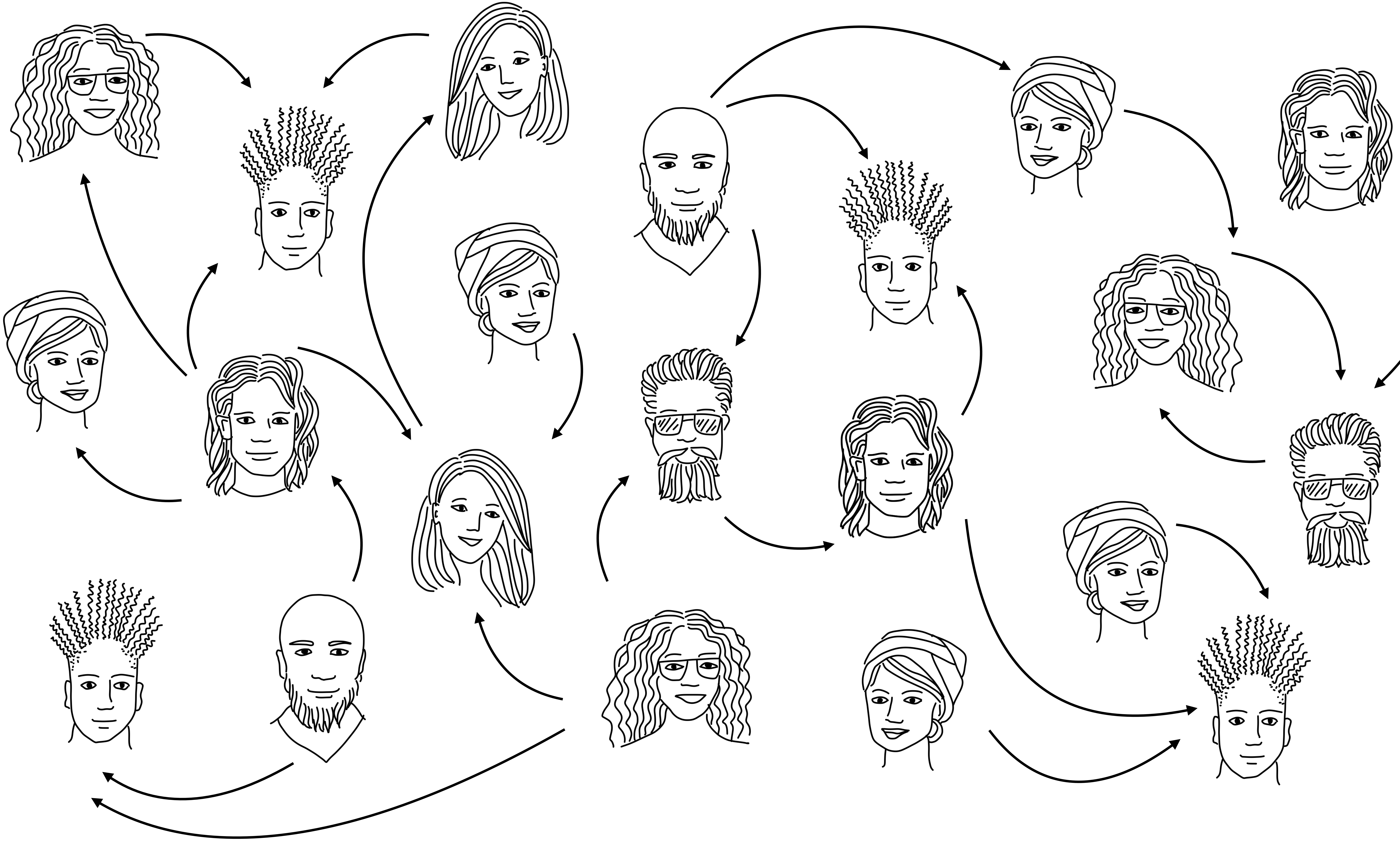
VISUALIZING
MULTIVARIATE NETWORKS

Alexander Lex

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



A Multivariate Network is Network Topology + Node and Edge Attributes

Tradeoff between Topology and Attributes

Choosing efficient encodings for one aspect often interferes with the ability to effectively visualize the other.

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

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STAR – State of The Art Report

The State of the Art in Visualizing Multivariate Networks

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[2]Johannes Kepler University Linz, Austria

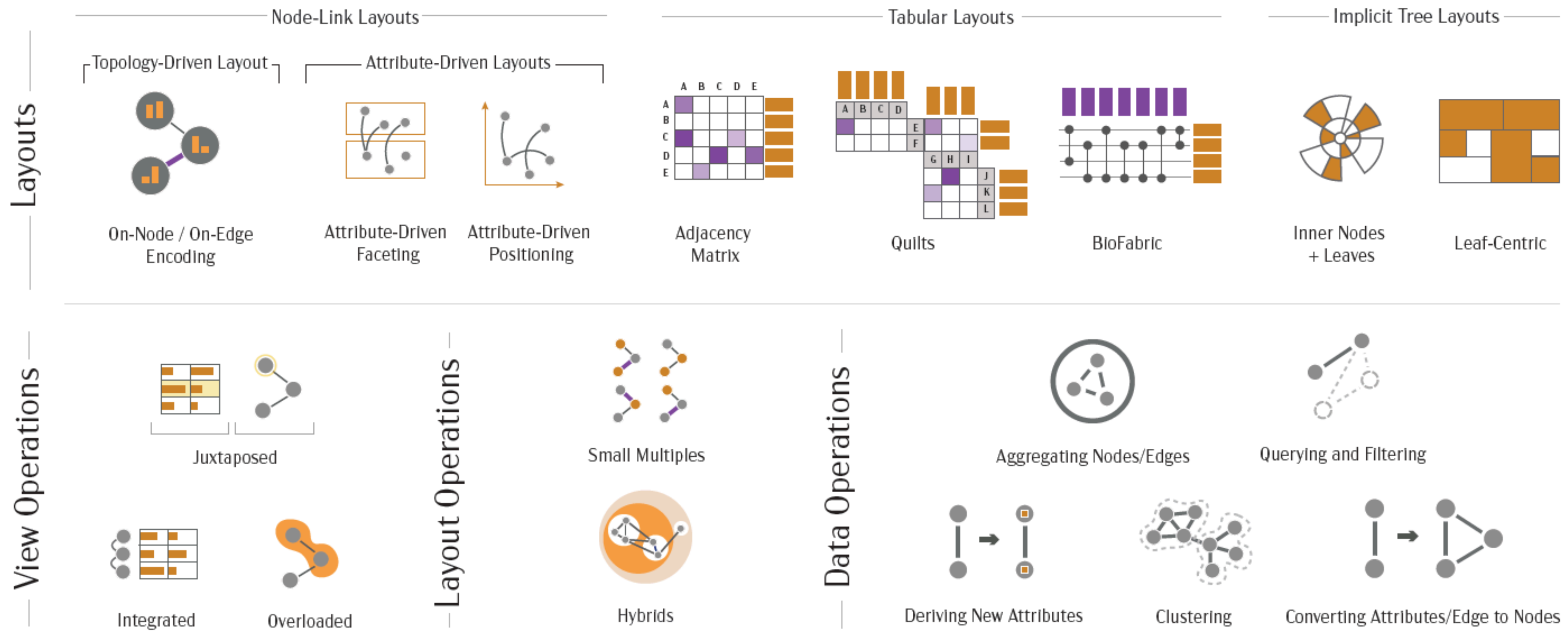
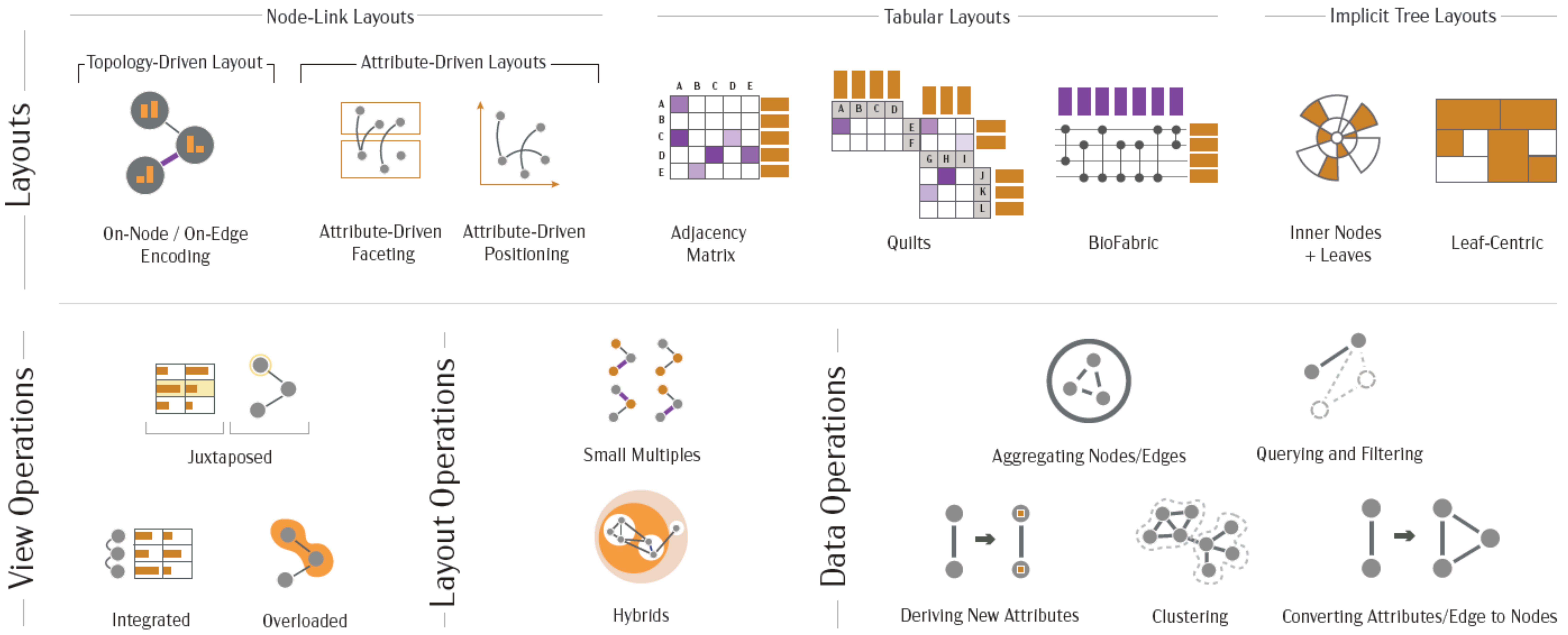


Figure 1: *A typology of operations and layouts used in multivariate network visualization.* ***Layouts*** *describe the fundamental choices for encoding multivariate networks.* ***View Operations*** *capture how topology and attribute focused visualizations can be combined.* ***Layout Operations*** *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
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Topology-Driven Layout
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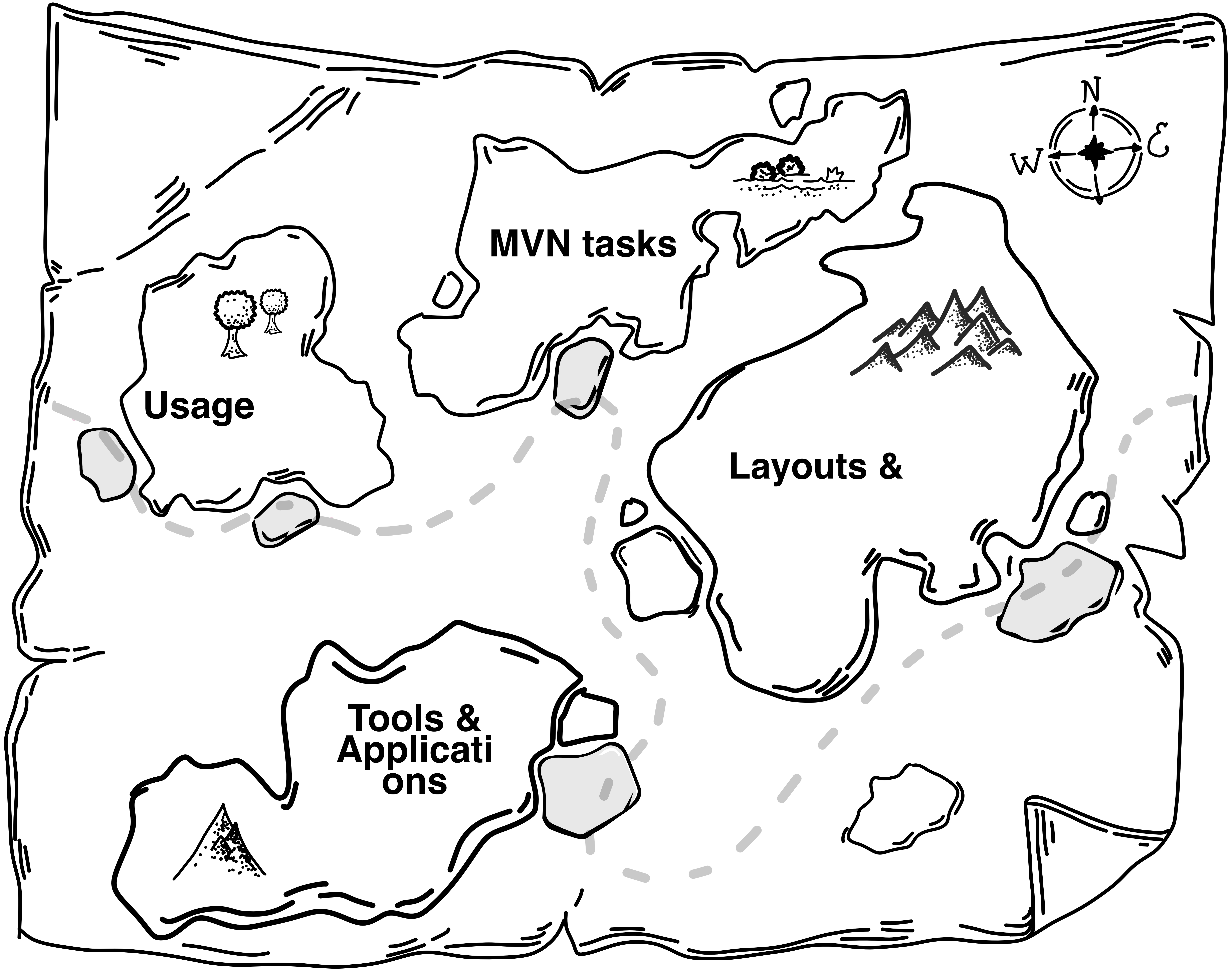
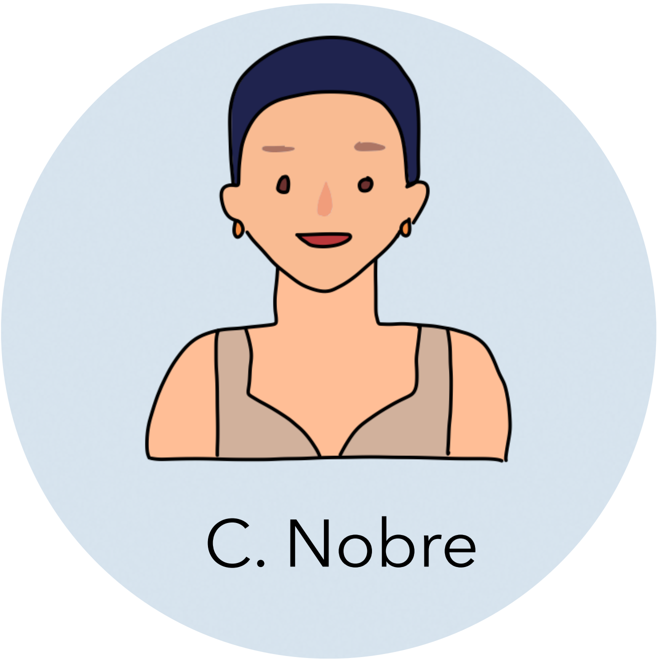
Land of Multivariate

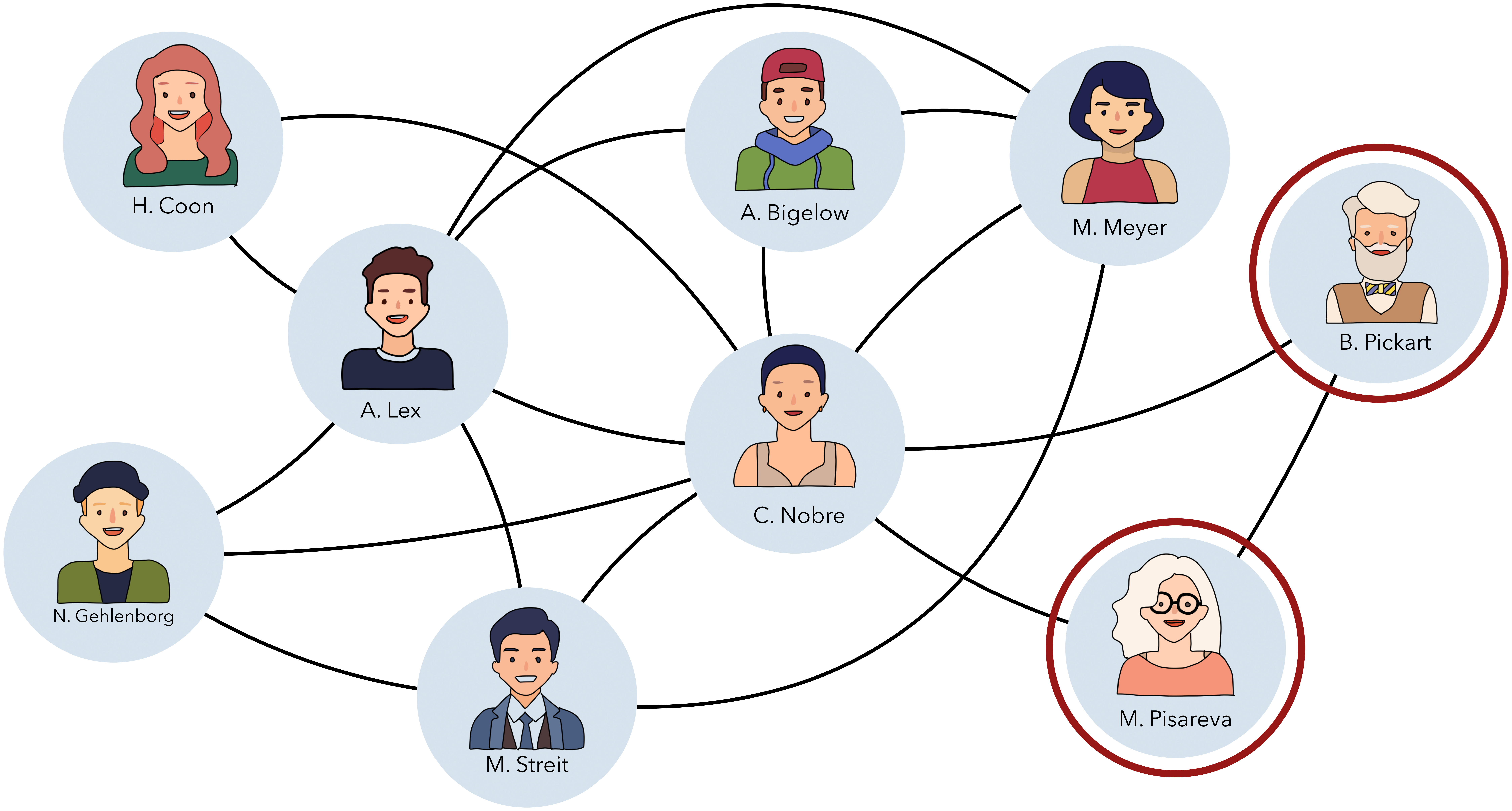


MVNV Tasks

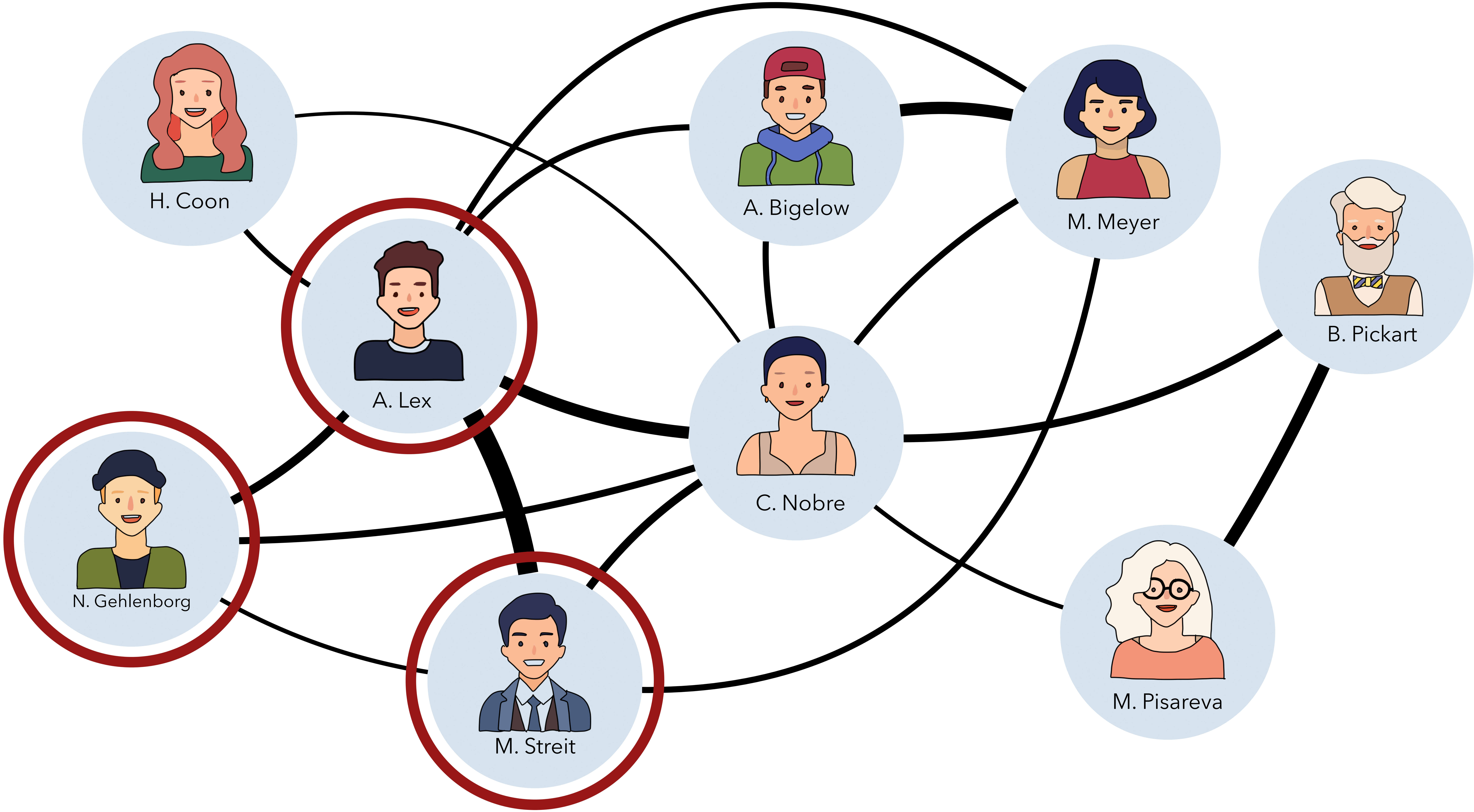
How is an MVN task different than a regular graph task?

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

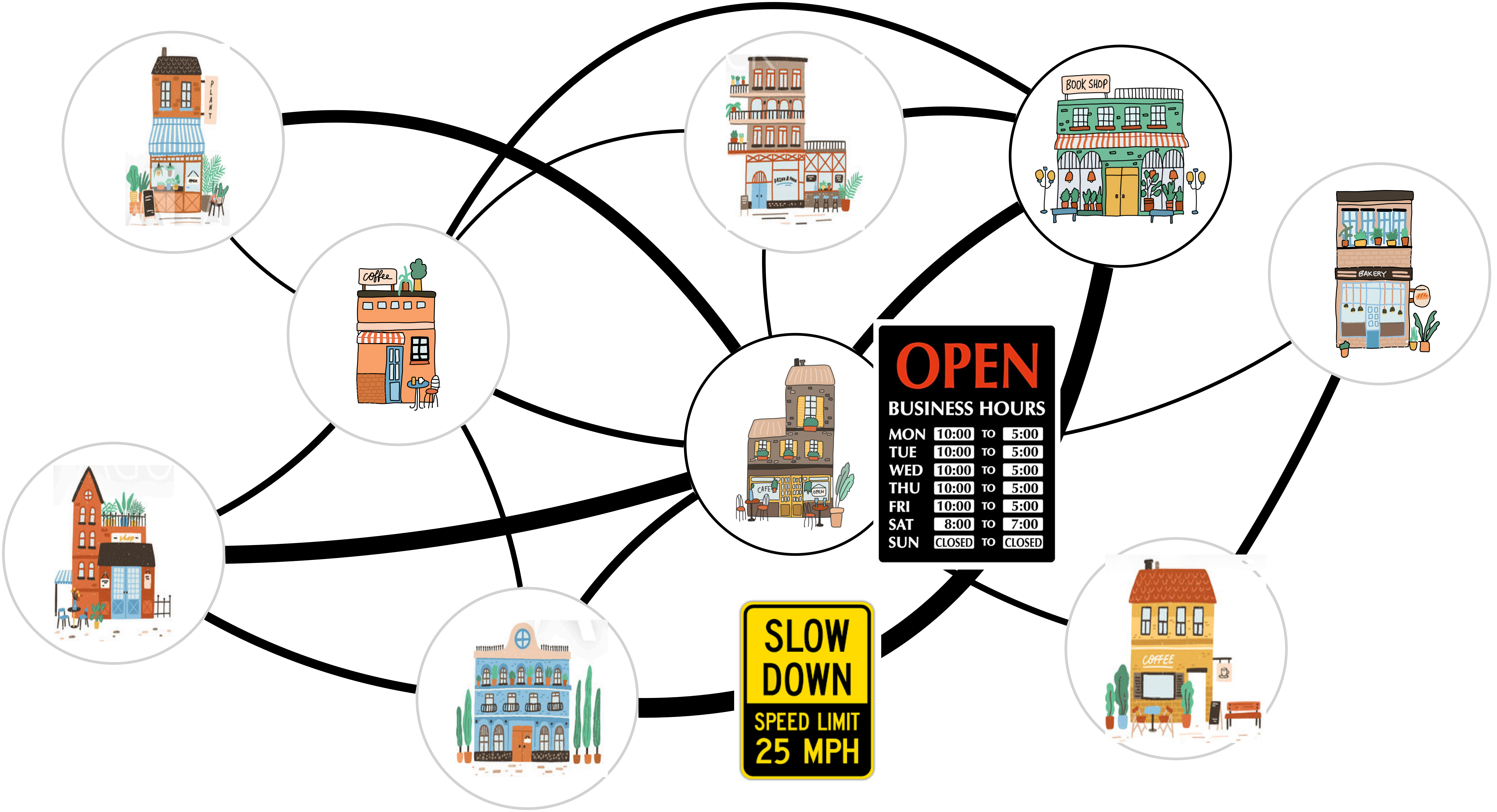

C. Nobre



How many of my collaborators are from the oceanography field?



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



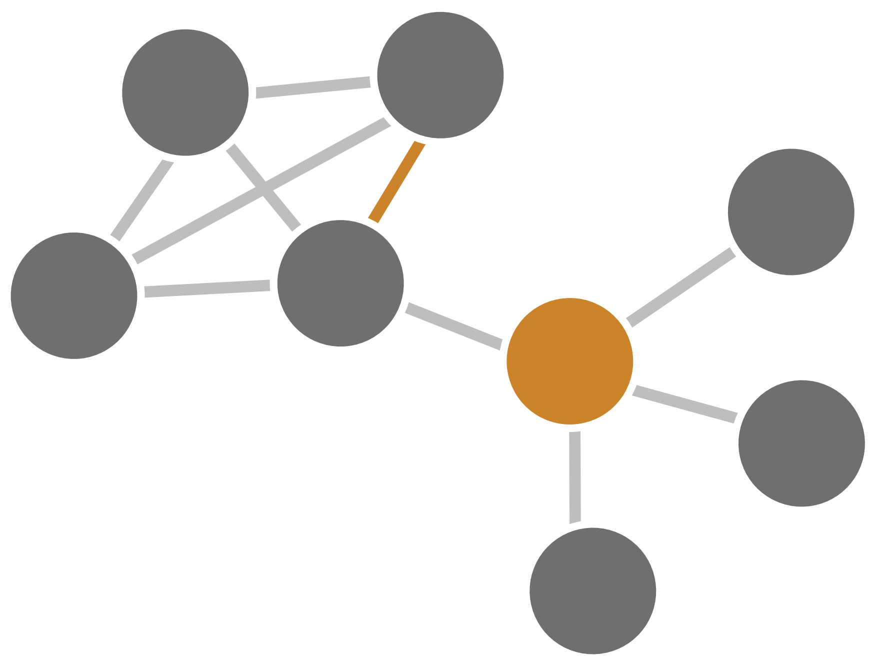
What is an efficient way I can complete all my errands?

- 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?

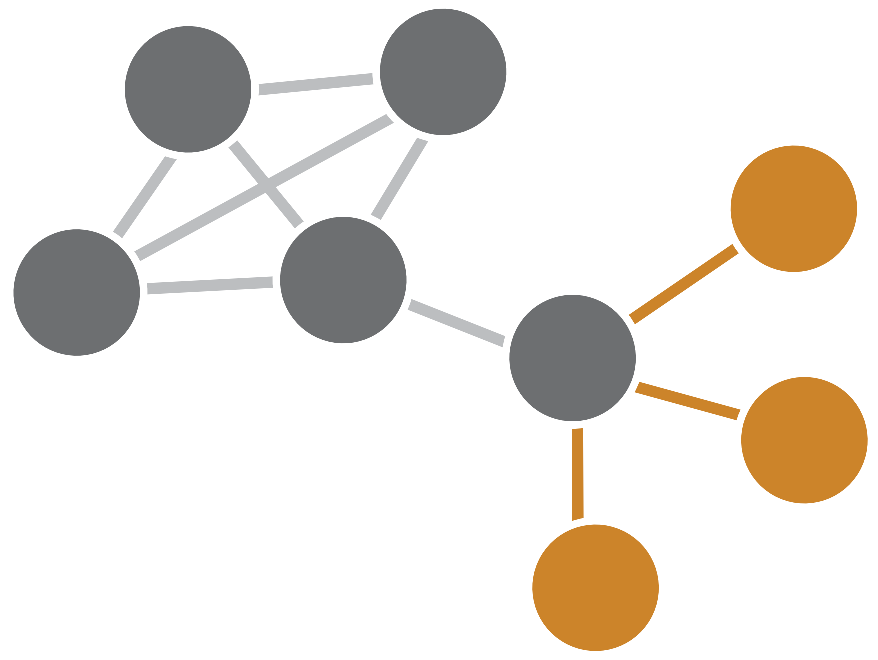
Tasks that rely on the **topology** of the network and the **attributes** of the nodes and edges

MVNV tasks are applied to topological structures

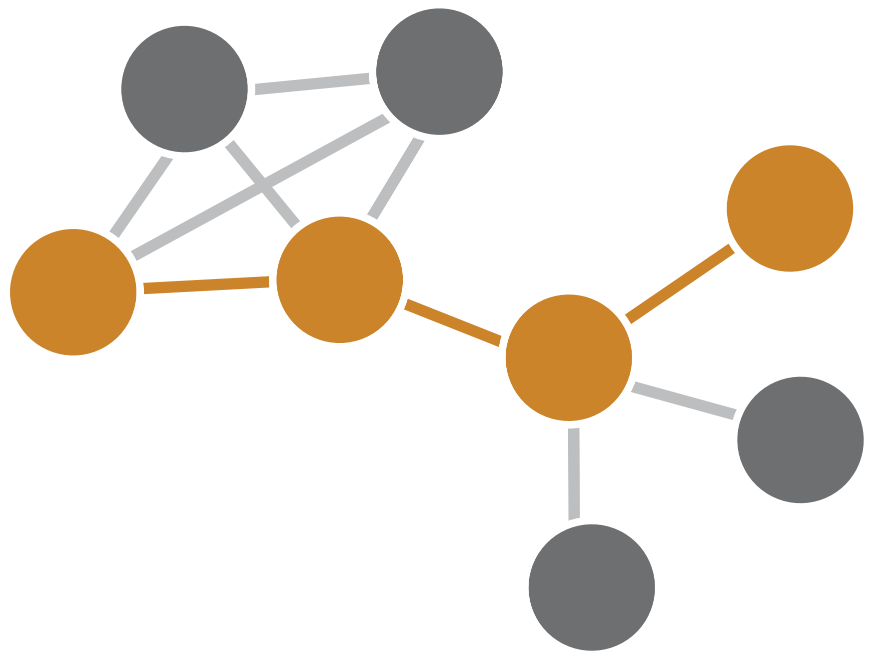
Single Node/Edge



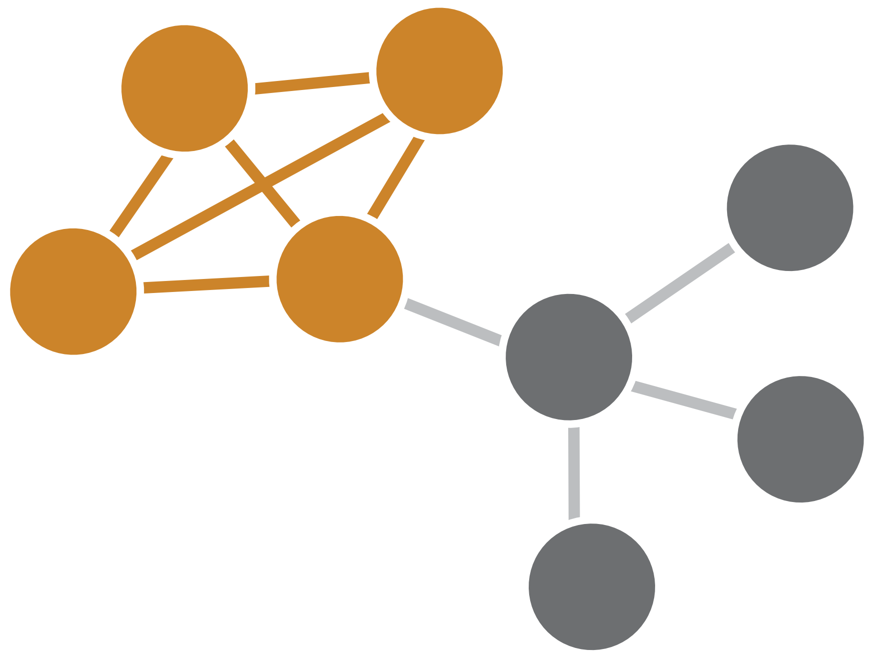
Node Neighbors



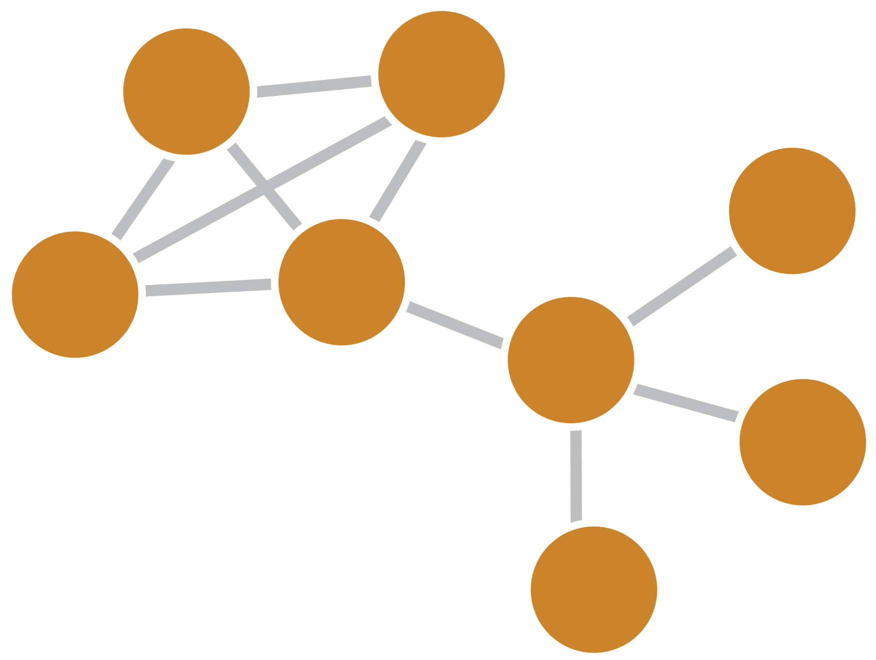
Path



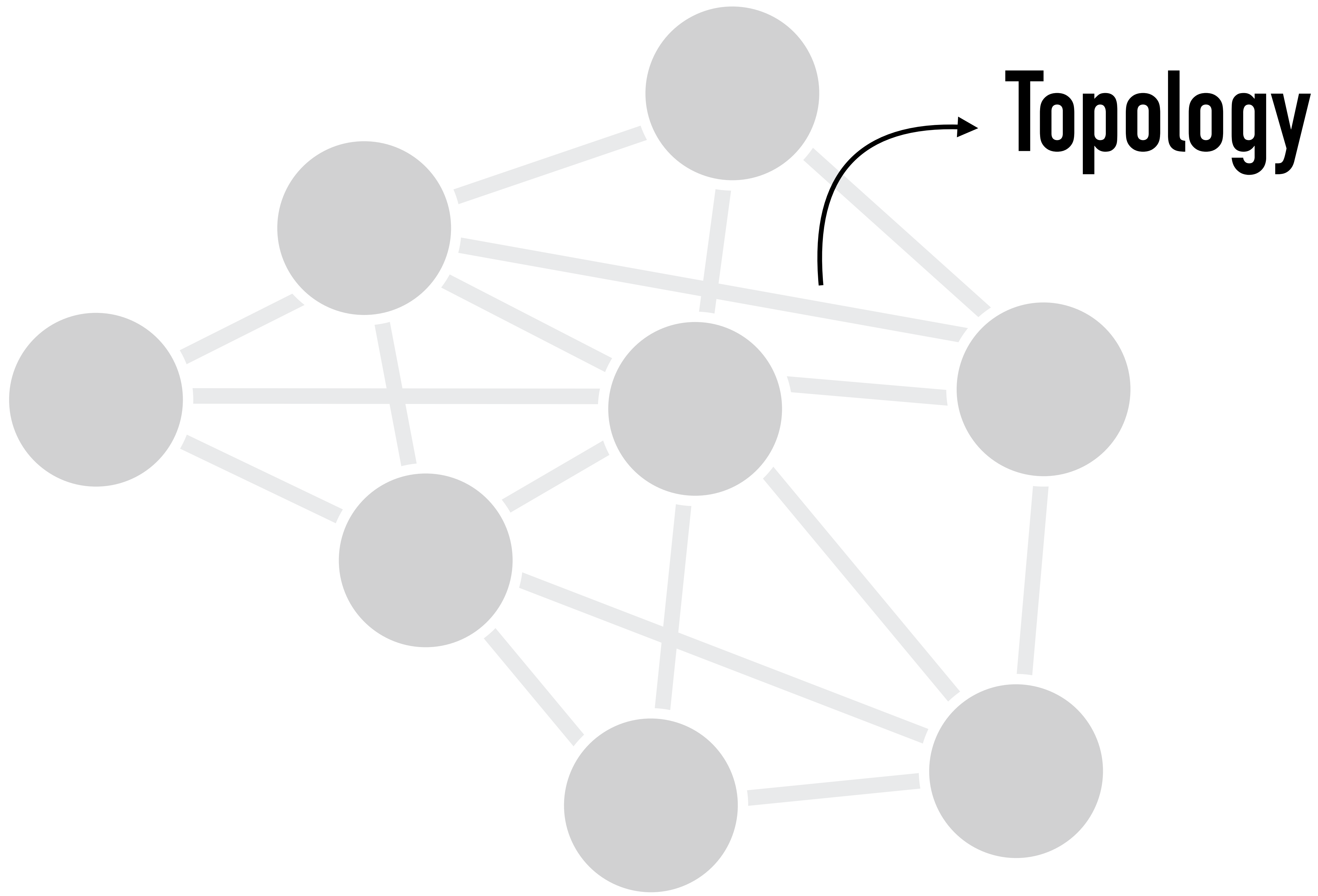
Cluster

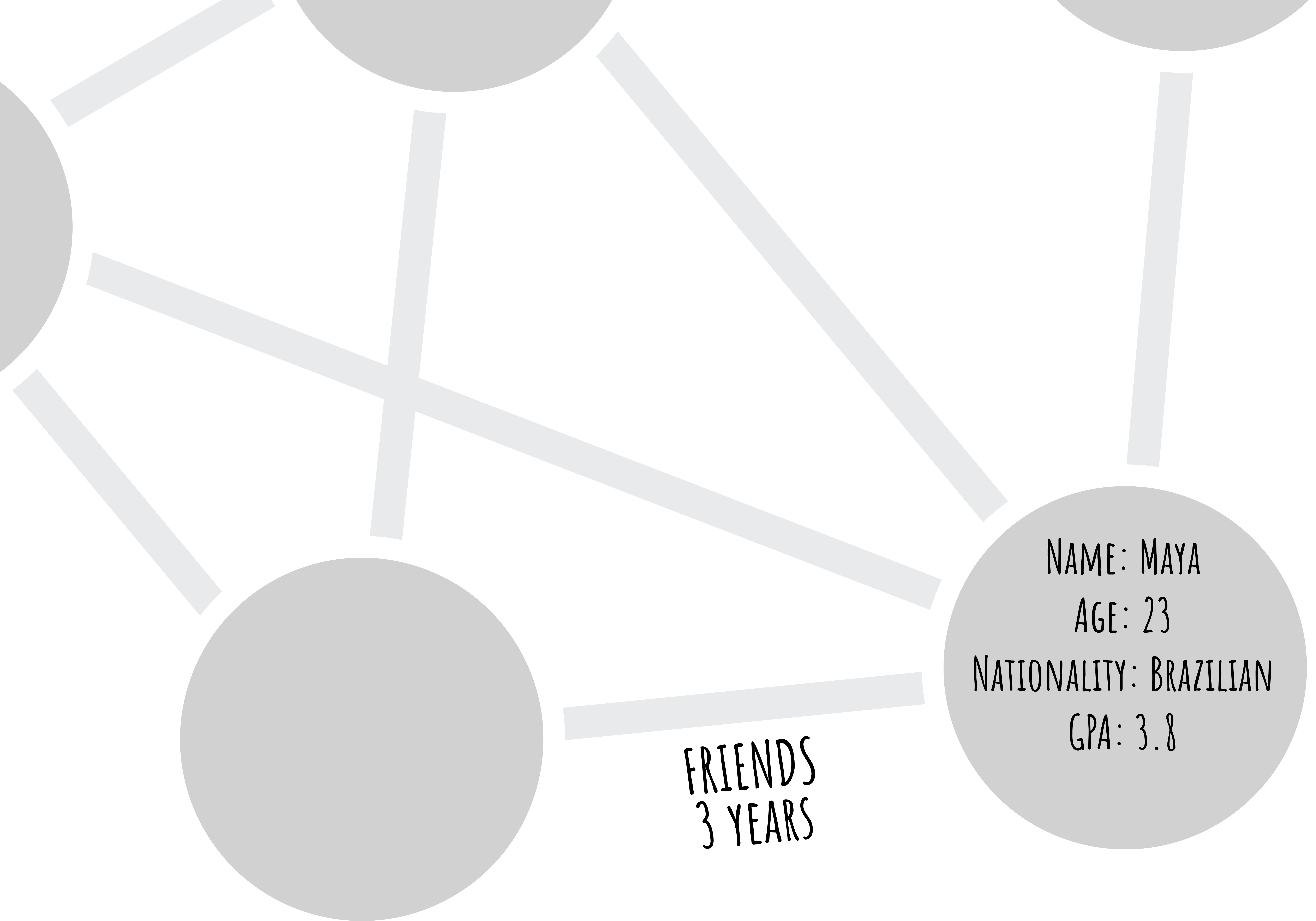


Network/Subnetwork



Network and Attribute Characteristics


Topology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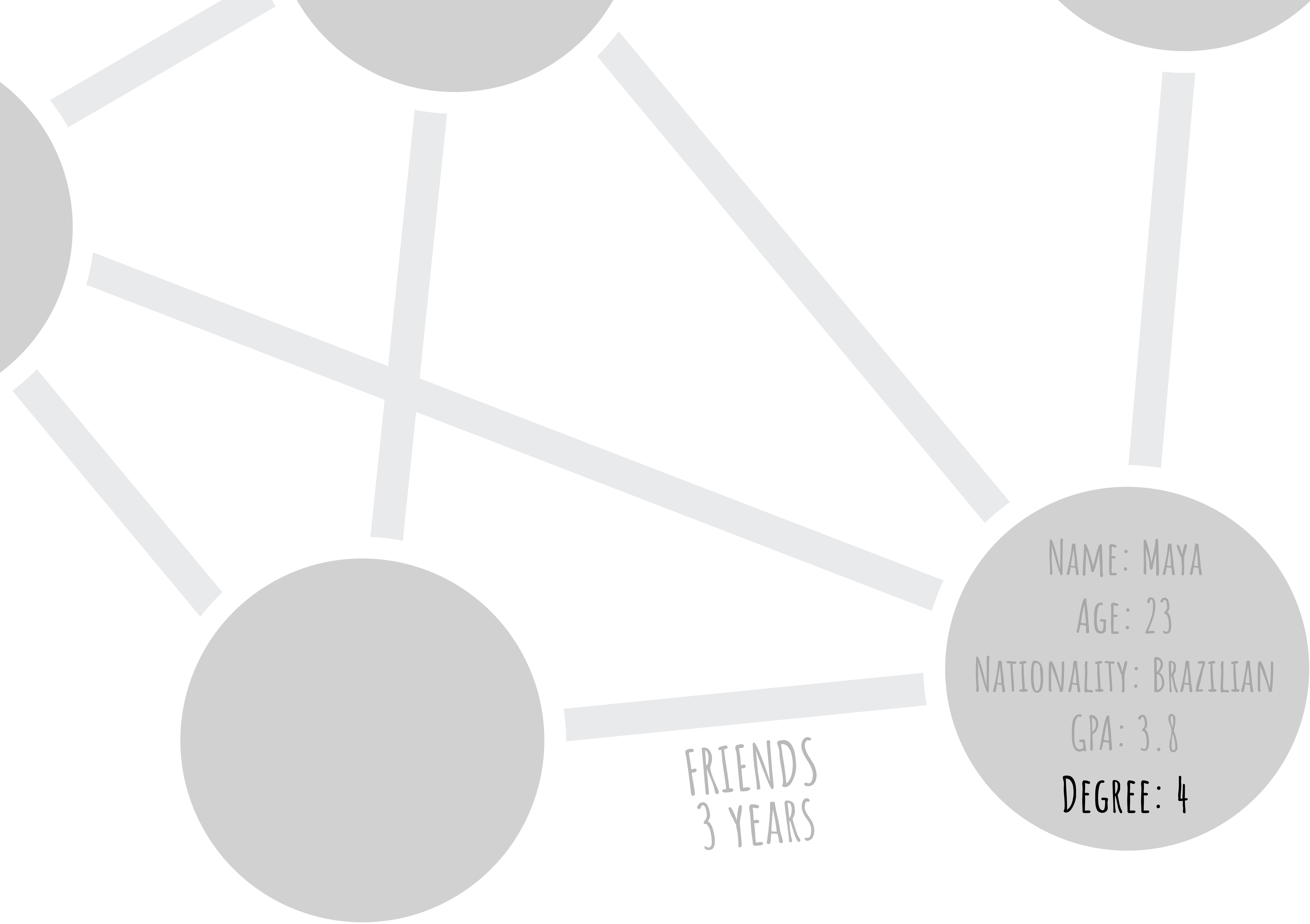
Age: 23
Nationality: Brazilian
GPA: 3.8
FRIENDS
3 YEARS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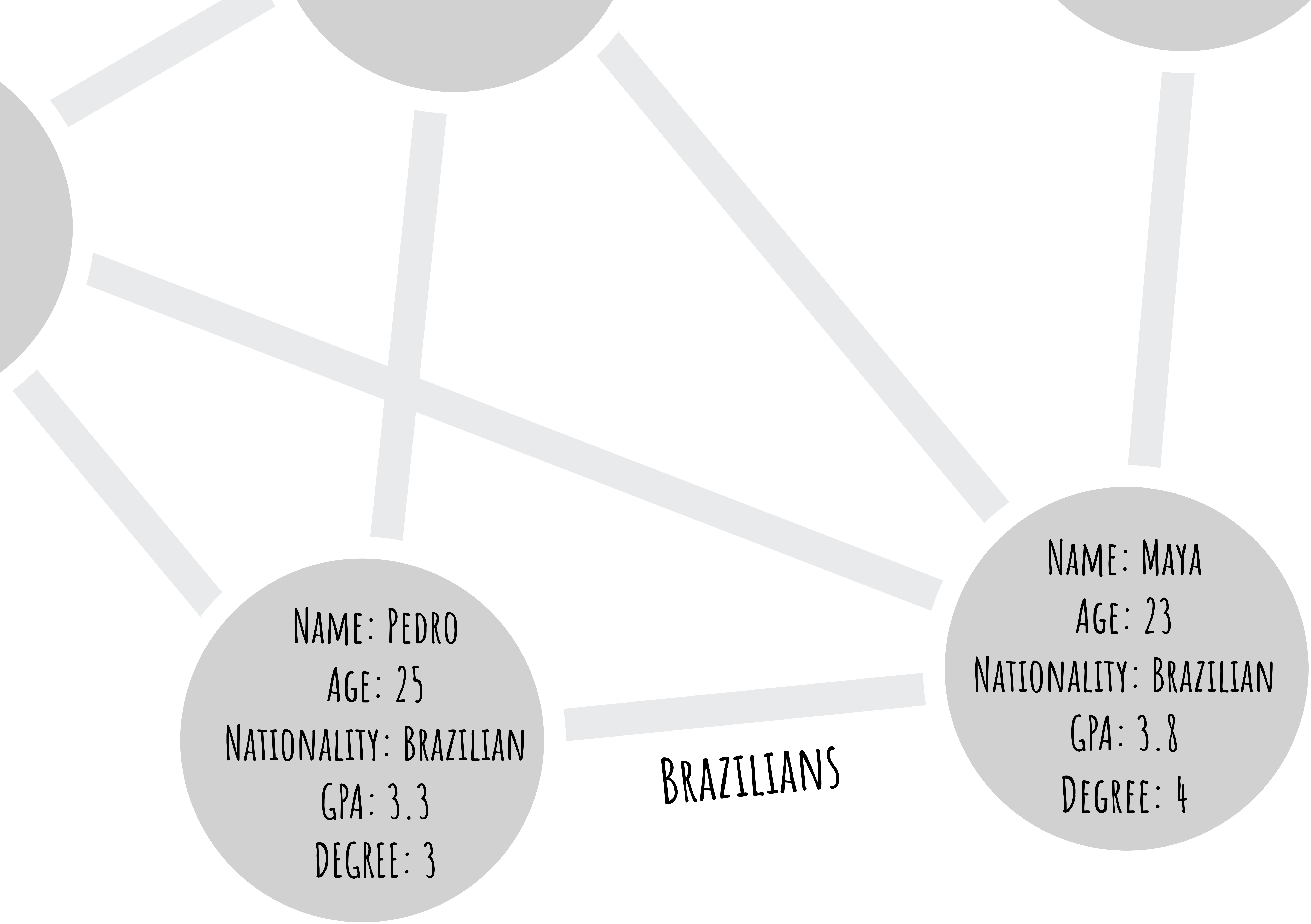
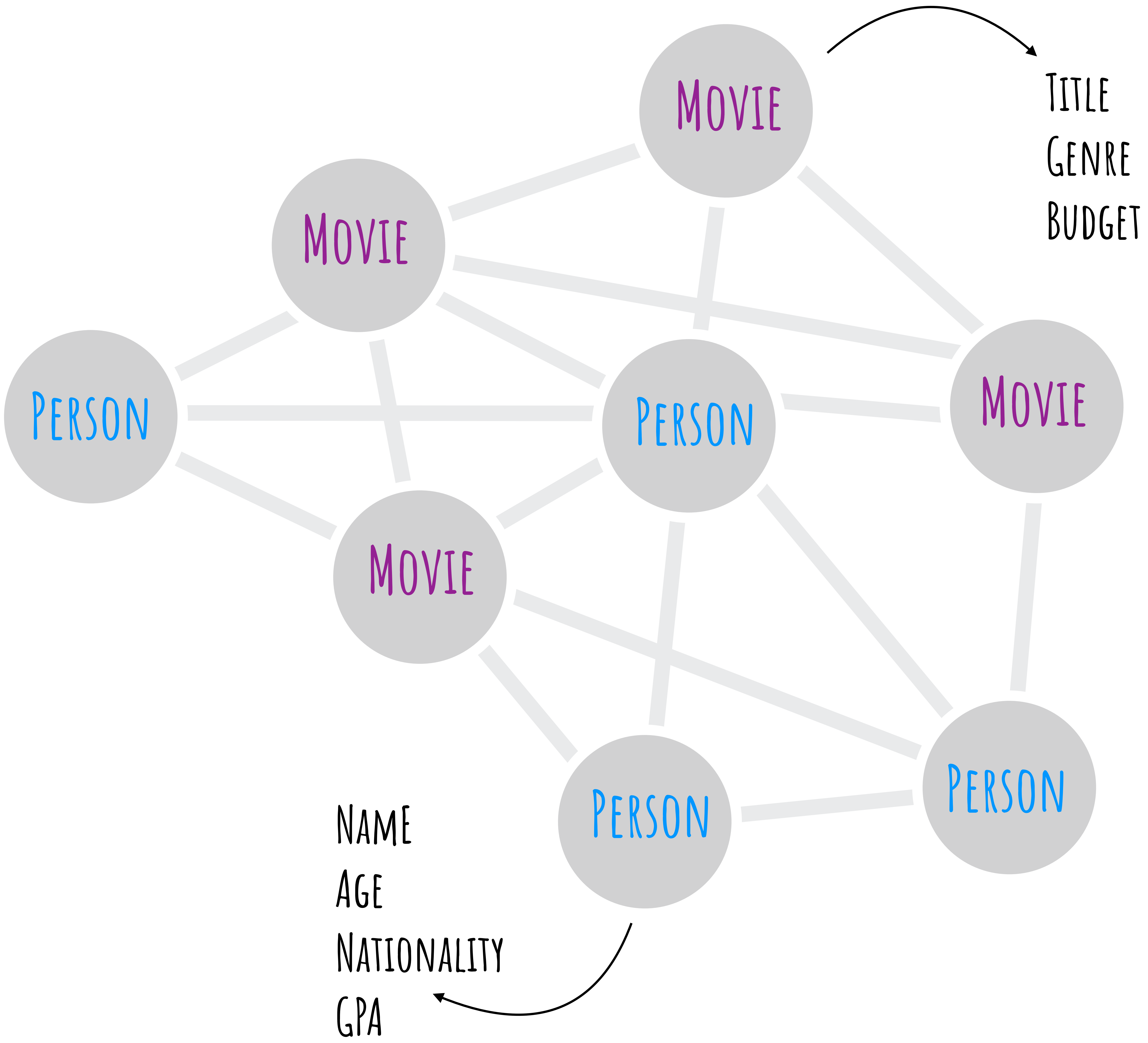
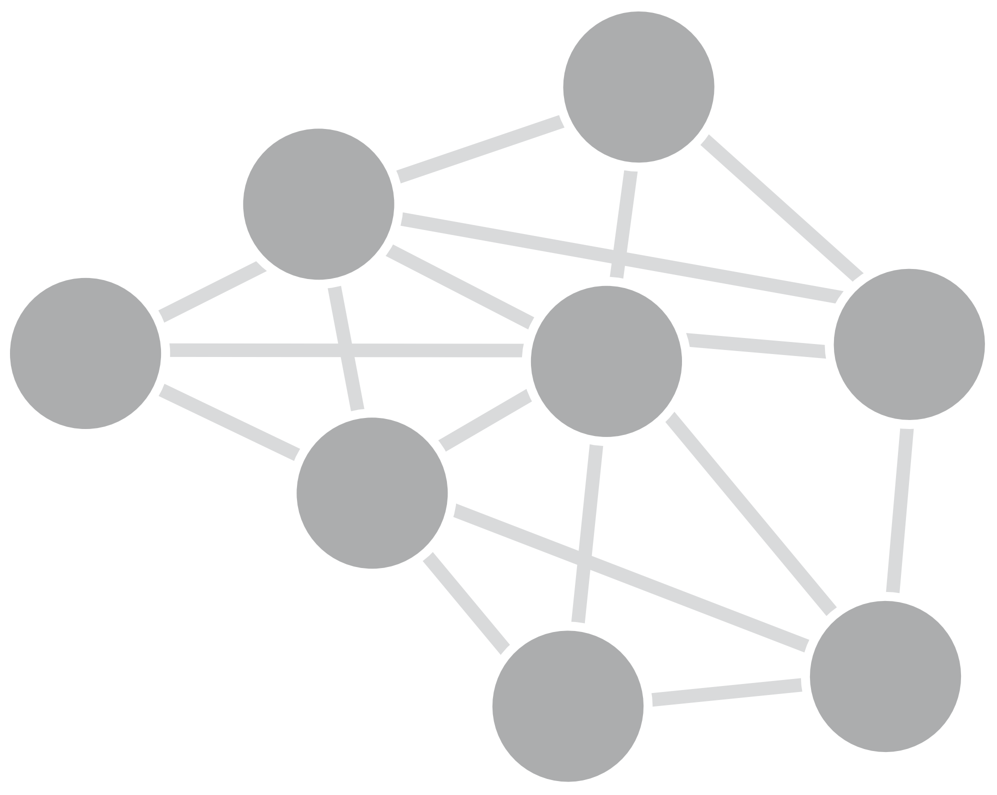
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
Friends
3 years

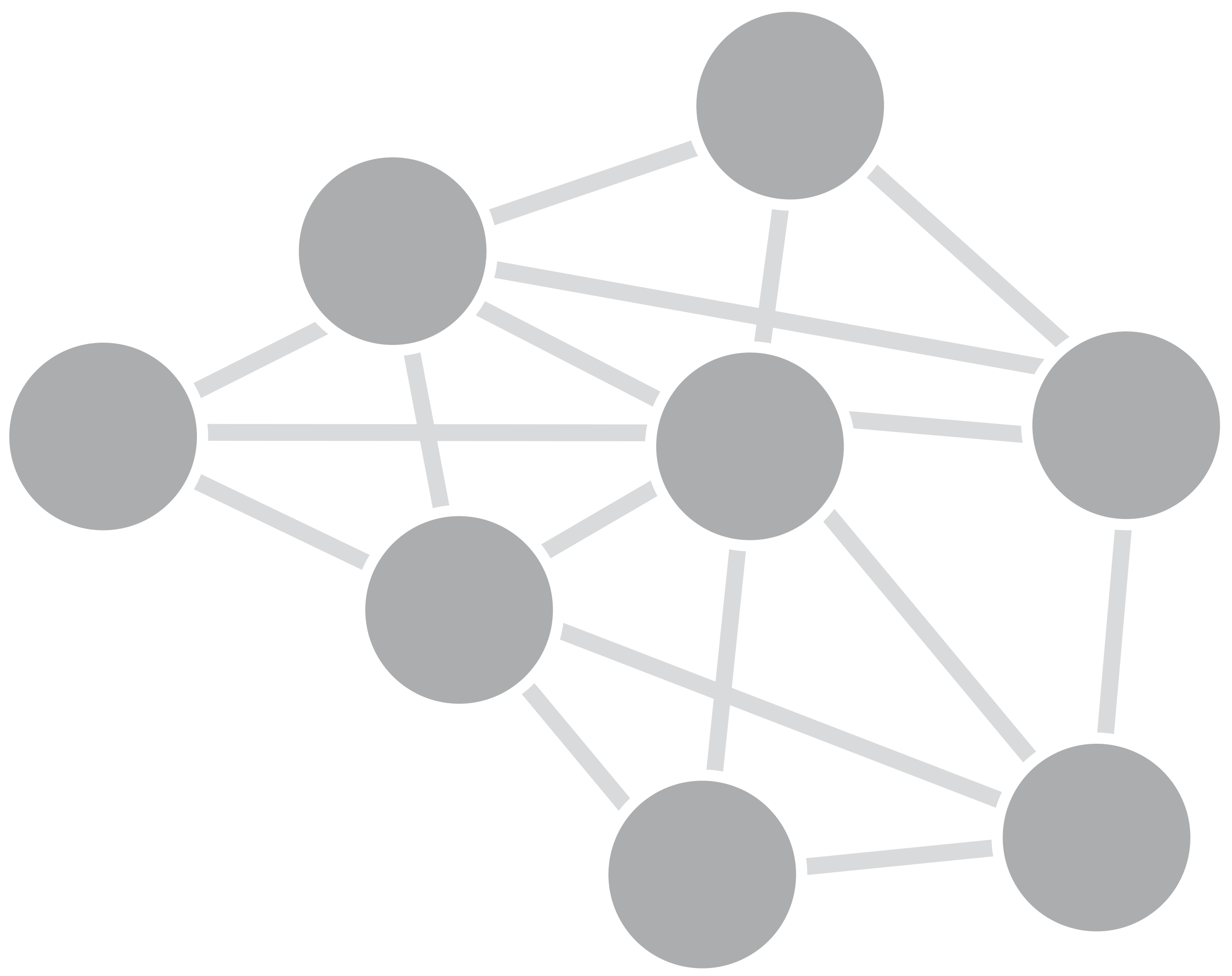

Name: Pedro
Age: 25
Nationality: Brazilian
GPA: 3.3
DEGREE: 3
Name: Maya
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
BRAZILIANS


Movie
Title
Genre
Budget
Movie
Person
Person
Movie
Movie
Name
Age
Nationality
GPA
Person
Person

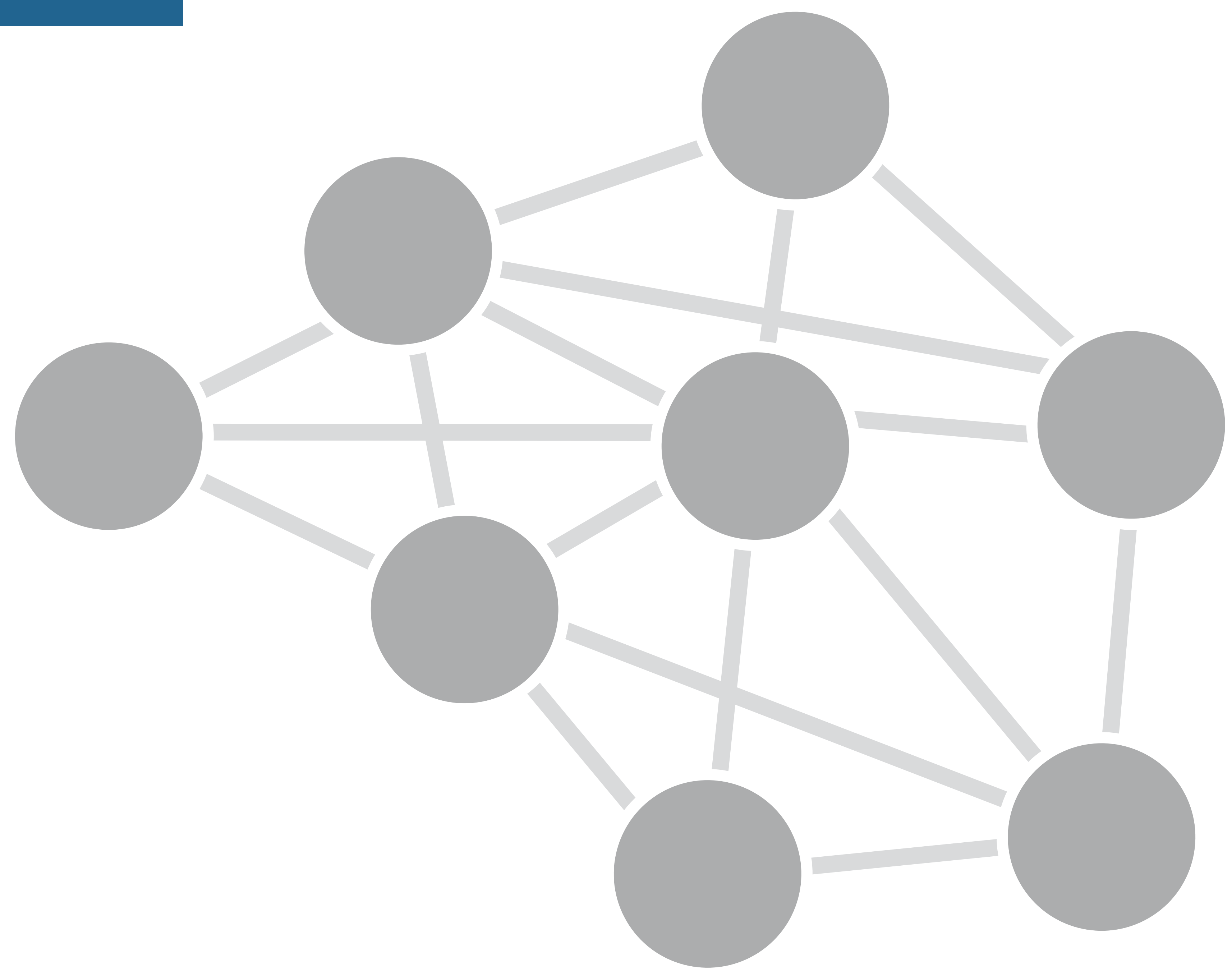
Network Size



Small
<100

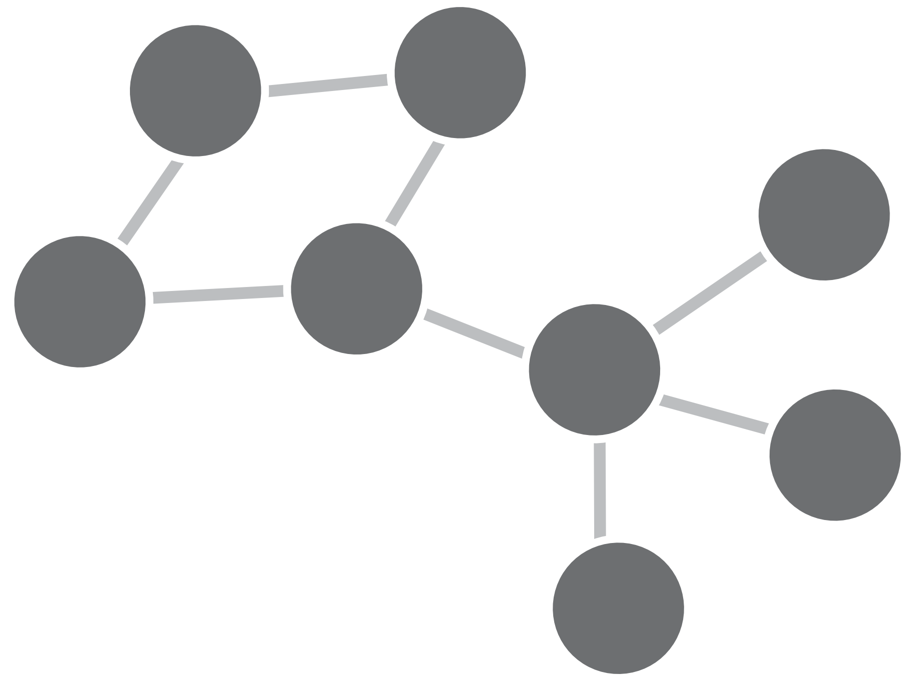


Medium
100–1000

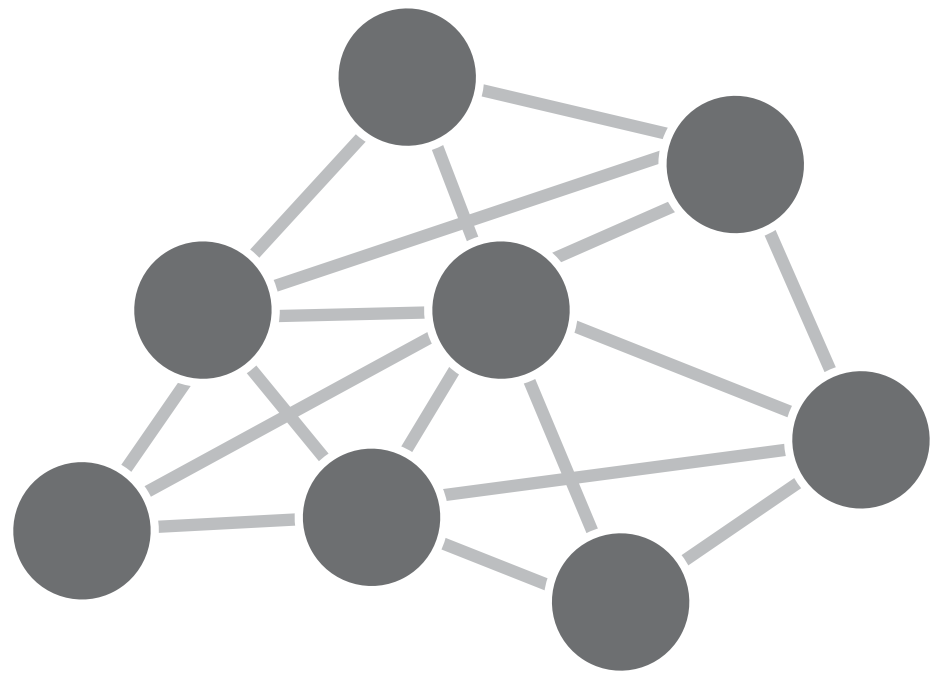


Large
>1000

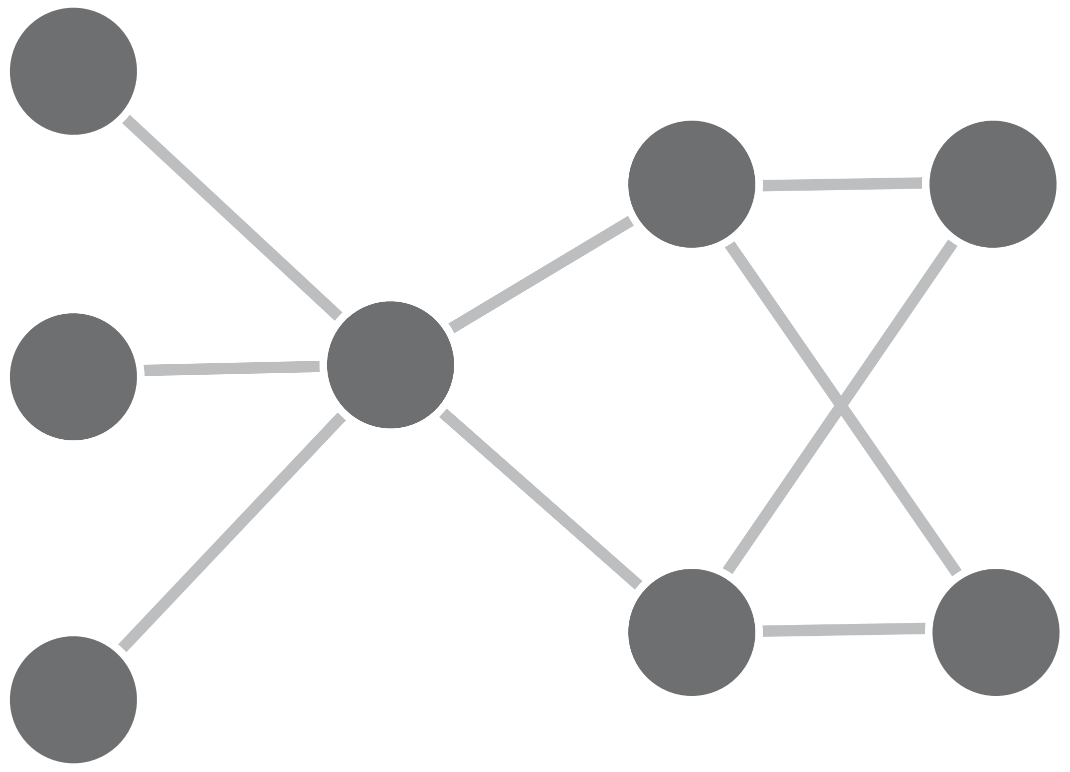
Network Types



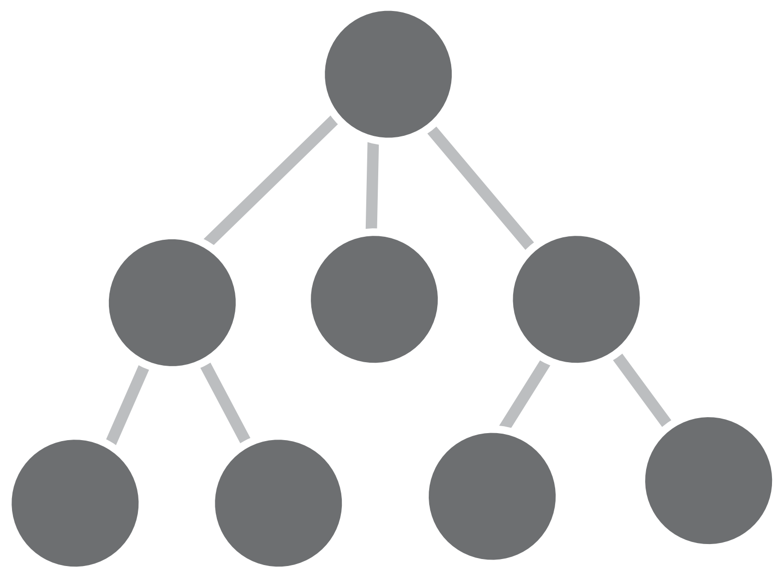
Sparse



Dense

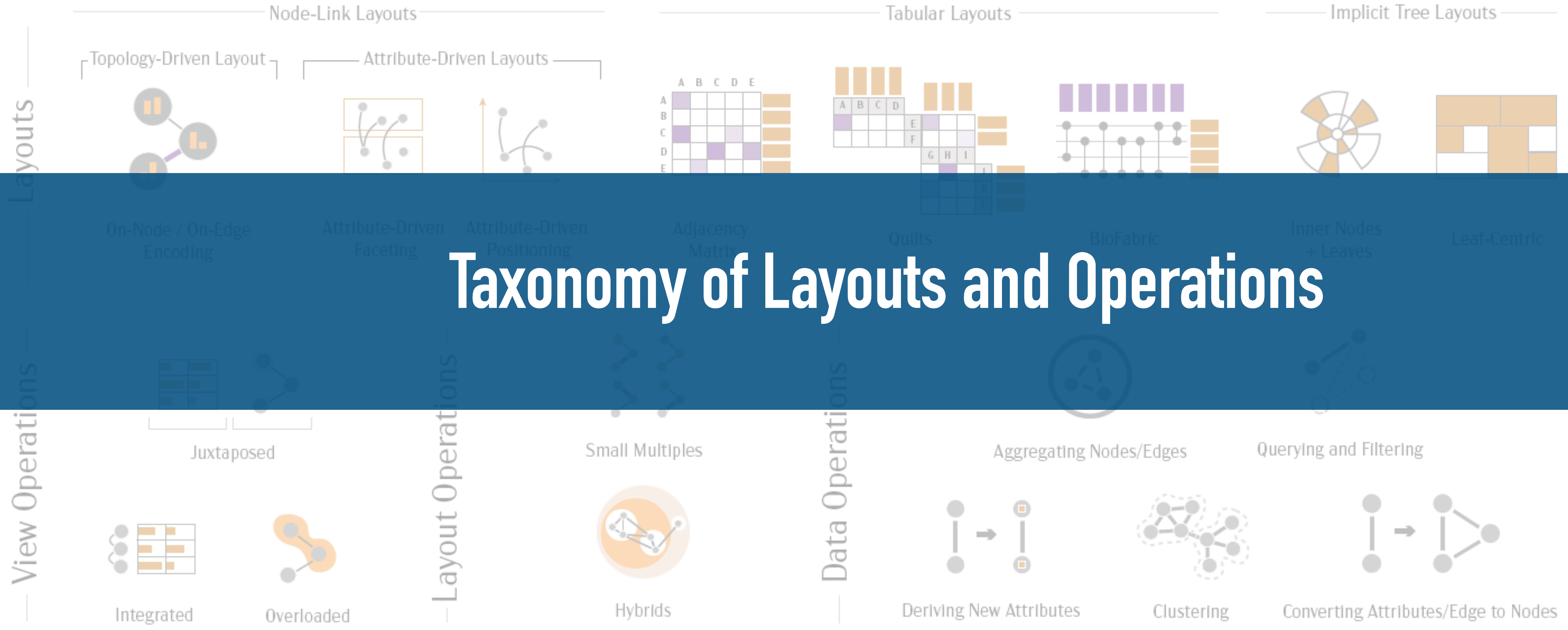


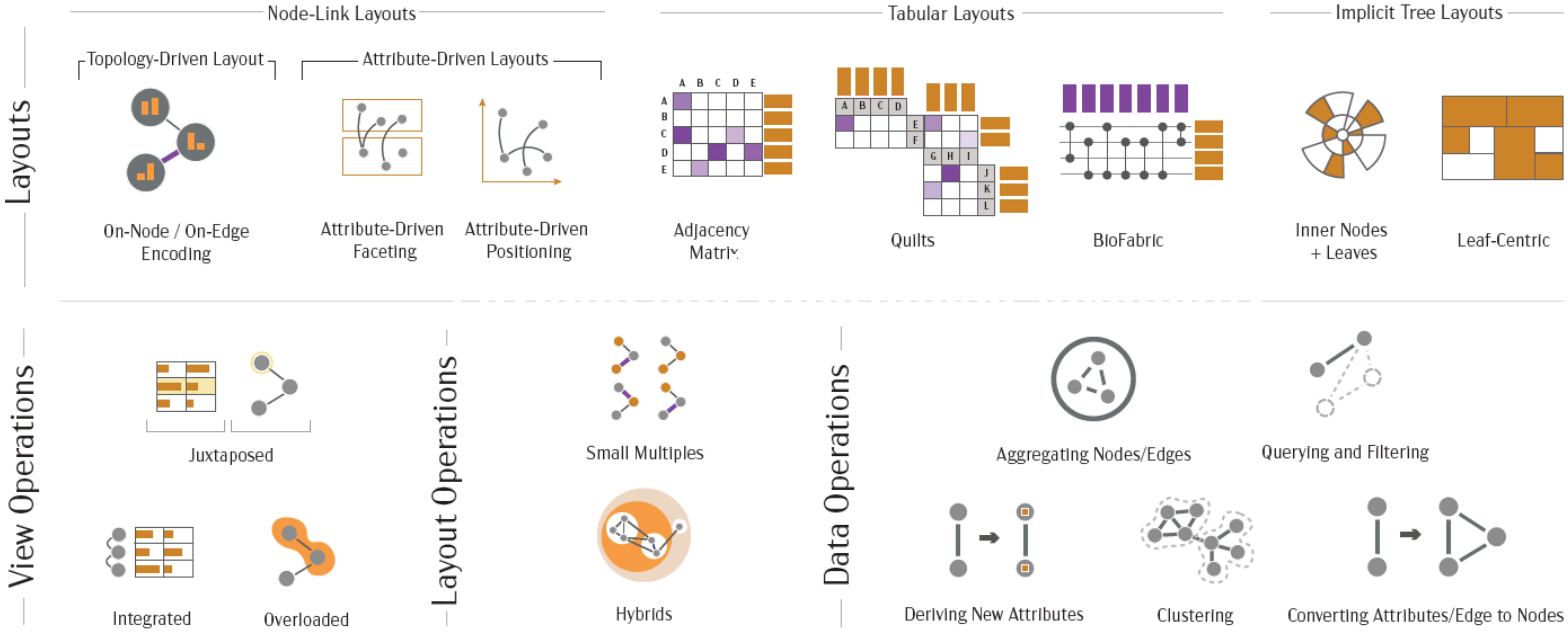
Layered



Trees

Taxonomy of Layouts and Operations

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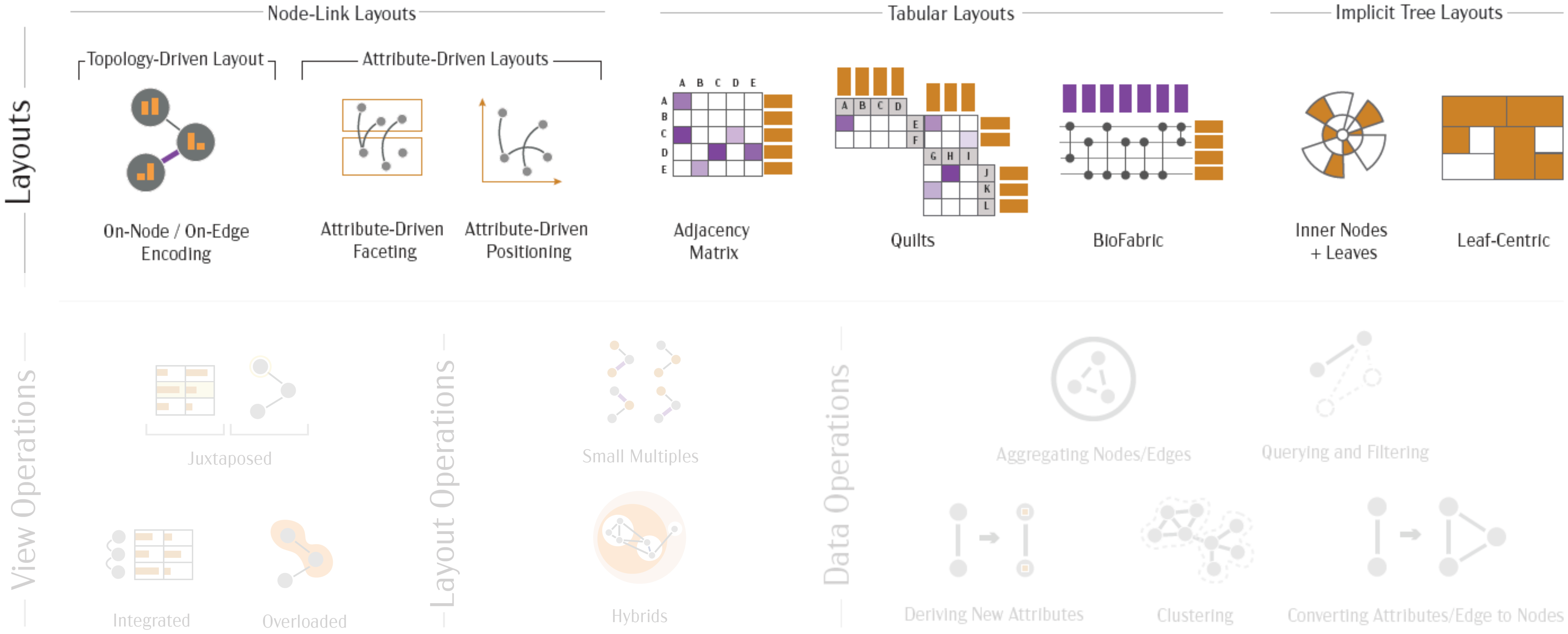

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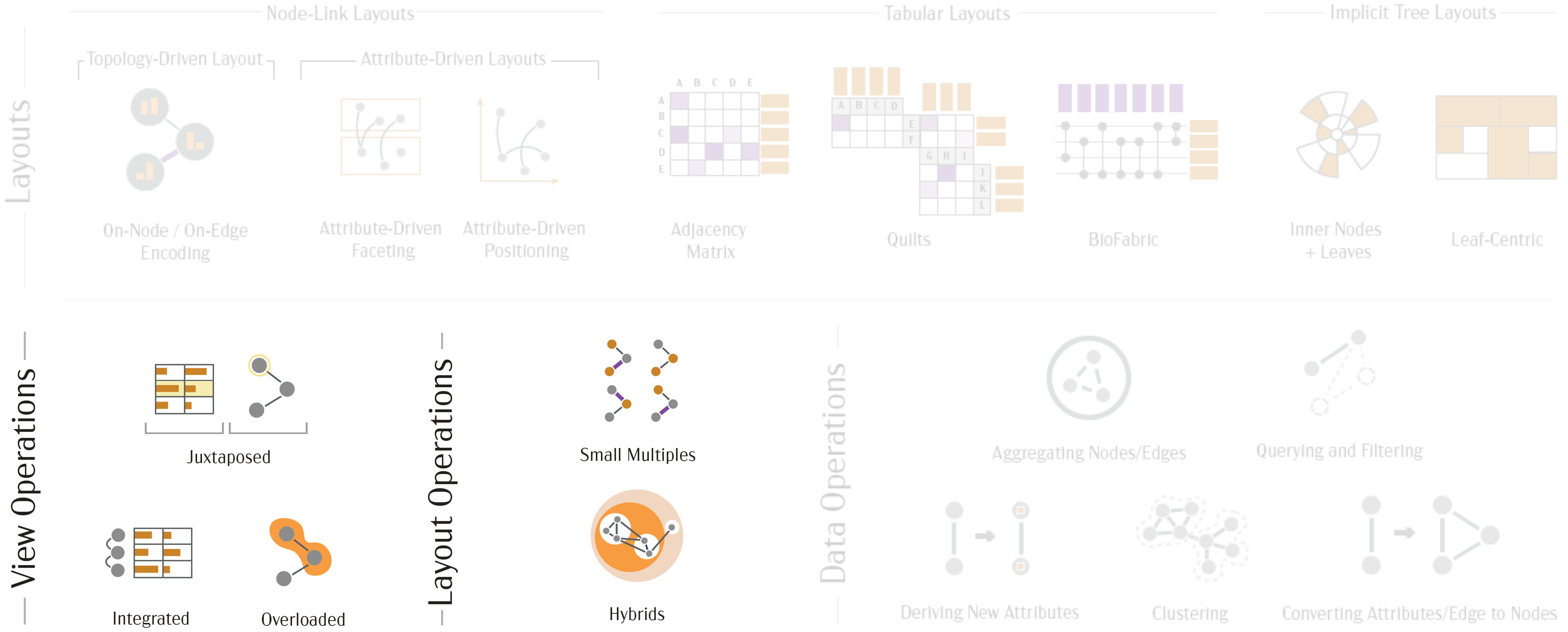

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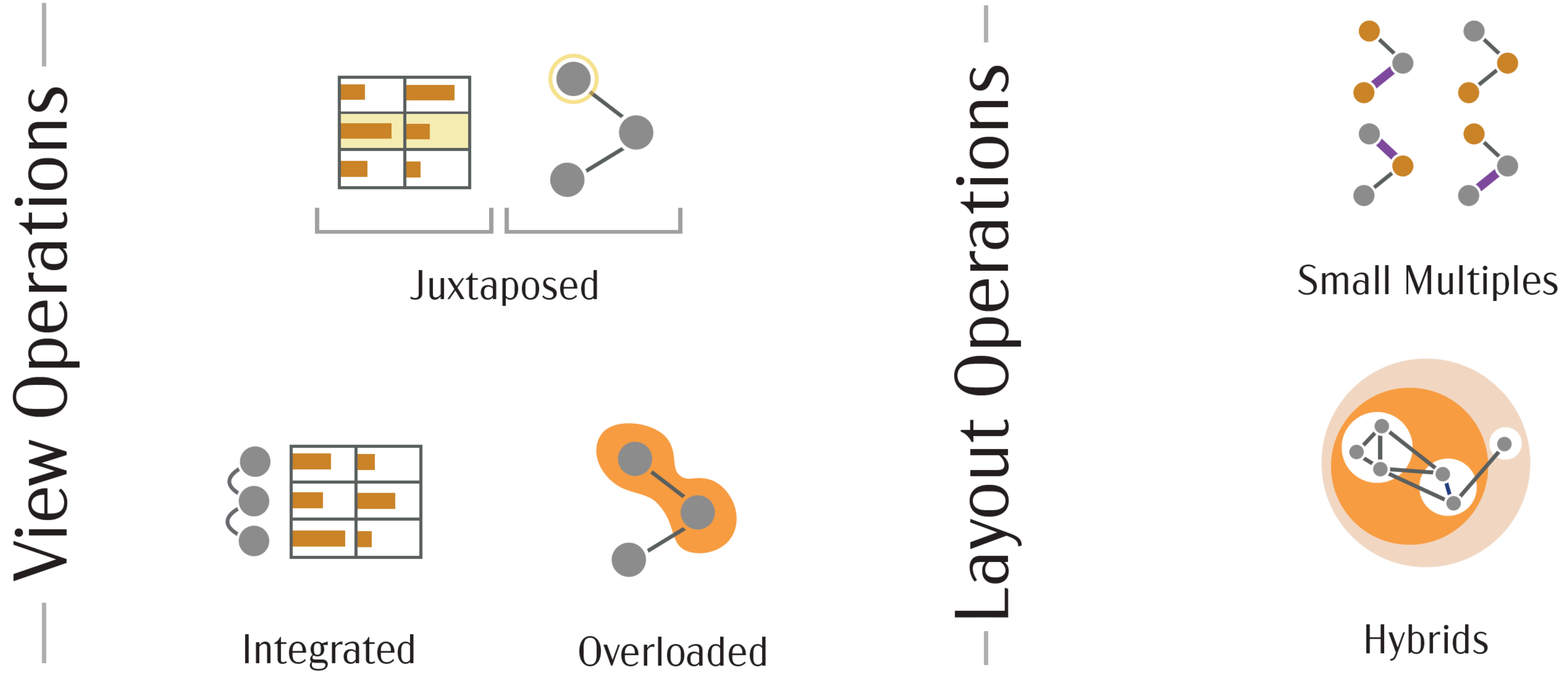
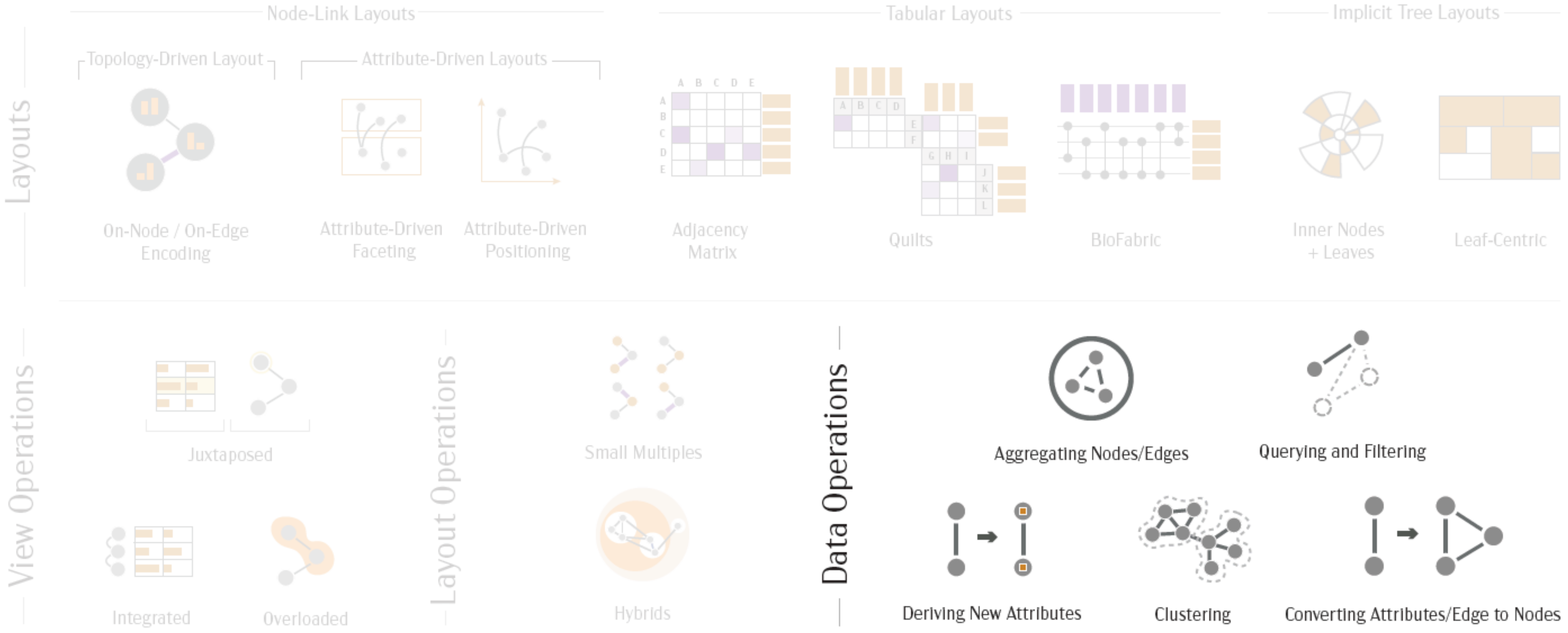


Separate views for Topology and Attributes

Multiple layouts for Topology or Attributes



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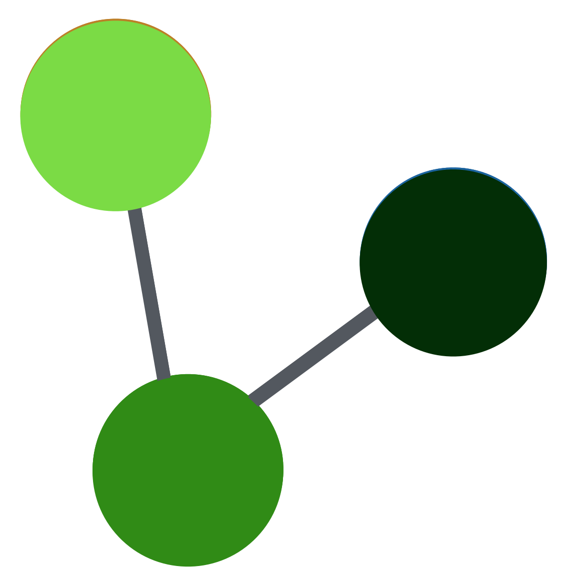
LAYOUTS		
VIEW OPERATIONS	LAYOUT OPERATIONS	DATA OPERATIONS

Node-Link Diagram with on-node encoding



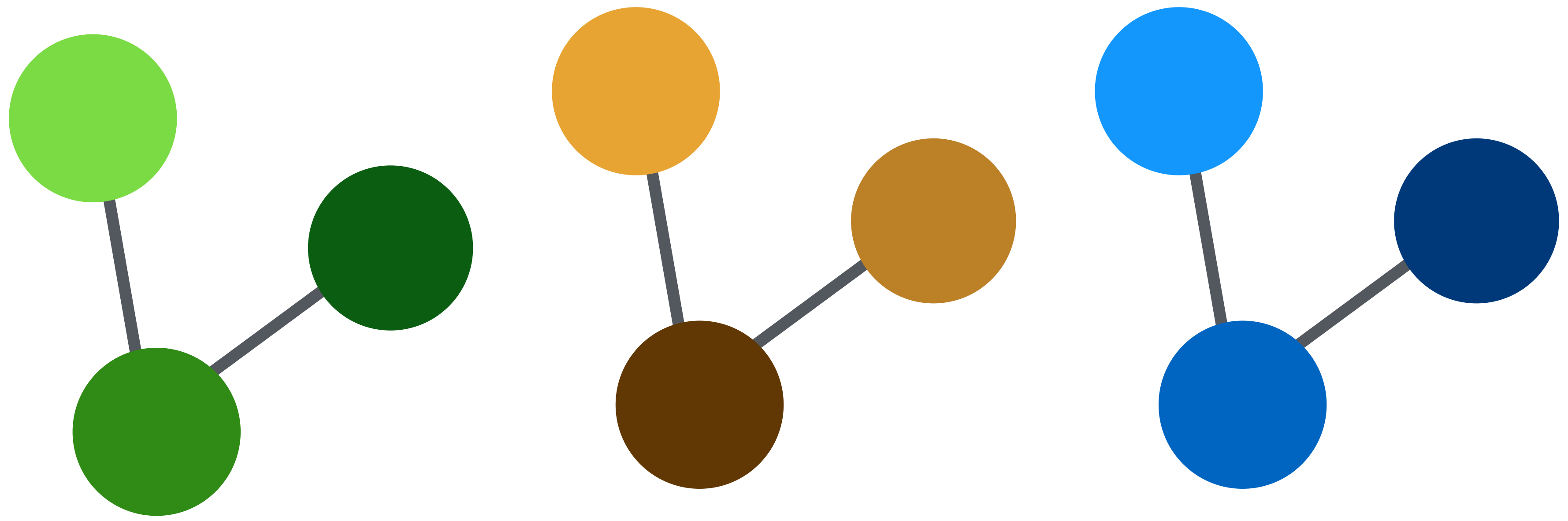
LAYOUTS

VIEW OPERATIONS

LAYOUT OPERATIONS

DATA OPERATIONS

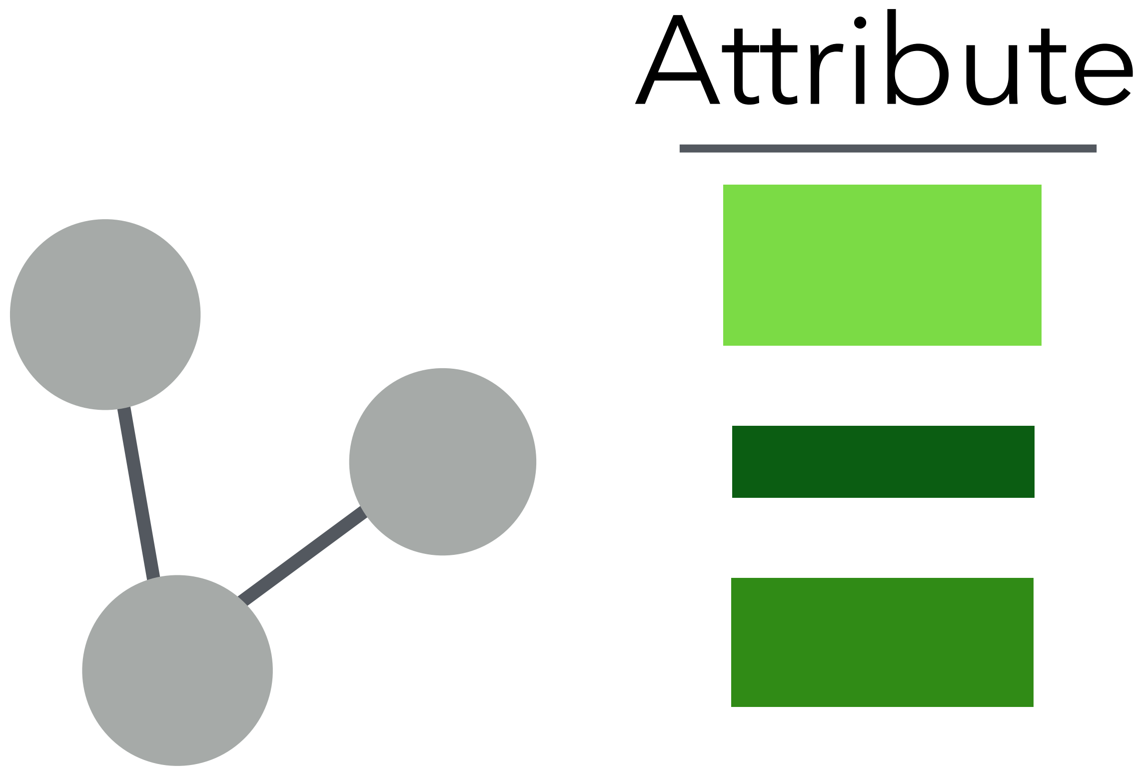
Small Multiples



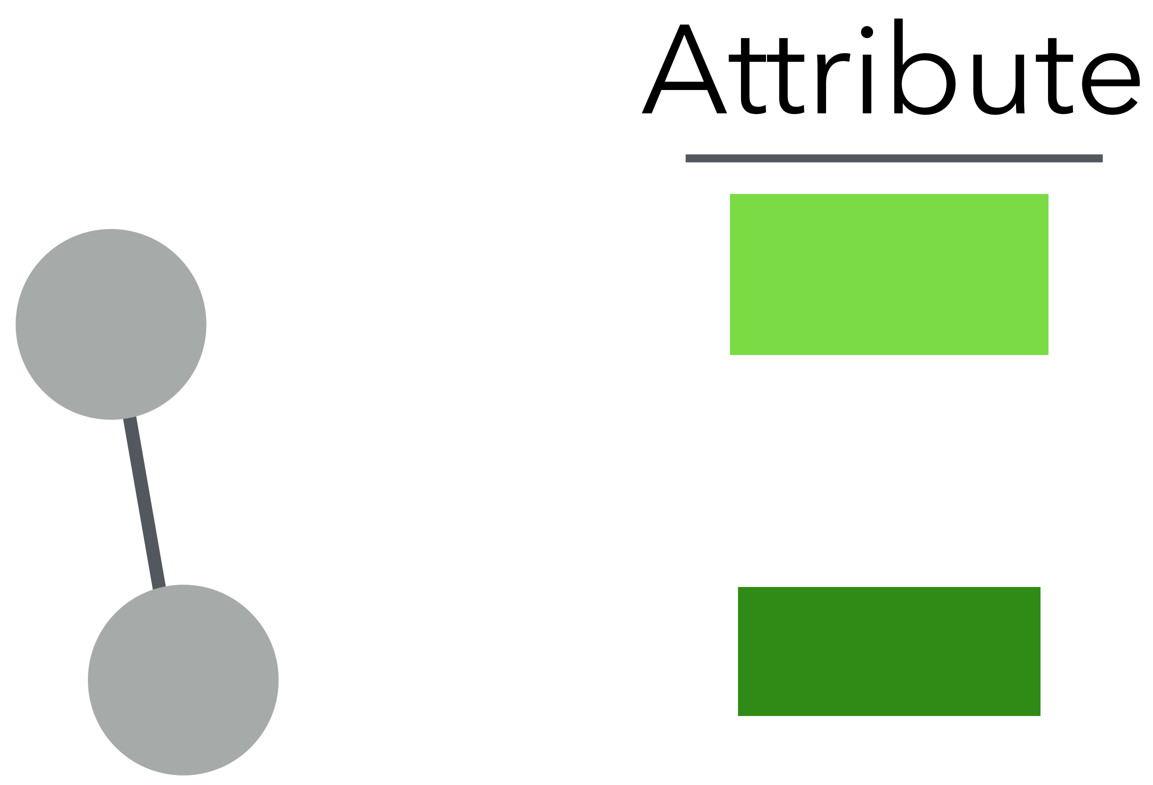
Juxtaposed Views

LAYOUTS

VIEW OPERATIONS	LAYOUT OPERATIONS	DATA OPERATIONS



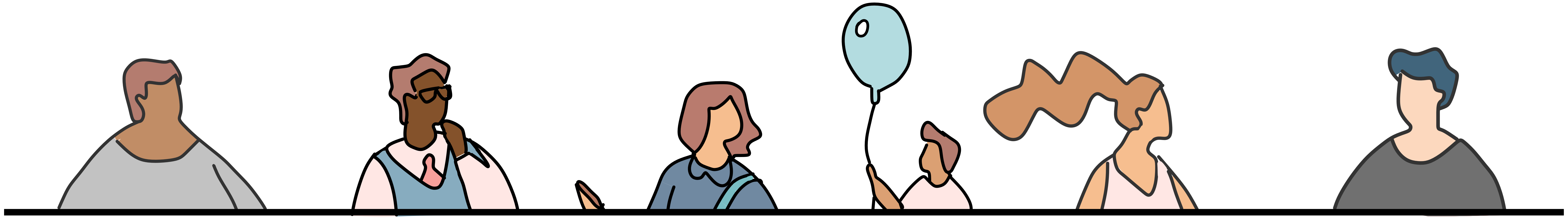
Filter Data



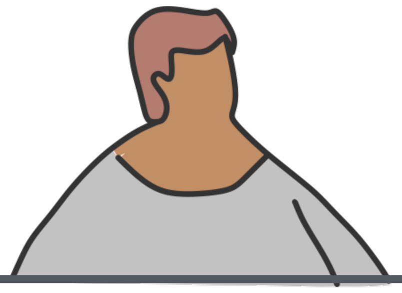
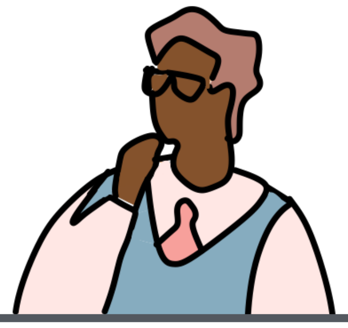
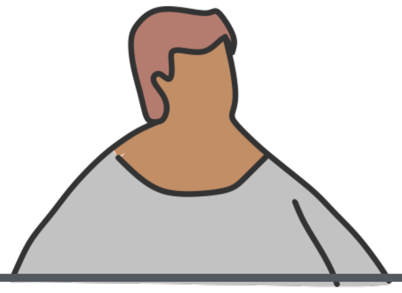
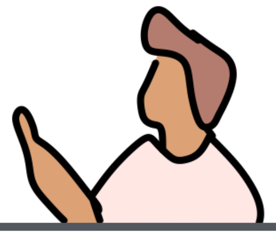
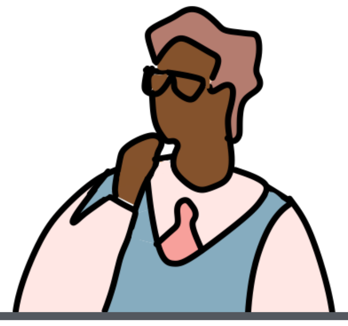
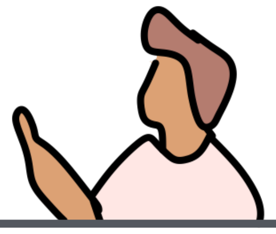
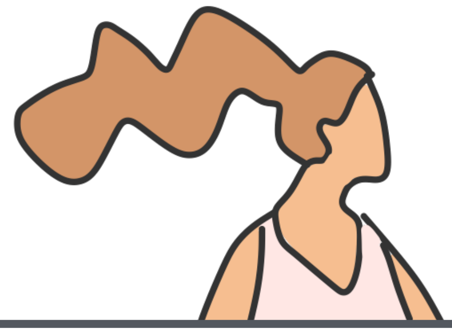
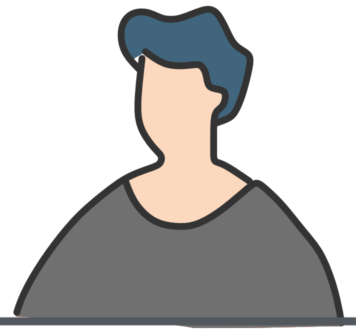
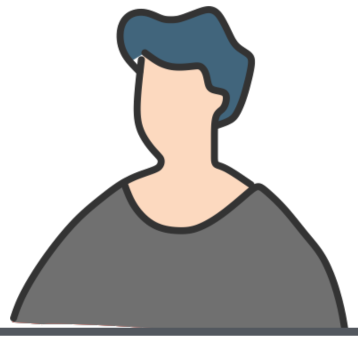
LAYOUTS

VIEW OPERATIONS	LAYOUT OPERATIONS	DATA OPERATIONS

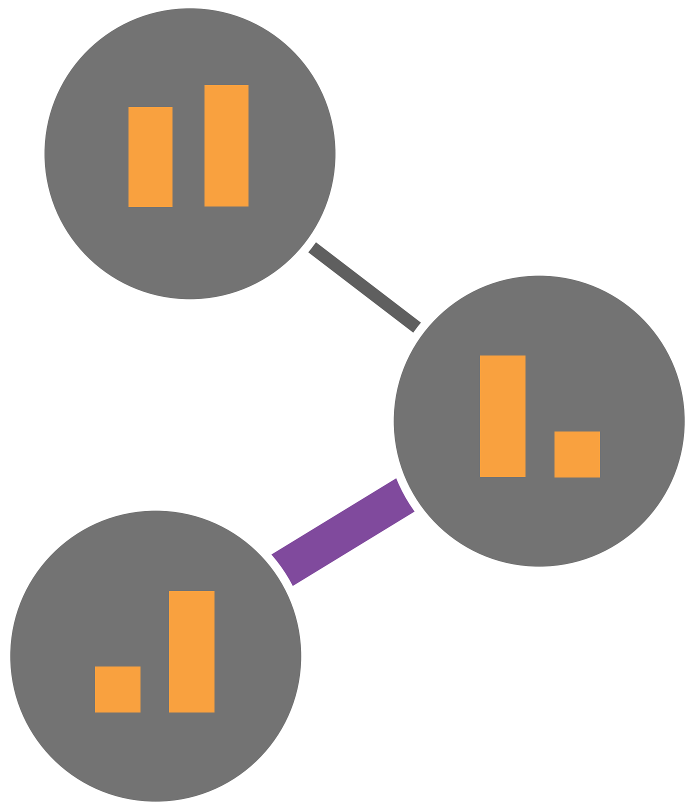

Friends
Friends
Co-workers
Mother
Tom
Abby
Jon
Sue
Mark
Cole
Dating
Married
Soccer Coach

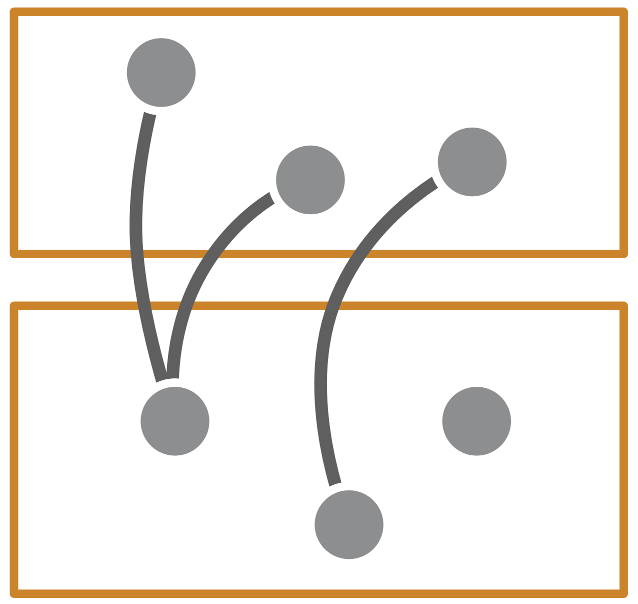


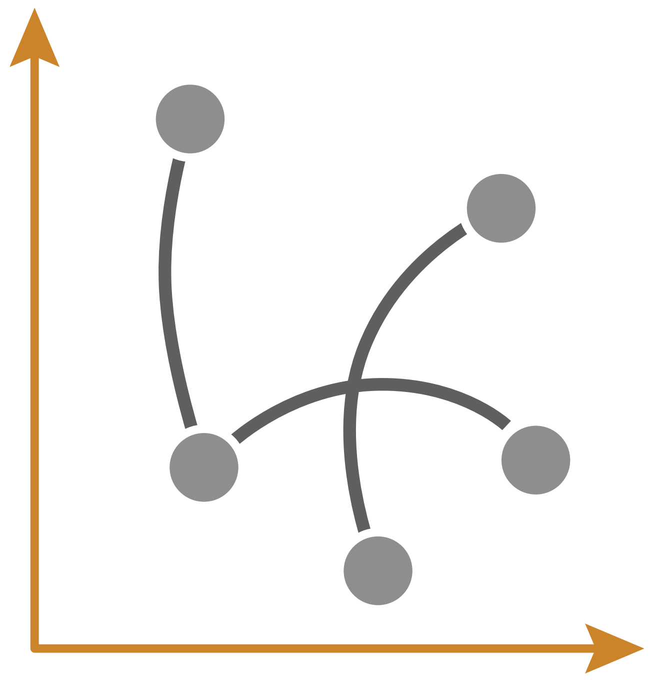
Name	Cole	Tom	Abby	Jon	Sue	Mark
Beverage	Port	Beer	Port	Coke	Coke	Beer
Day 1	1	0	4	3	3	5
Day 2	0	2	5	3	5	5
Day 3	4	1	2	2	4	3

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

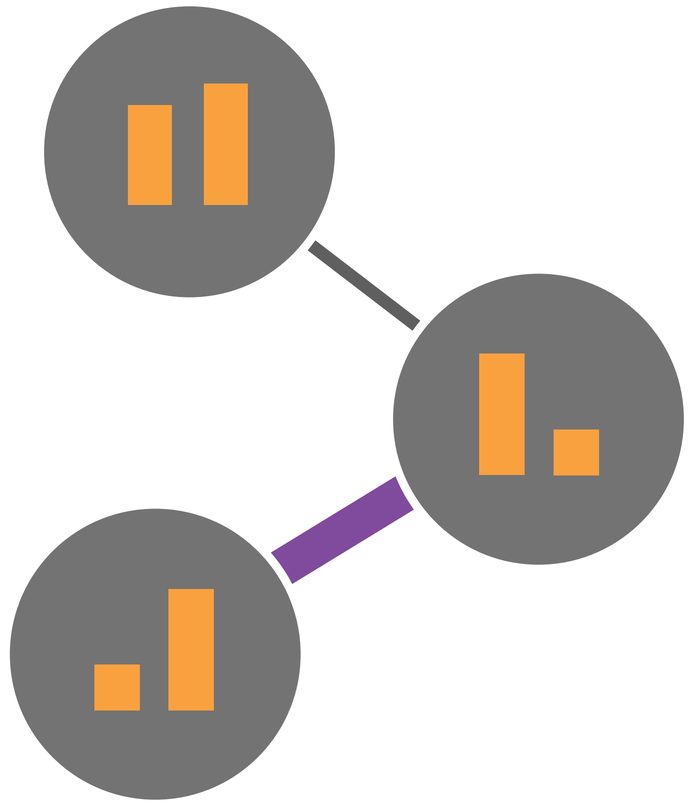
Node-Link Layouts



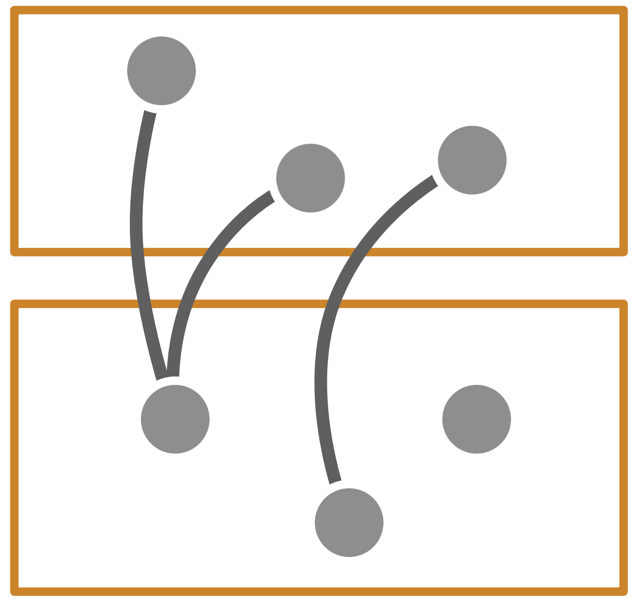


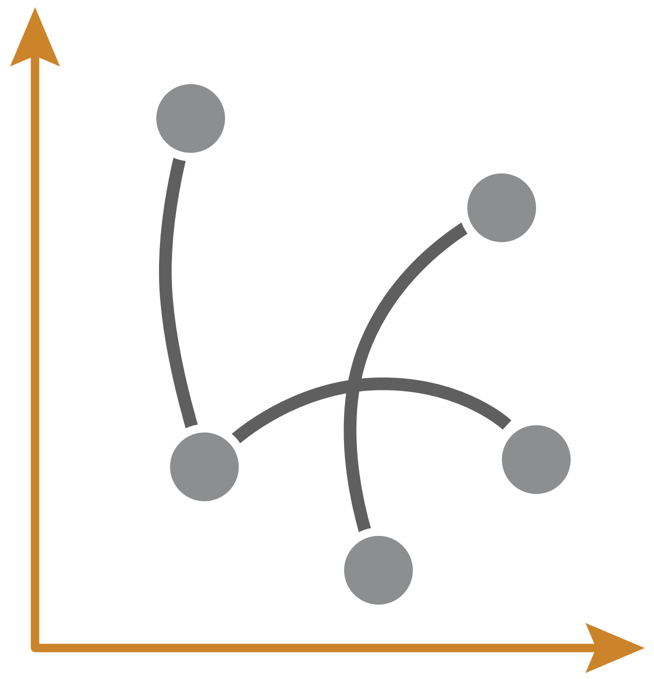


Topology Driven Layout

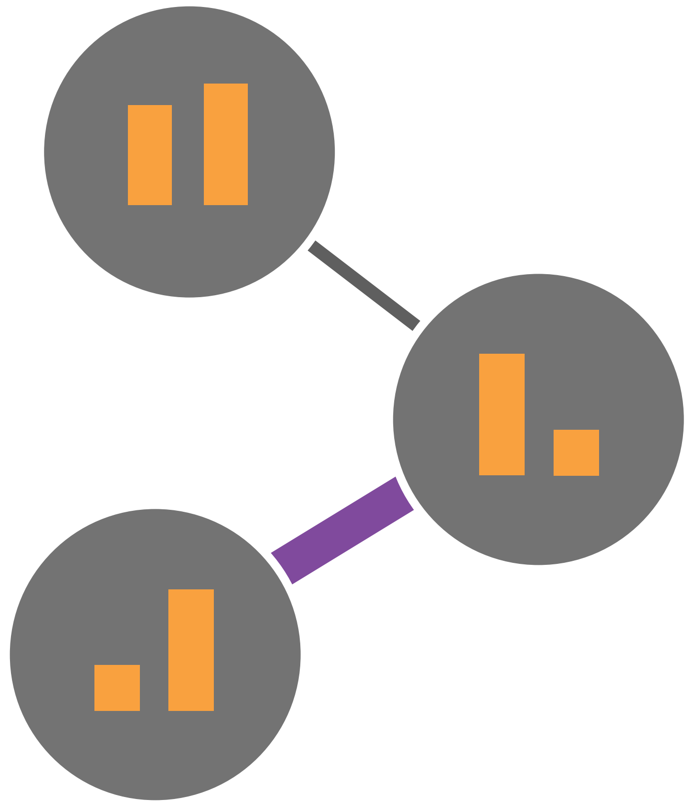


Attribute Driven Layouts



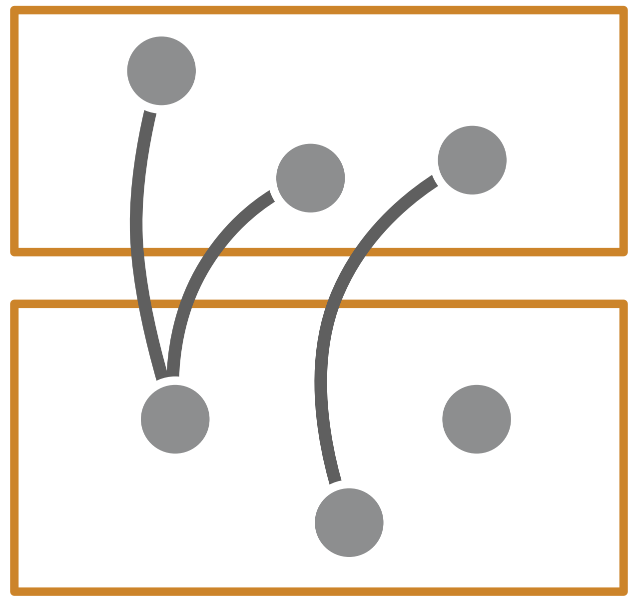


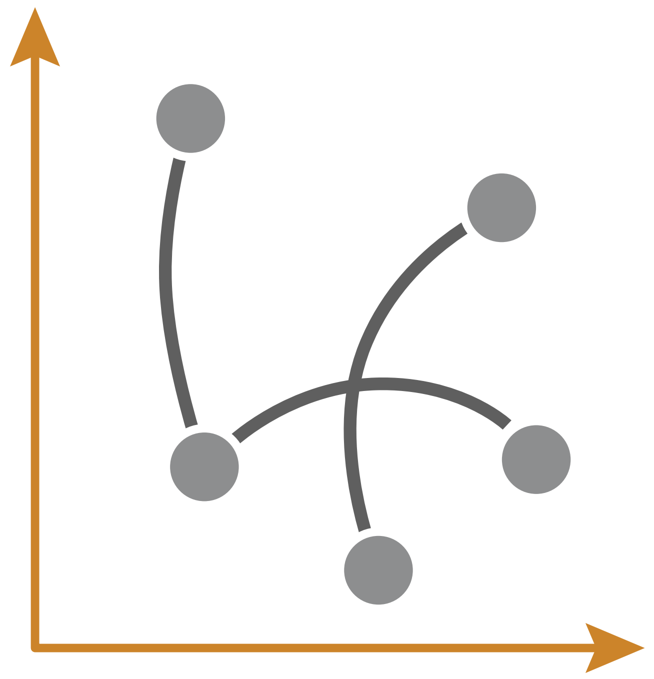
Topology Driven Layout



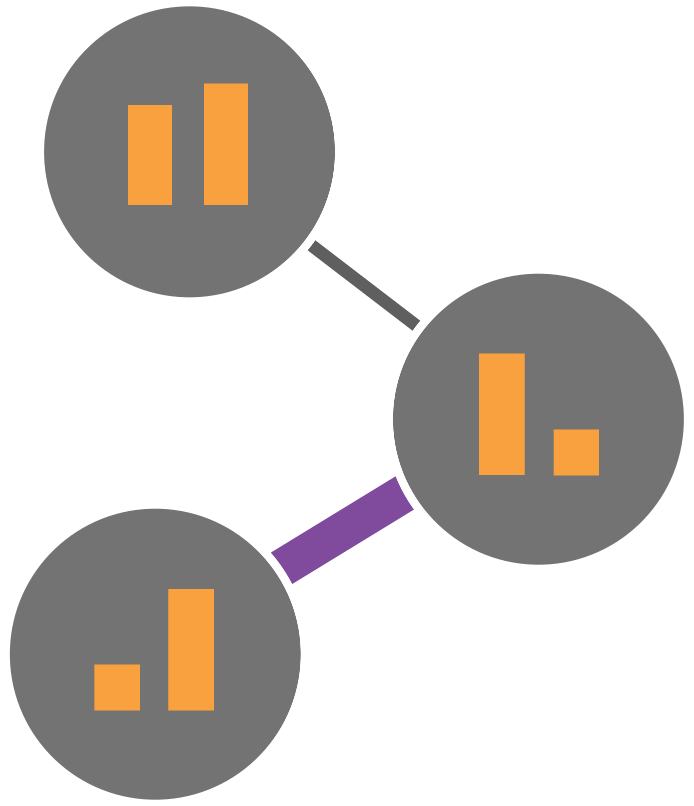
On-Node / On-Edge
Encoding

Attribute Driven Layouts



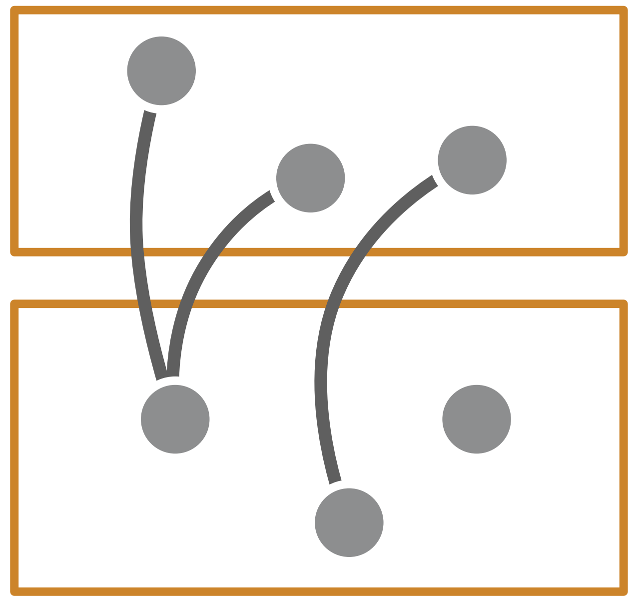


Topology Driven Layout

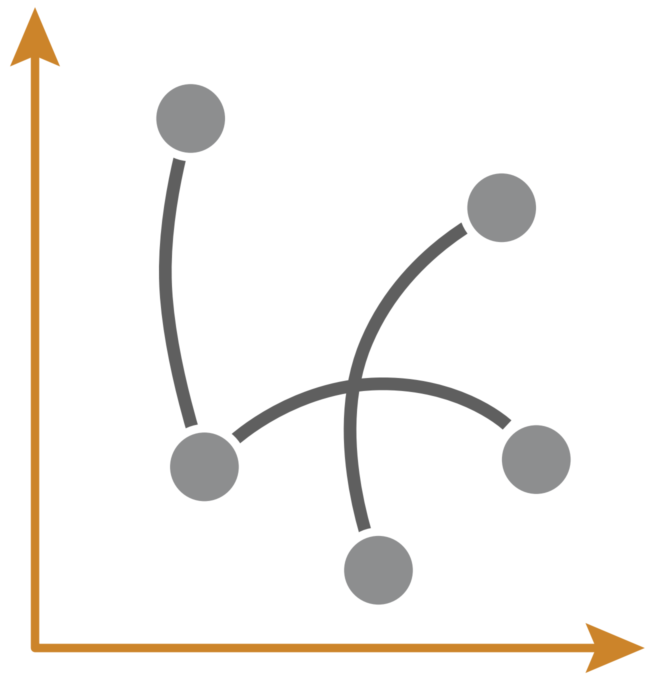


On-Node / On-Edge Encoding

Attribute Driven Layouts

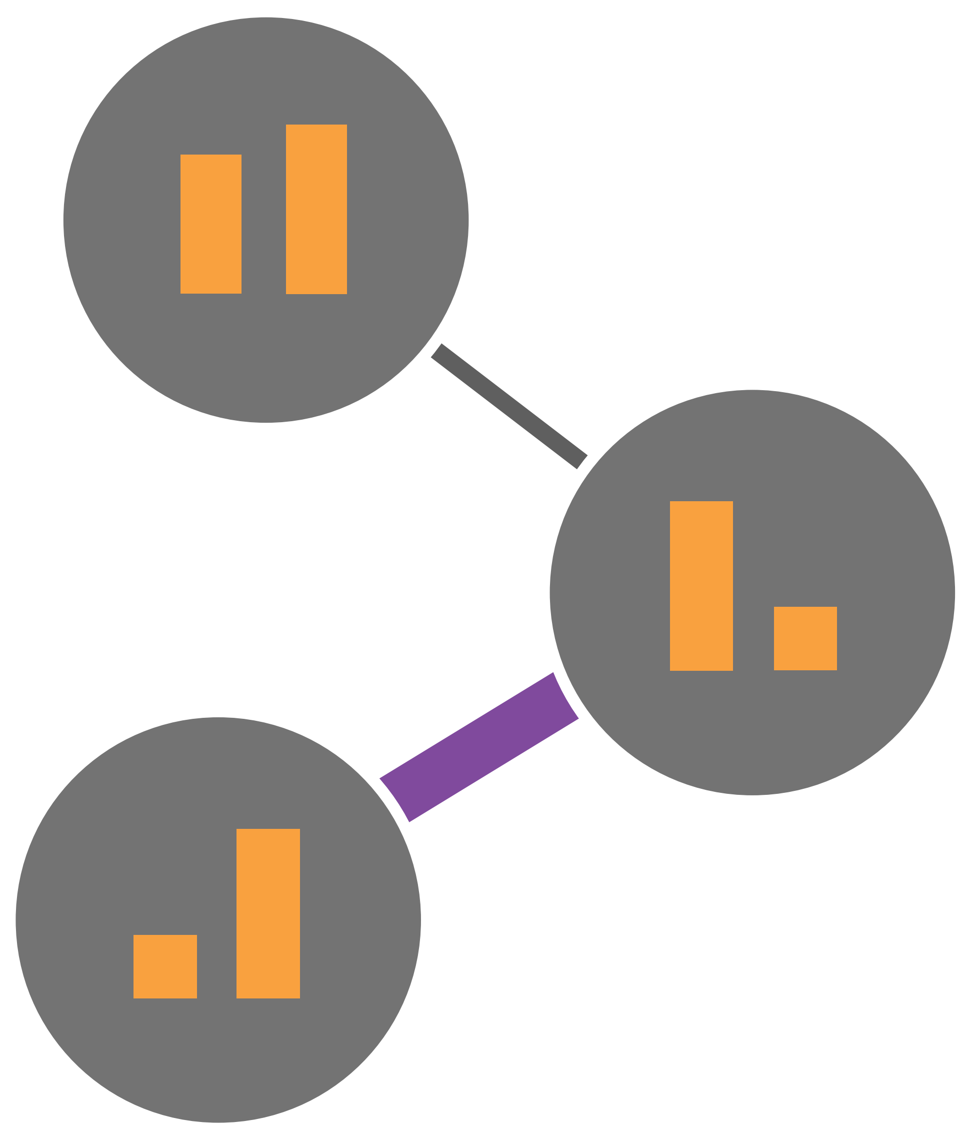


Attribute-Driven Faceting

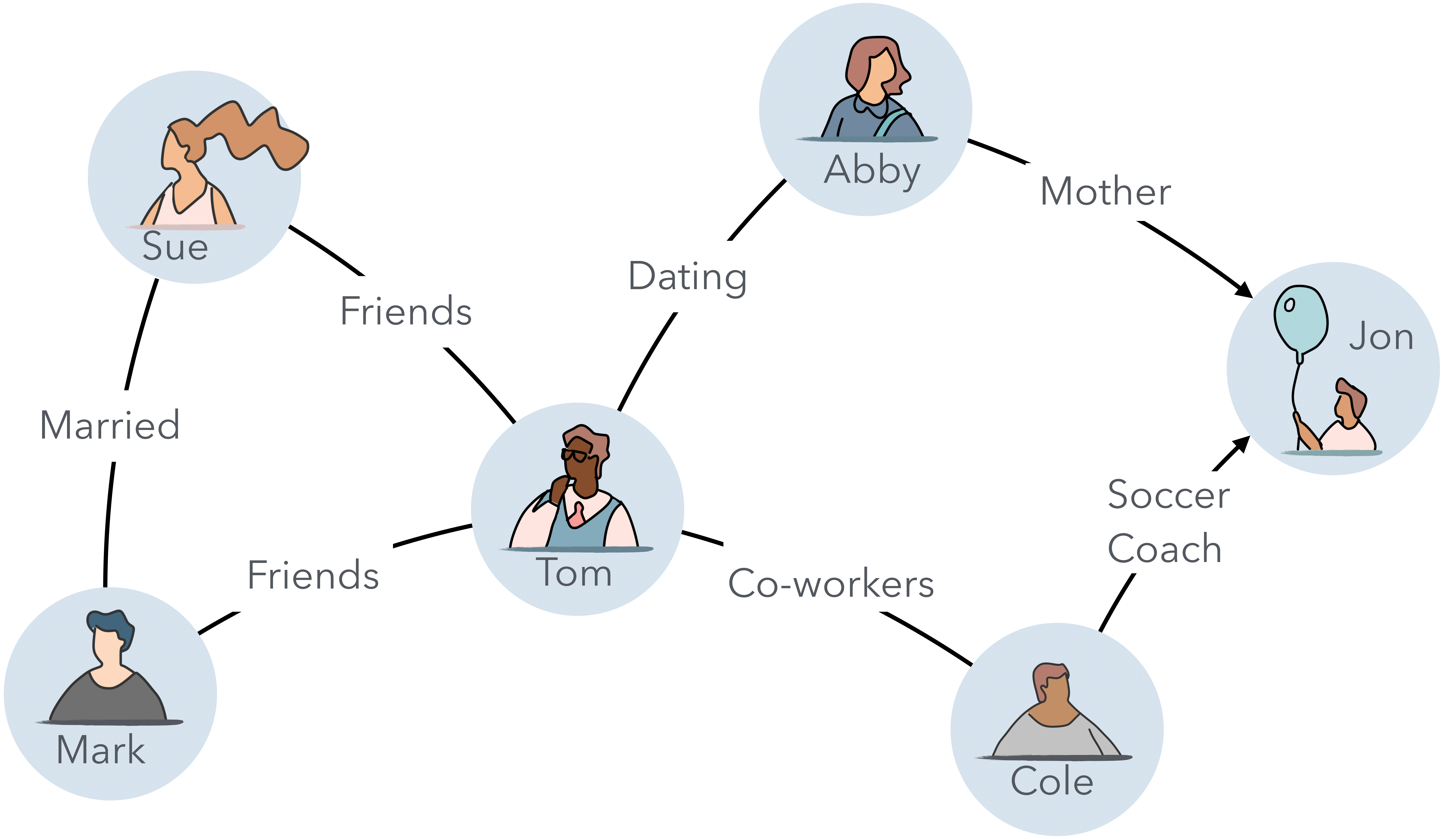


Attribute-Driven Positioning

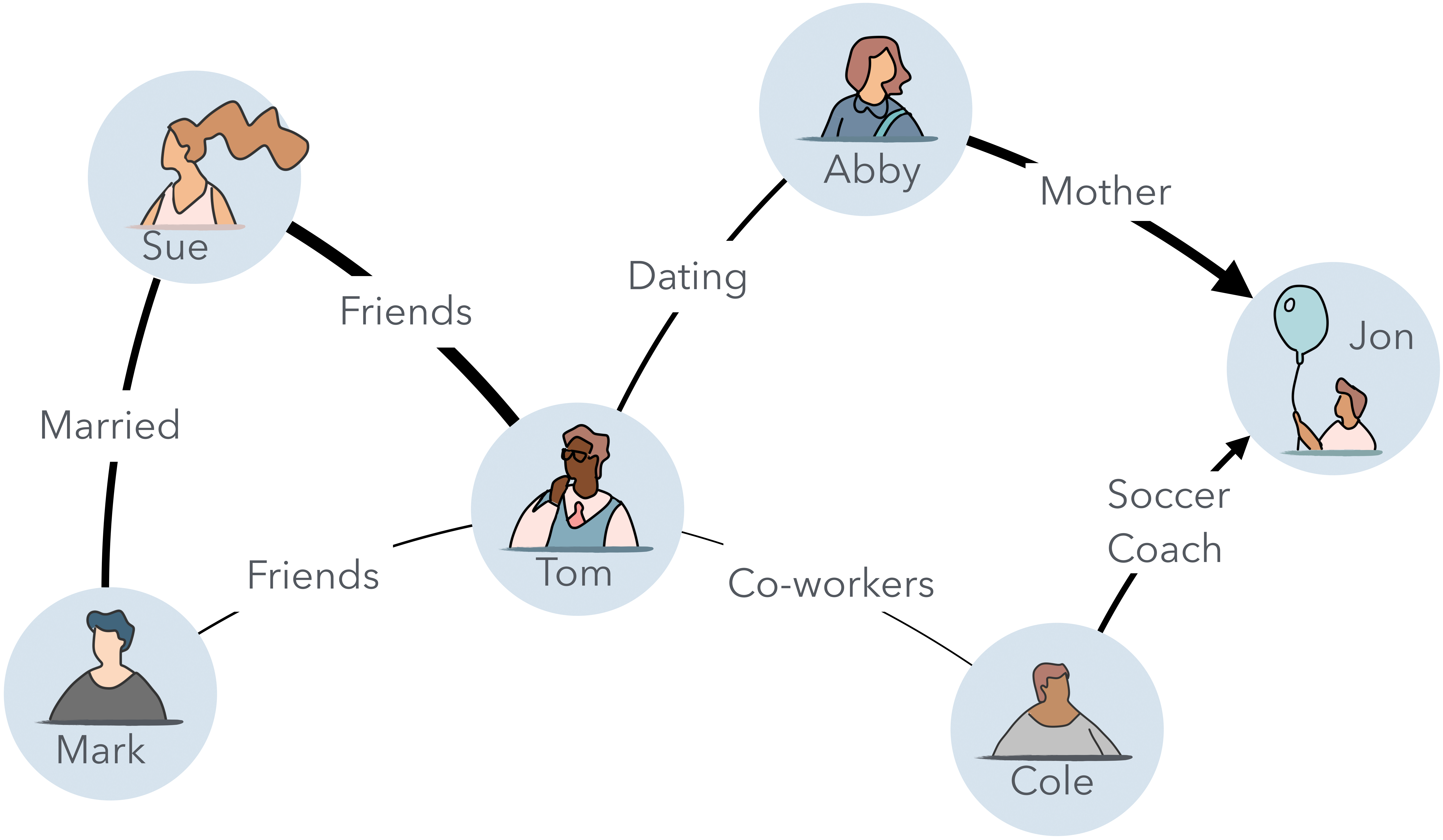
On-Node / On-Edge Encoding

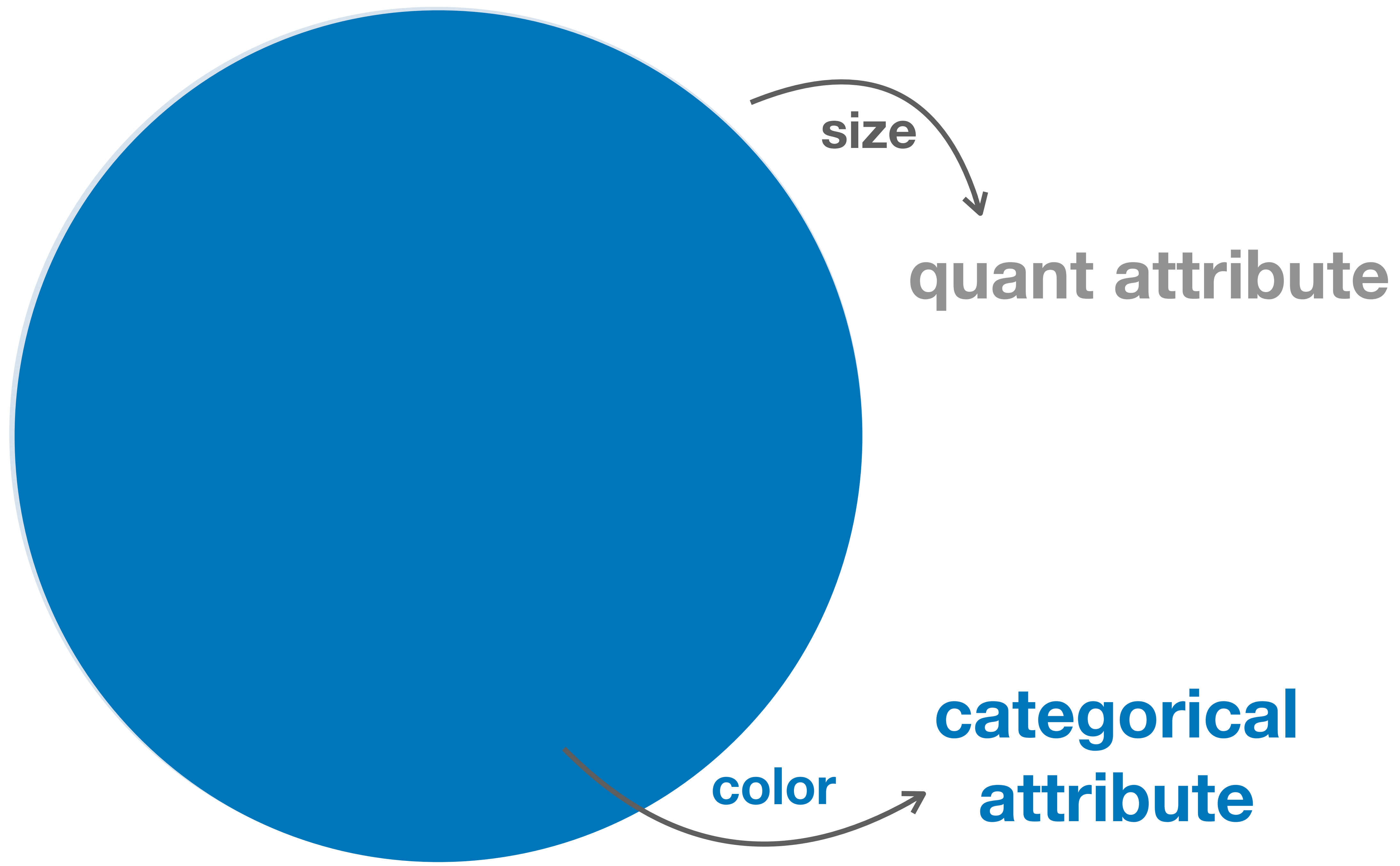


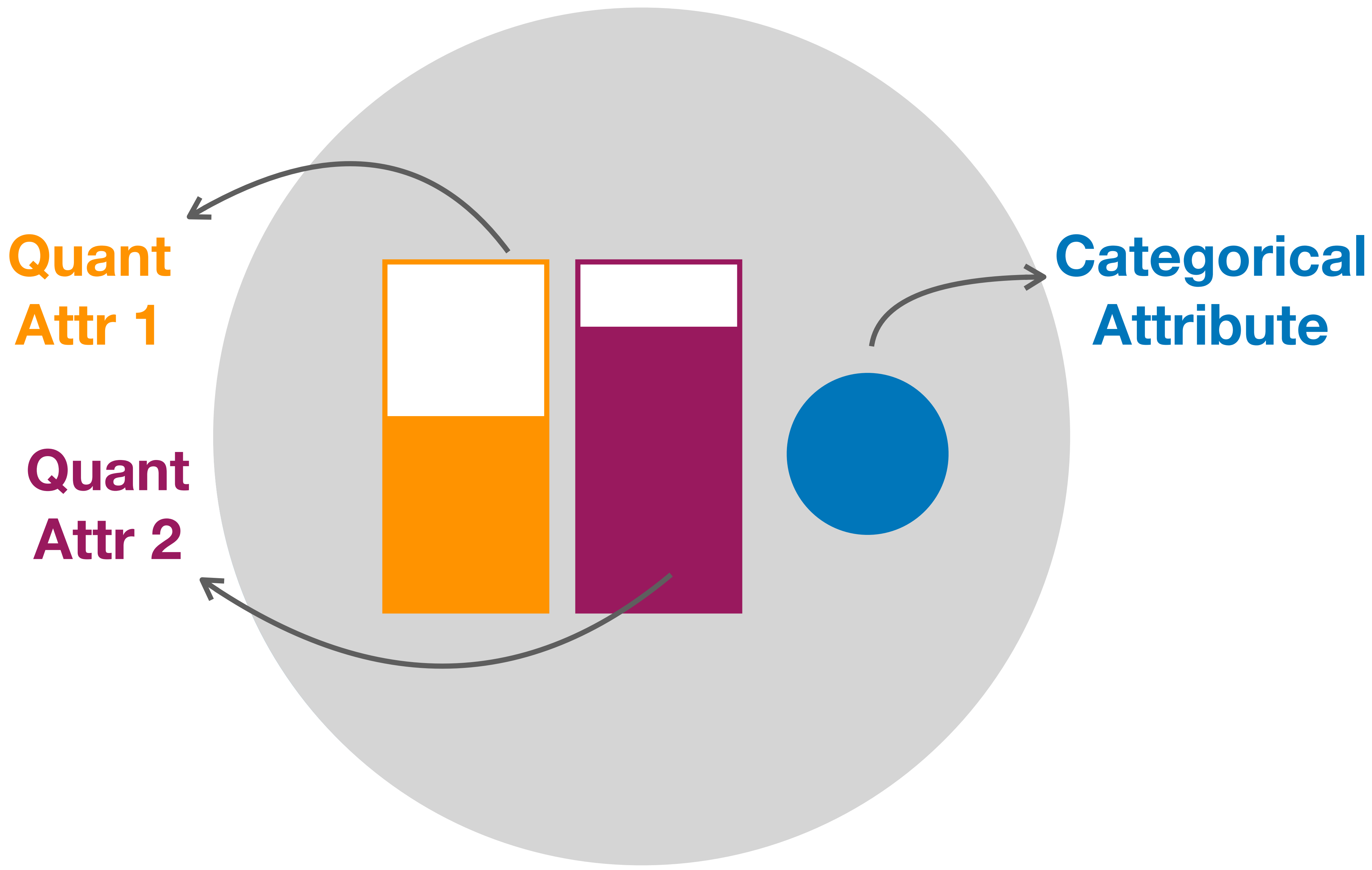

Mark
Sue
Tom
Abby
Cole
Jon

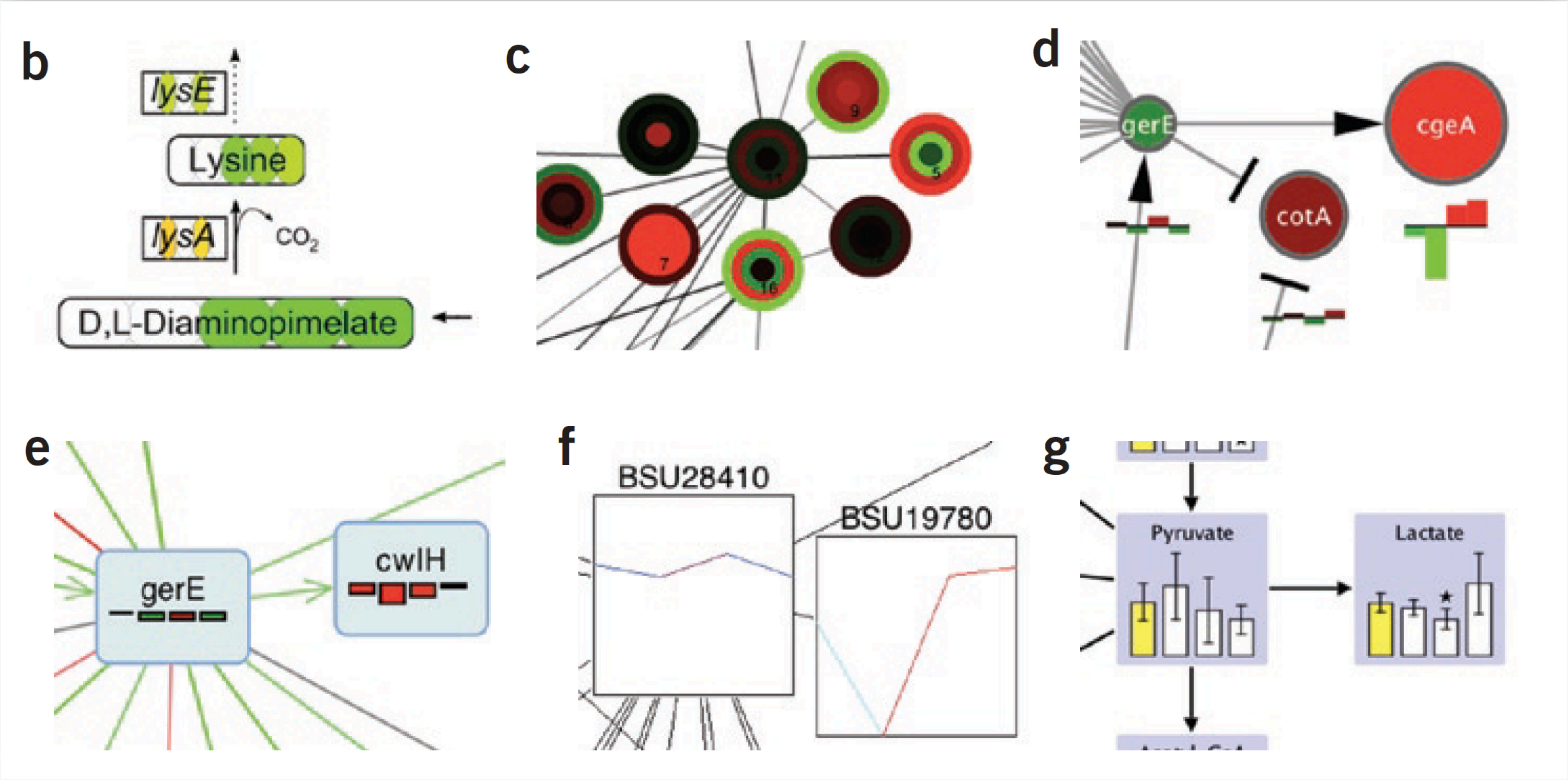


Abby
Sue
Mother
Dating
Friends
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole

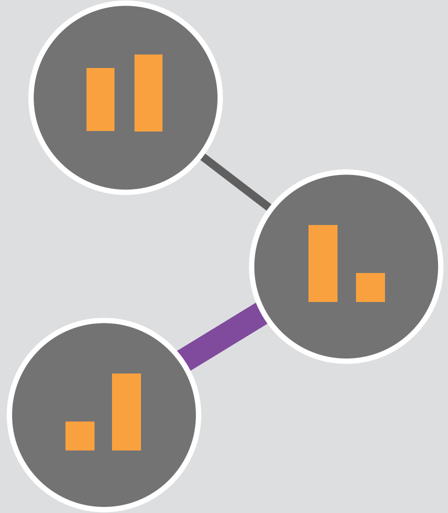

Sue
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole


size
quant attribute
color
categorical attribute

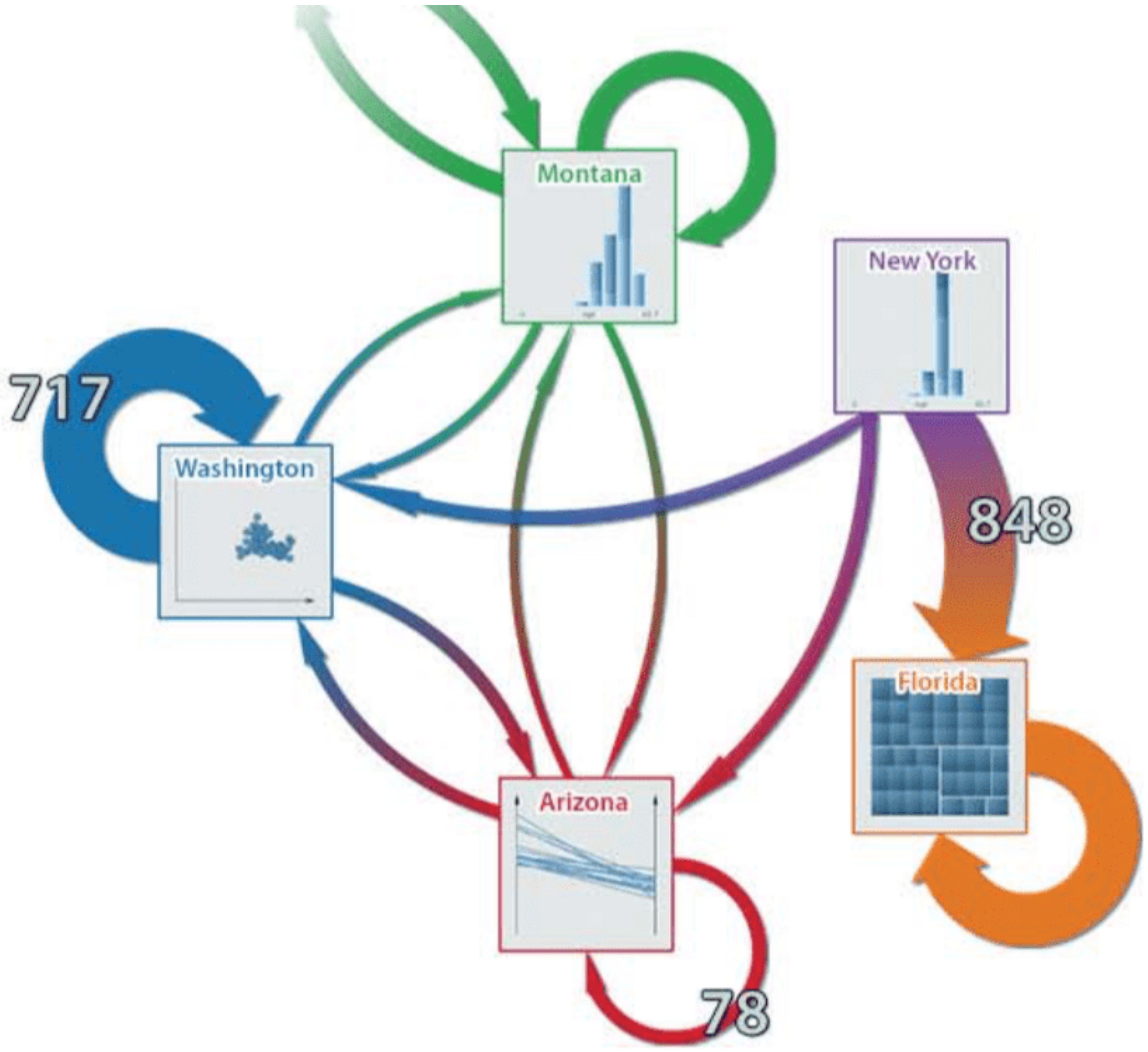

Quant
Attr 1
Quant
Attr 2
Categorical
Attribute



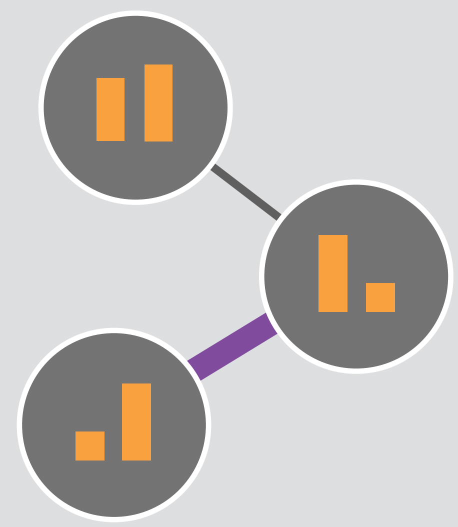
Gehlenborg et al. 2010



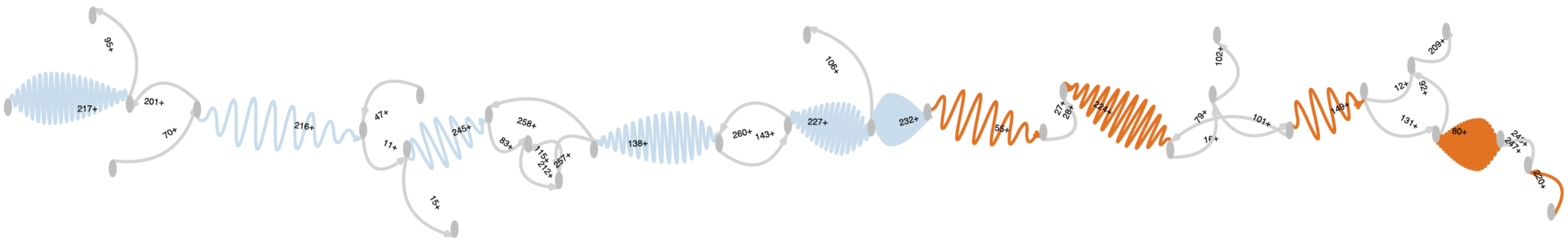
On-Node / On-Edge Encoding



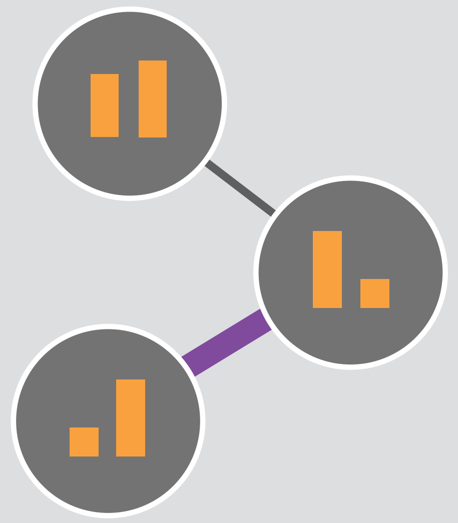
Elzen and Wijk, 2014



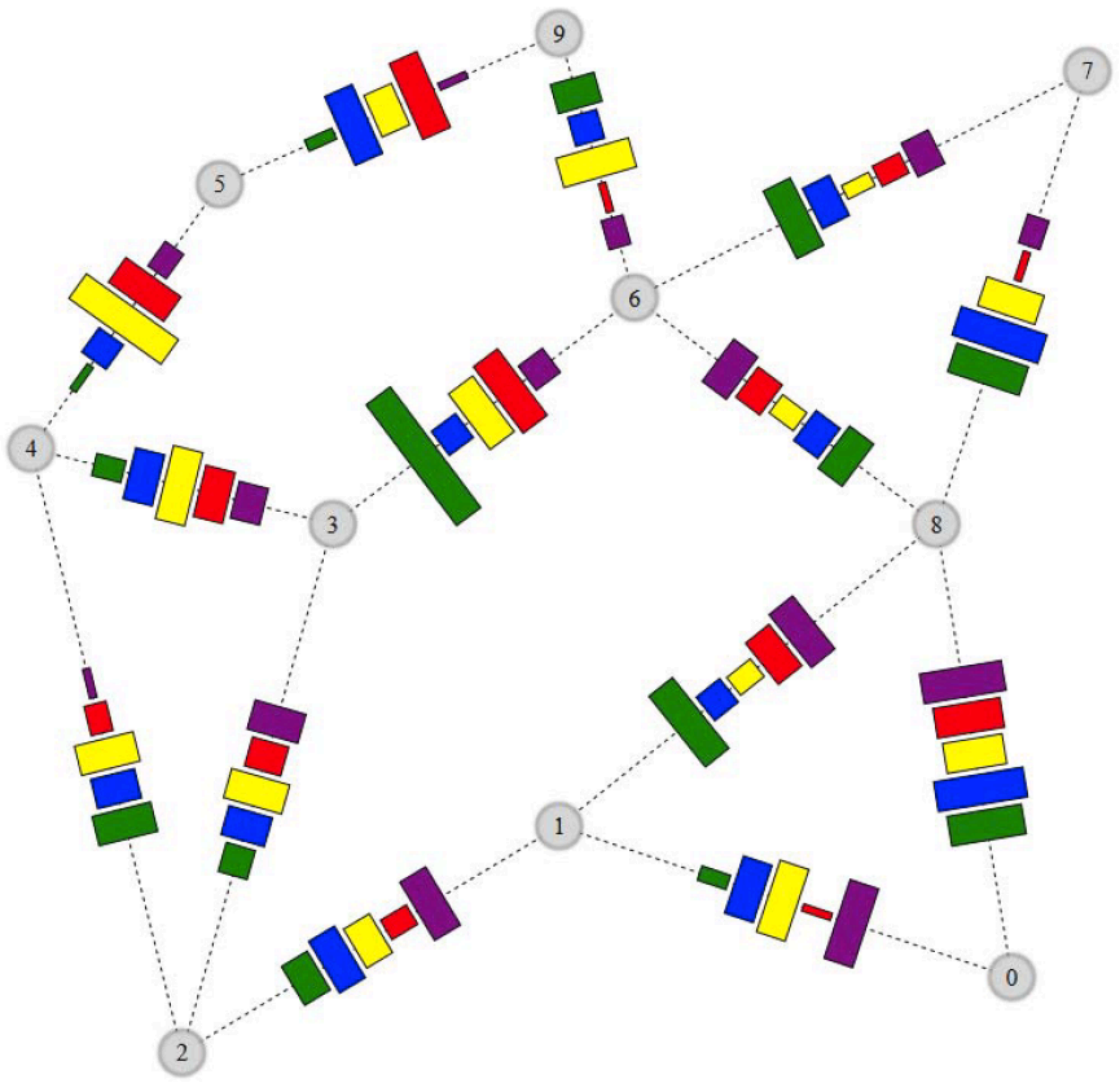
On-Node / On-Edge Encoding

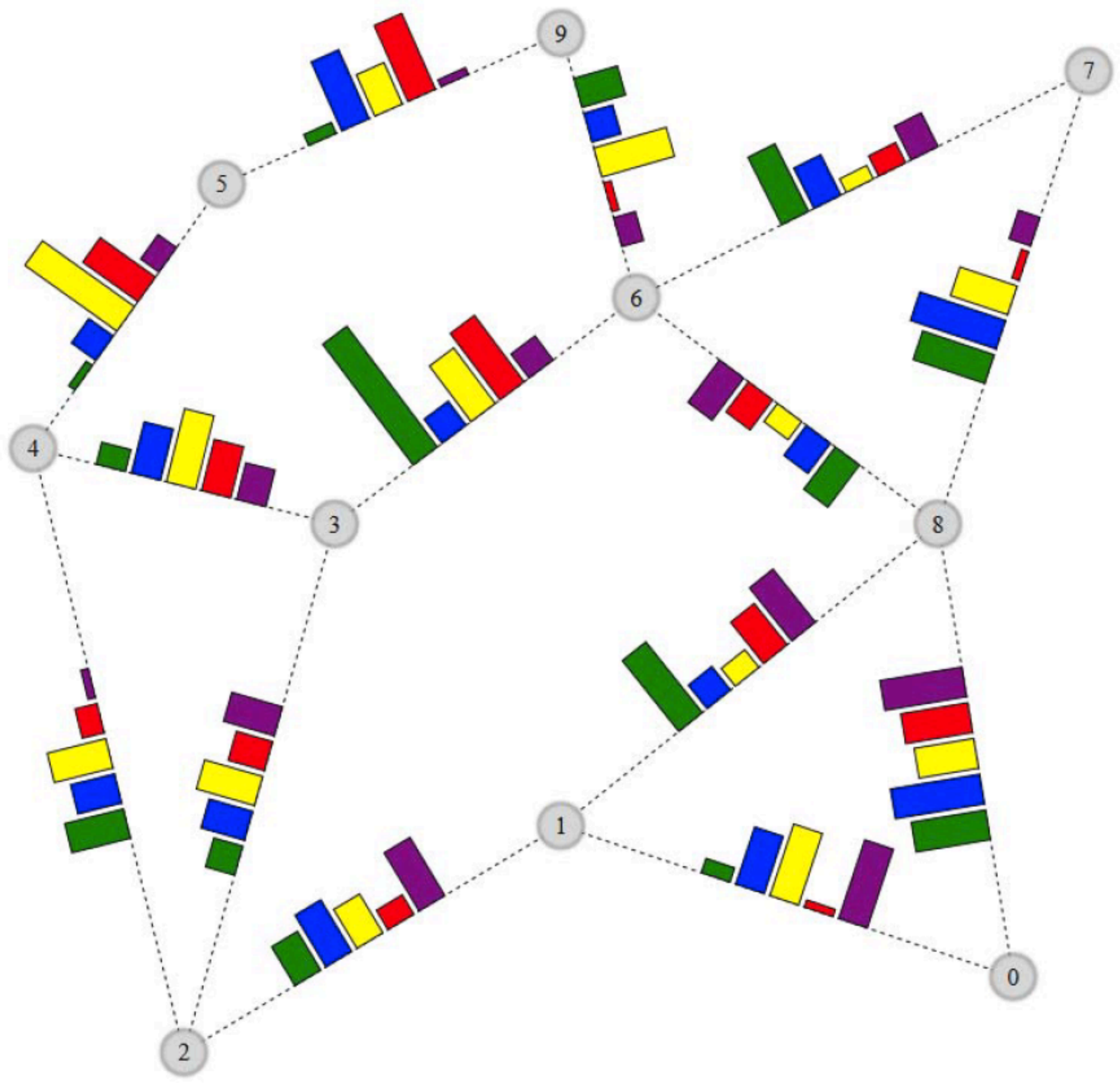


Nielsen, 2009

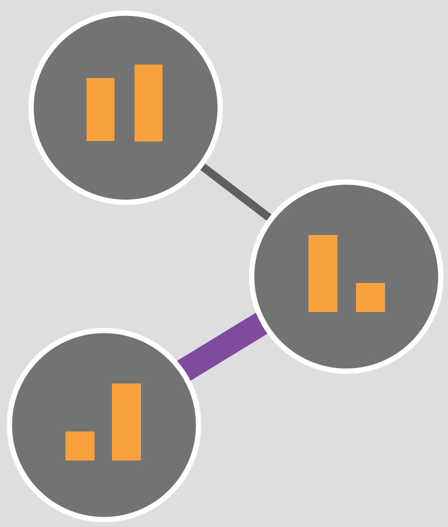


On-Node / On-Edge
Encoding

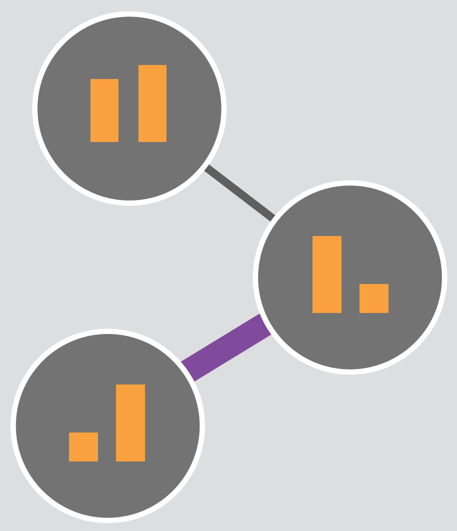




Schöffel et al, 2016



On-Node / On-Edge Encoding



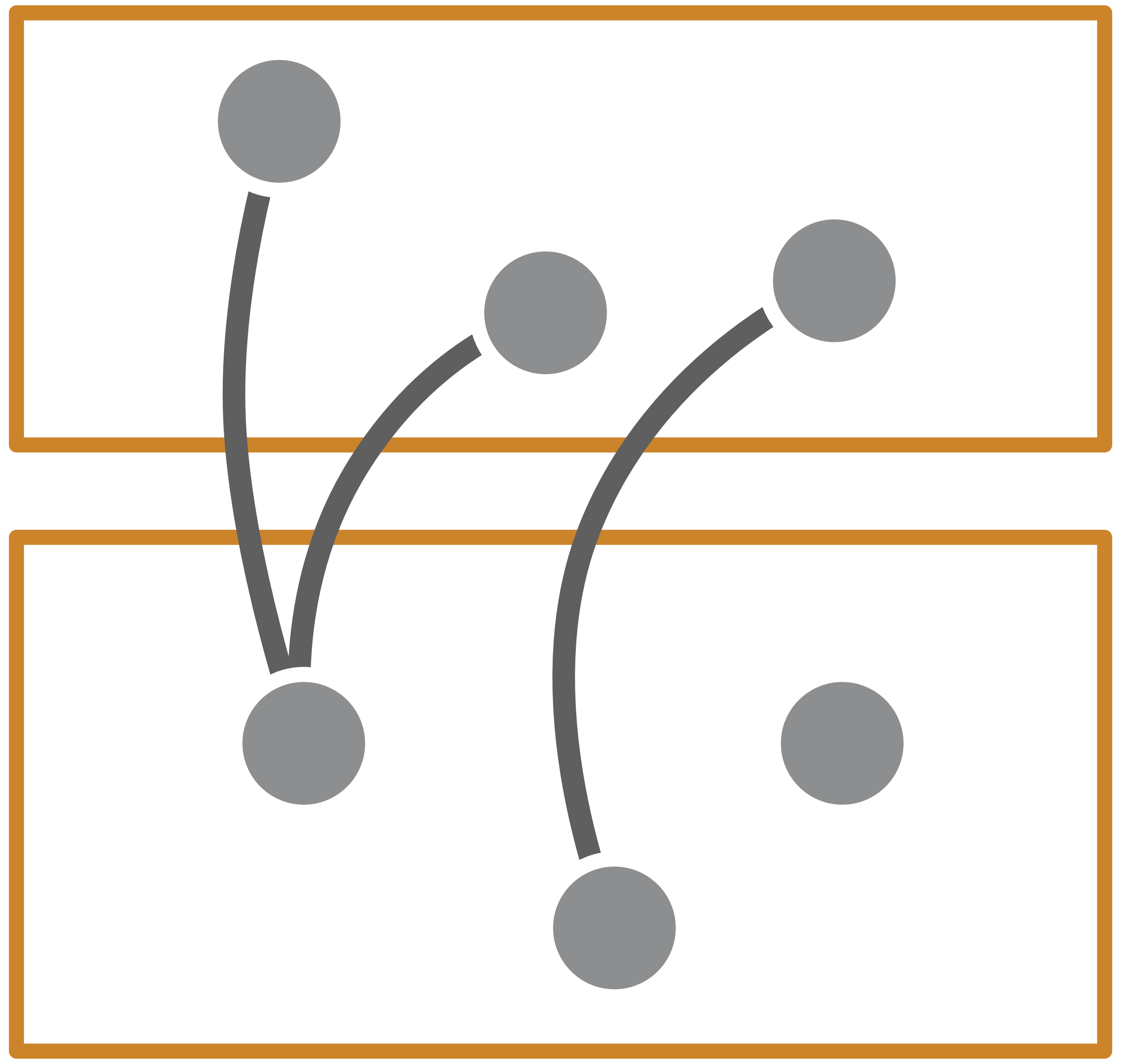
On-Node / On-Edge Encoding

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

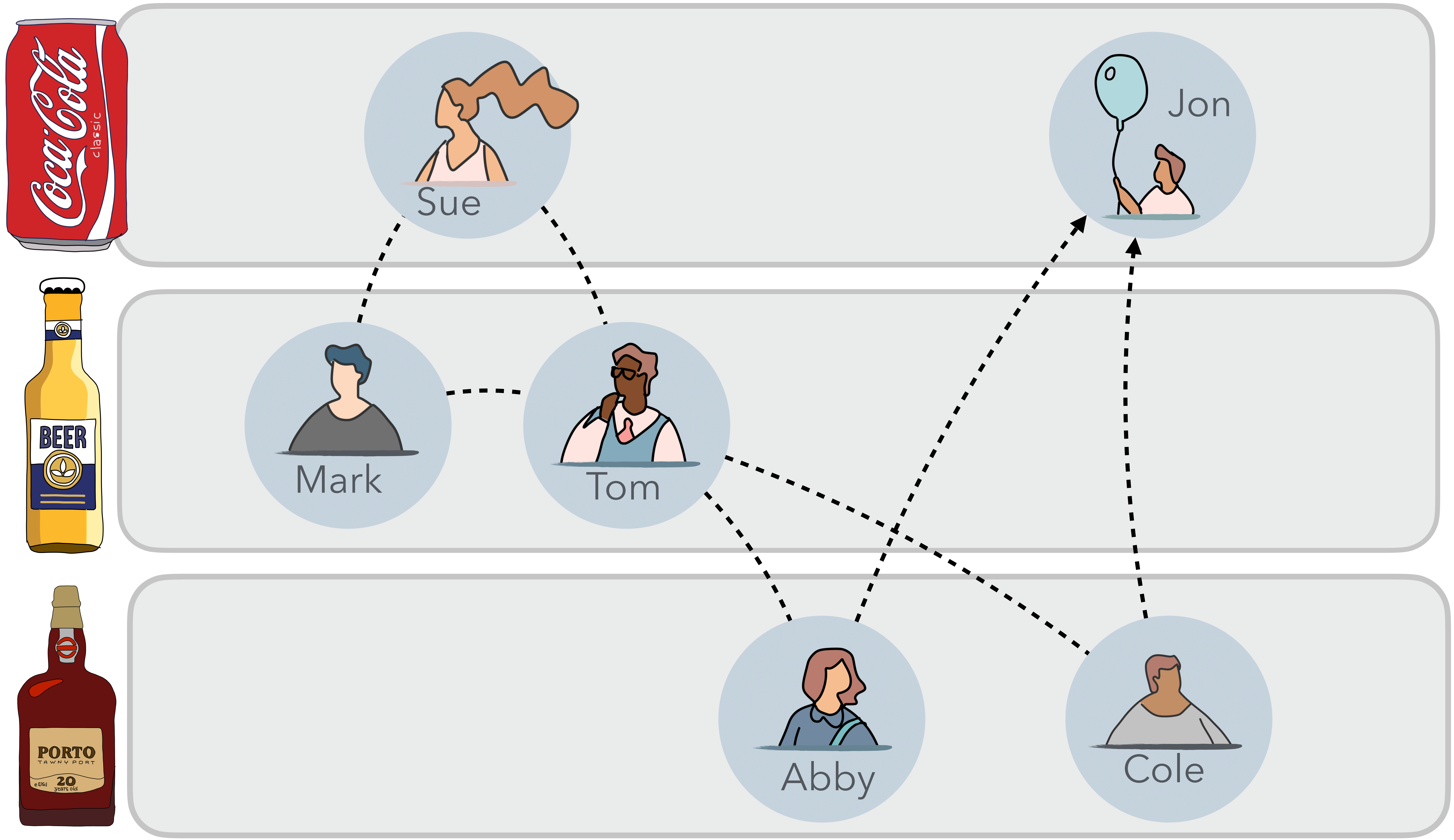


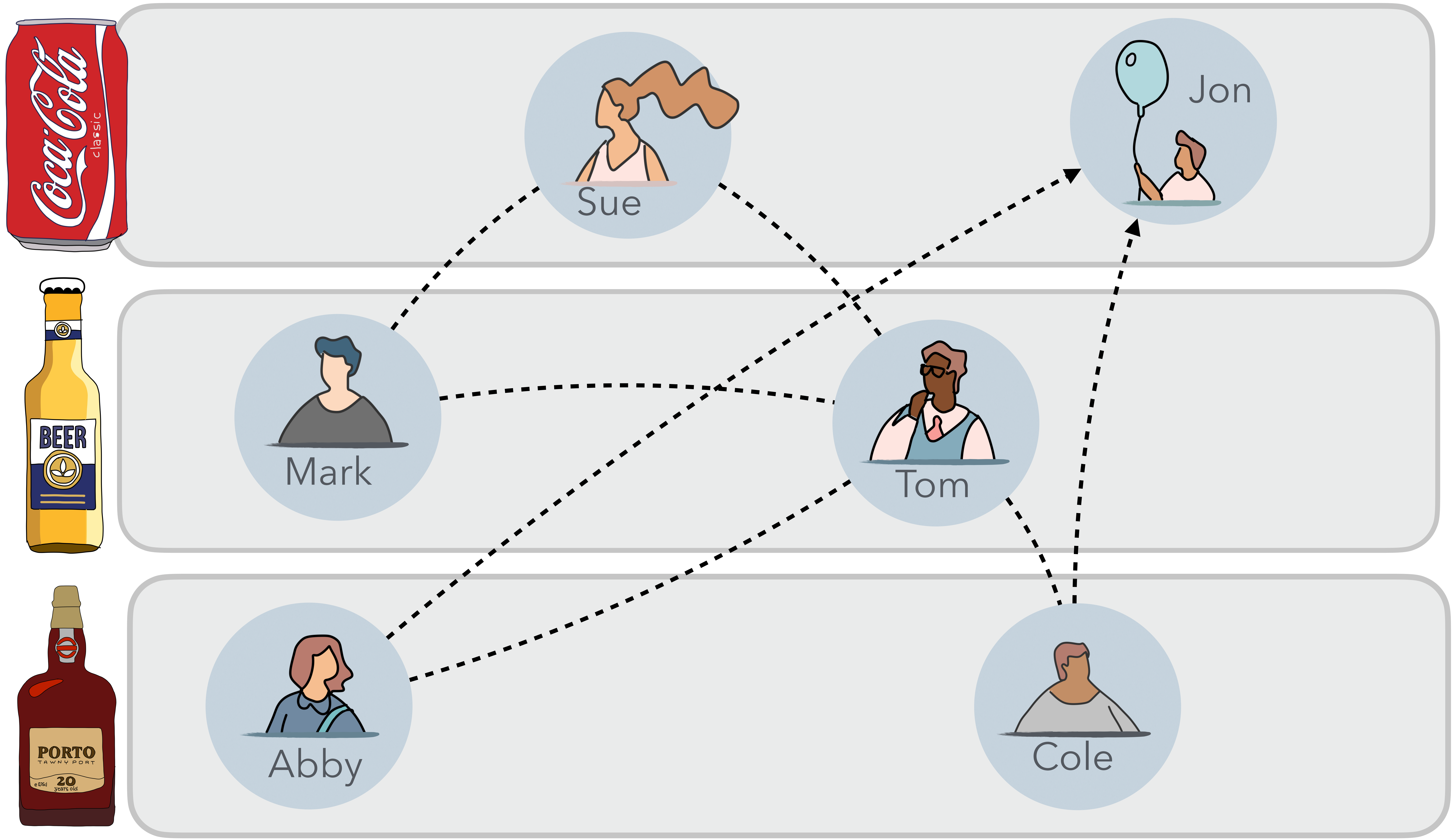

Coca-Cola
classic
BEER
PORTO
TAWNY PORT
e 0,75cl
20
years old


Coca-Cola
classic


BEER

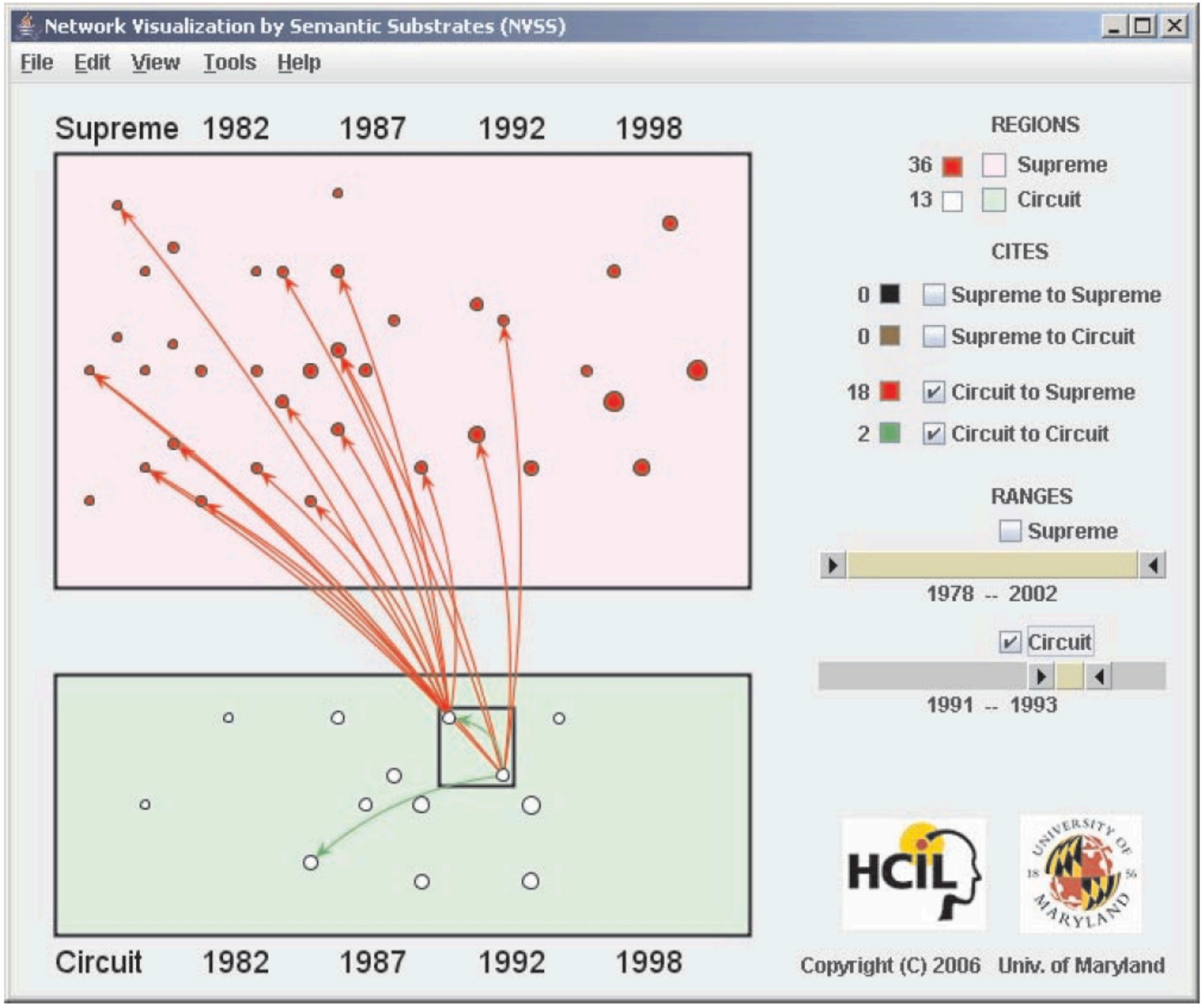

PORTO
TAWNY PORT
20
years old

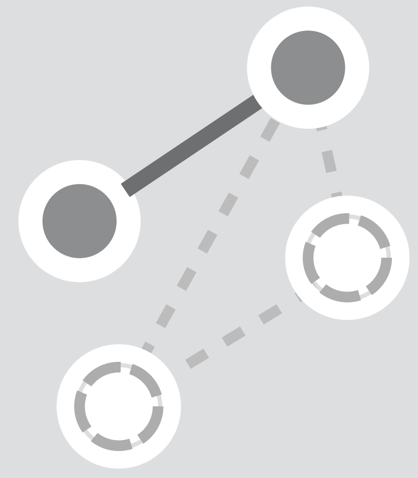

Coca-Cola classic
BEER
PORTO
TAWNY PORT
20
years old
Sue
Jon
Mark
Tom
Abby
Cole



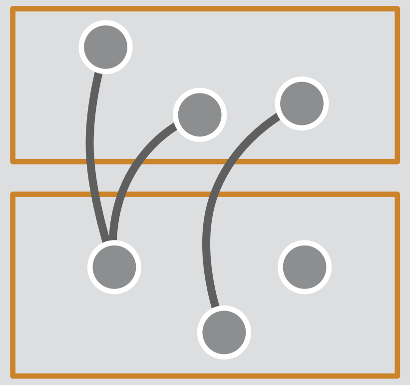
Coca-Cola
classic
BEER
PORTO
TAWNY PORT
20
years old
Sue
Jon
Mark
Tom
Abby
Cole

Semantic Substrates *Shneiderman and Aris, 2006*

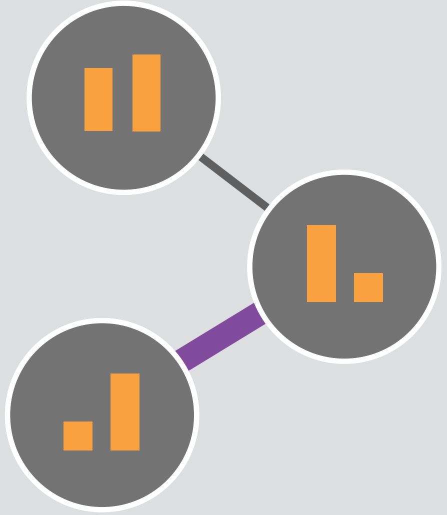




Querying and Filtering

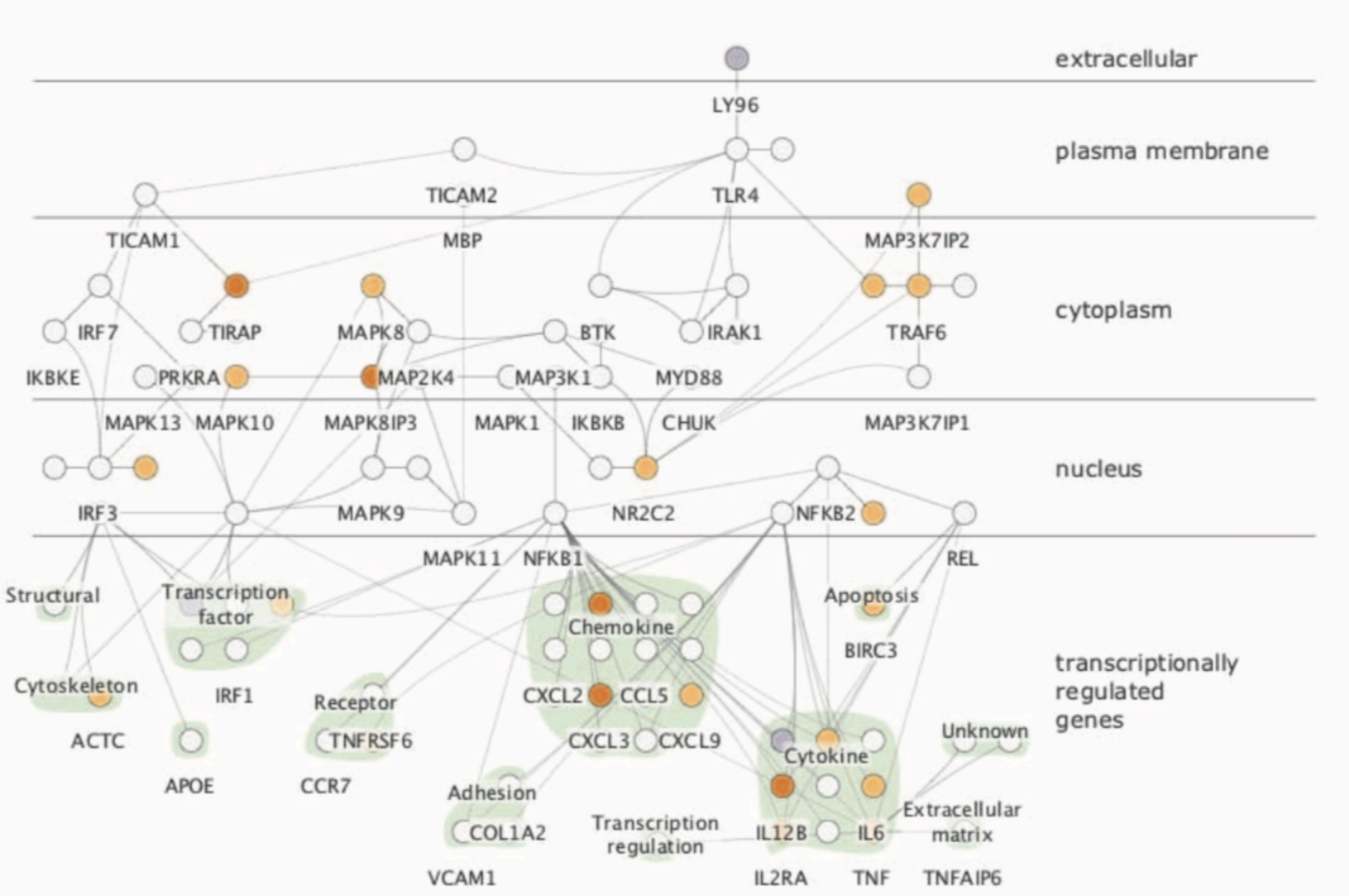


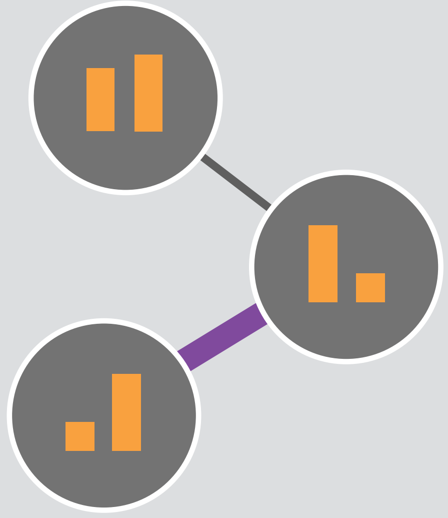
Attribute-Driven Faceting



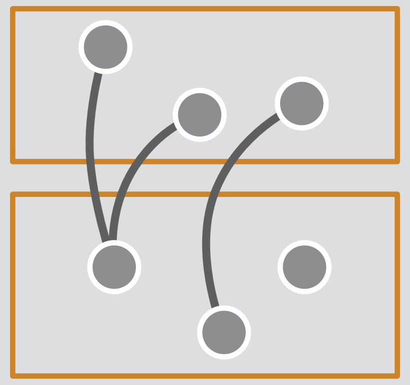
On-Node / On-Edge Encoding

Cerebral *Barskey et al. 2008*

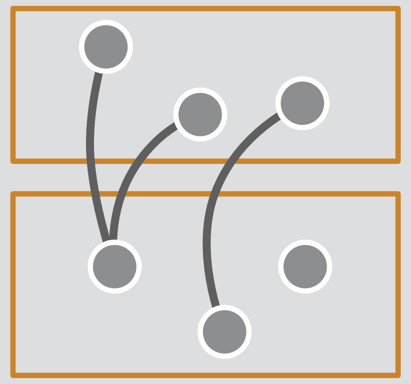




On-Node / On-Edge Encoding



Attribute-Driven Faceting



Attribute-Driven Faceting

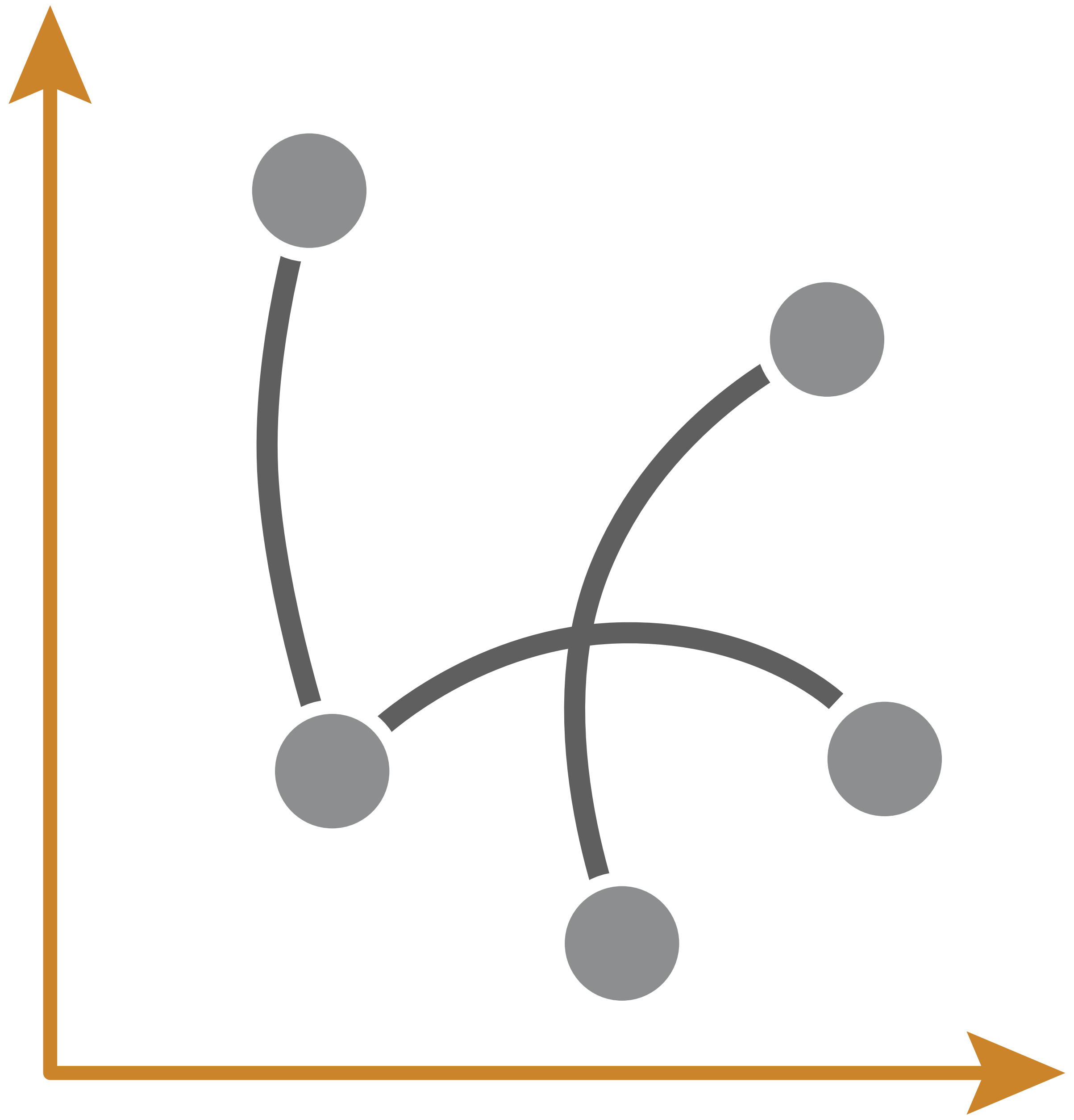
Well suited for networks with different node types or with an important categorical or set-like attribute.

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.

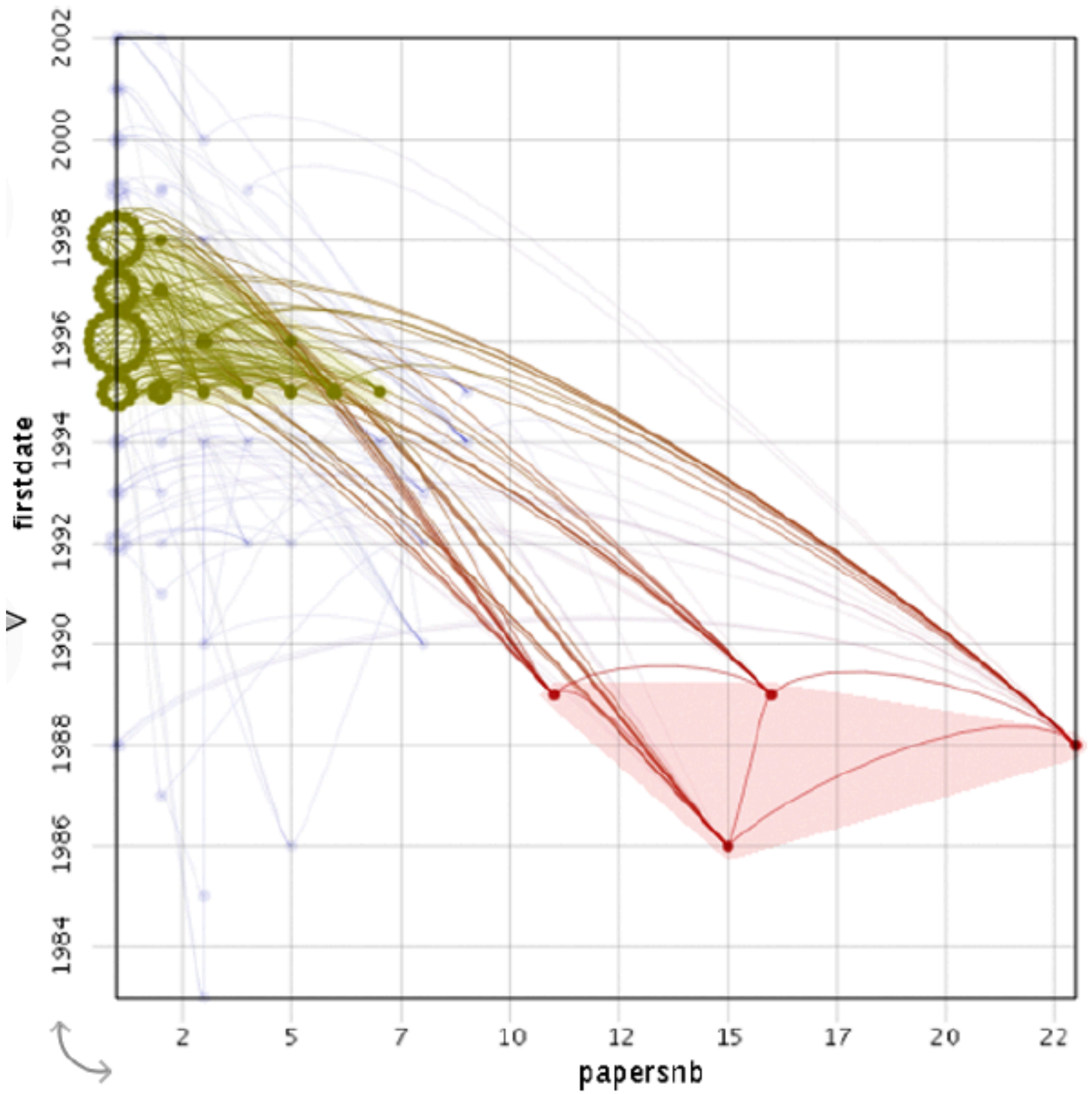
Recommended for networks where nodes can be separated into groups easily and where these groups are central to the analysis

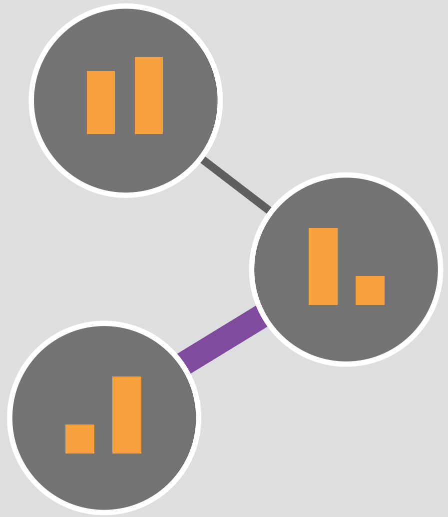
Attribute-Driven Positioning



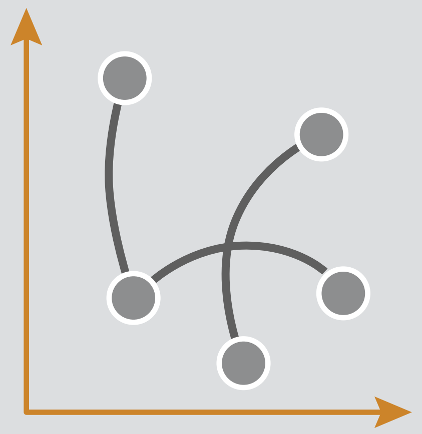

ANCHORAGE
VANCOUVER
EDMONTON
SEATTLE
PORTLAND
SAN FRANCISCO
DENVER
MINNEAPOLIS / ST. PAUL
CHICAGO
KANSAS CITY
DALLAS
TORONTO
CLEVELAND
MONTREAL
BALTIMORE
WASHINGTON D.C.
PHILADELPHIA
NEW YORK
JFK & NEWARK
BOSTON
HALIFAX
TAMPA BAY
ORLANDO
ICELAND
HELSINKI
STOCKHOLM
OSLO
GOTHENBURG
BERGEN
COPENHAGEN
BILLUND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

Graph Dice *Bezerianos et al. 2010*



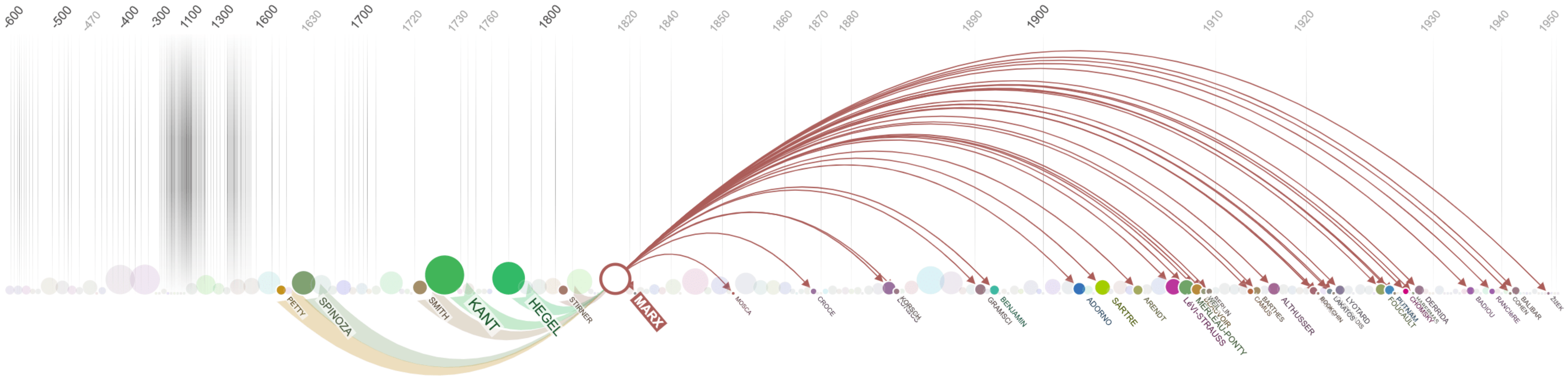


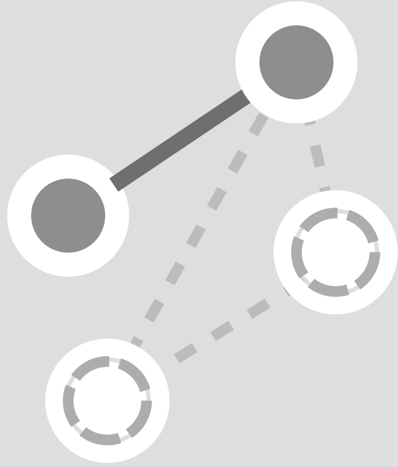
On-Node / On-Edge Encoding



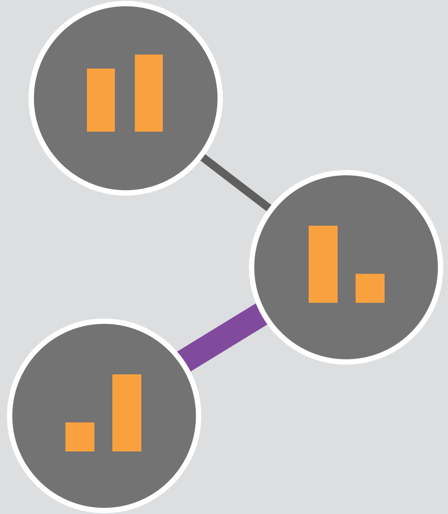
Attribute-Driven Positioning

Edge Map *Dork et al. 2011*

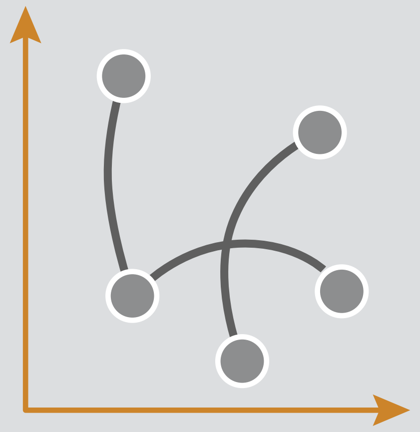




Querying and Filtering



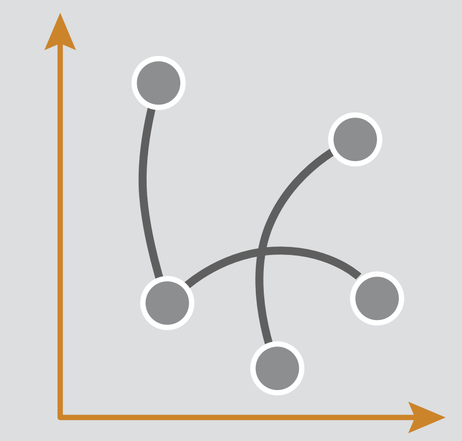
On-Node / On-Edge Encoding



Attribute-Driven Positioning

Well suited for quantitative attributes

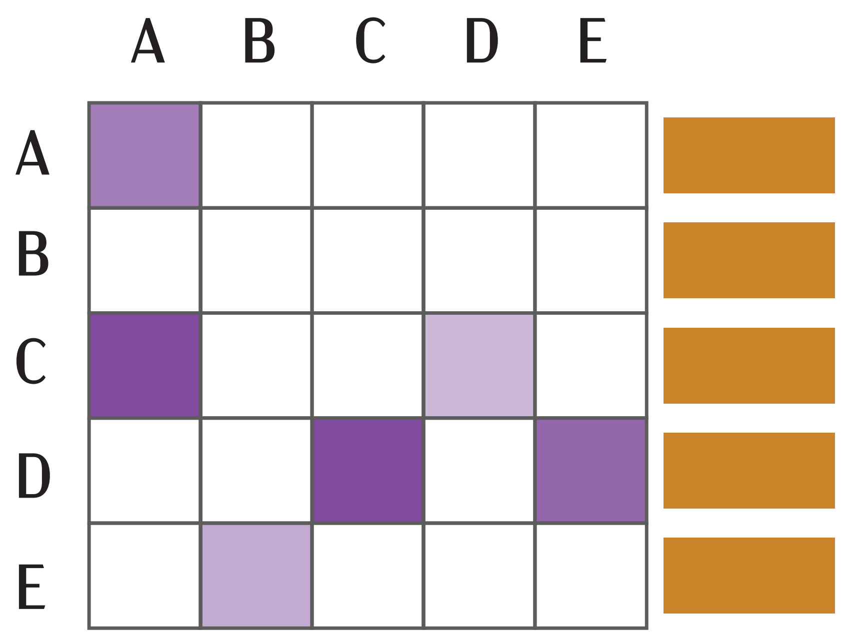
Does not lend itself well to visualizing the topology of the network.



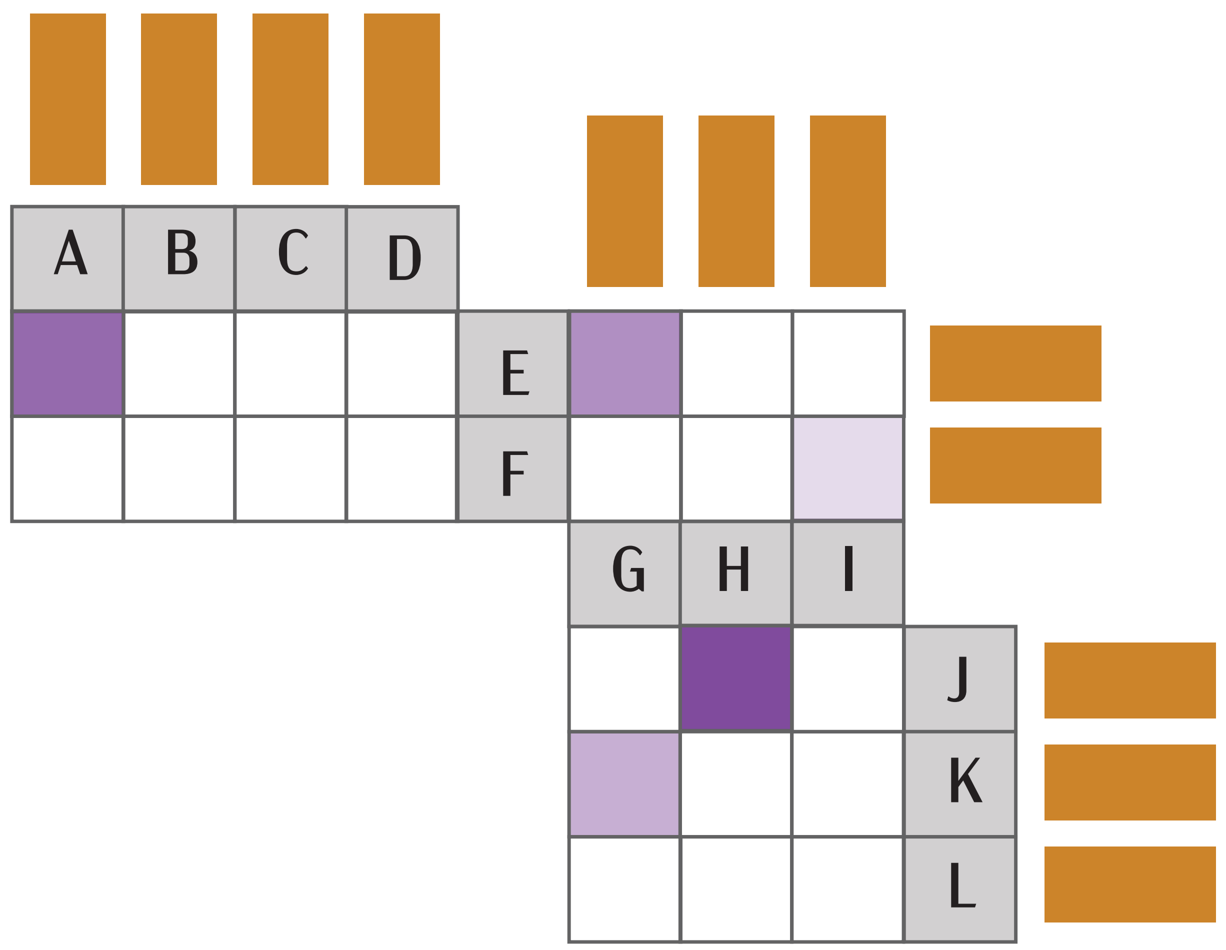
Attribute-Driven Positioning

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

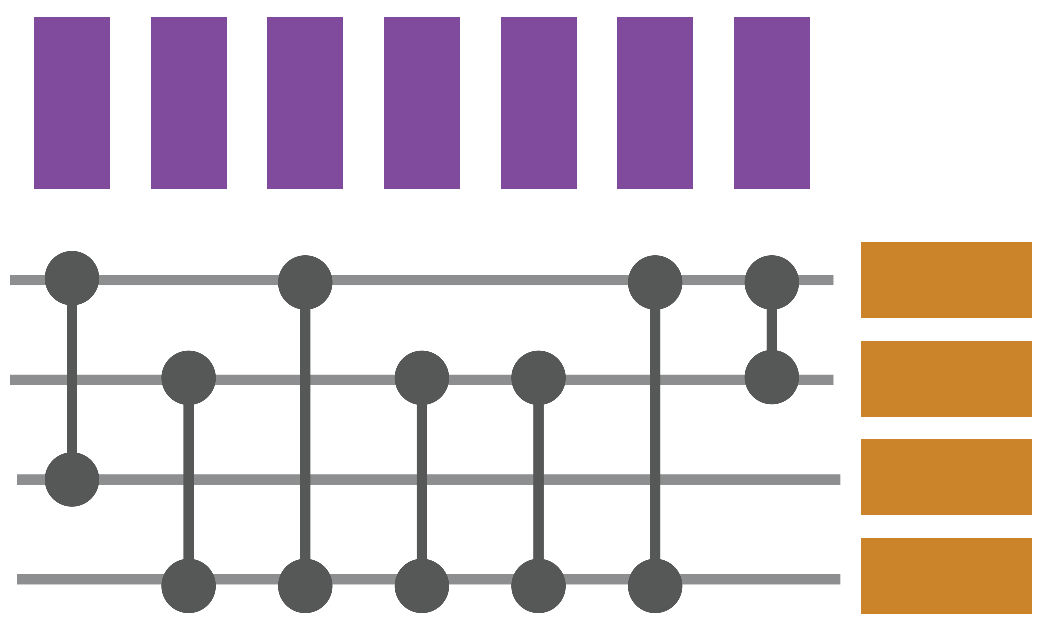
Tabular Layouts



Adjacency Matrix

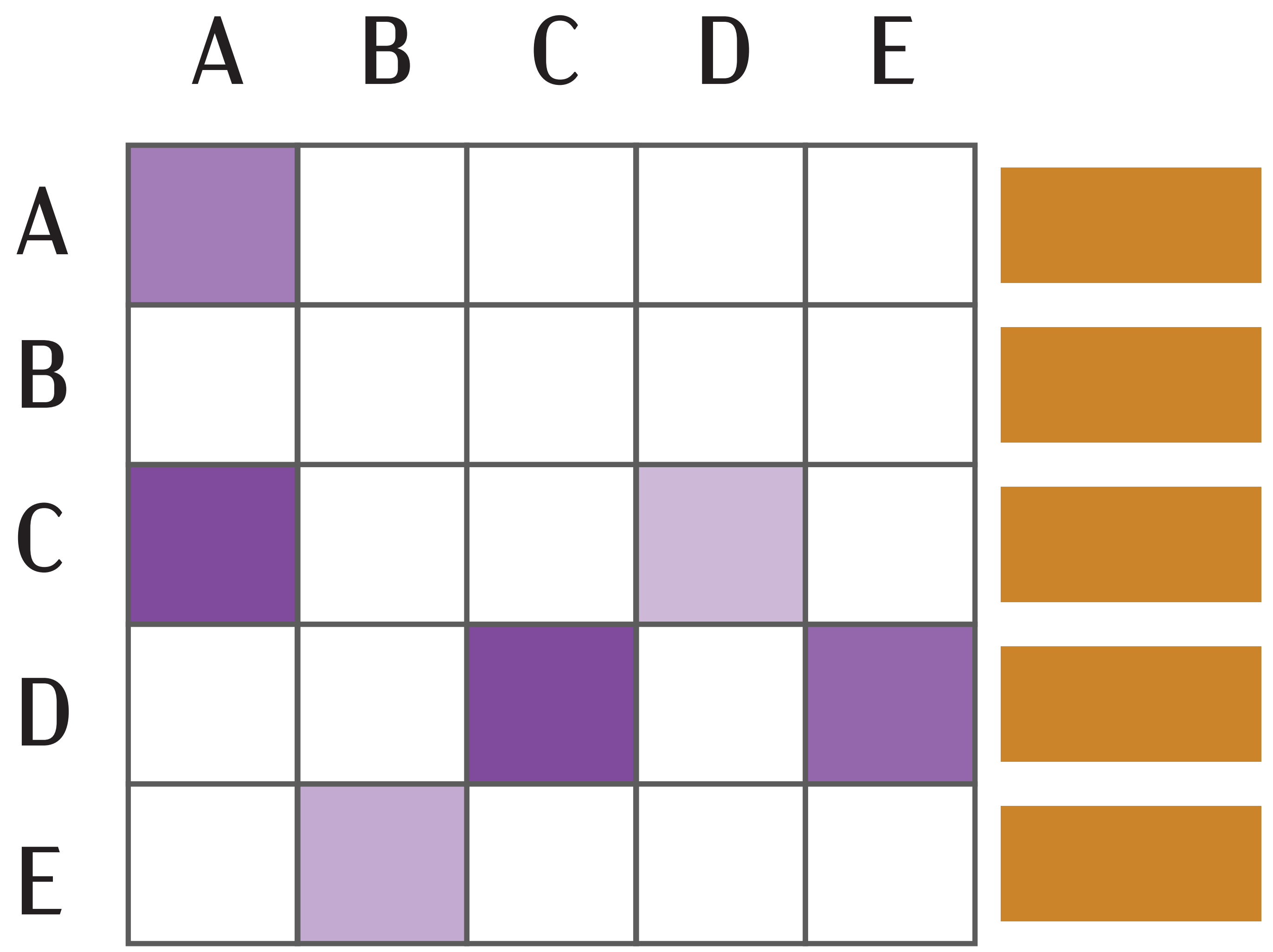


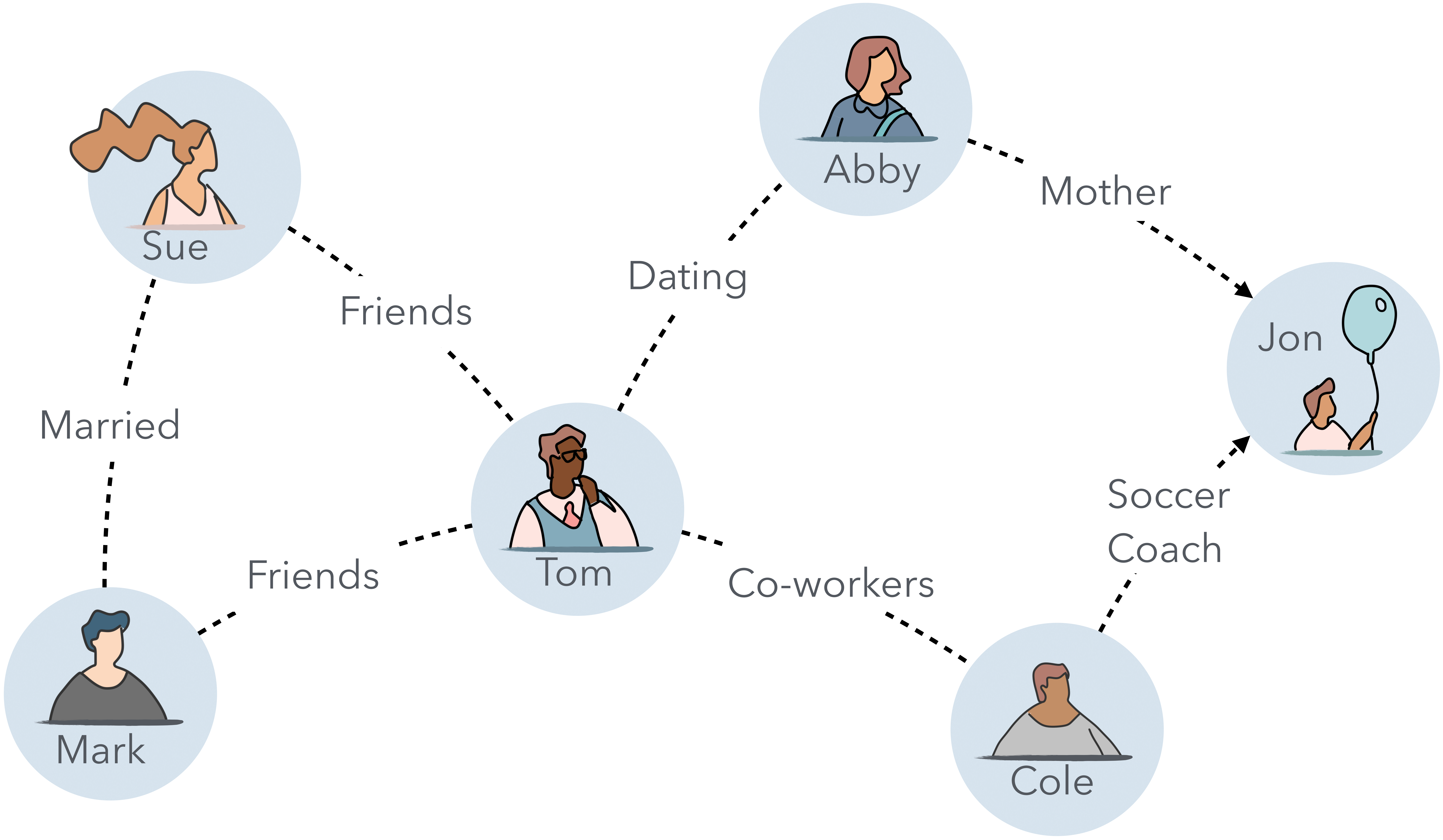
Quilts



BioFabric

Adjacency Matrix

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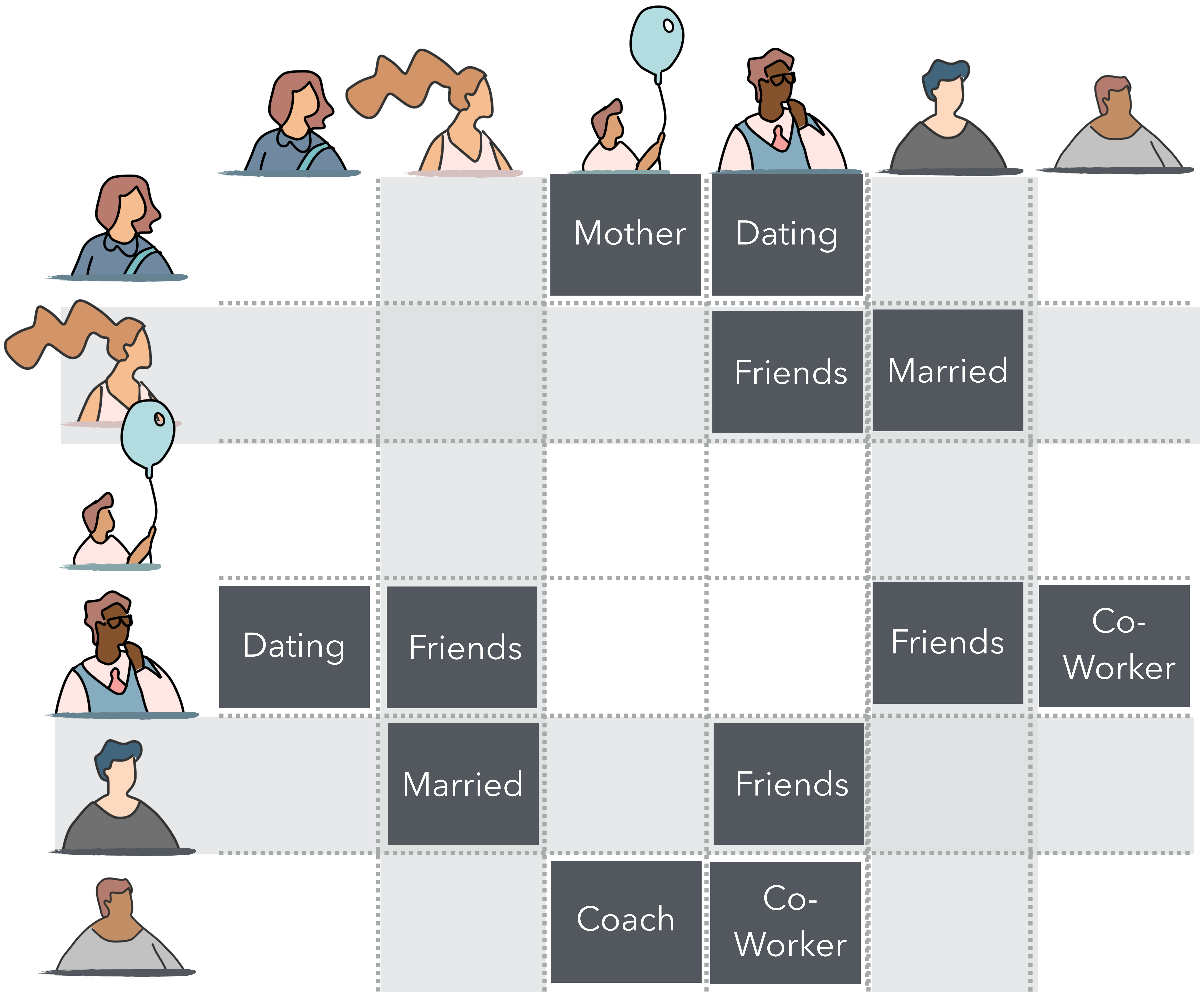
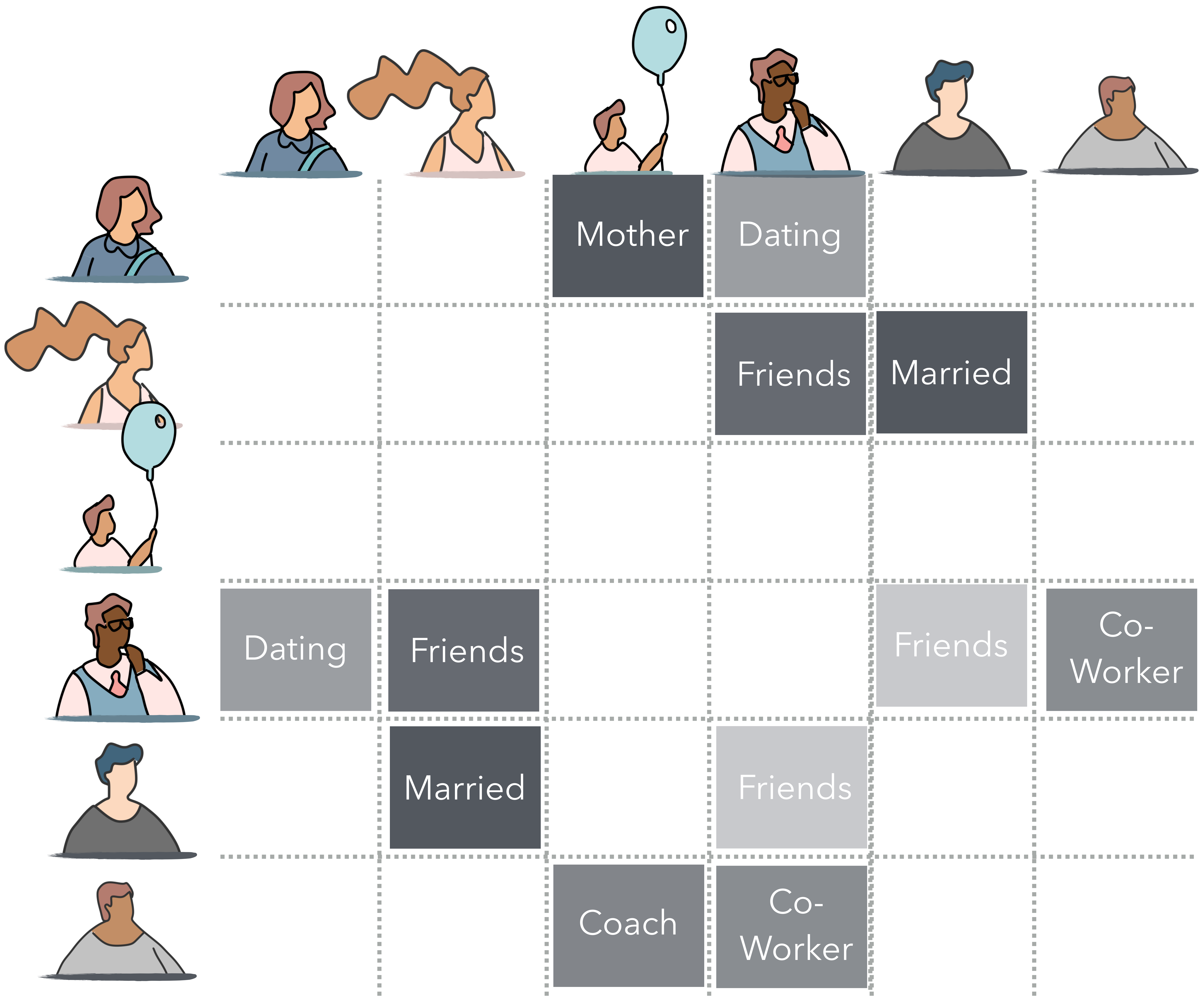
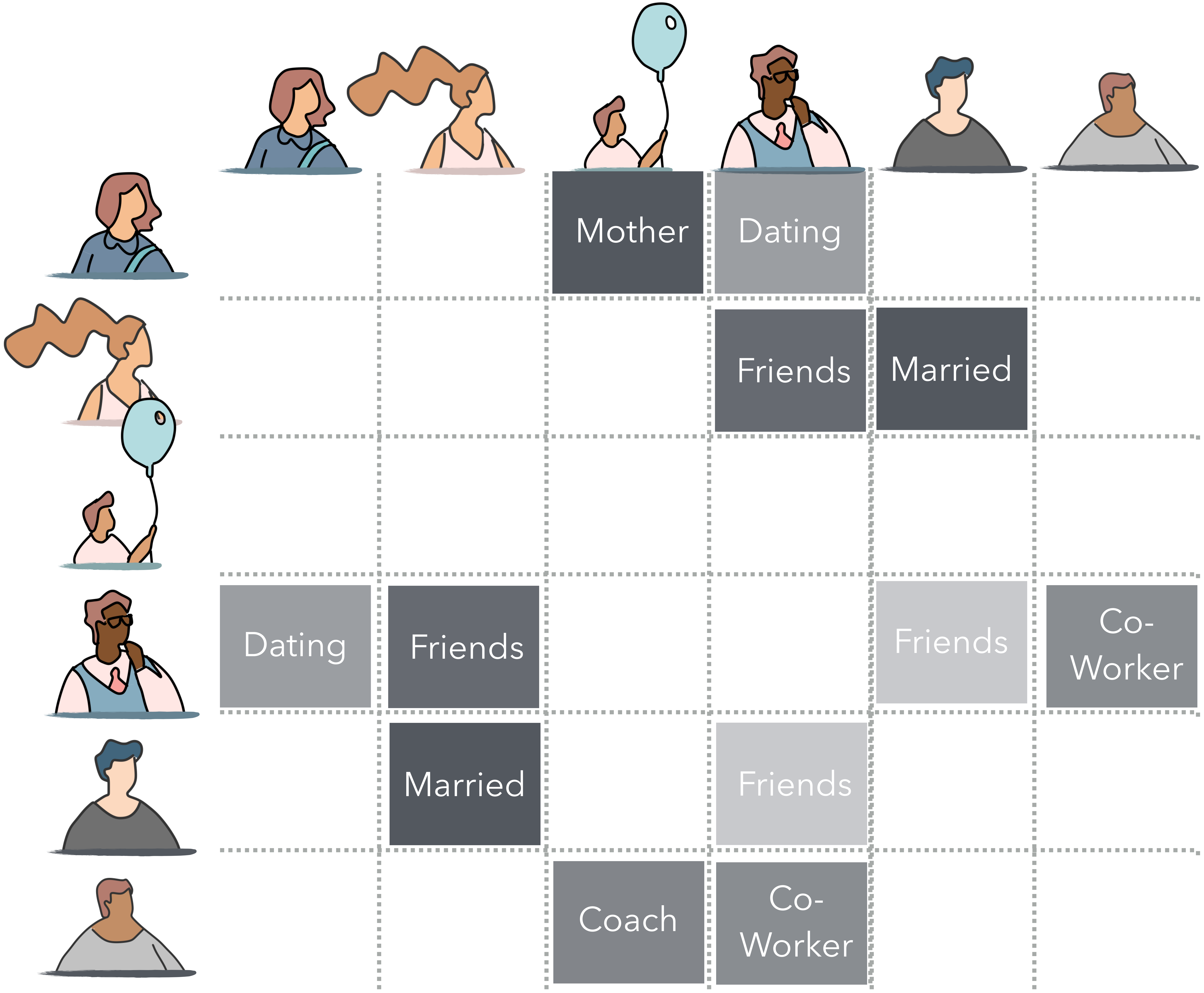
Sue
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole

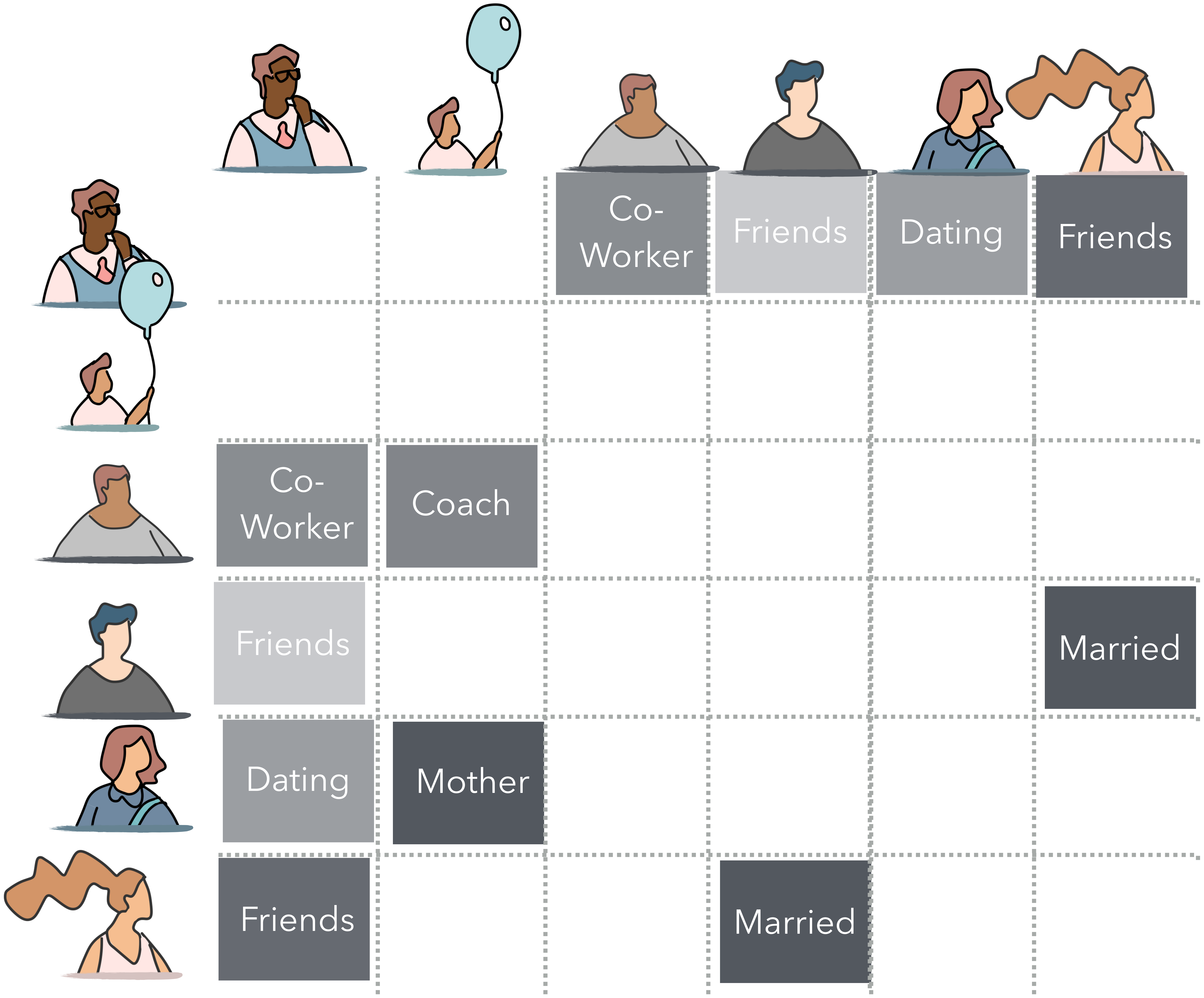

Mother
Dating
Friends
Married
Dating
Friends
Friends
Co-Worker
Married
Friends
Coach
Co-Worker



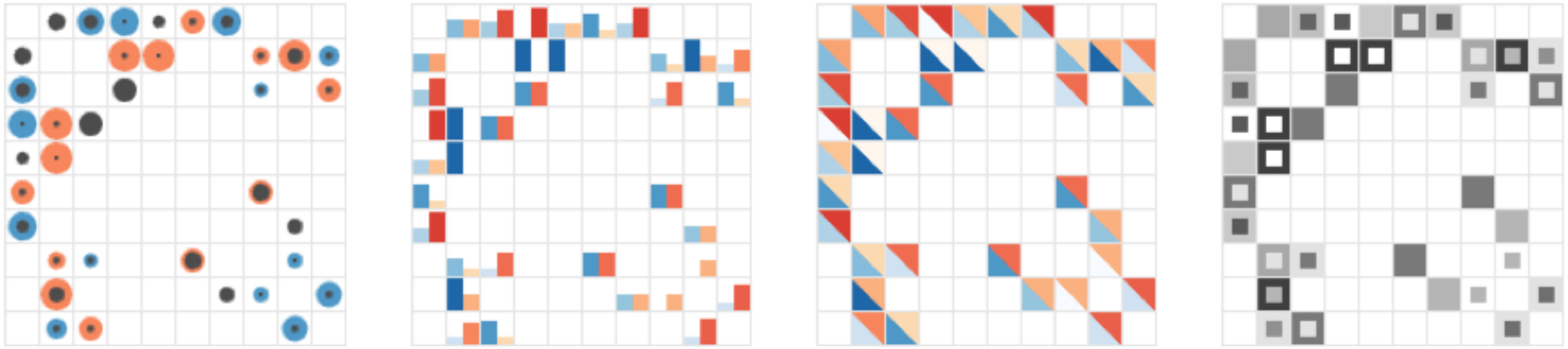
Mother
Dating
Friends
Married
Dating
Friends
Friends
Co-Worker
Married
Friends
Coach
Co-Worker



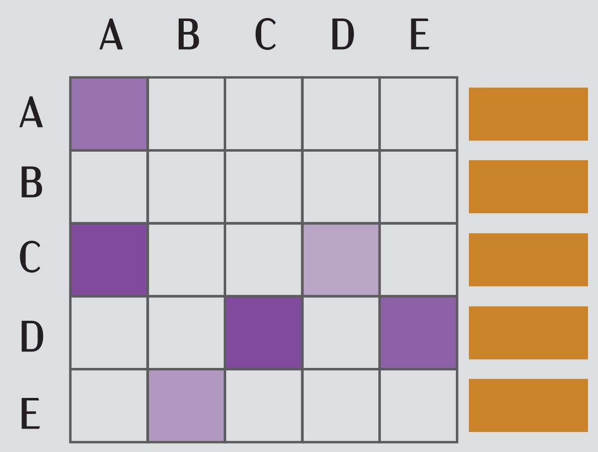
Name	Beverage	Day 1
Abby	Port	1
Sue	Coke	0
Jon	Coke	4
Tom	Beer	5
Mark	Beer	2
Cole	Port	3



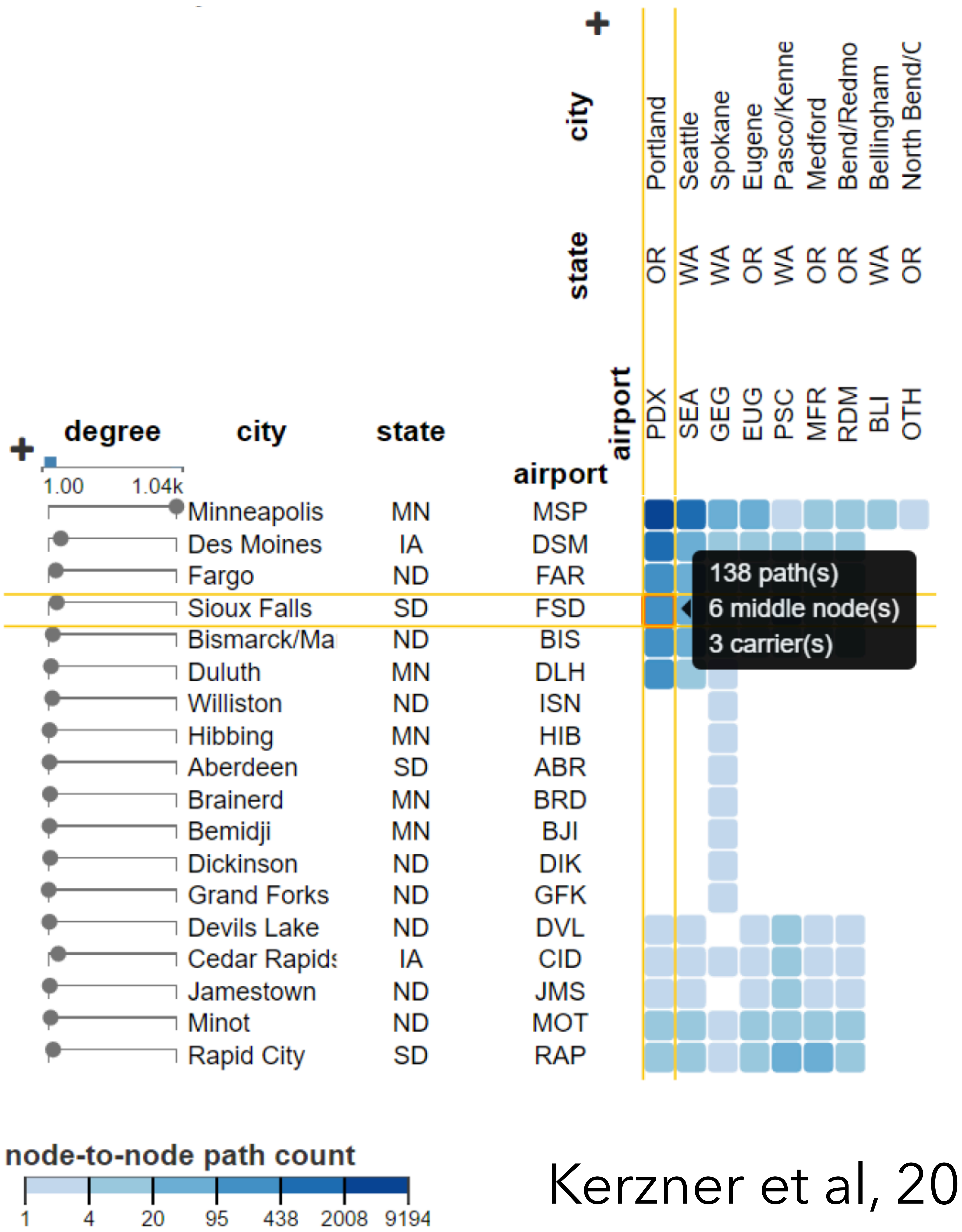
Name	Beverage	Day 1
Tom	Beer	5
Jon	Coke	4
Cole	Port	3
Mark	Beer	2
Abby	Port	1
Sue	Coke	0



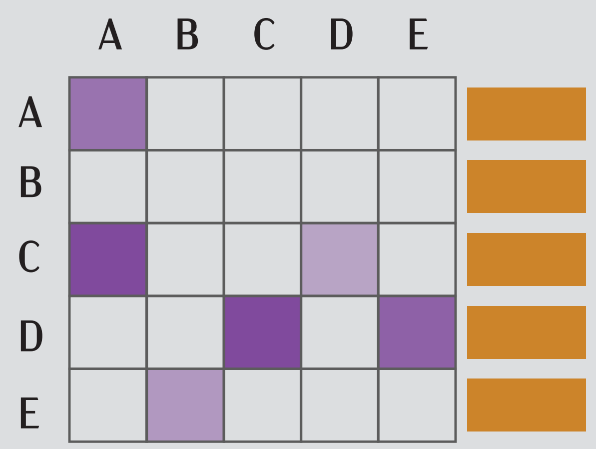
Alper et al, 2013



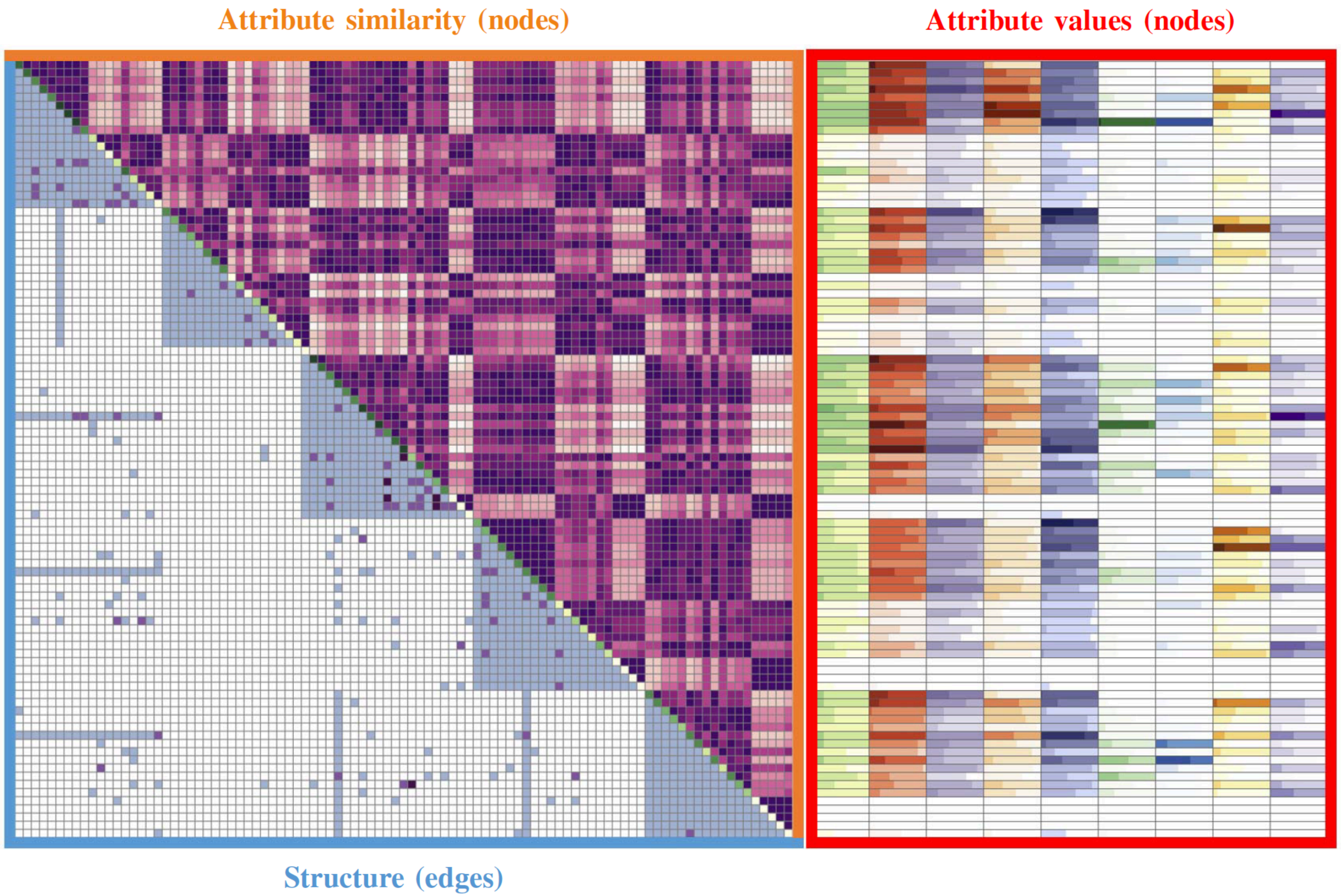
Adjacency Matrix



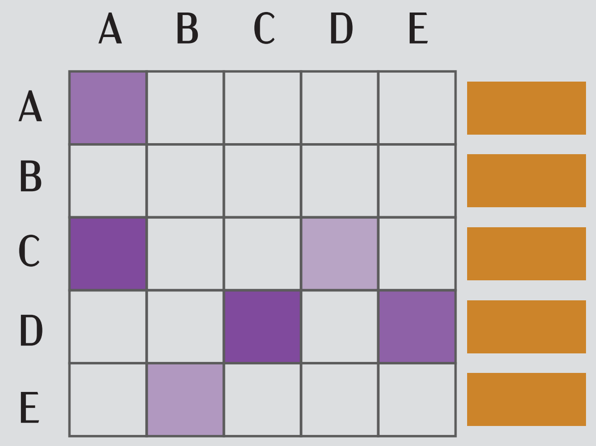
Kerzner et al, 2017



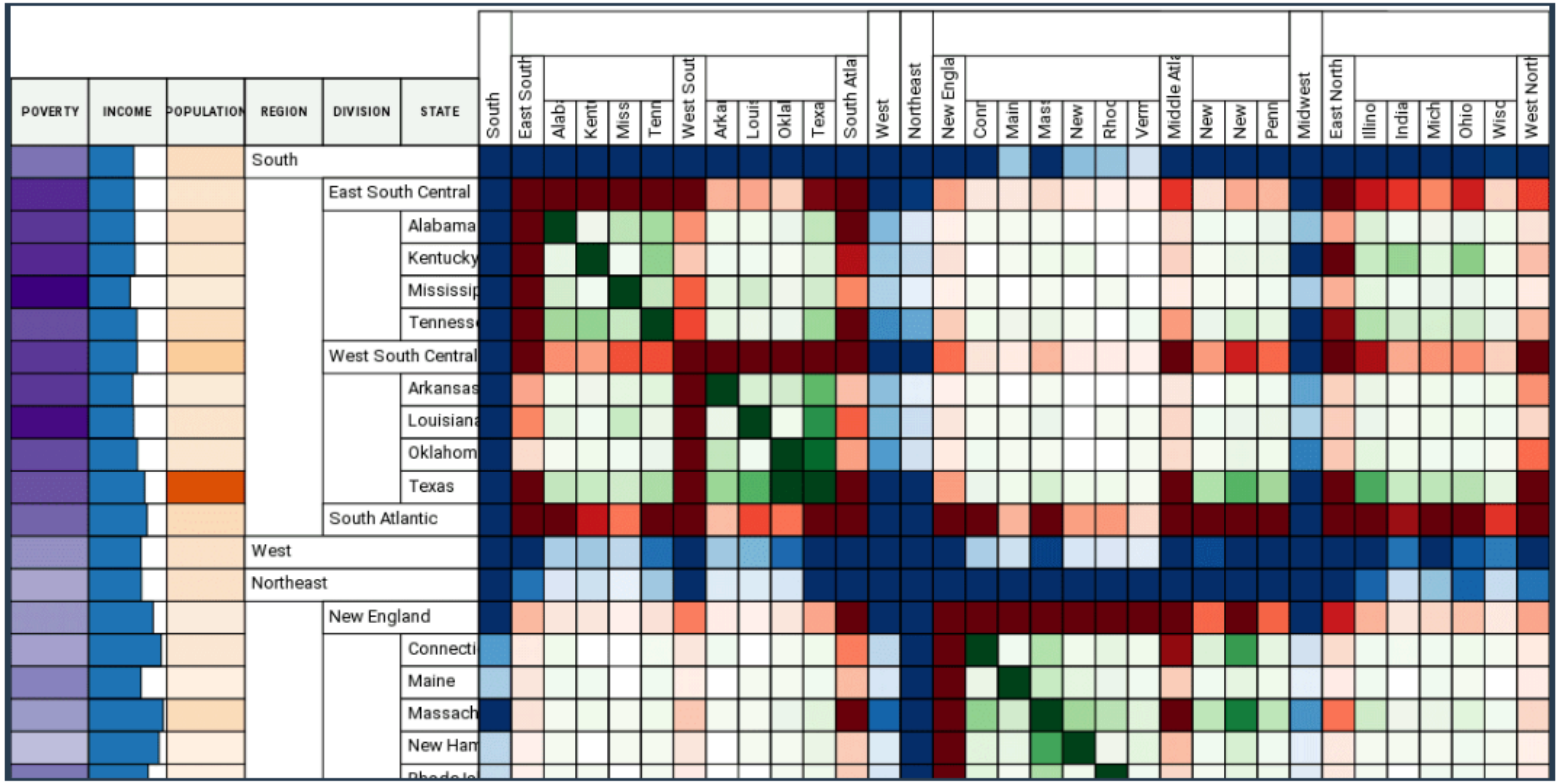
Adjacency Matrix

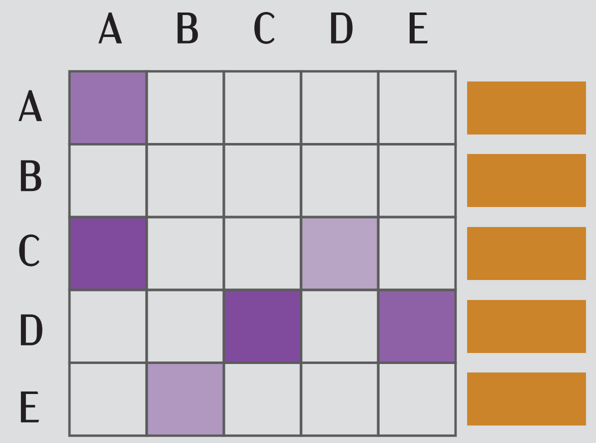


Berger et al, 2019



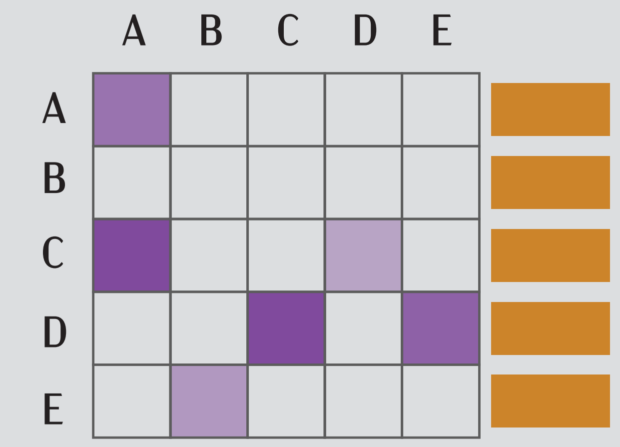
Adjacency Matrix





Adjacency Matrix

Safarli and Lex, 2019



Adjacency
Matrix

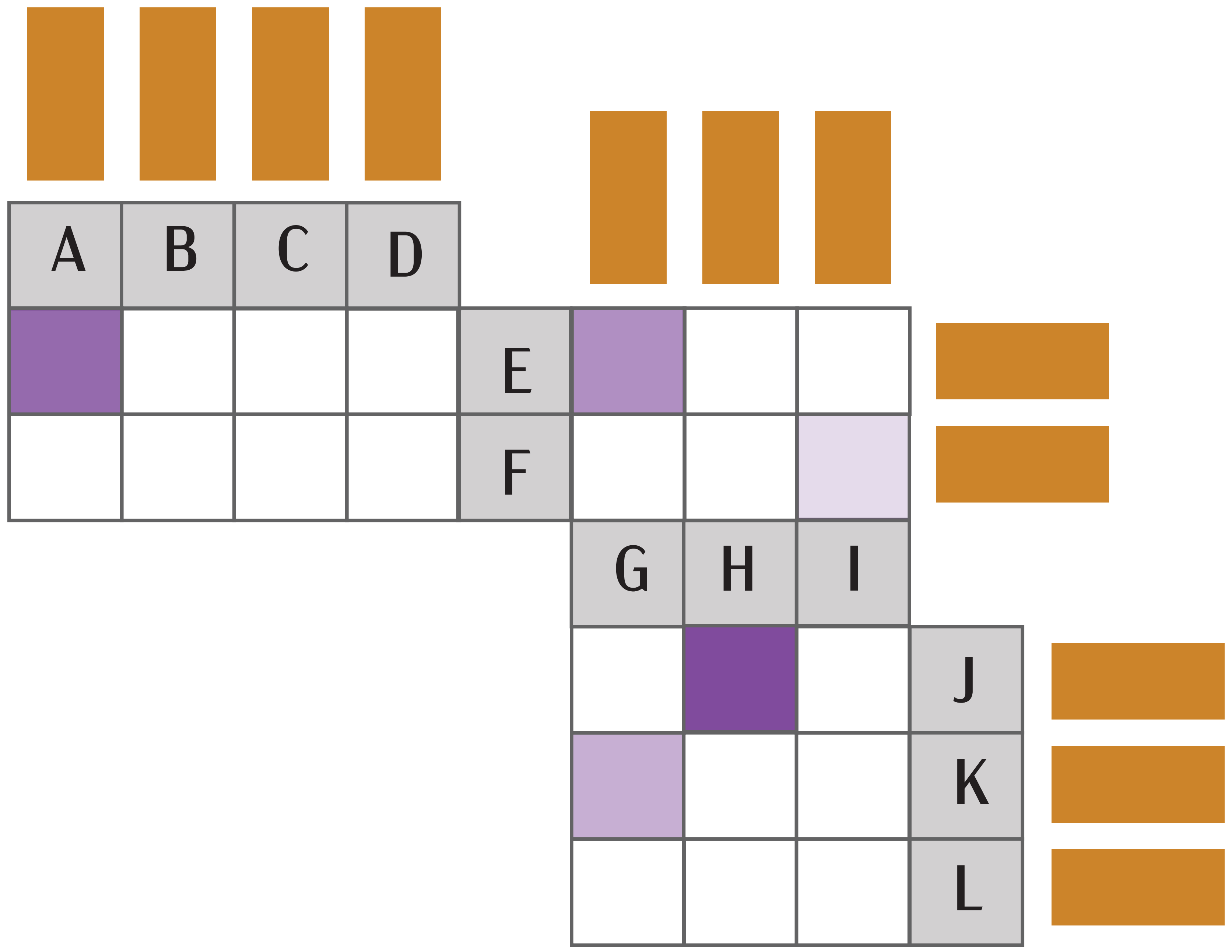
Ideal for dense and completely connected networks

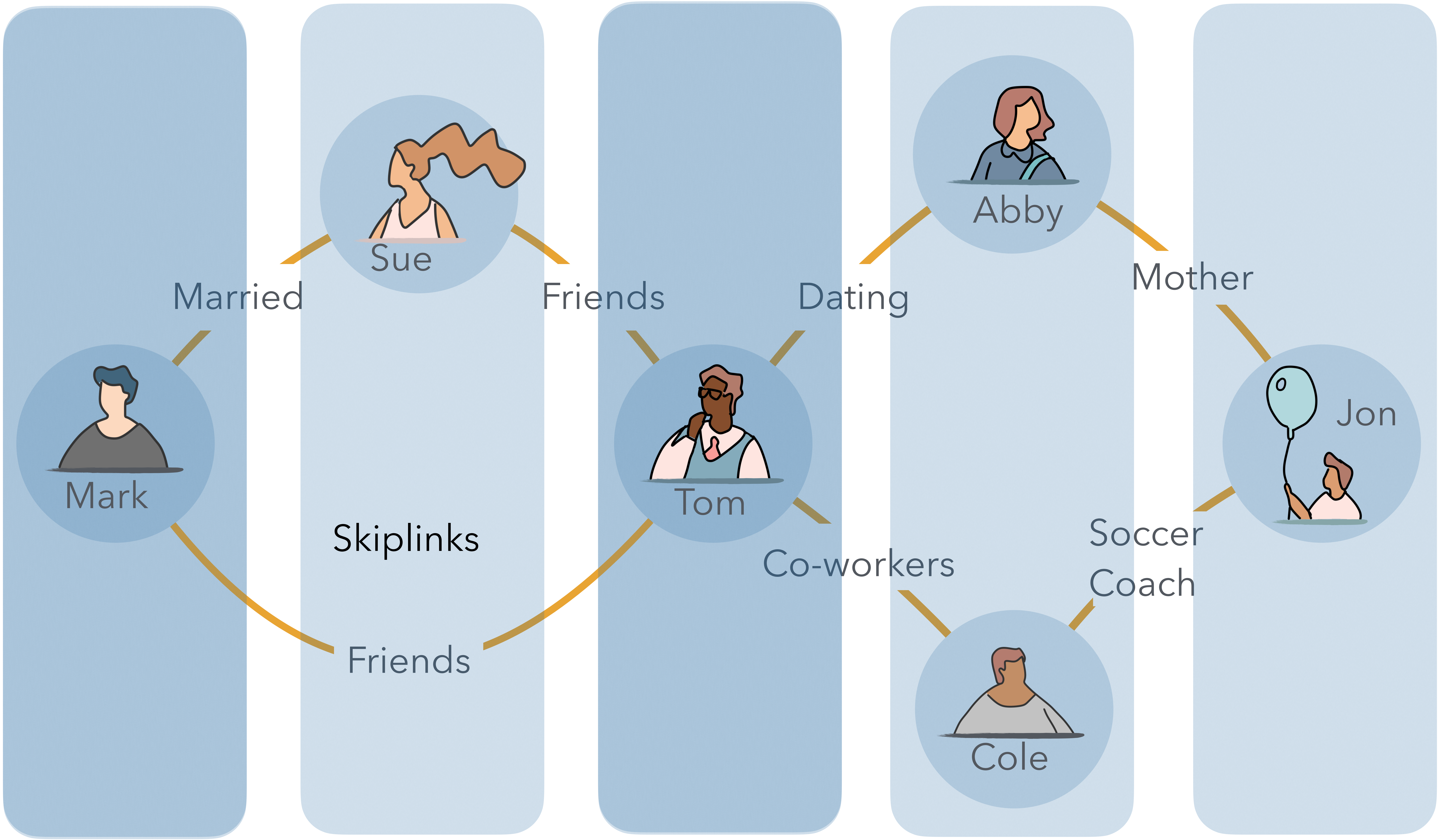
Requires quadratic space with respect to the number of nodes.

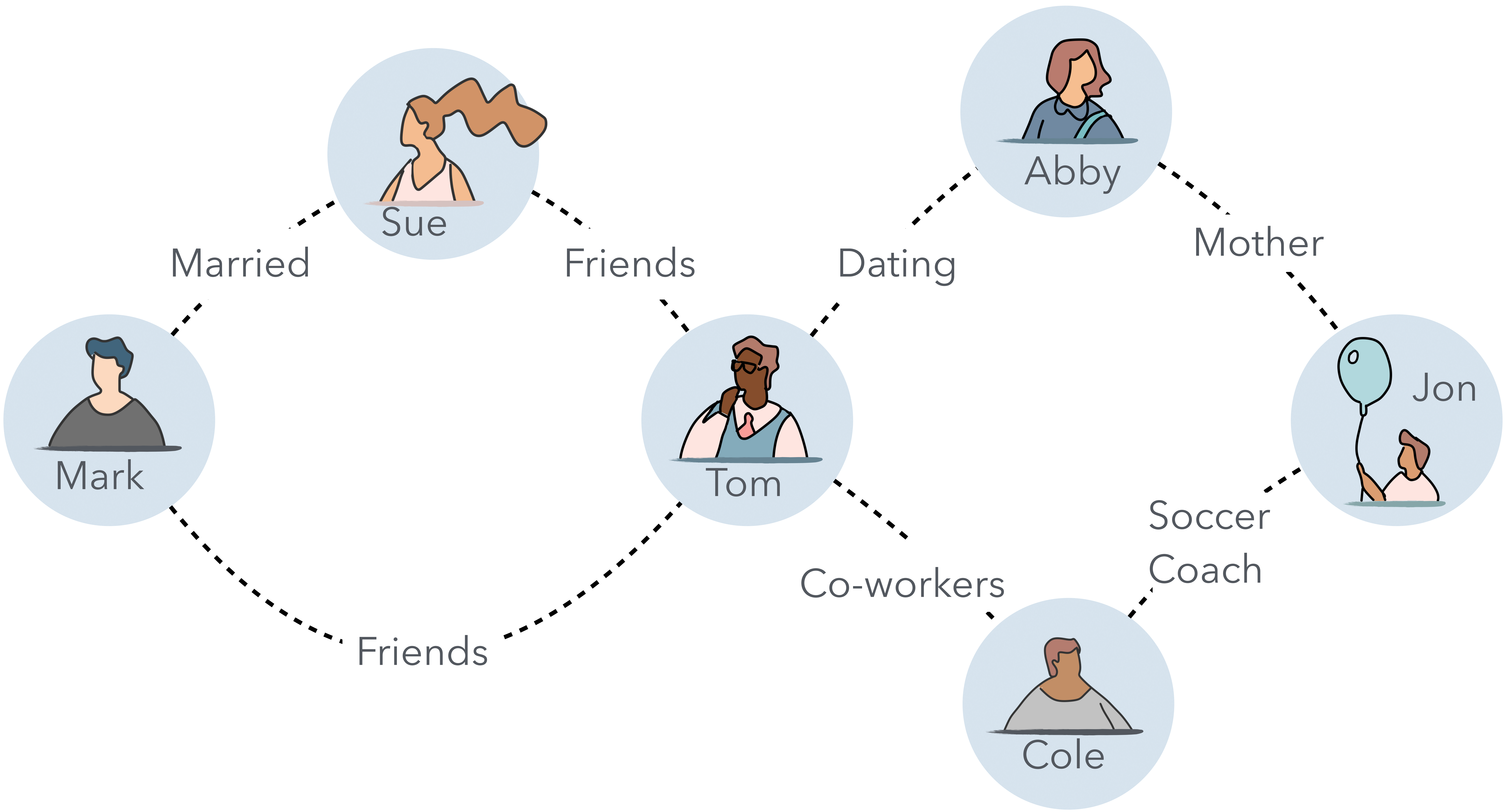
Complexity of choosing the right reordering algorithm

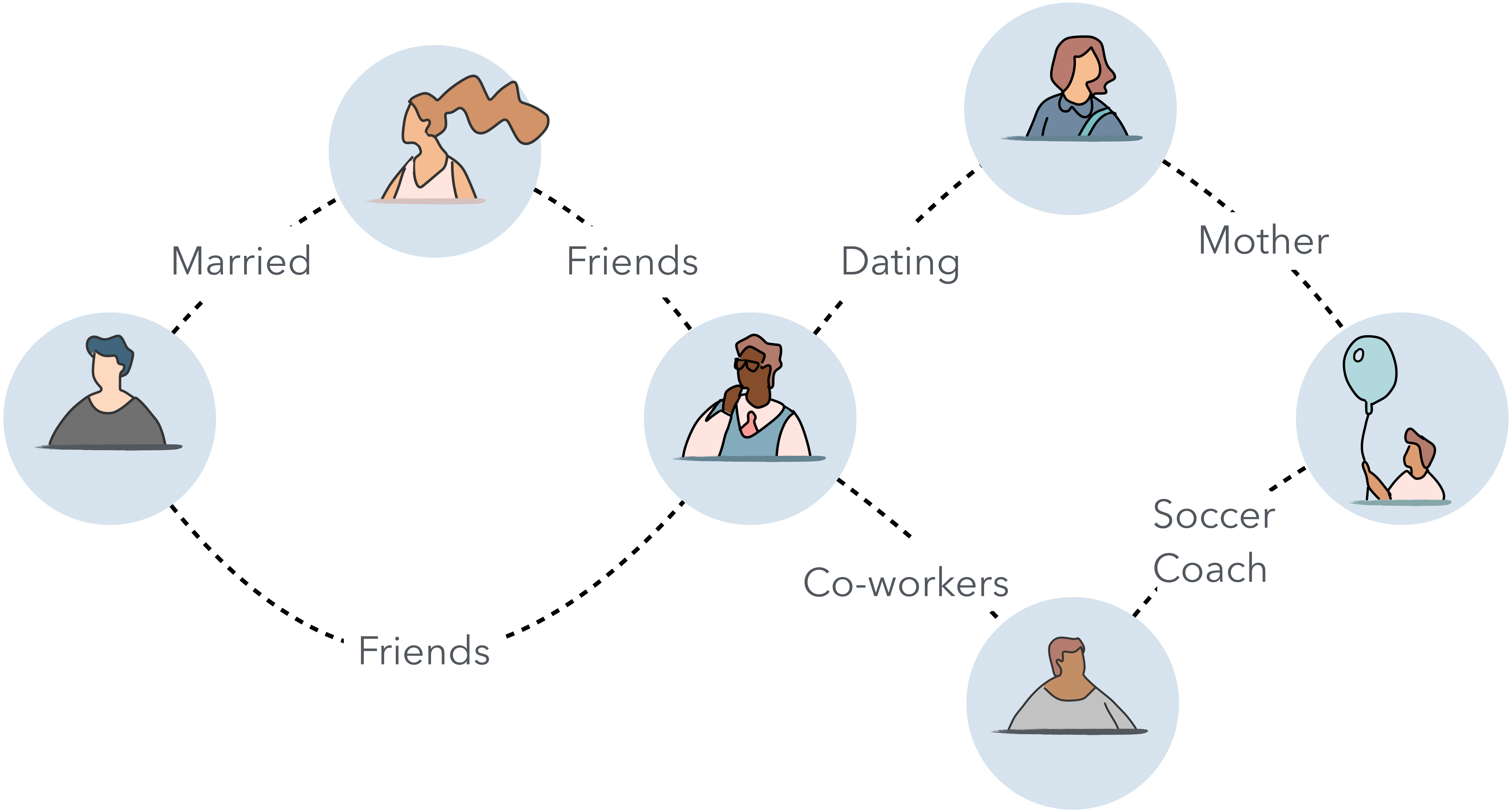
Recommended for smaller, complex and dense networks with rich node and/or edge attributes, for all tasks except for those involving paths

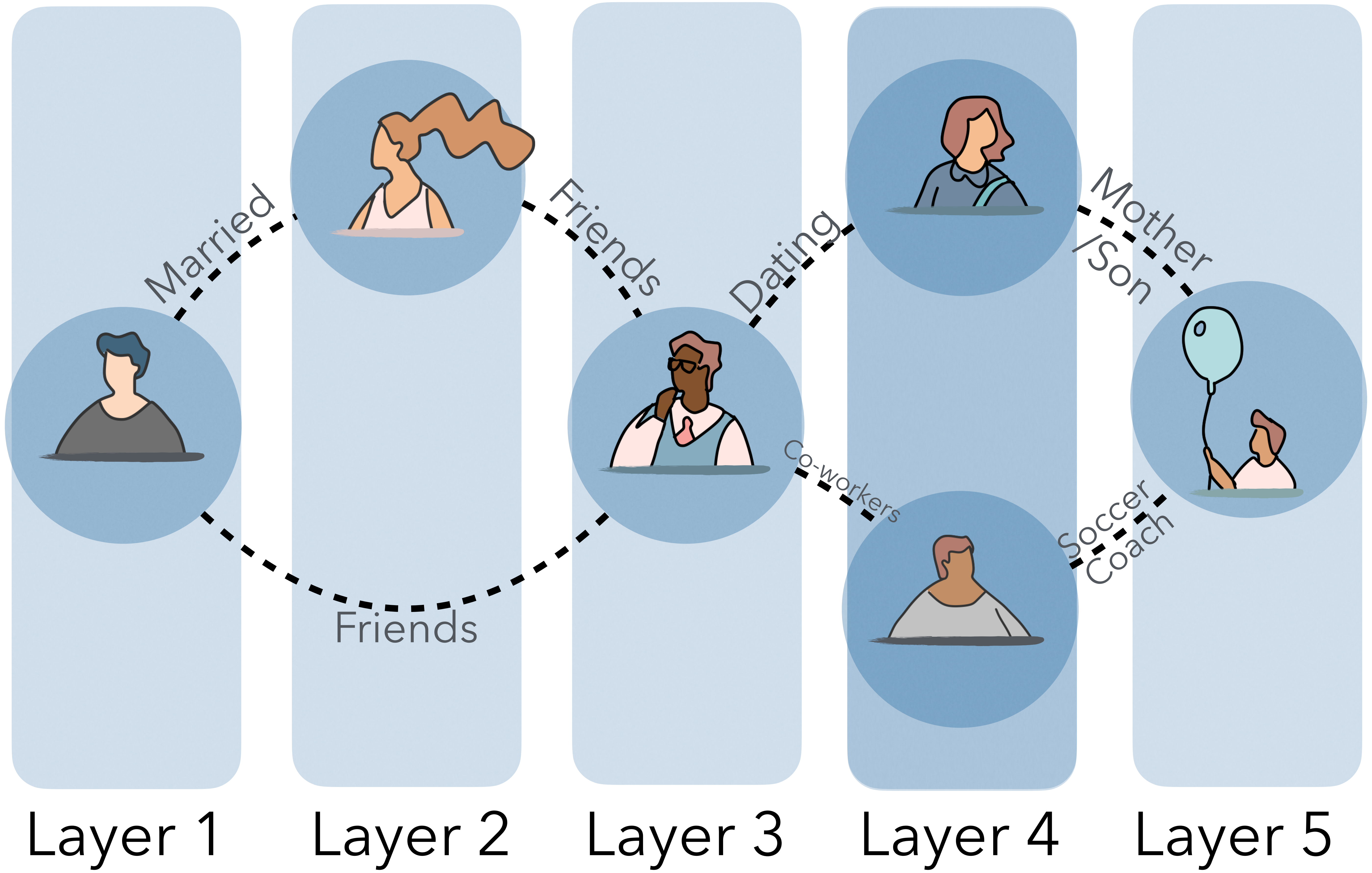
Quilts

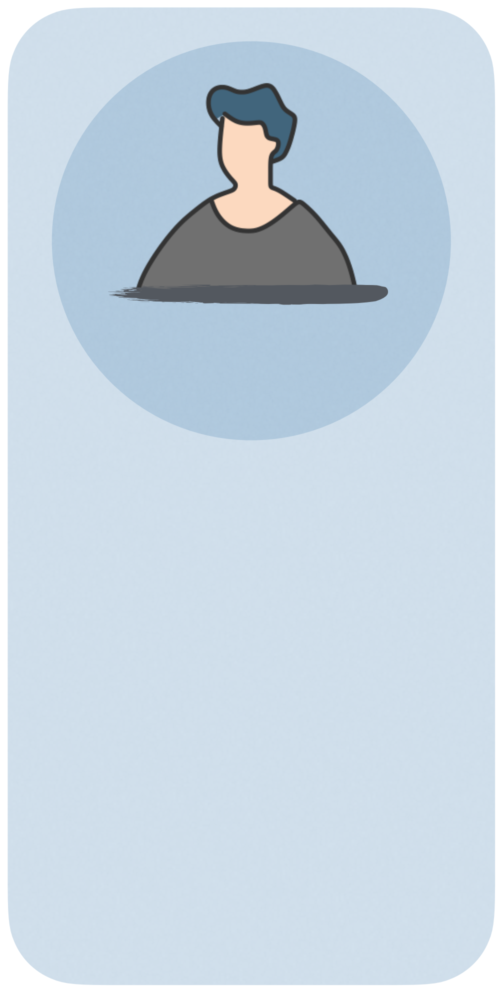


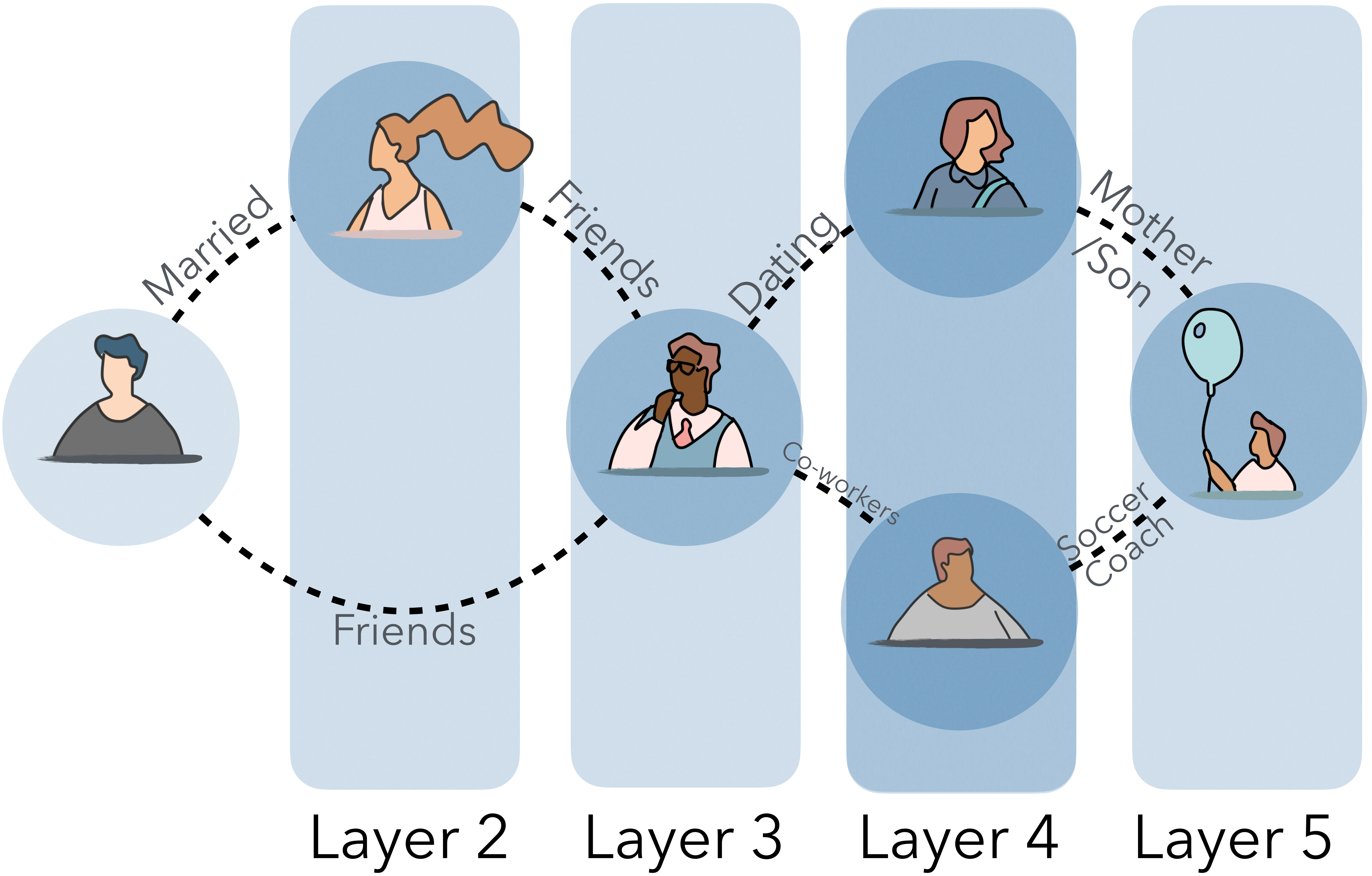

Sue
Abby
Married
Friends
Dating
Mother
Jon
Mark
Tom
Skiplinks
Co-workers
Soccer
Coach
Friends
Cole

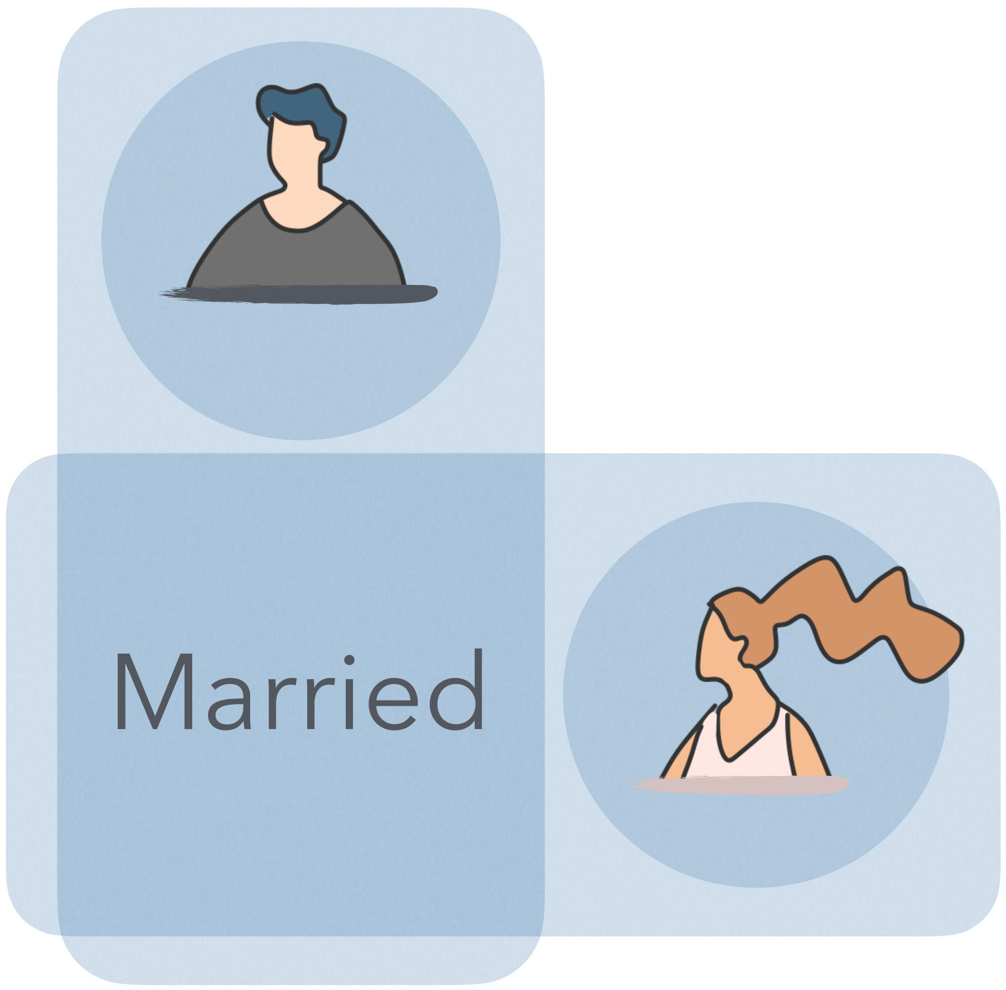

Sue
Abby
Married
Friends
Dating
Mother
Mark
Tom
Jon
Soccer Coach
Co-workers
Friends
Cole


Married
Friends
Dating
Mother
Soccer
Coach
Co-workers
Friends


Married
Friends
Friends
Dating
Co-workers
Mother
/Son
Soccer
Coach
Layer 1
Layer 2
Layer 3
Layer 4
Layer 5




Married
Friends
Friends
Dating
Co-workers
Mother /Son
Soccer Coach
Layer 2
Layer 3
Layer 4
Layer 5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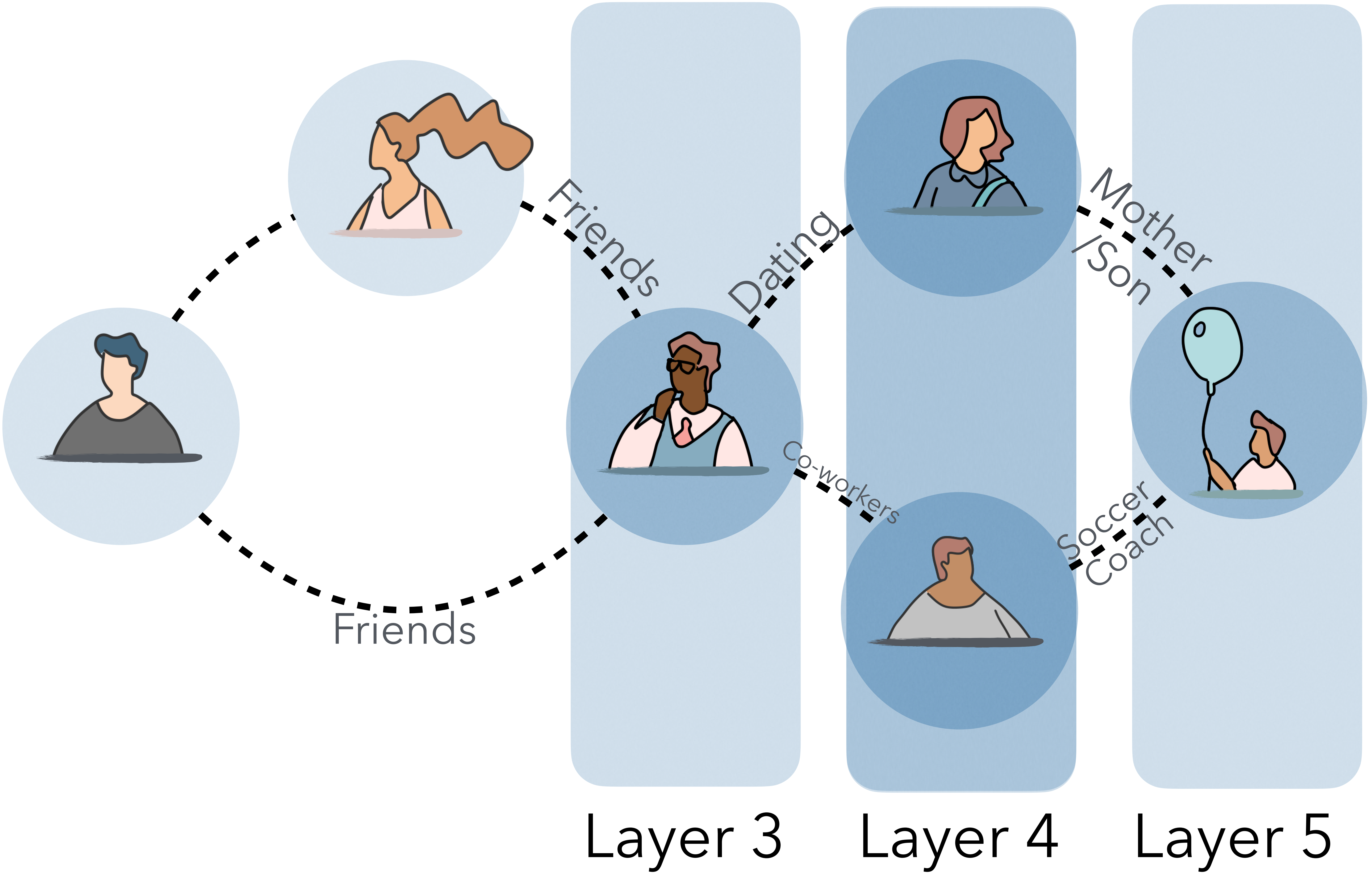
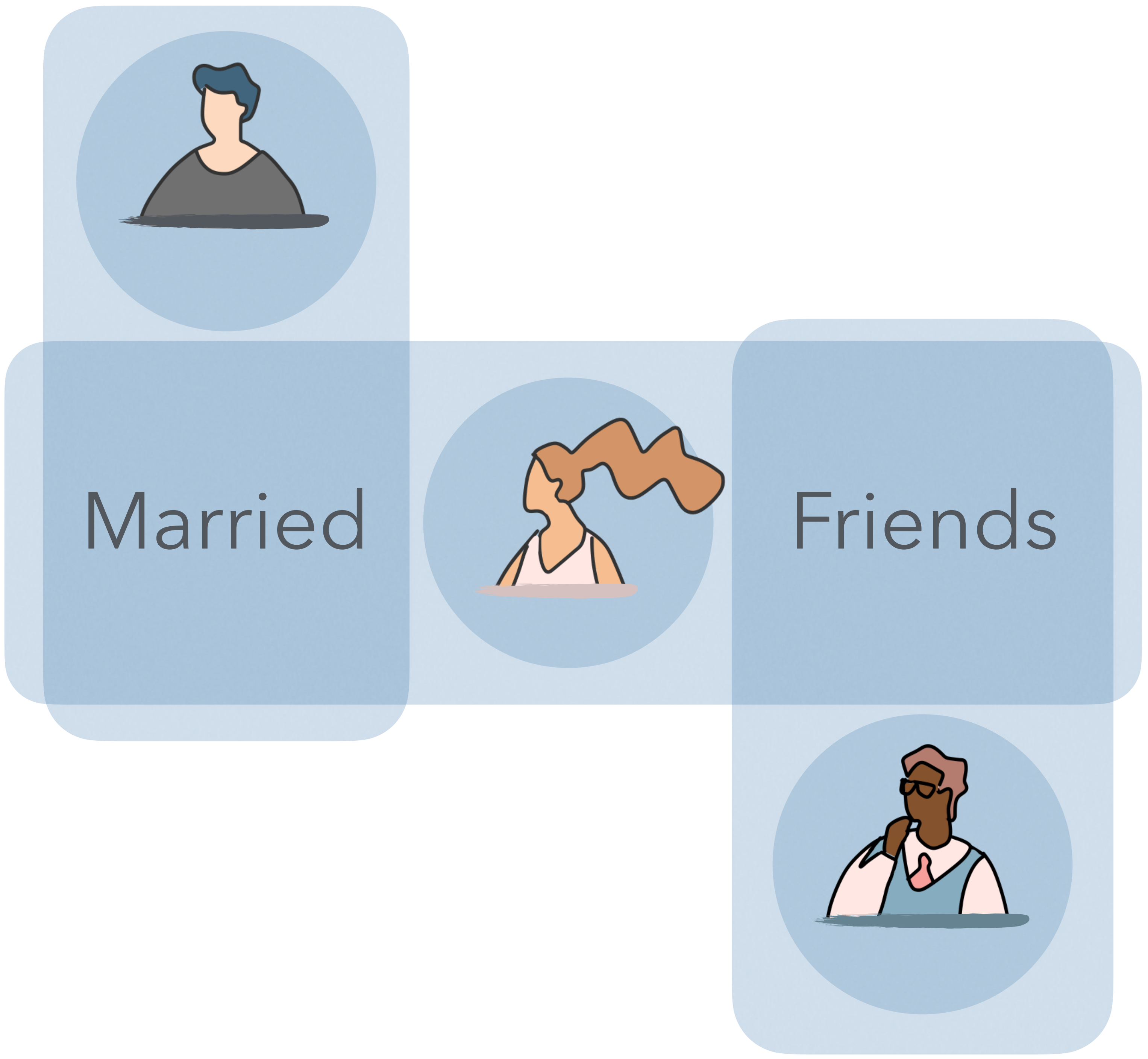
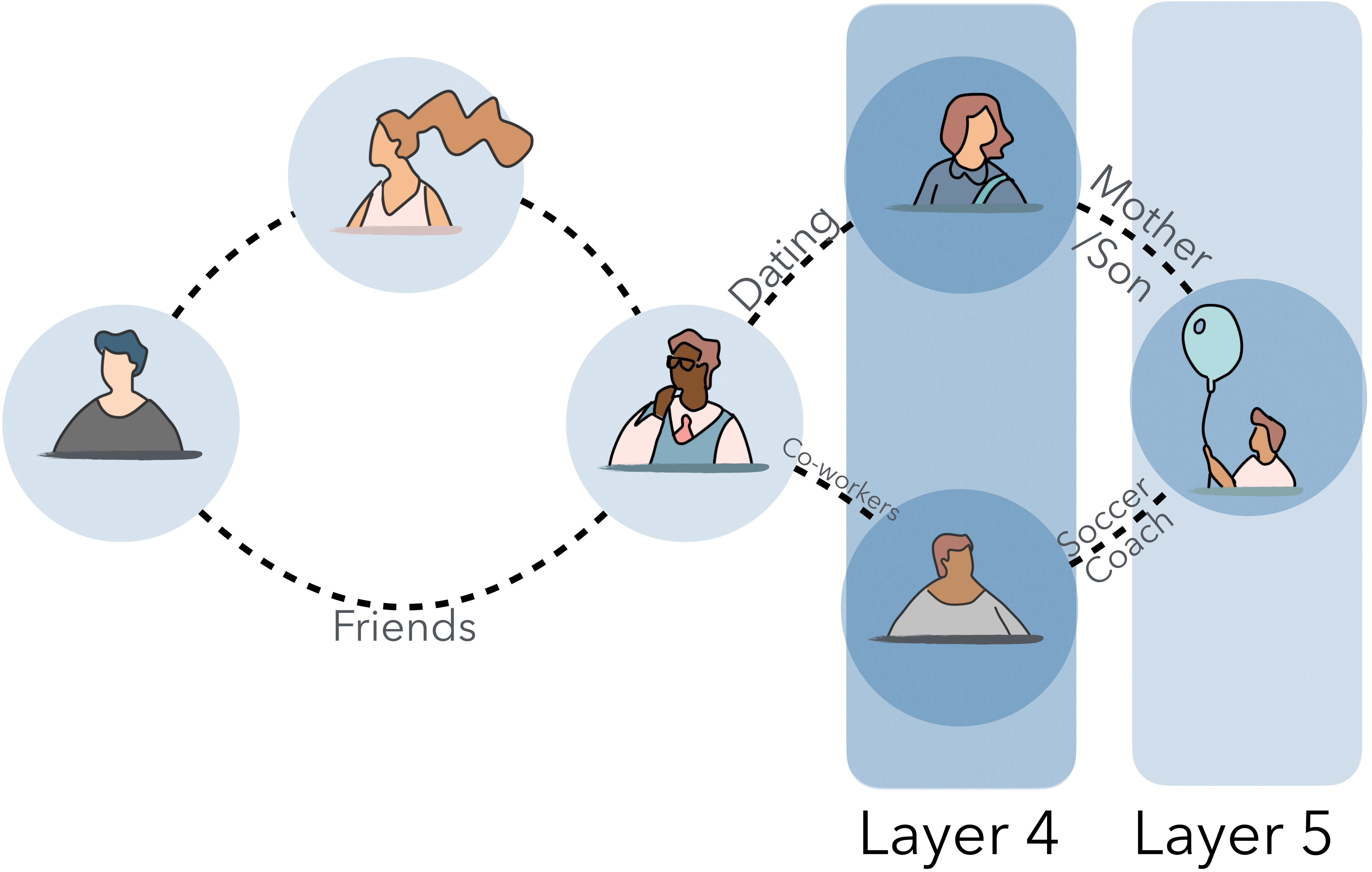
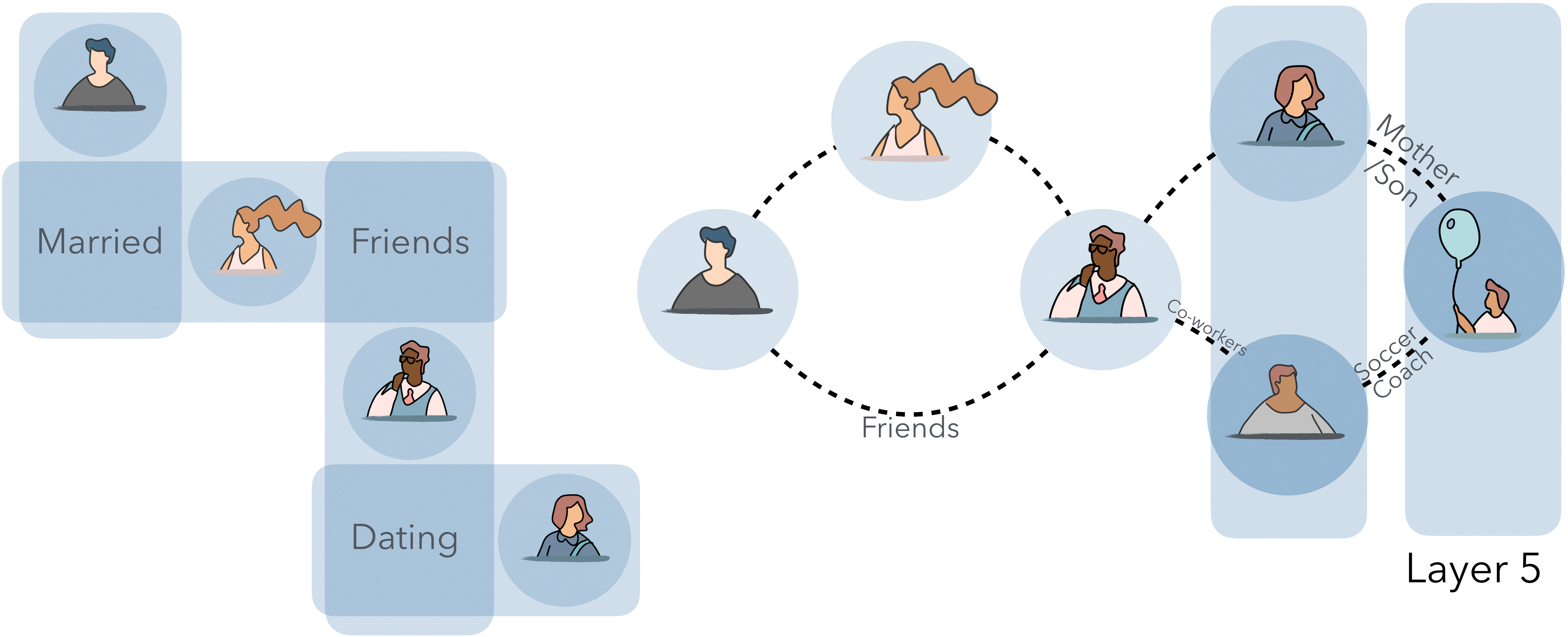
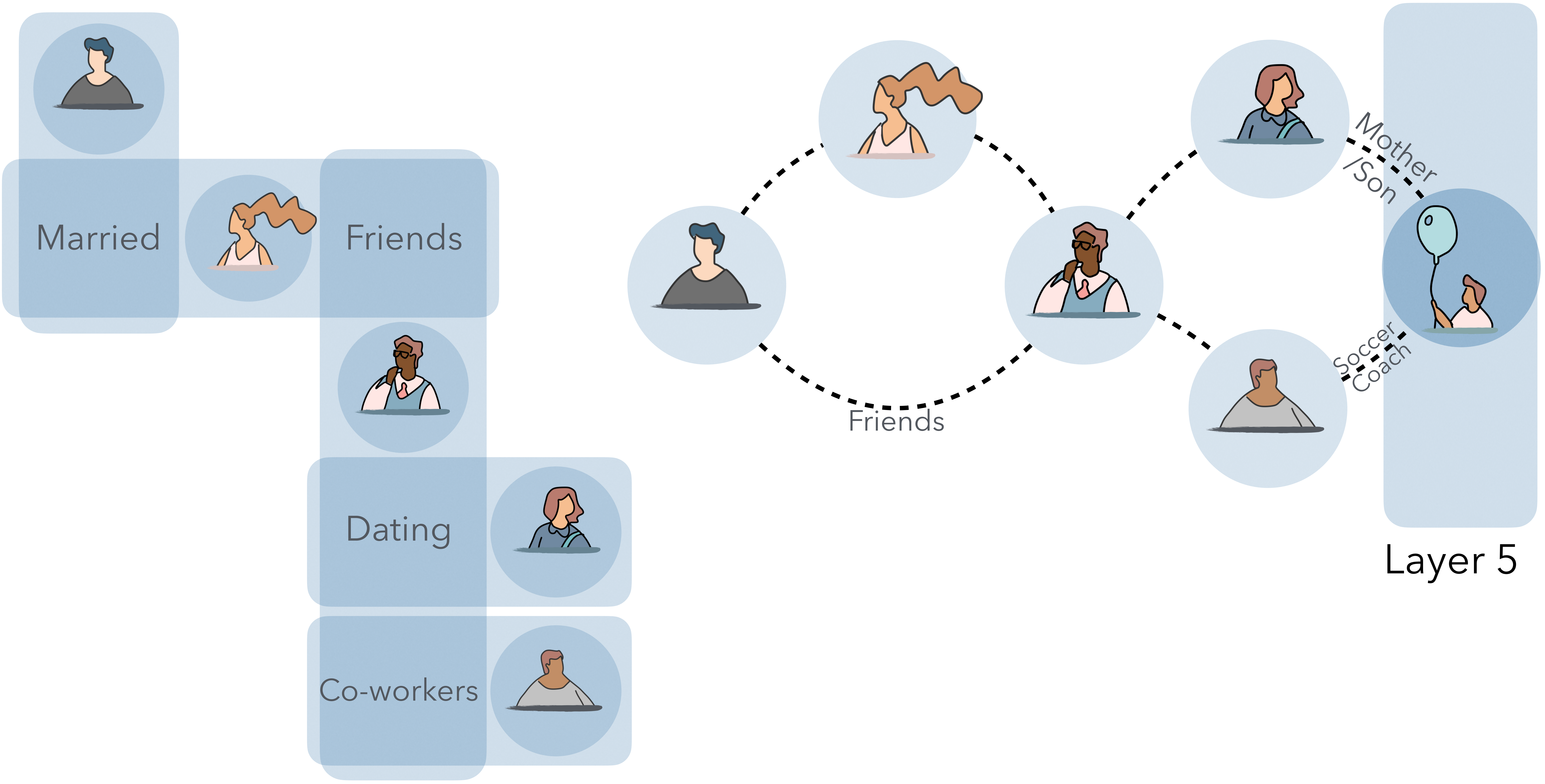

Friends
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach
Layer 3
Layer 4
Layer 5

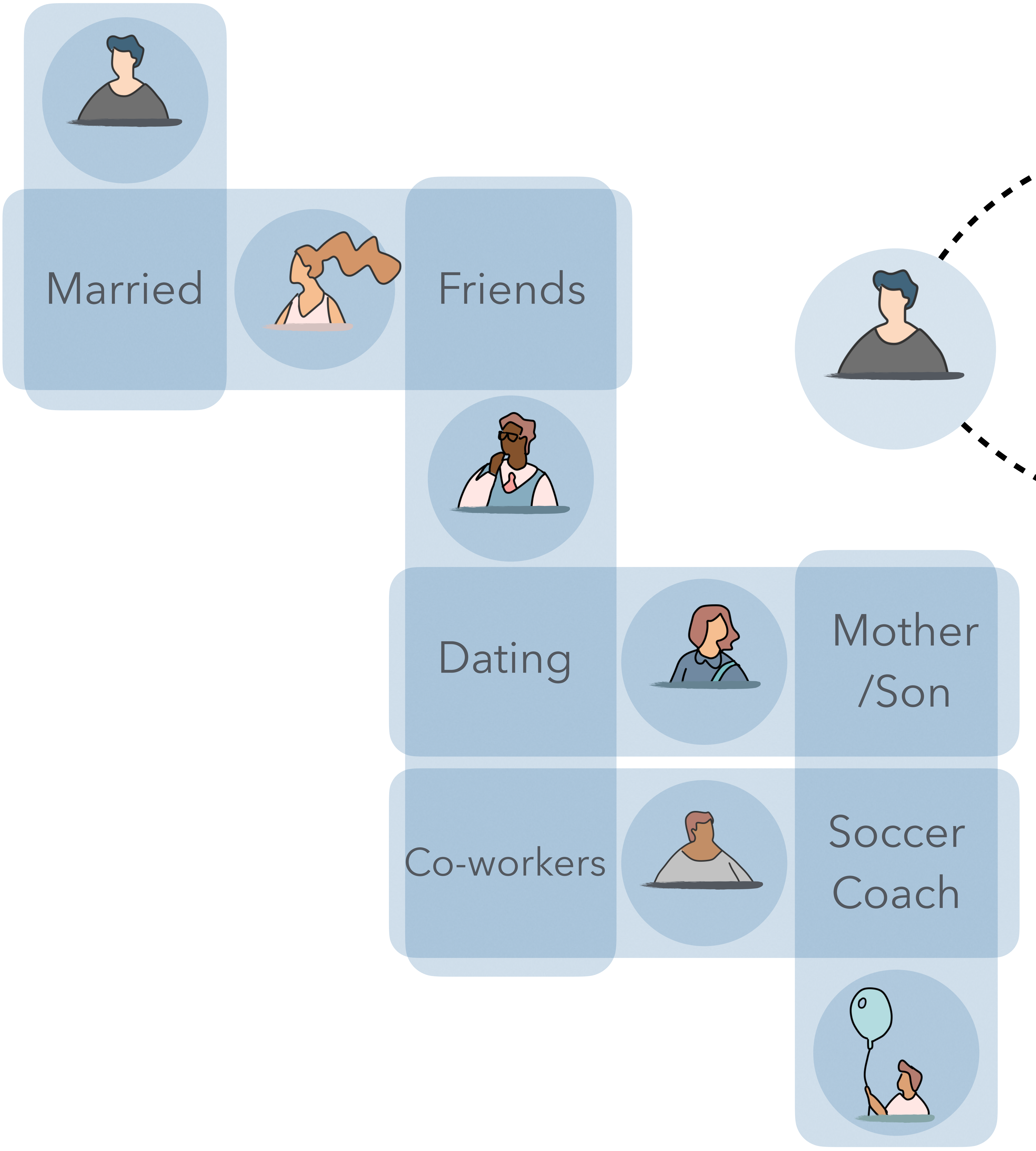
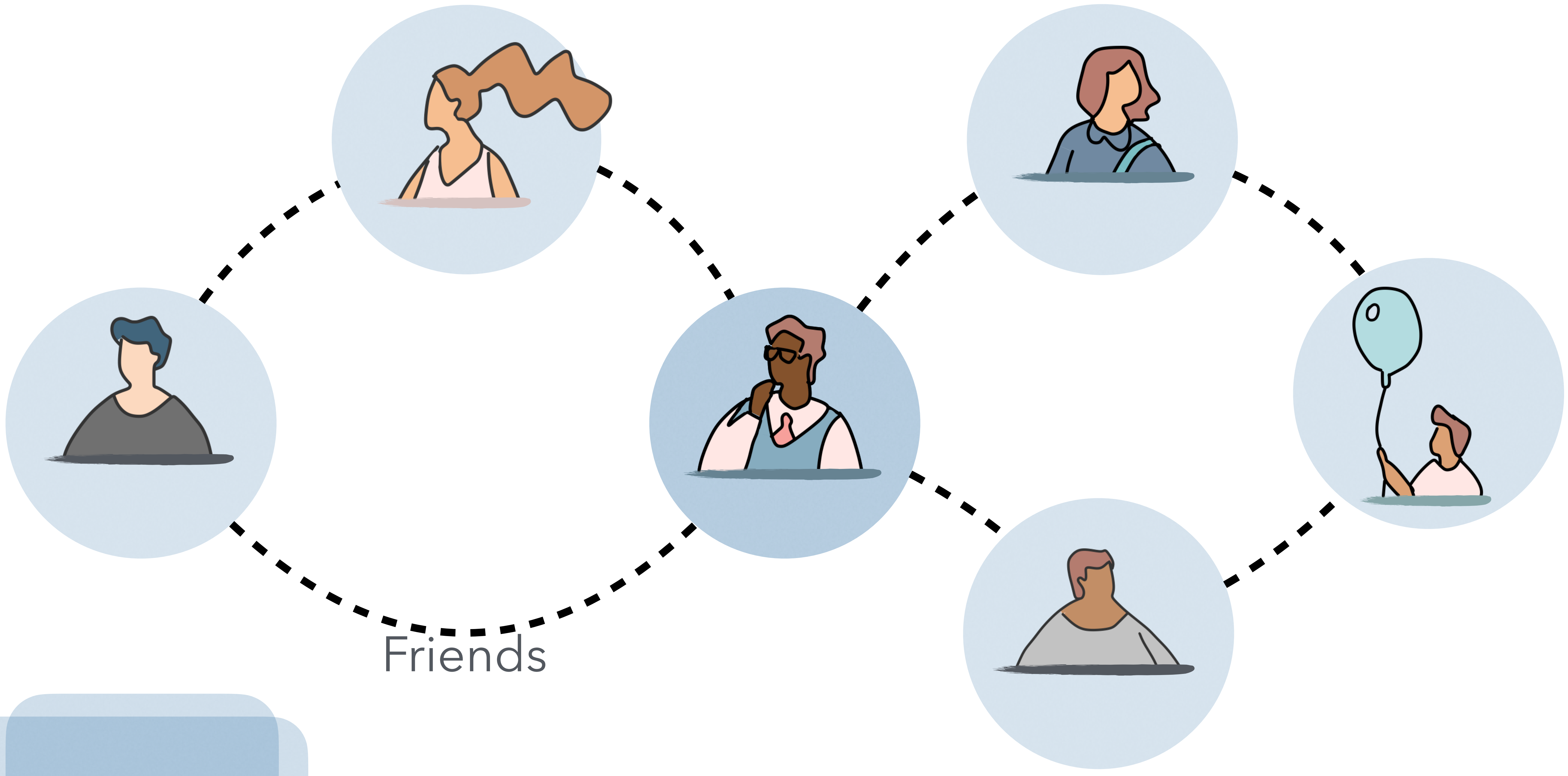

Married
Friends

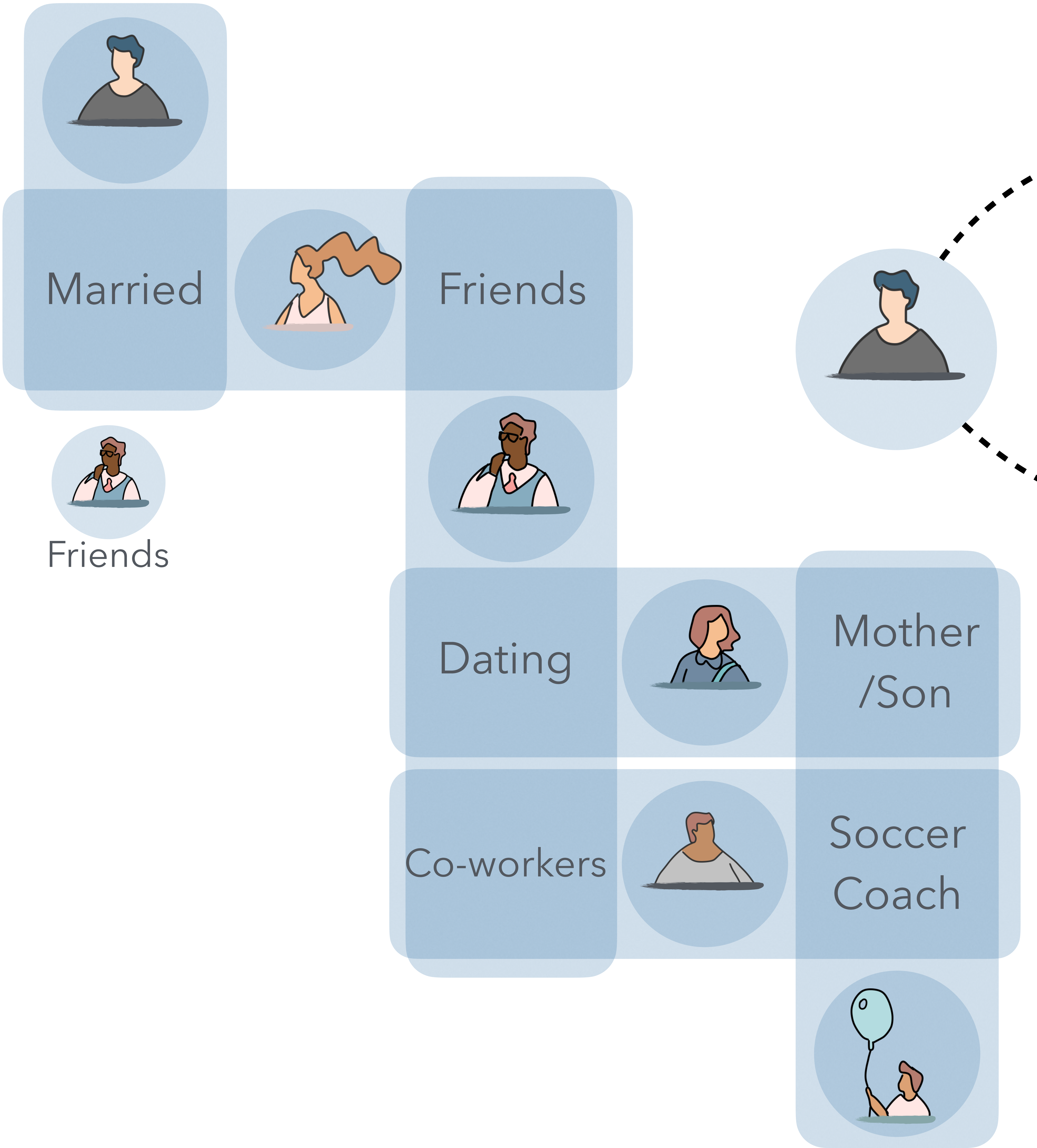

Friends
Dating
Co-workers
Mother /Son
Soccer Coach
Layer 4
Layer 5

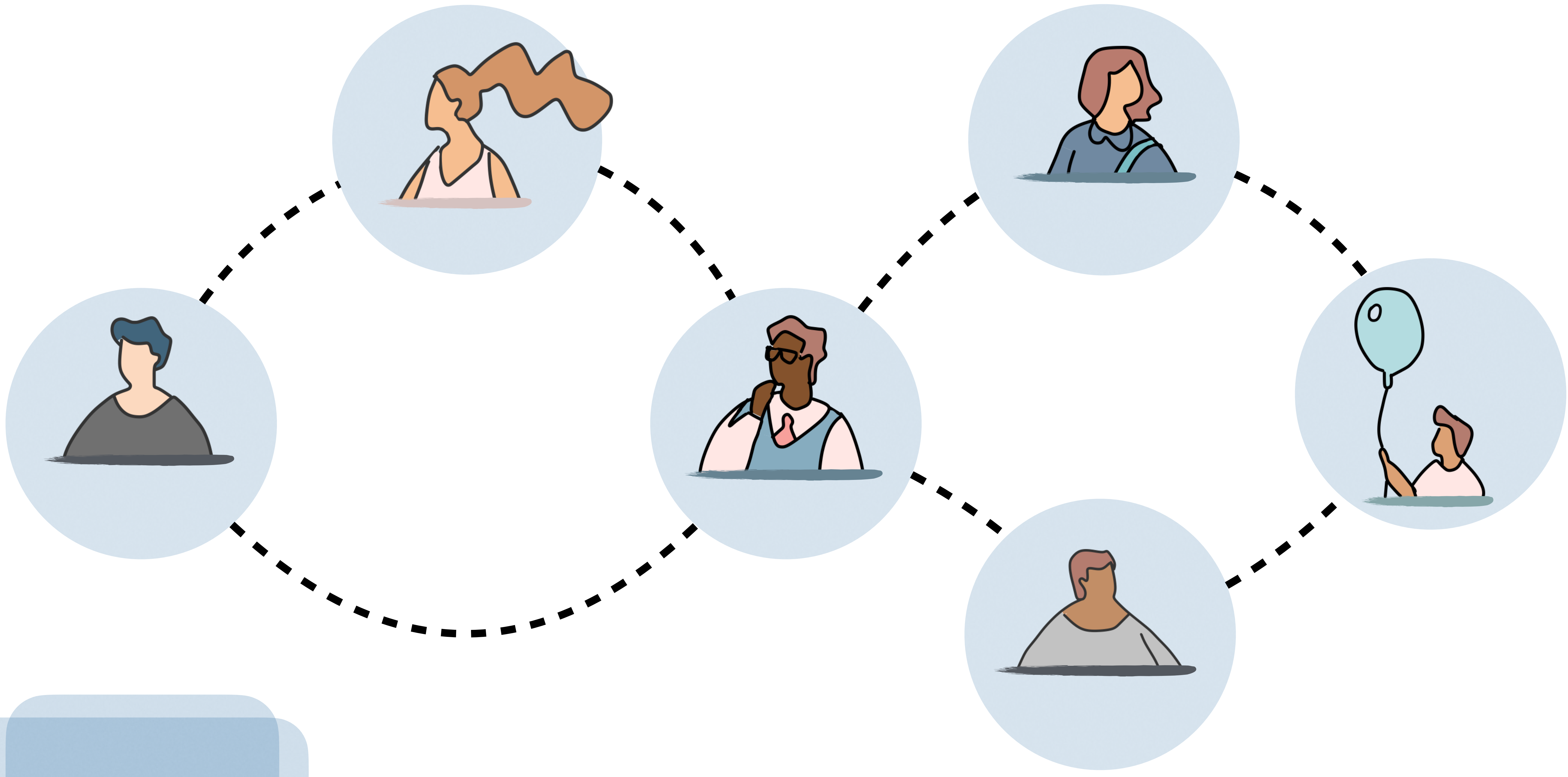


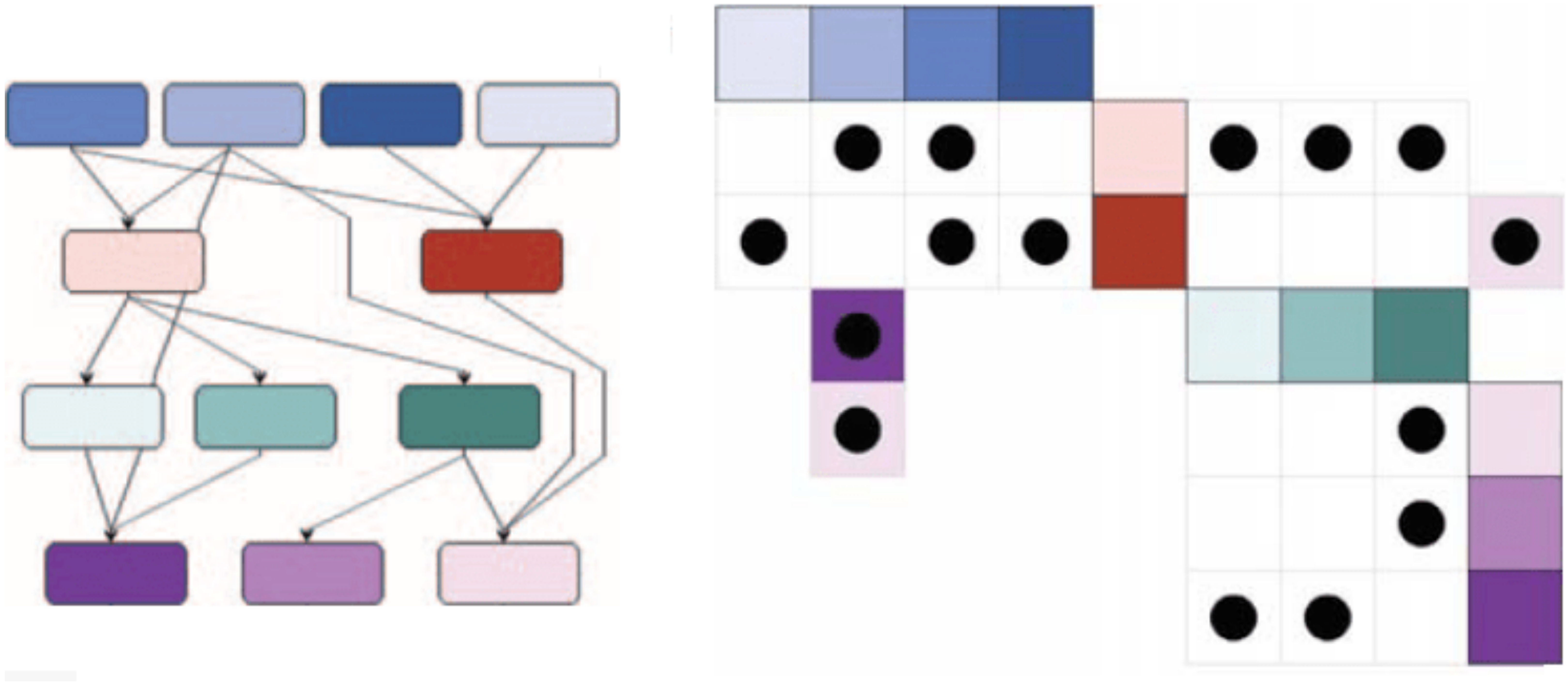
Married
Friends
Dating
Friends
Co-workers
Mother
/Son
Soccer
Coach
Layer 5

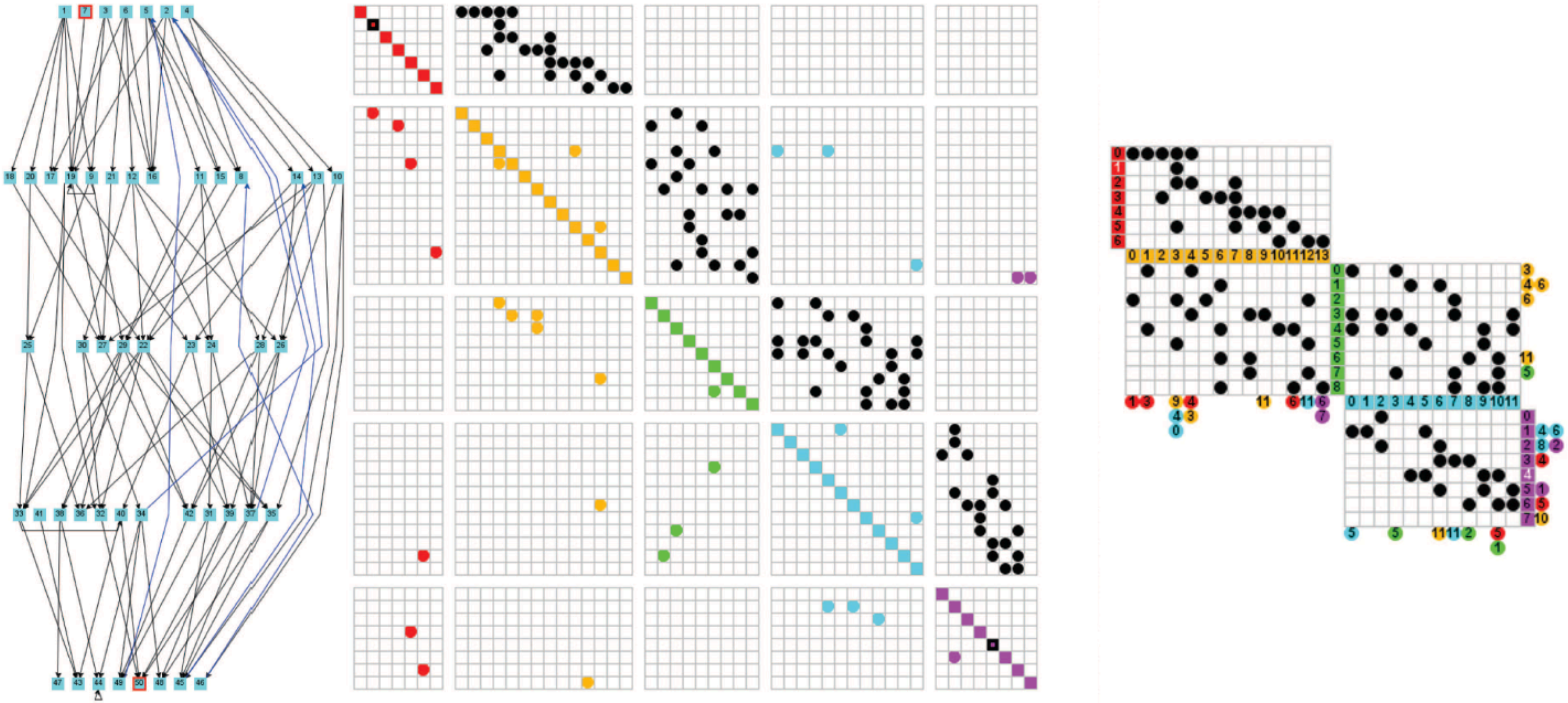

Married
Friends
Dating
Co-workers
Friends
Mother /Son
Soccer Coach
Layer 5

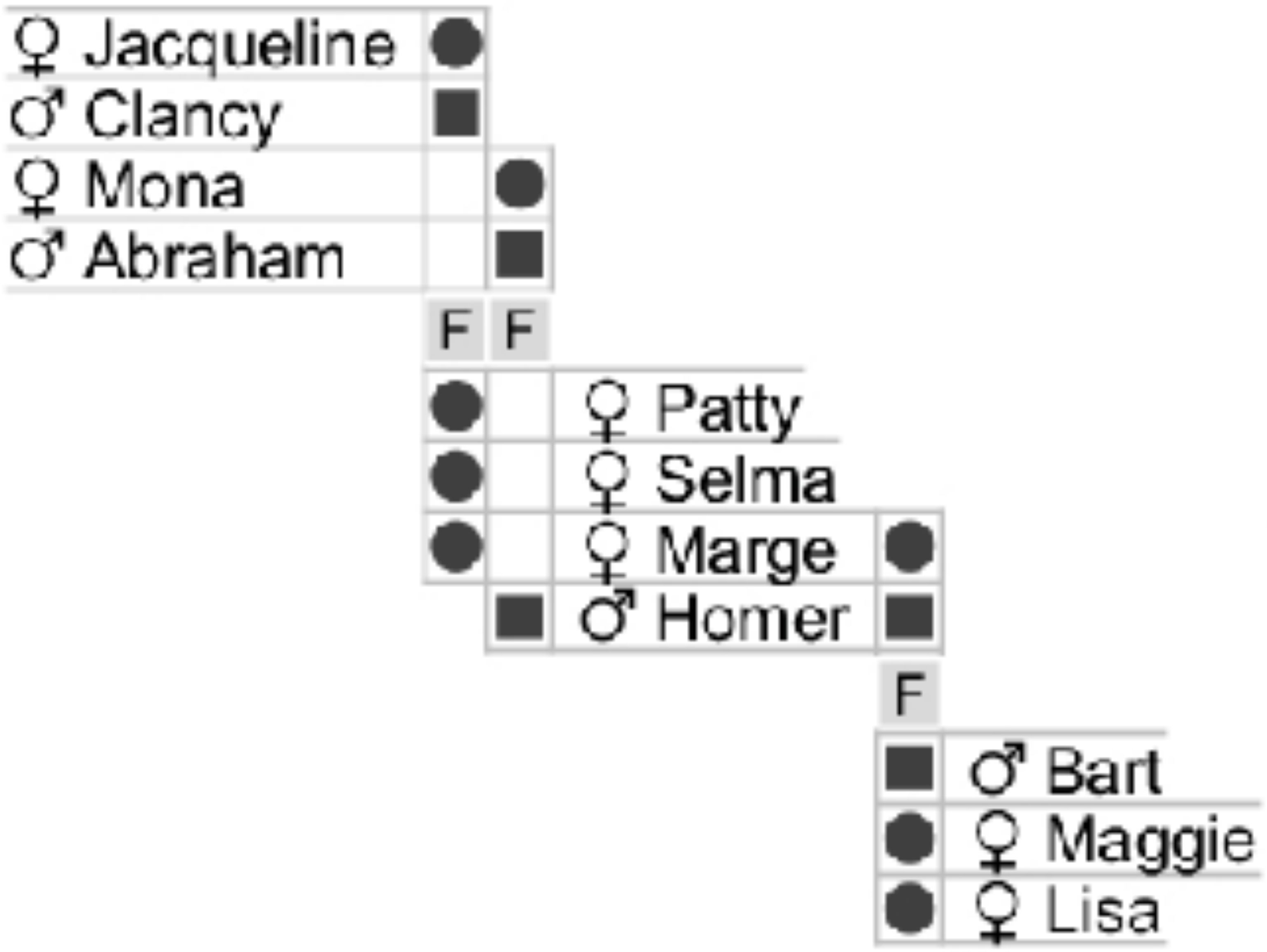

Married
Friends
Dating
Mother
/Son
Co-workers
Soccer
Coach

Friends

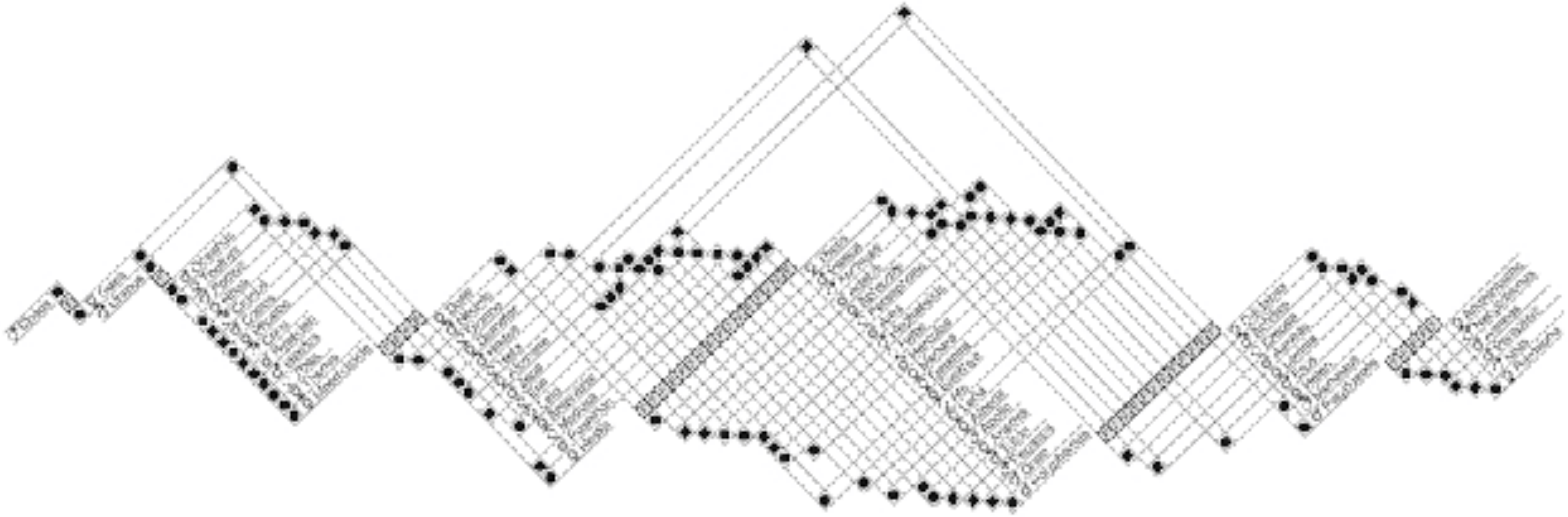

Married
Friends
Friends
Dating
Mother /Son
Co-workers
Soccer Coach








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

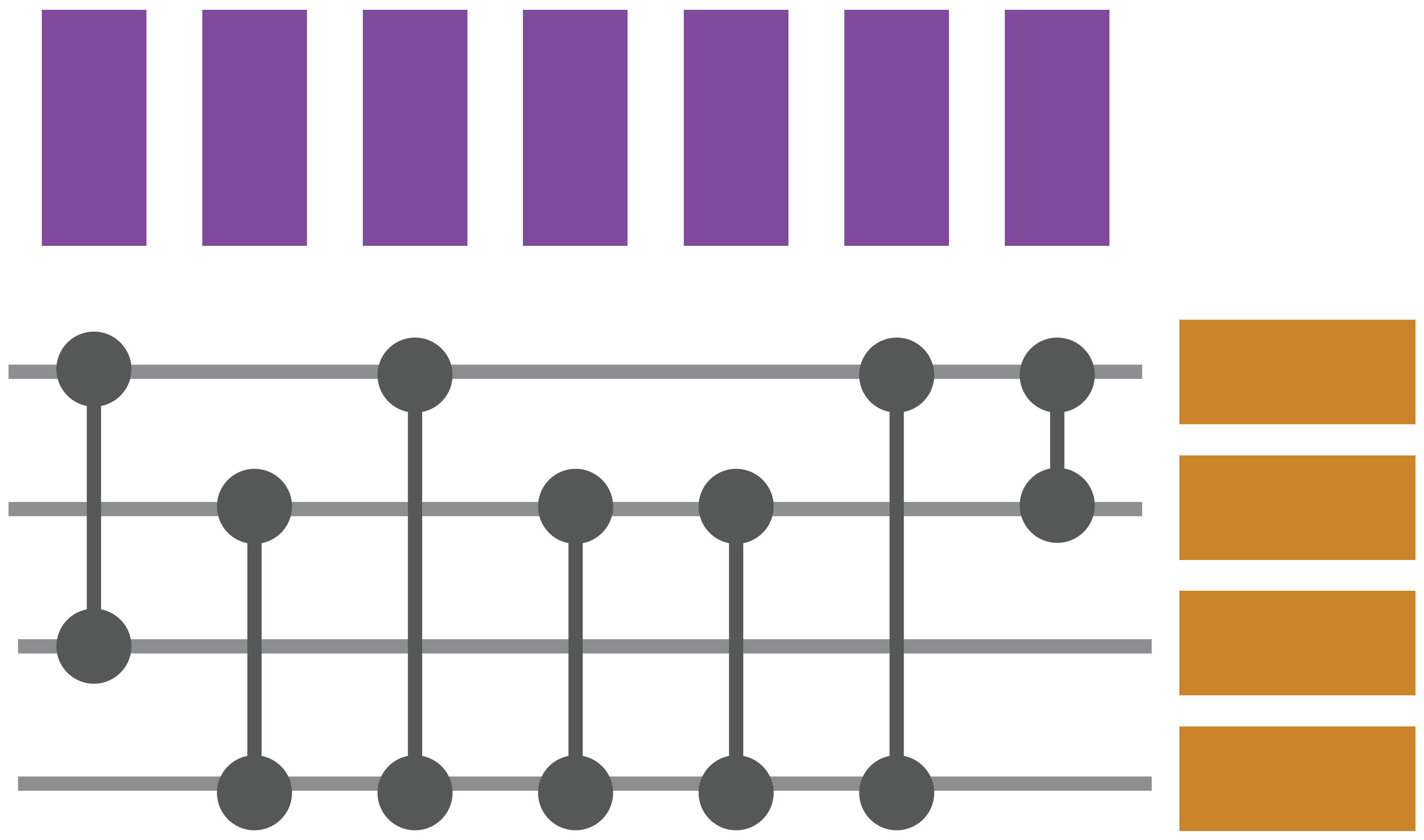


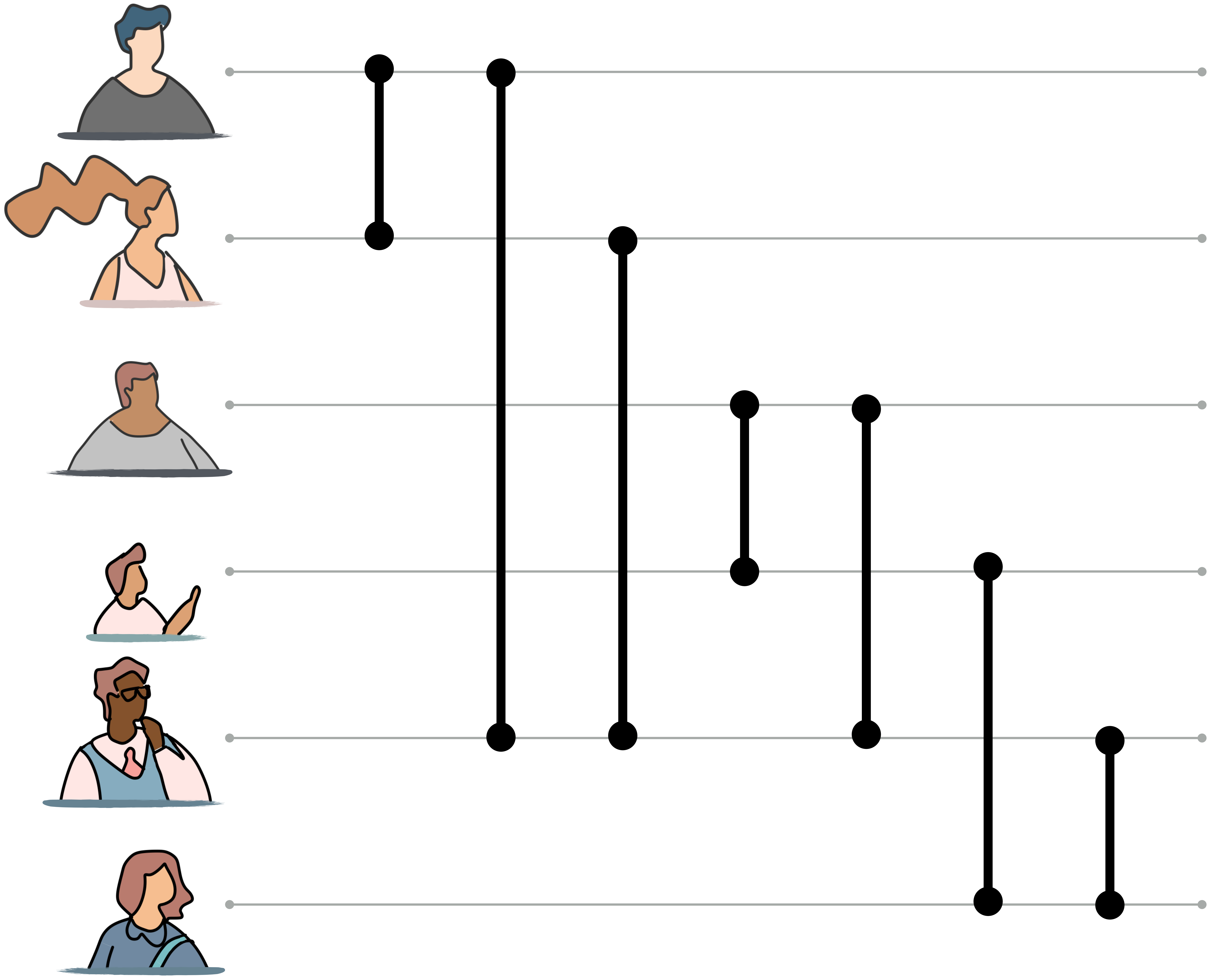
Well suited for layered networks

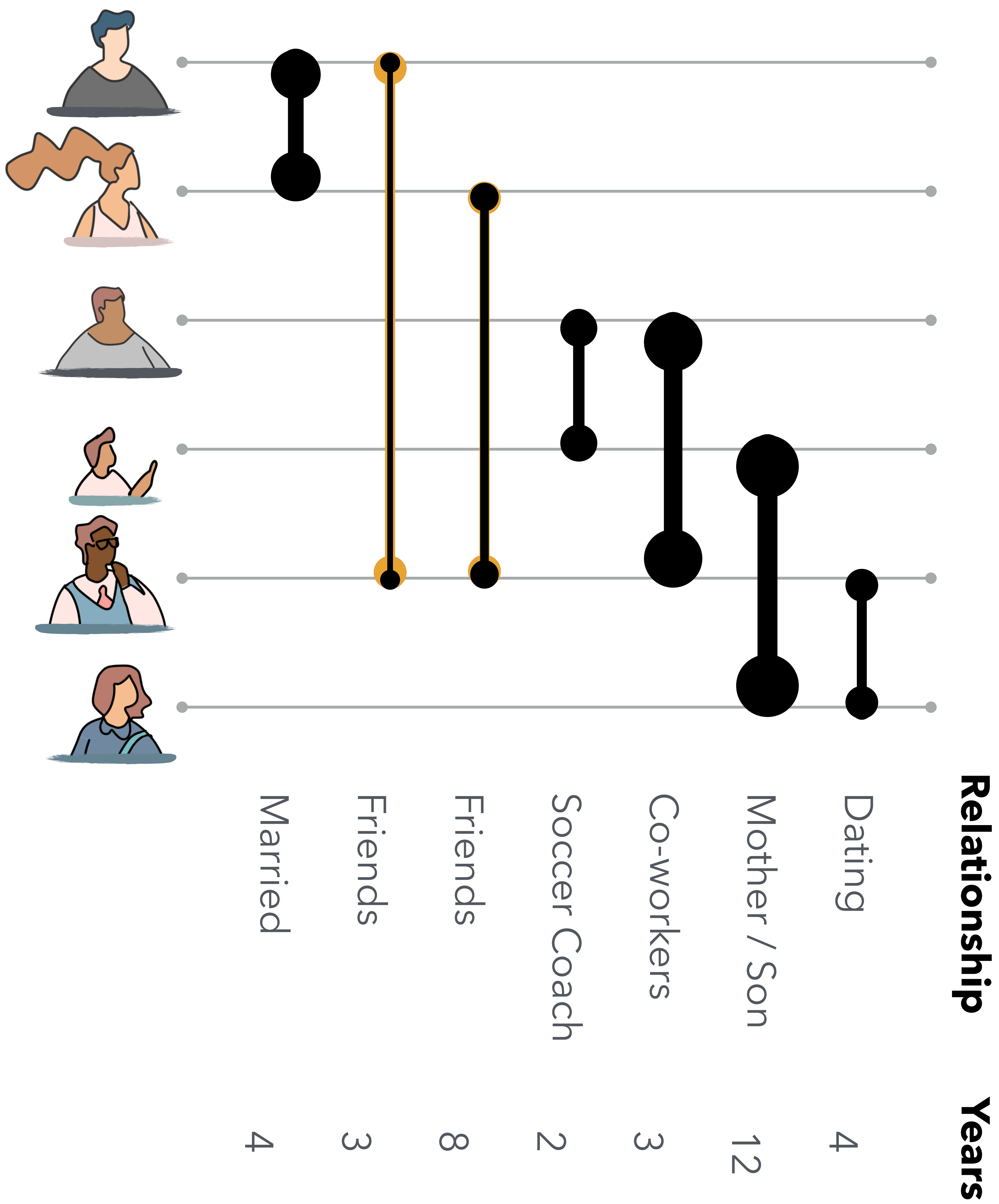
Links between nonconsecutive layers can be problematic to integrate and non-intuitive

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

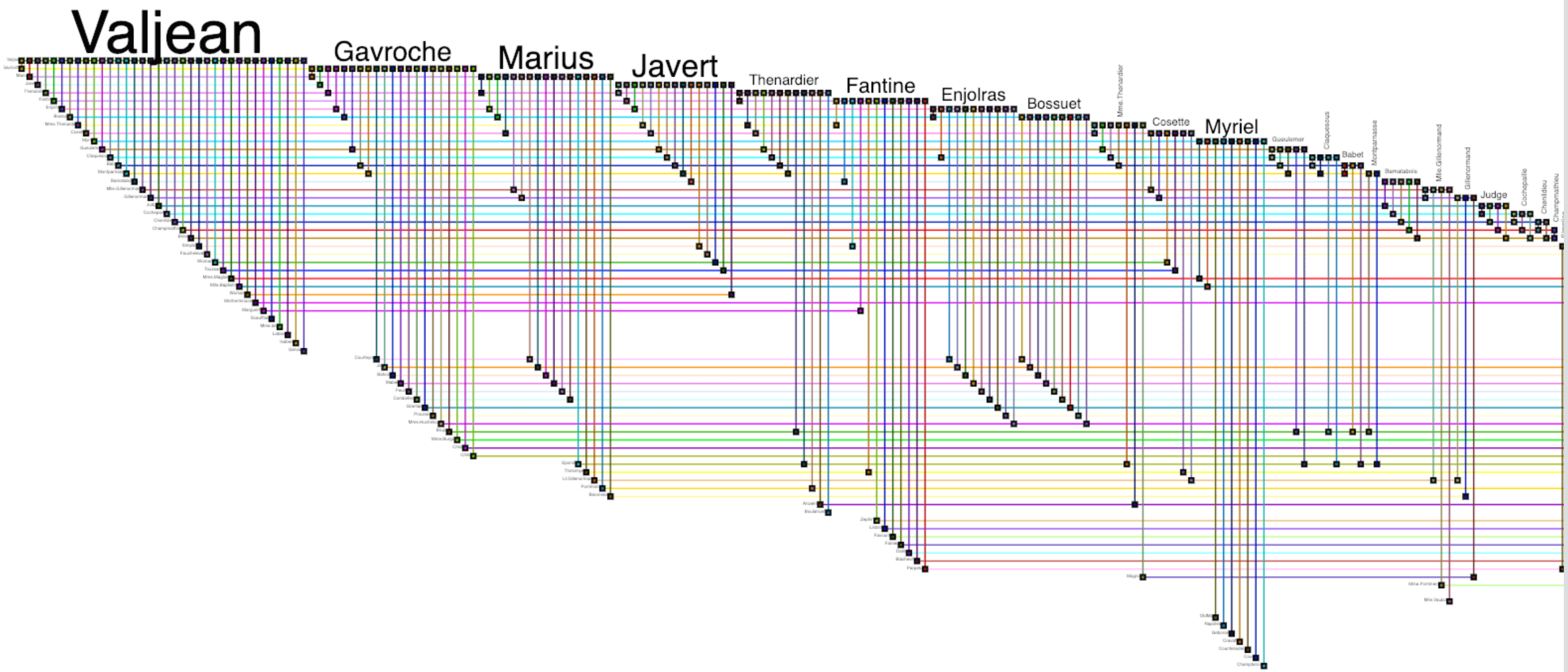
BioFabric



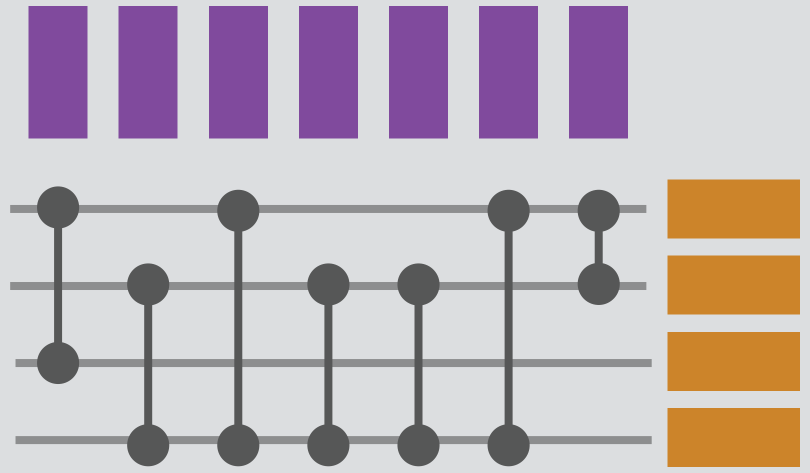




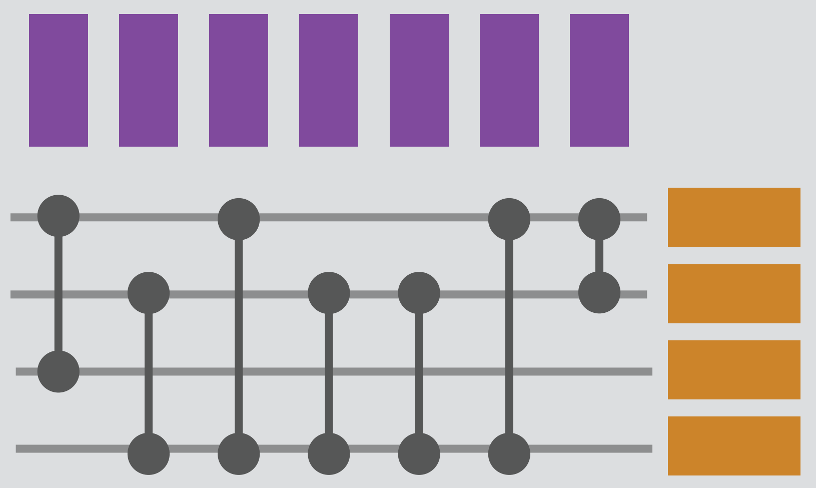
Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3



Longabaugh, 2012



BioFabric



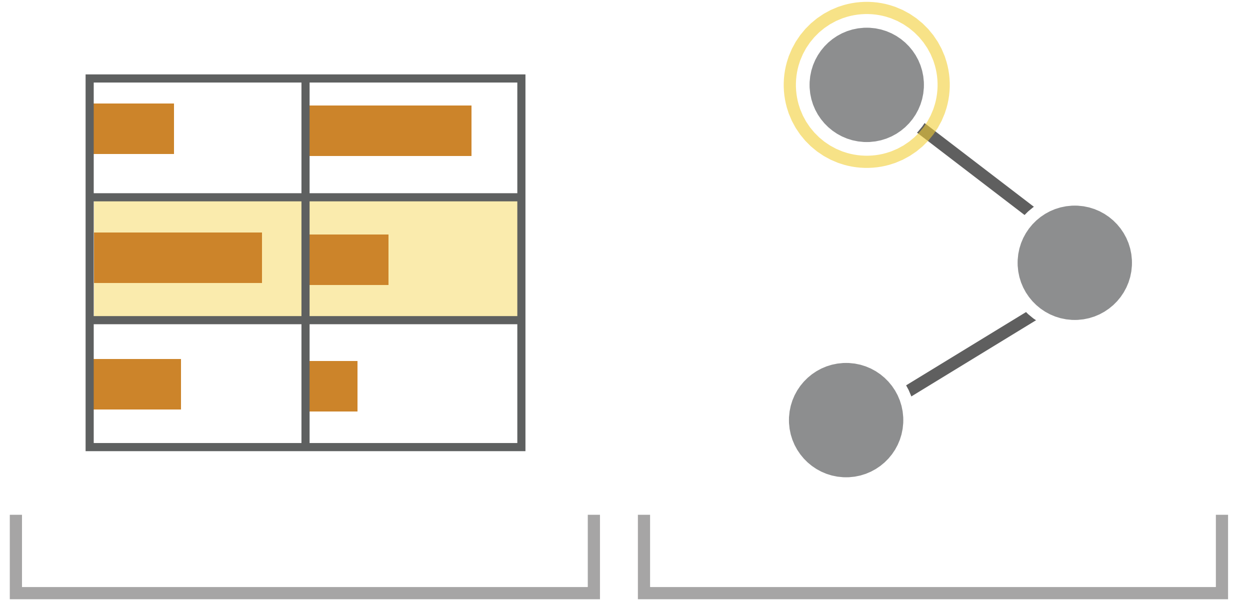
BioFabric

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

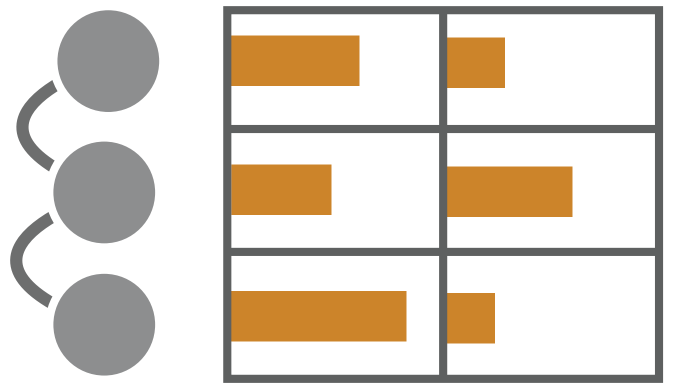
More difficult to discover neighbors and clusters in Biofabric compared to matrices.

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

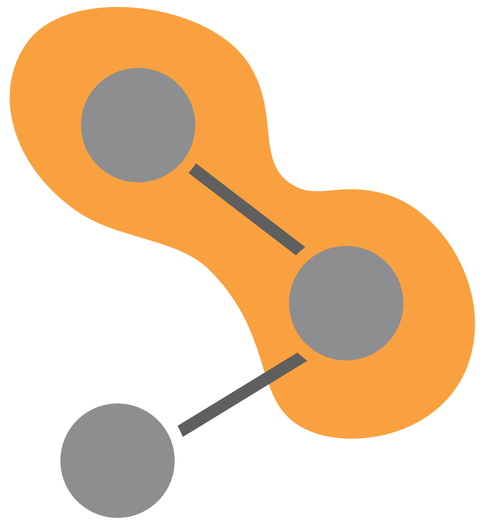
View Operations



Juxtaposed

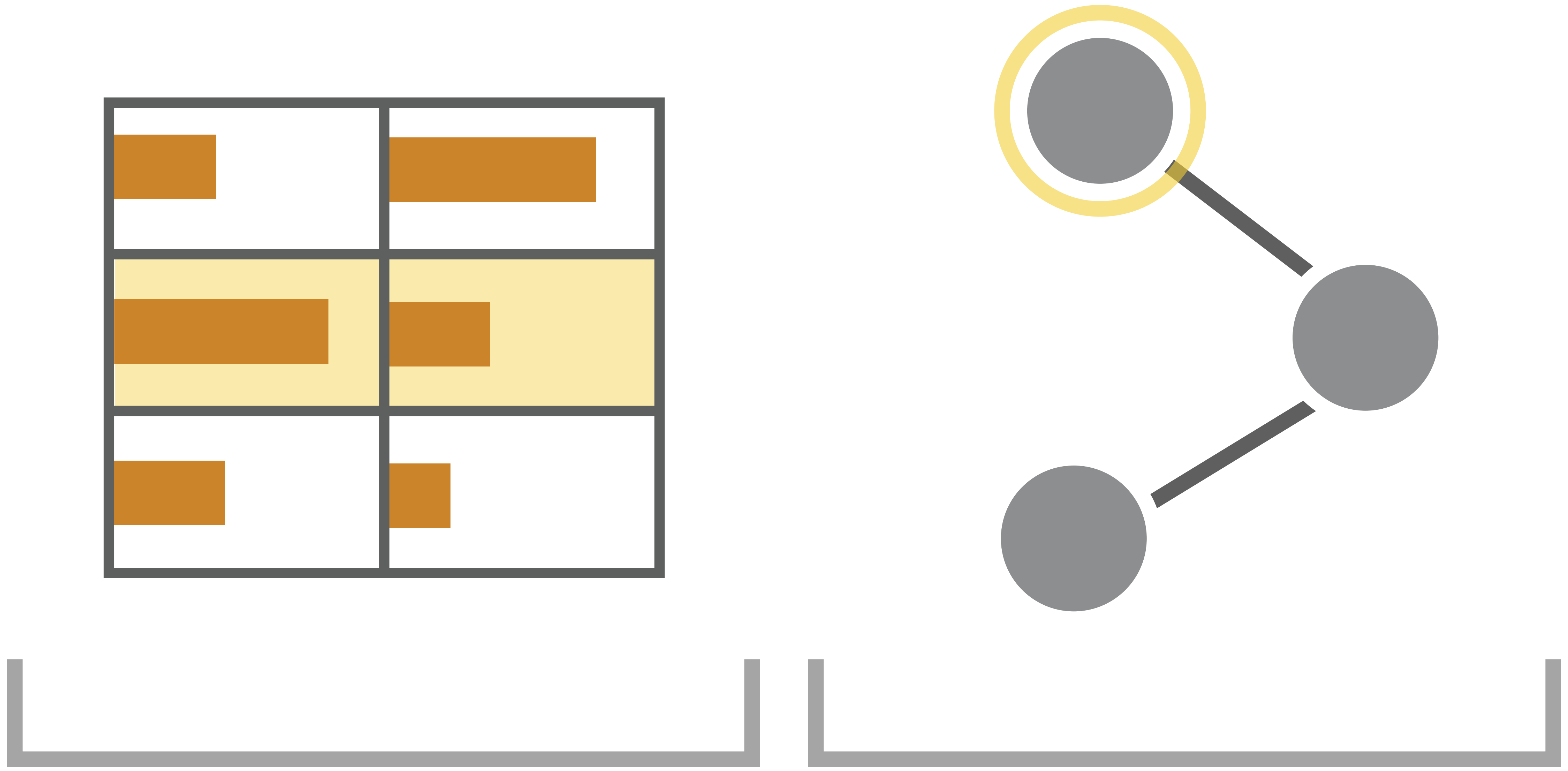


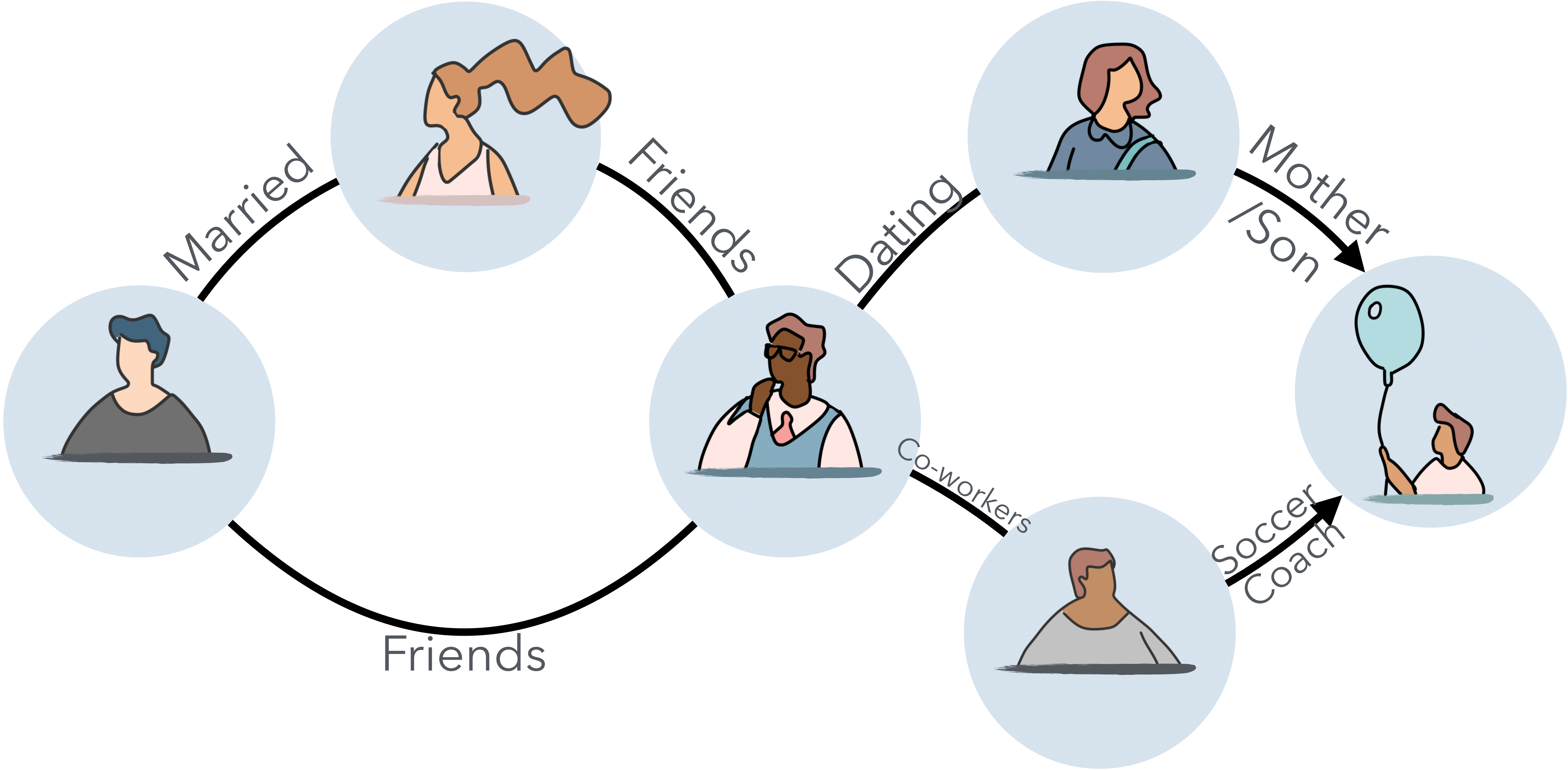
Integrated

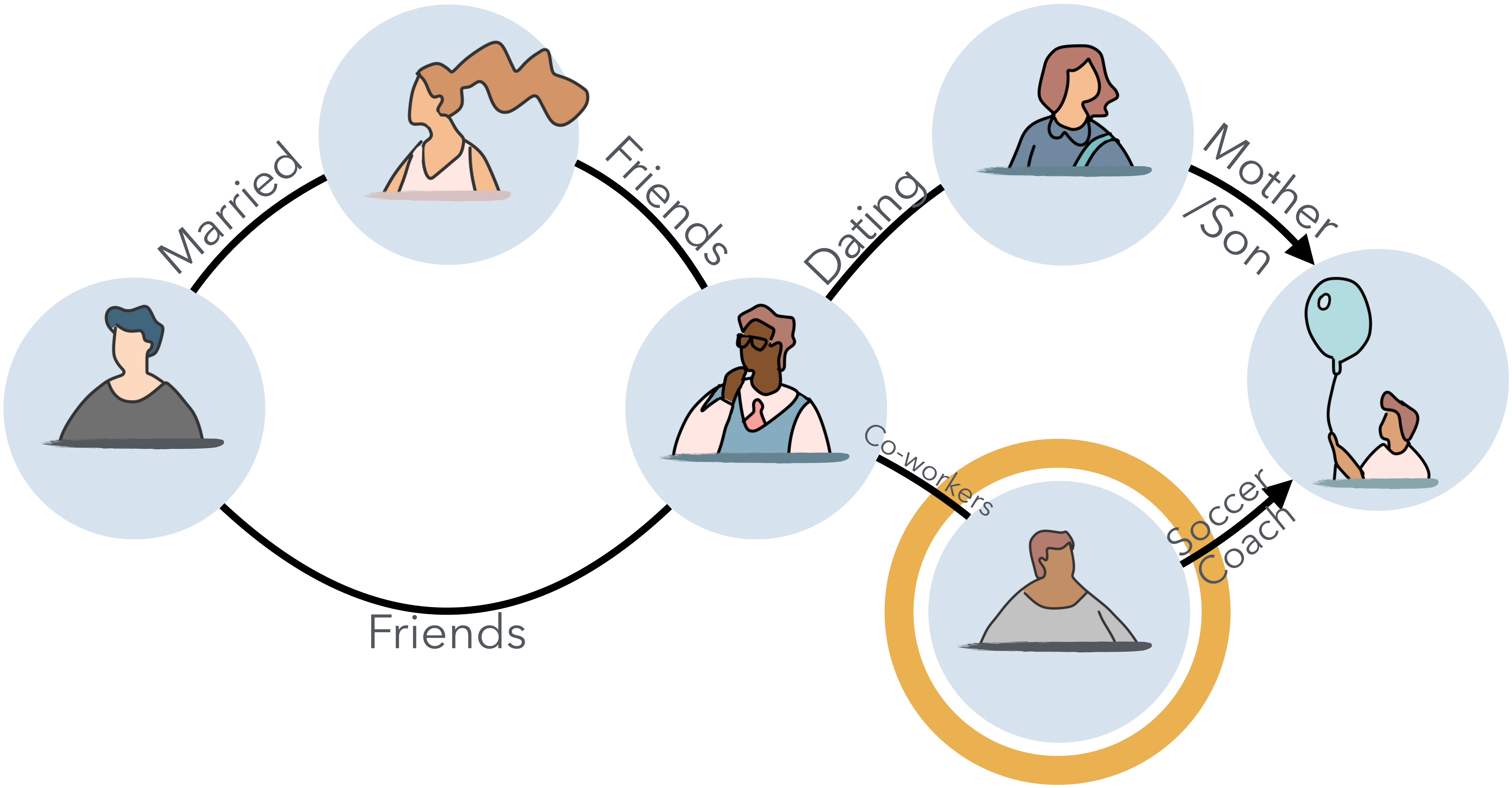


Overloaded

Juxtaposed




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



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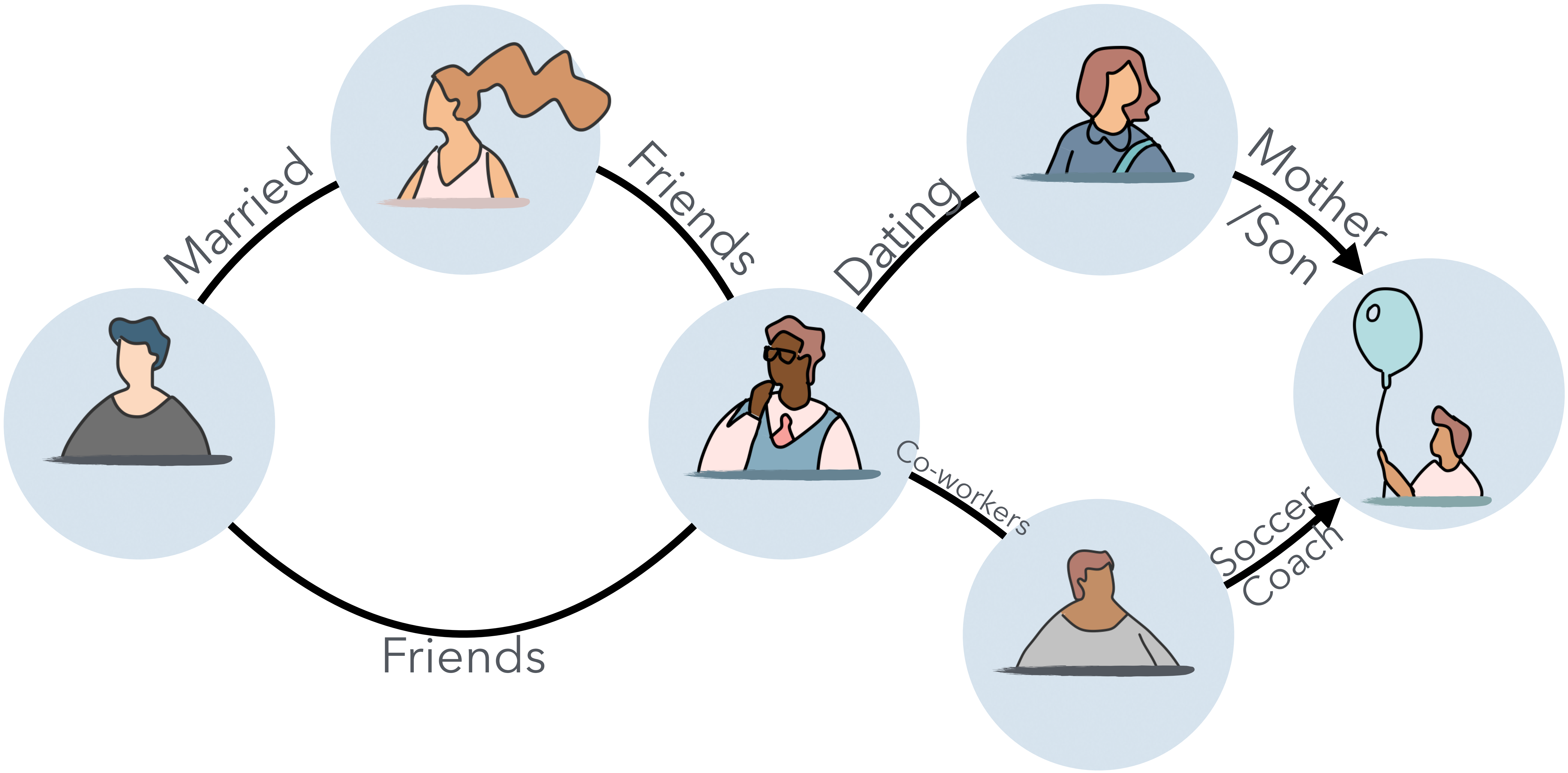
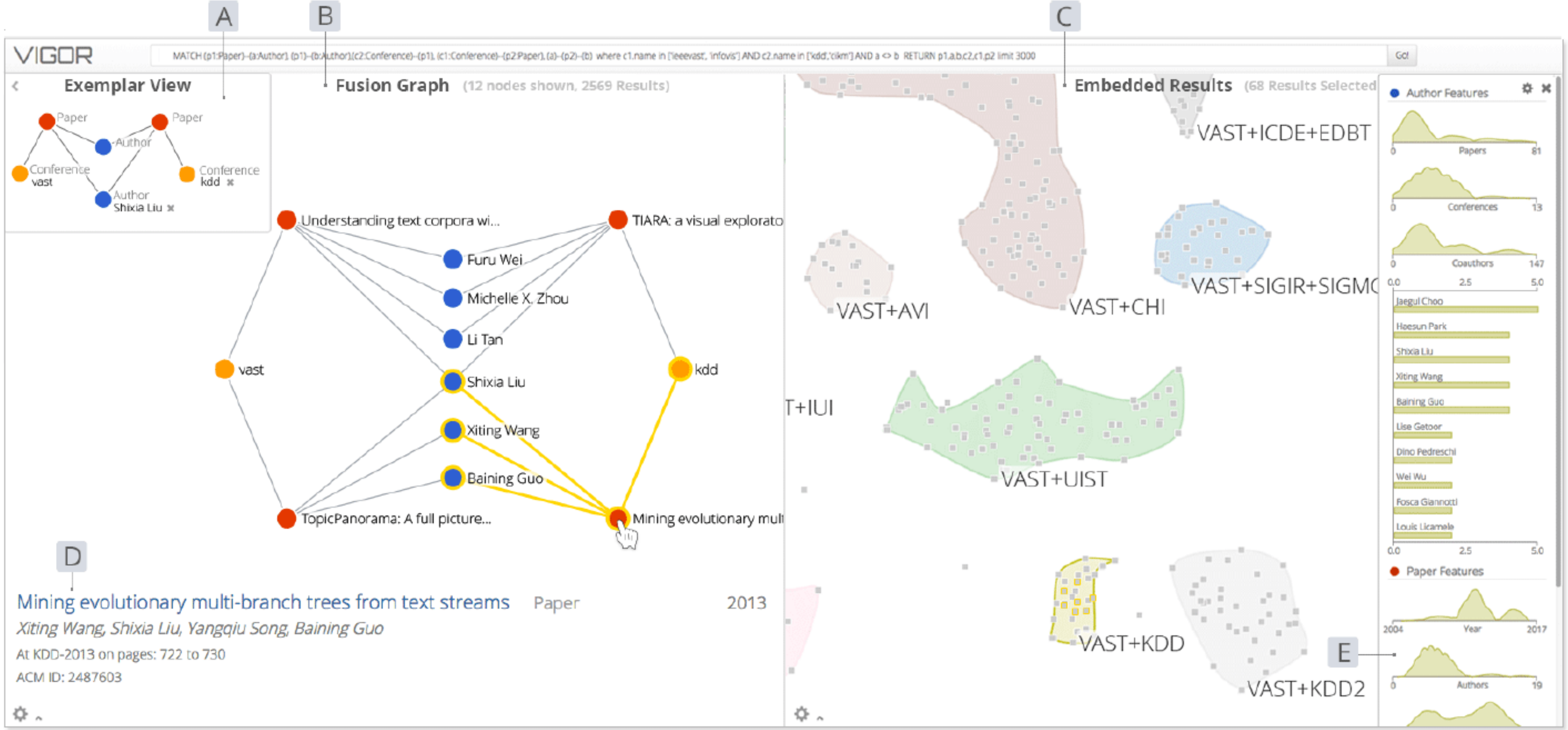
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

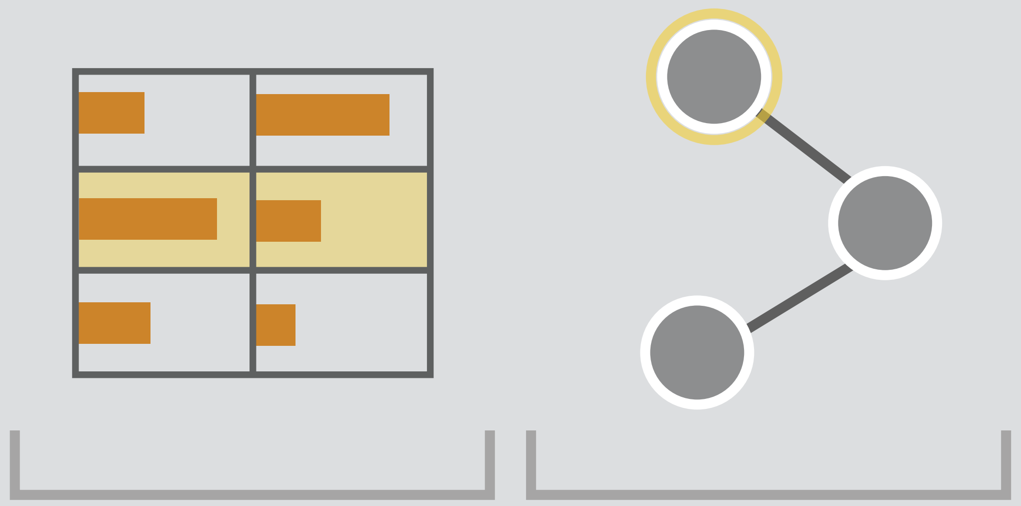


Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

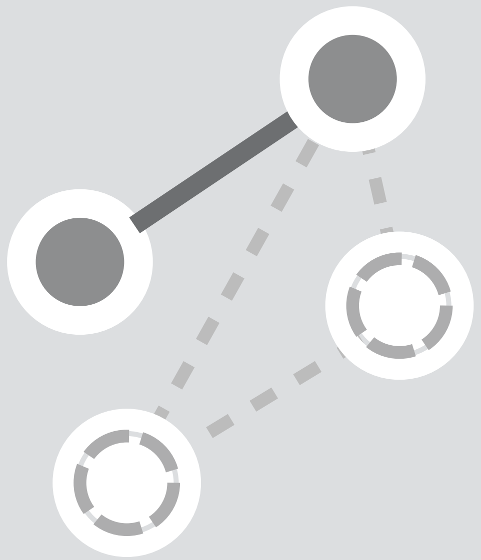
Relationship	Years
Dating	4
Mother / Son	12
Co-workers	3
Soccer Coach	2
Friends	8
Friends	3
Married	4



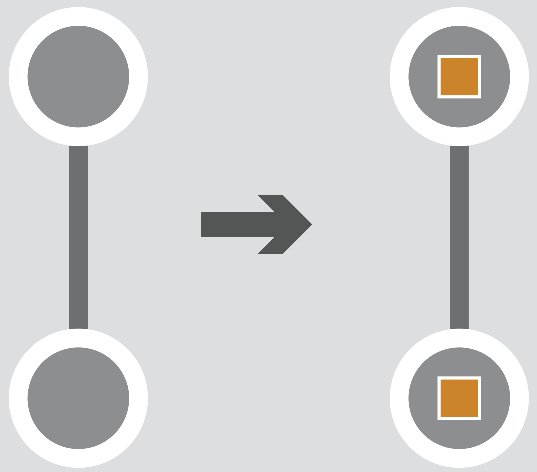
VIGOR *Pienta et al. 2018*



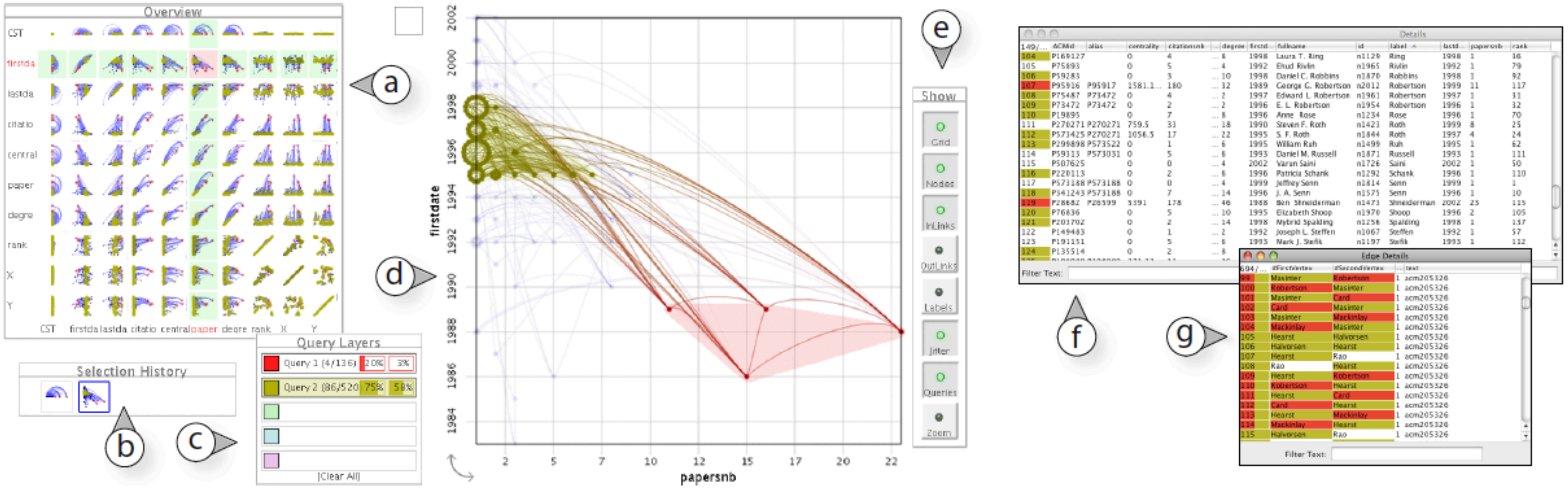
Juxtaposed

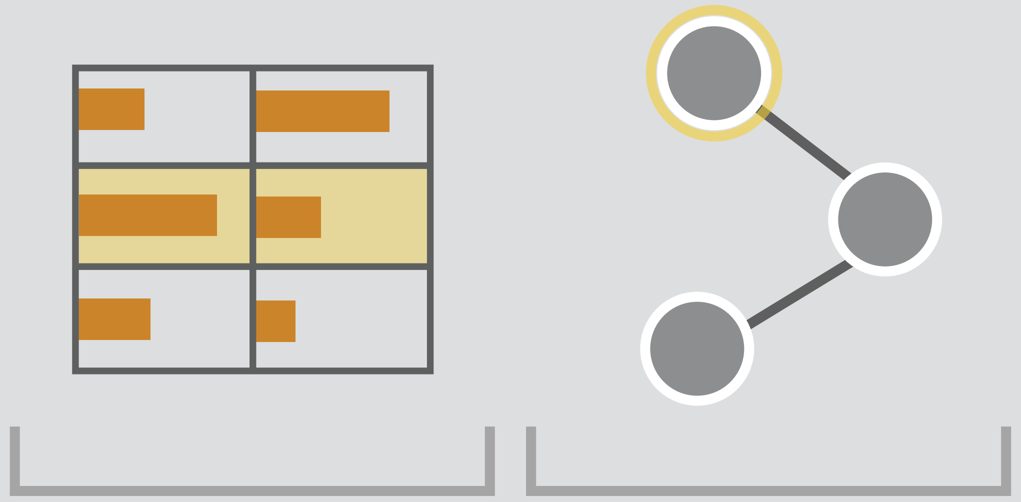


Querying and Filtering



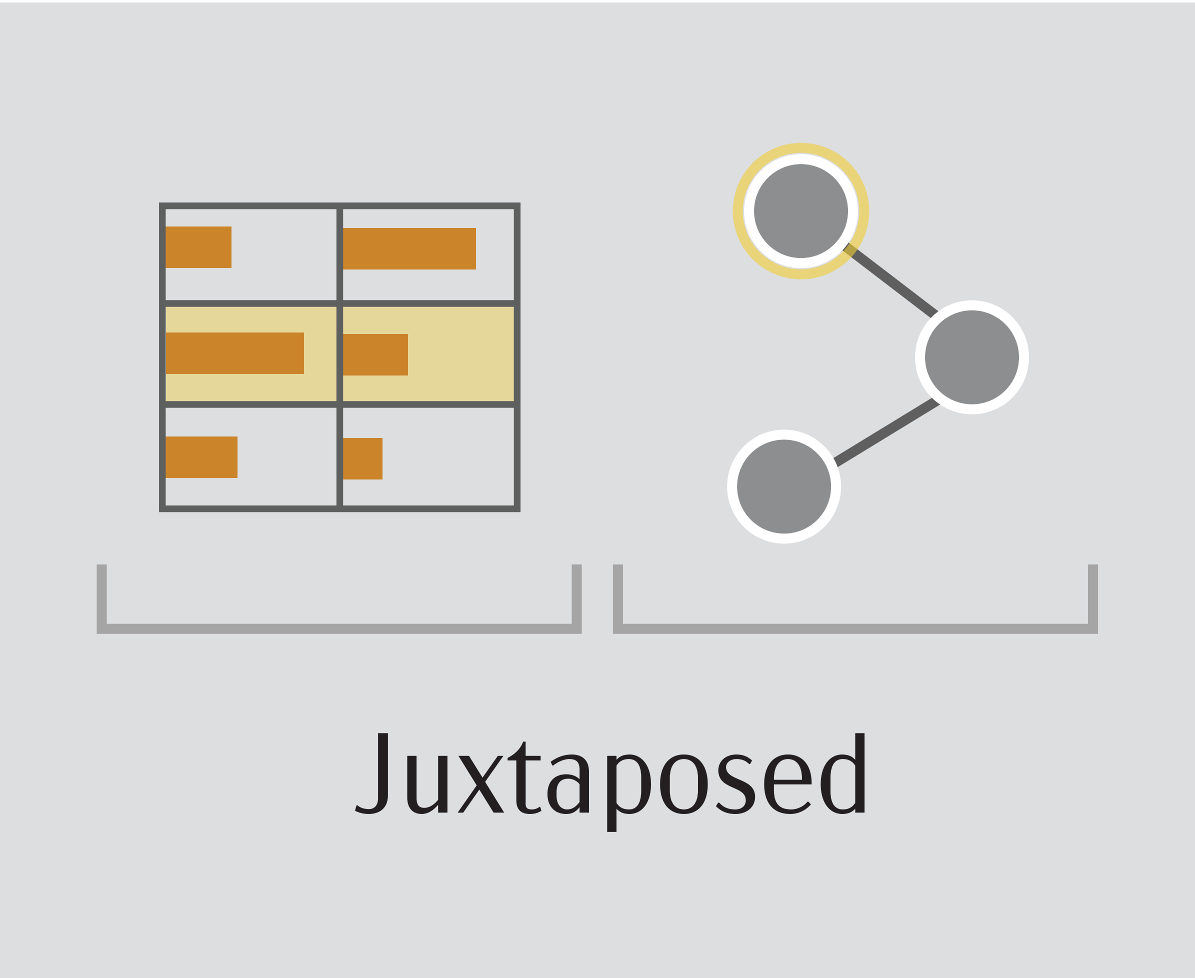
Deriving New Attributes





Juxtaposed

Graph Dice *Bezerianos et al. 2010*

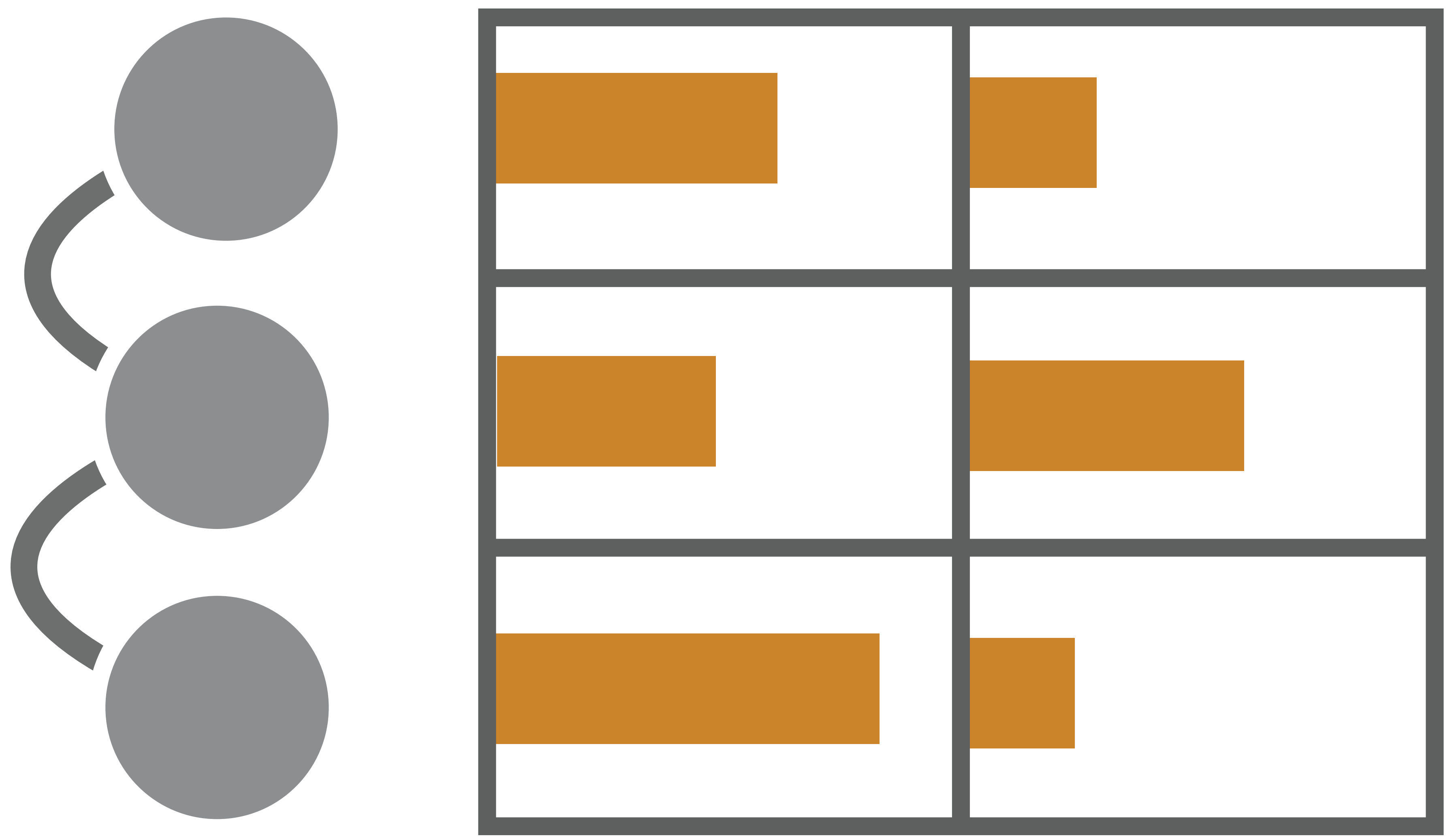


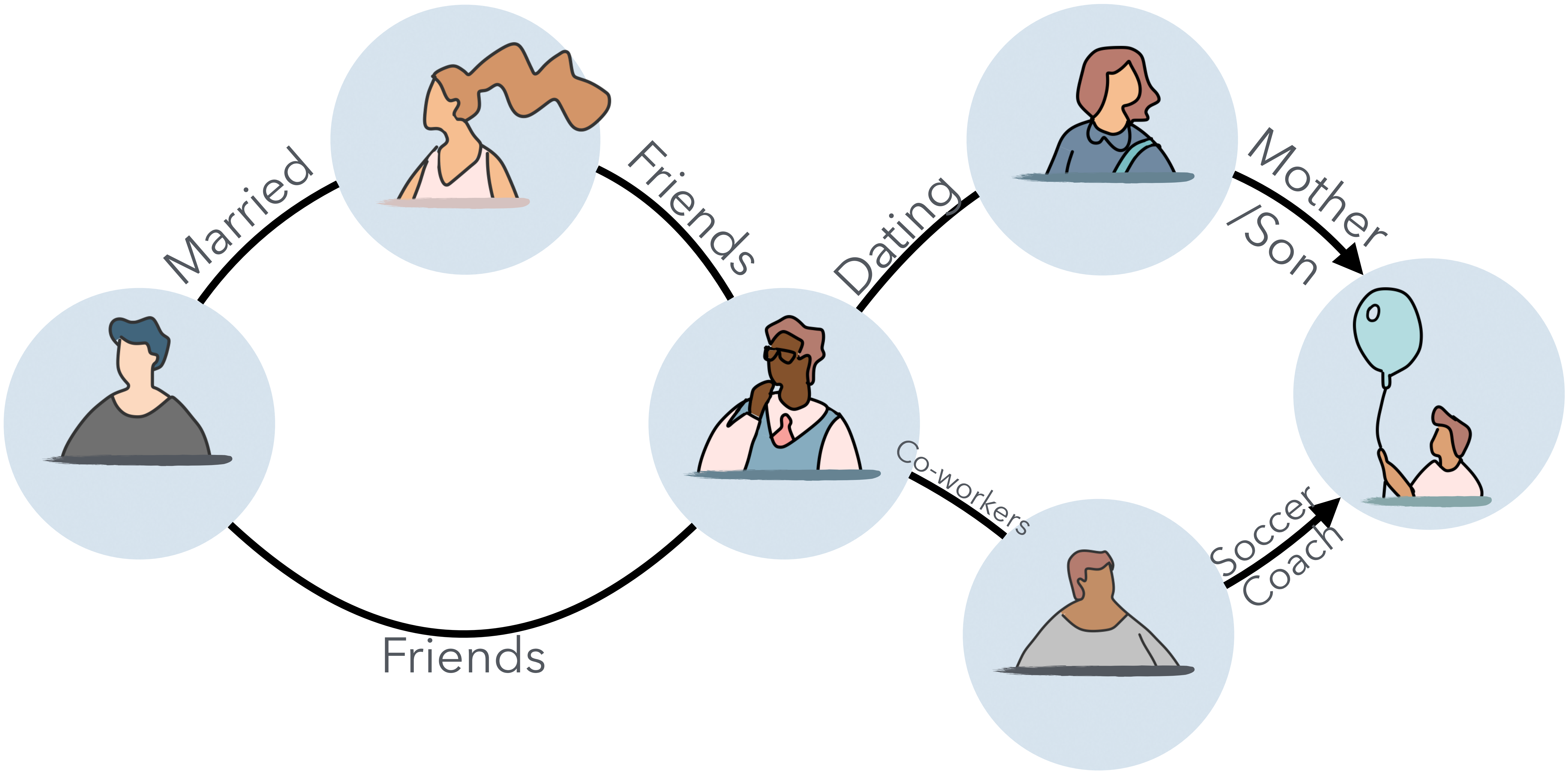
Independent views can optimize for topology and attribute independently.

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

Integrated





Name	Beverage	Day 1
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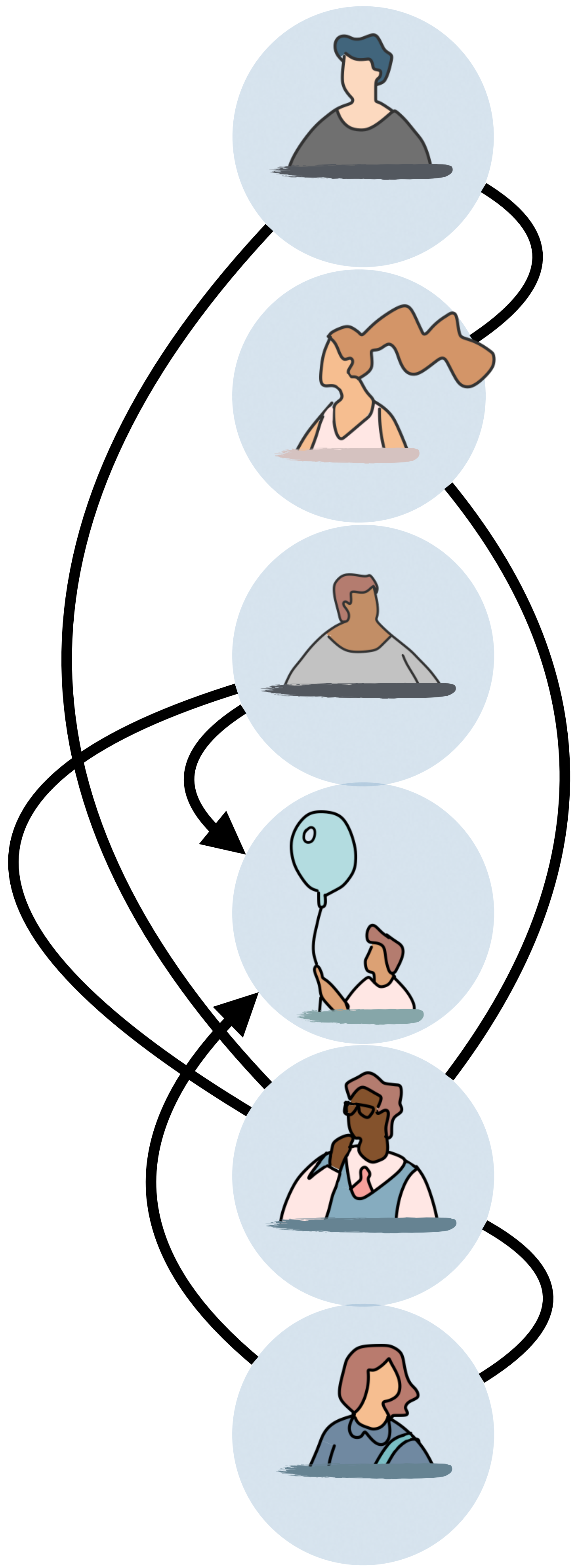

Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
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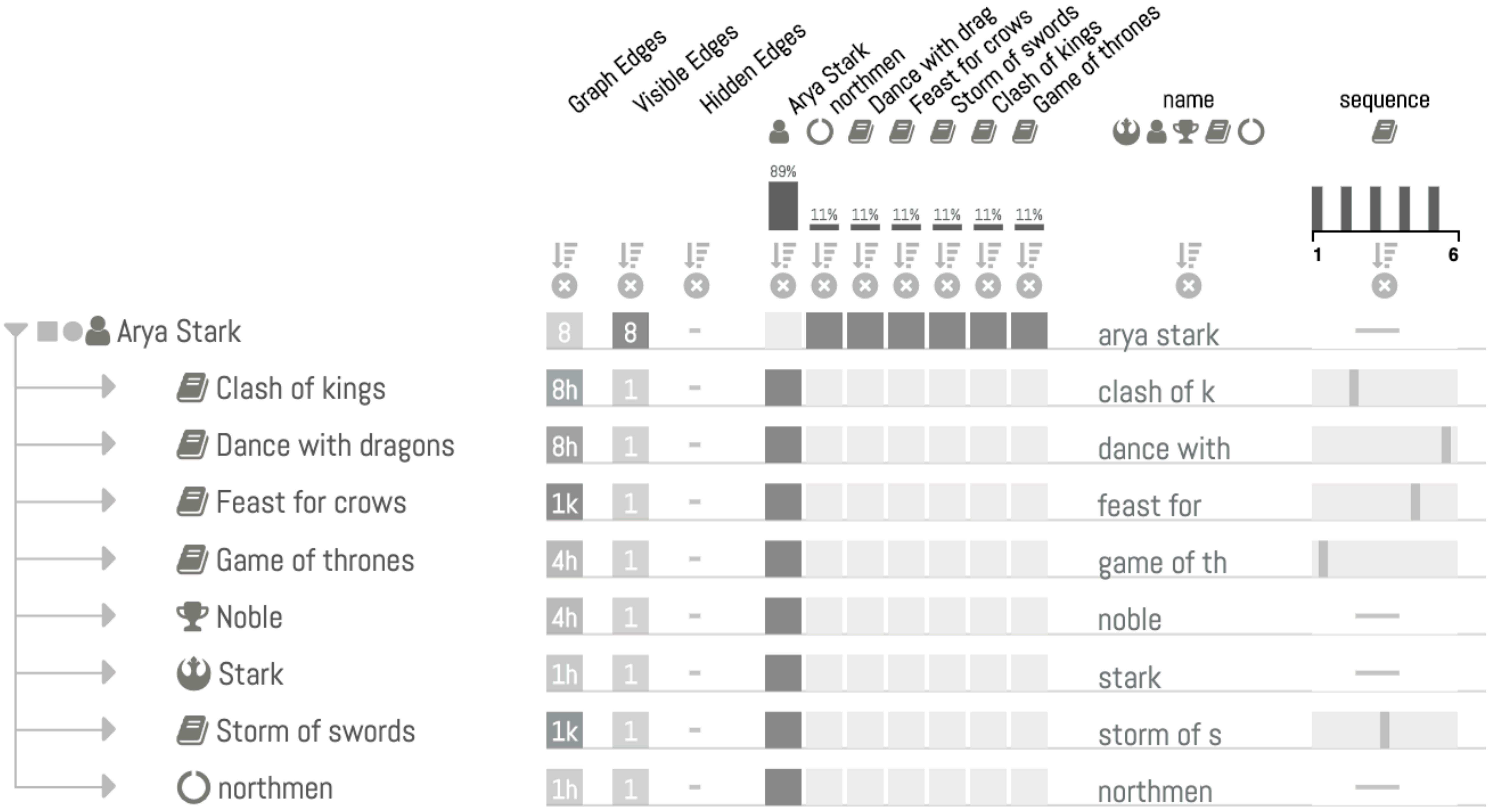
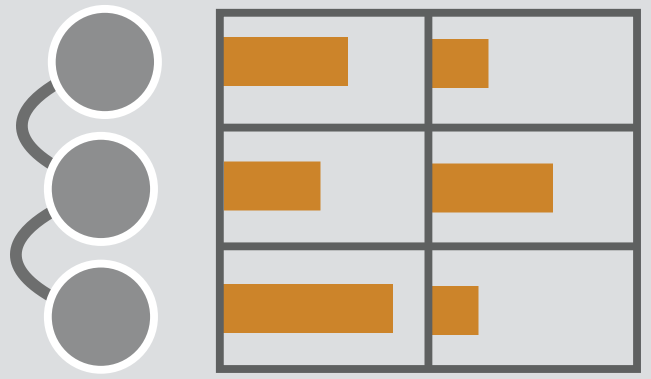


Juniper *Nobre et al. 2018*



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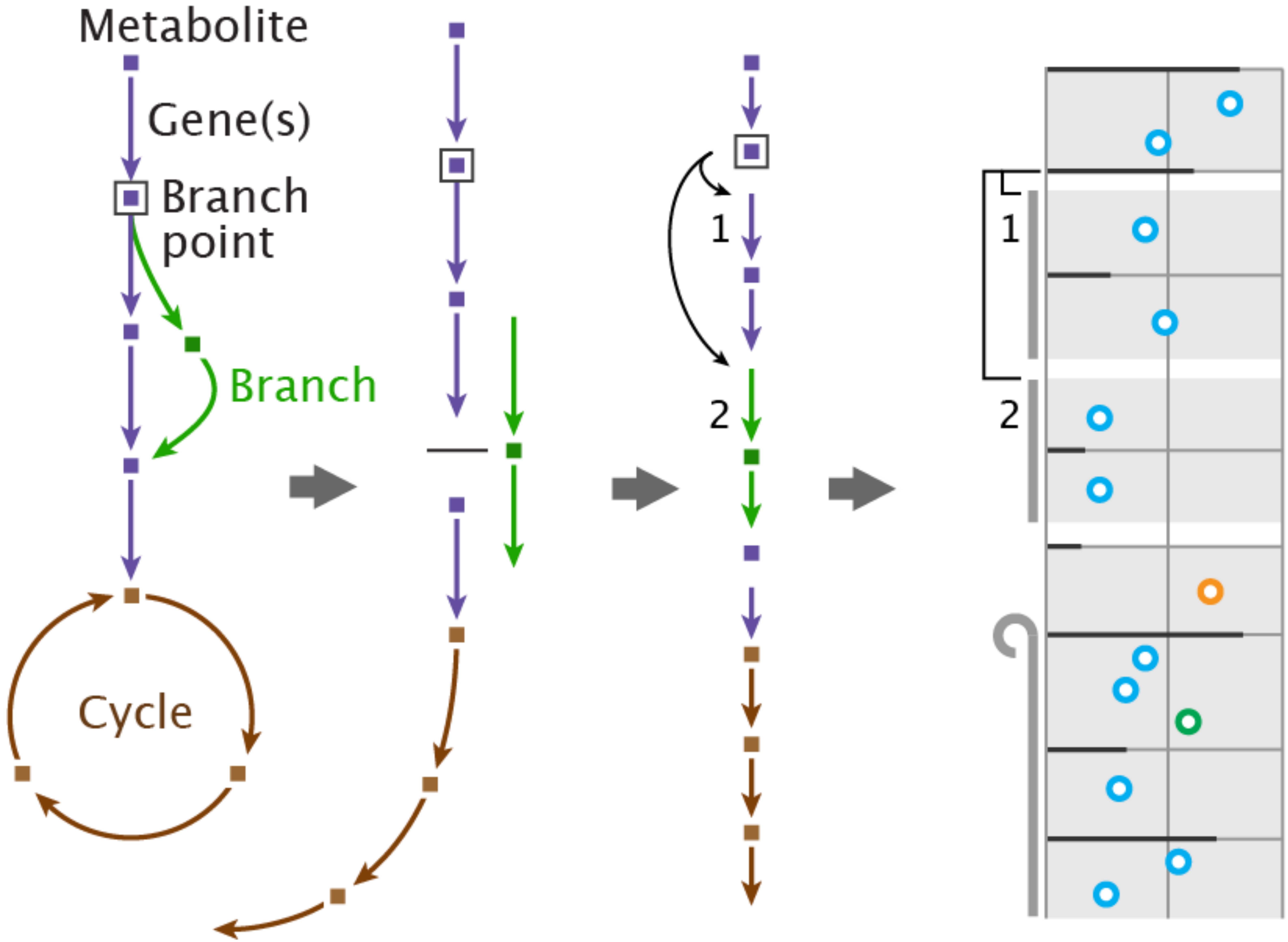
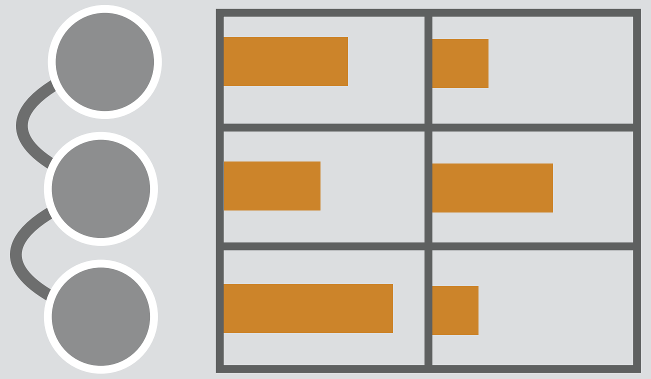


Pathline Meyer *et al. 2010*



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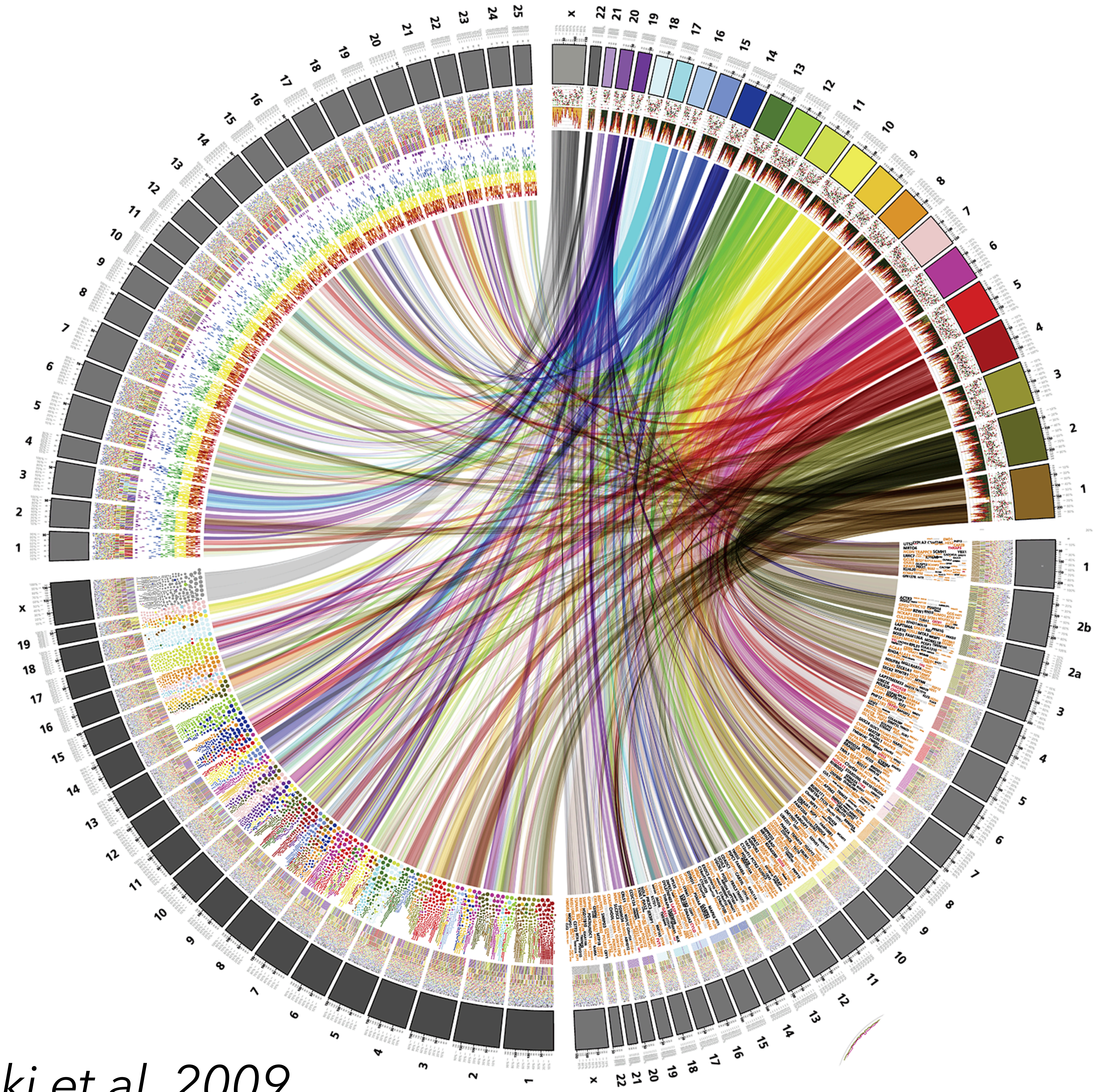
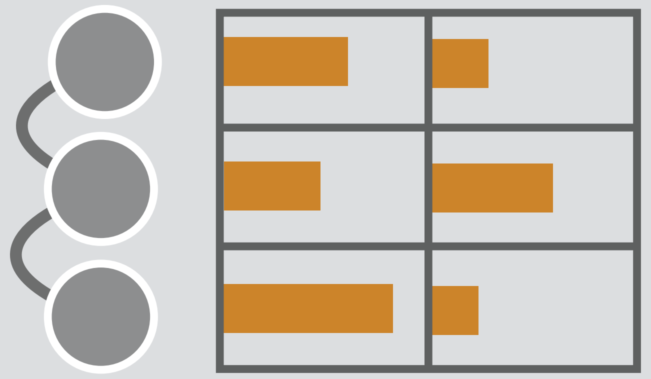
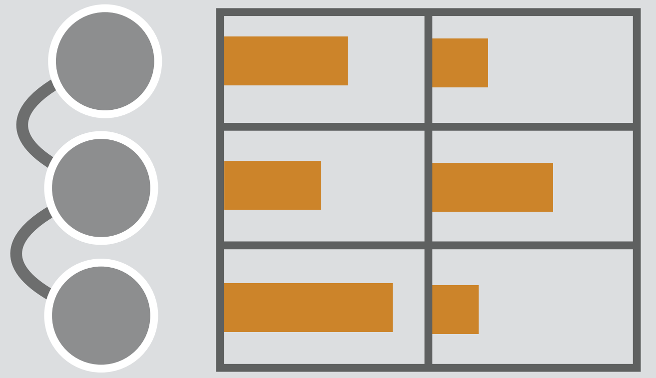




Integrated

Circos

Krzywinski et al. 2009



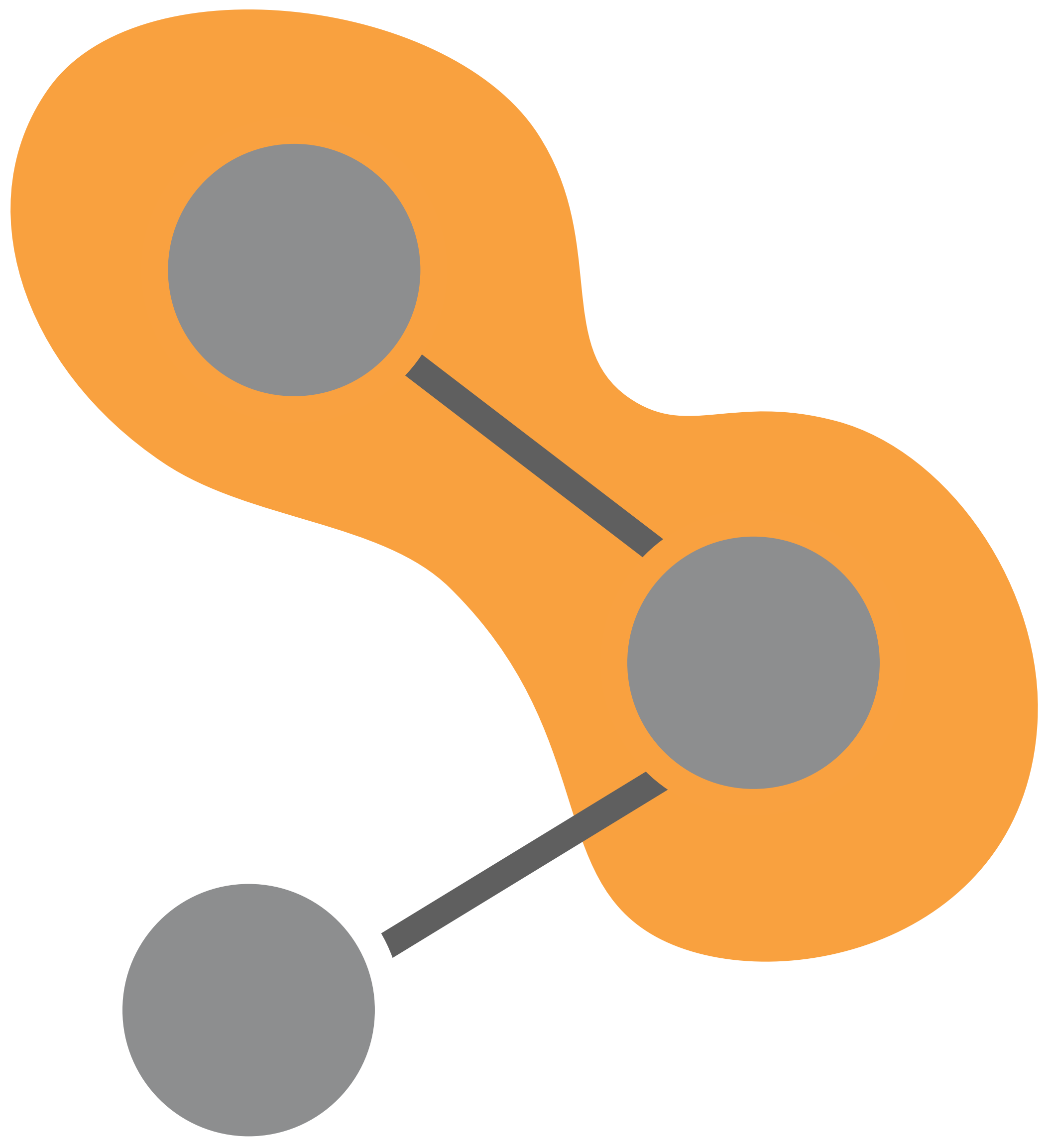
Integrated

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

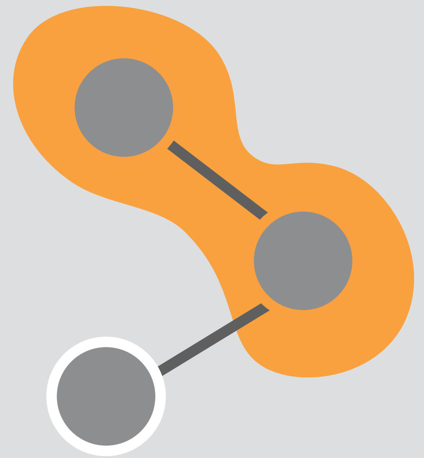
Not suitable for networks that can not be sensibly linearized.

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*



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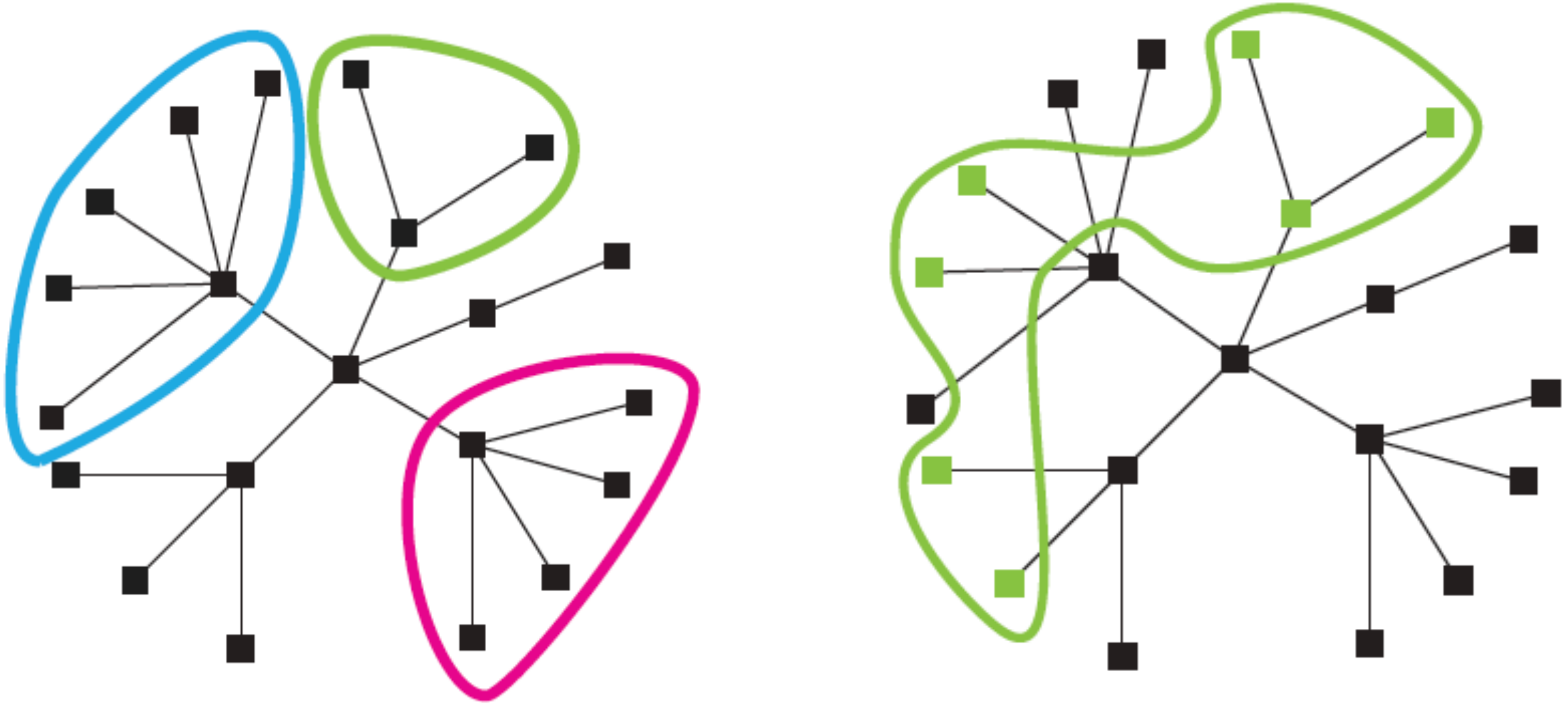
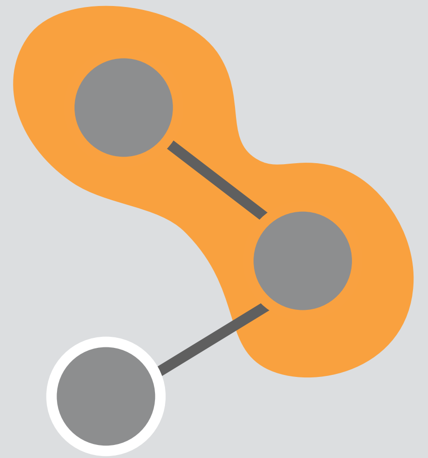


Bubble Sets *Collins et al. 2009*



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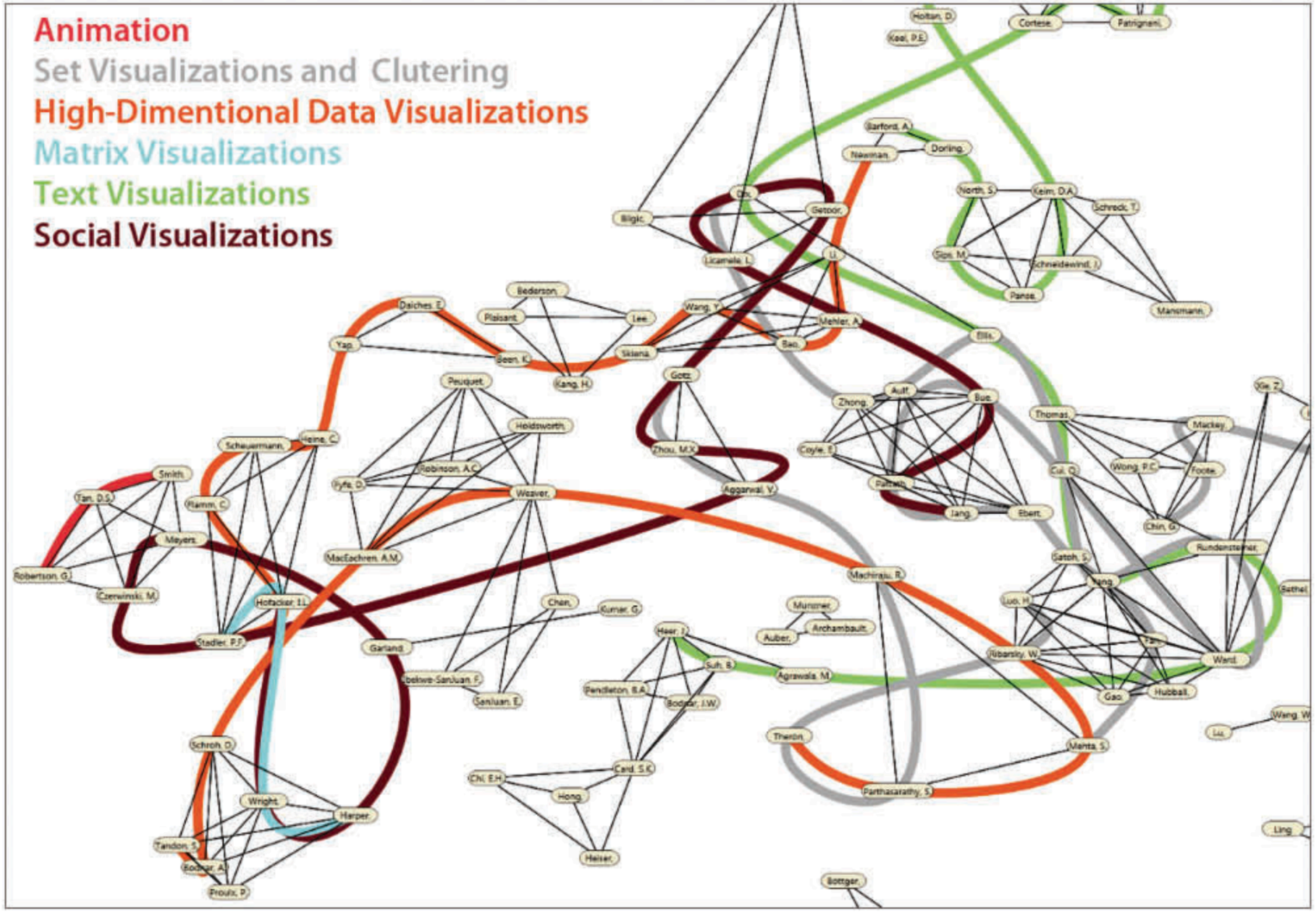
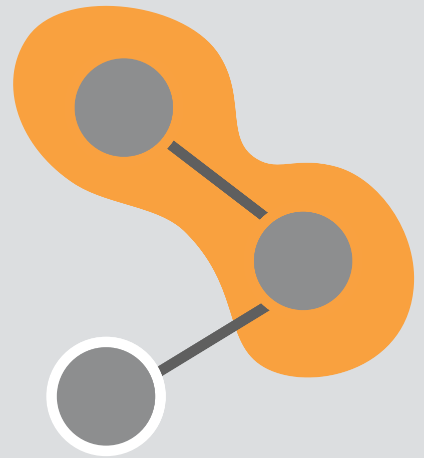


LineSets *Alper et al. 2011*



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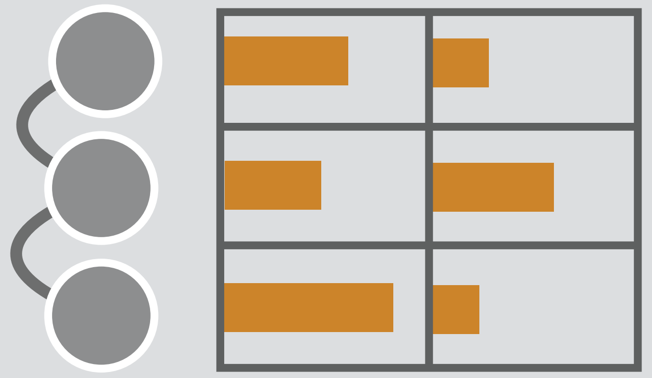


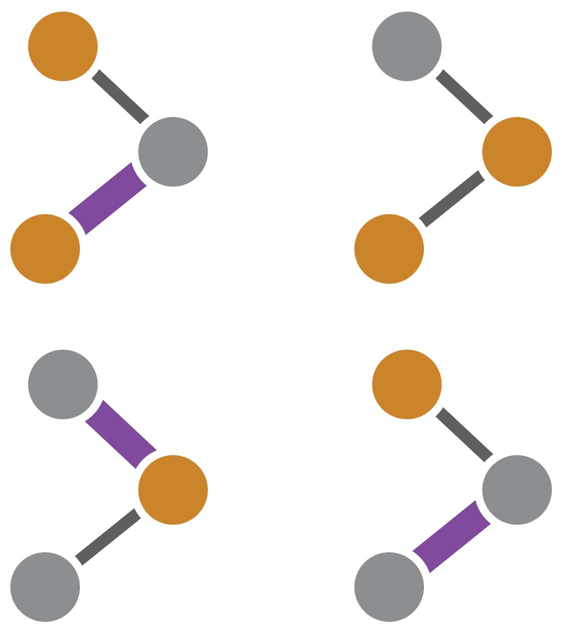
Integrated

good at displaying sets and clusters

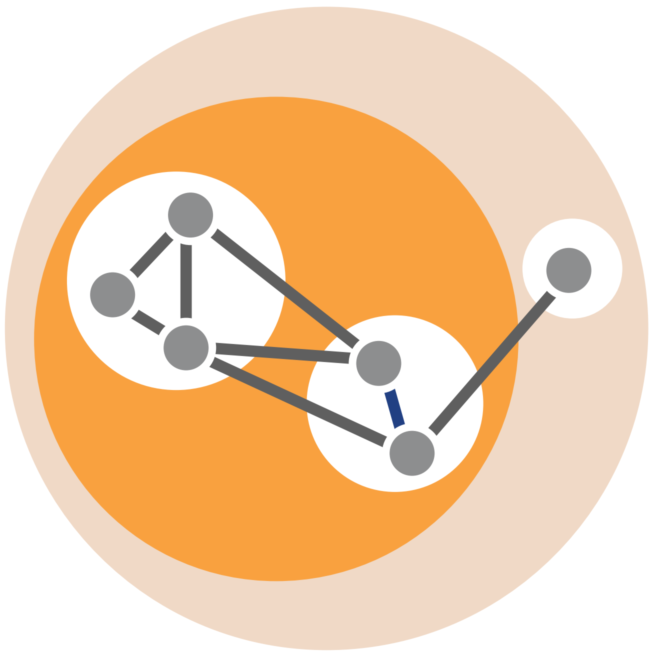
Not suitable for displaying more than one or two attributes at a time.

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

Layout Operations

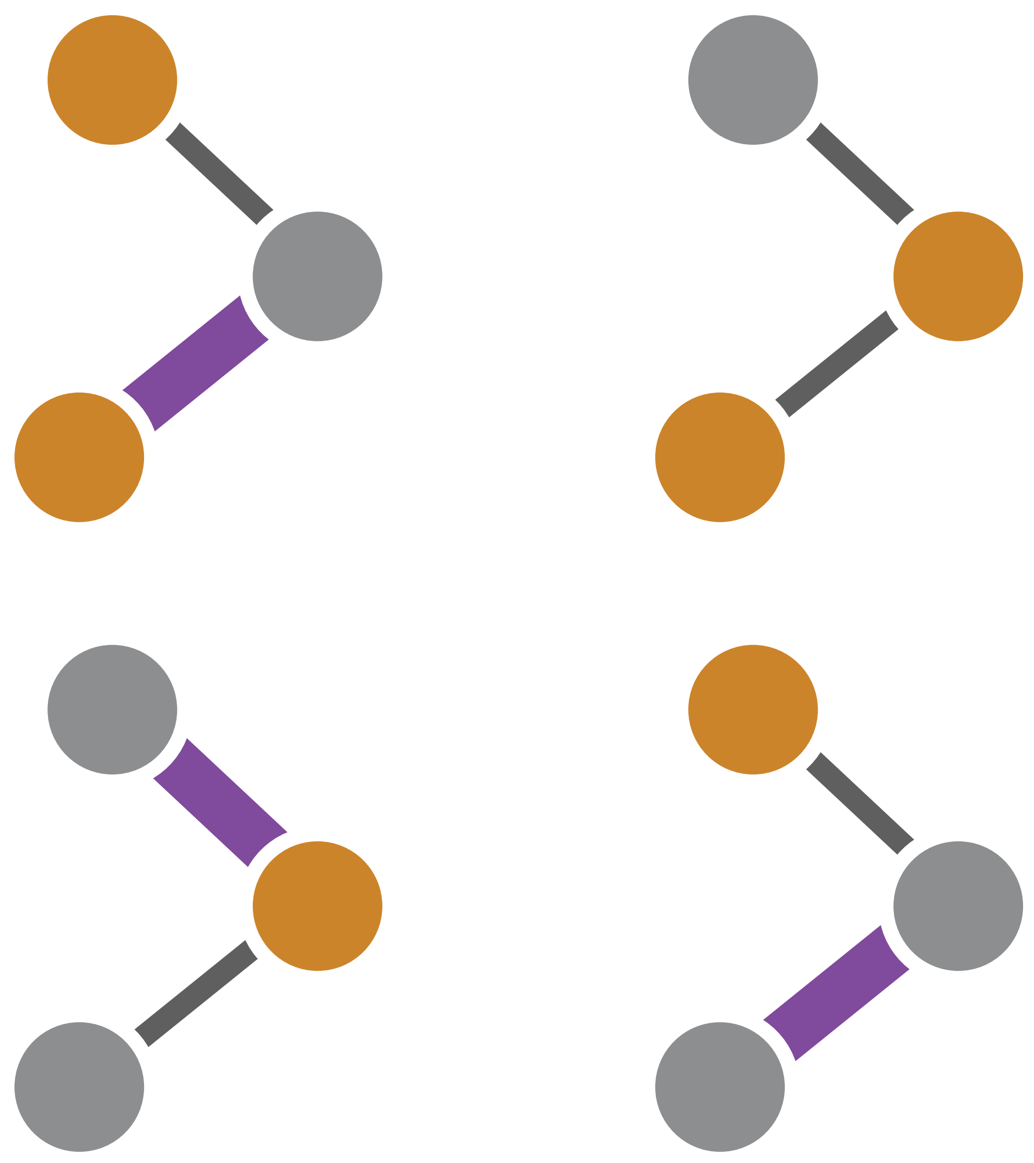


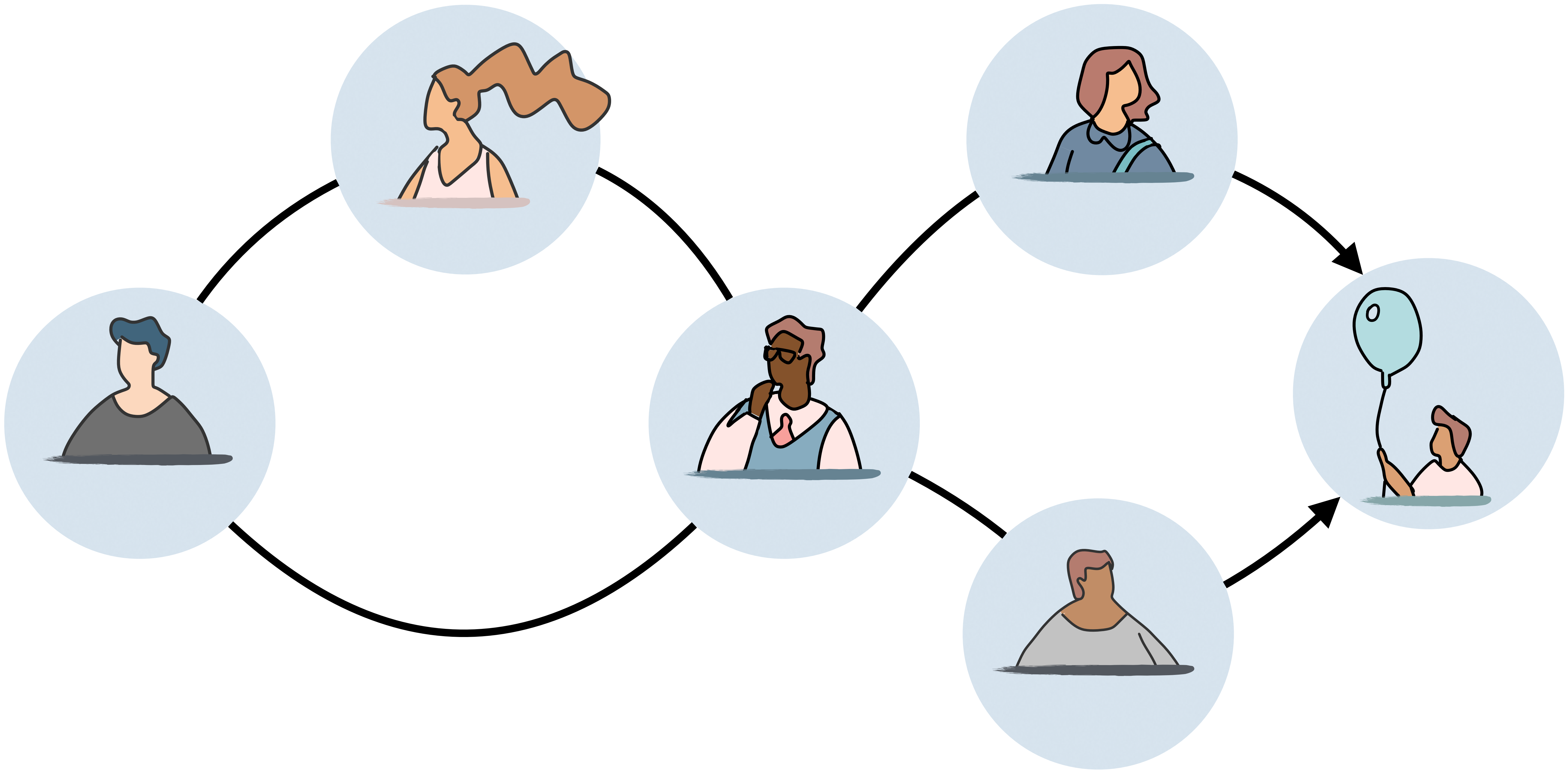
Small Multiples



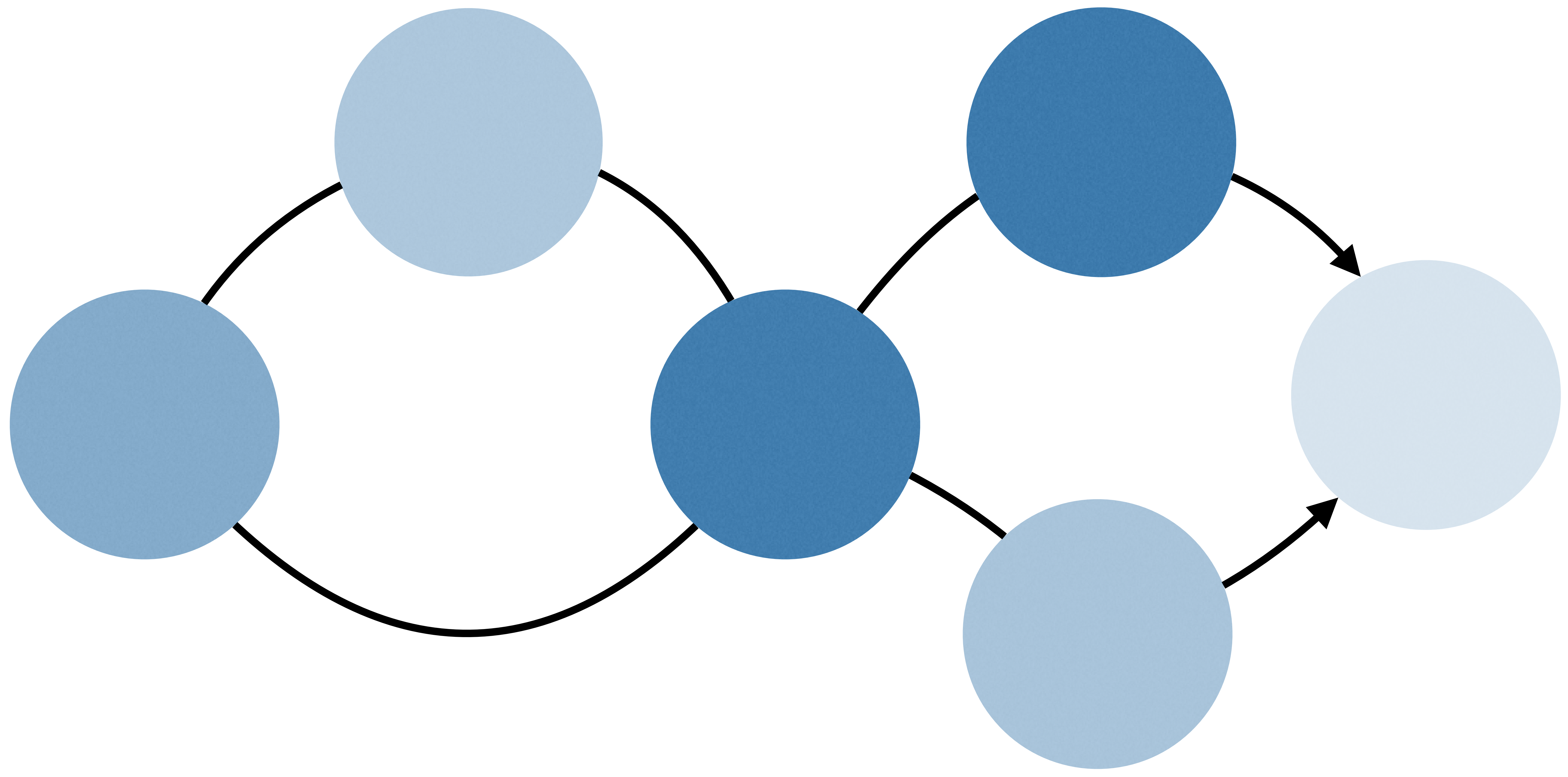
Hybrids

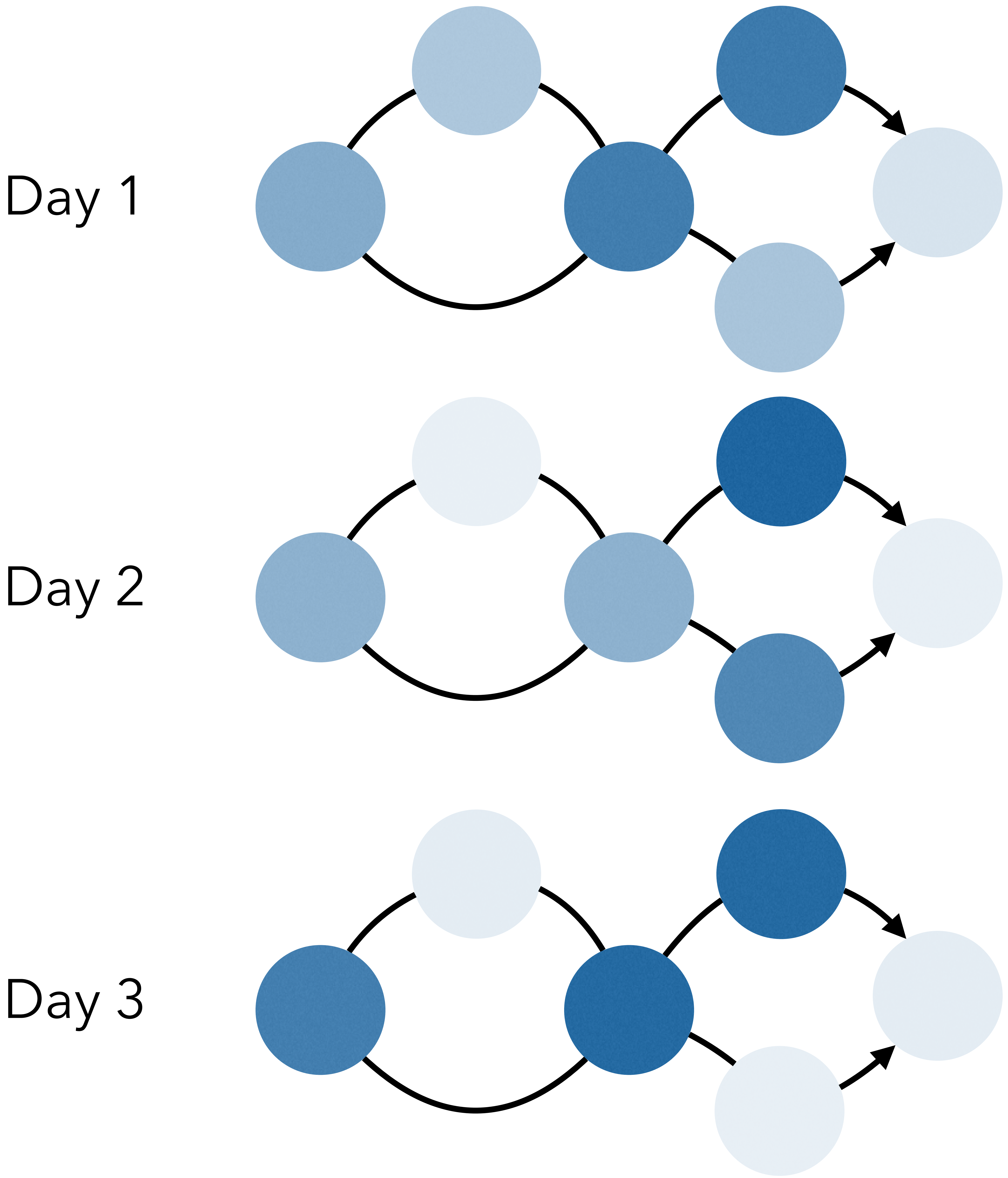
Small Multiples

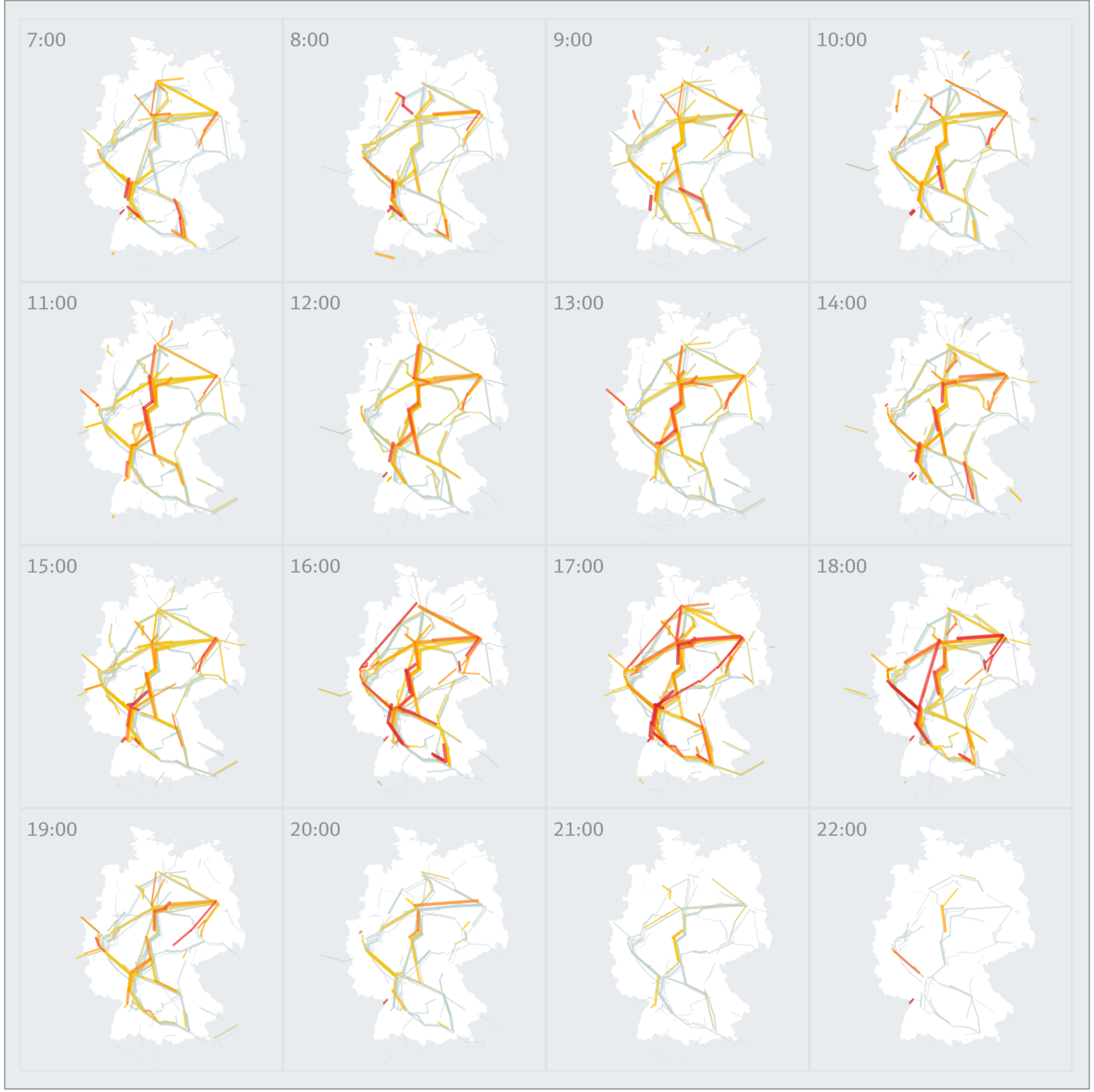




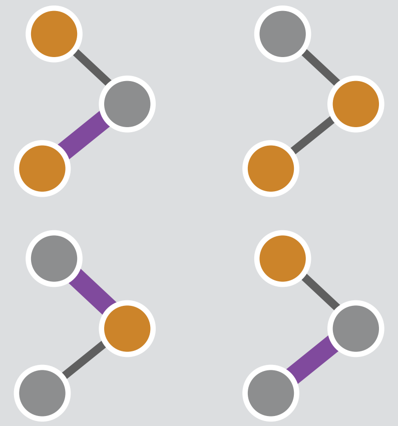
Day 1



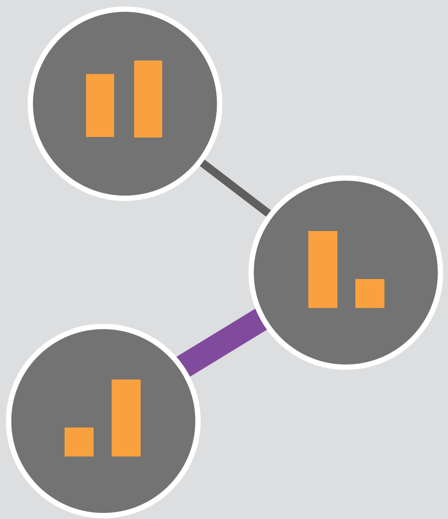

Day 1
Day 2
Day 3



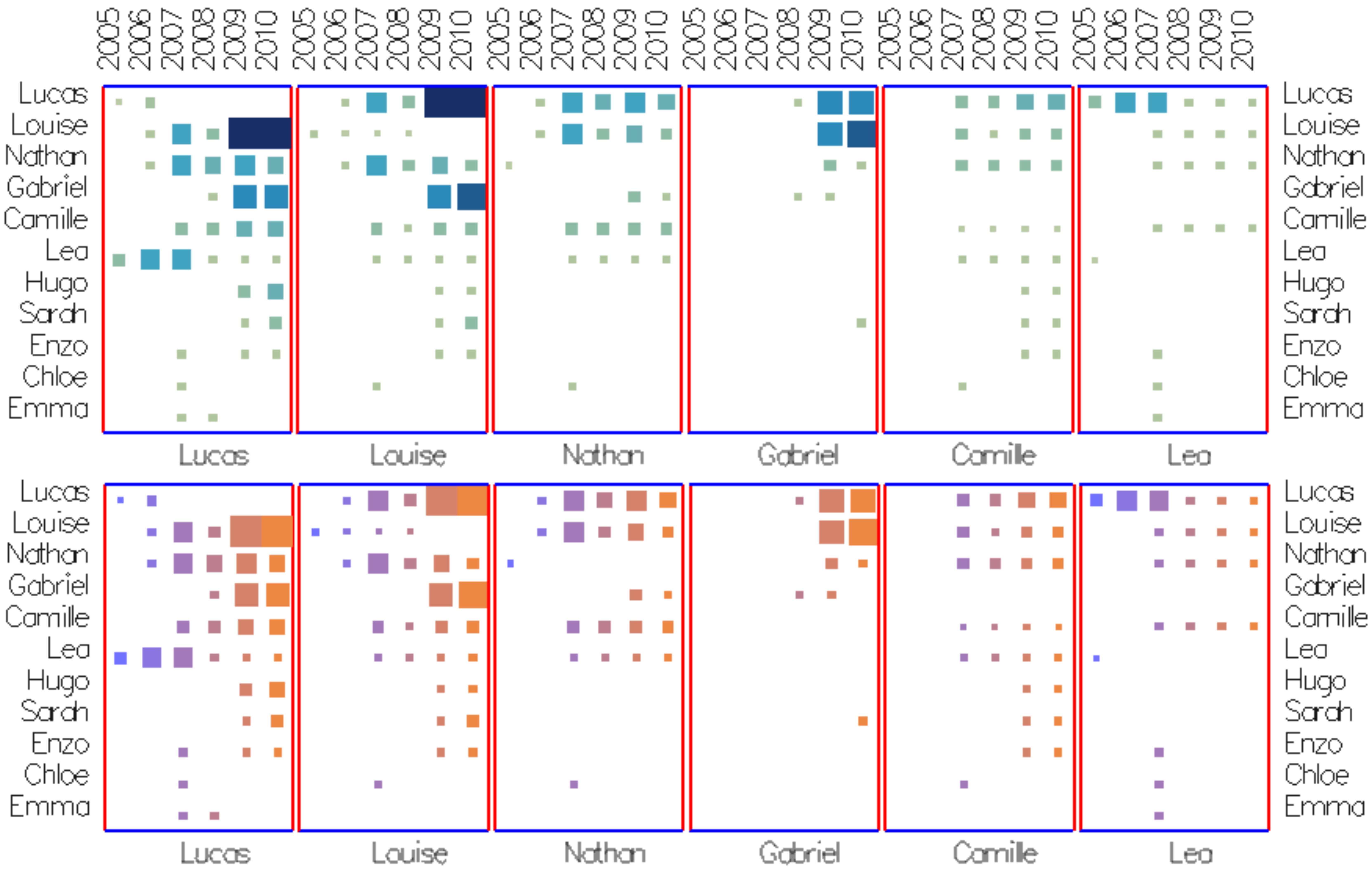
Peakspotting - https://truth-and-beauty.net/projects/peakspotting



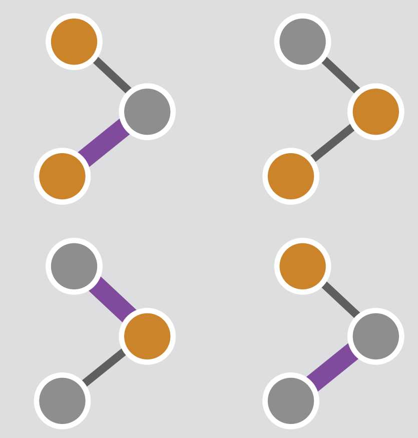
Small Multiples



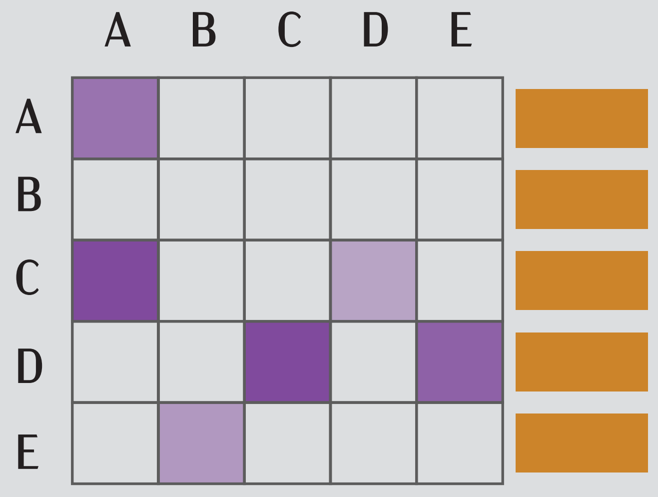
On-Node / On-Edge Encoding



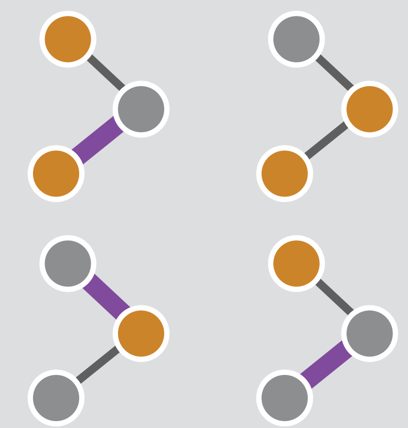
Bach et al. 2014



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

Multivariate Network Visualization Techniques

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

HOME TECHNIQUES WIZARD

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/