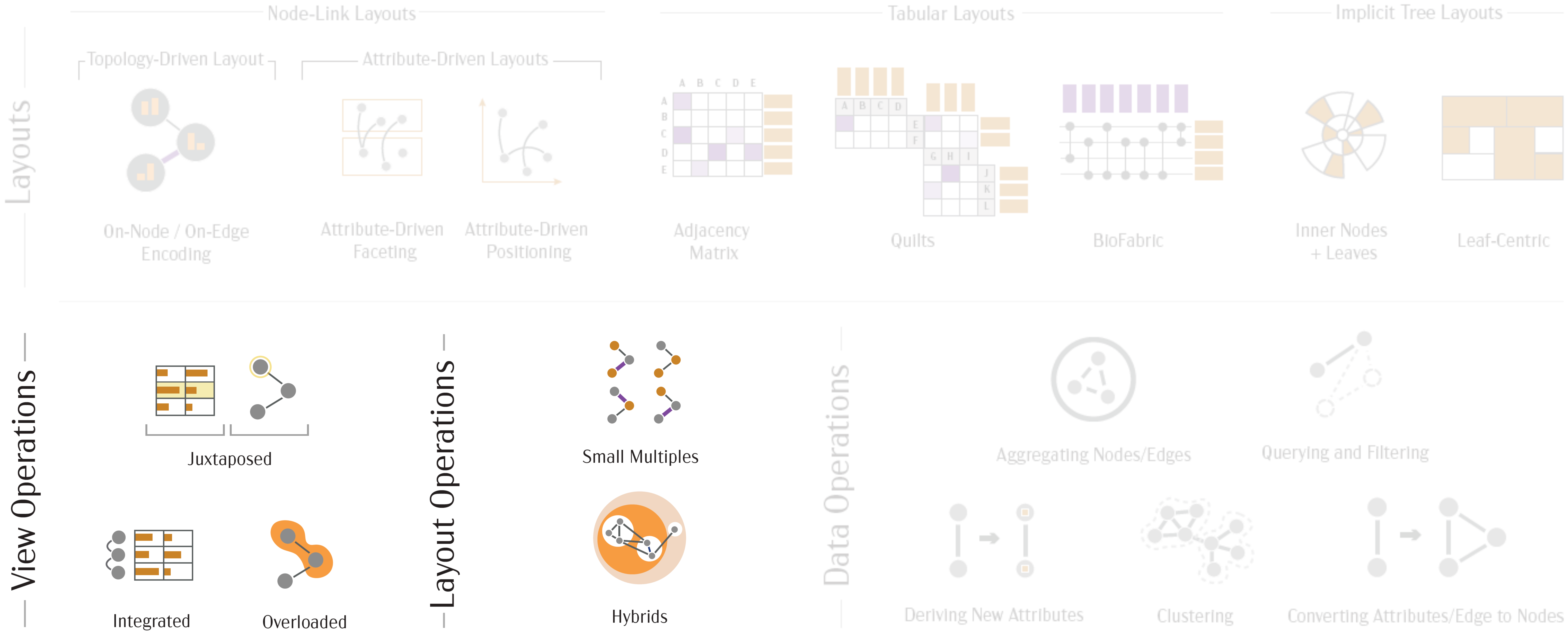
NODE LINK
N ATTR
E ATTR
S.SUBSTRATES
PRETORIUS 08
TABULAR
MATLINK
HONEYCOMB
PATH COUNT
MCV
N/E ATTR
TABLE
GRAPH CHARTER
JUMPER
N ATTR
E ATTR
HYBRIDS
SMALL MULTIPLES
IMPLICIT


NODE LINK
S.SUBSTRATES
PRETORIUS 08
TABULAR
N ATTR
E ATTR
MCV
N.L
TABLE
GRAPH CHARTER
TOP
N/E ATTR
JUNIPER
HYBRIDS
SMALL MULTIPLES
IMPLICIT


Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
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

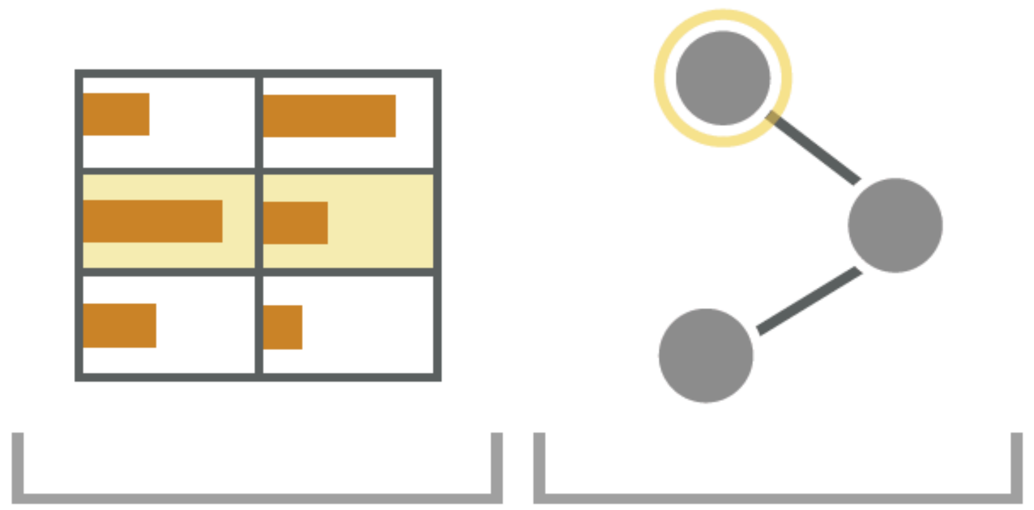


Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Tabular Layouts
Adjacency Matrix
Quilts
BioFabric
Implicit Tree Layouts
Inner Nodes + Leaves
Leaf-Centric
View Operations
Juxtaposed
Integrated
Overloaded
Layout Operations
Small Multiples
Hybrids
Data Operations
Aggregating Nodes/Edges
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

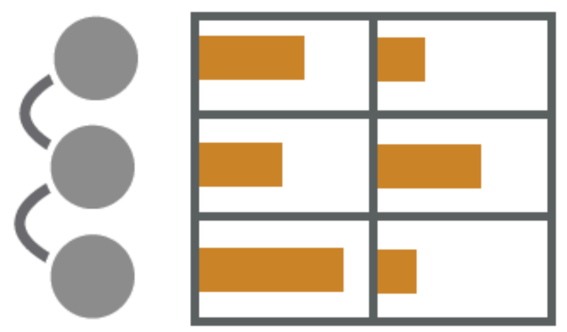


Node-Link Layouts
Tabular Layouts
Implicit Tree Layouts
Topology-Driven Layout
Attribute-Driven Layouts
Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Adjacency Matrix
Quilts
BioFabric
Inner Nodes + Leaves
Leaf-Centric
View Operations
Juxtaposed
Integrated
Overloaded
Layout Operations
Small Multiples
Hybrids
Data Operations
Aggregating Nodes/Edges
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

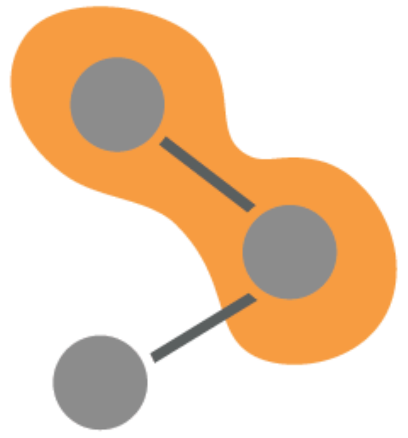
View Operations



Juxtaposed



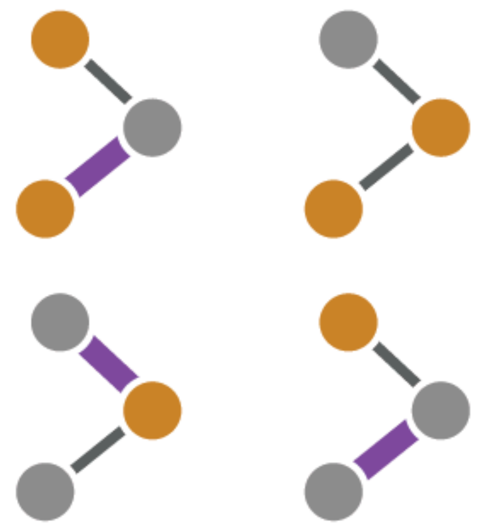
Integrated



Overloaded

Separate views for Topology and Attributes

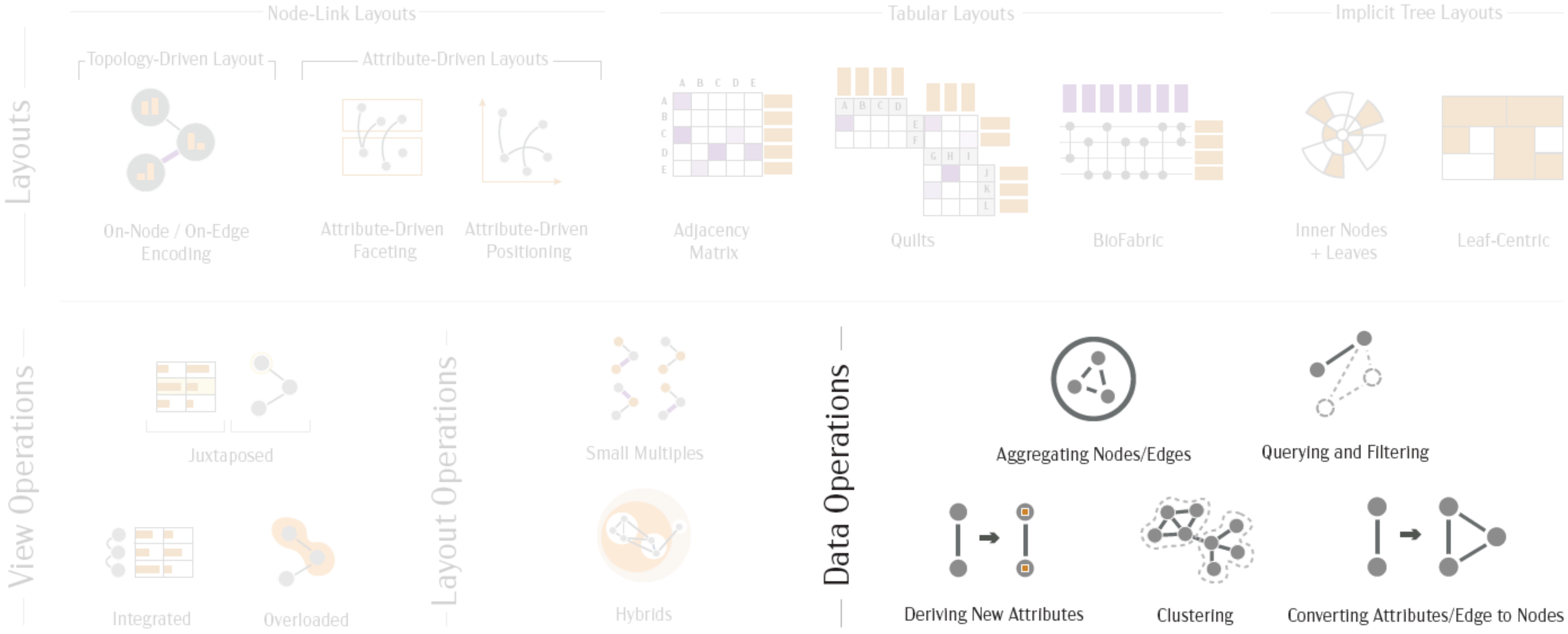
Layout Operations



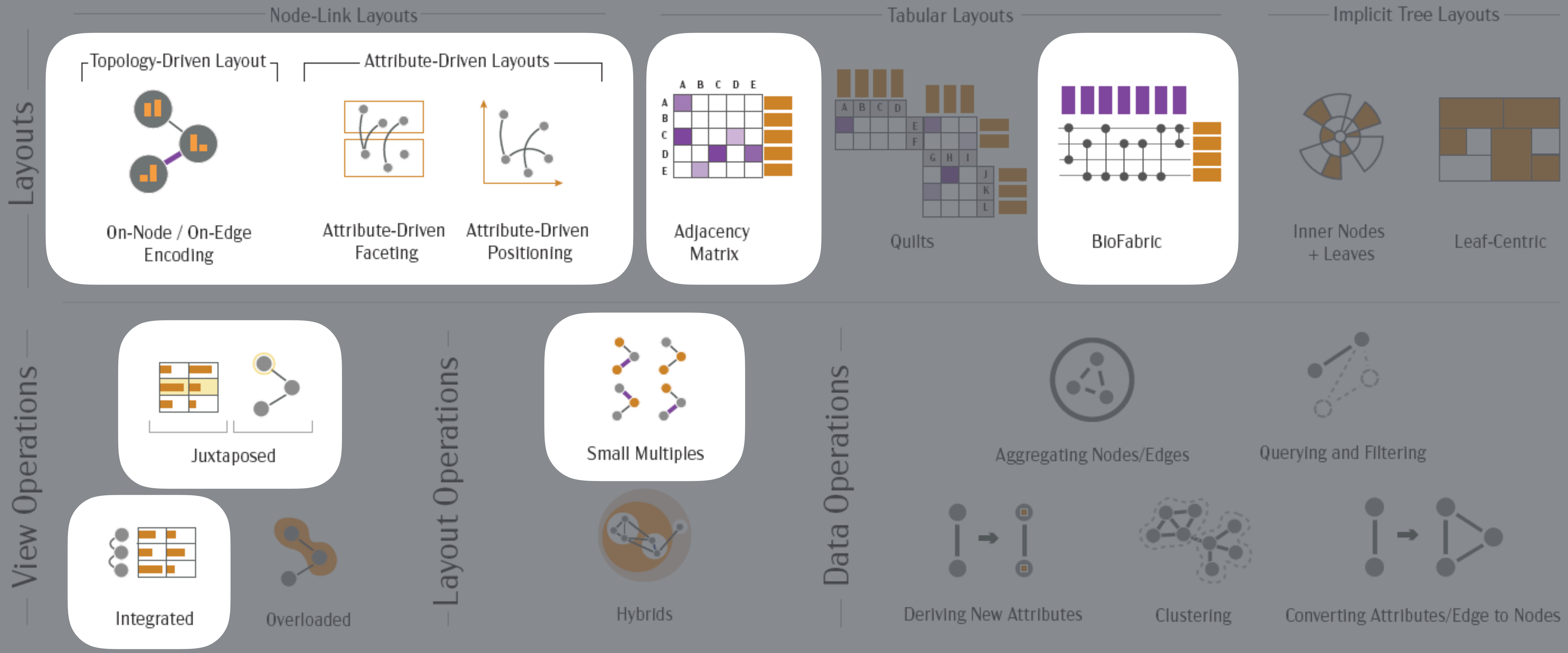
Small Multiples

Hybrids

Multiple layouts for Topology or Attributes



Node-Link Layouts
Tabular Layouts
Implicit Tree Layouts
Topology-Driven Layout
Attribute-Driven Layouts
Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Adjacency Matrix
Quilts
BioFabric
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
Tabular Layouts
Implicit Tree Layouts
Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Adjacency Matrix
Quilts
BioFabric
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

LAYOUTS
Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Tabular Layouts
Adjacency Matrix
Quilts
BioFabric
Implicit Tree Layouts
Inner Nodes + Leaves
Leaf-Centric
VIEW OPERATIONS
View Operations
Integrated
Overloaded
LAYOUT OPERATIONS
Layout Operations
Hybrids
DATA OPERATIONS
Data Operations
Aggregating Nodes
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

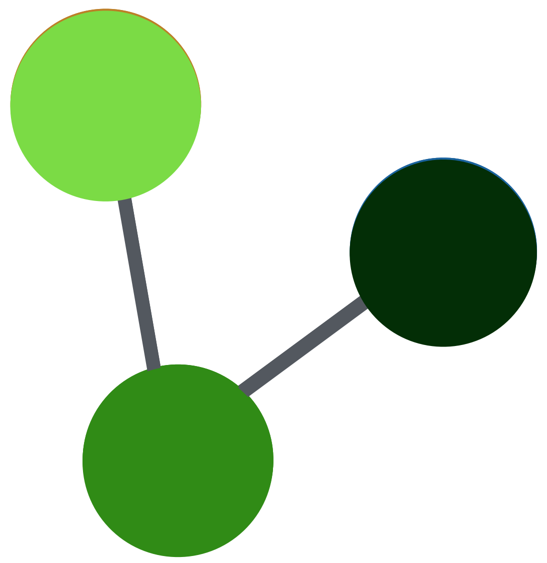
Node-Link Diagram with on-node encoding

LAYOUTS

VIEW OPERATIONS

LAYOUT OPERATIONS

DATA OPERATIONS



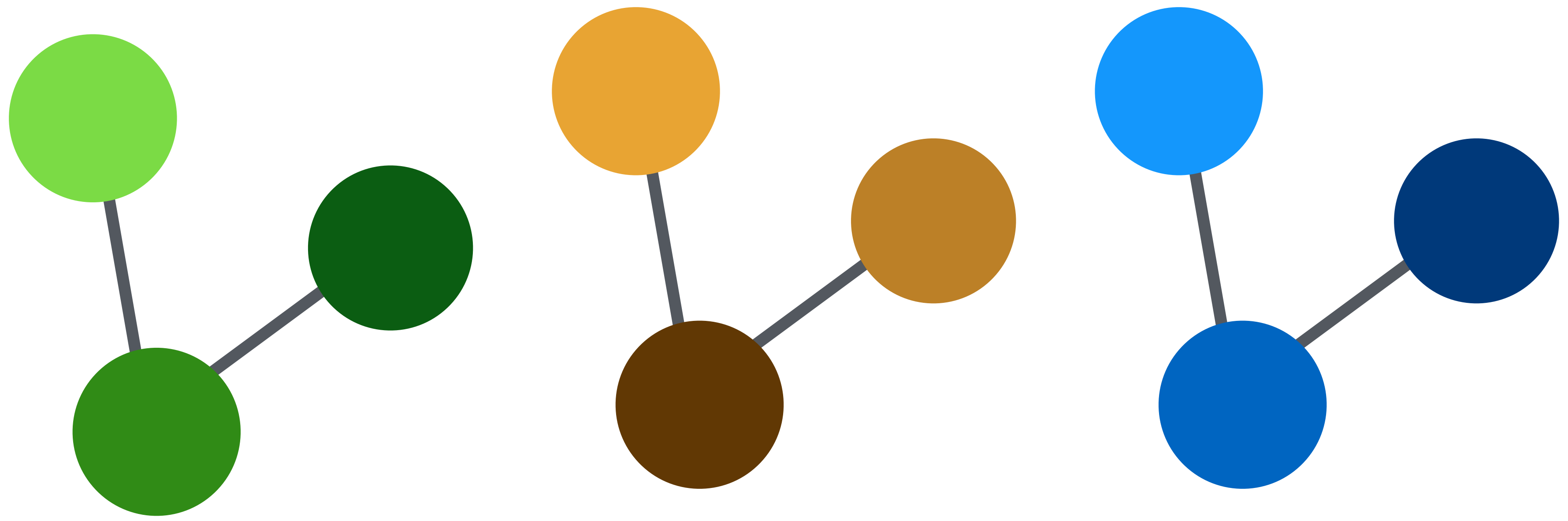
LAYOUTS

VIEW OPERATIONS

LAYOUT OPERATIONS

DATA OPERATIONS

Small Multiples



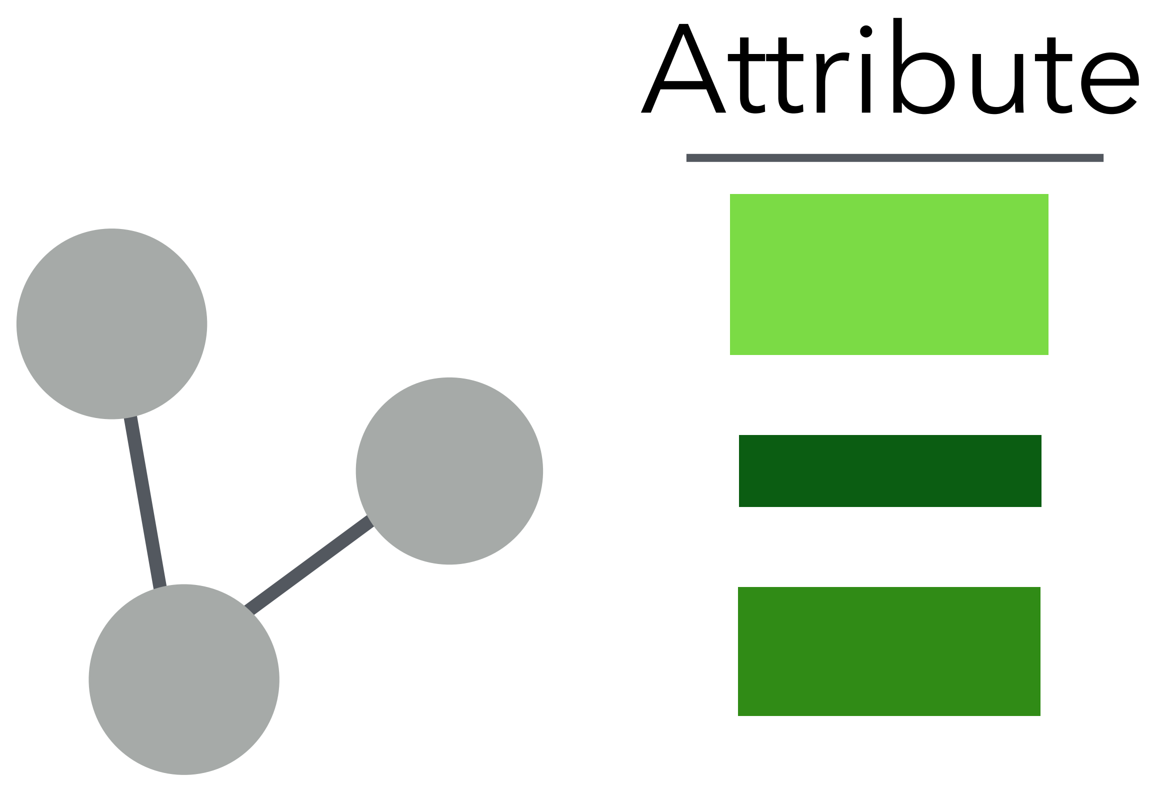
LAYOUTS

VIEW OPERATIONS

LAYOUT OPERATIONS

DATA OPERATIONS

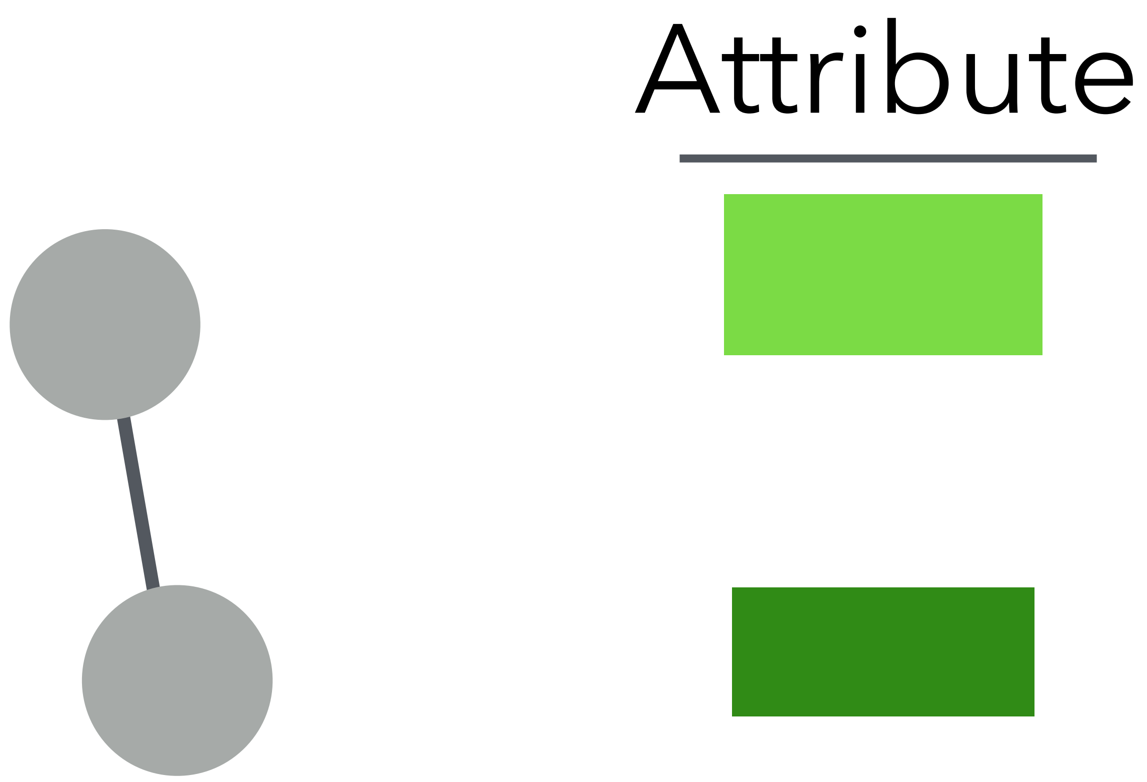
Juxtaposed Views

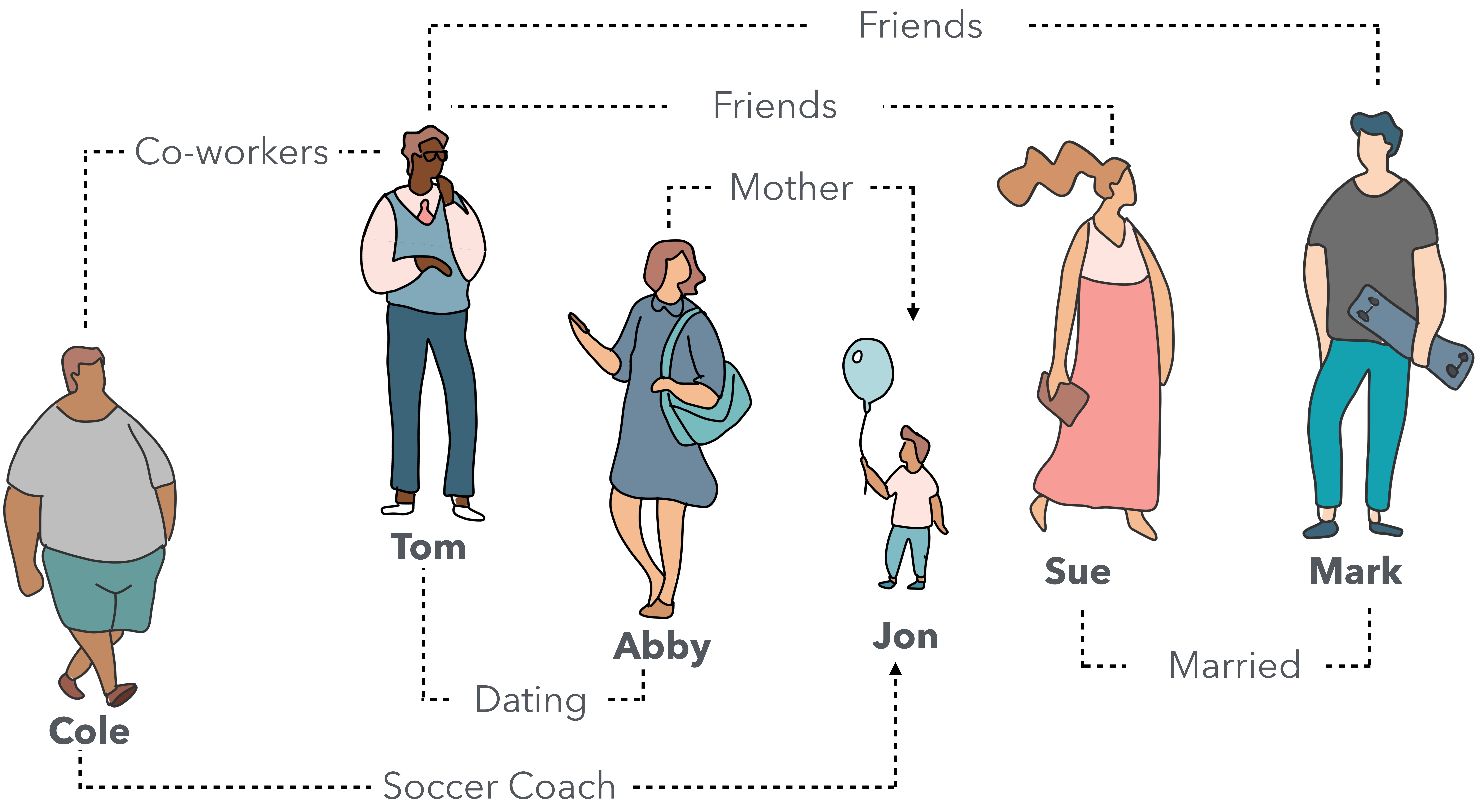


Filter Data

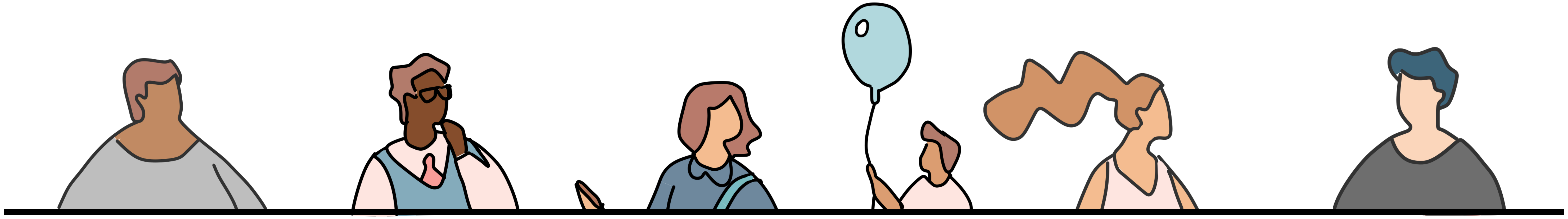
LAYOUTS

VIEW OPERATIONS | **LAYOUT OPERATIONS** | **DATA OPERATIONS**

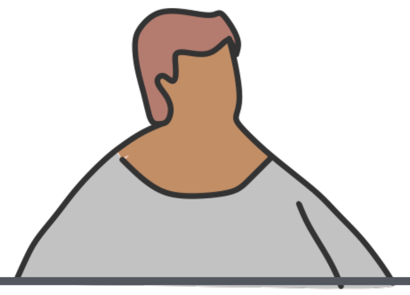
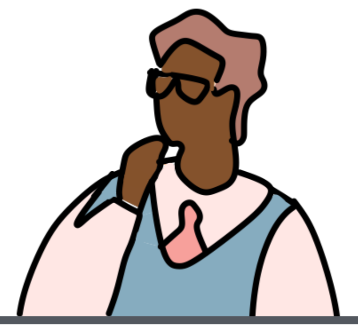
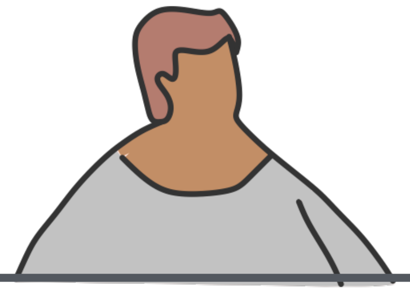
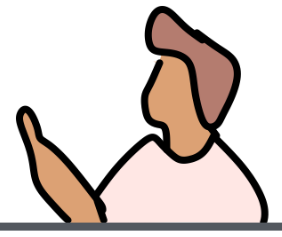
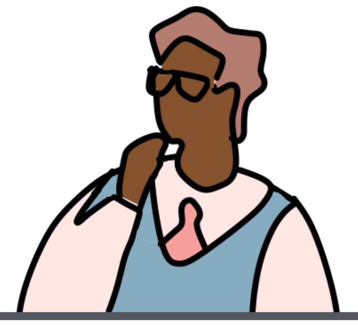
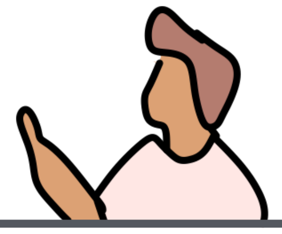
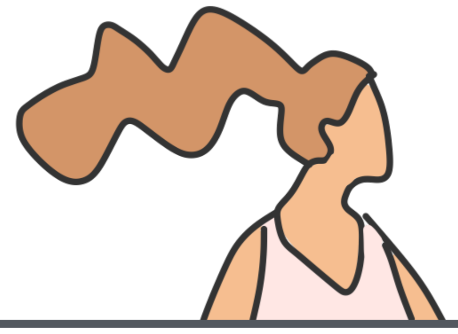
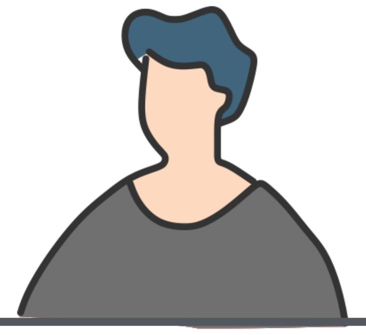
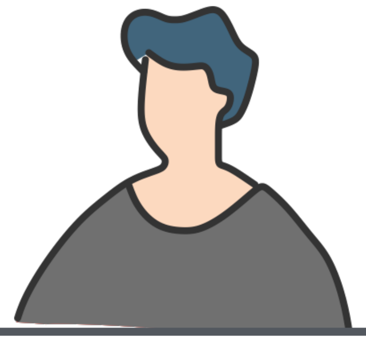




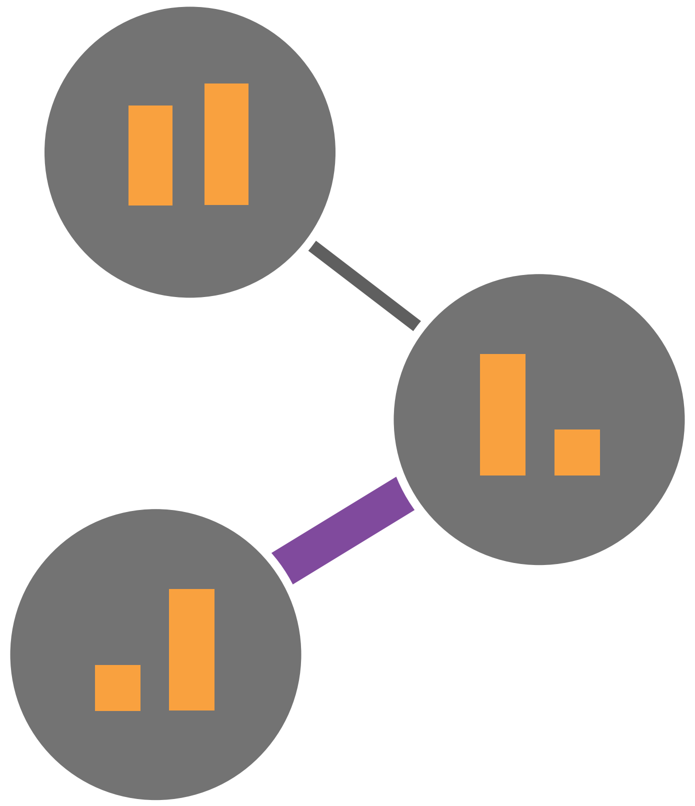
Friends
Friends
Co-workers
Mother
Tom
Abby
Jon
Sue
Mark
Cole
Dating
Married
Soccer Coach

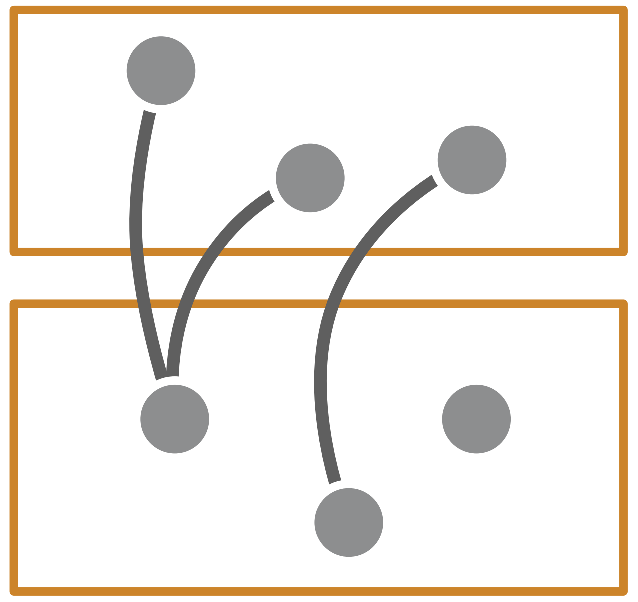


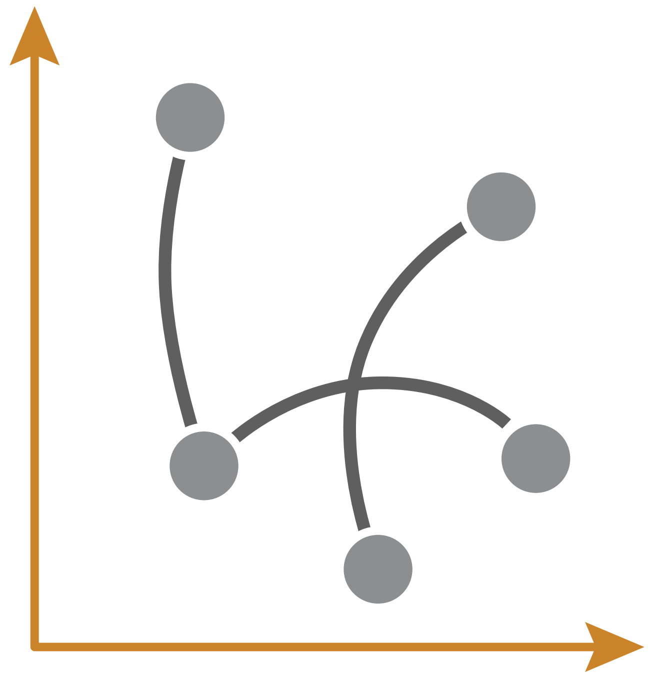
Name	Cole	Tom	Abby	Jon	Sue	Mark
Beverage	Port	Beer	Port	Coke	Coke	Beer
Day 1	1	0	4	3	3	5
Day 2	0	2	5	3	5	5
Day 3	4	1	2	2	4	3

Source	Target	Type	Duration
		Co-workers	3 years
		Soccer Coach	2 years
		Dating	1 year
		Mother / Son	7 years
		Friends	12 years
		Friends	3 years
		Married	6 years

Node-Link Layouts

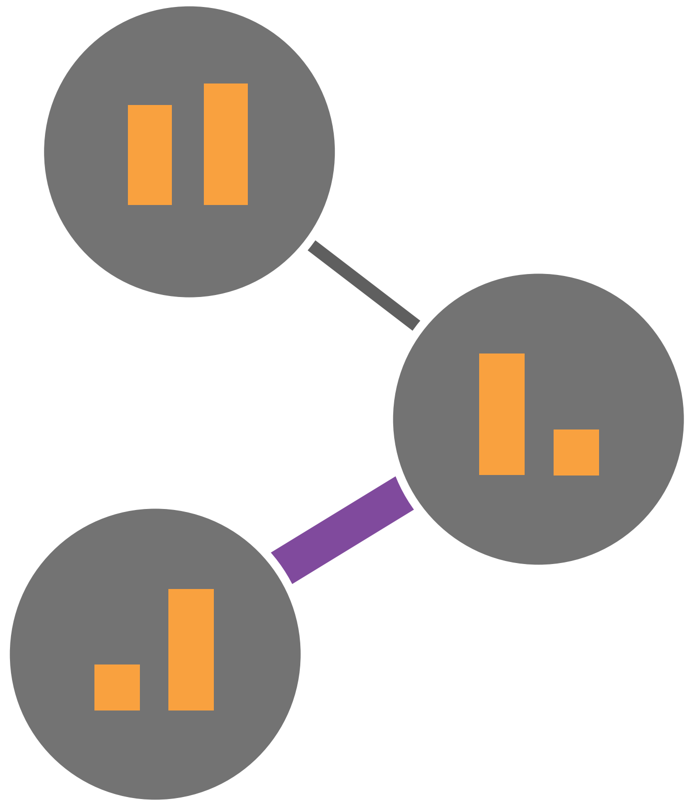




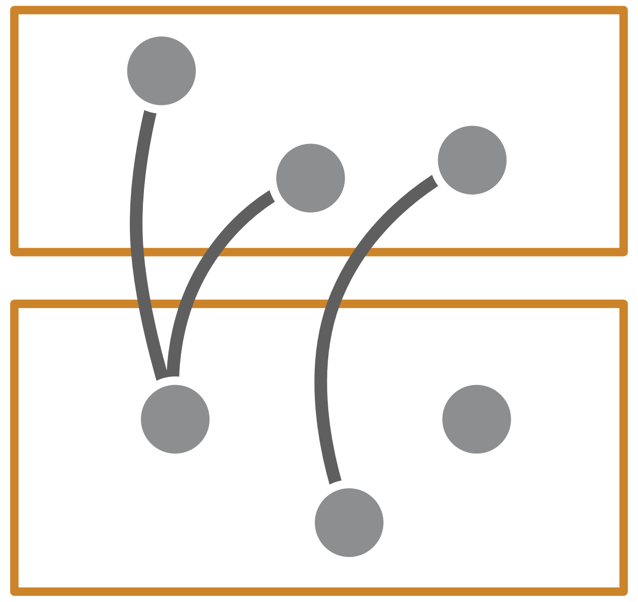


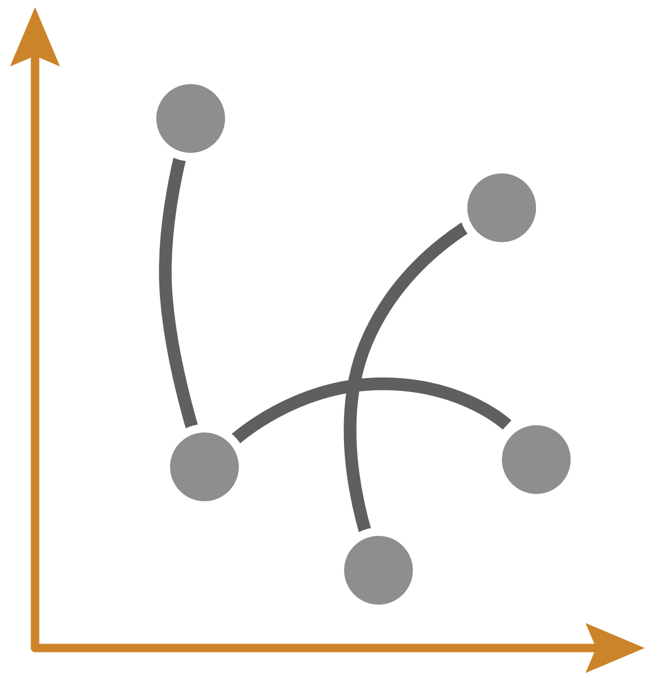
Node-Link Layouts

Topology Driven Layout



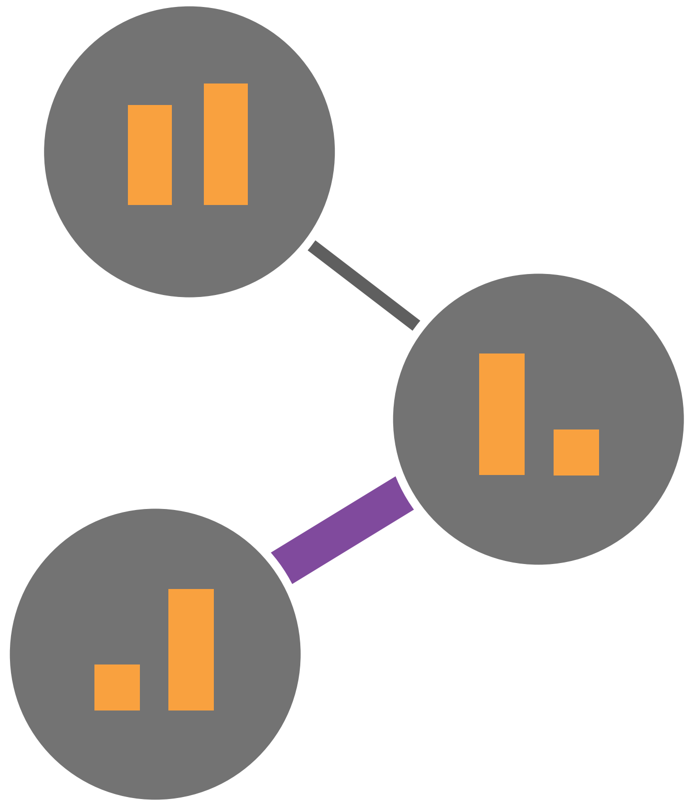
Attribute Driven Layouts





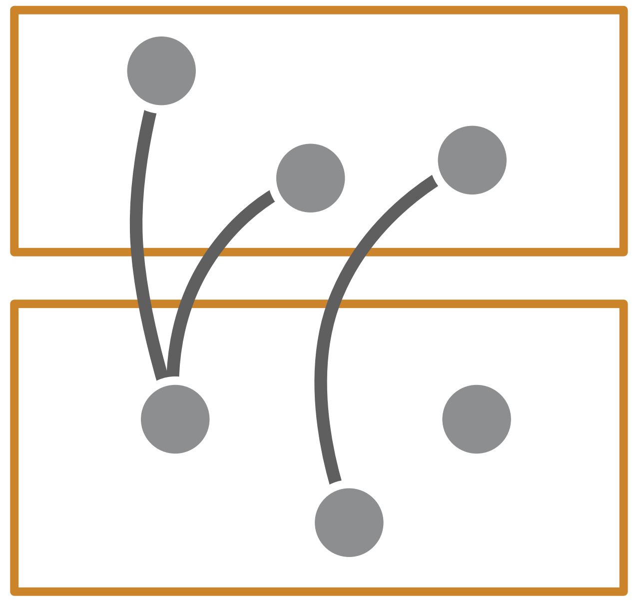
Node-Link Layouts

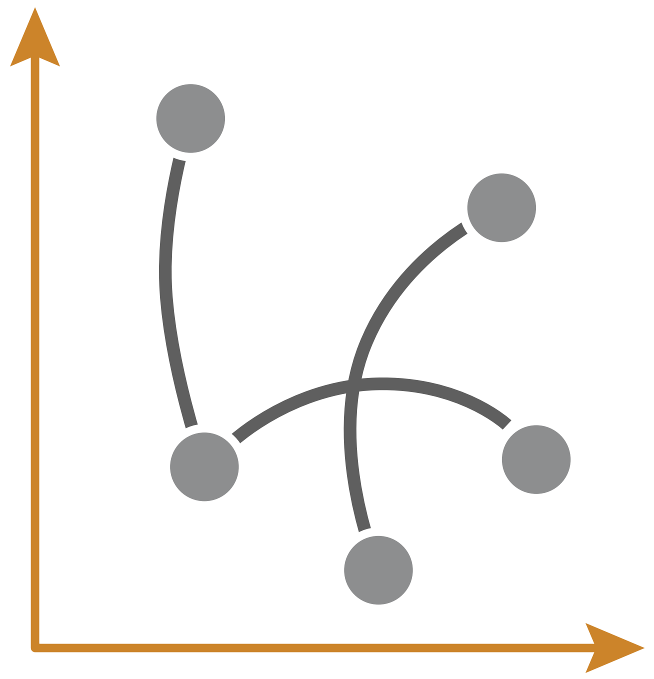
Topology Driven Layout



On-Node / On-Edge
Encoding

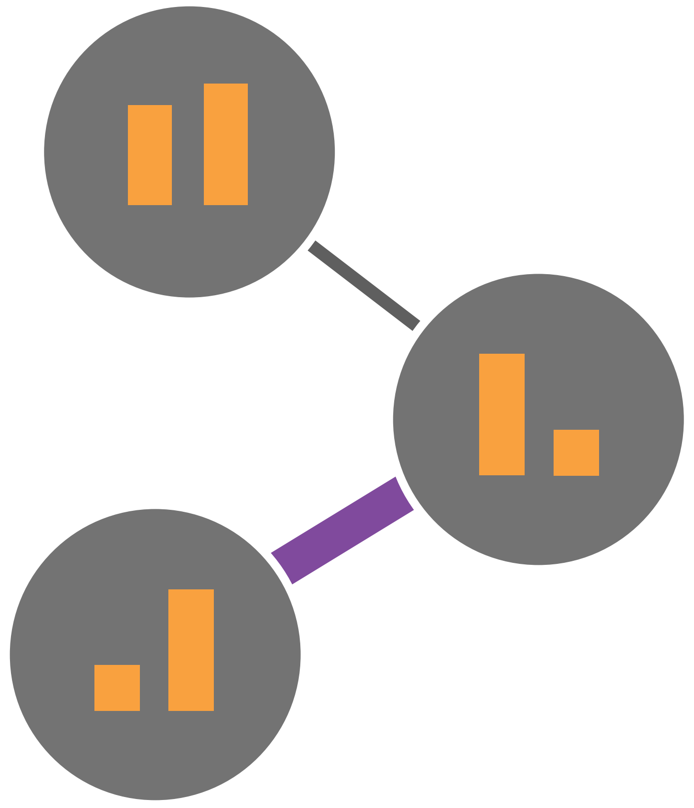
Attribute Driven Layouts





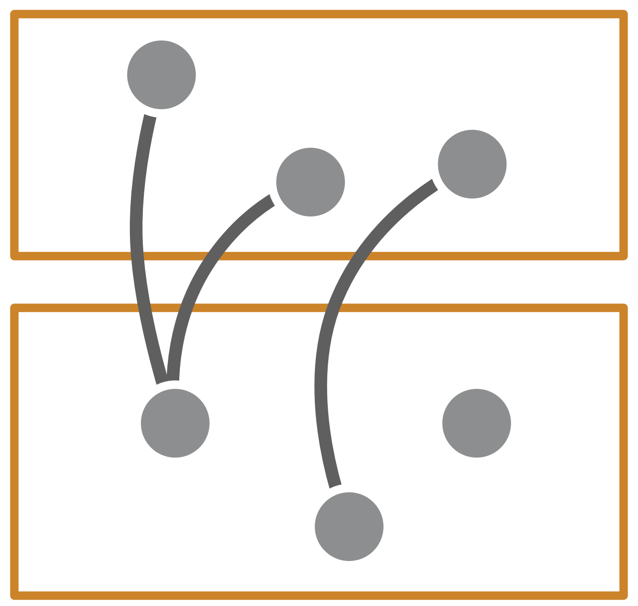
Node-Link Layouts

Topology Driven Layout

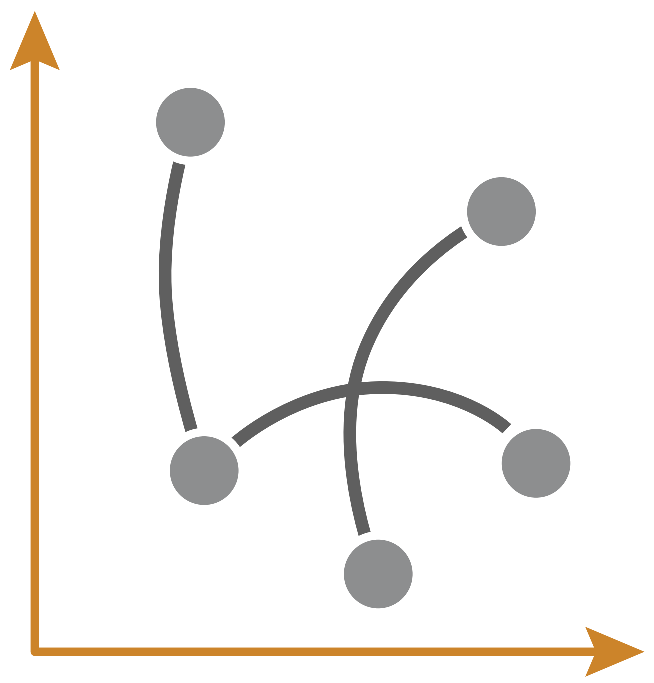


On-Node / On-Edge
Encoding

Attribute Driven Layouts

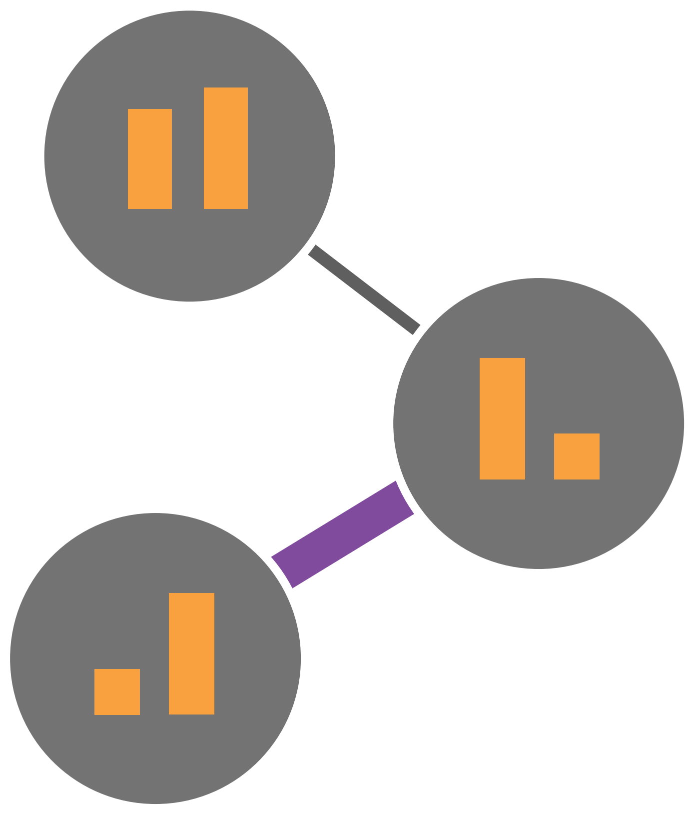


Attribute-Driven
Faceting

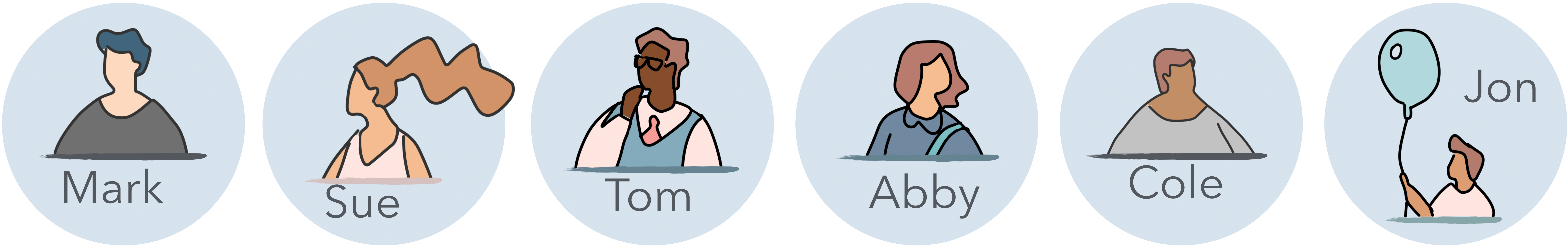


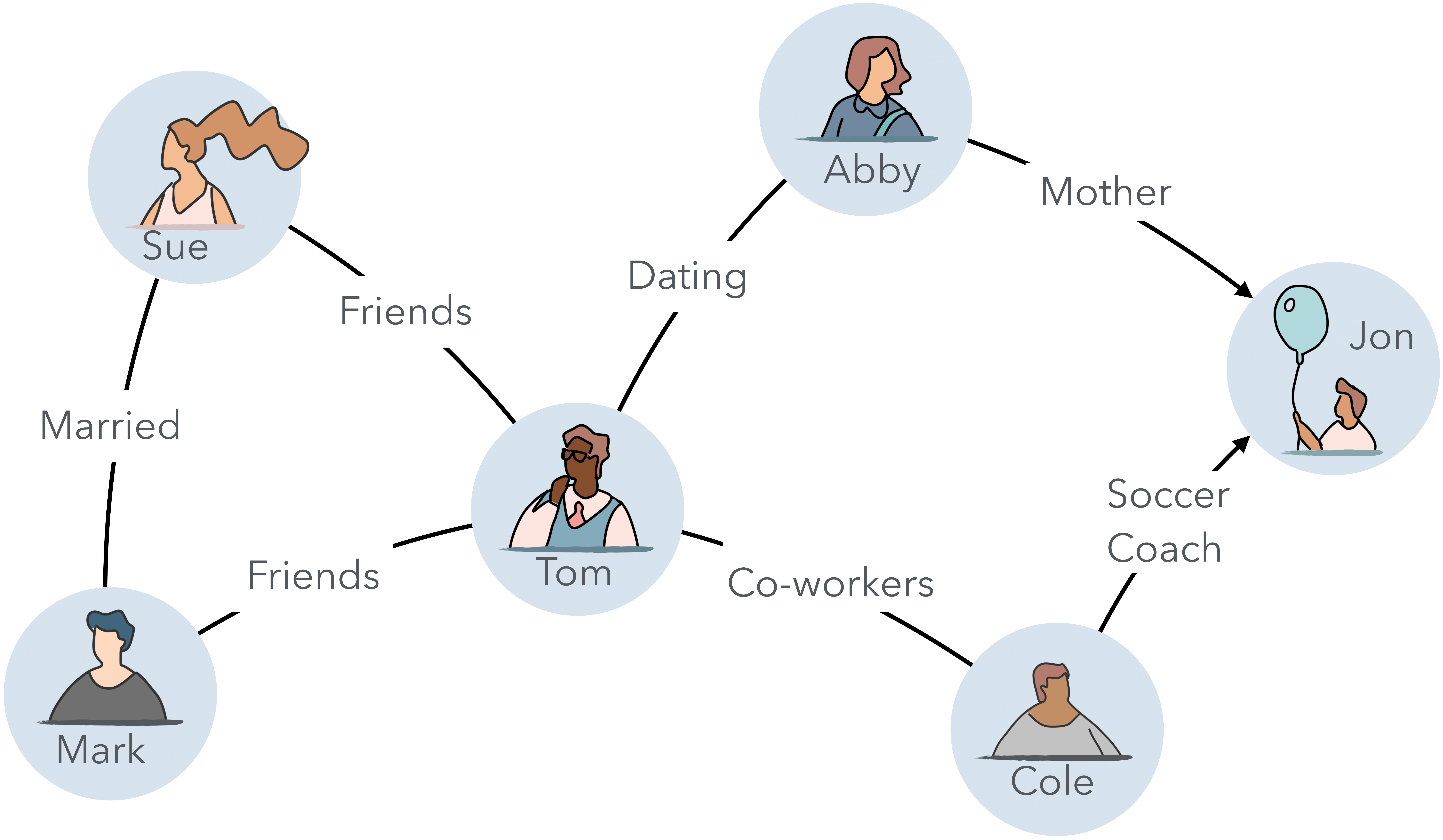
Attribute-Driven
Positioning

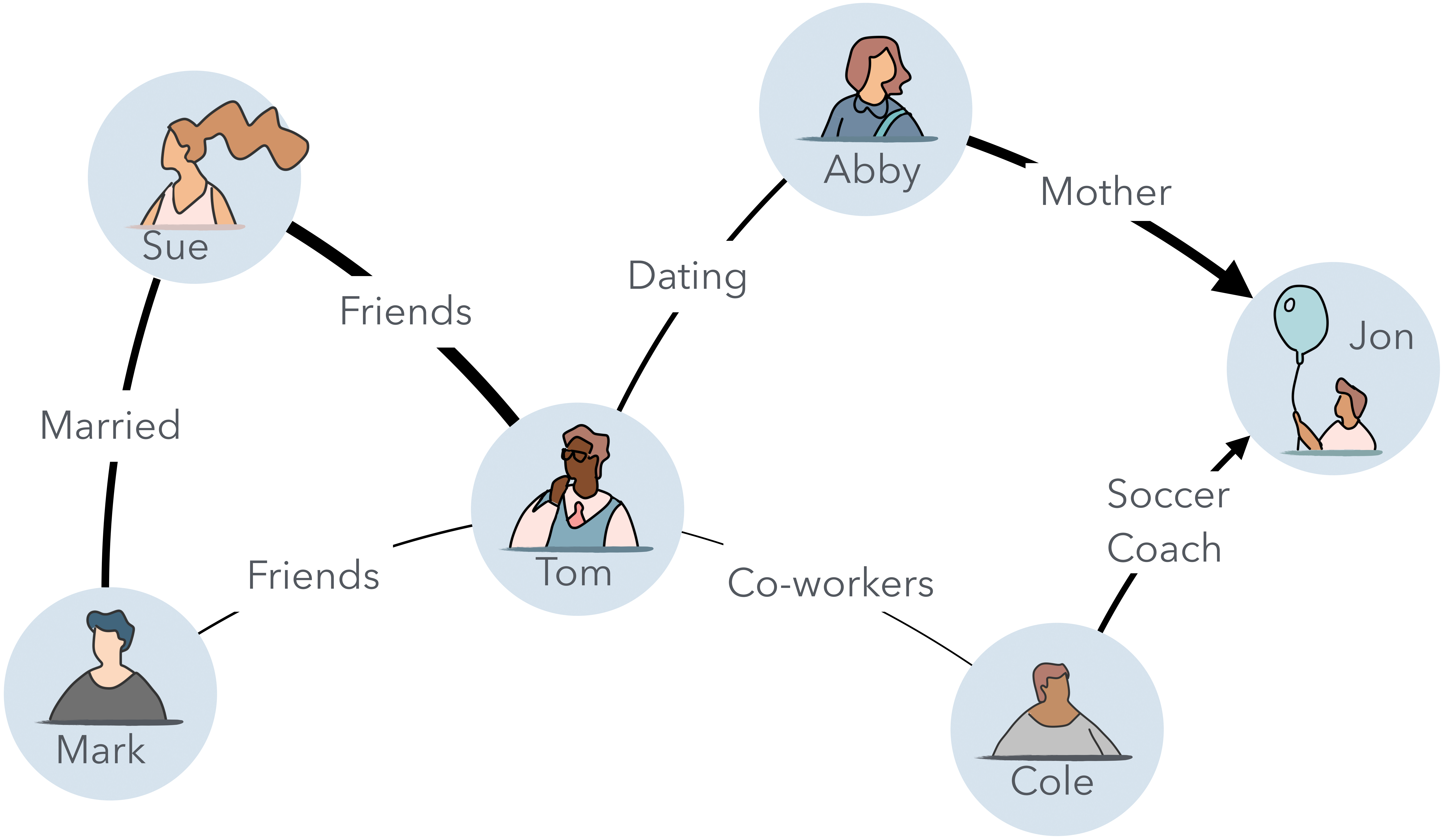
Topology Driven Layout

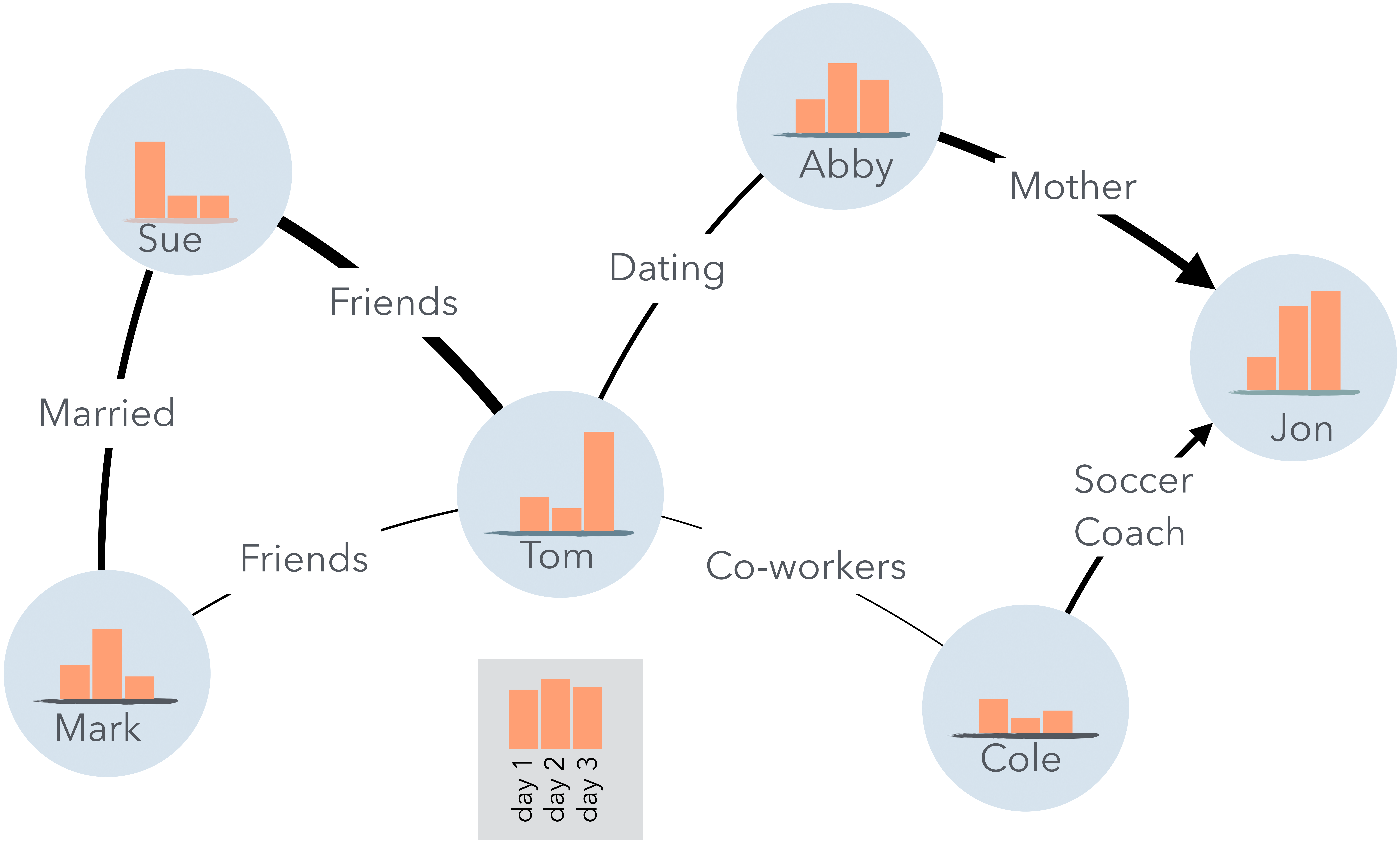


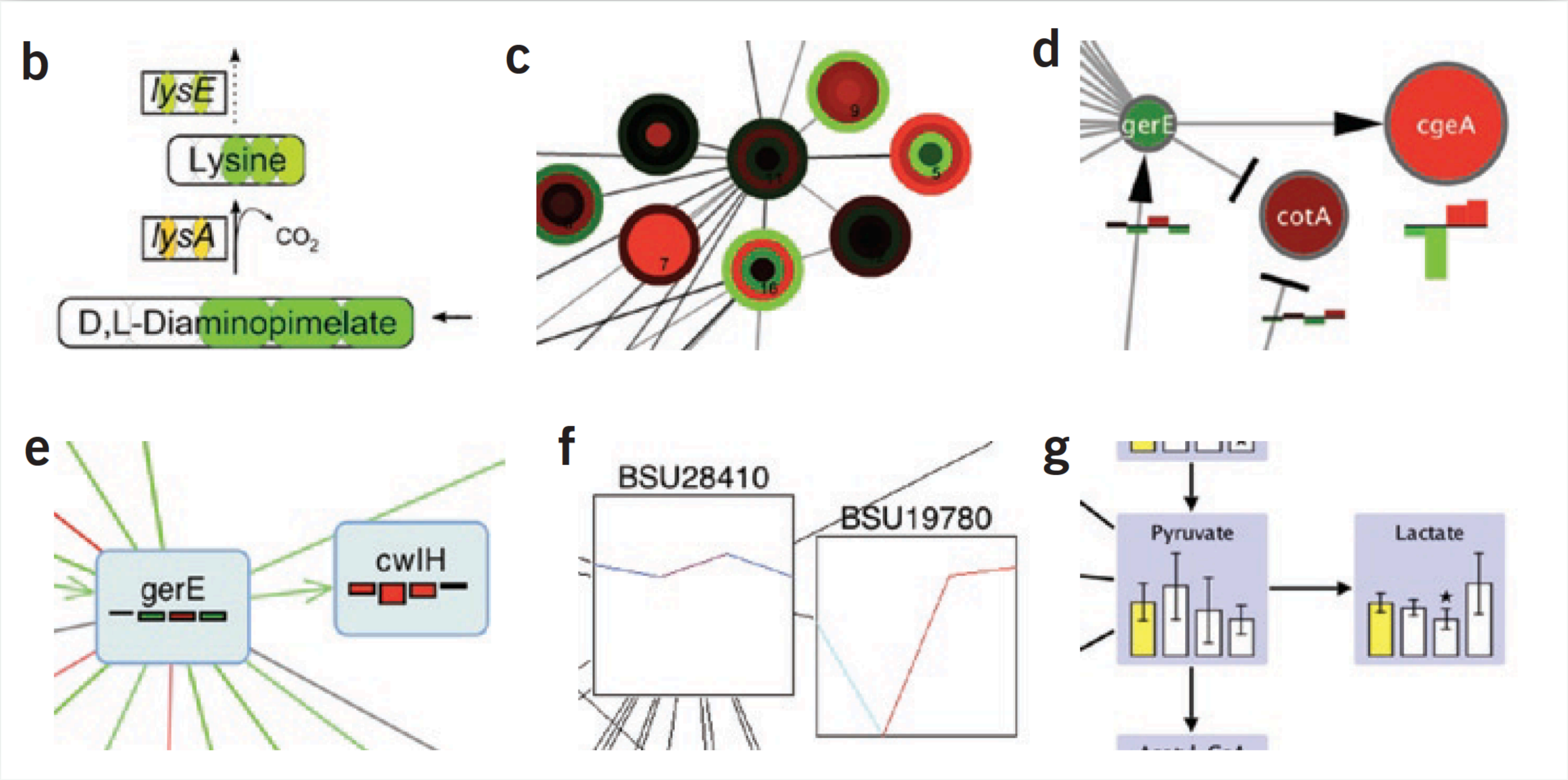
On-Node / On-Edge
Encoding


Mark
Sue
Tom
Abby
Cole
Jon

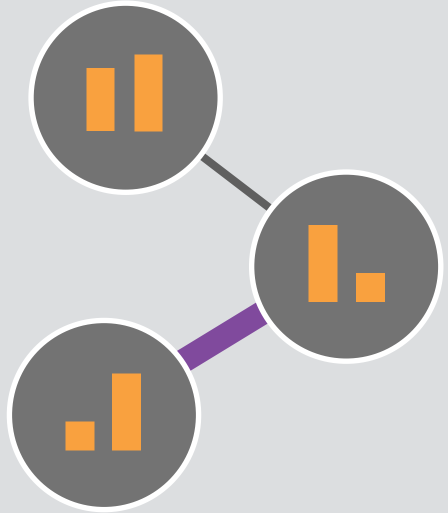

Sue
Abby
Mother
Dating
Jon
Friends
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole


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

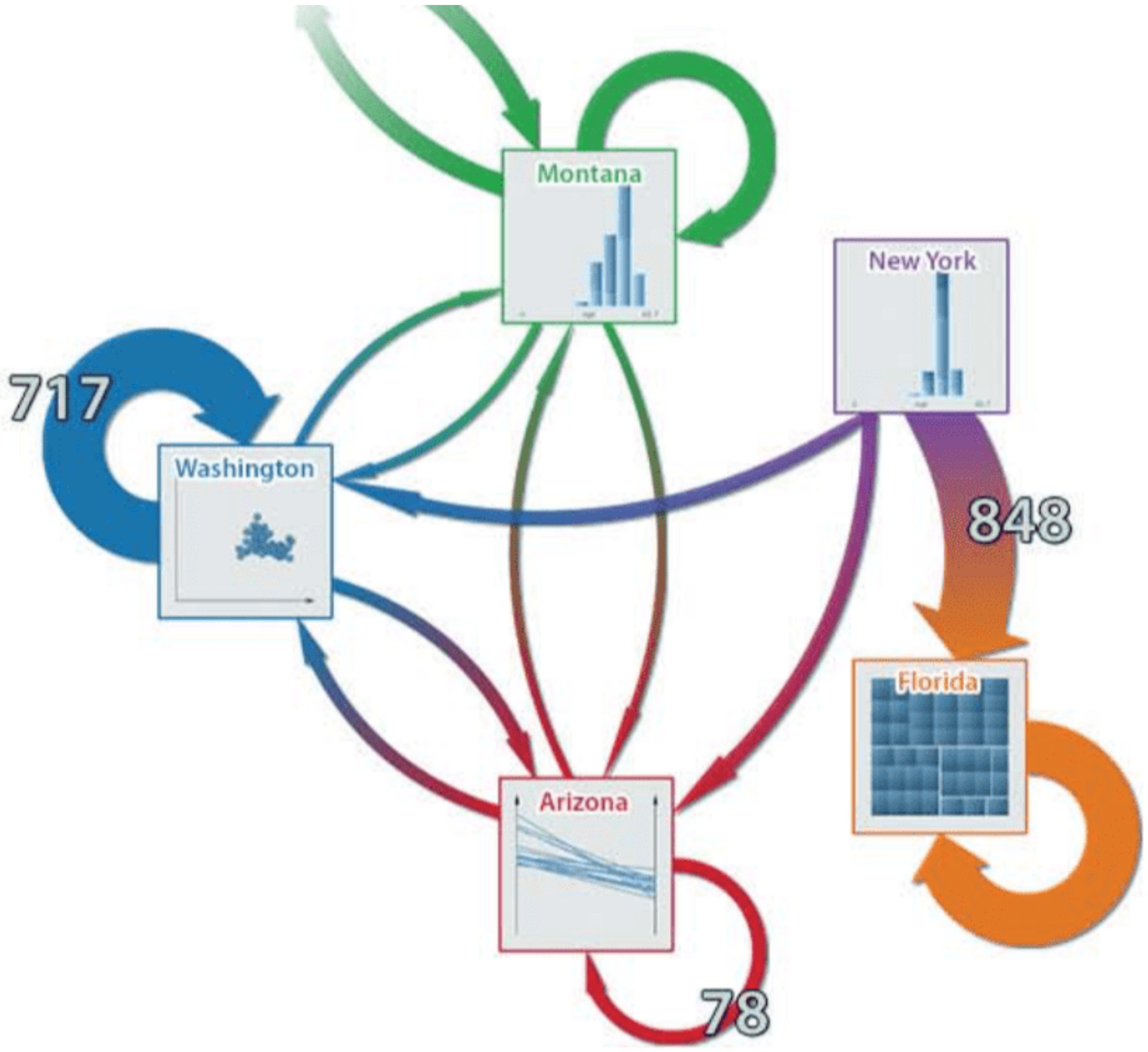

Sue
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole
day 1
day 2
day 3



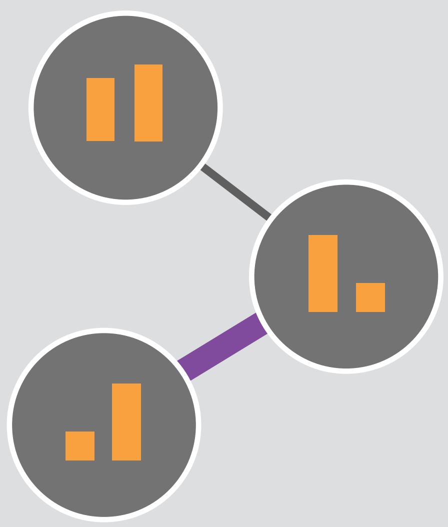
Gehlenborg et al. 2010



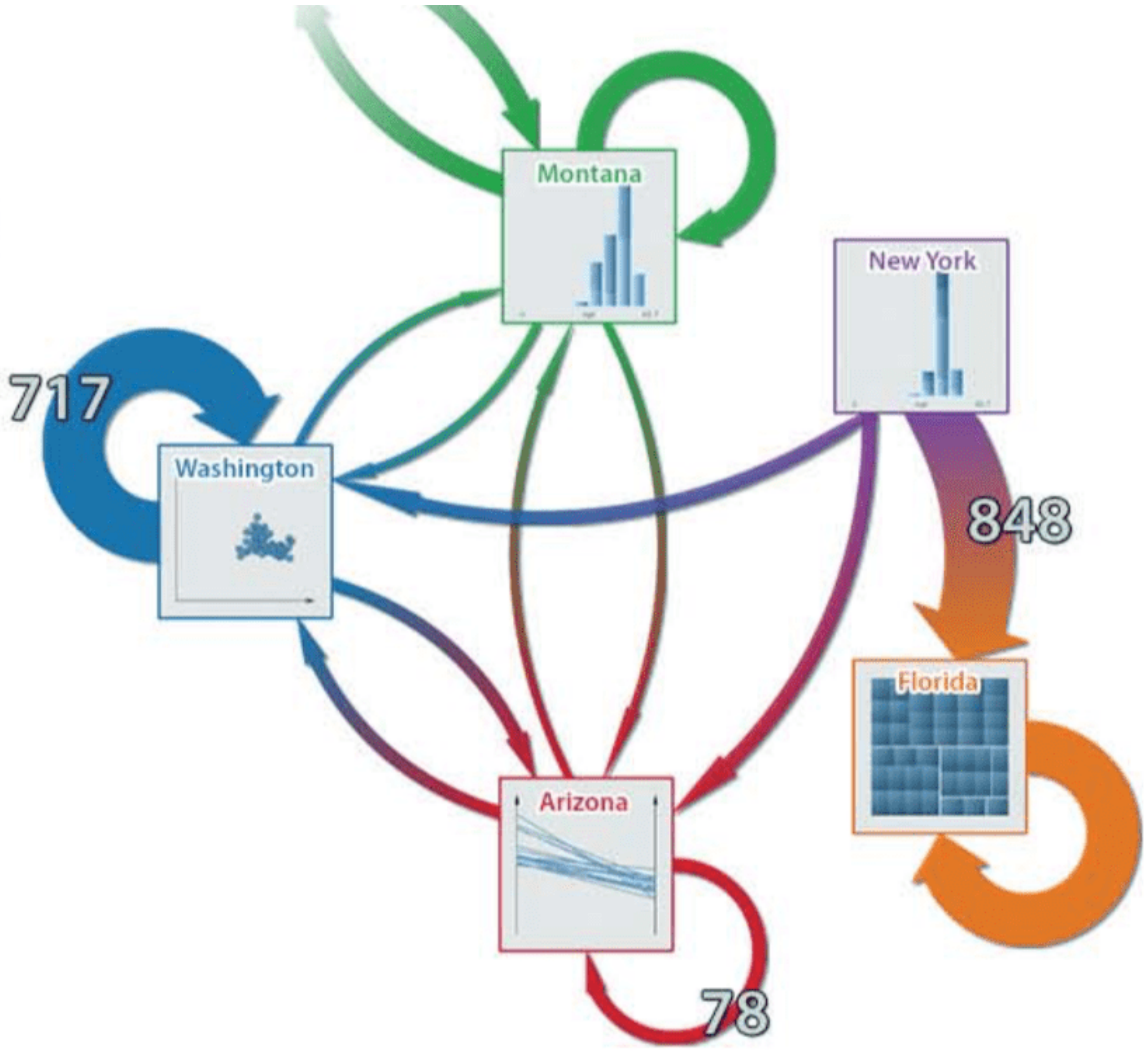
On-Node / On-Edge Encoding



Elzen and Wijk, 2014

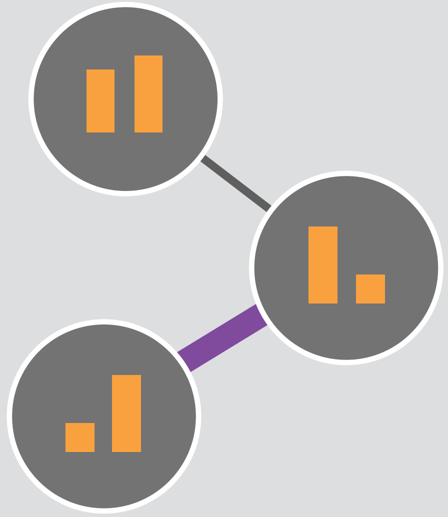


On-Node / On-Edge Encoding

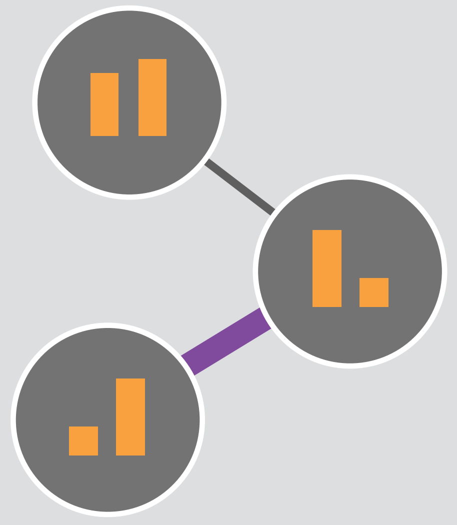


Elzen and Wijk, 2014

Aggregating Nodes/Edges



On-Node / On-Edge
Encoding



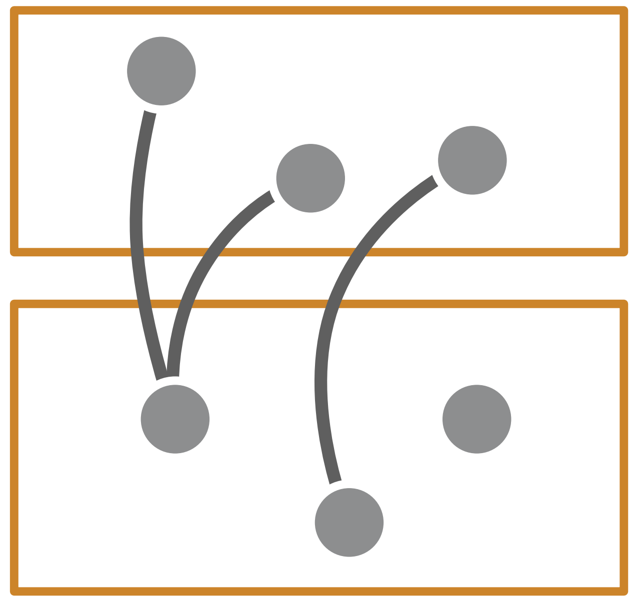
On-Node / On-Edge Encoding

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 Layouts



Attribute-Driven Faceting

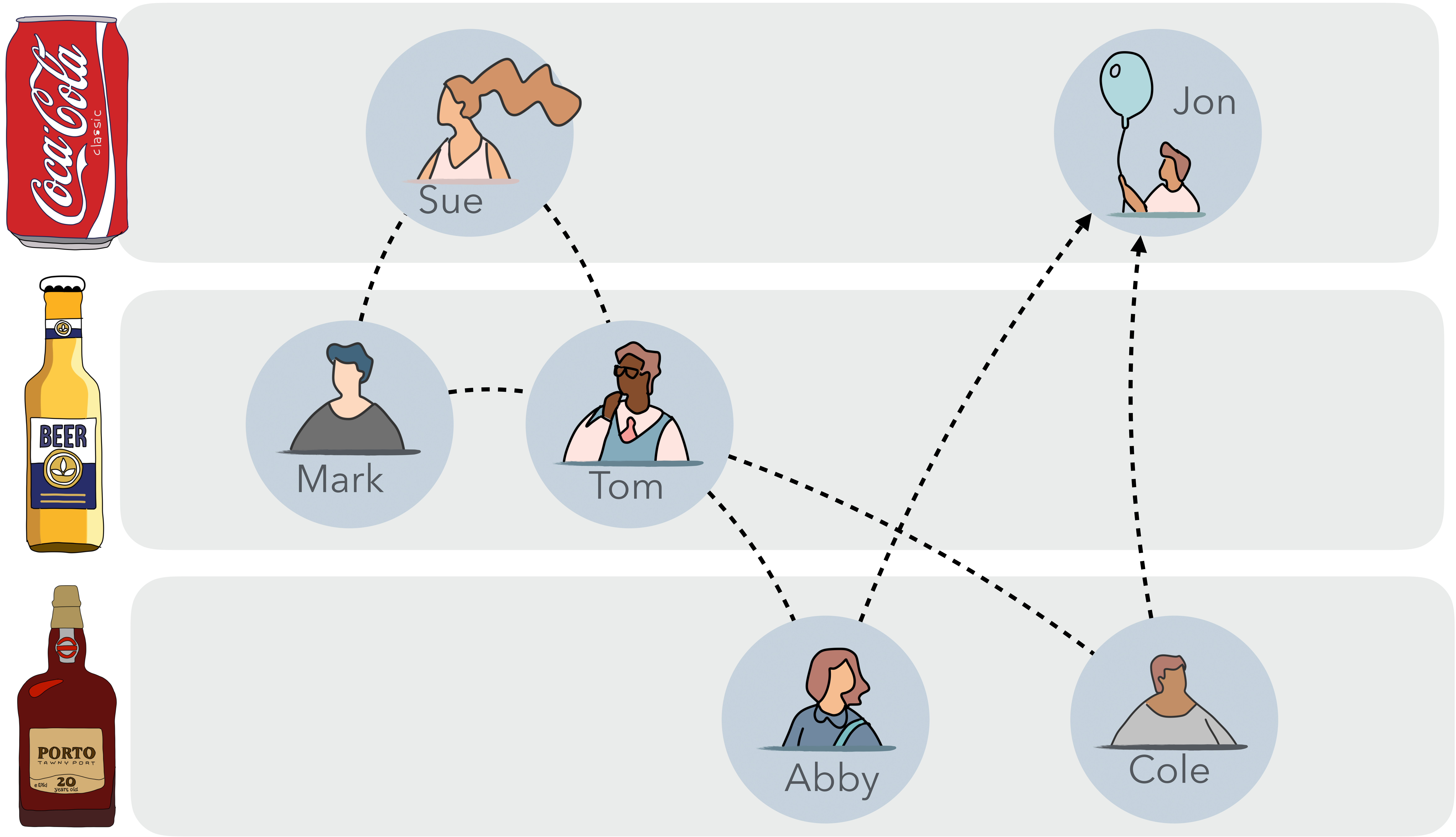
Attribute-Driven Positioning


Coca-Cola
classic
BEER
PORTO
TAWNY PORT
e 0,75cl
20
years old

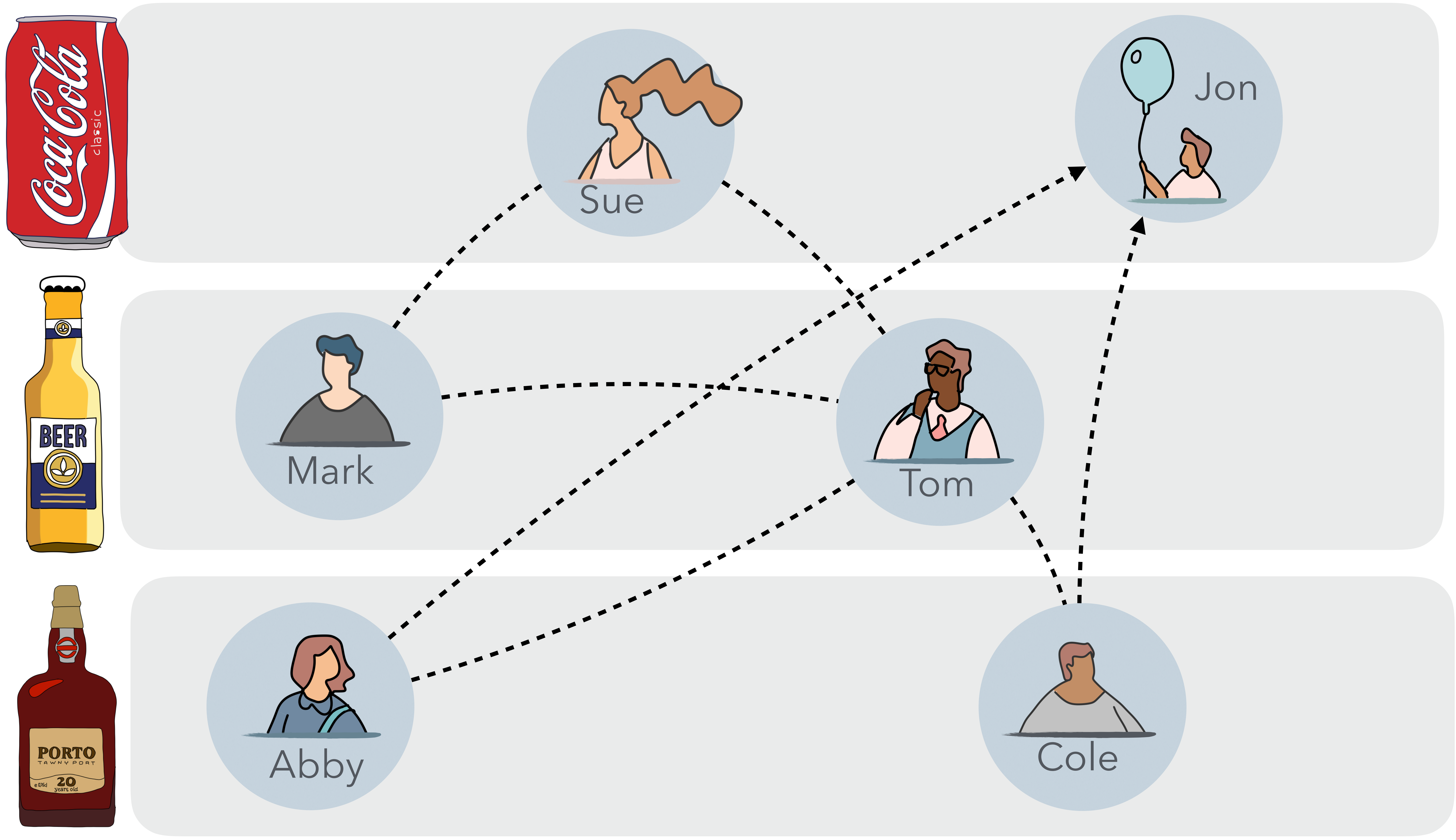

Coca-Cola
classic


BEER

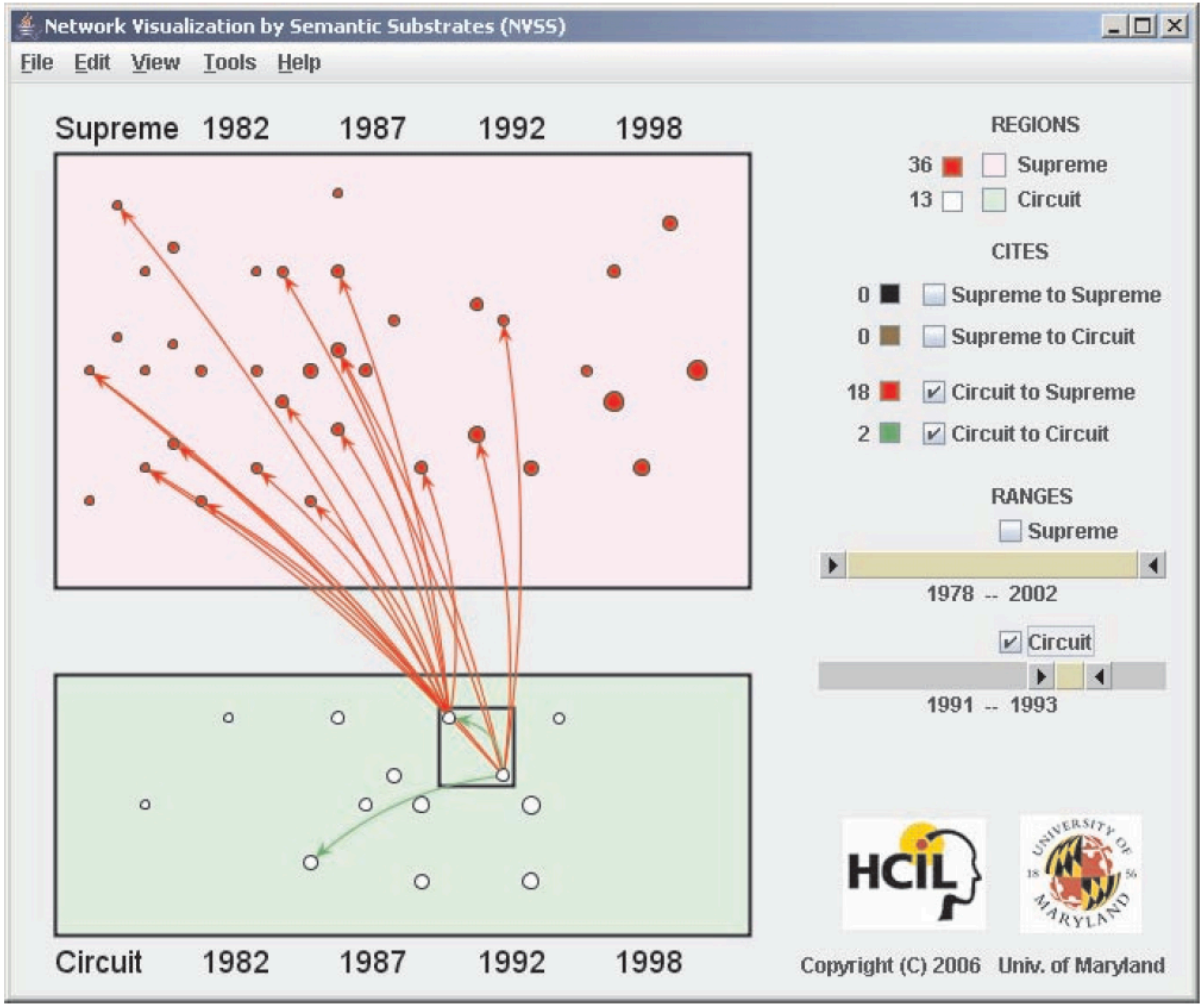

PORTO
TAWNY PORT
20
years old

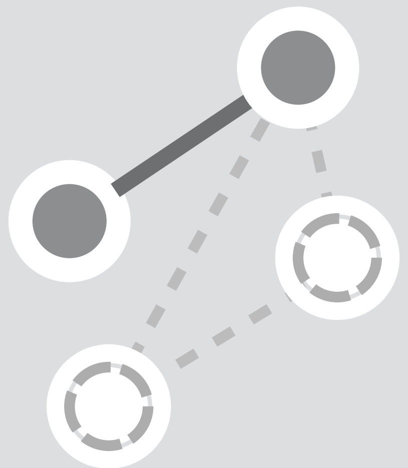


Coca-Cola
classic
BEER
PORTO
TAWNY PORT
20
years old
Sue
Jon
Mark
Tom
Abby
Cole

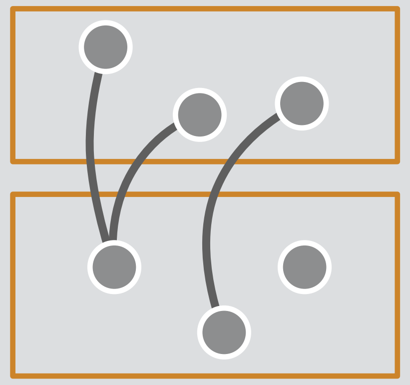

Coca-Cola
classic
BEER
PORTO
TAWNY PORT
20
years old
Sue
Jon
Mark
Tom
Abby
Cole

Semantic Substrates *Shneiderman and Aris, 2006*

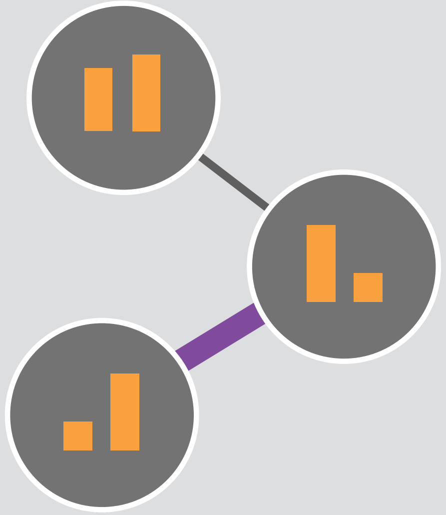




Querying and Filtering

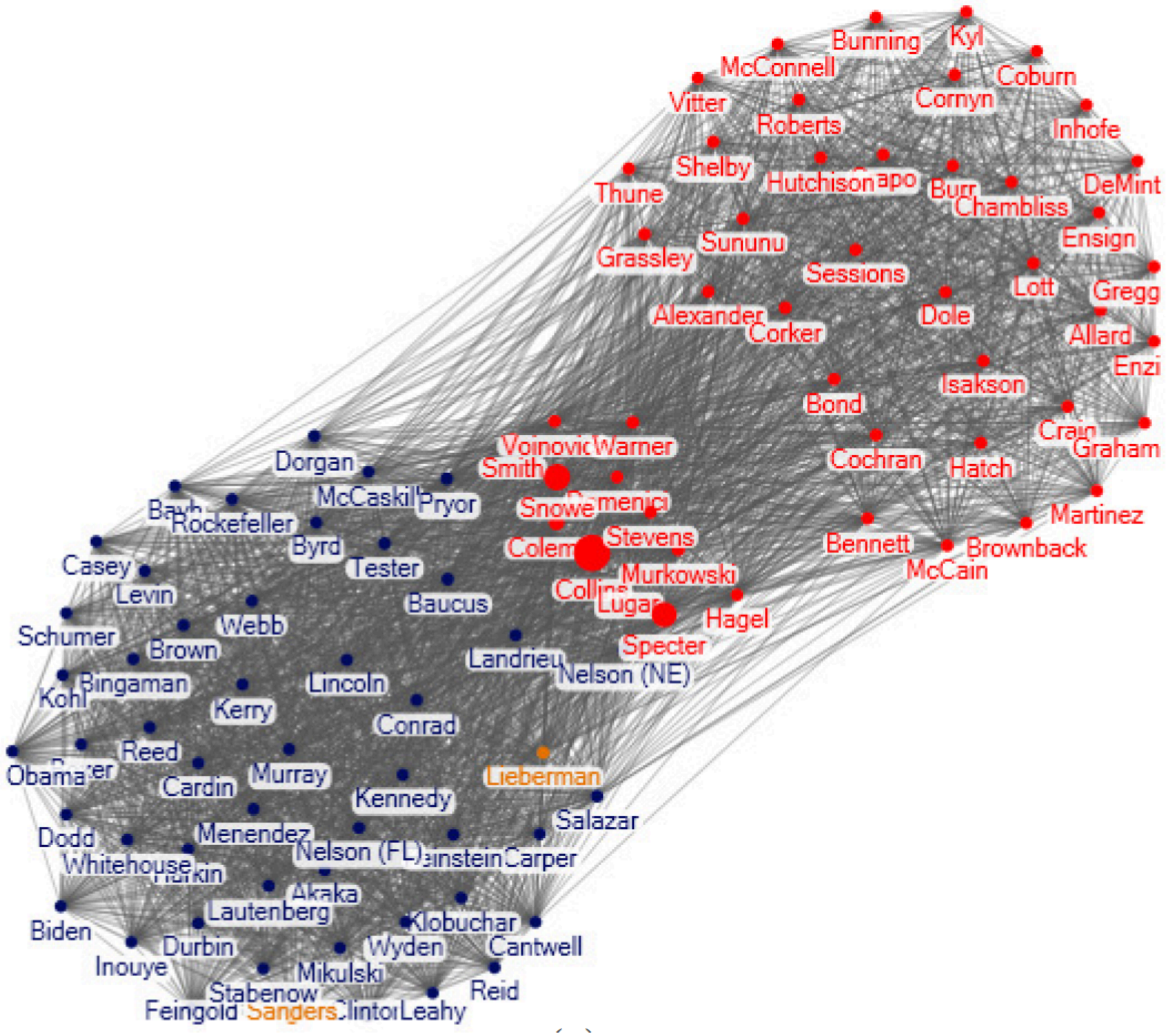


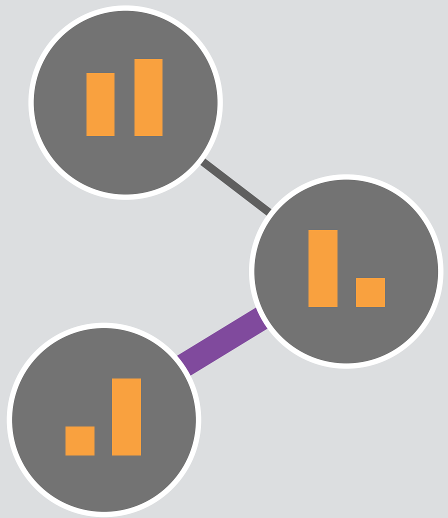
Attribute-Driven Faceting



On-Node / On-Edge Encoding

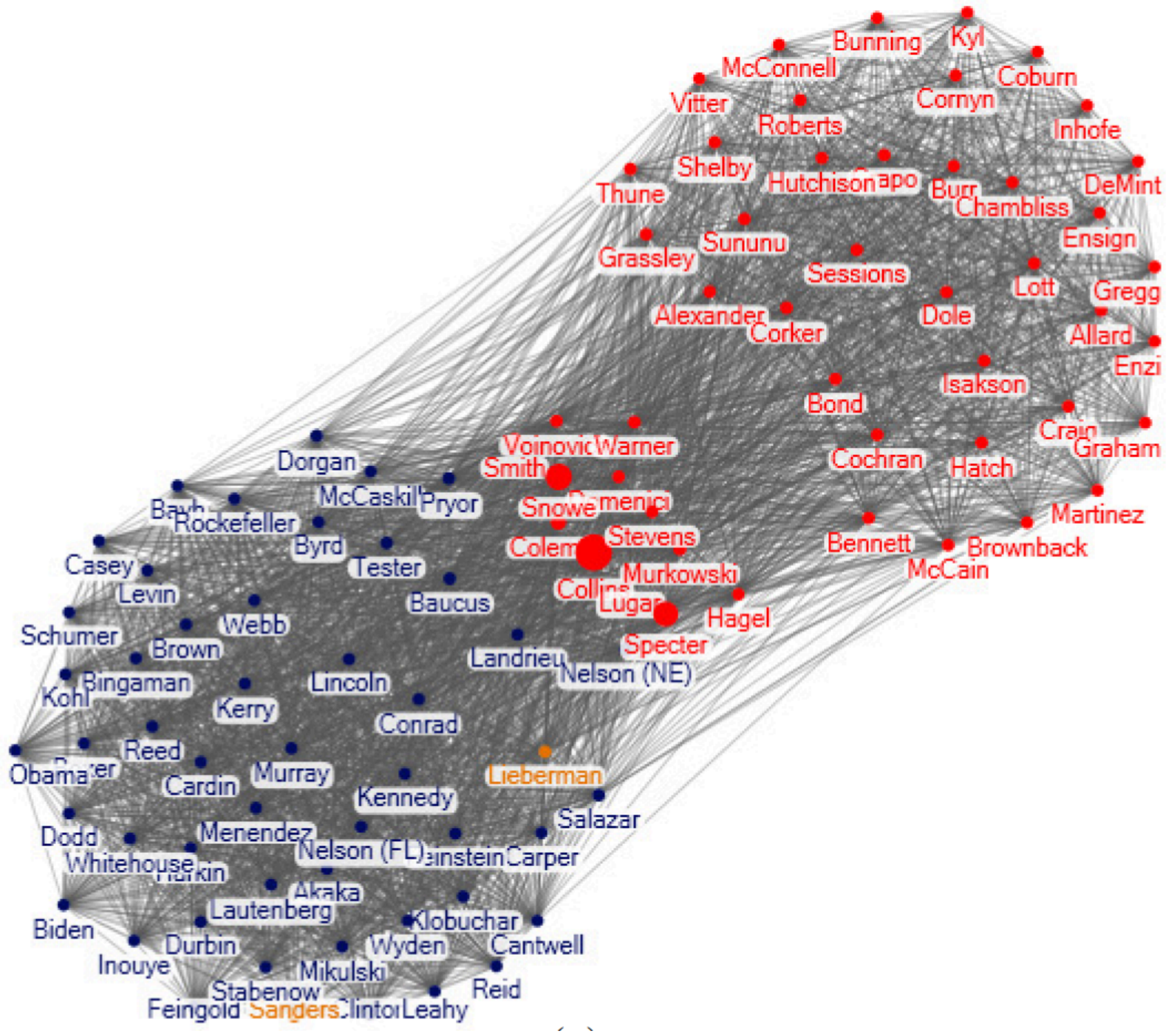
Group-in-a-box *Rodrigues et al. 2011*

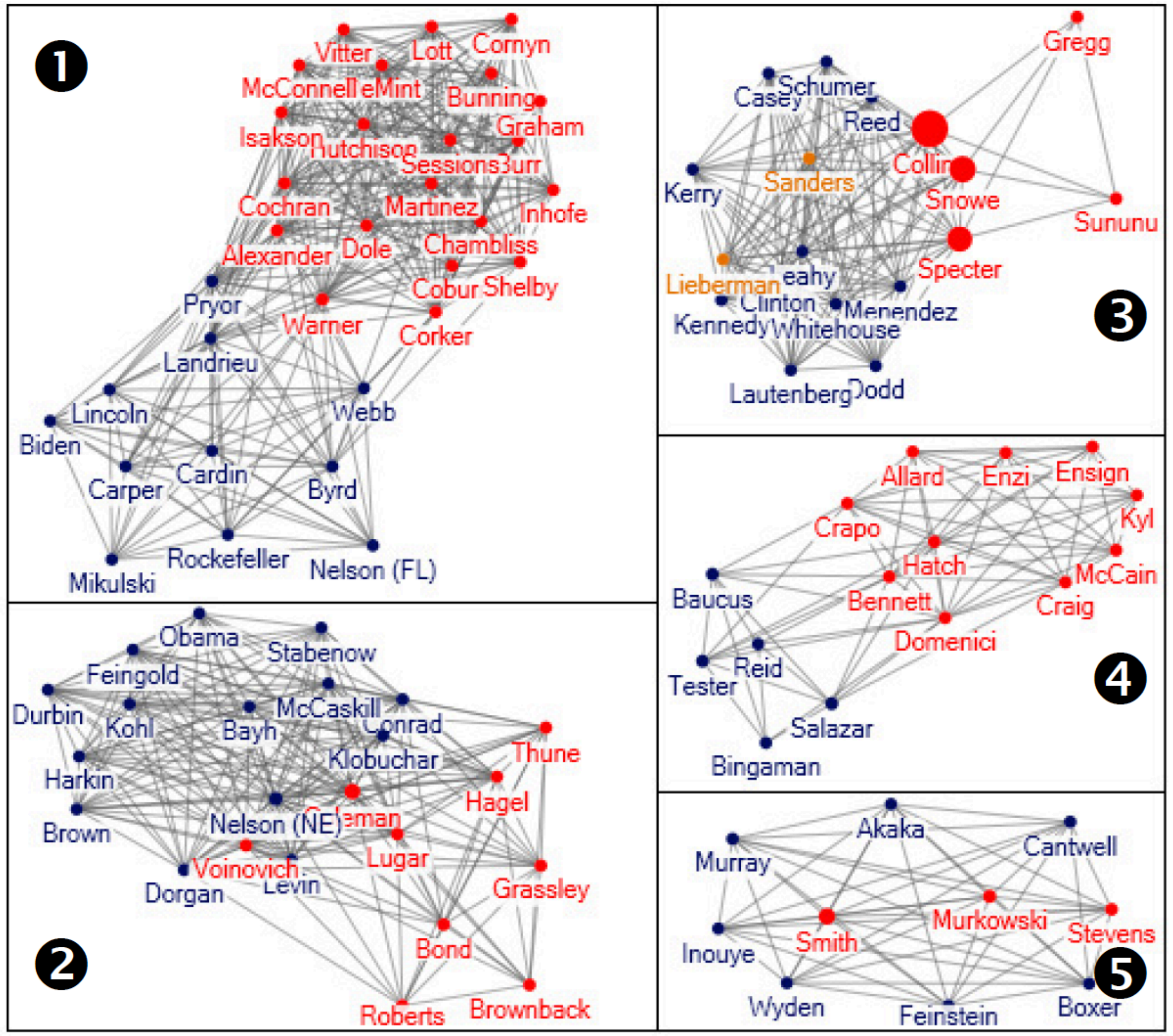


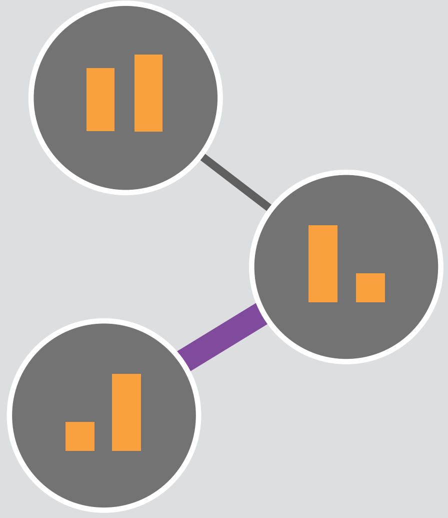


On-Node / On-Edge Encoding

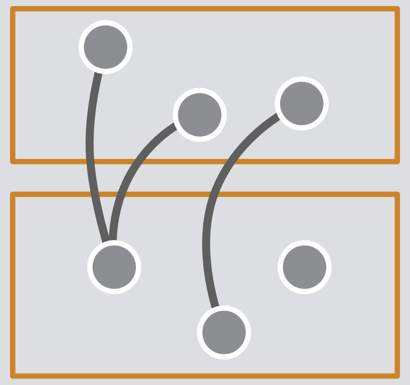
Group-in-a-box *Rodrigues et al. 2011*



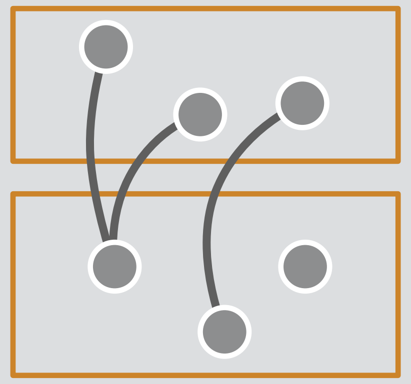




On-Node / On-Edge Encoding



Attribute-Driven Faceting



Attribute-Driven Faceting

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

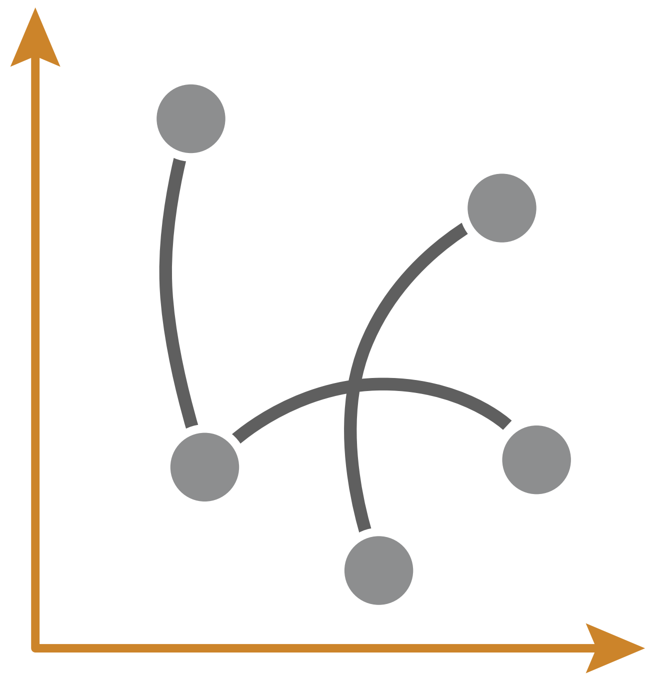
Less scalable with respect to the number of nodes and network density than node-link layouts.

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 Layouts

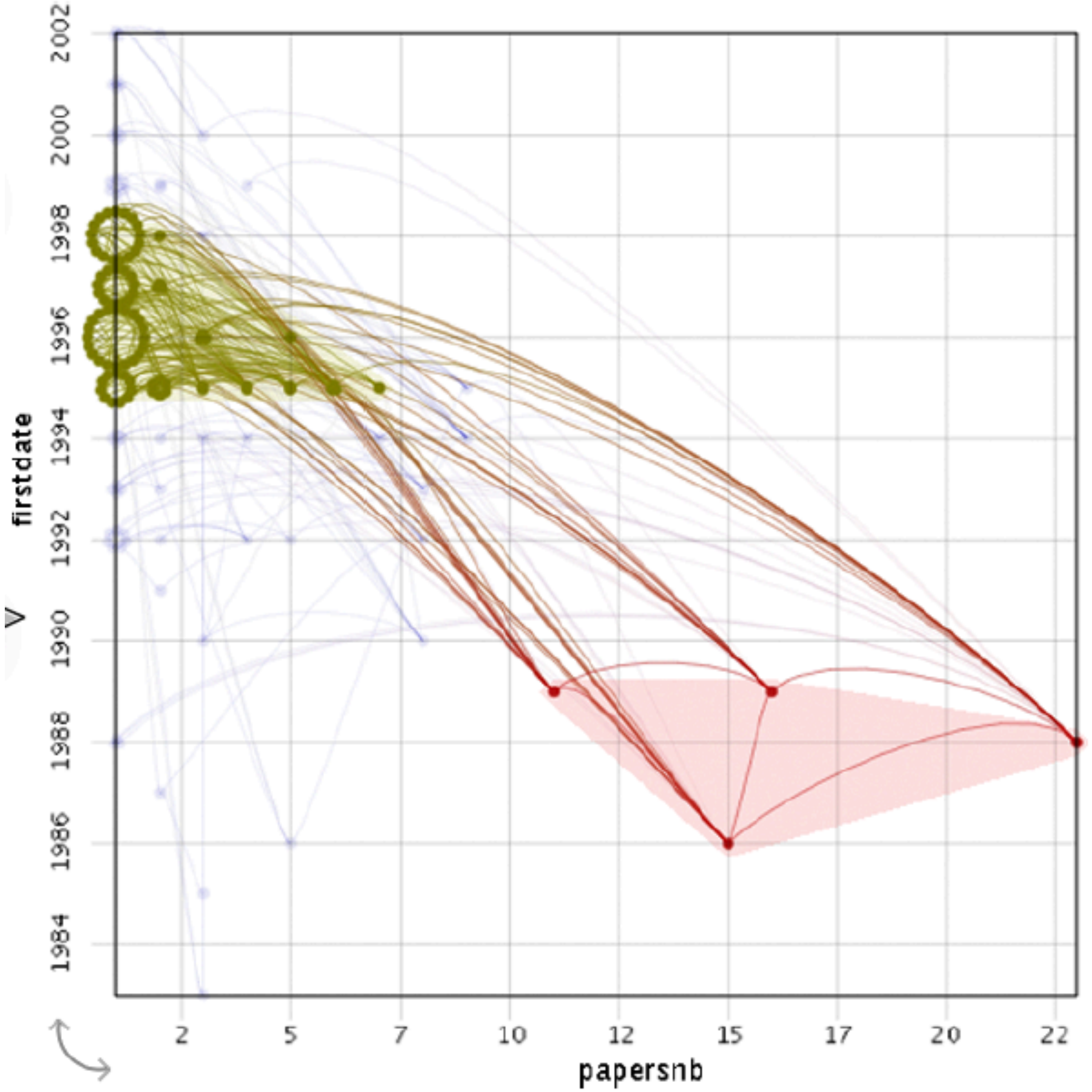
Attribute-Driven Faceting

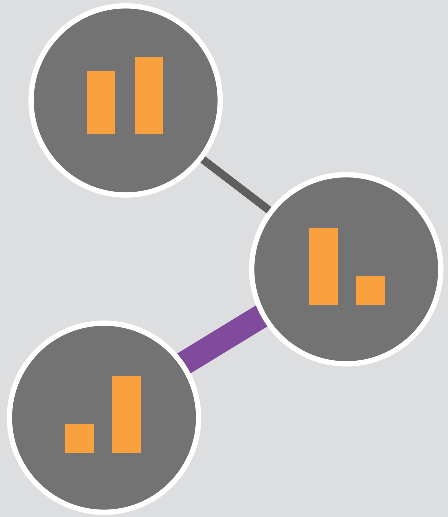


Attribute-Driven Positioning

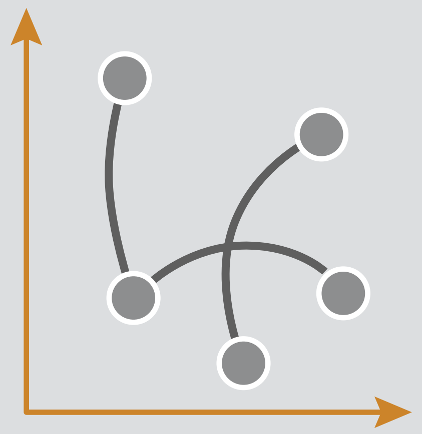

ANCHORAGE
VANCOUVER
EDMONTON
SEATTLE
PORTLAND
SAN FRANCISCO
DENVER
MINNEAPOLIS / ST. PAUL
CHICAGO
KANSAS CITY
DALLAS
TORONTO
CLEVELAND
MONTREAL
BALTIMORE
WASHINGTON D.C.
PHILADELPHIA
NEW YORK
JFK & NEWARK
BOSTON
HALIFAX
TAMPA BAY
ORLANDO
ICELAND
HELSINKI
STOCKHOLM
OSLO
GOTHENBURG
BERGEN
COPENHAGEN
BILLUND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

Graph Dice *Bezerianos et al. 2010*



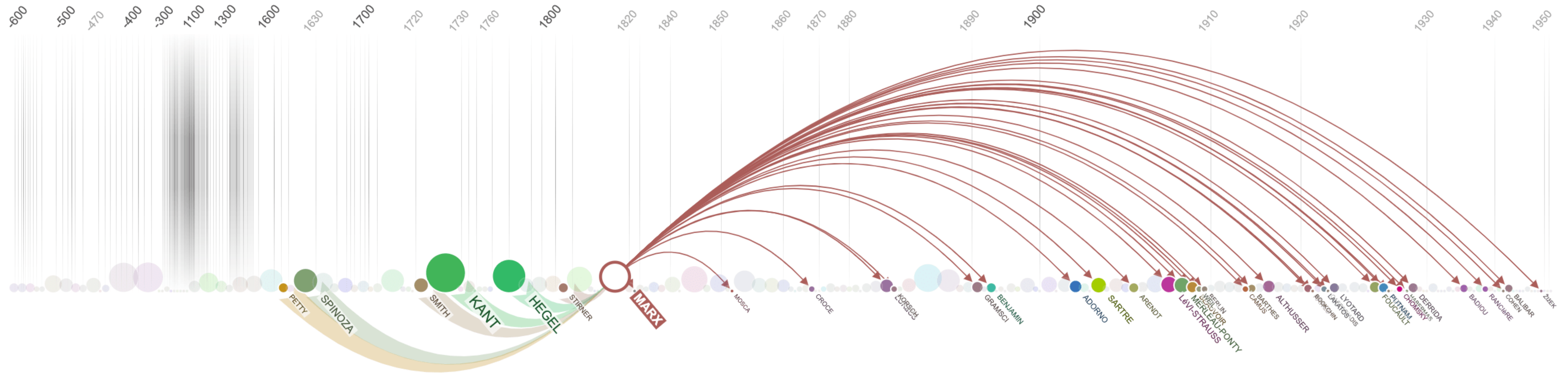


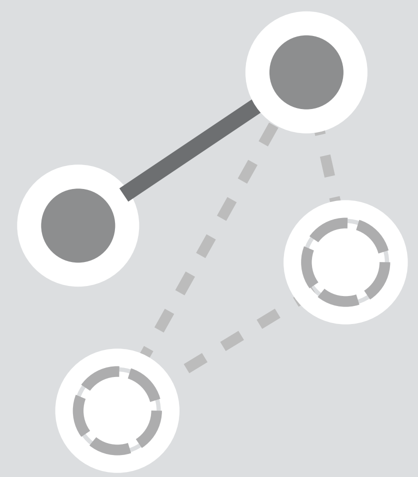
On-Node / On-Edge Encoding



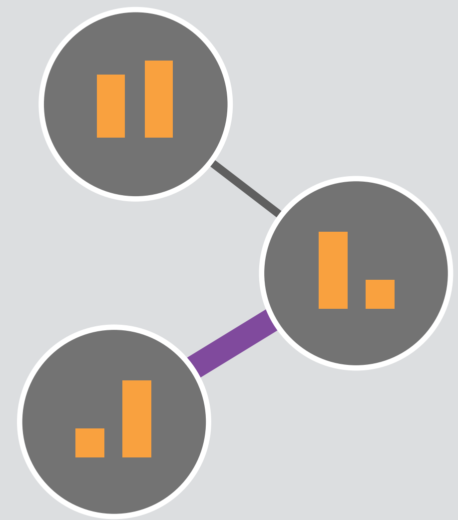
Attribute-Driven Positioning

Edge Map *Dork et al. 2011*

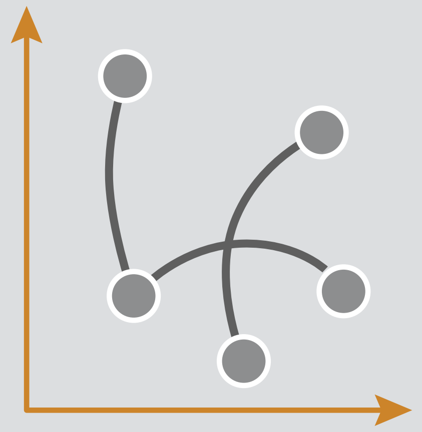




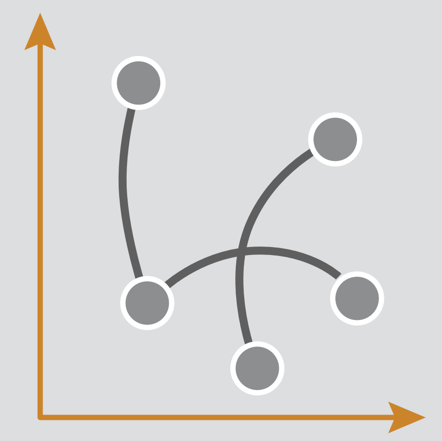
Querying and Filtering



On-Node / On-Edge Encoding



Attribute-Driven Positioning



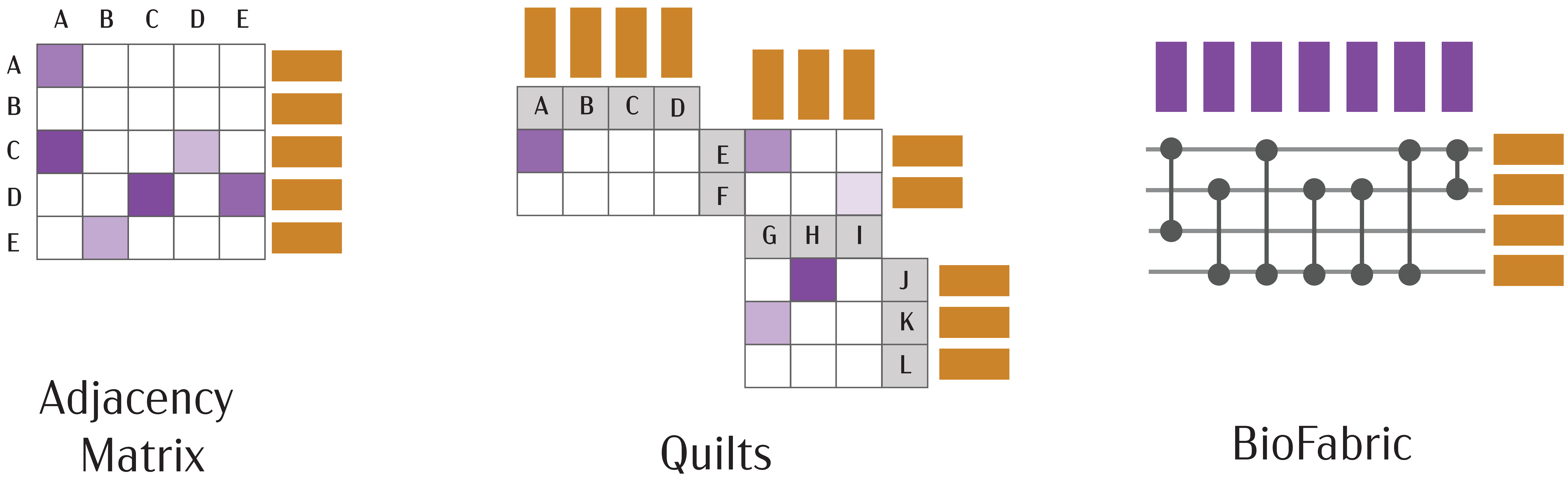
Attribute-Driven Positioning

Well suited for quantitative attributes

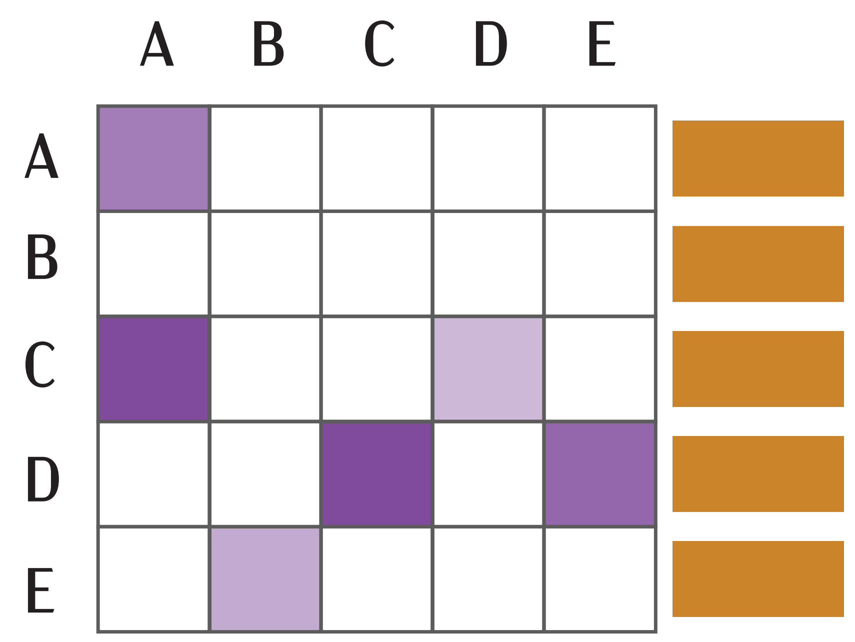
Does not lend itself well to visualizing the topology of the network.

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

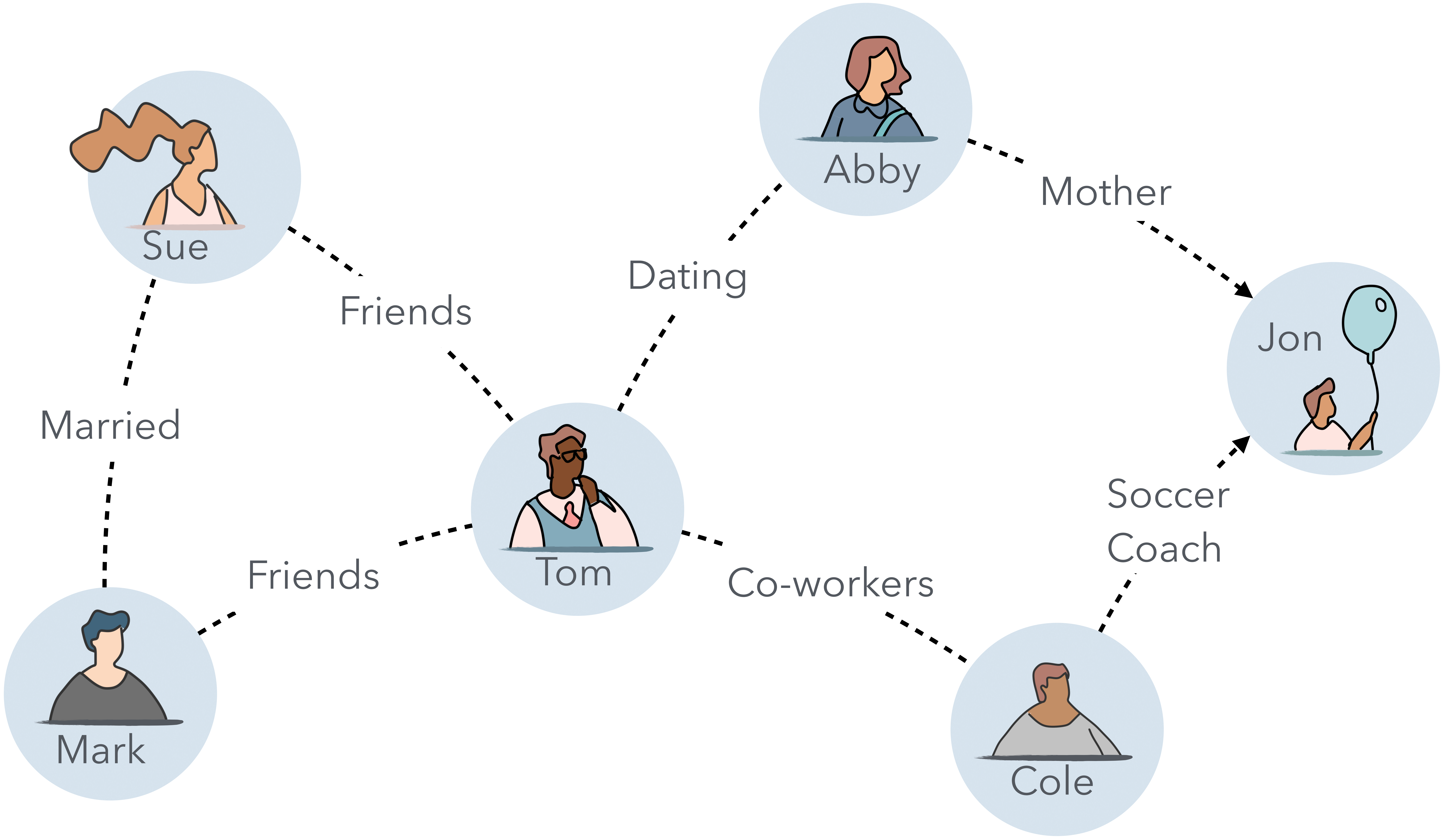
Tabular Layouts



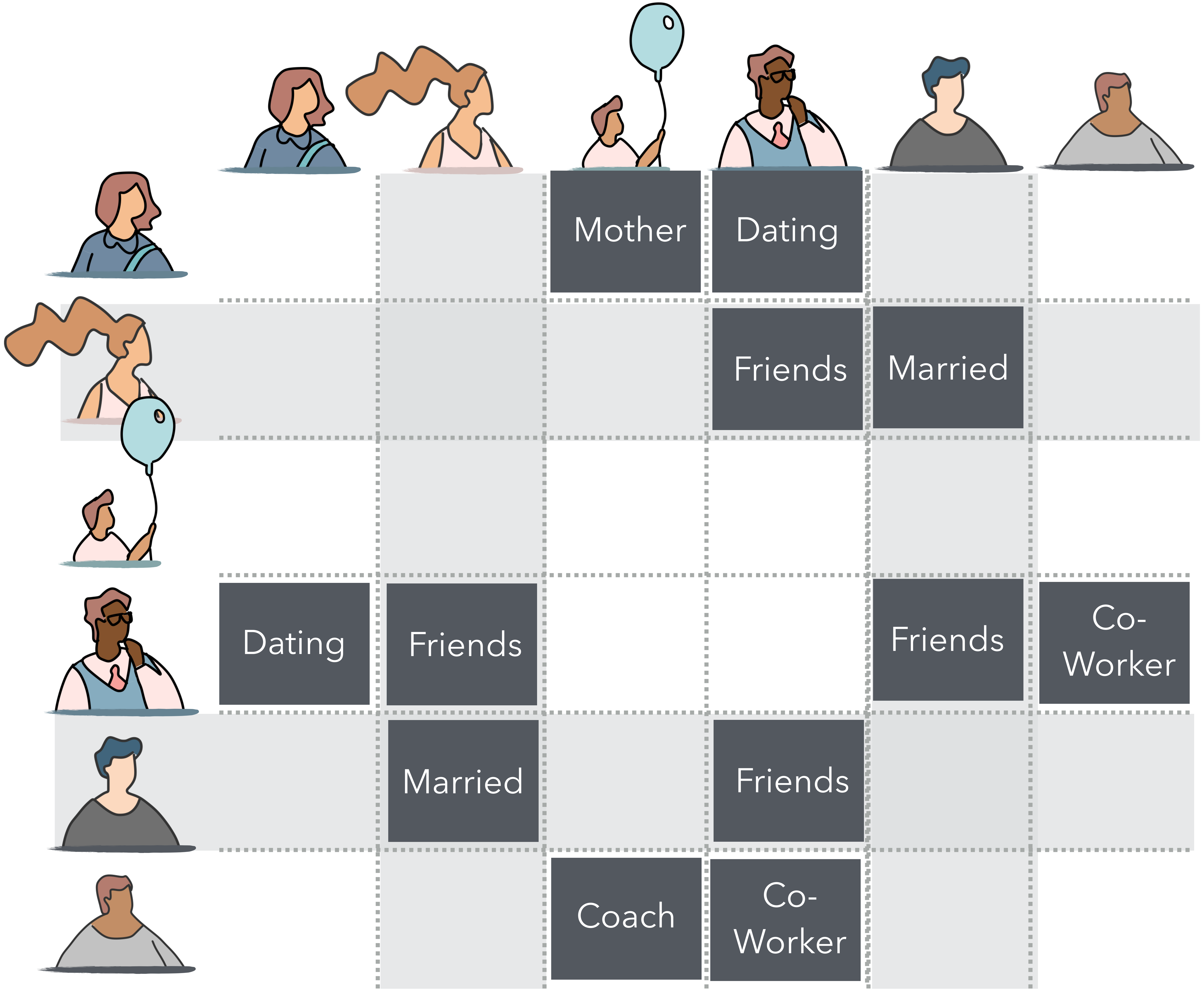
Tabular Layouts

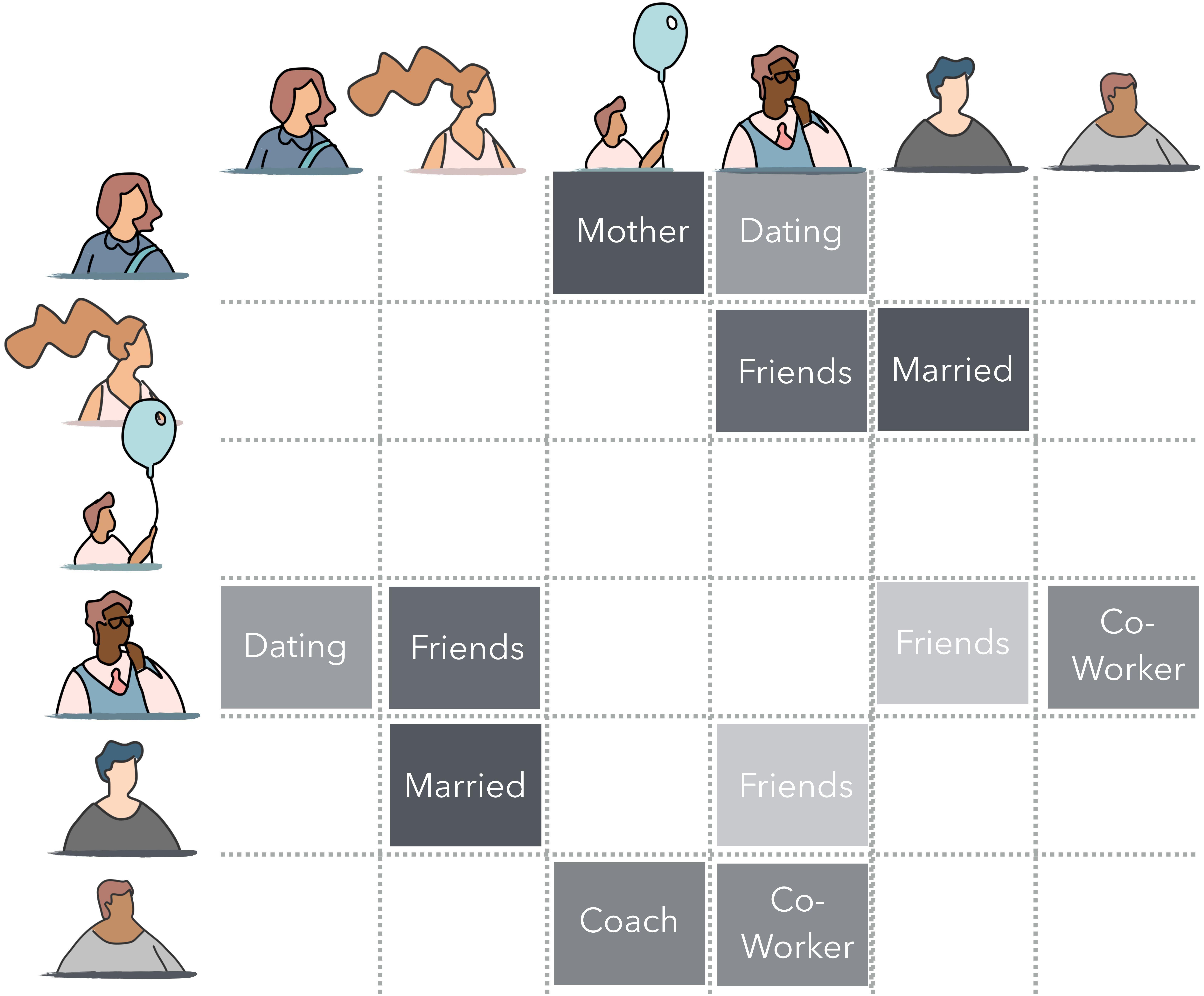


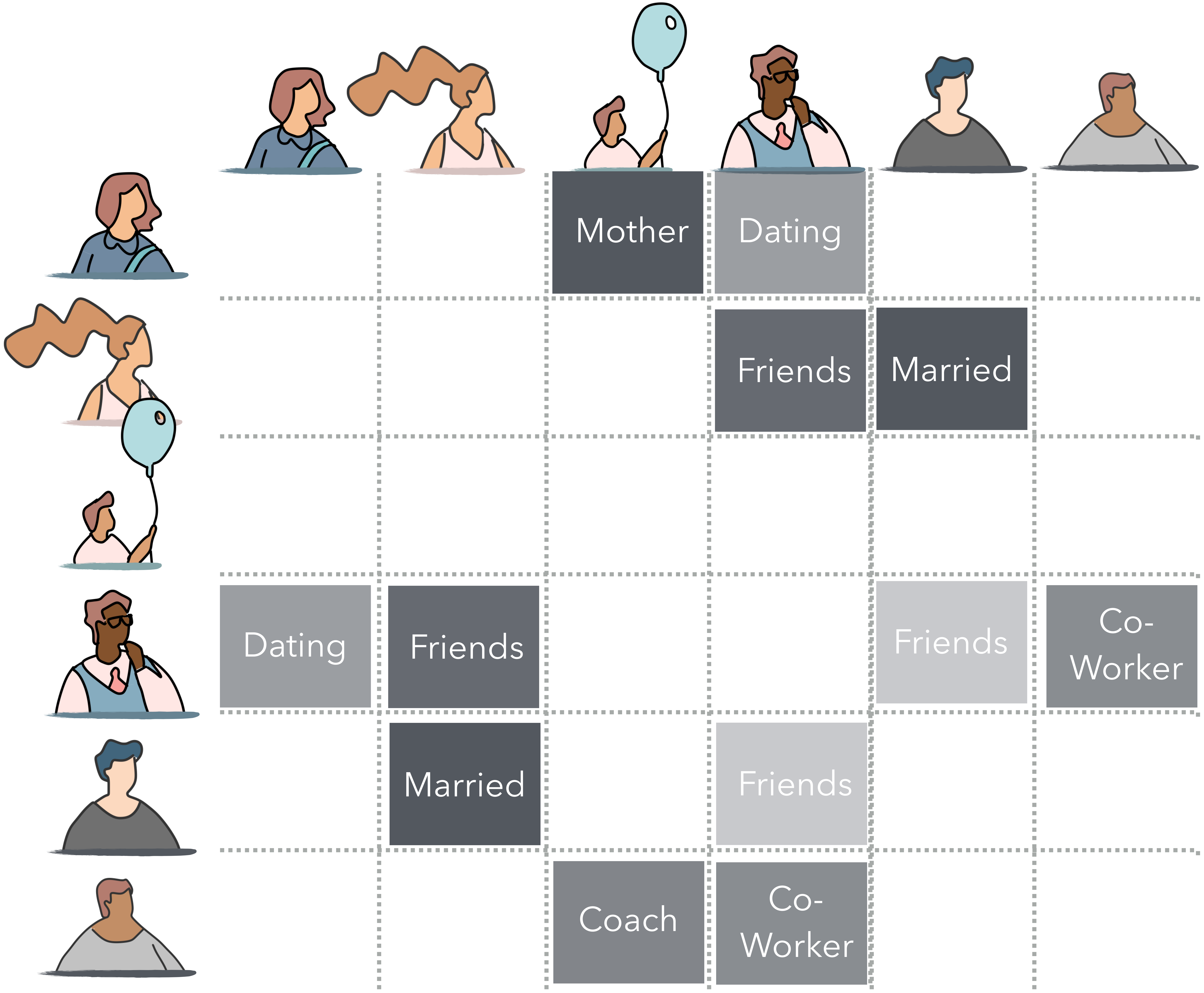
Adjacency
Matrix



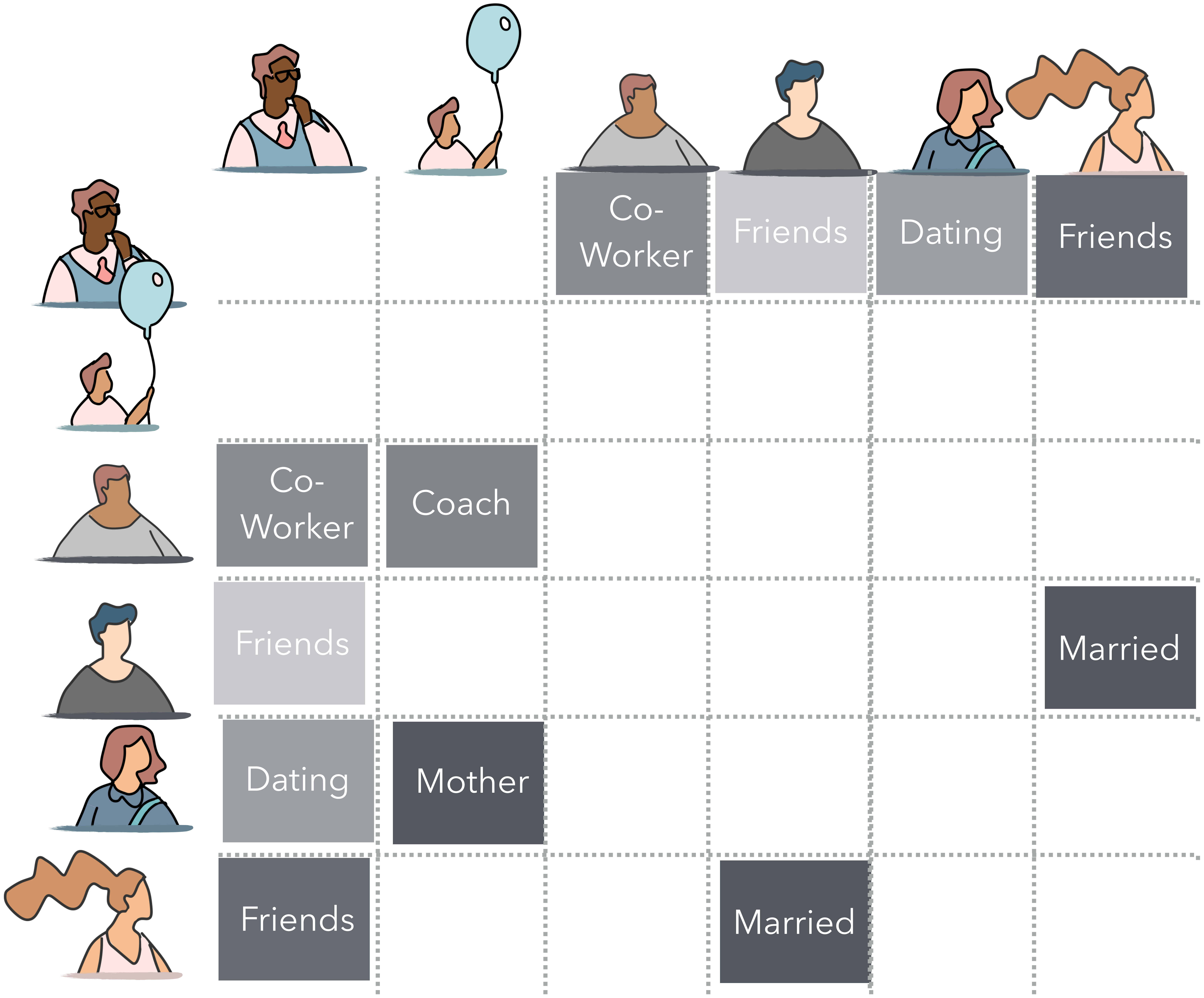
Sue
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole


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


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

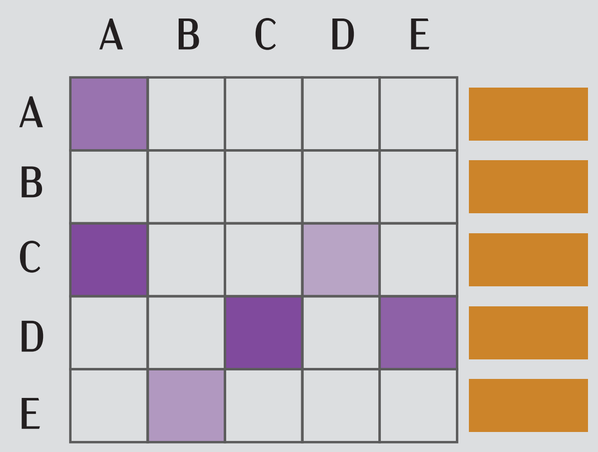


Name	Beverage	Day 1
Abby	Port	1
Sue	Coke	0
Jon	Coke	4
Tom	Beer	5
Mark	Beer	2
Cole	Port	3

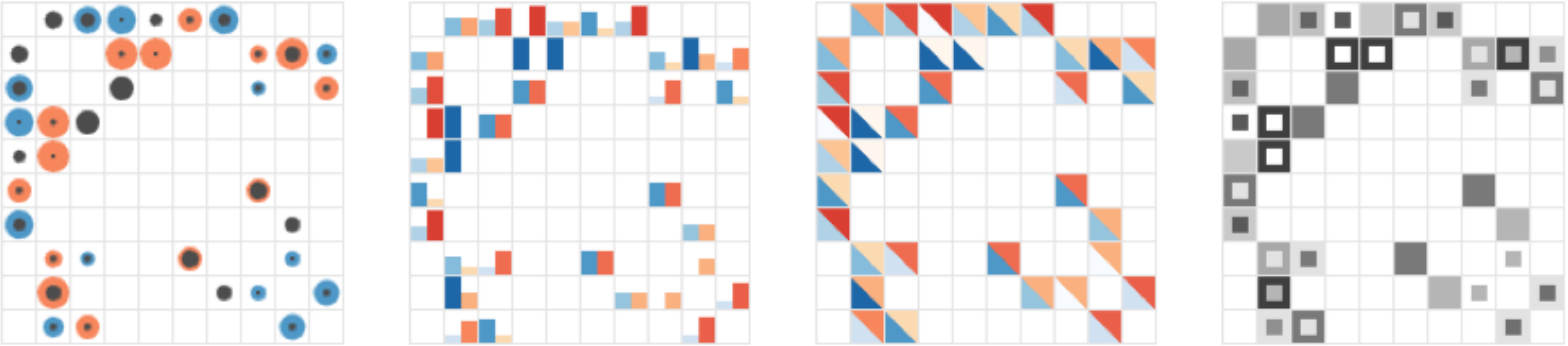


Name	Beverage	Day 1
Tom	Beer	5
Jon	Coke	4
Cole	Port	3
Mark	Beer	2
Abby	Port	1
Sue	Coke	0

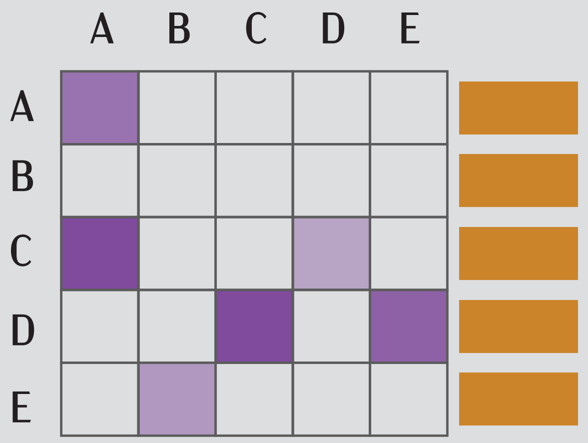
Moritz Stefaner, Musli Ingredient Network. https://truth-and-beauty.net/projects/muesli-ingredient-network



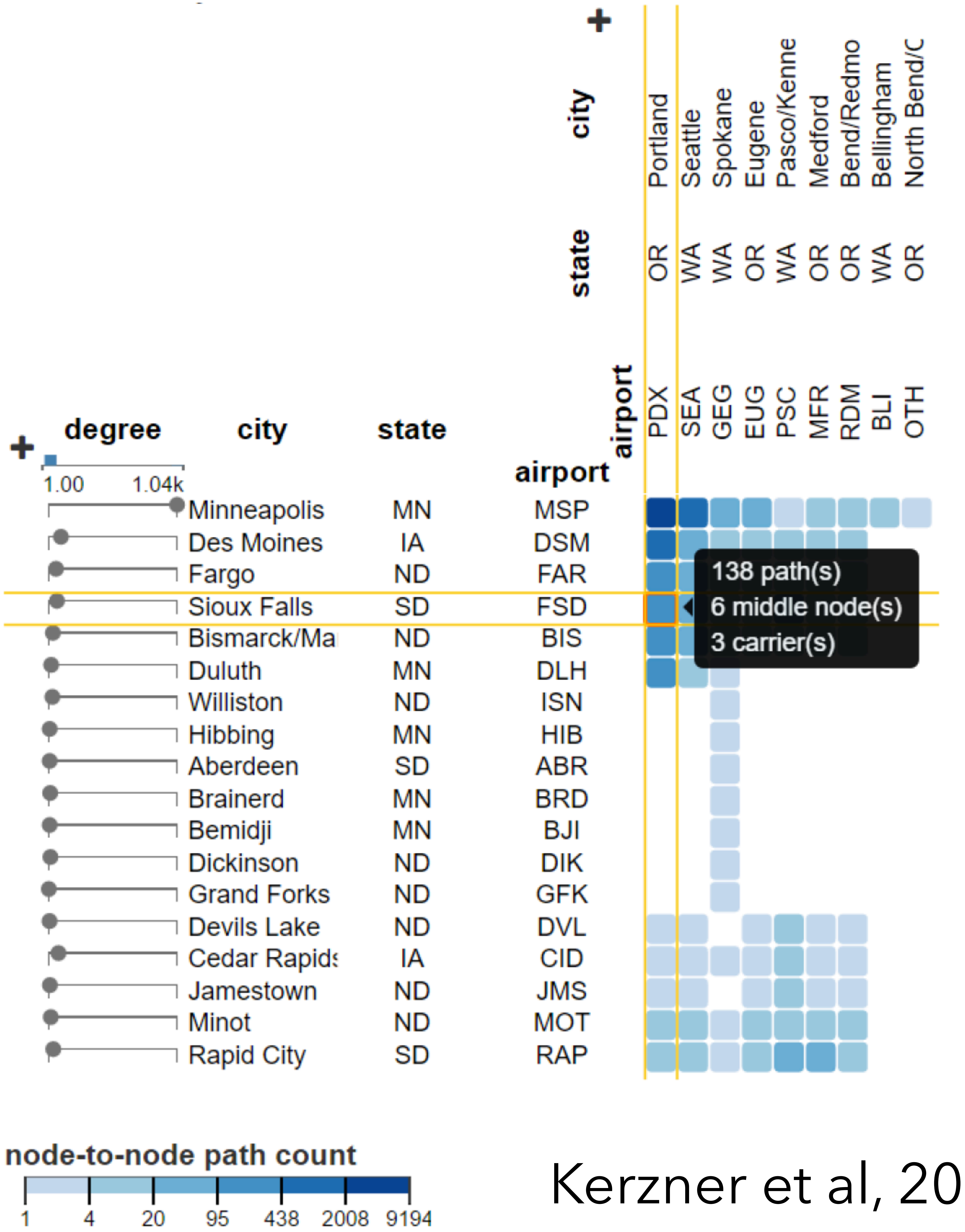
Adjacency Matrix



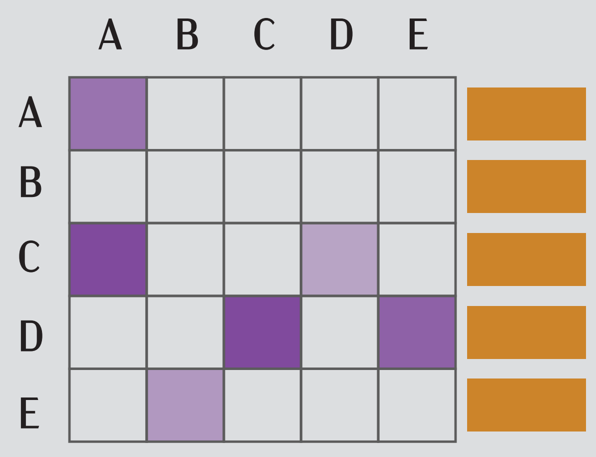
Alper et al, 2013



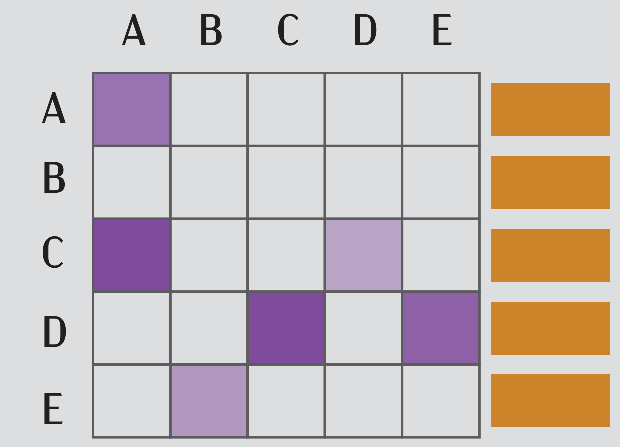
Adjacency Matrix



Kerzner et al, 2017



Adjacency Matrix



Adjacency Matrix

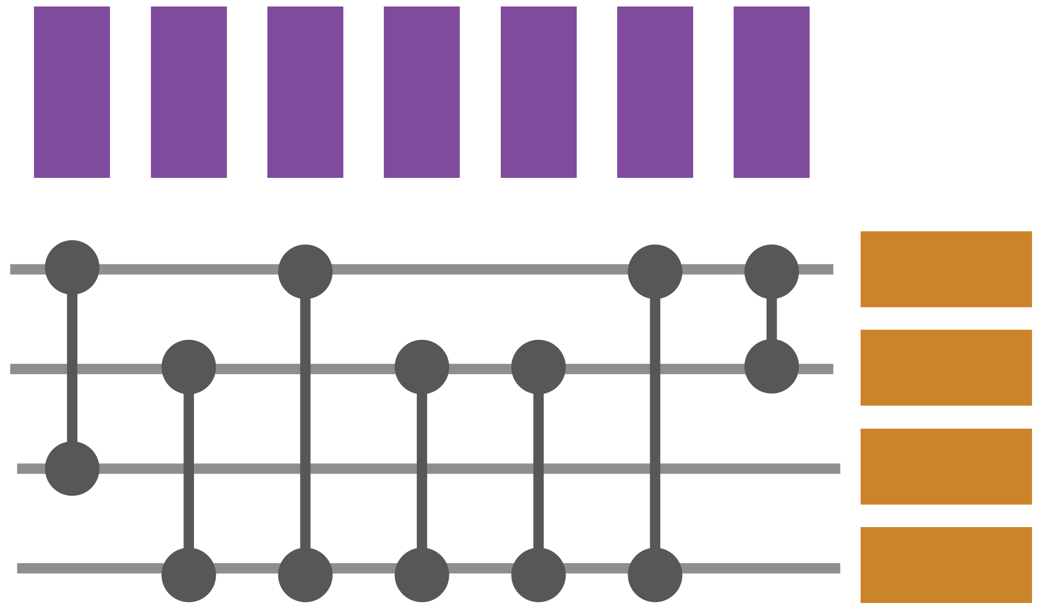
Ideal for dense and completely connected networks

Requires quadratic space with respect to the number of nodes.

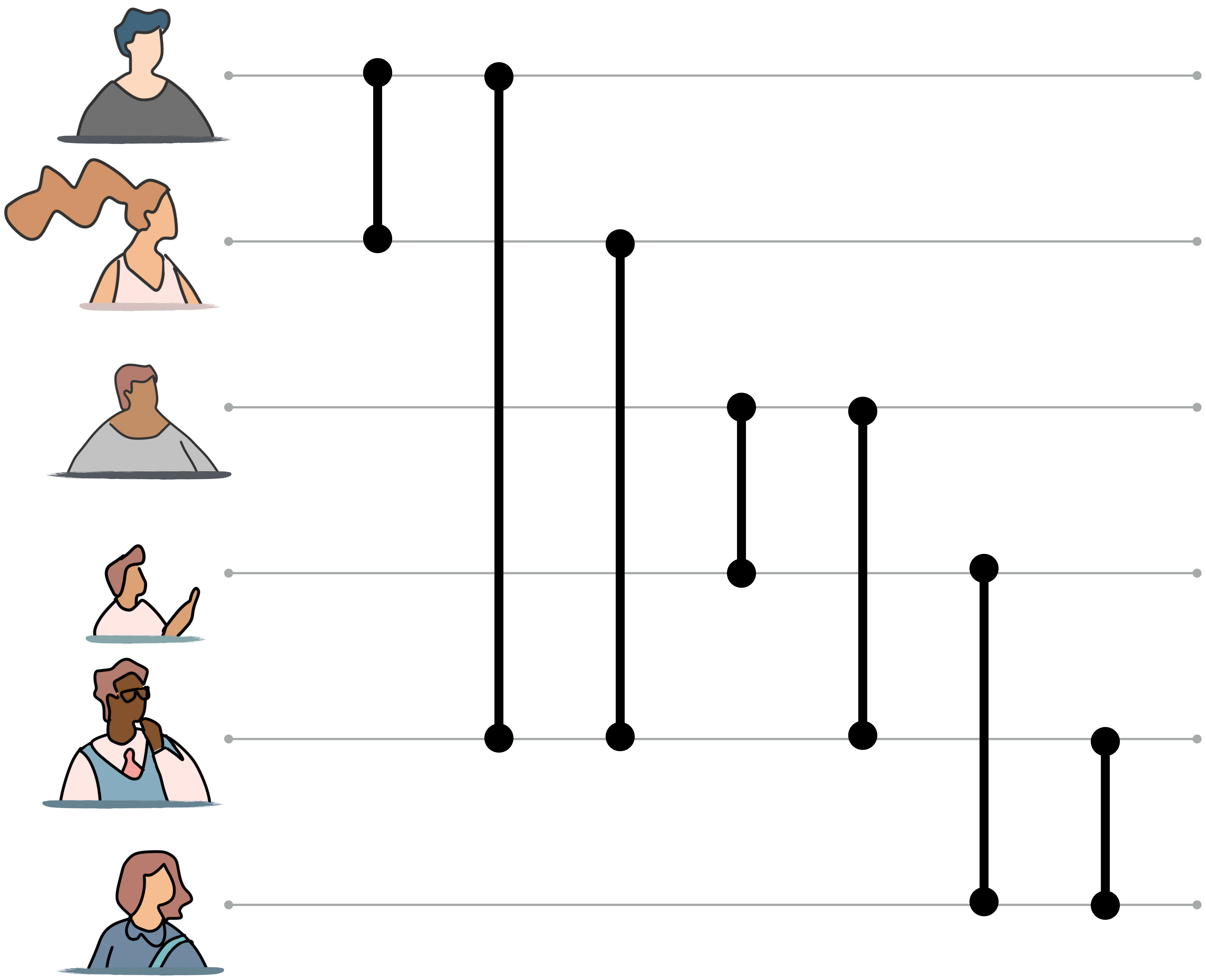
Complexity of choosing the right reordering algorithm

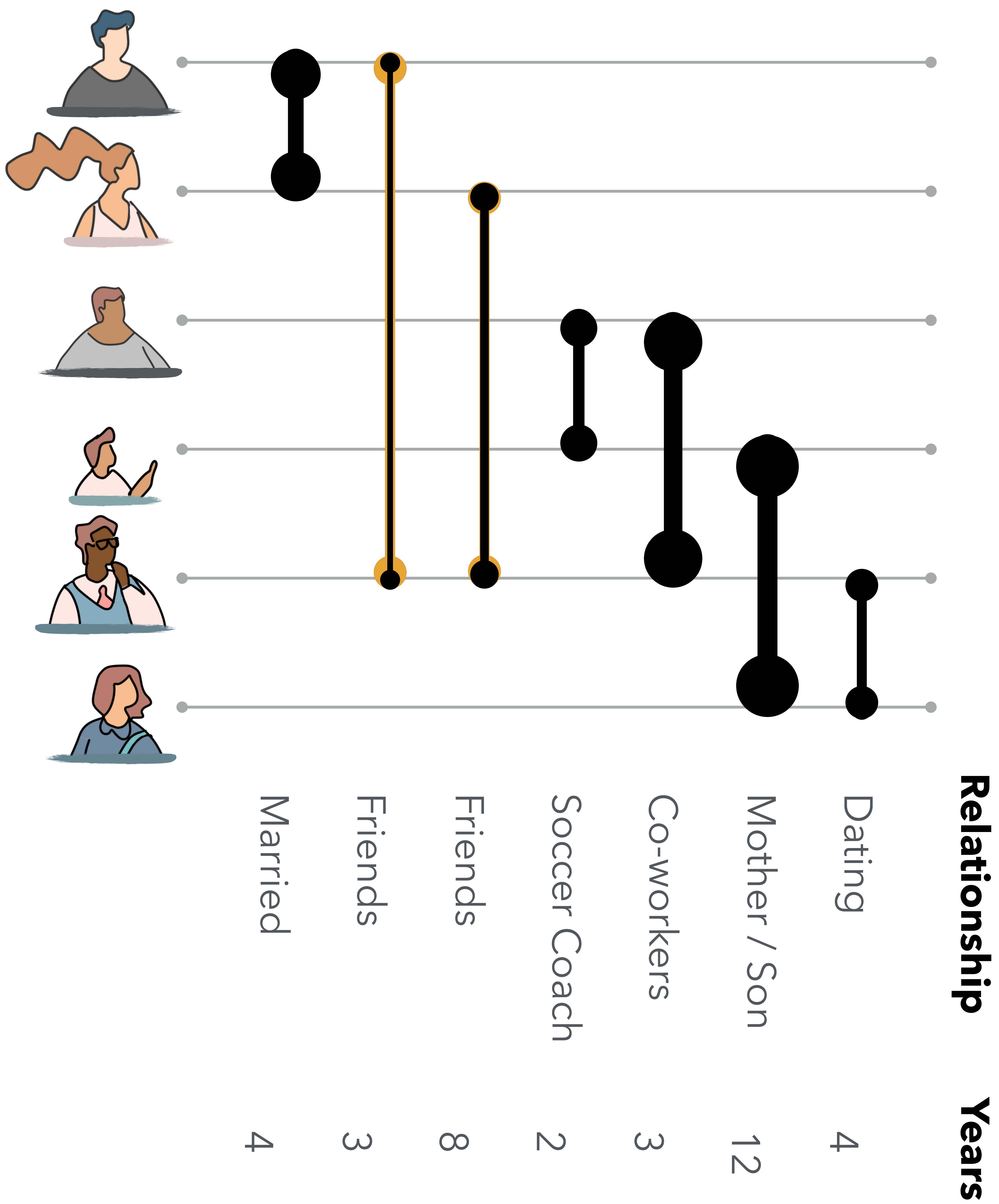
Recommended for smaller, complex and dense networks with rich node and/or edge attributes, for all tasks except for those involving paths

Tabular Layouts

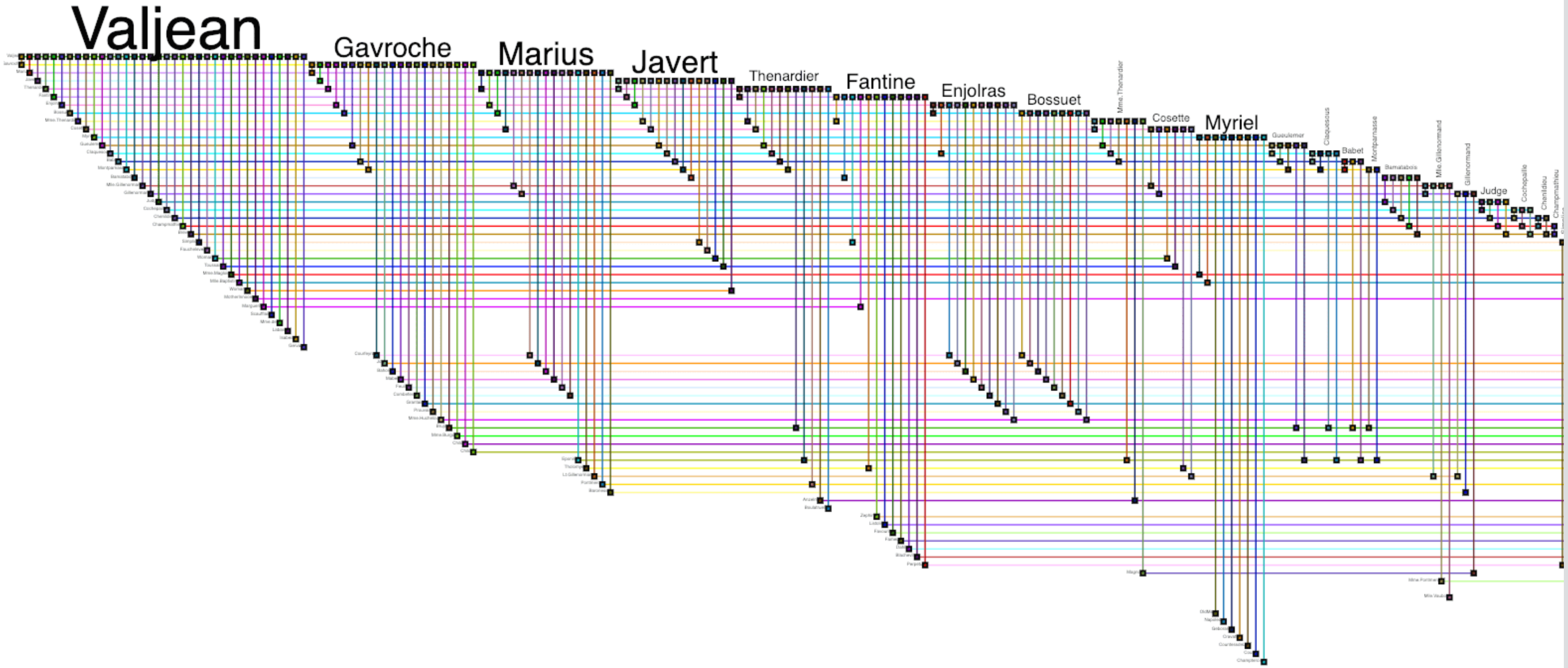


BioFabric

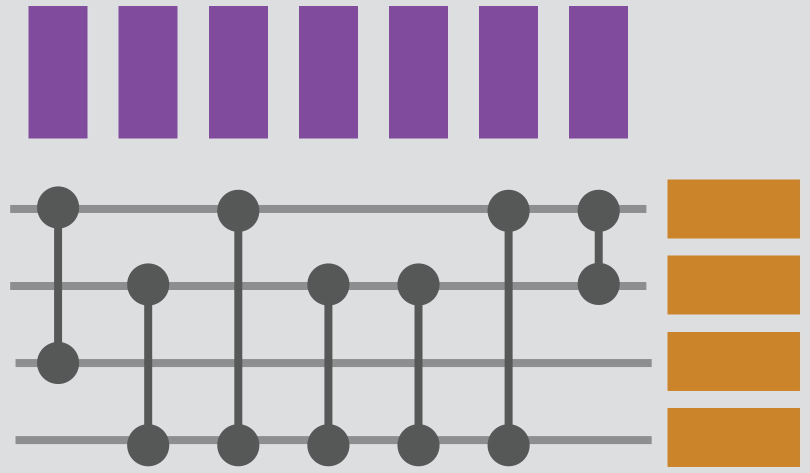




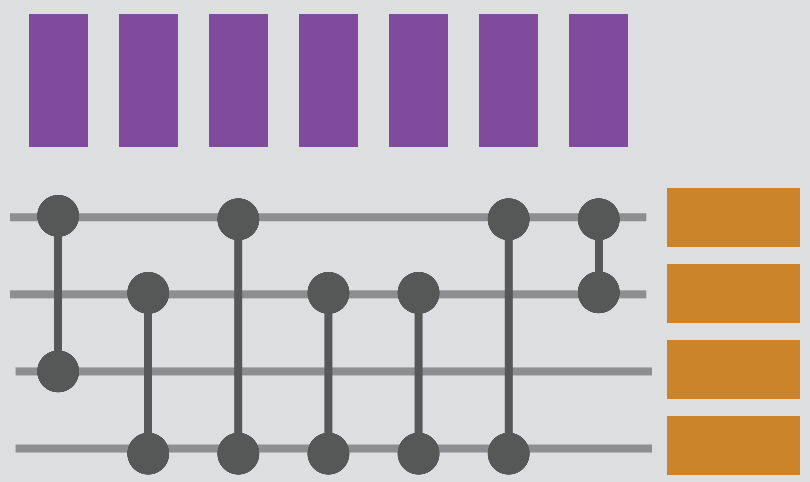
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



Longabaugh, 2012



BioFabric



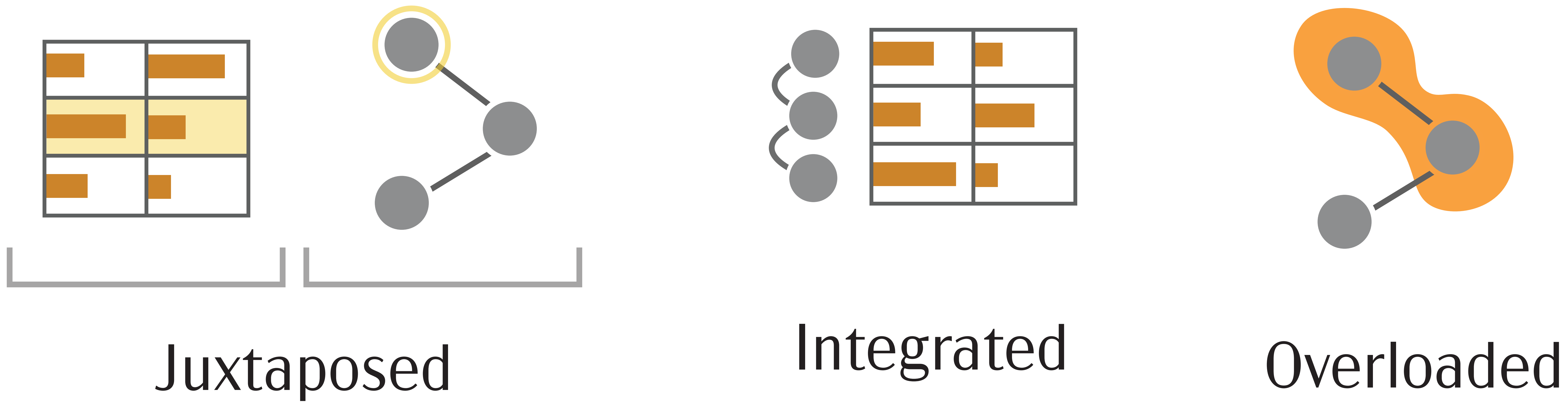
BioFabric

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

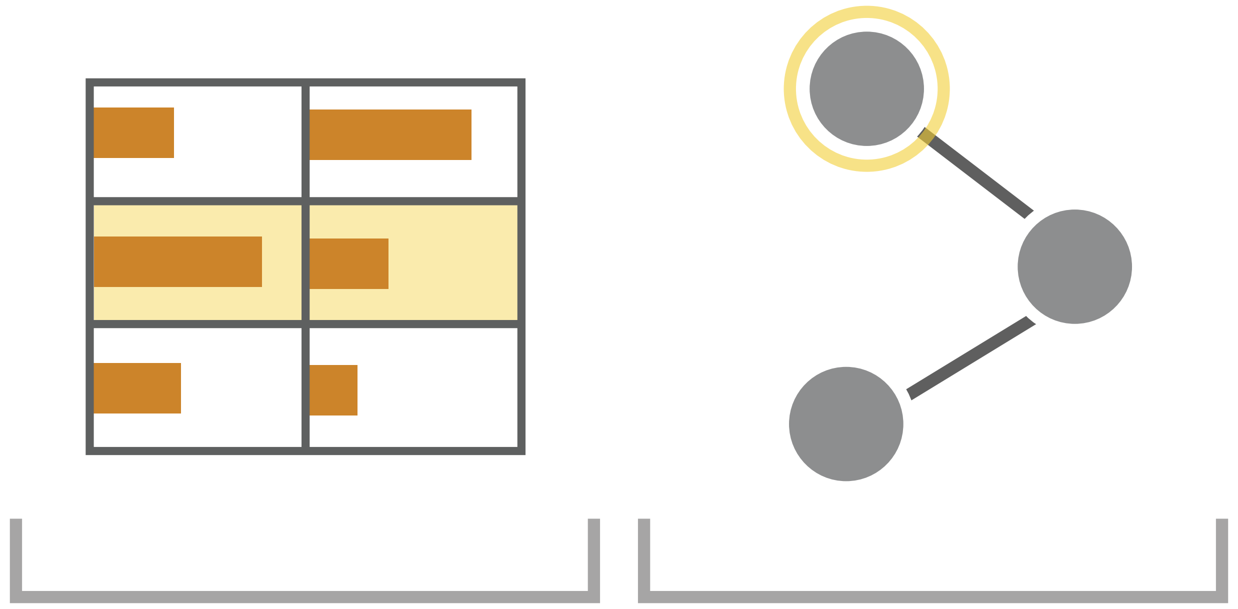
More difficult to discover neighbors and clusters in Biofabric compared to matrices.

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

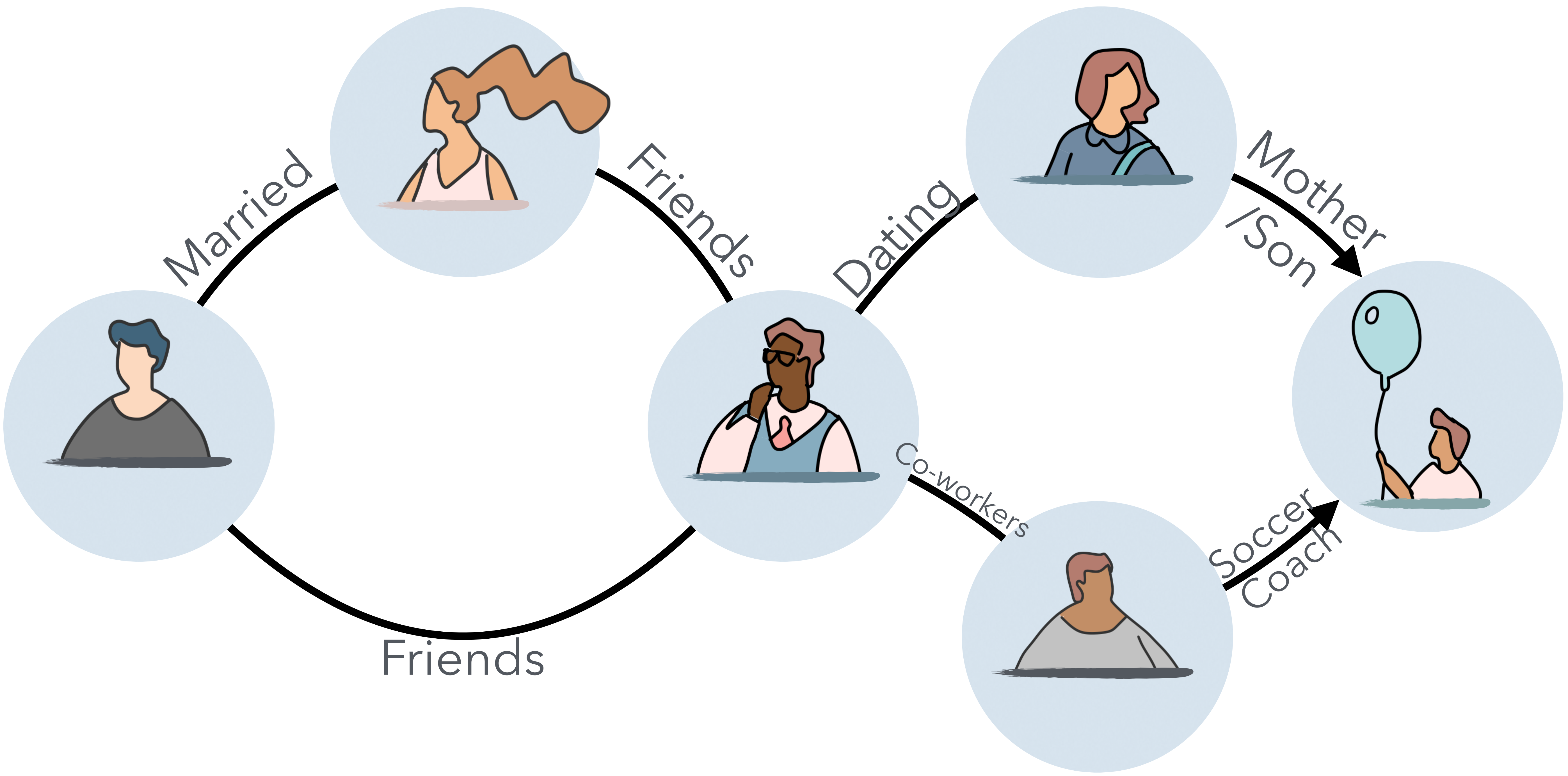
View Operations

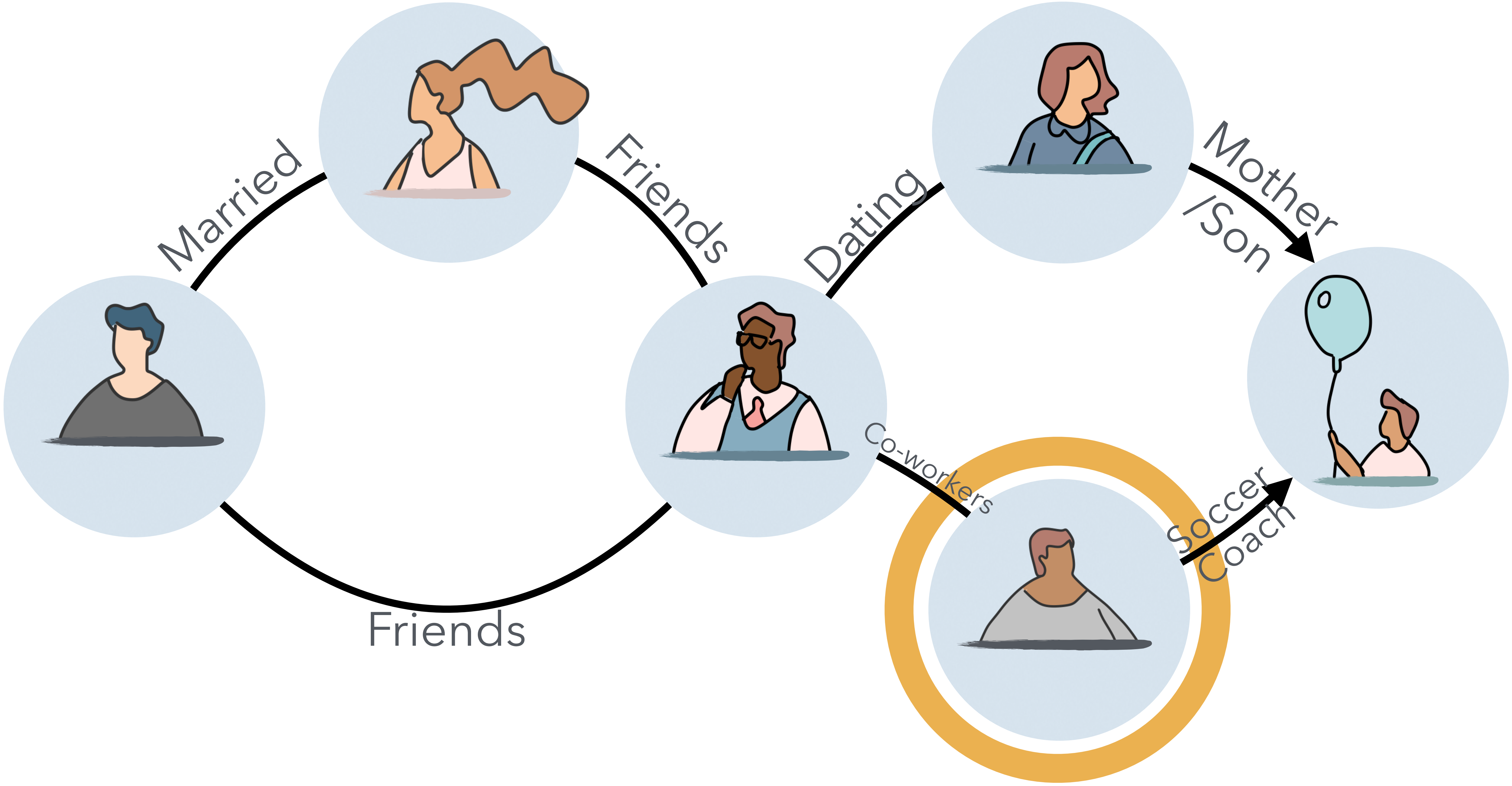


View Operations

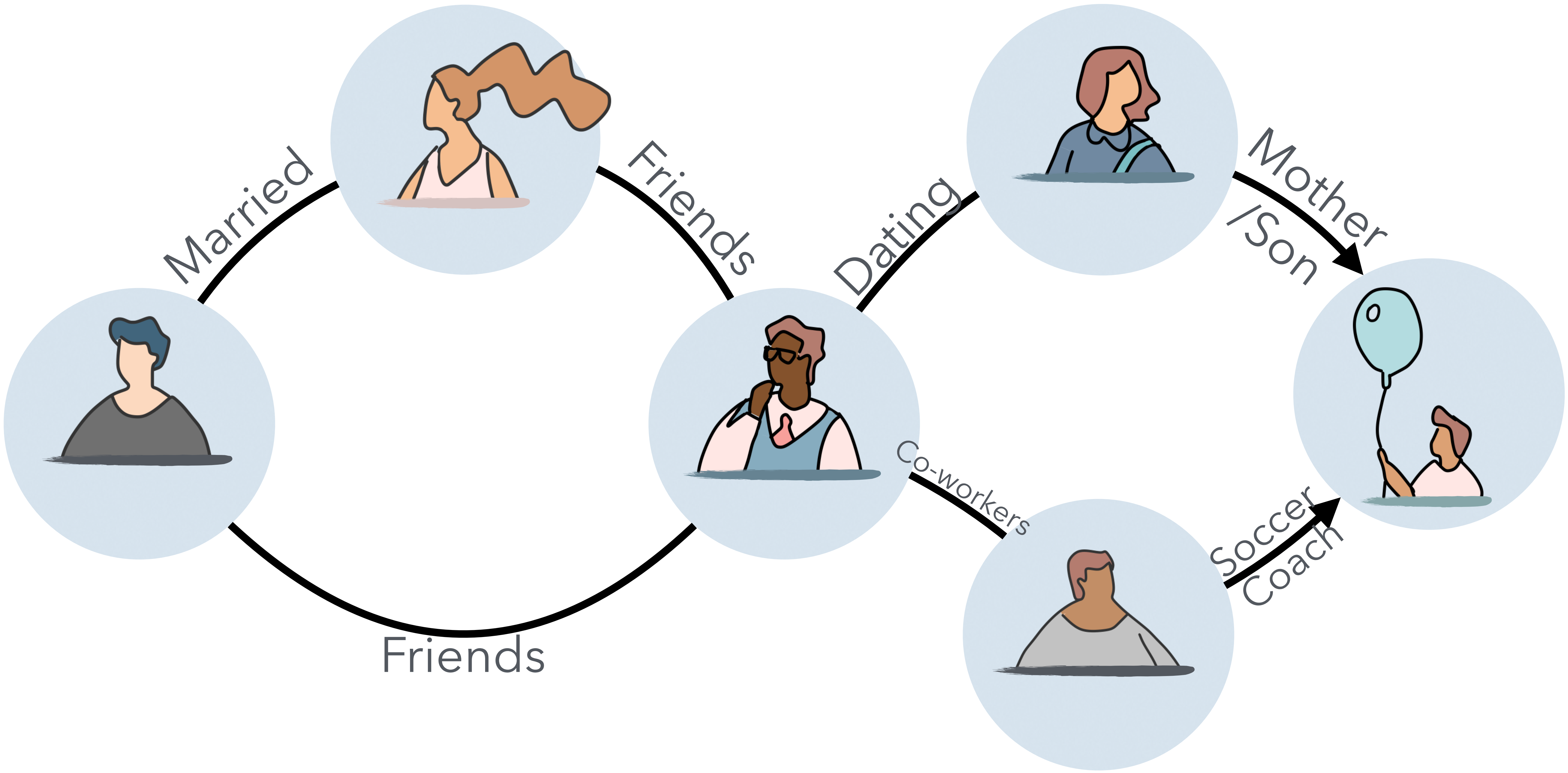


Juxtaposed


Married
Friends
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach

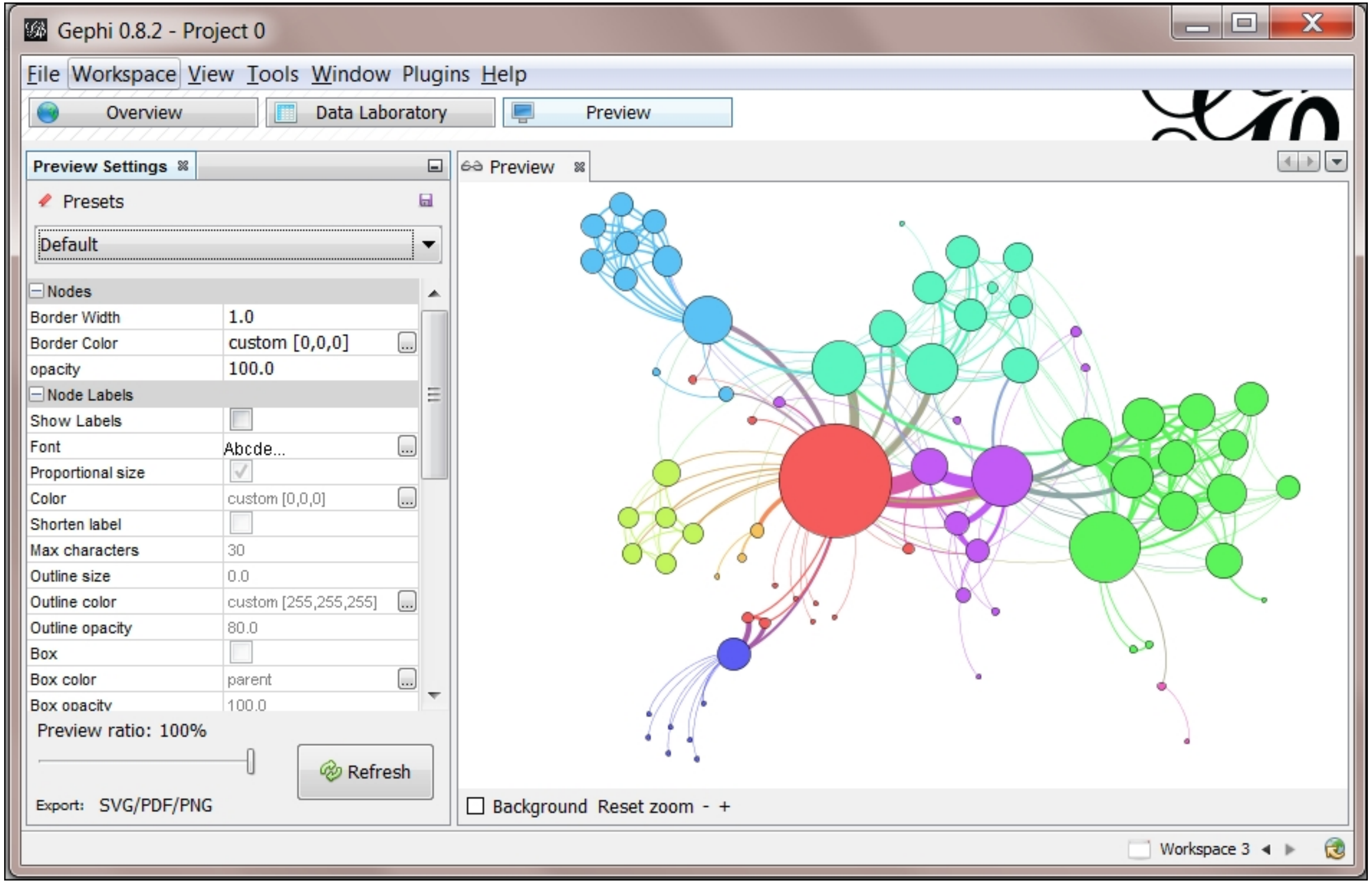


Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

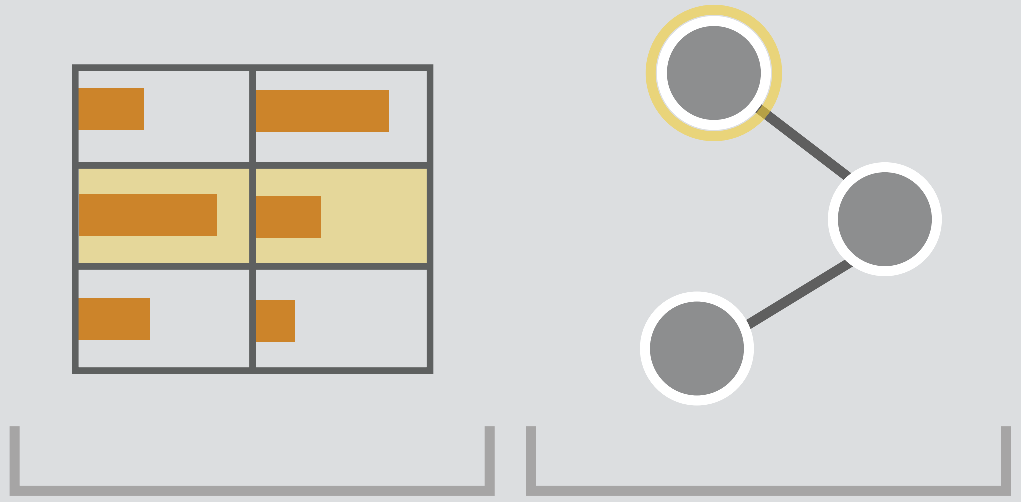


Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

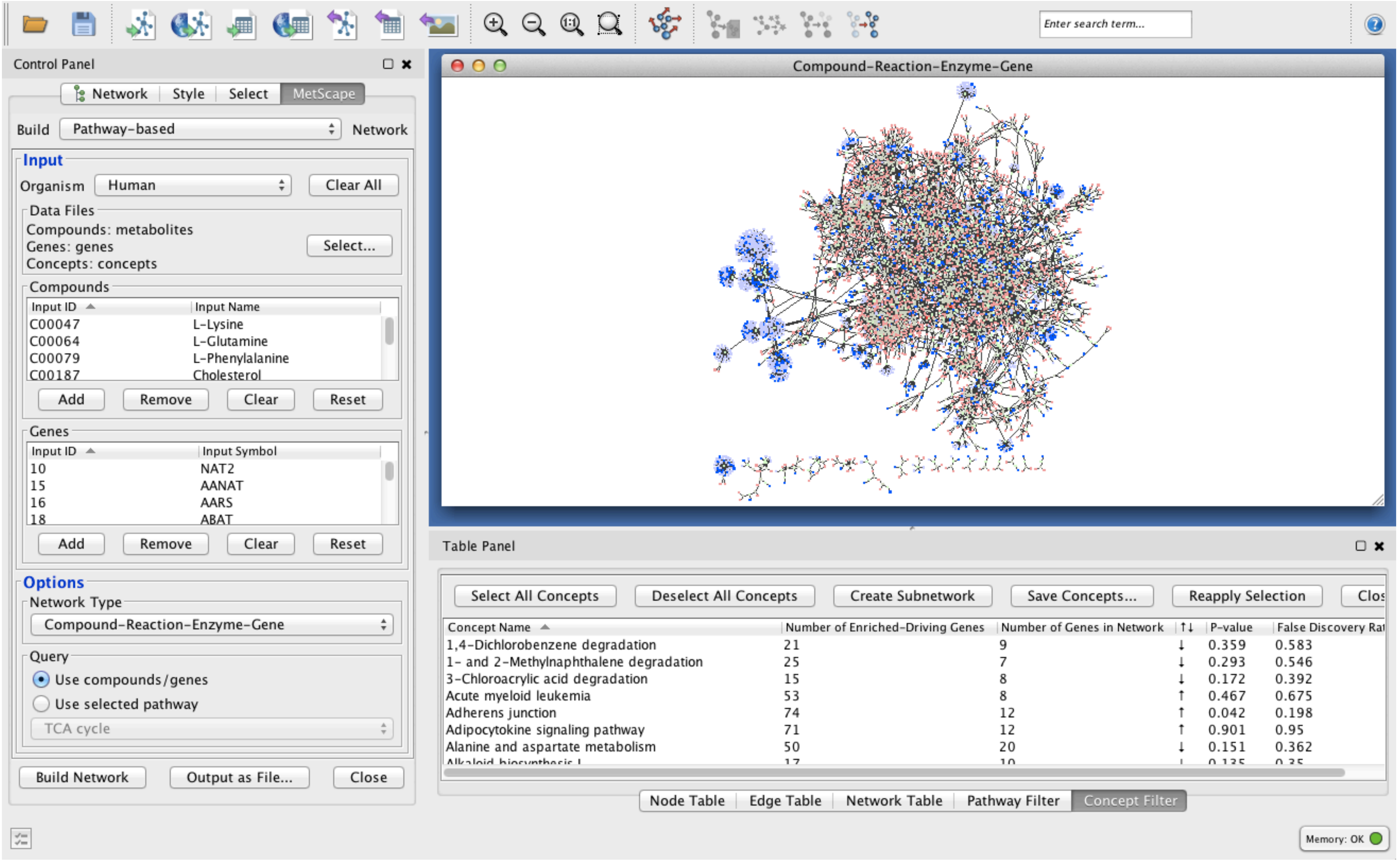
Relationship	Years
Dating	4
Mother / Son	12
Co-workers	3
Soccer Coach	2
Friends	8
Friends	3
Married	4

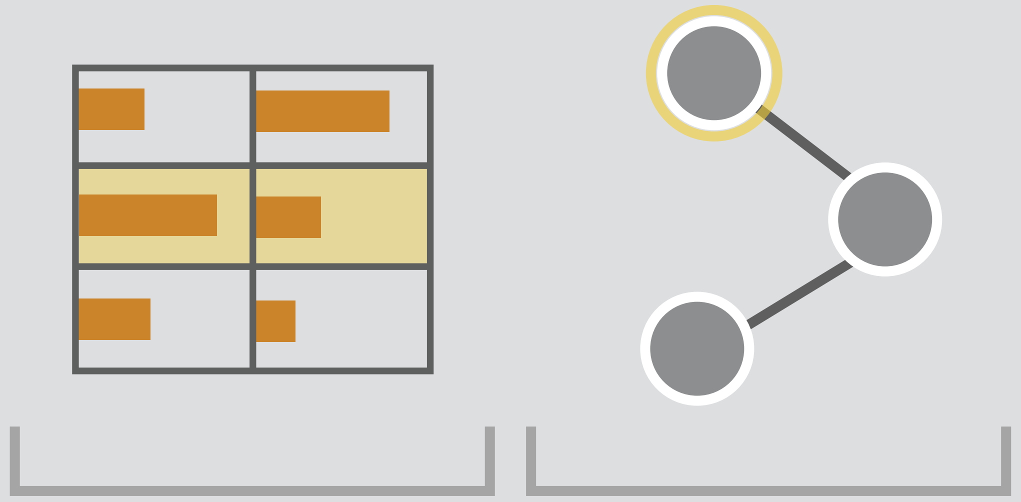


Gephi



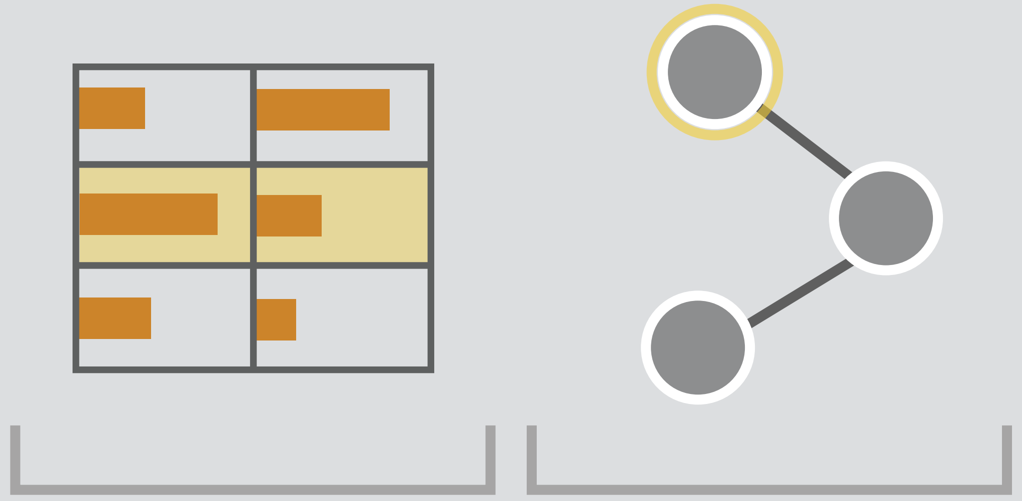
Juxtaposed





Juxtaposed

Cytoscape



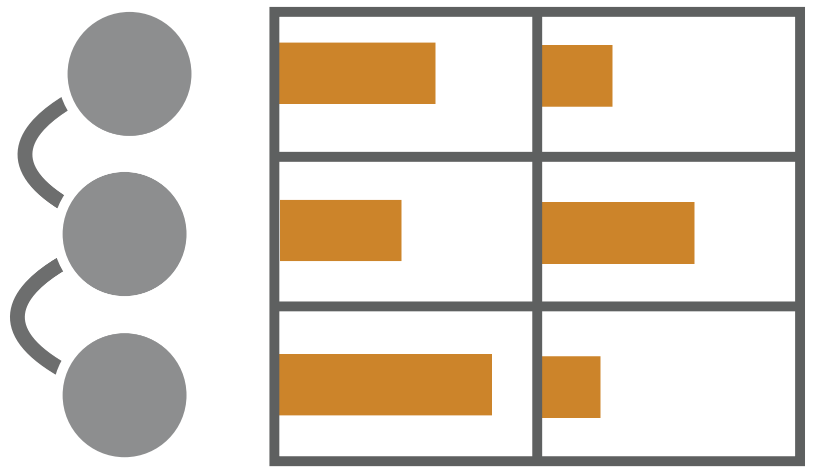
Juxtaposed

Independent views can optimize for topology and attribute independently.

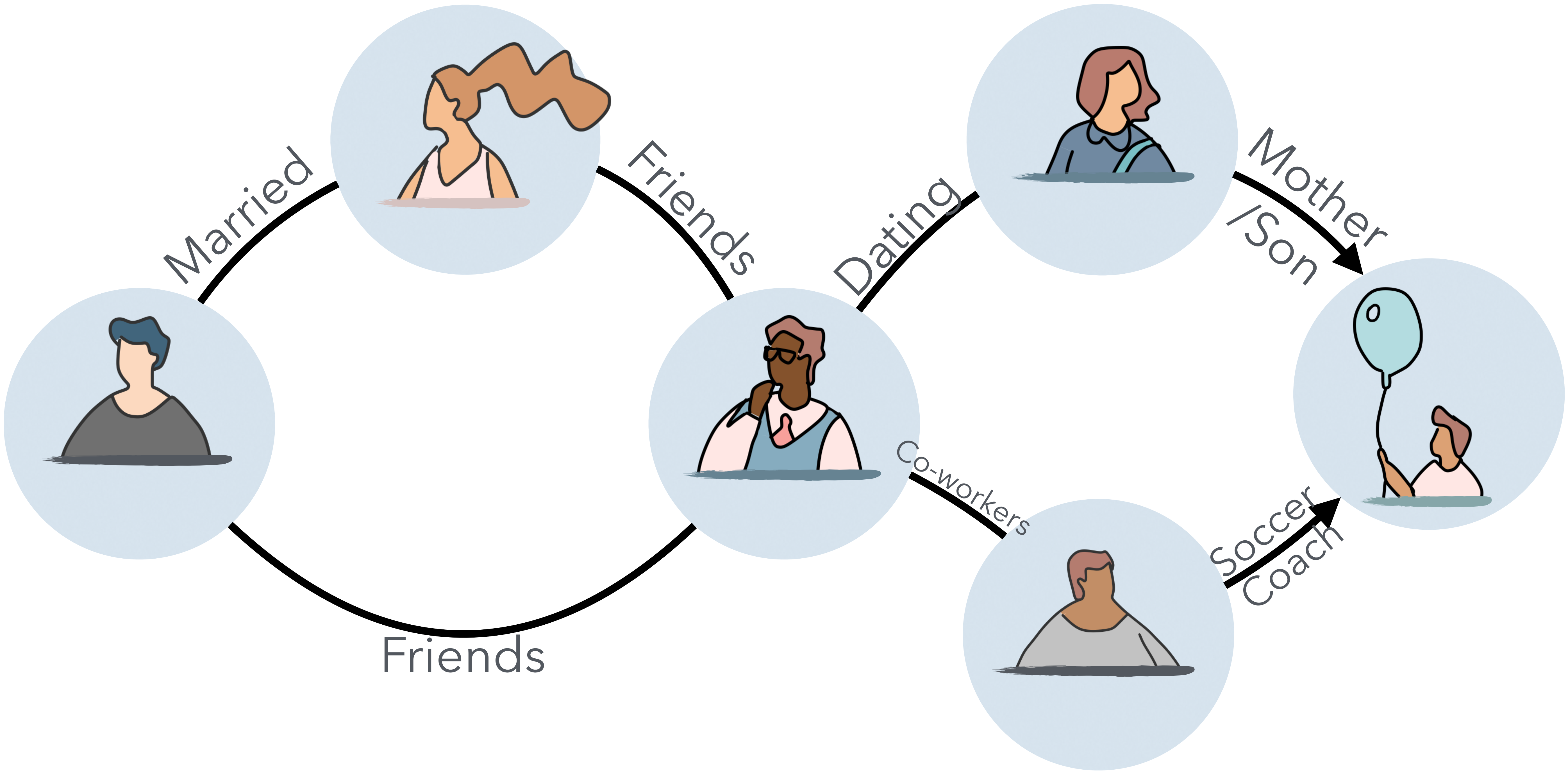
Not great for tasks on topological structures beyond a single node or edge.

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

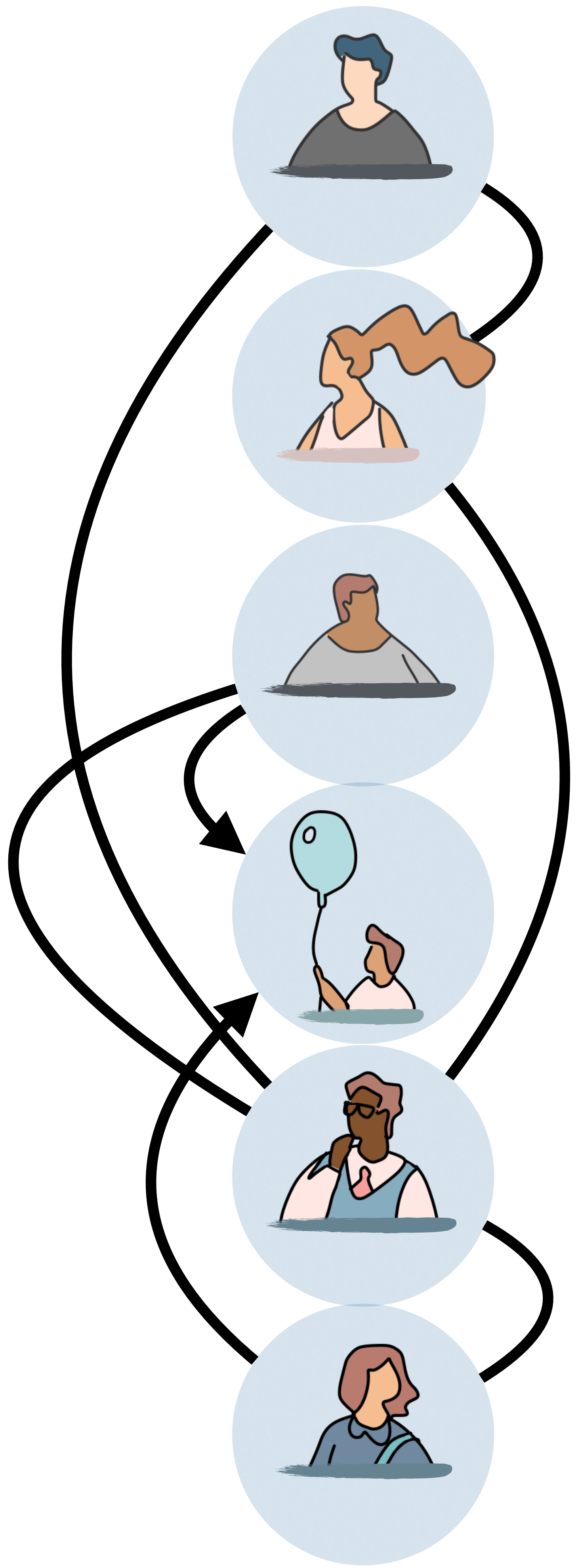
View Operations



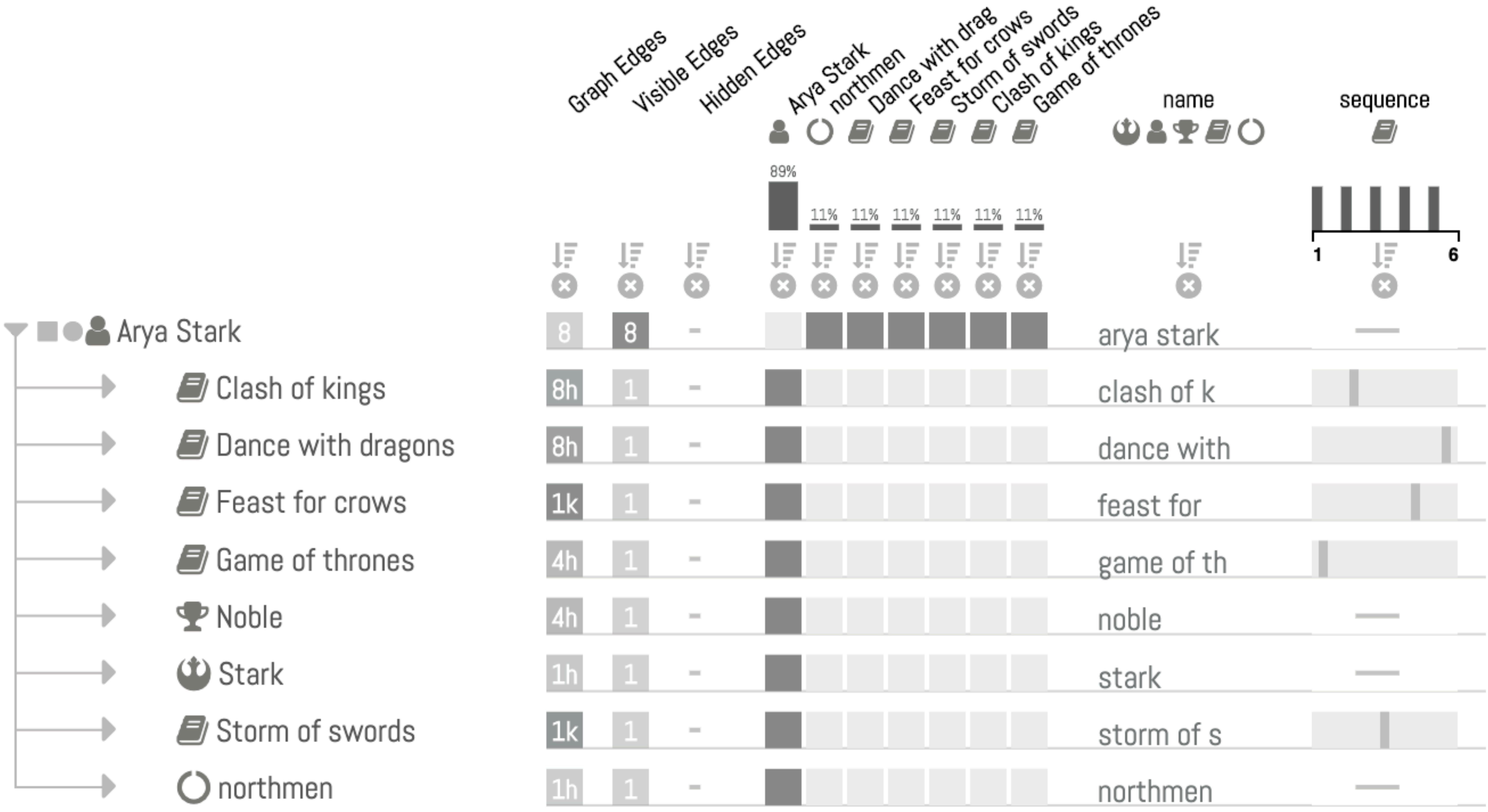
Integrated



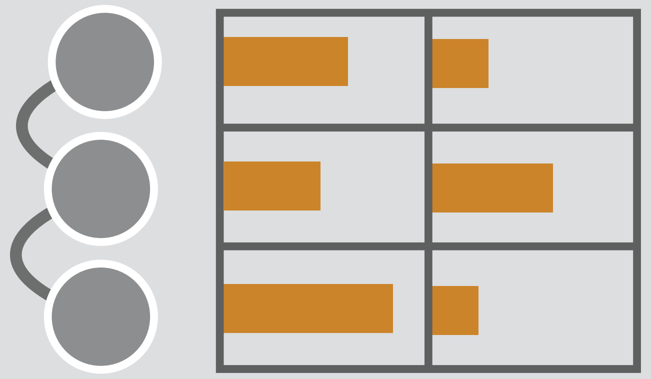
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



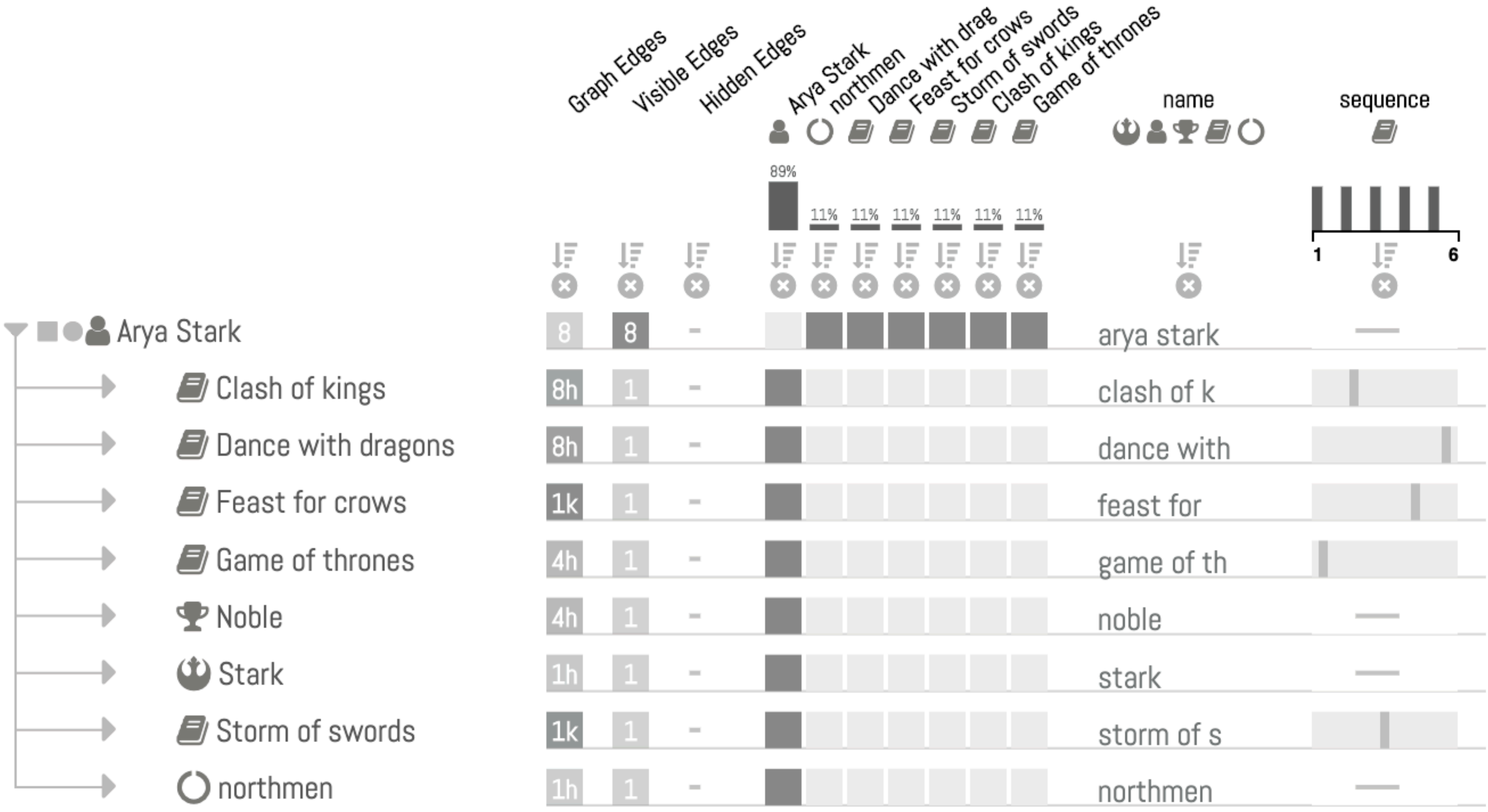
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



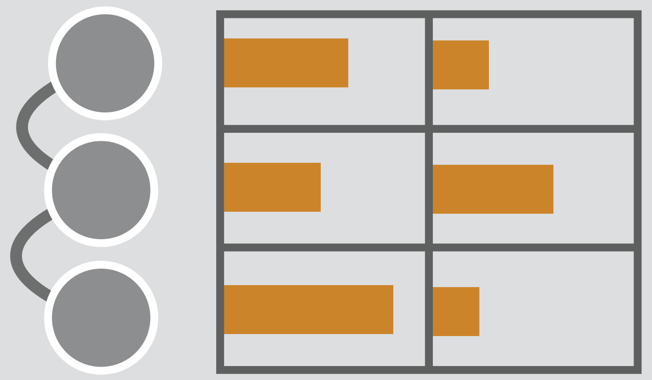
Juniper *Nobre et al. 2018*



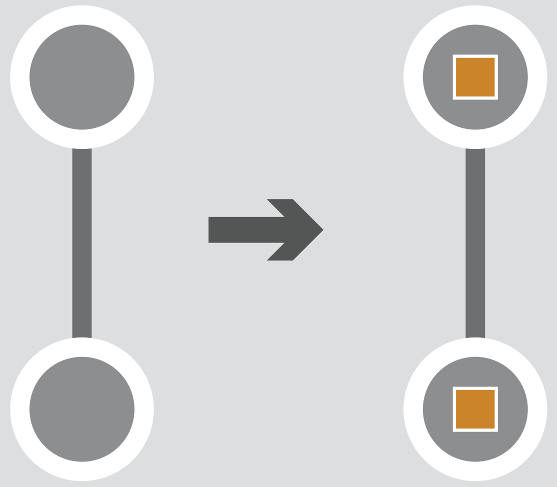
Integrated



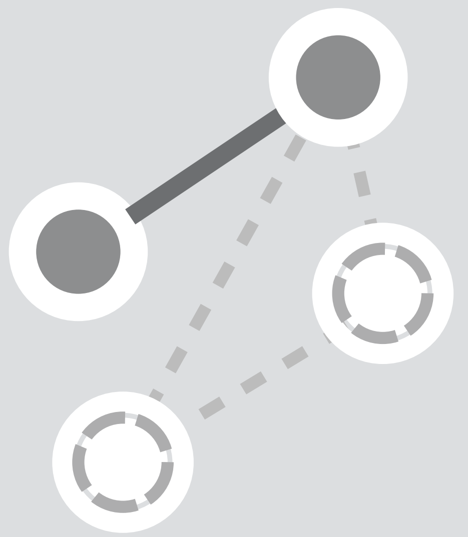
Juniper *Nobre et al. 2018*



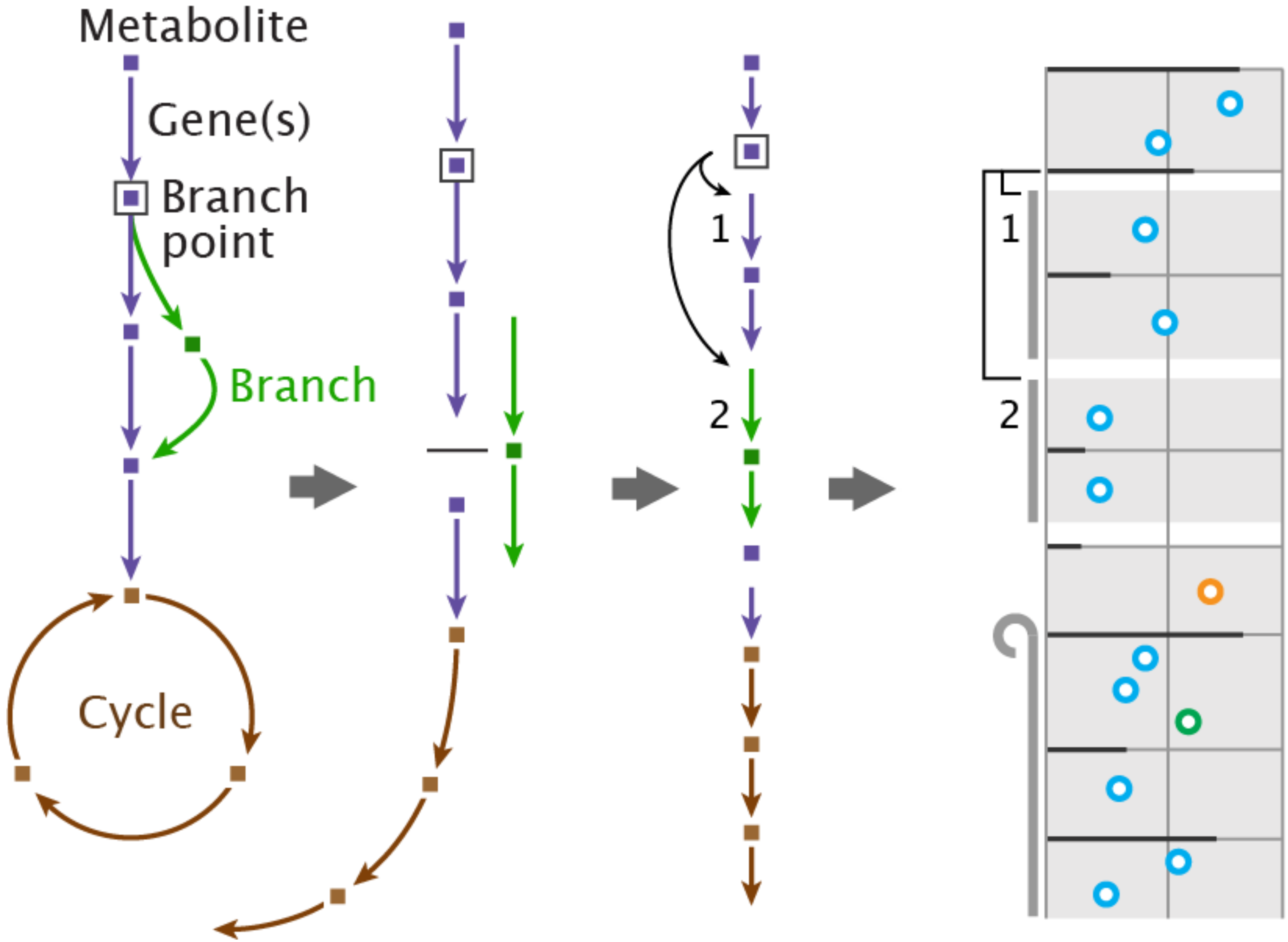
Integrated



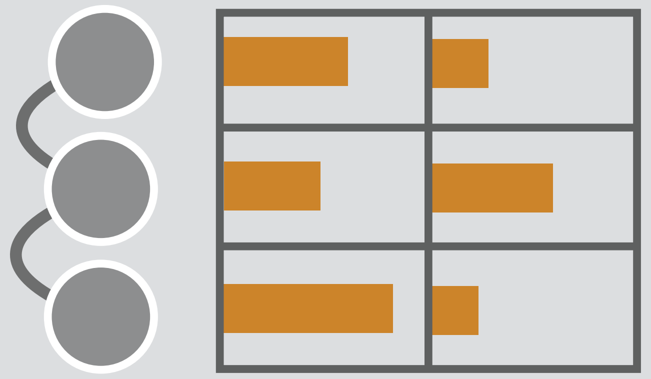
Deriving New Attributes



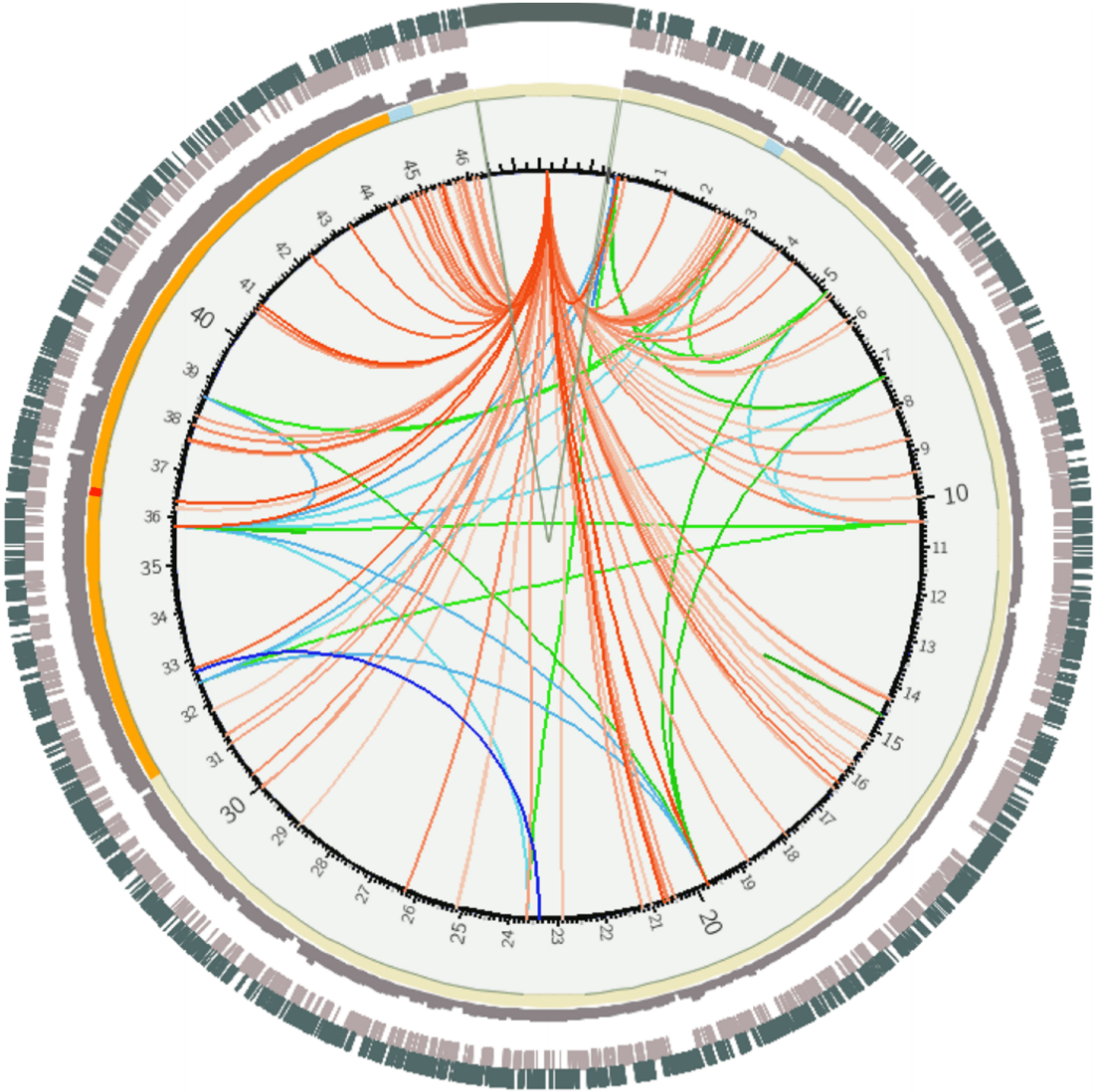
Querying and Filtering



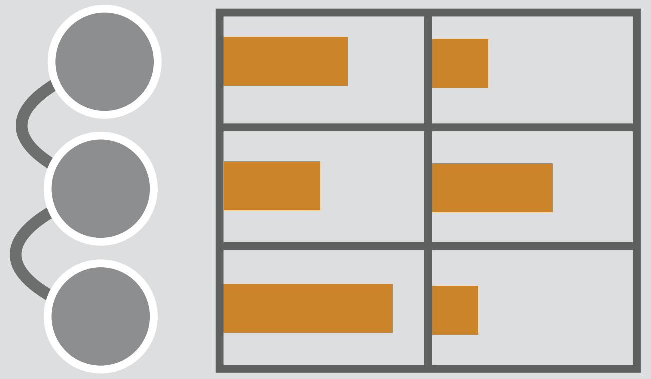
Pathline Meyer *et al. 2010*



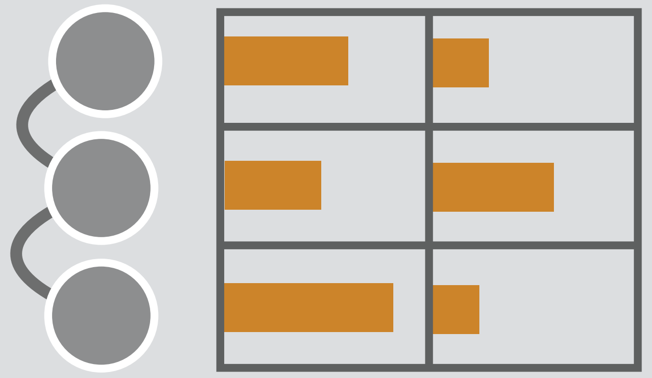
Integrated



Circos *Krzywinski et al. 2009*



Integrated



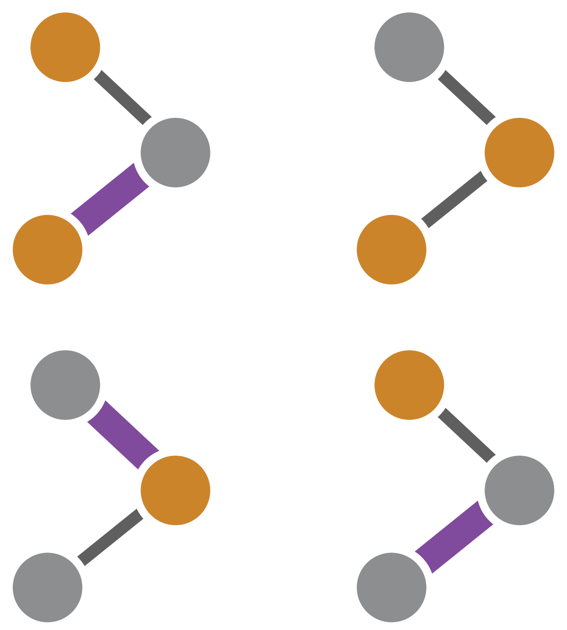
Integrated

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

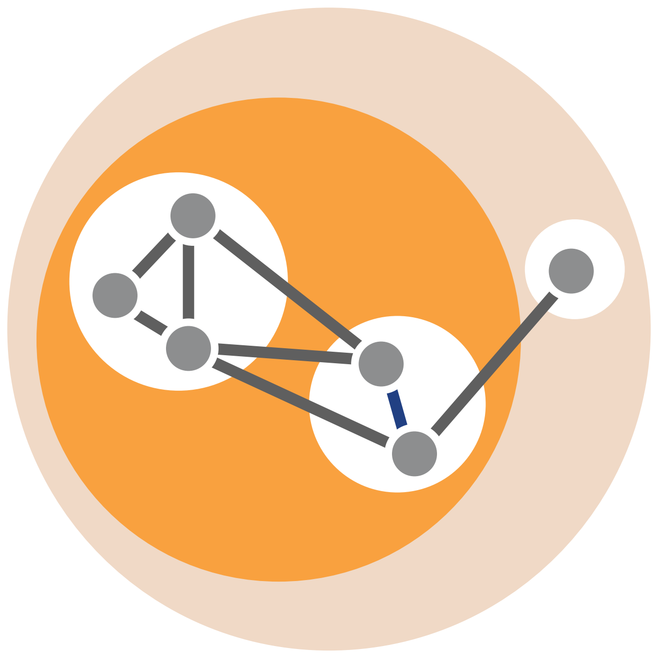
Not suitable for networks that can not be sensibly linearized.

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

Layout Operations

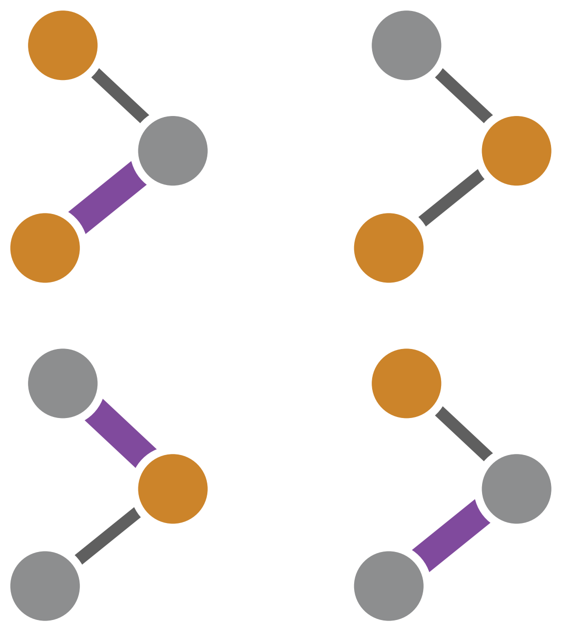


Small Multiples

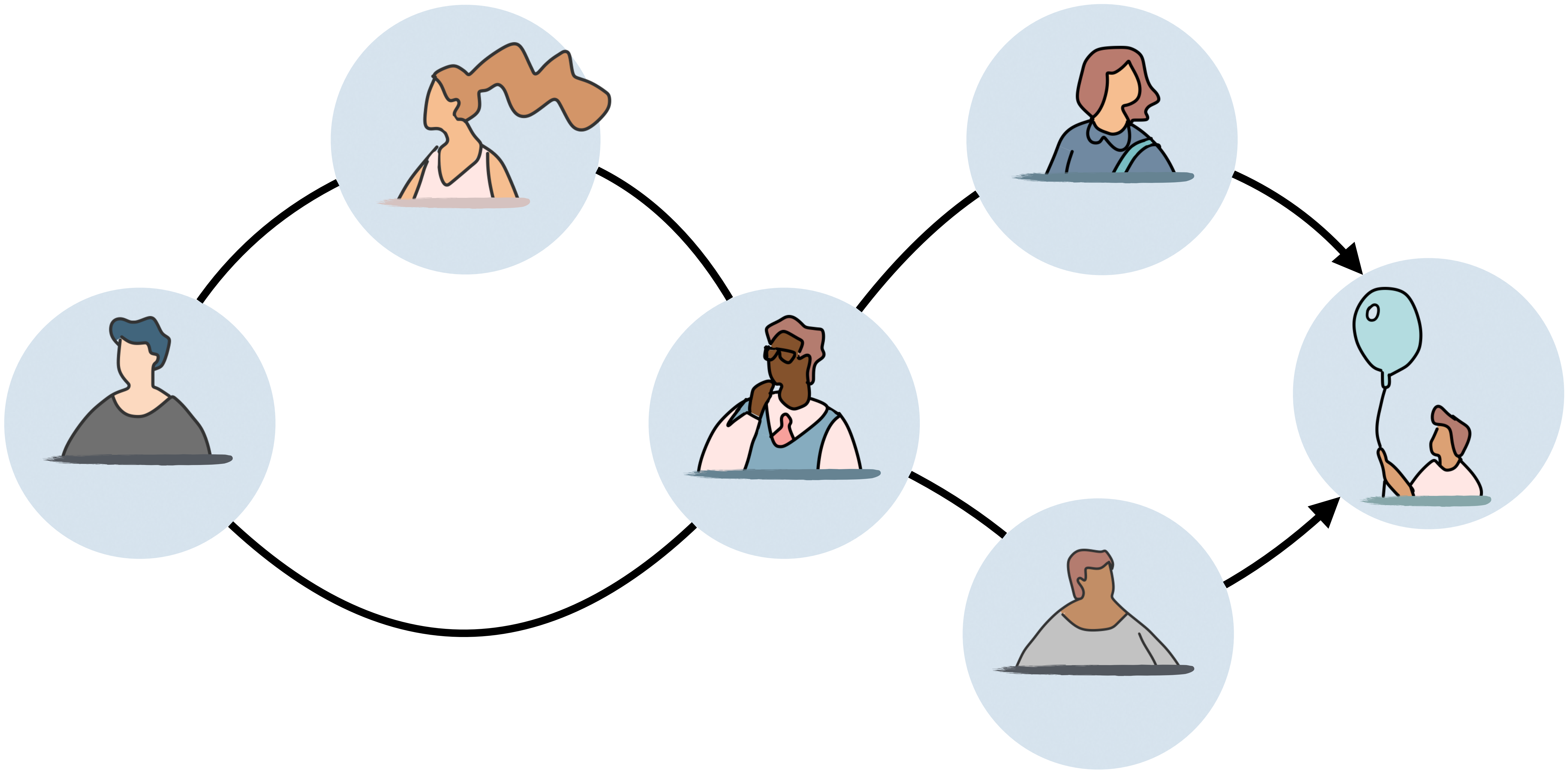


Hybrids

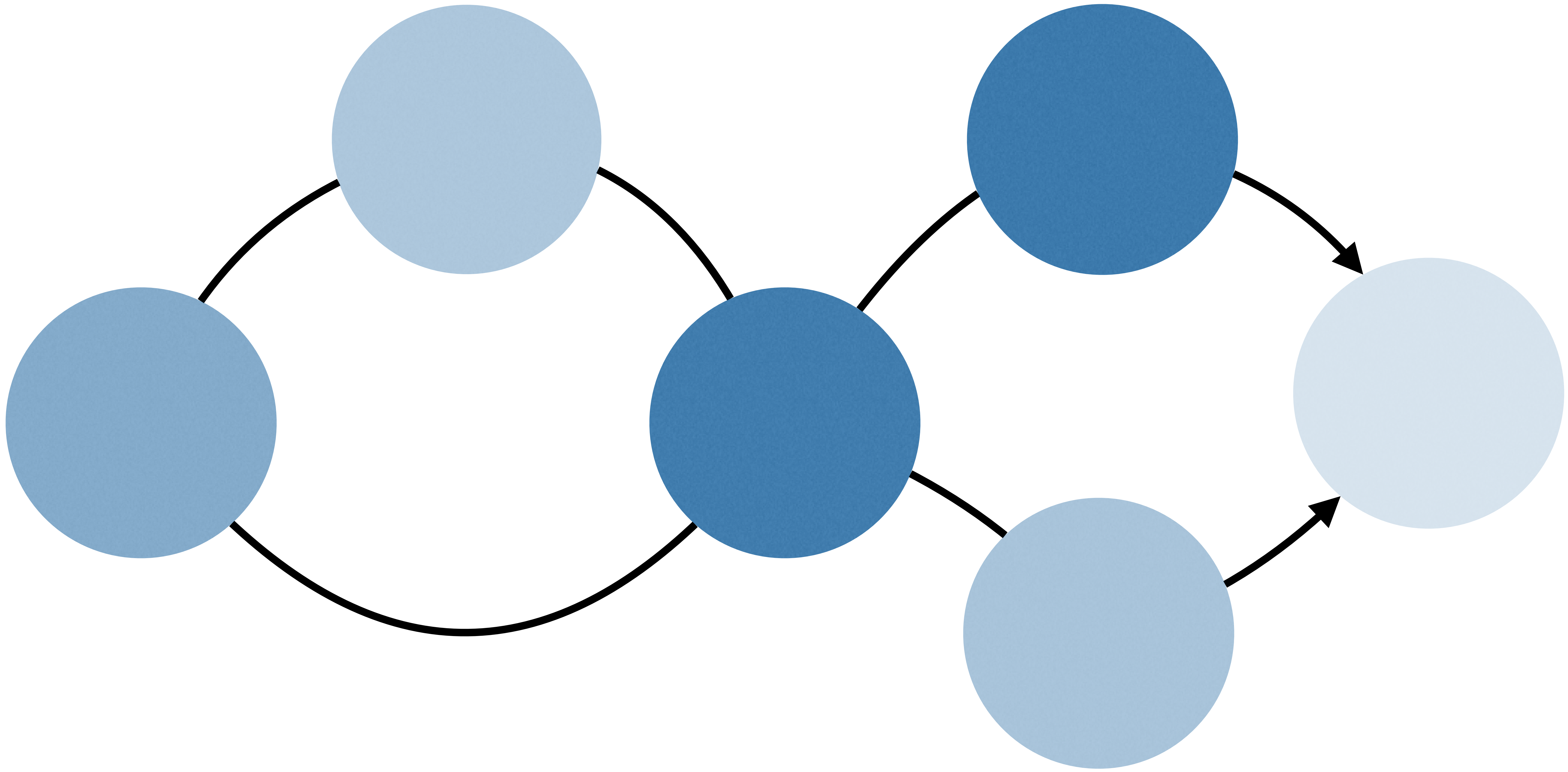
Layout Operations

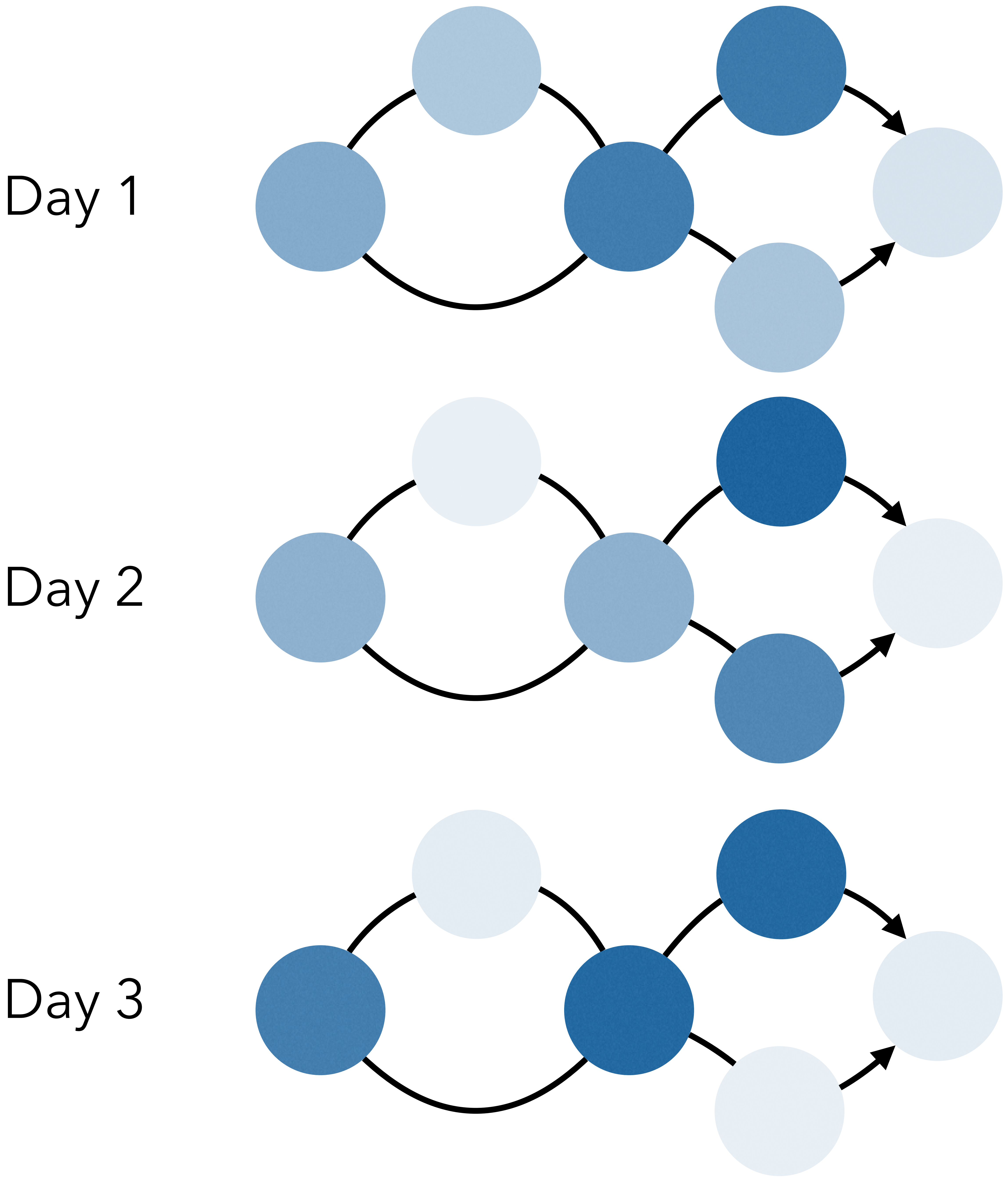


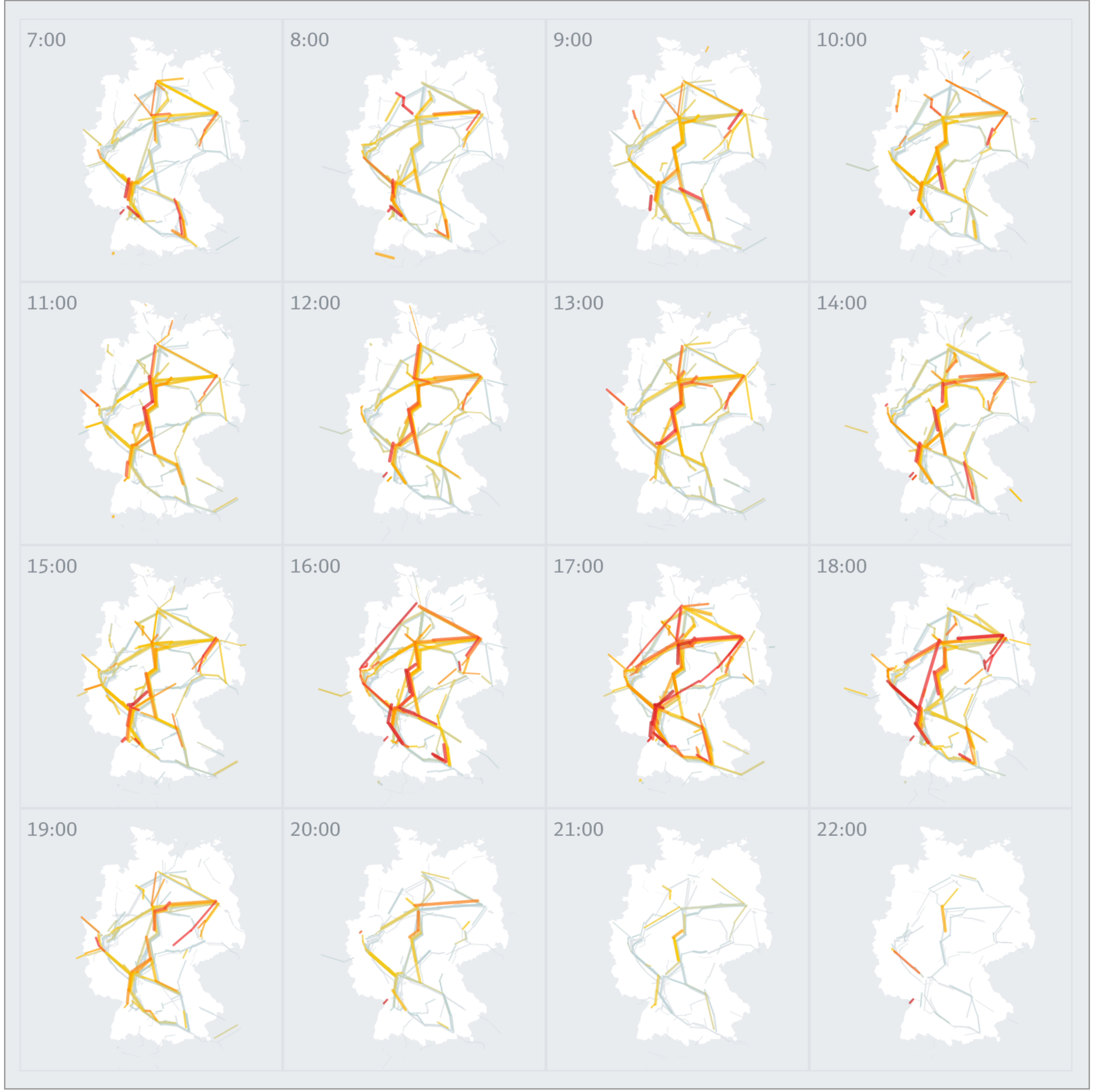
Small Multiples

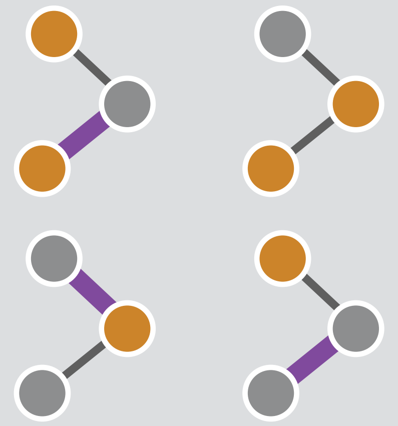


Day 1

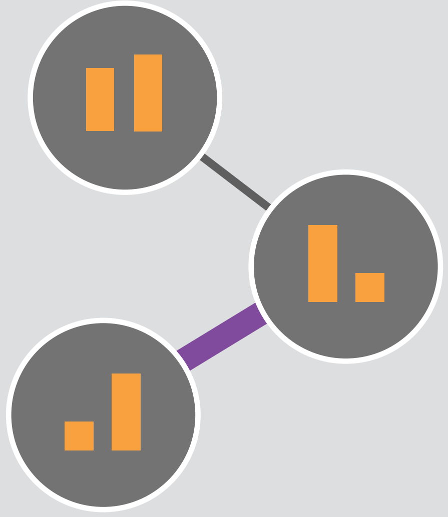



Day 1
Day 2
Day 3



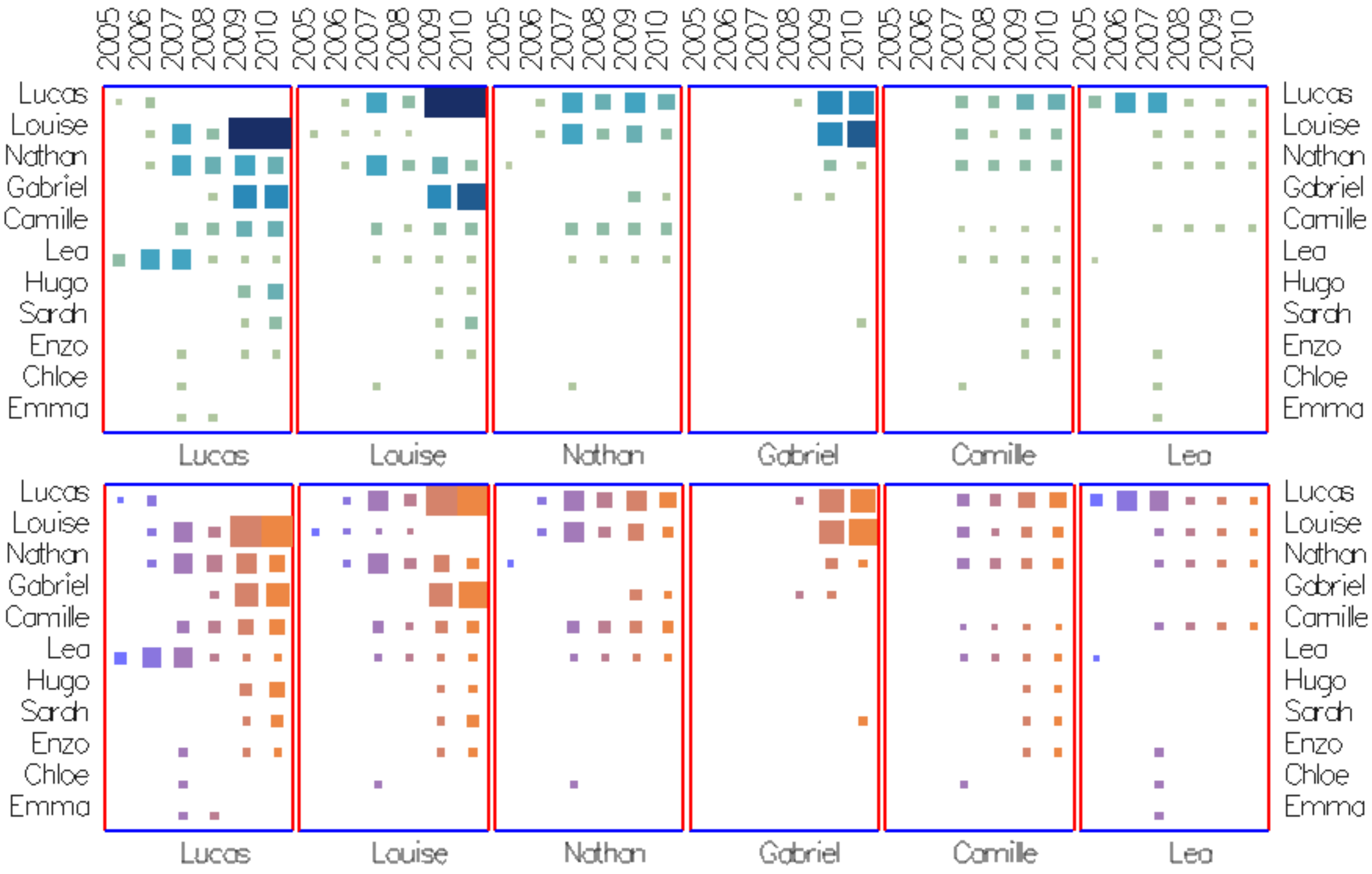


Small Multiples

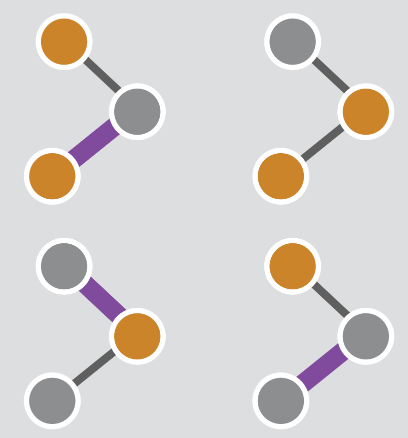


On-Node / On-Edge Encoding

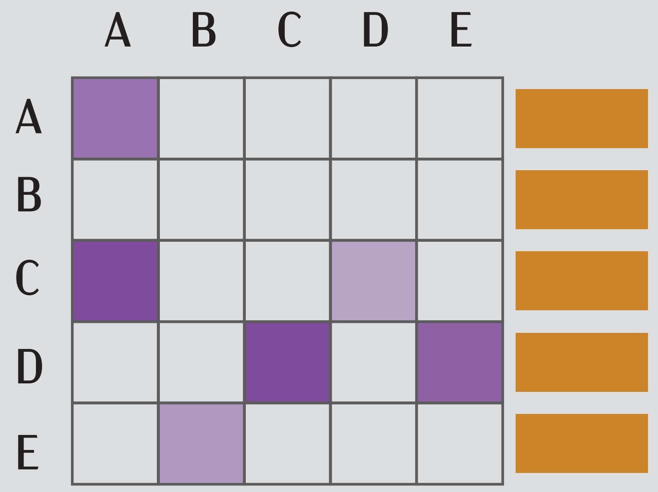
Peakspotting - https://truth-and-beauty.net/projects/peakspotting



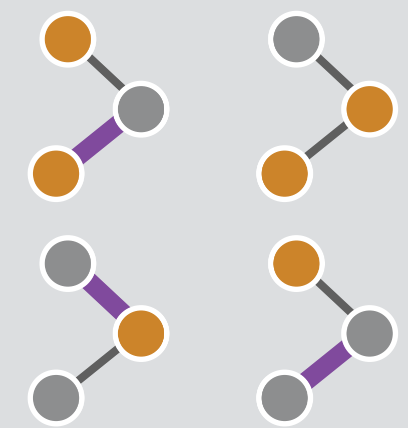
Bach et al. 2014



Small Multiples



Adjacency Matrix



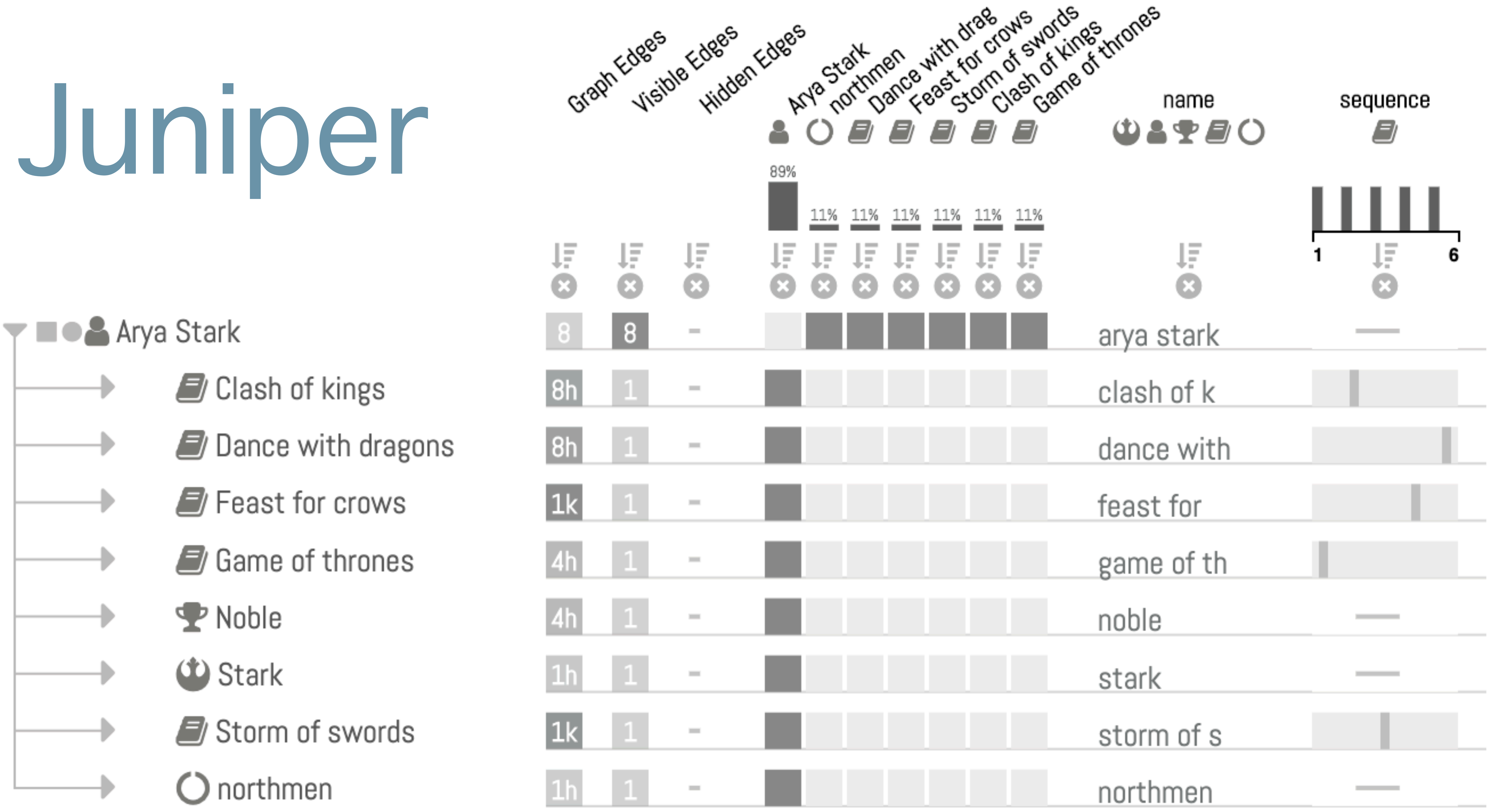
Small Multiples

Common layout facilitates attribute comparisons in specific topological features

Not ideal for large networks, or tasks on clusters

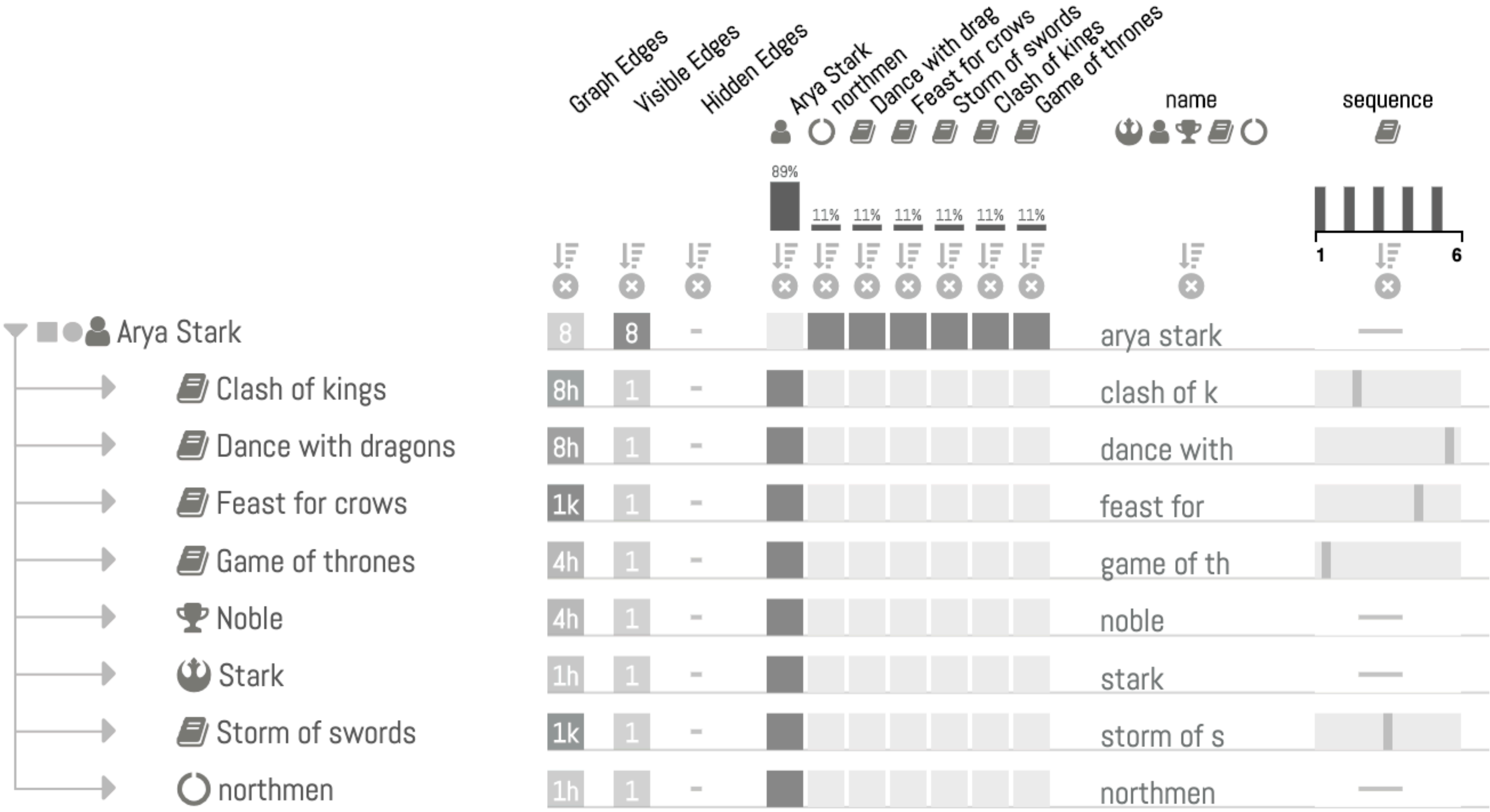
Recommended for small networks where the tasks are focused on attribute comparison

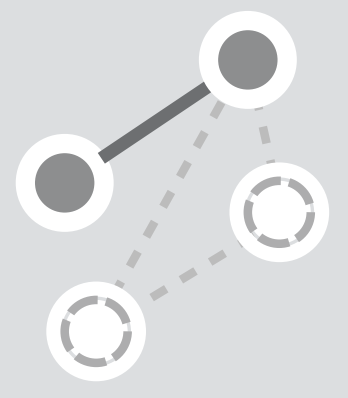
Juniper



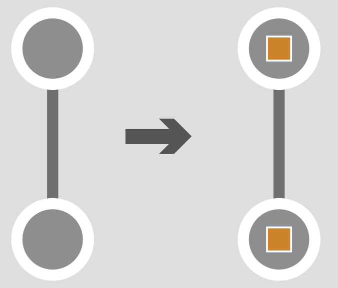
Graph Edges
Visible Edges
Hidden Edges
Arya Stark
northmen
Dance with drag
Feast for crows
Storm of swords
Clash of kings
Game of thrones
name
sequence
89%
11%
11%
11%
11%
11%
11%
1
6
Arya Stark
8
8
-
arya stark
Clash of kings
8h
1
-
clash of k
Dance with dragons
8h
1
-
dance with
Feast for crows
1k
1
-
feast for
Game of thrones
4h
1
-
game of th
Noble
4h
1
-
noble
Stark
1h
1
-
stark
Storm of swords
1k
1
-
storm of s
northmen
1h
1
-
northmen


Root
Select Subgraph
Extract a spanning tree
Linearize
Add Attributes
Querying and Filtering
Deriving New Attributes
Attribute-Driven Positioning
Integrated

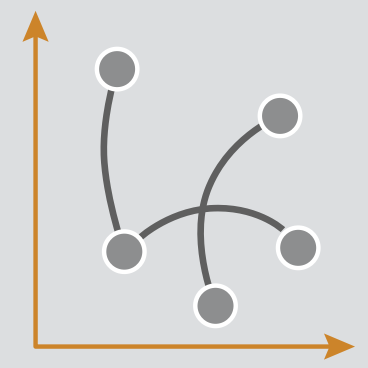




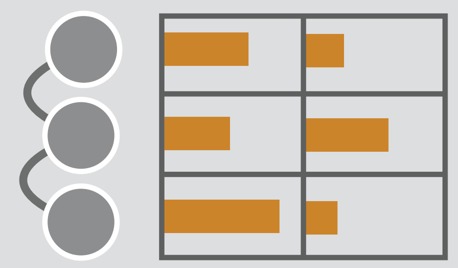
Querying and Filtering



Deriving New Attributes



Attribute-Driven Positioning



Integrated

Multivariate Network Visualization Techniques

A companion website for the STAR Report on Multivariate Network Visualization Techniques.

About

This is a companion website for a review article on multivariate network visualization techniques.

Multivariate networks are networks where both the structure of the network and the attributes of the nodes and edges matter. It turns out, these are very common. Every person in a social network, for example, has both, relationships and lots of other characteristics, such as their age, the school they went to, or the city they live in. Multivariate network visualization techniques are designed to be able to show both, these attributes and the structure. Using these visualization techniques, we can analyze, for example, if a network of friends predominantly went to the same high school.

The visualization research community has developed many techniques to visualize these kinds of networks, and our review article – and this website – are designed to help you sort through these options.

Browse through the techniques illustrated below, or use our wizard to find the right multivariate network visualization technique for your datasets and tasks!

Get in touch if you have questions or comments.

Use the Wizard

Technique recommendations to fit your needs!

Navigate to the wizard tab and select your specific network characteristics, such as the size of the network and its type, and what tasks are relevant for your analysis and receive technique recommendations that are best suited to your selection.

Read the Review Article

The State of the Art in Visualizing Multivariate Networks
Carolina Nobre, Miriah Meyer, Marc Streit, and Alexander Lex
To appear in Computer Graphics Forum (EuroVis 2019)

vdl.sci.utah.edu/mvnv/

Thank You!

@carolinanobre84
www.vdl.sci.utah.edu

visualization design lab

THE UNIVERSITY OF UTAH

JOHANNES KEPLER UNIVERSITY LINZ

NSF

HEALTH
Utah Genome Project

NIH