VISUALIZING
MULTIVARIATE NETWORKS

Carolina Nobre


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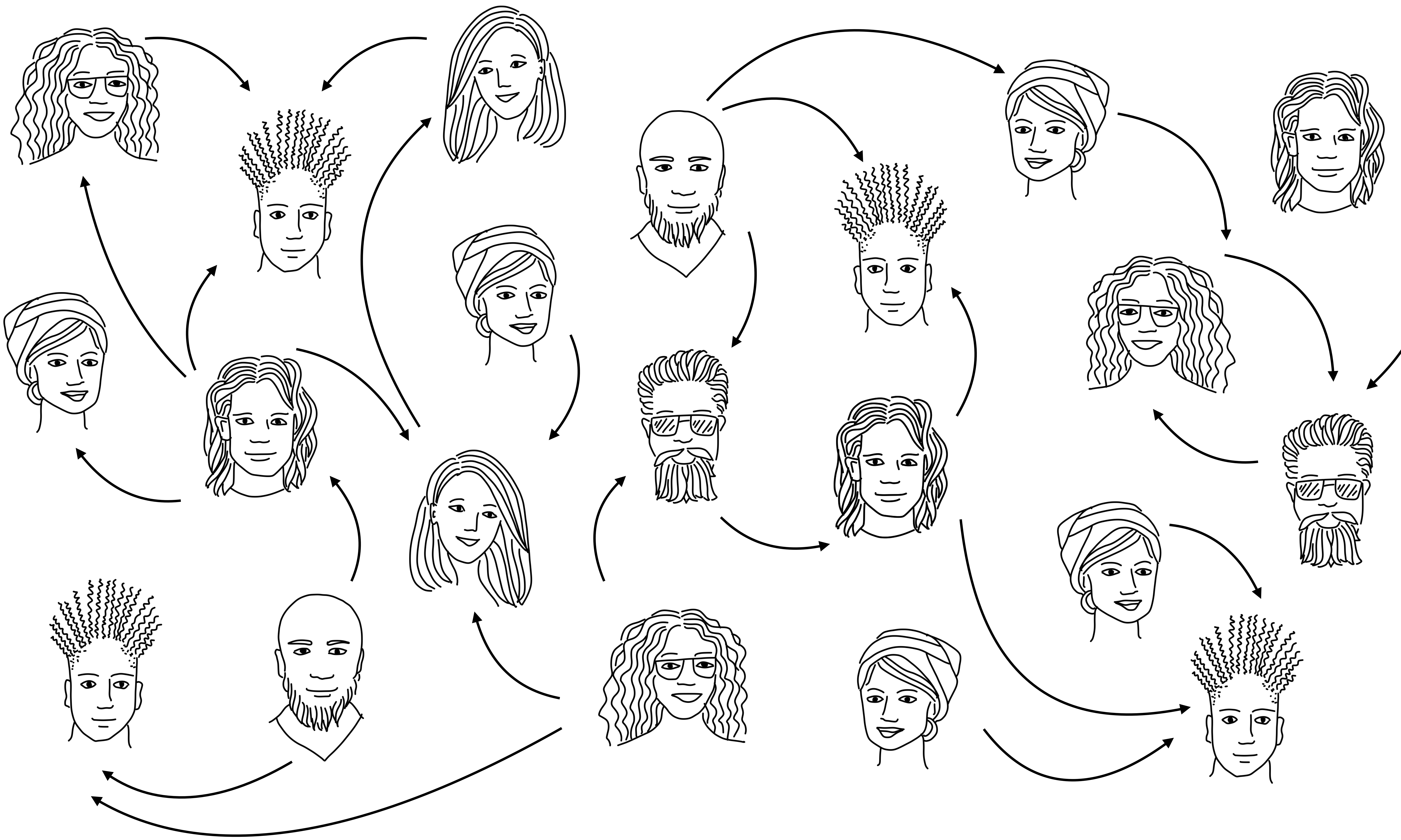
Glyoxylate cycle
OXALYL-CoA
OXALATE
OXALYL-CoA DECARBOXYLASE
OXALATE DECARBOXYLASE
OXALATE-CoA-TRANSFERASE
CoA-SH
H_2O
CO_2
FERREDIOXIN (red)
FERREDIOXIN (ox.)
2-OXO-GLUTARATE SYNTHASE
Deficient in hyperoxaluria I
PYRUVATE
ALANINE-GLYOXYLATE TRANSAMINASE
PyrP
L-ALANINE
ThPP
GLYOXYLATE DEHYDROGENASE (ACYLATING)
NADPH + H+
NADP+
(S)-2-HYDROXY ACID DEHYDROGENASE
$FMNH_2$ · E
FMN · E
O_2
H_2O_2
GLYOXYLATE
GLYOXYLATE REDUCTASE
NAD+
NADH + H+
GLYCOLATE
(S)-2-HYDROXY-ACID OXIDASE
D-AMINO ACID OXIDASE
NH_3
FAD
GLYCINE TRANSAMINASE
L-GLUT-
2-OXO-GLUTARATE
Mg++
TOSE,
EROL
LUORO-
ITRATE



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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EUROVIS 2019
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(Guest Editors)

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

The State of the Art in Visualizing Multivariate Networks

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

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

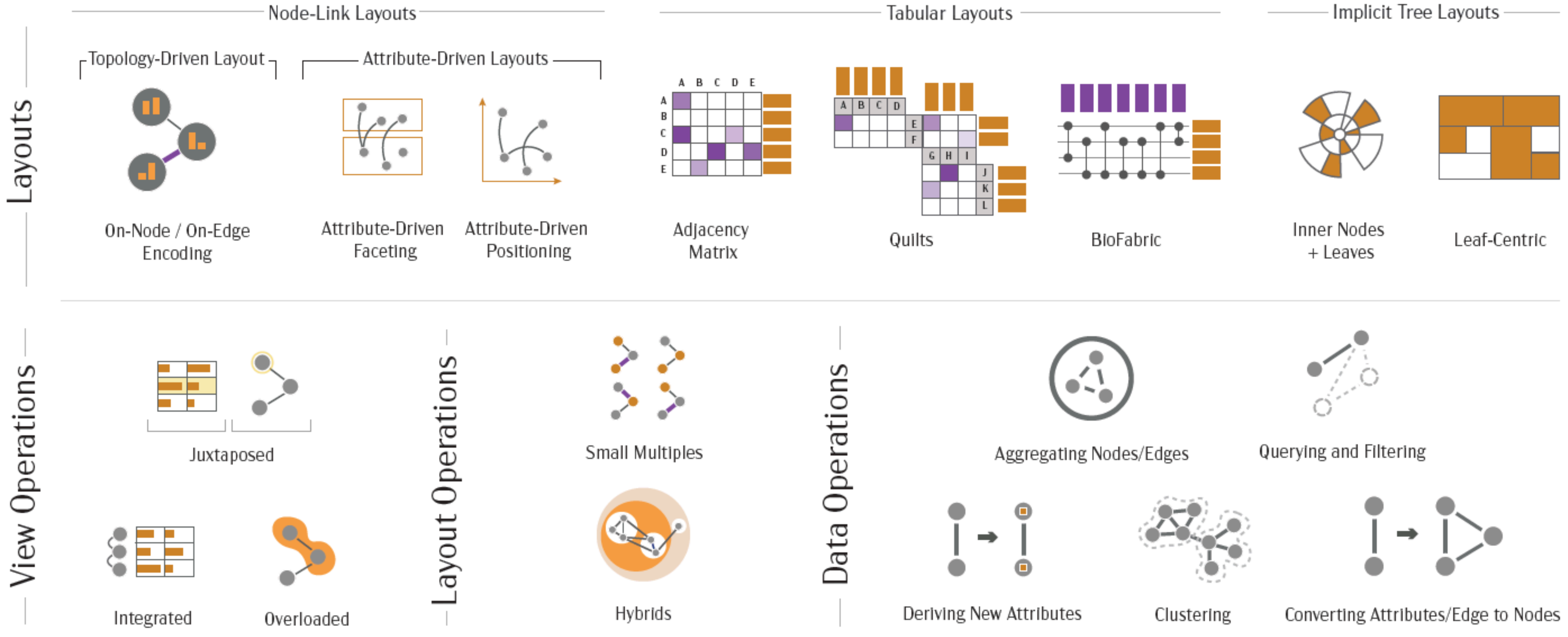
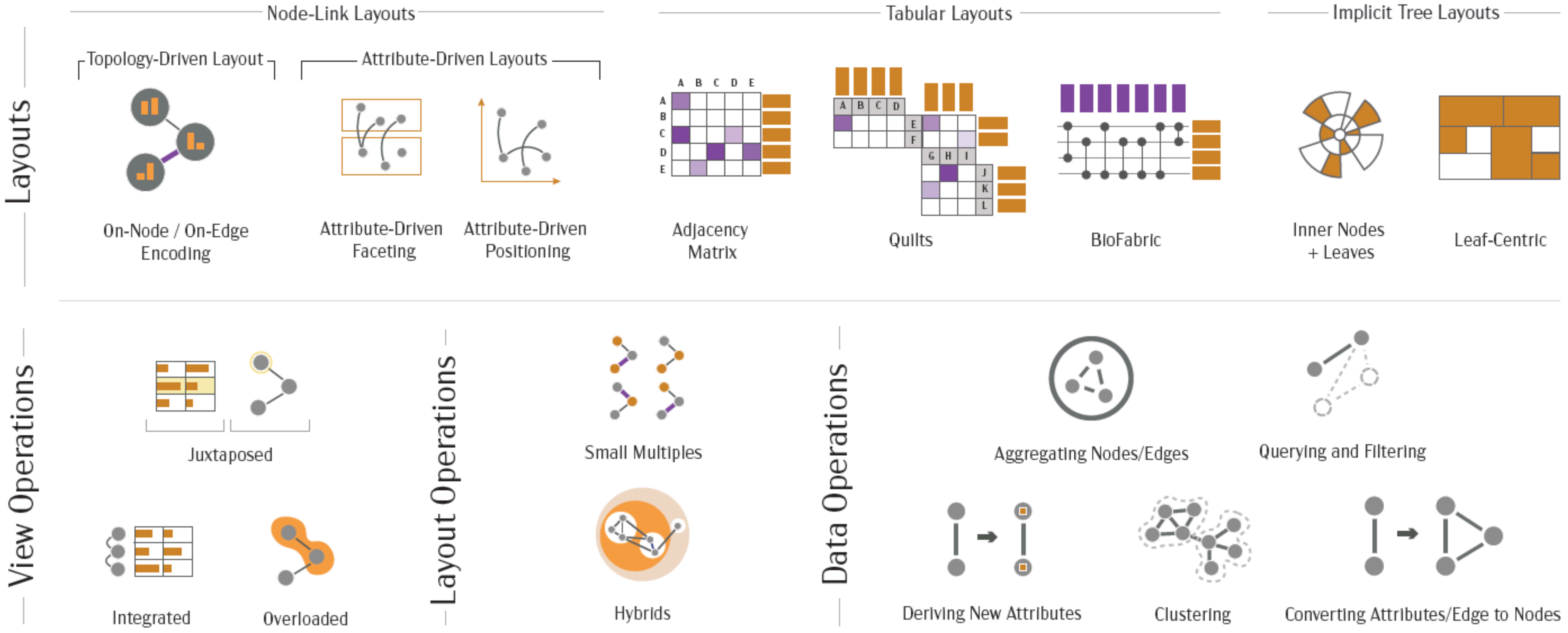


Figure 1: *A typology of operations and layouts used in multivariate network visualization.* ***Layouts*** *describe the fundamental choices for encoding multivariate networks.* ***View Operations*** *capture how topology and attribute focused visualizations can be combined.* ***Layout Operations***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

Abstract

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


Layouts
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Topology-Driven Layout
Attribute-Driven Layouts
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Small Multiples
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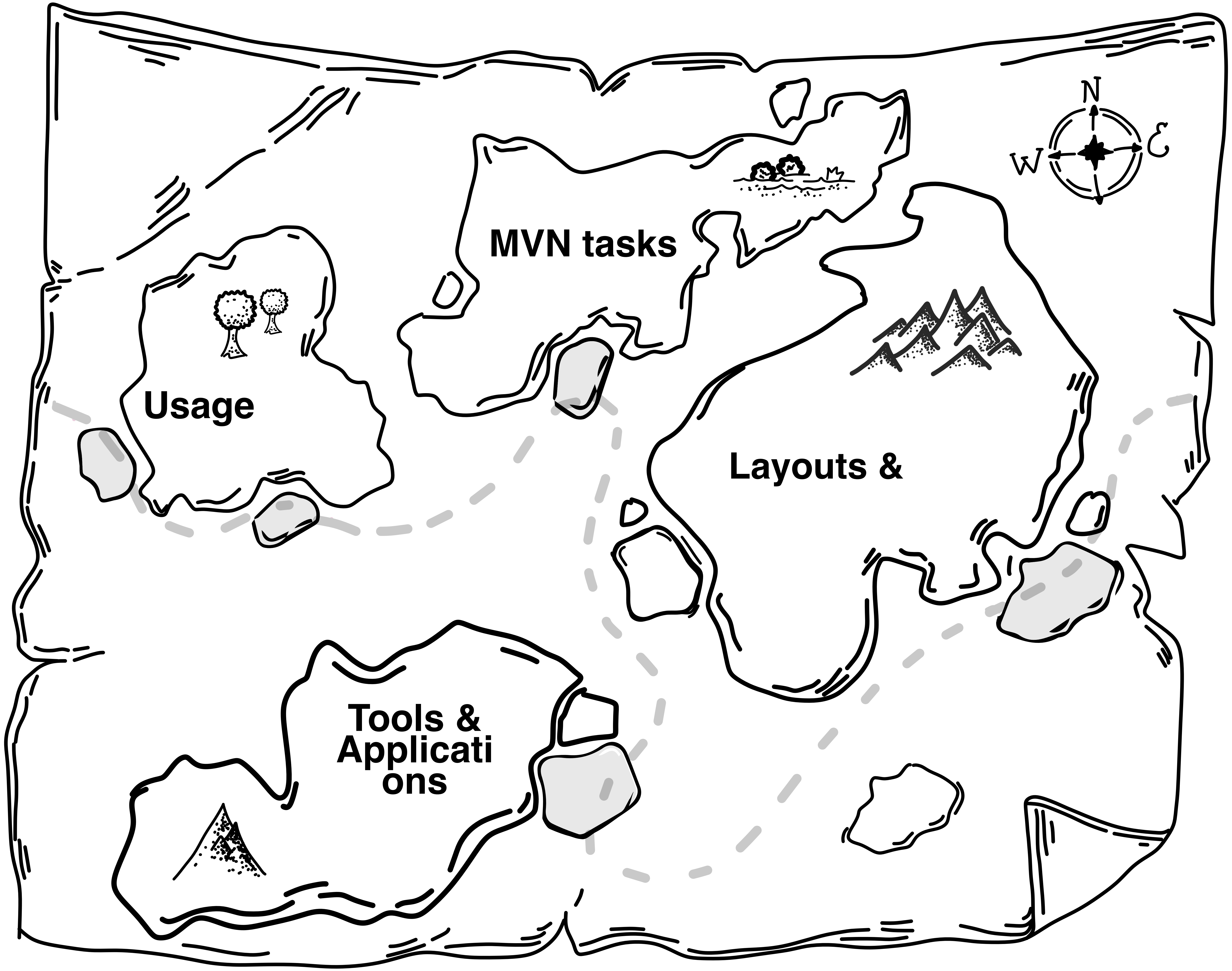
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

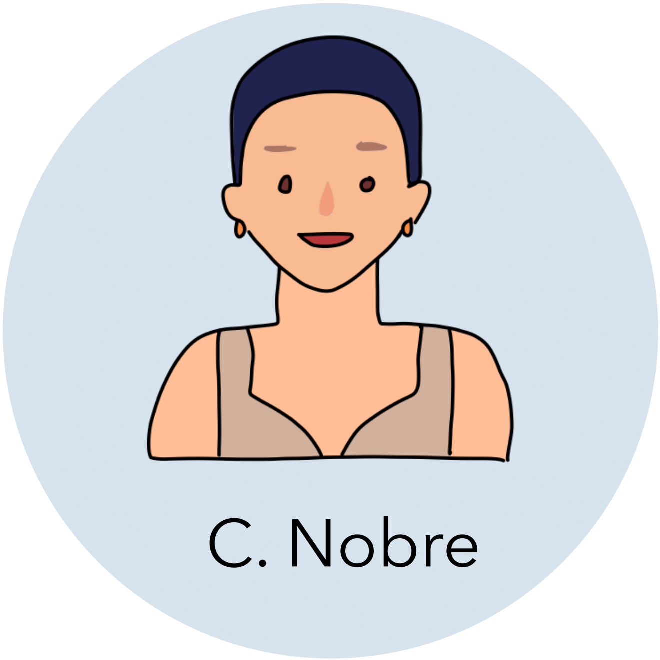
Land of Multivariate

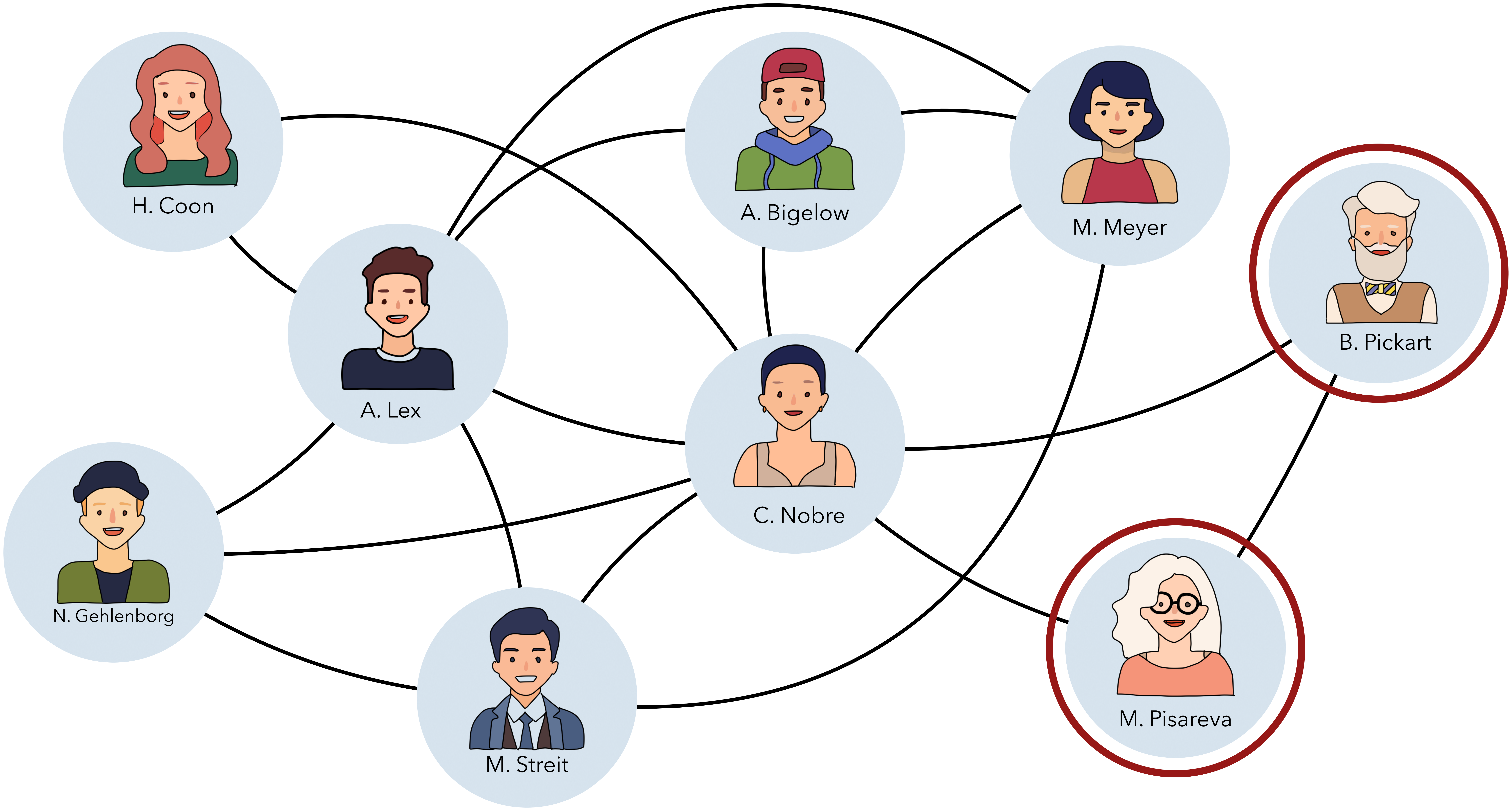


MVNV Tasks

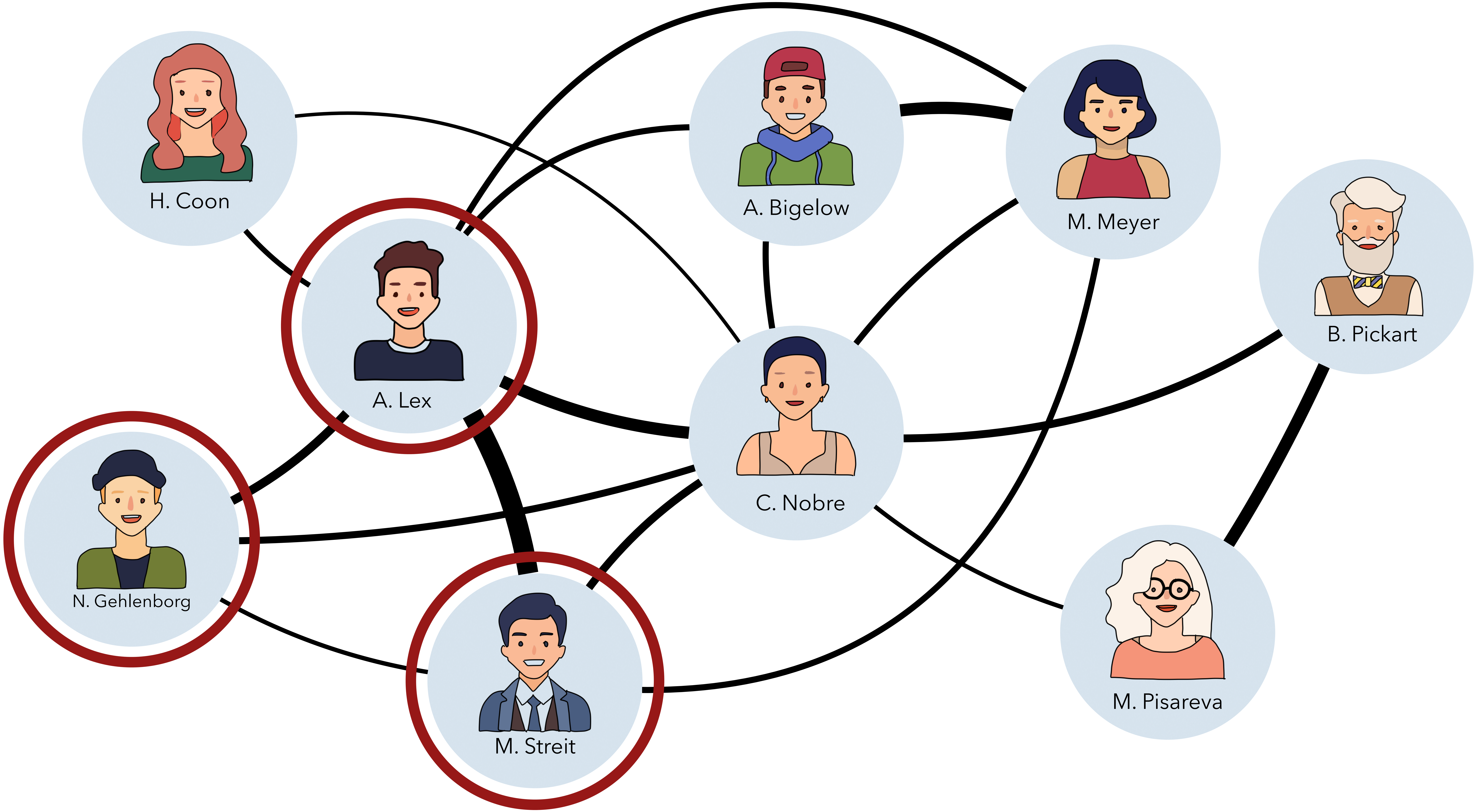
How is an MVN task different than a regular graph task?

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

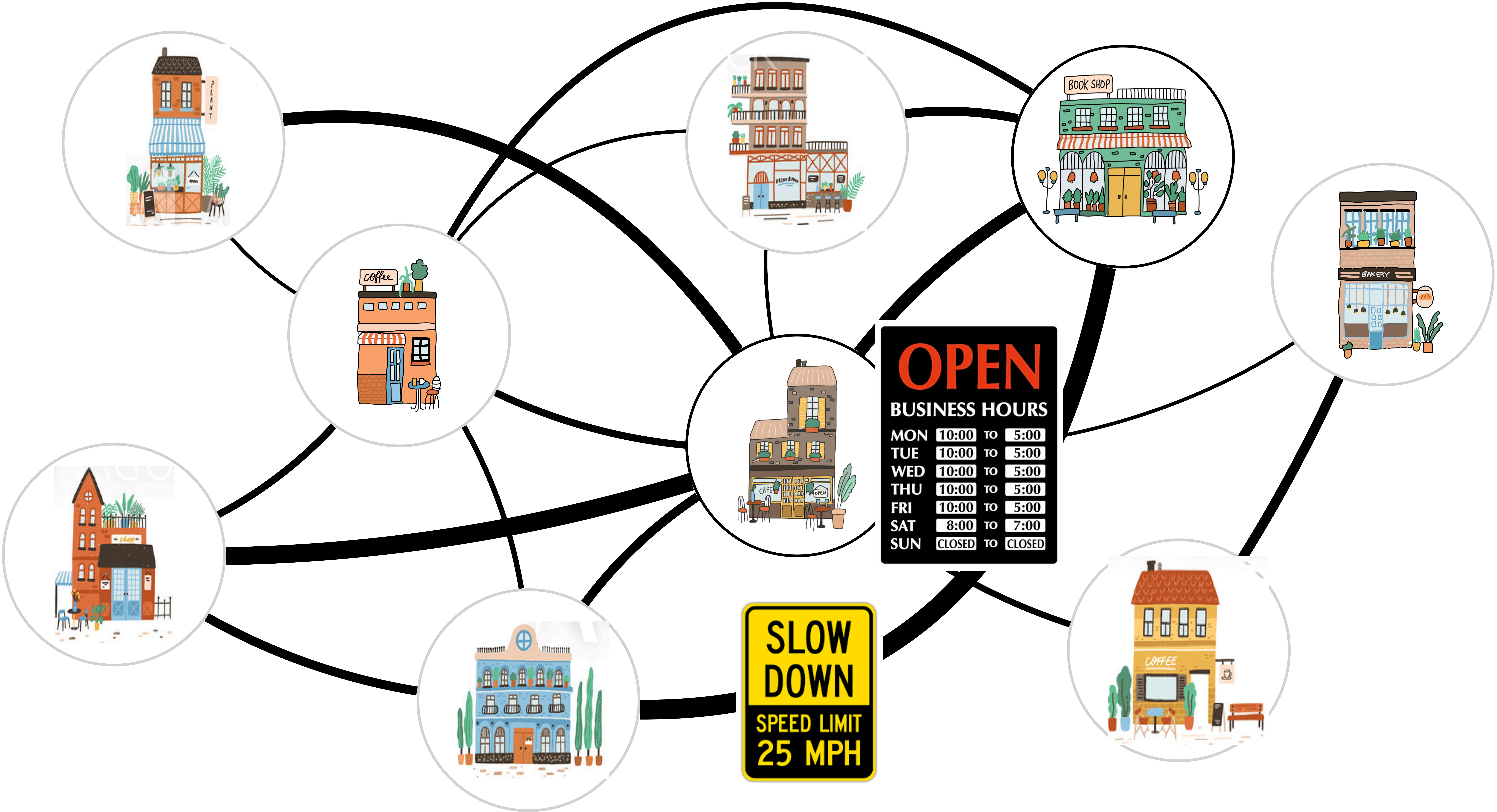

C. Nobre



How many of my collaborators are from the oceanography field?



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



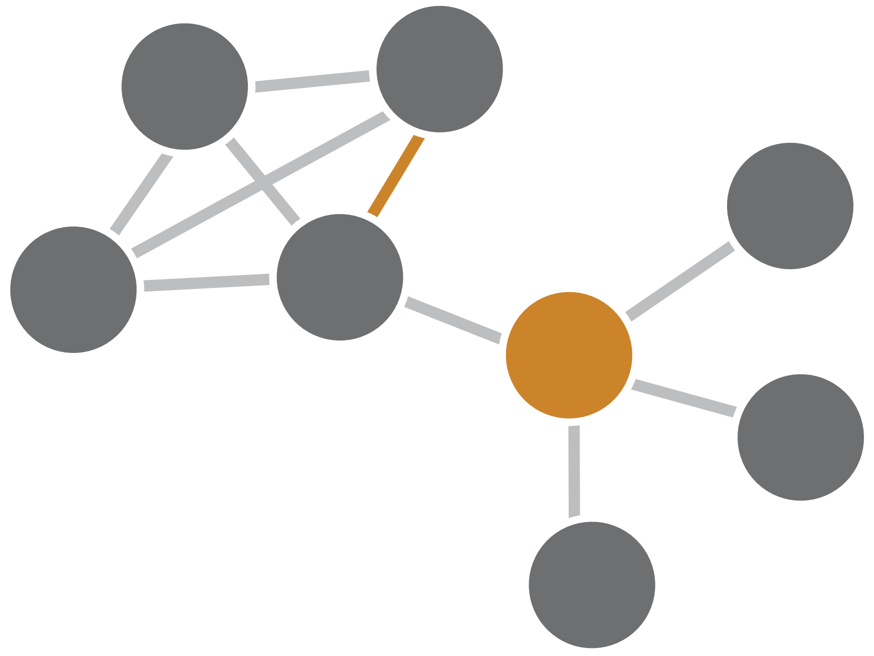
What is an efficient way I can complete all my errands?

- 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?

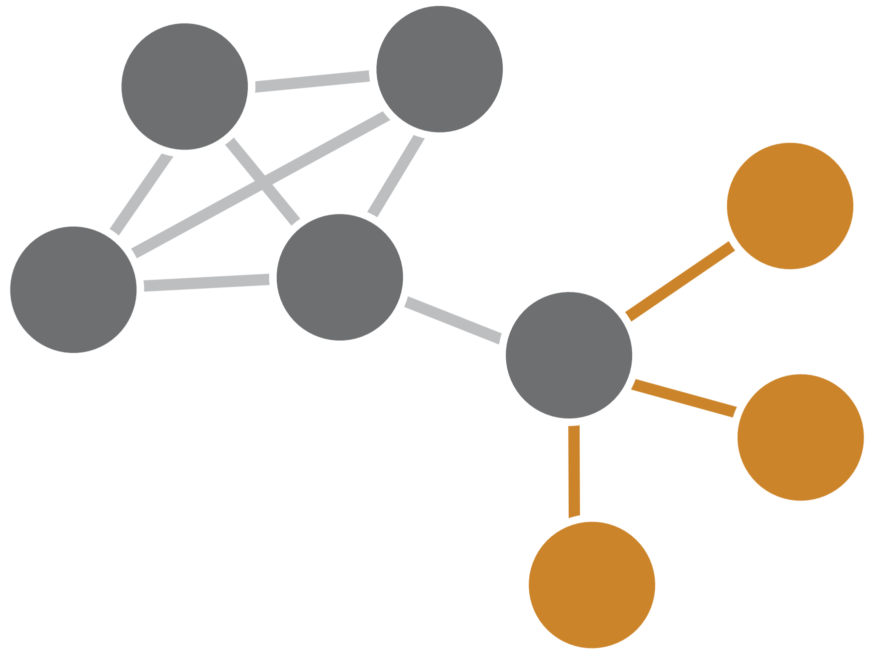
Tasks that rely on the **topology** of the network and the **attributes** of the nodes and edges

MVNV tasks are applied to topological structures

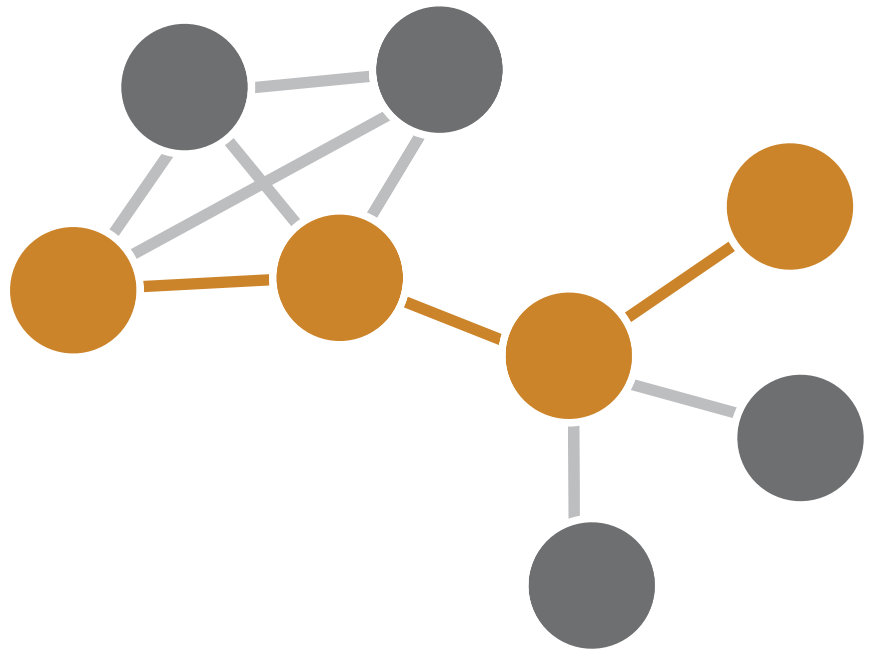
Single Node/Edge



Node Neighbors



Path



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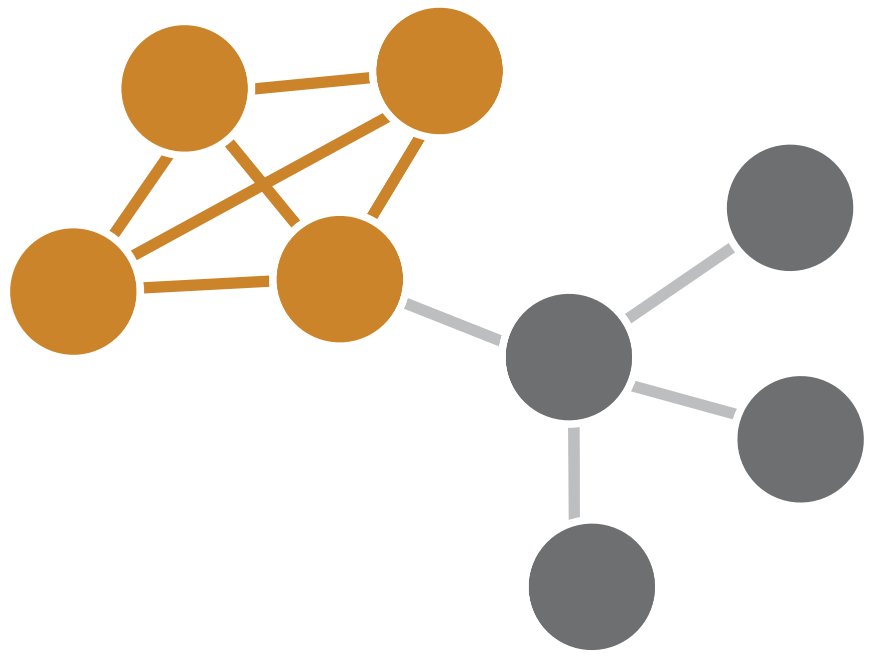
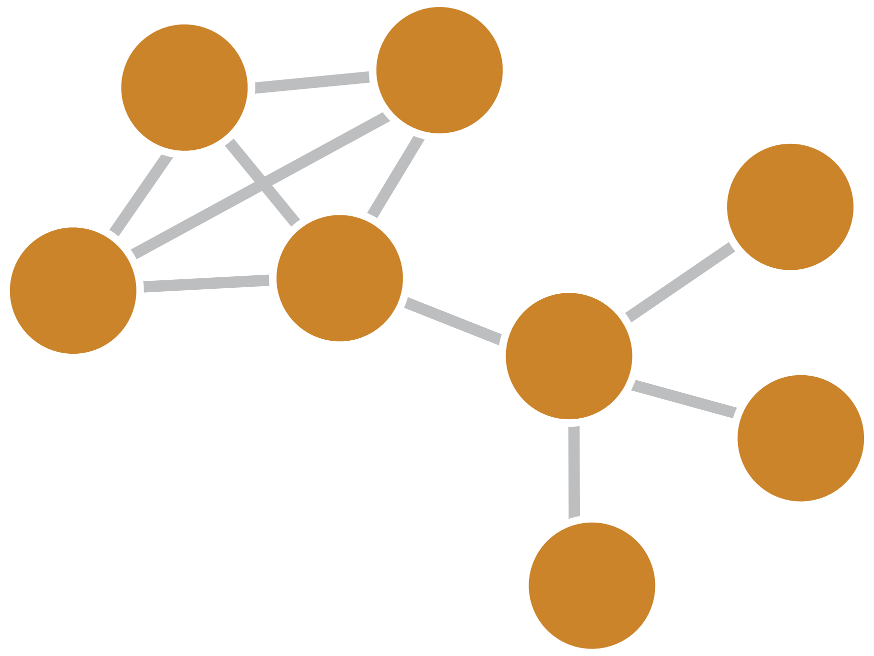
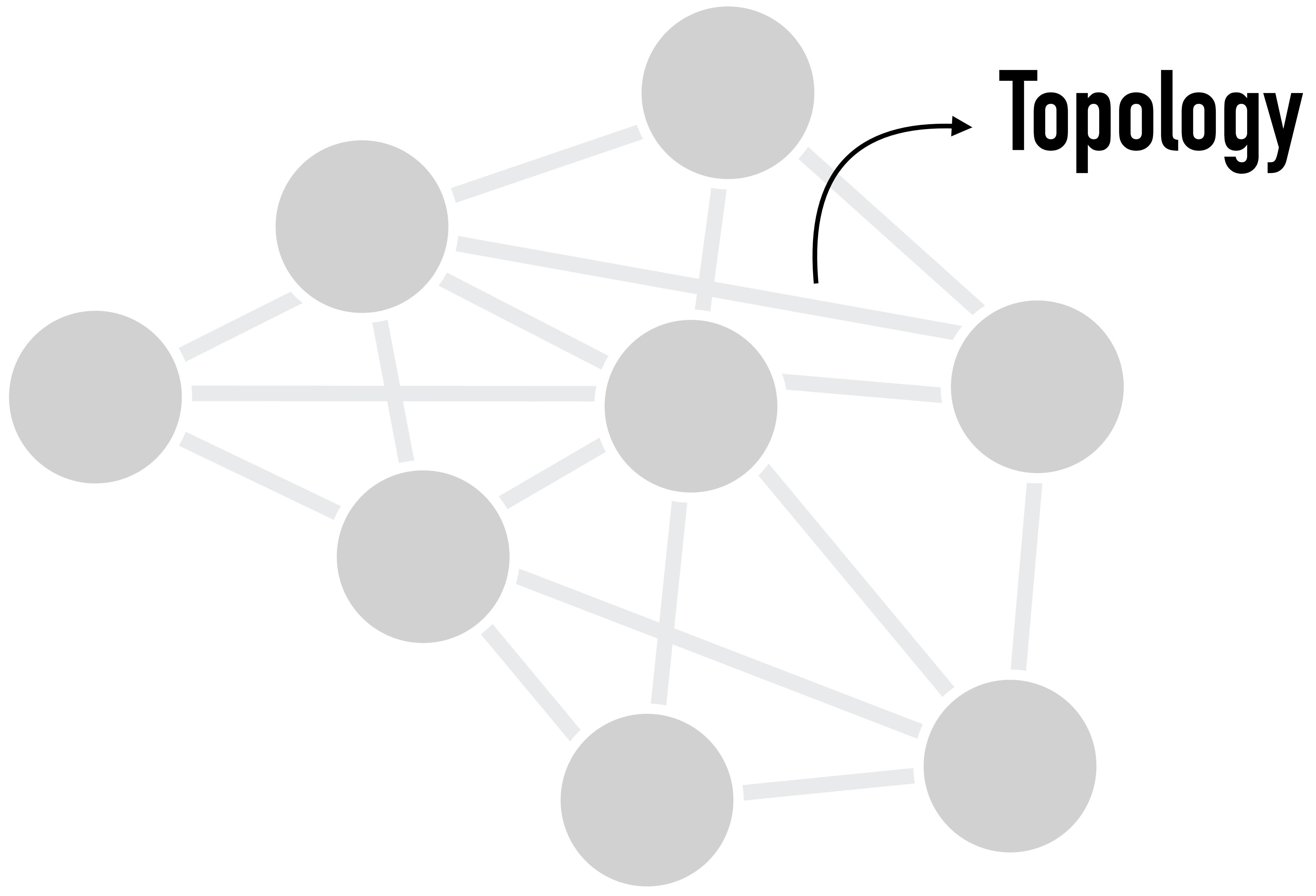
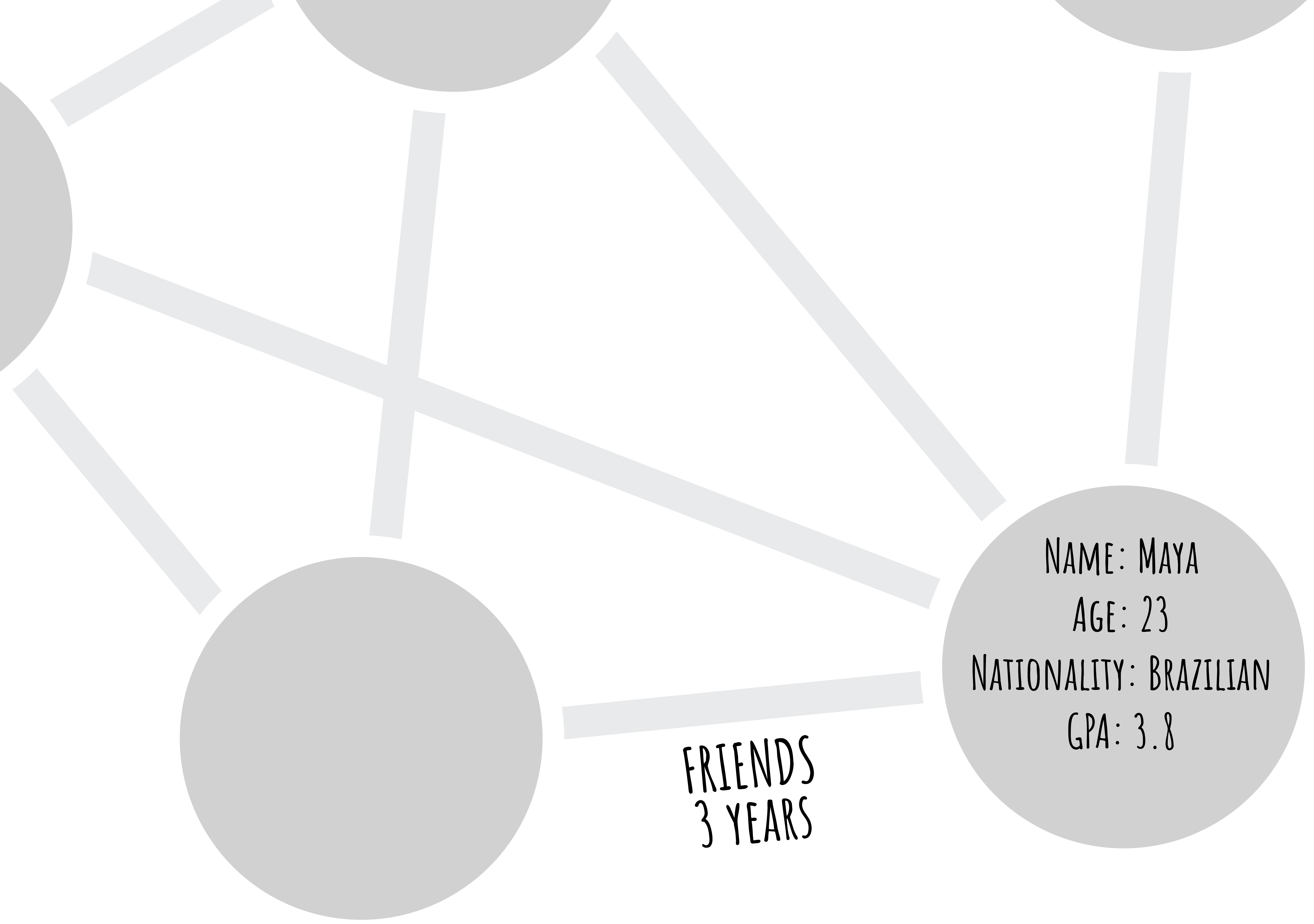


Network/Subnetwork



Network and Attribute Characteristics


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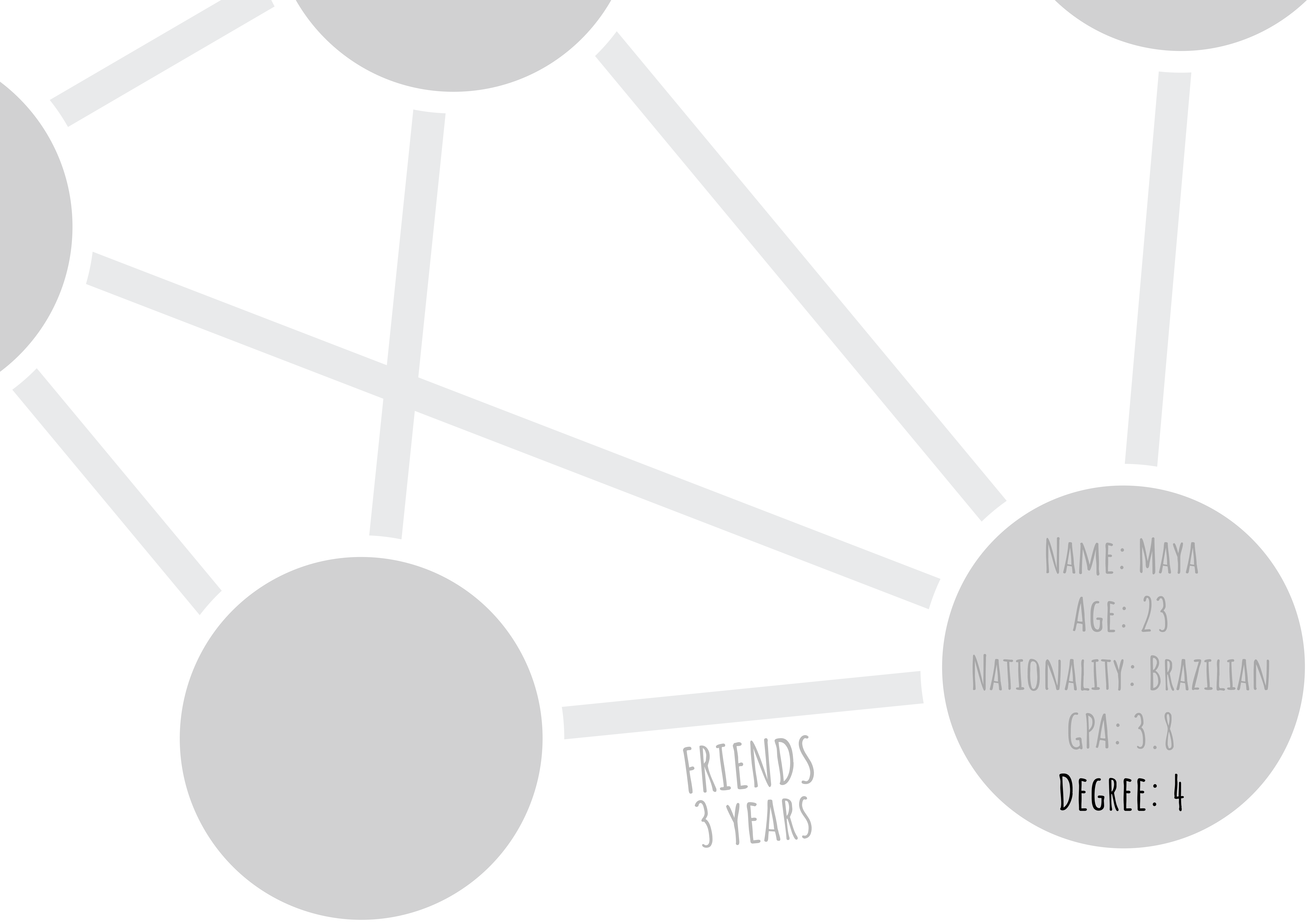
Age: 23
Nationality: Brazilian
GPA: 3.8
FRIENDS
3 YEARS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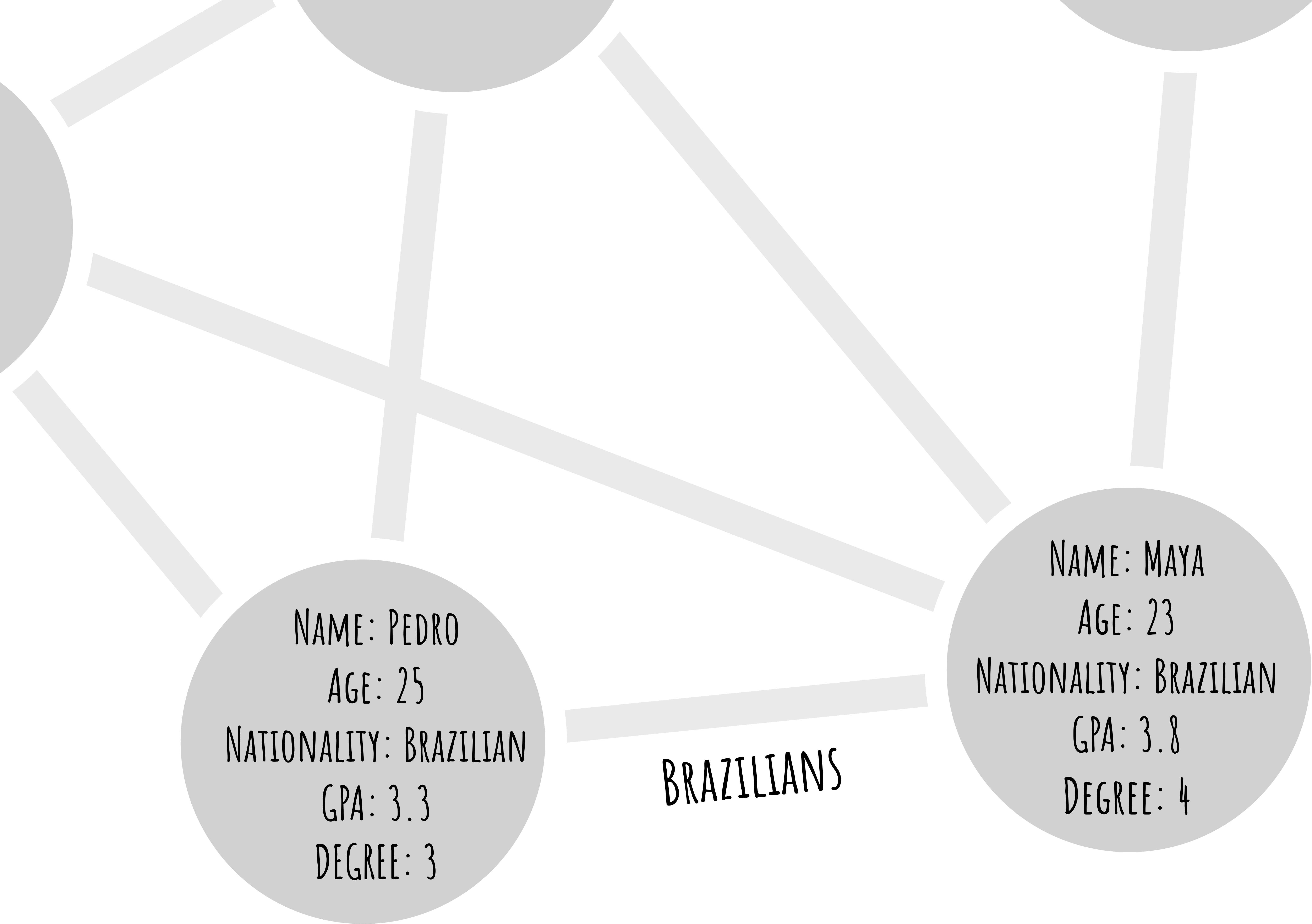
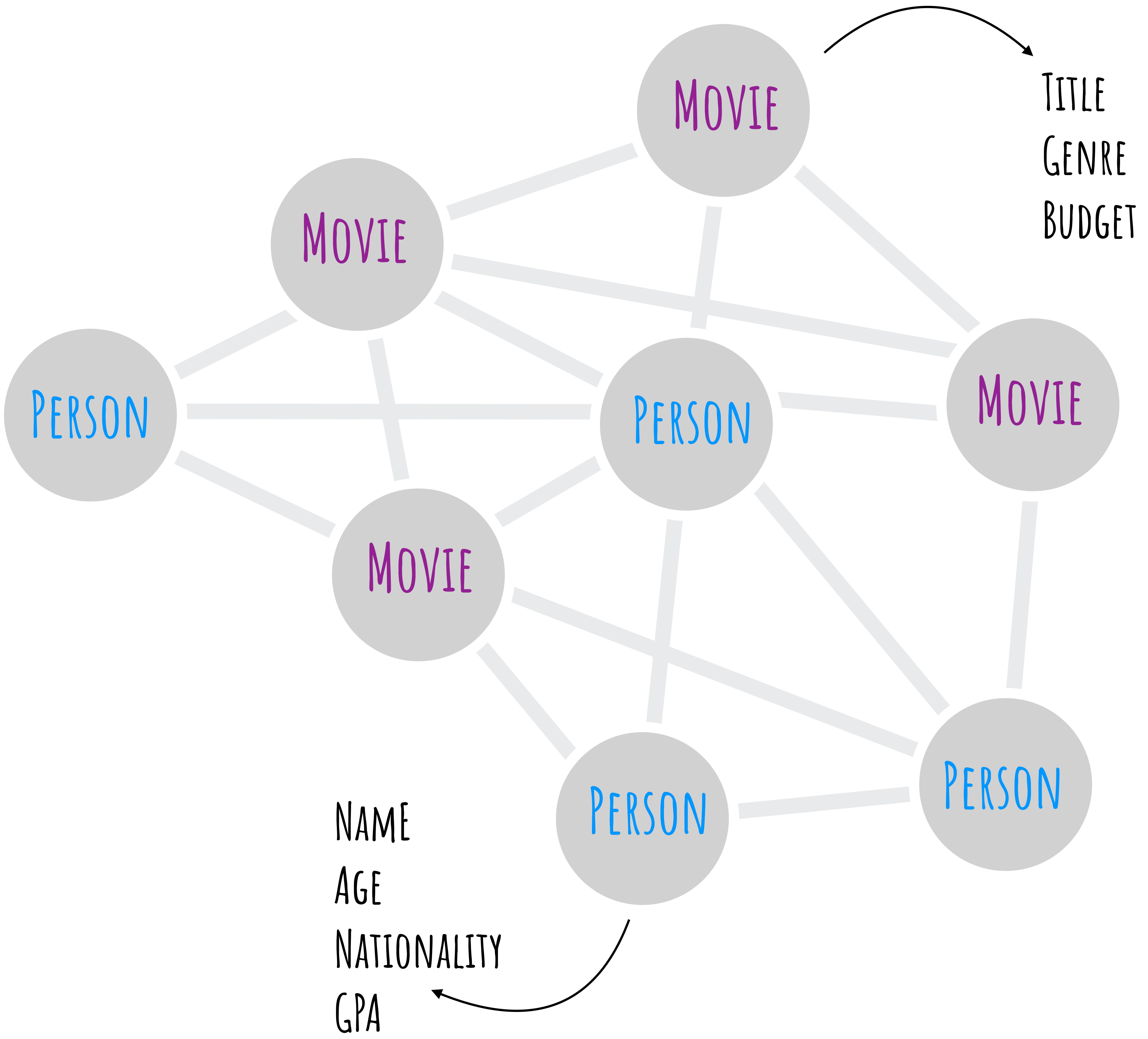
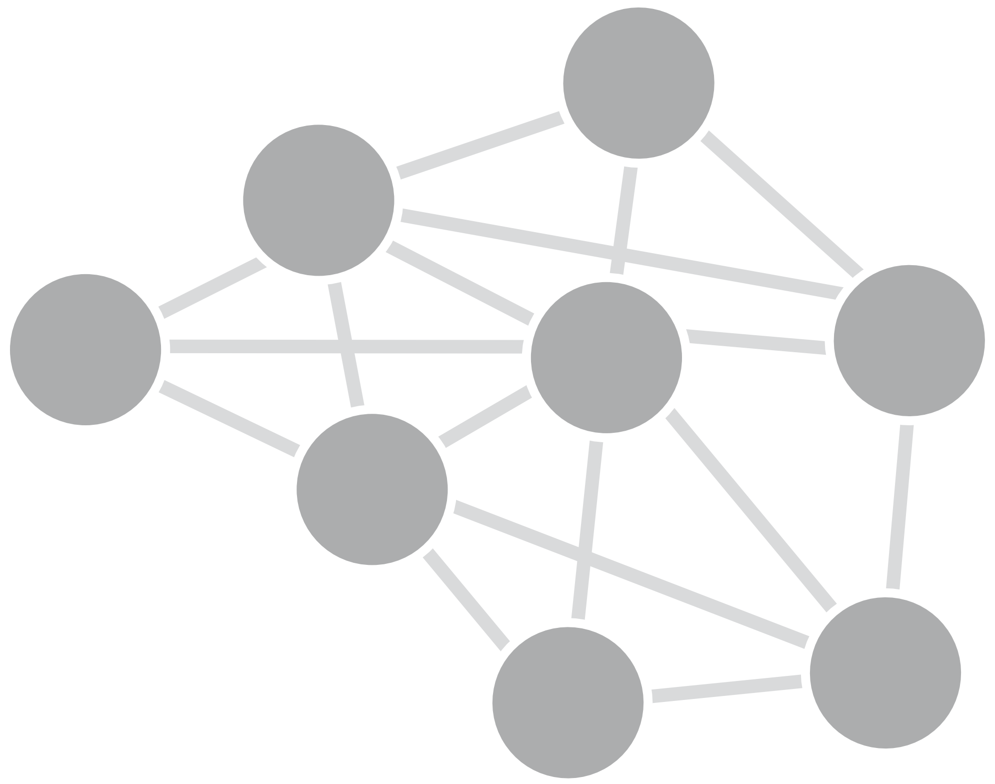
Age: 23
Nationality: Brazilian
GPA: 3.8
Degree: 4
FRIENDS
3 YEARS


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


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

Network Size



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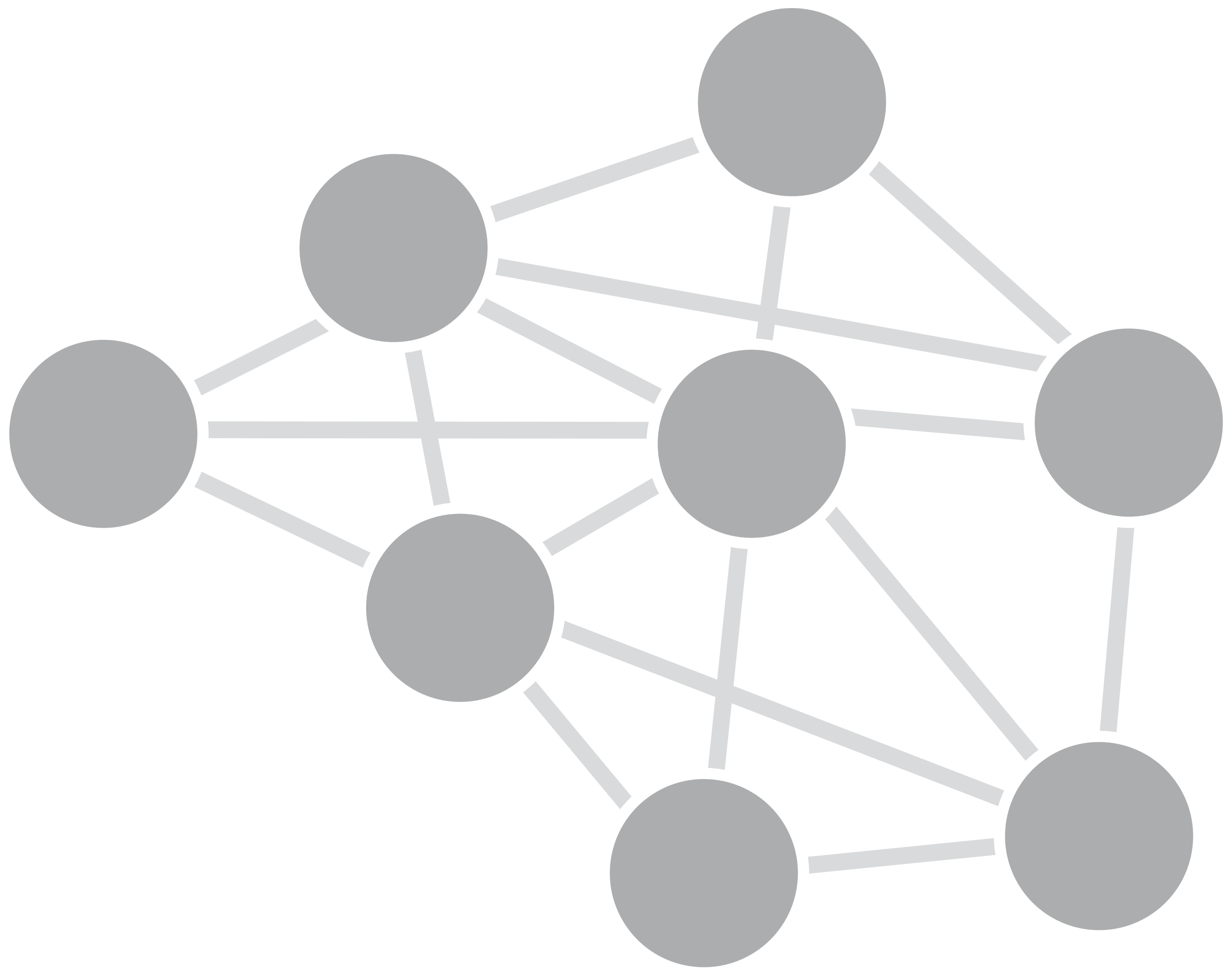
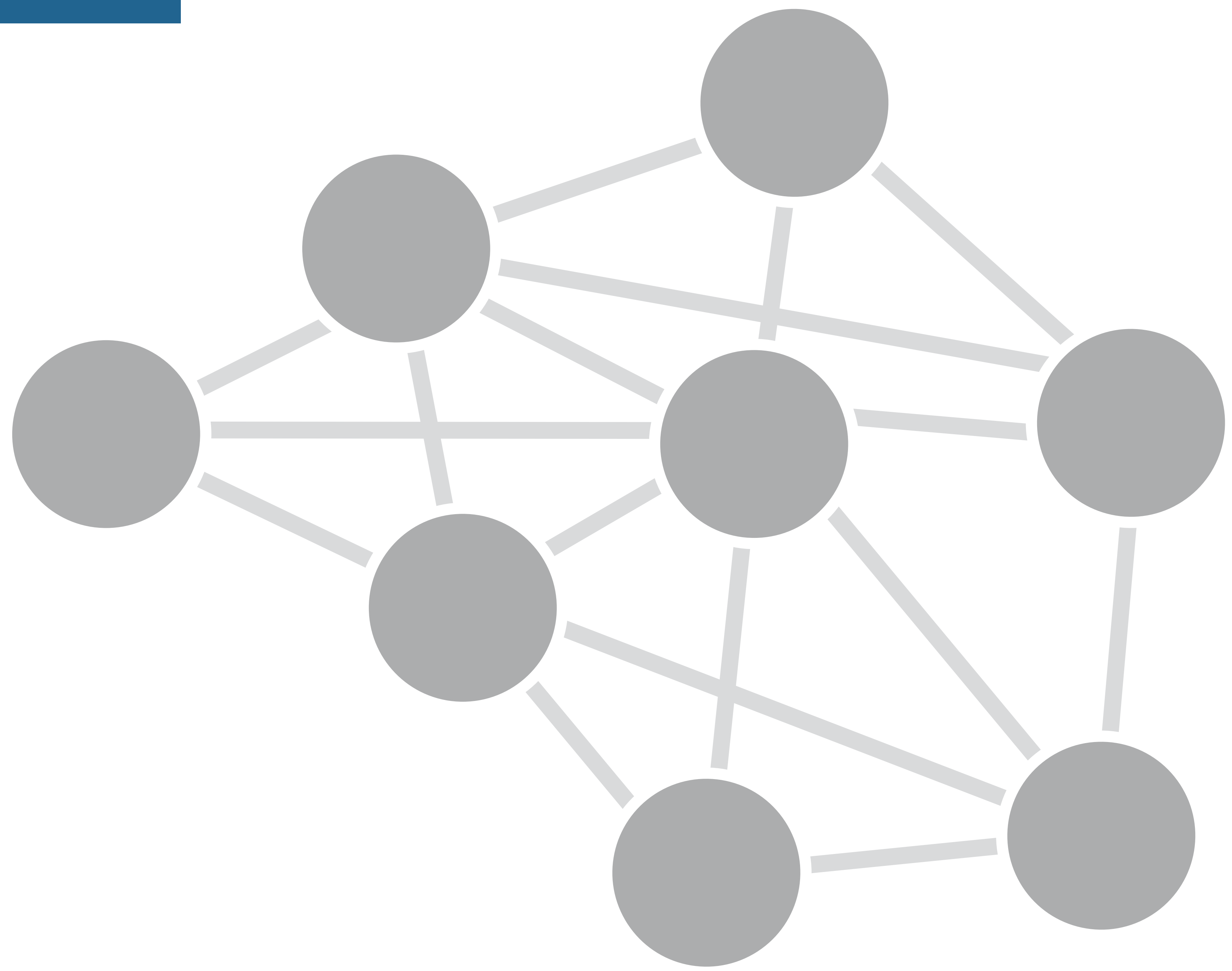


Medium
100–1000



Large
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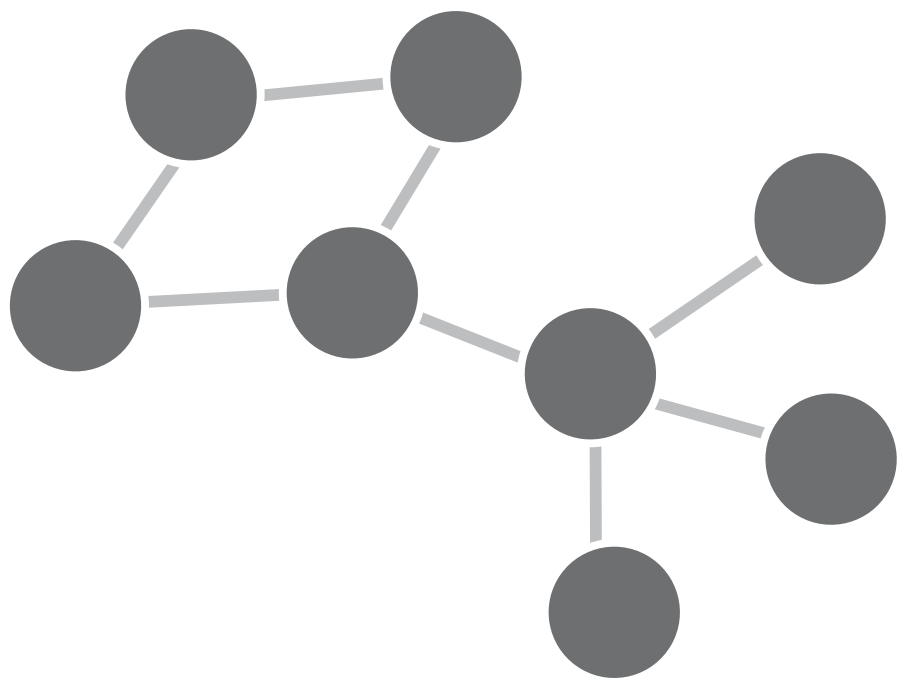
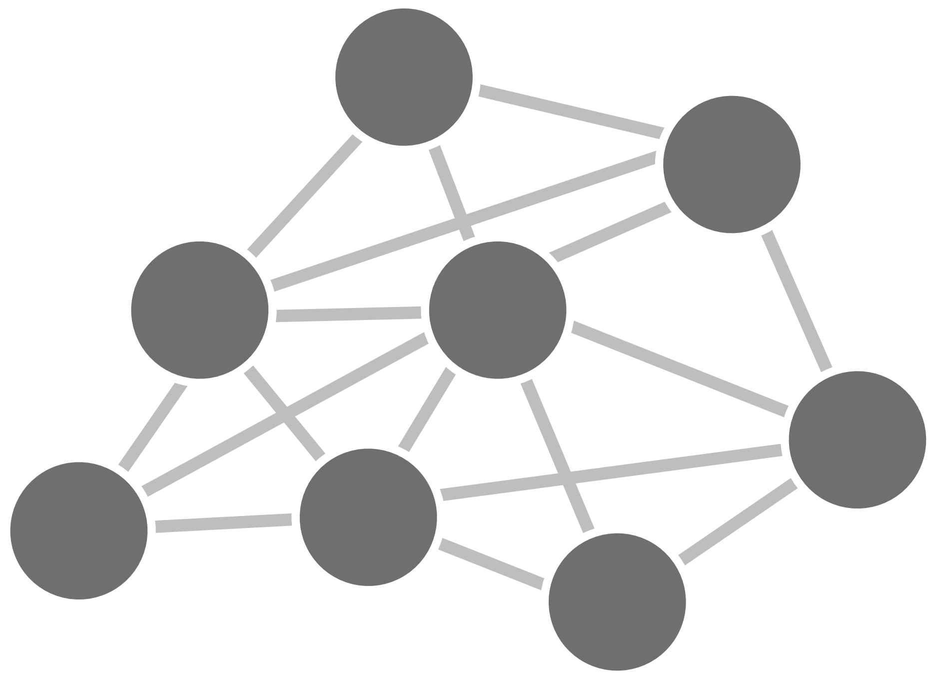
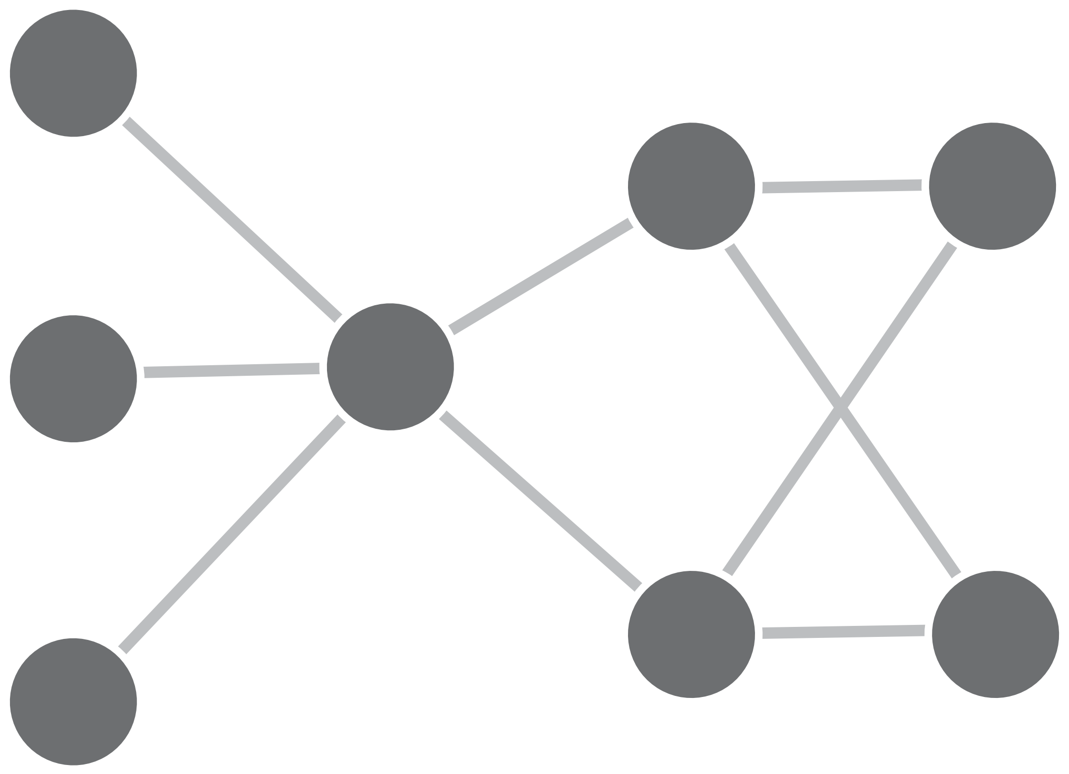
Network Types



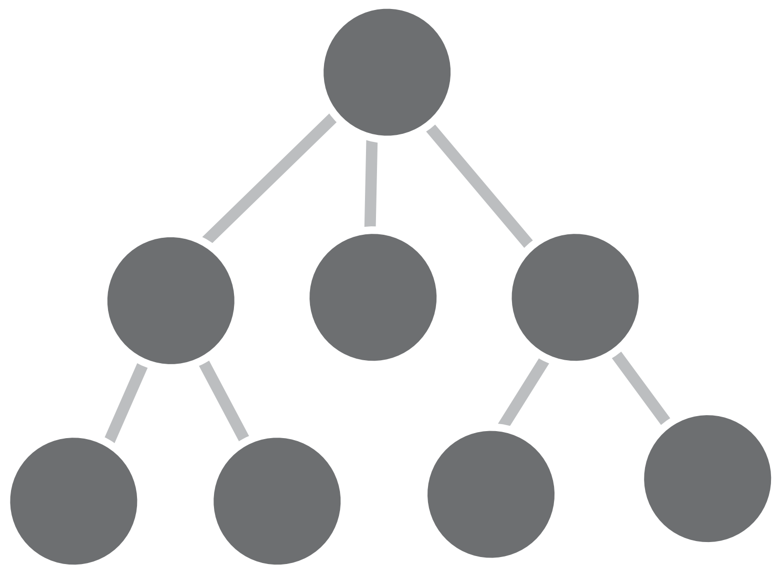
Sparse



Dense

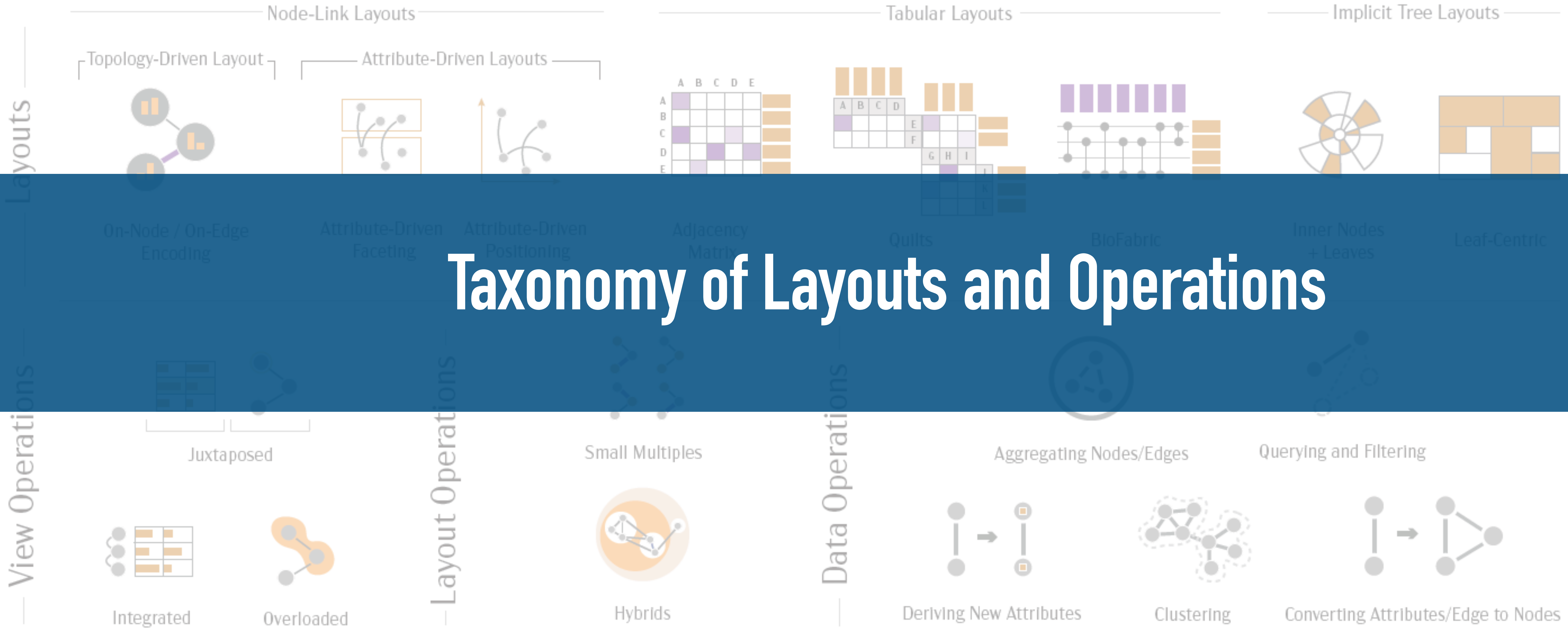


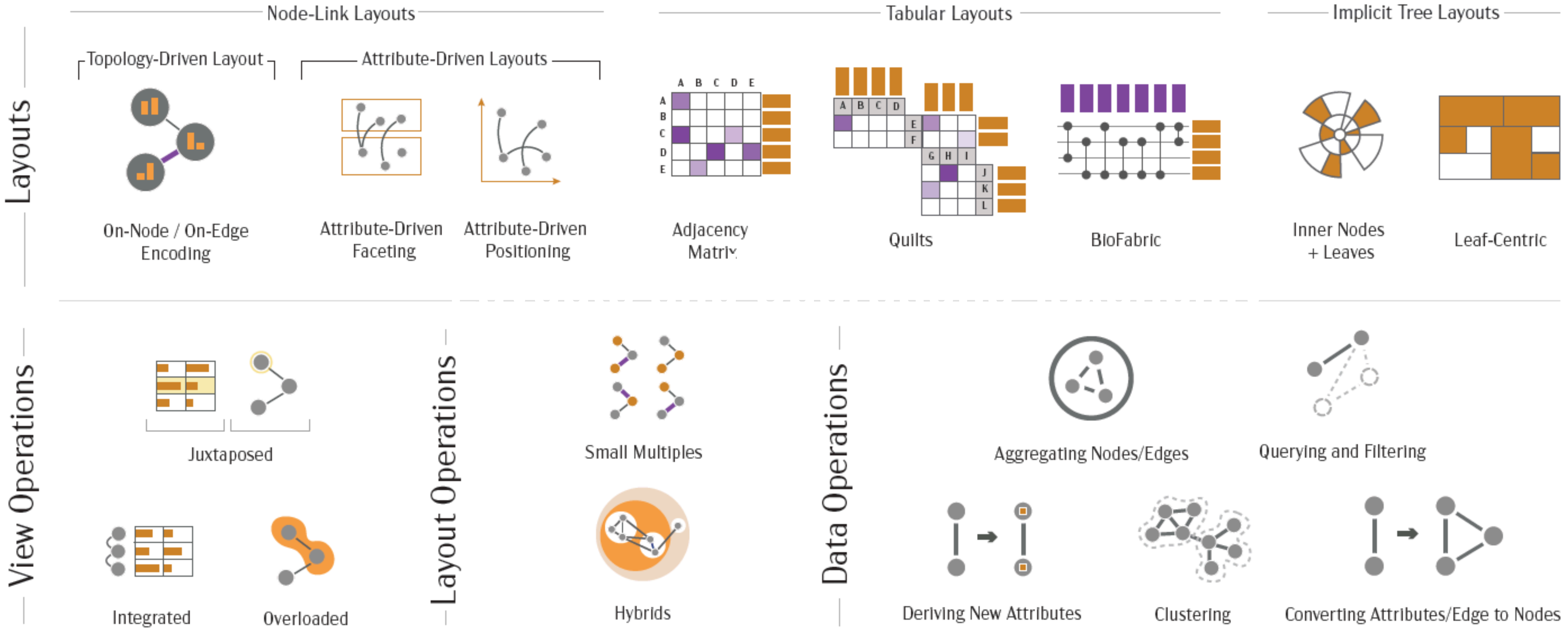
Layered



Trees

Taxonomy of Layouts and Operations

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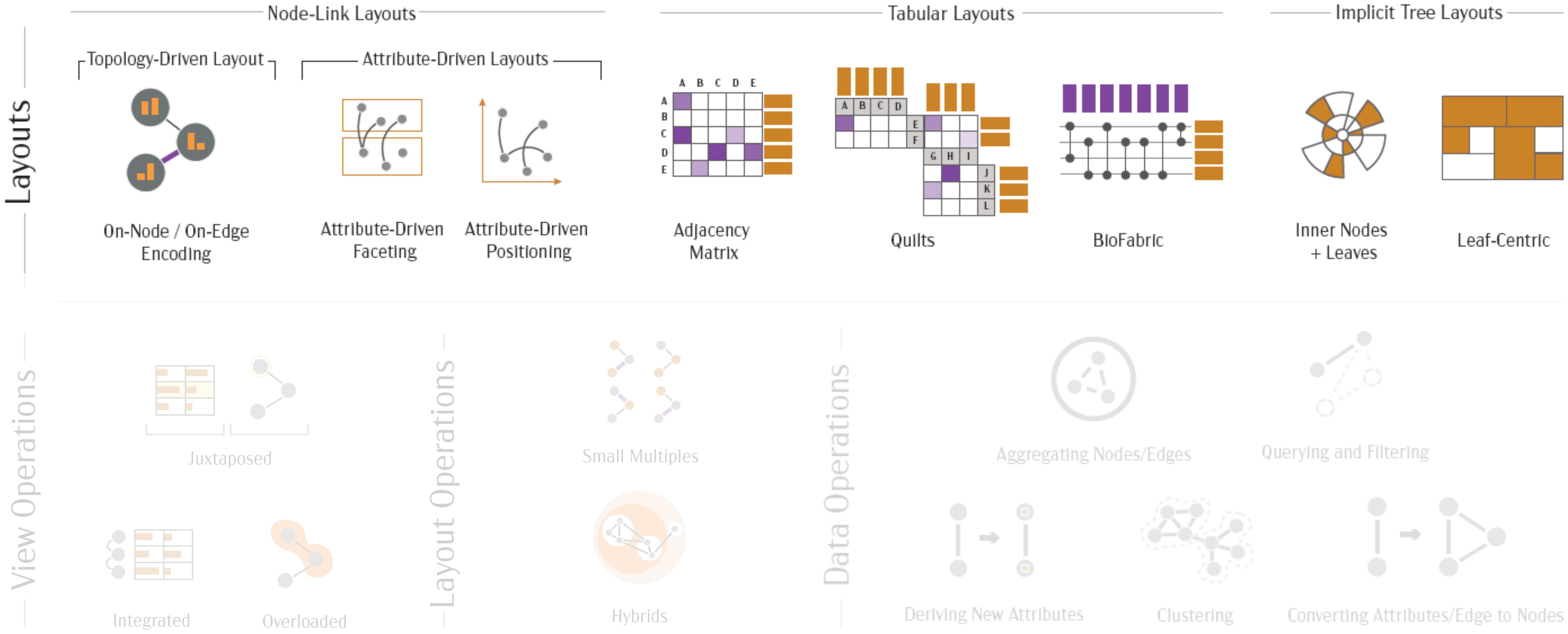
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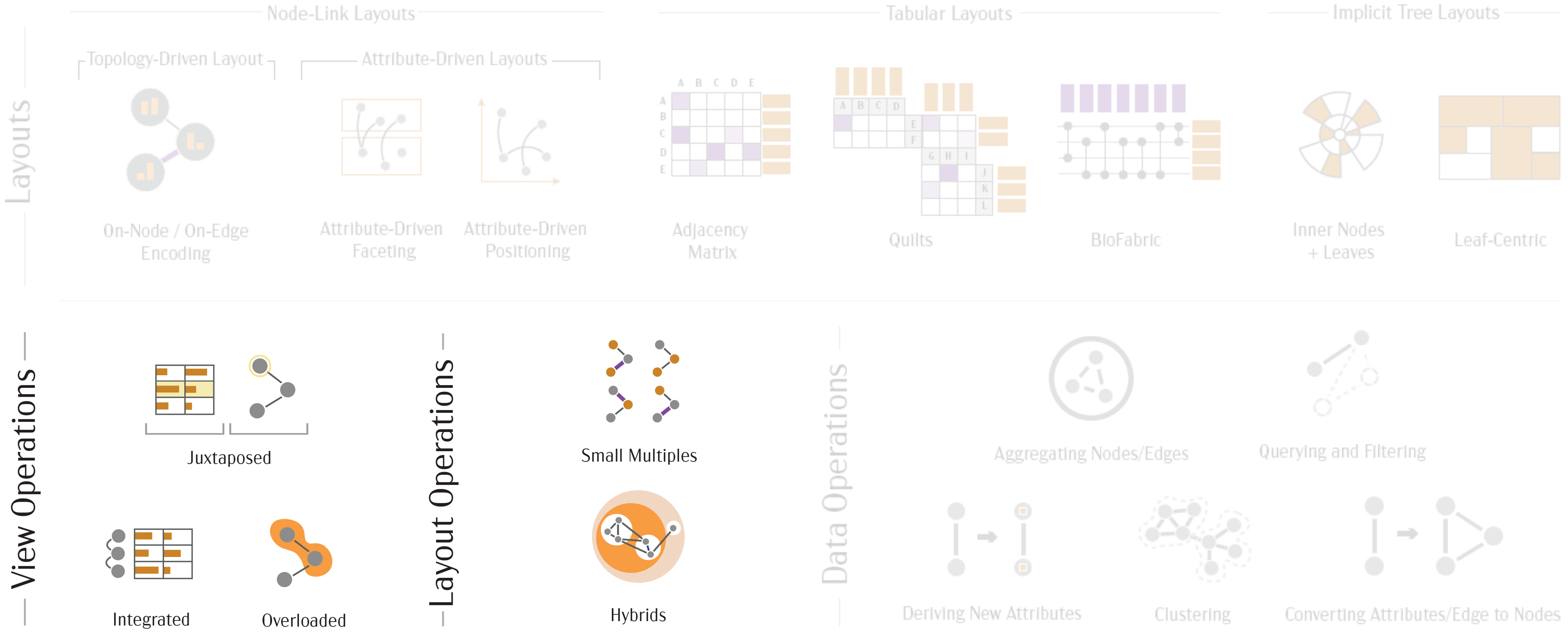
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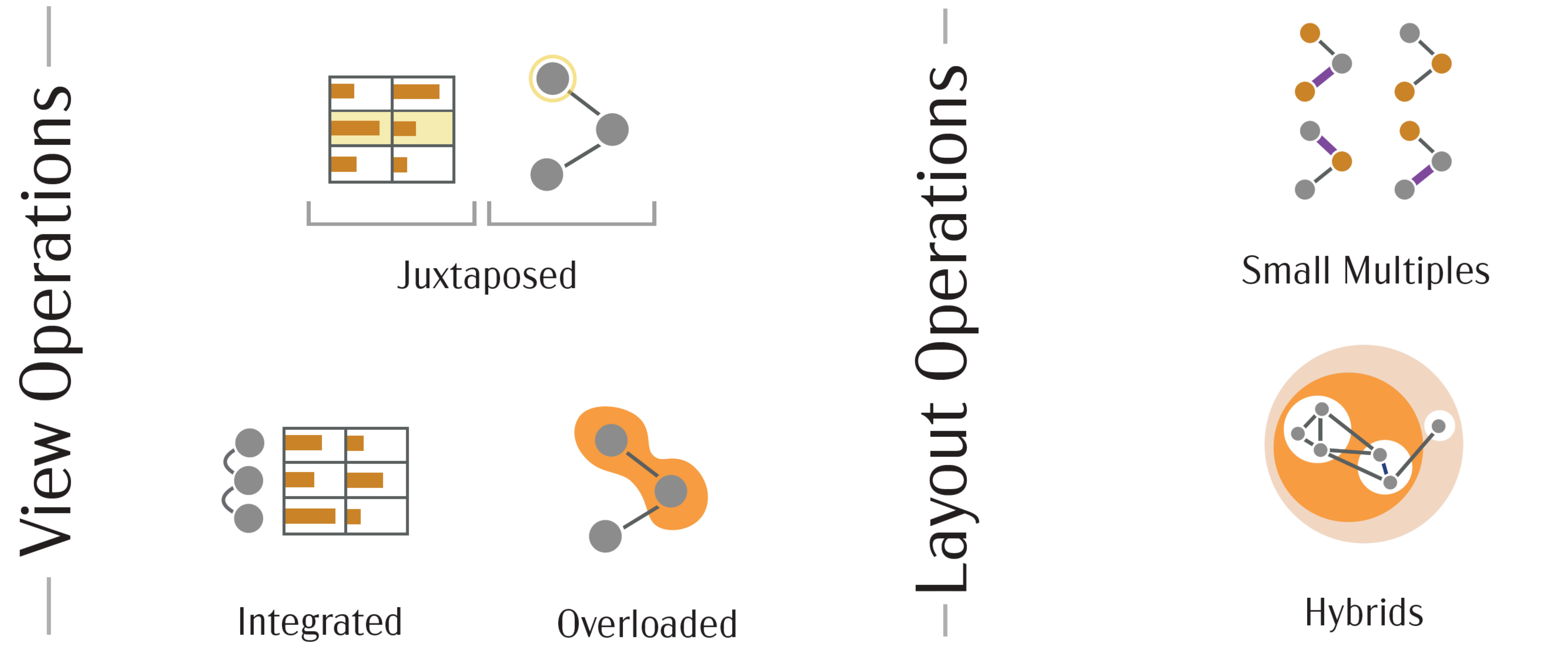
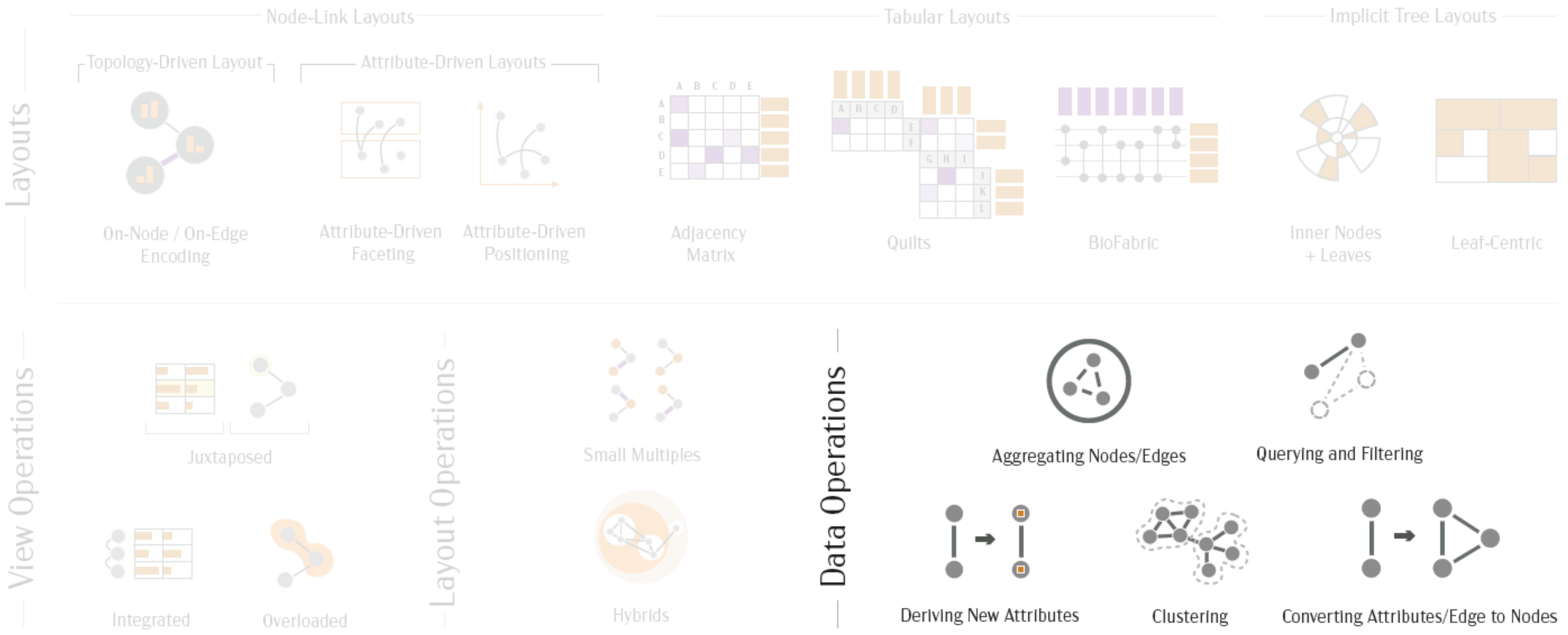


Separate views for Topology and Attributes

Multiple layouts for Topology or Attributes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Tabular Layouts
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Layouts
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LAYOUTS
VIEW OPERATIONS
LAYOUT OPERATIONS
DATA OPERATIONS
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Node-Link Layouts
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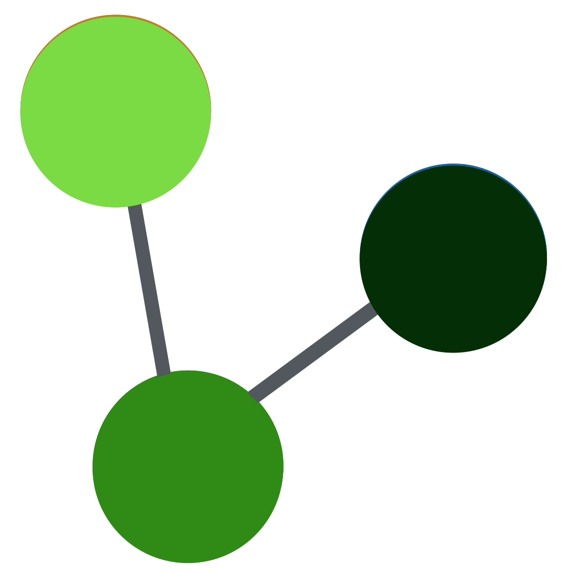
Node-Link Diagram with on-node encoding

LAYOUTS

VIEW OPERATIONS

LAYOUT OPERATIONS

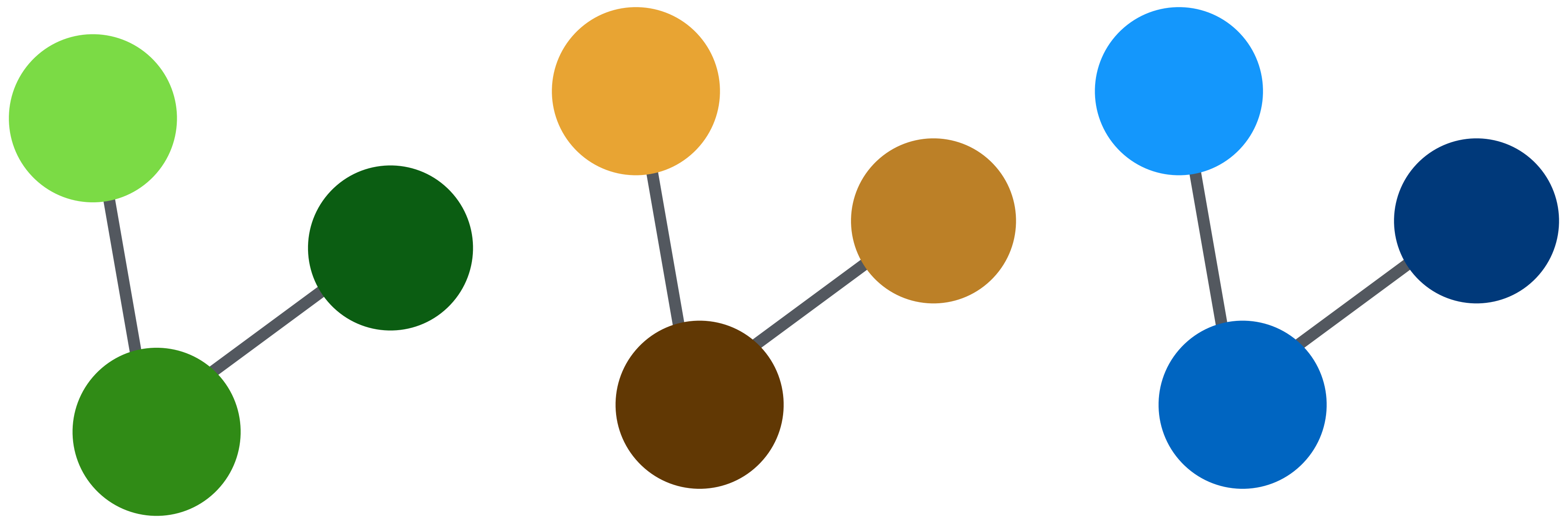
DATA OPERATIONS



LAYOUTS

VIEW OPERATIONS | LAYOUT OPERATIONS | DATA OPERATIONS

Small Multiples



LAYOUTS

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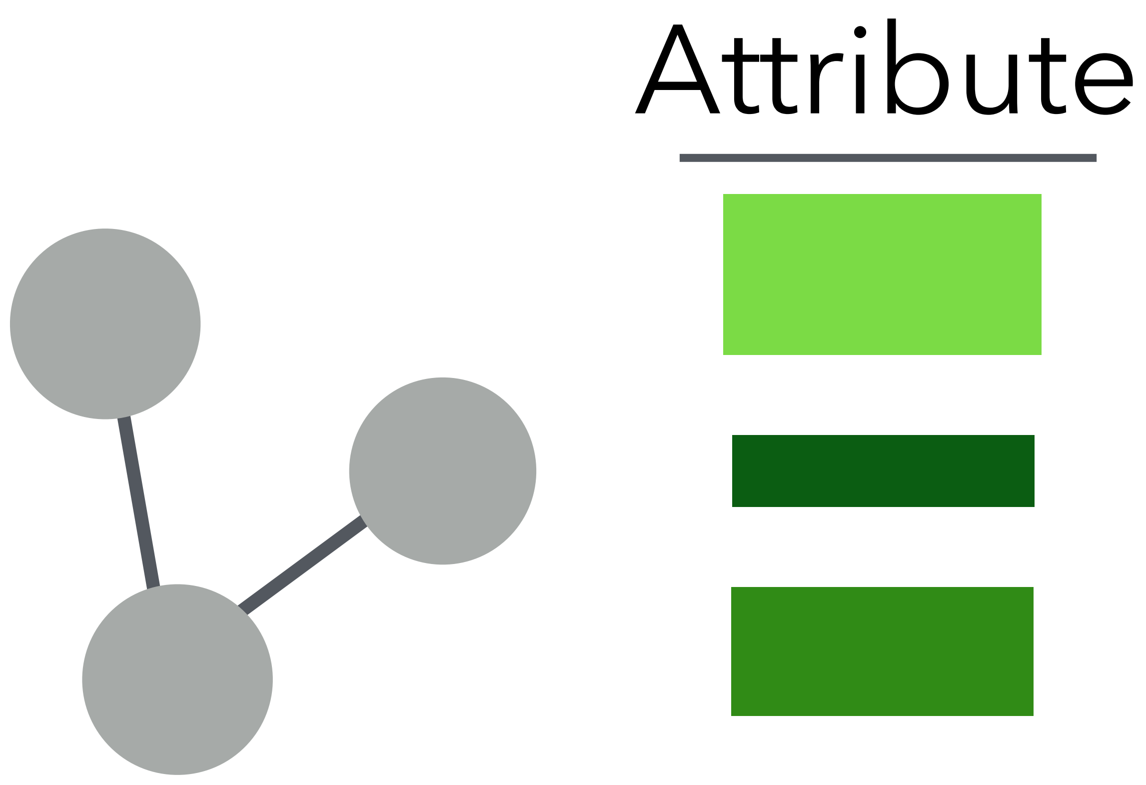
LAYOUT OPERATIONS

DATA OPERATIONS

Juxtaposed Views



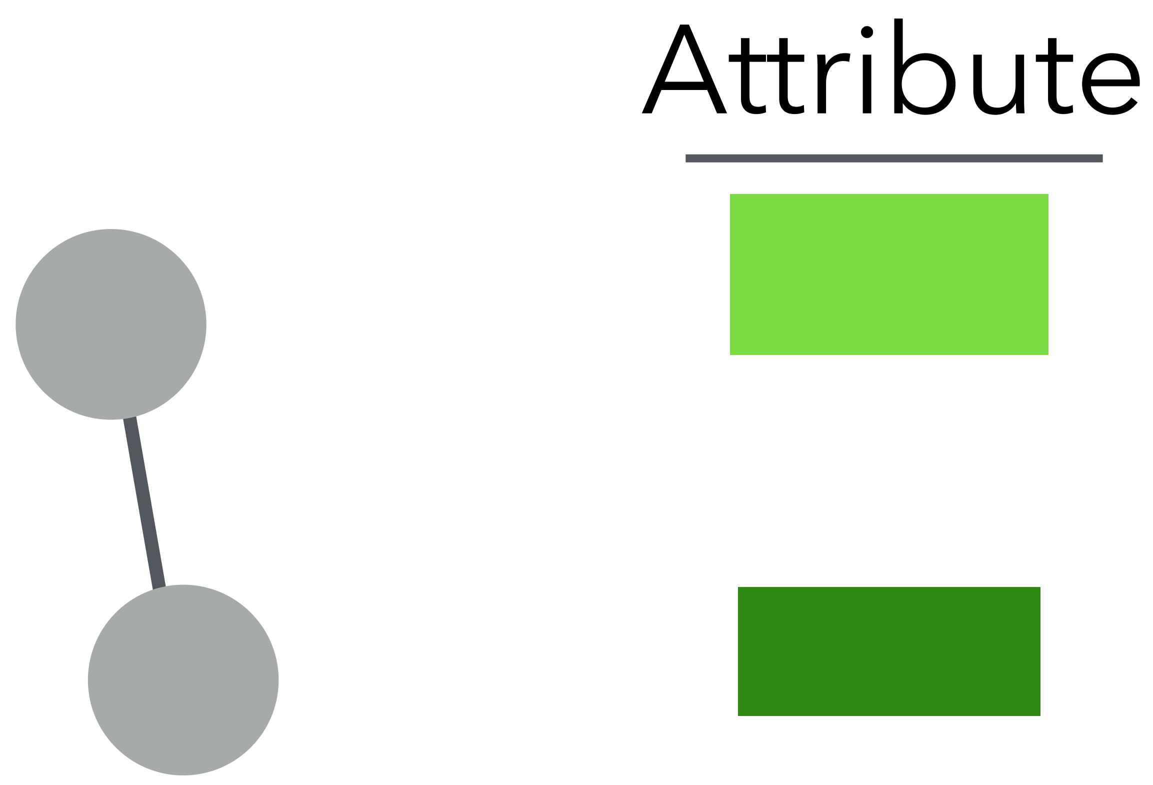
LAYOUTS

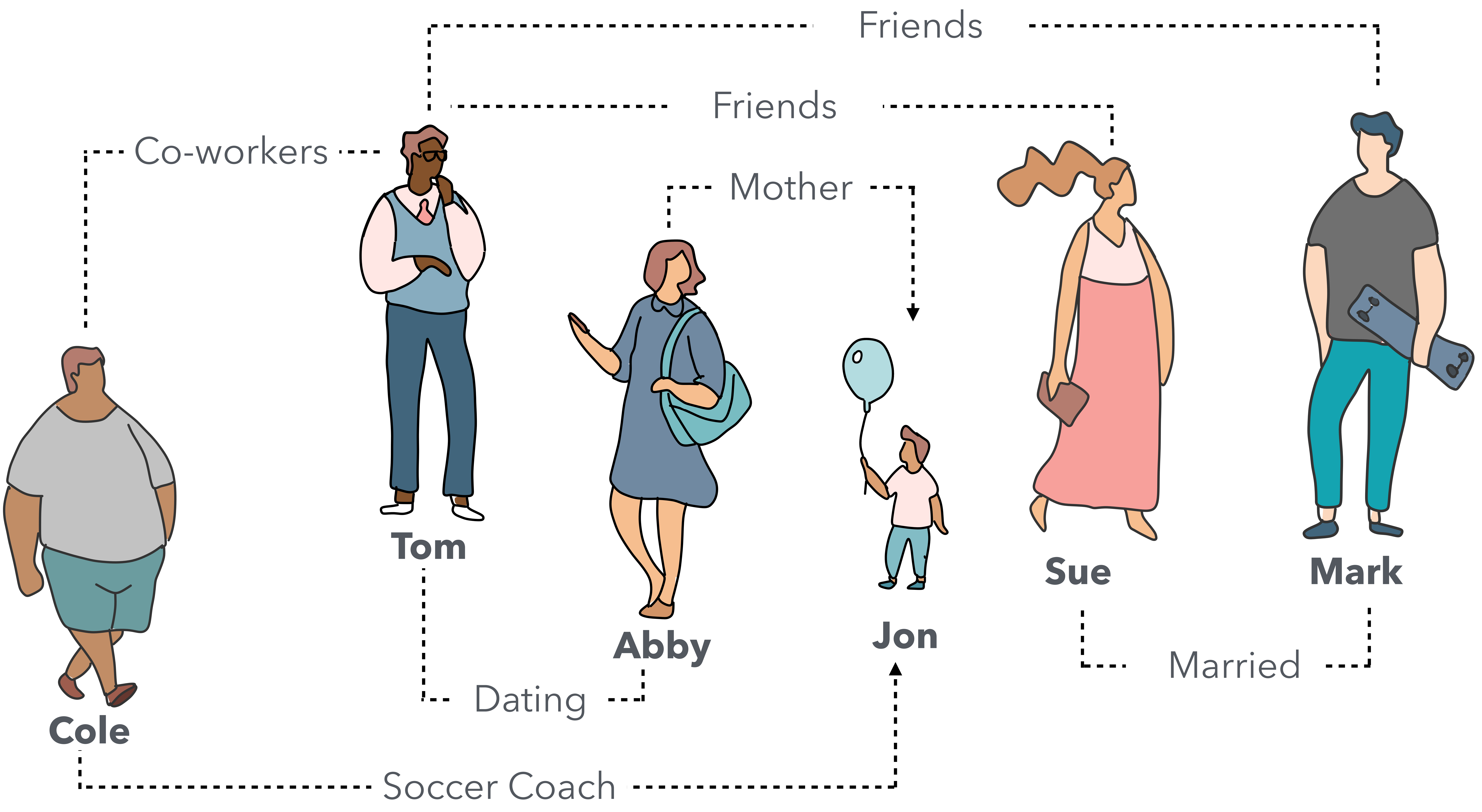
VIEW OPERATIONS

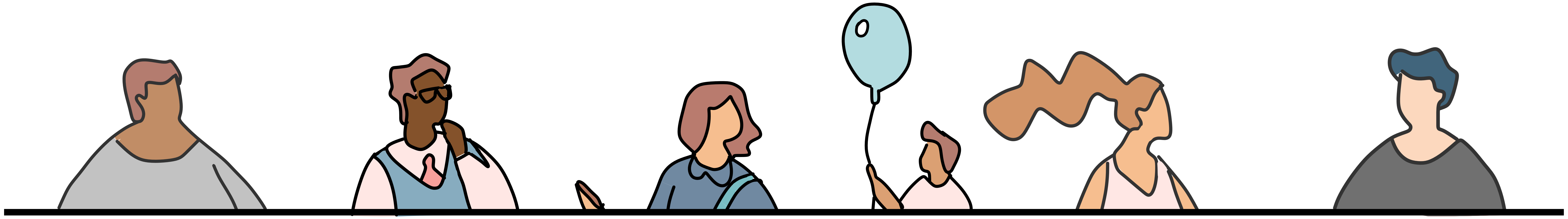
LAYOUT OPERATIONS

DATA OPERATIONS

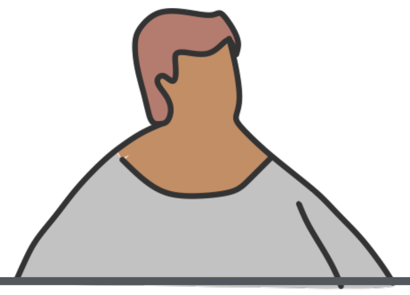
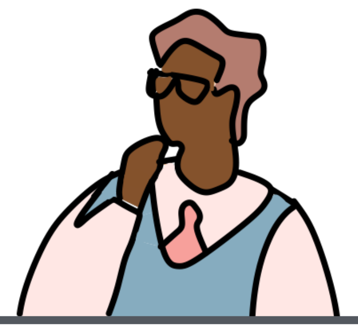
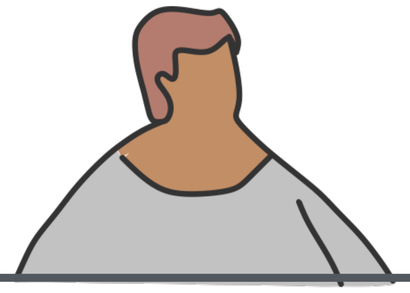
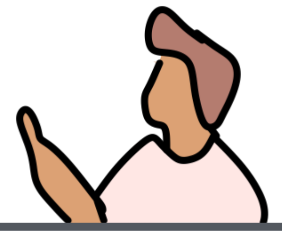
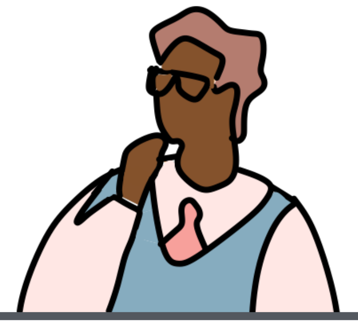
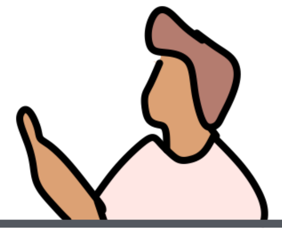
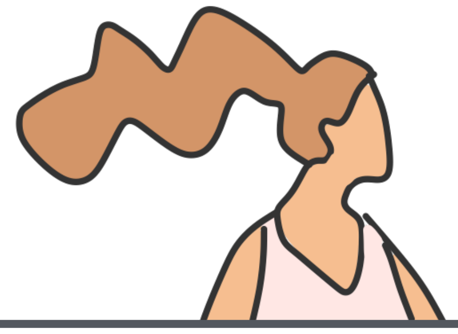
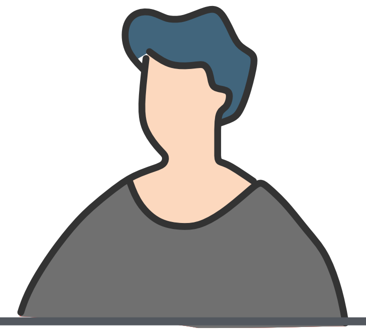
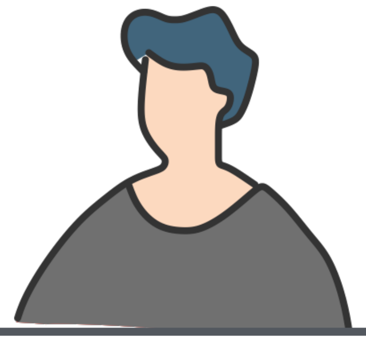
Filter Data



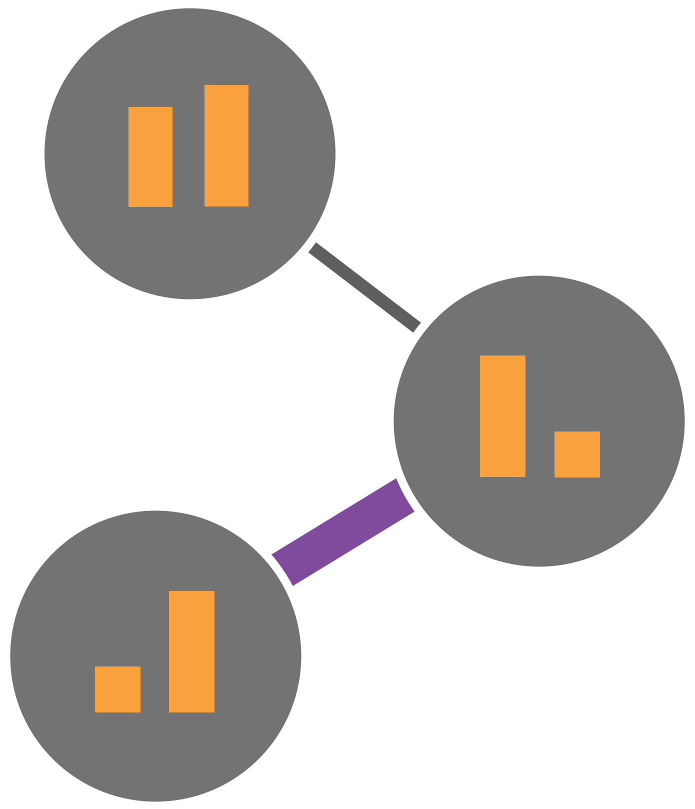

Friends
Friends
Co-workers
Mother
Tom
Sue
Mark
Abby
Jon
Married
Dating
Cole
Soccer Coach

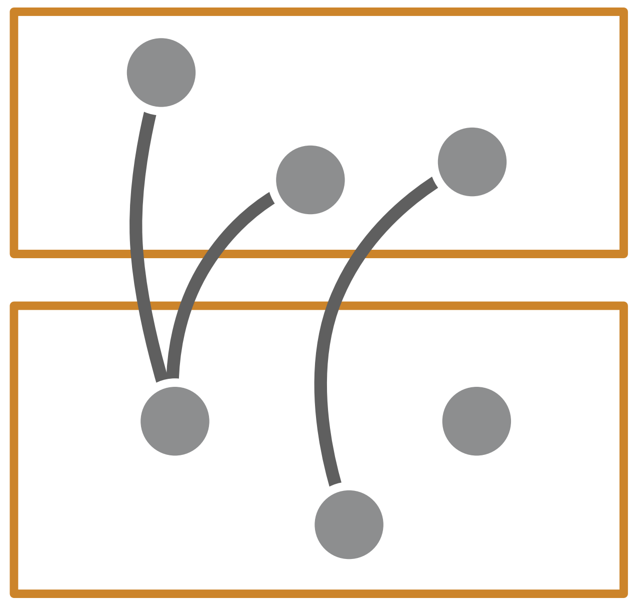


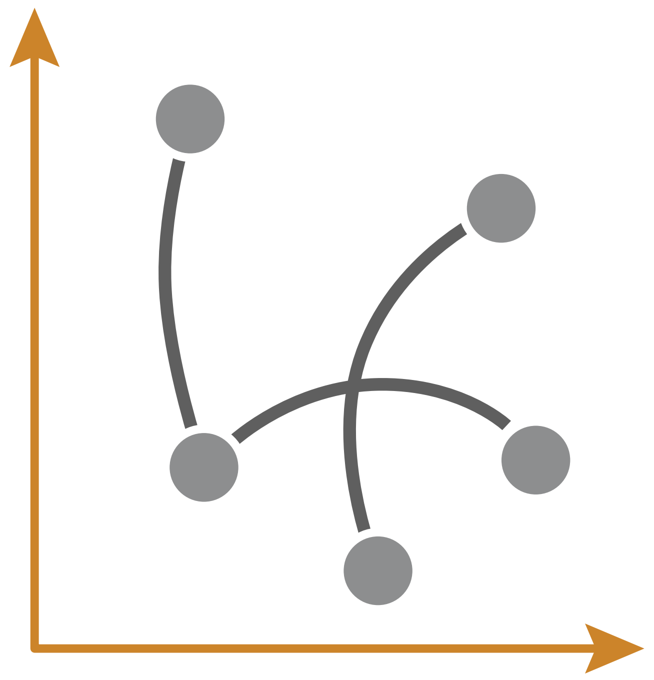
Name	Cole	Tom	Abby	Jon	Sue	Mark
Beverage	Port	Beer	Port	Coke	Coke	Beer
Day 1	1	0	4	3	3	5
Day 2	0	2	5	3	5	5
Day 3	4	1	2	2	4	3

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

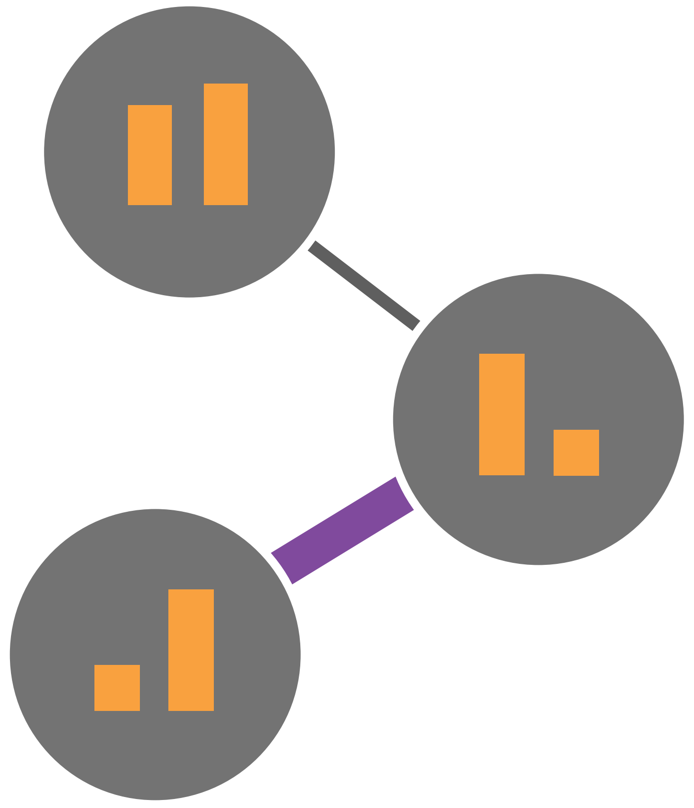
Node-Link Layouts



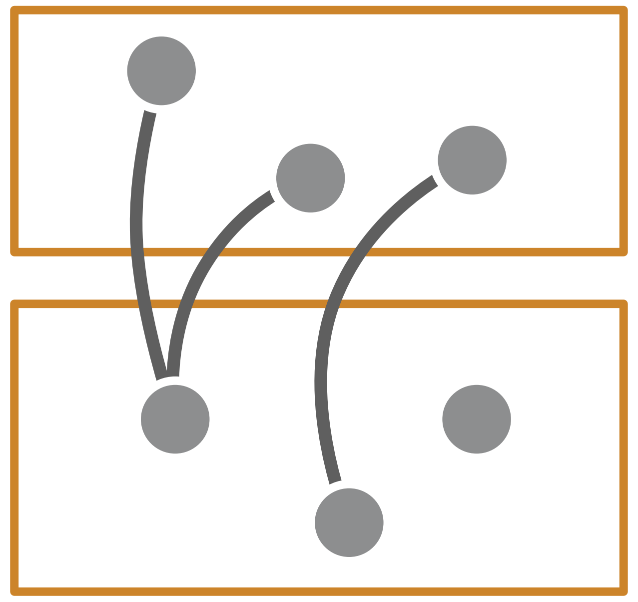


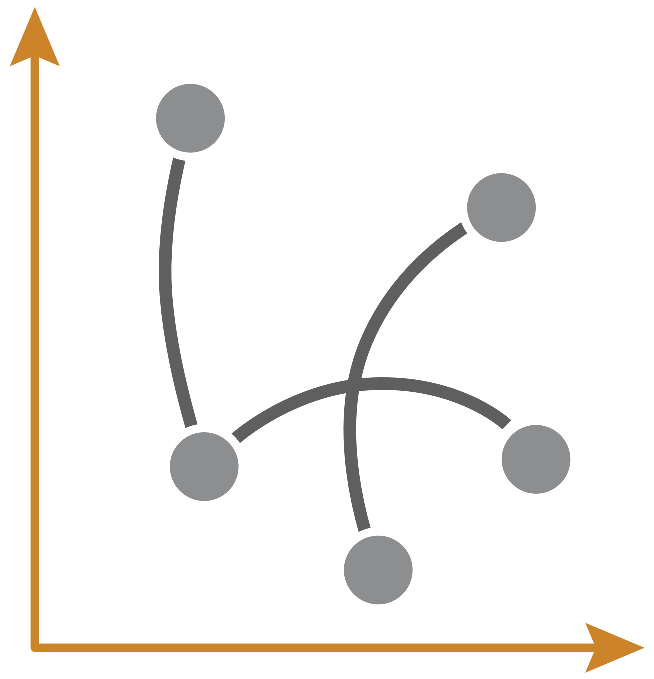


Topology Driven Layout

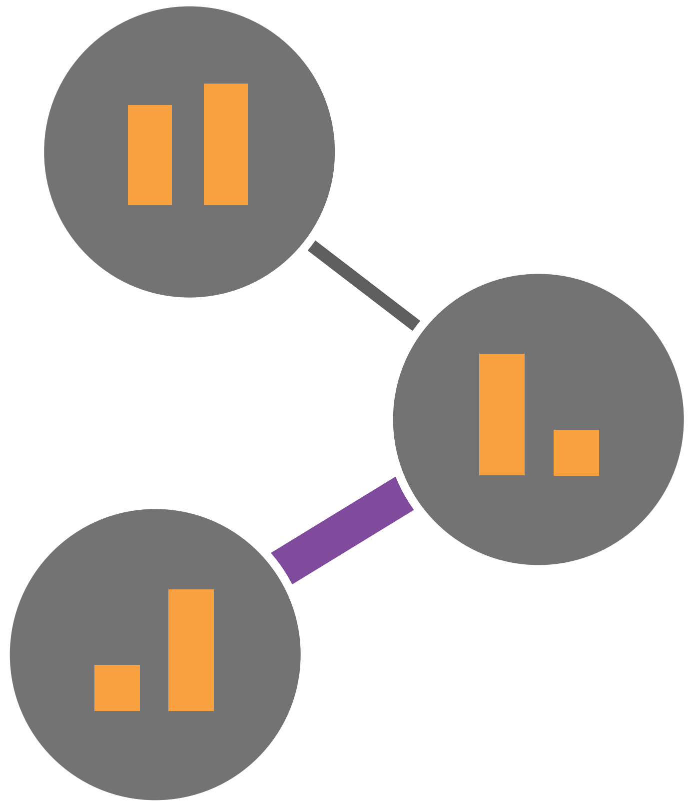


Attribute Driven Layouts



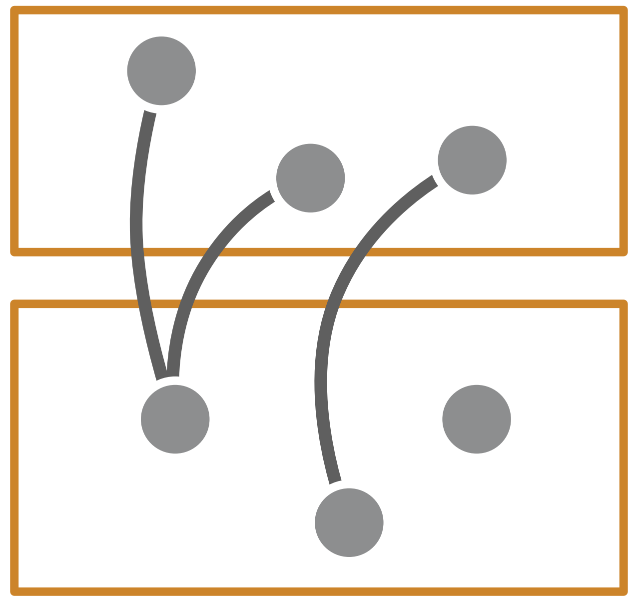


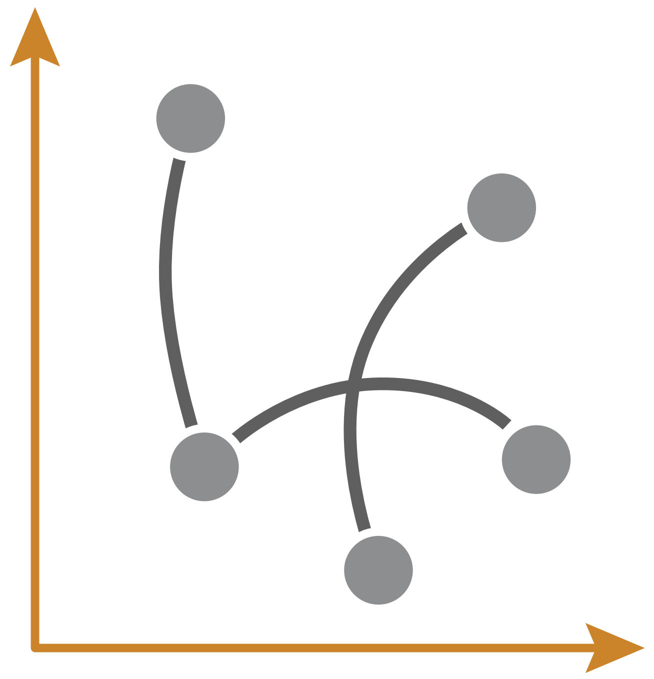
Topology Driven Layout



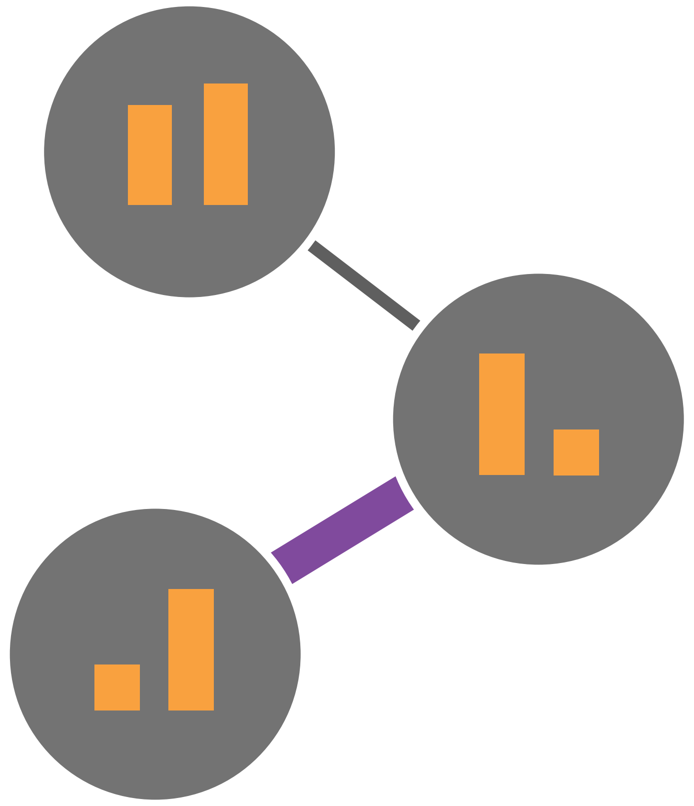
On-Node / On-Edge
Encoding

Attribute Driven Layouts



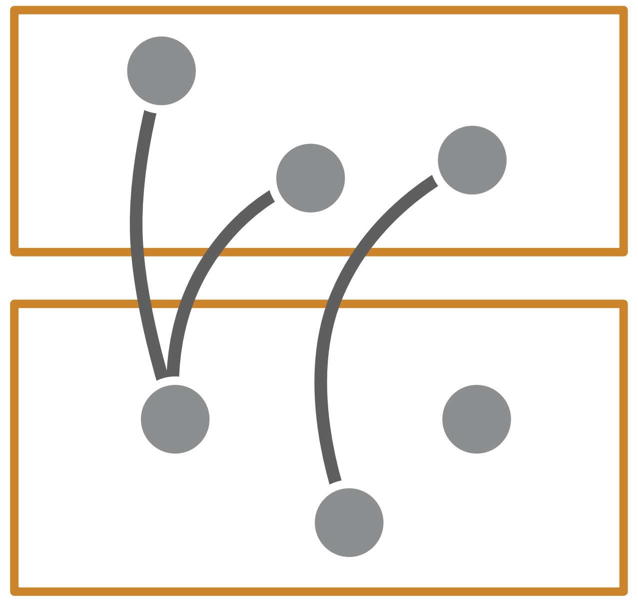


Topology Driven Layout

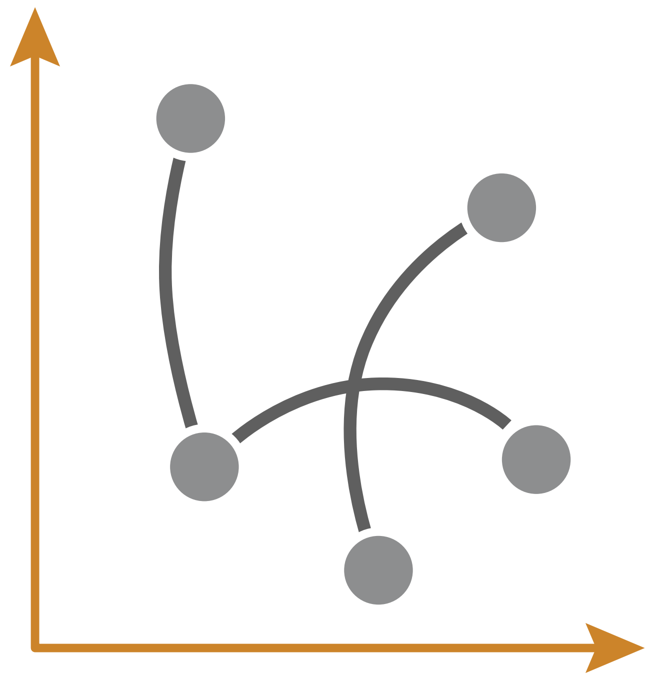


On-Node / On-Edge
Encoding

Attribute Driven Layouts

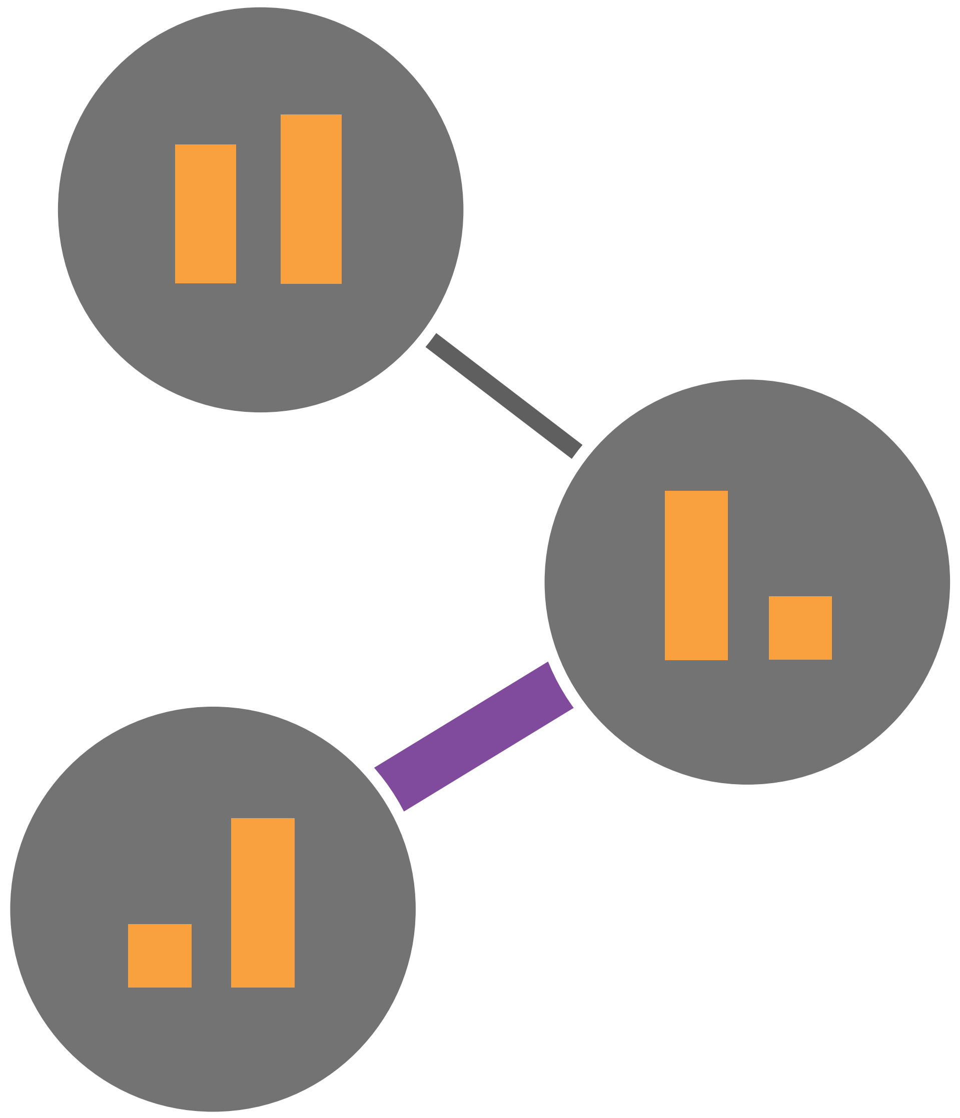


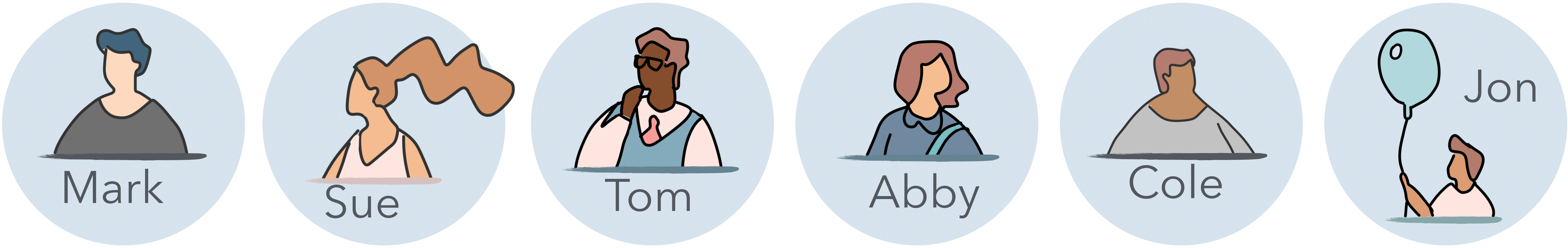
Attribute-Driven
Faceting

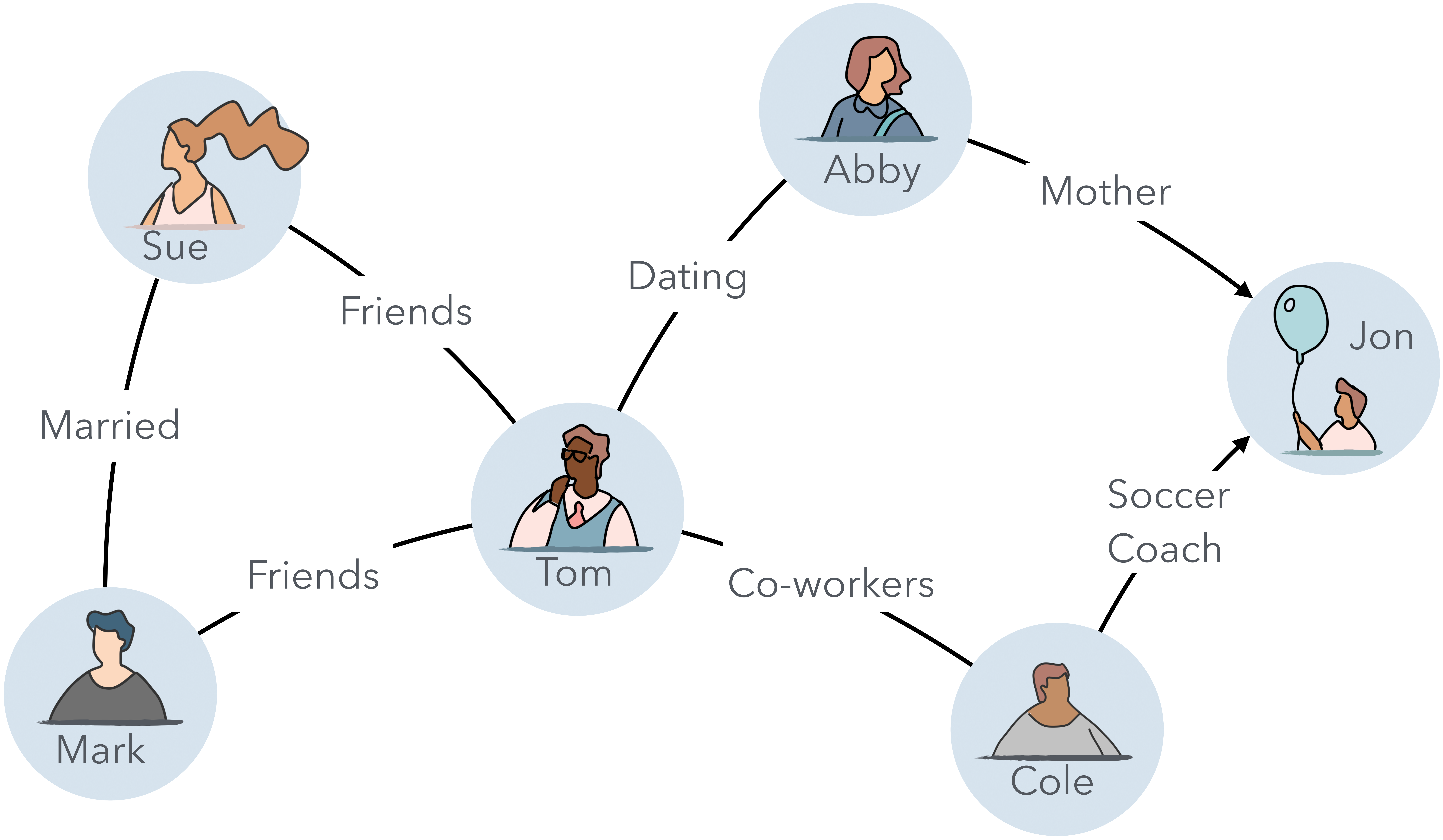


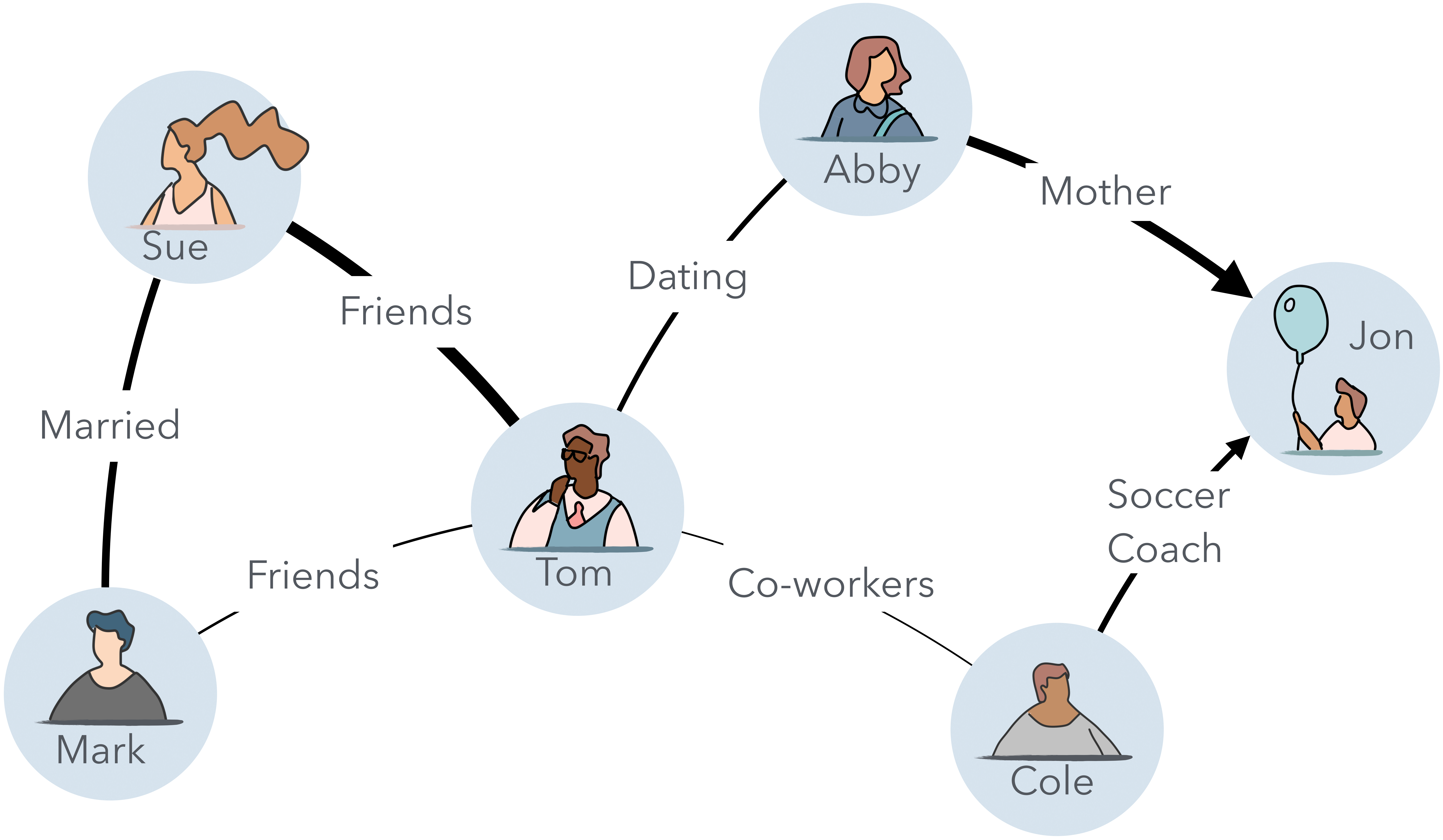
Attribute-Driven
Positioning

On-Node / On-Edge Encoding




Mark
Sue
Tom
Abby
Cole
Jon


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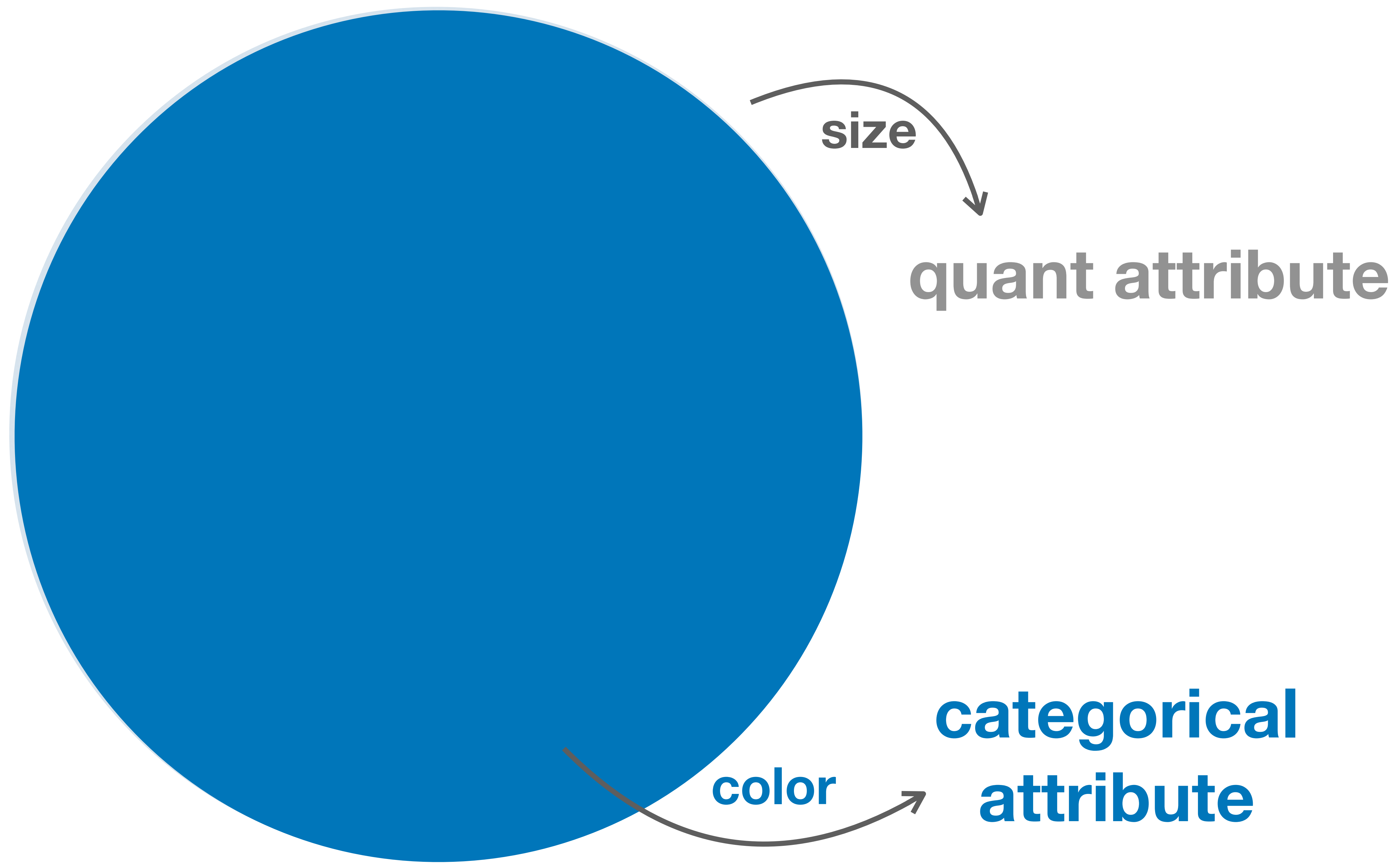
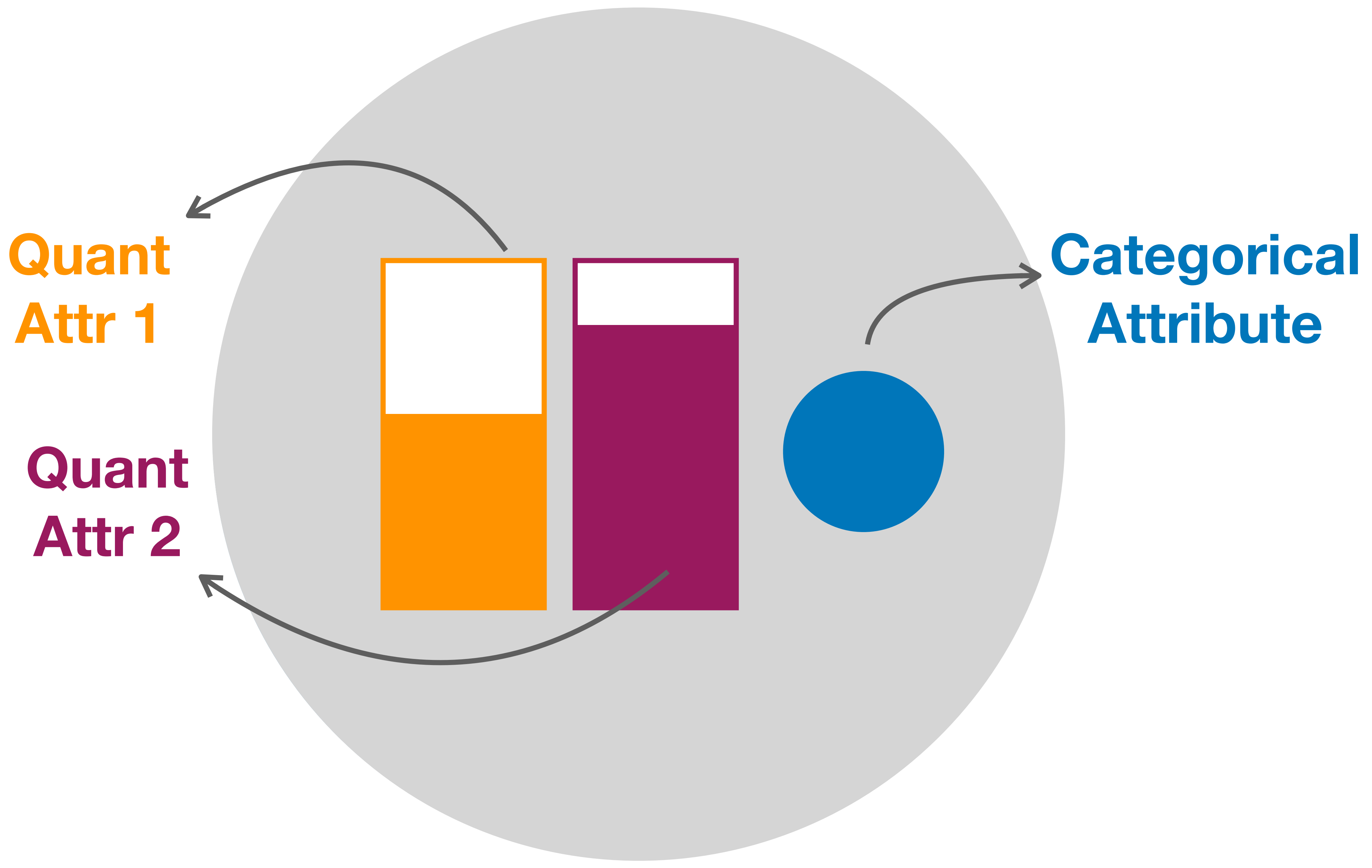
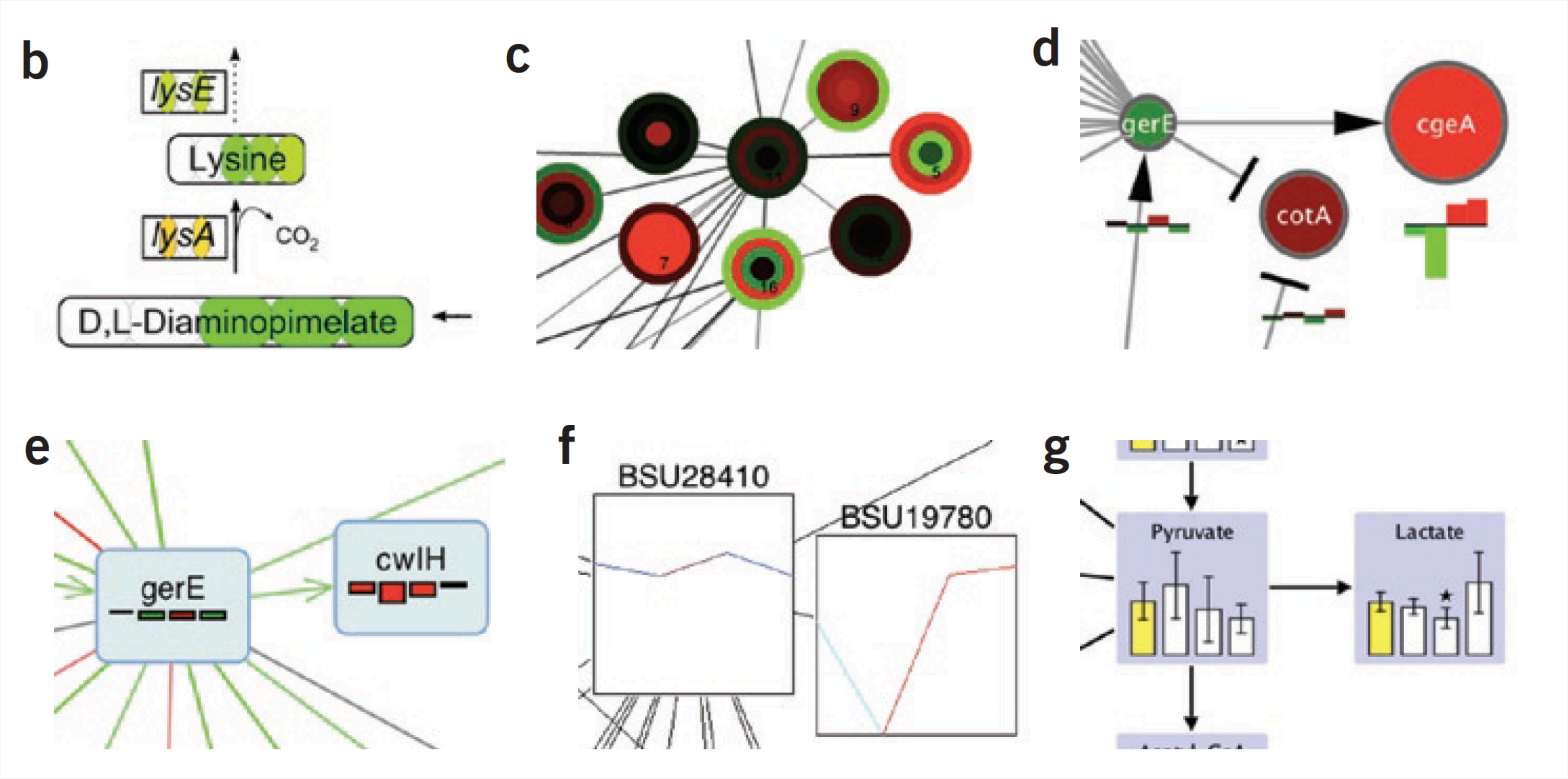
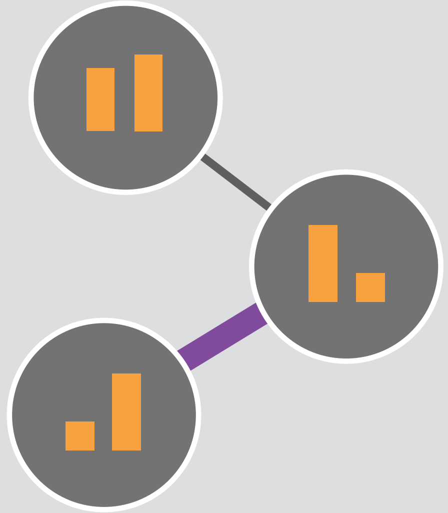

size
quant attribute
color
categorical
attribute

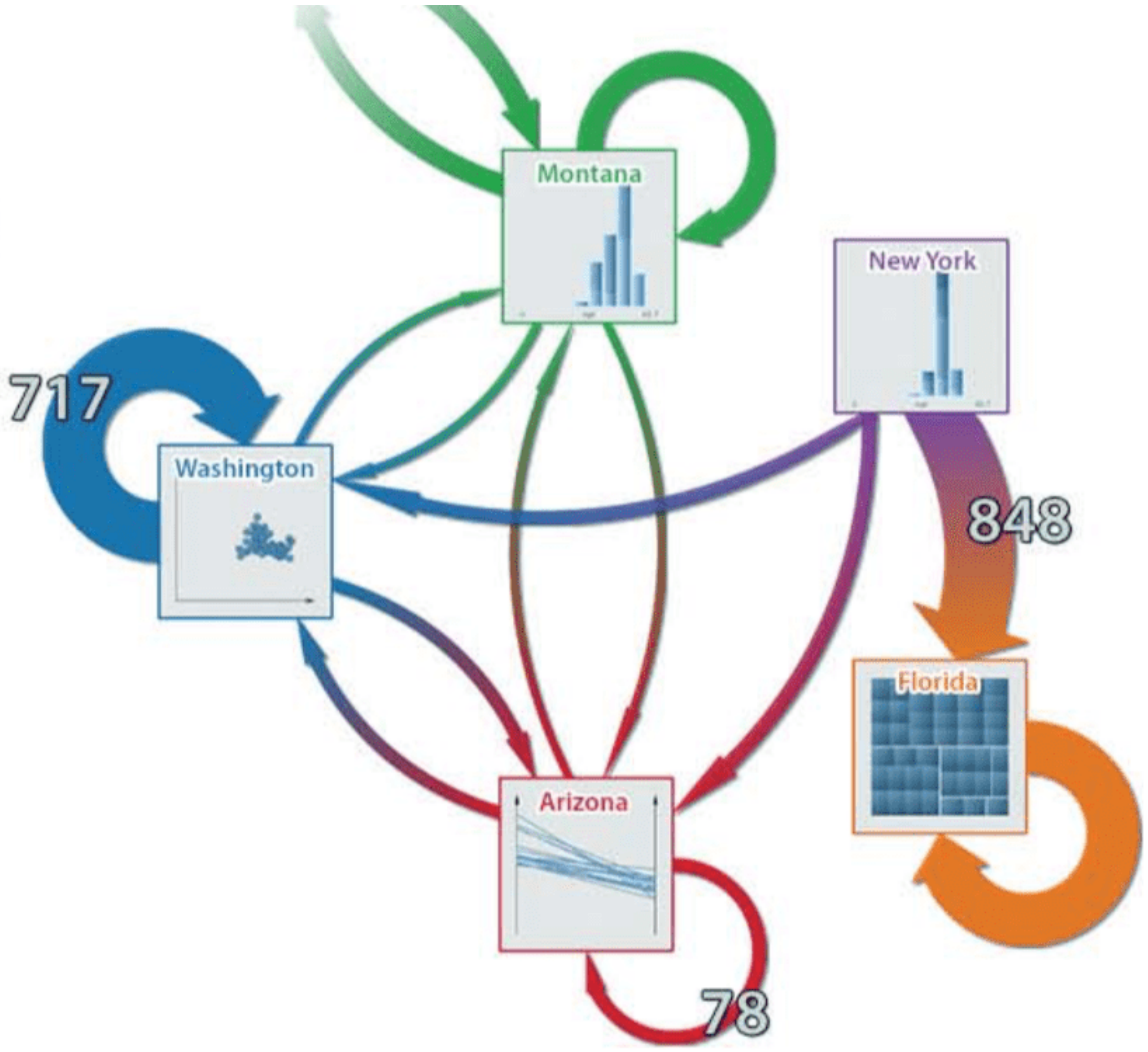

Quant
Attr 1
Quant
Attr 2
Categorical
Attribute



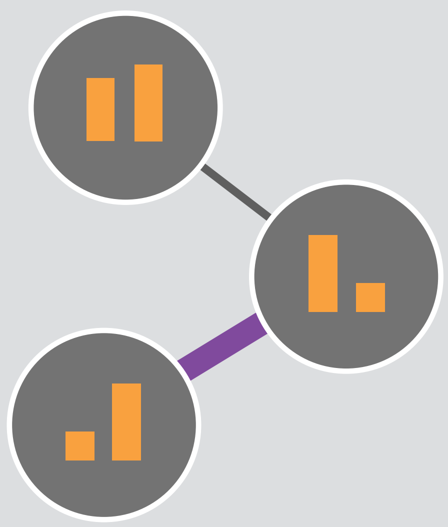
Gehlenborg et al. 2010



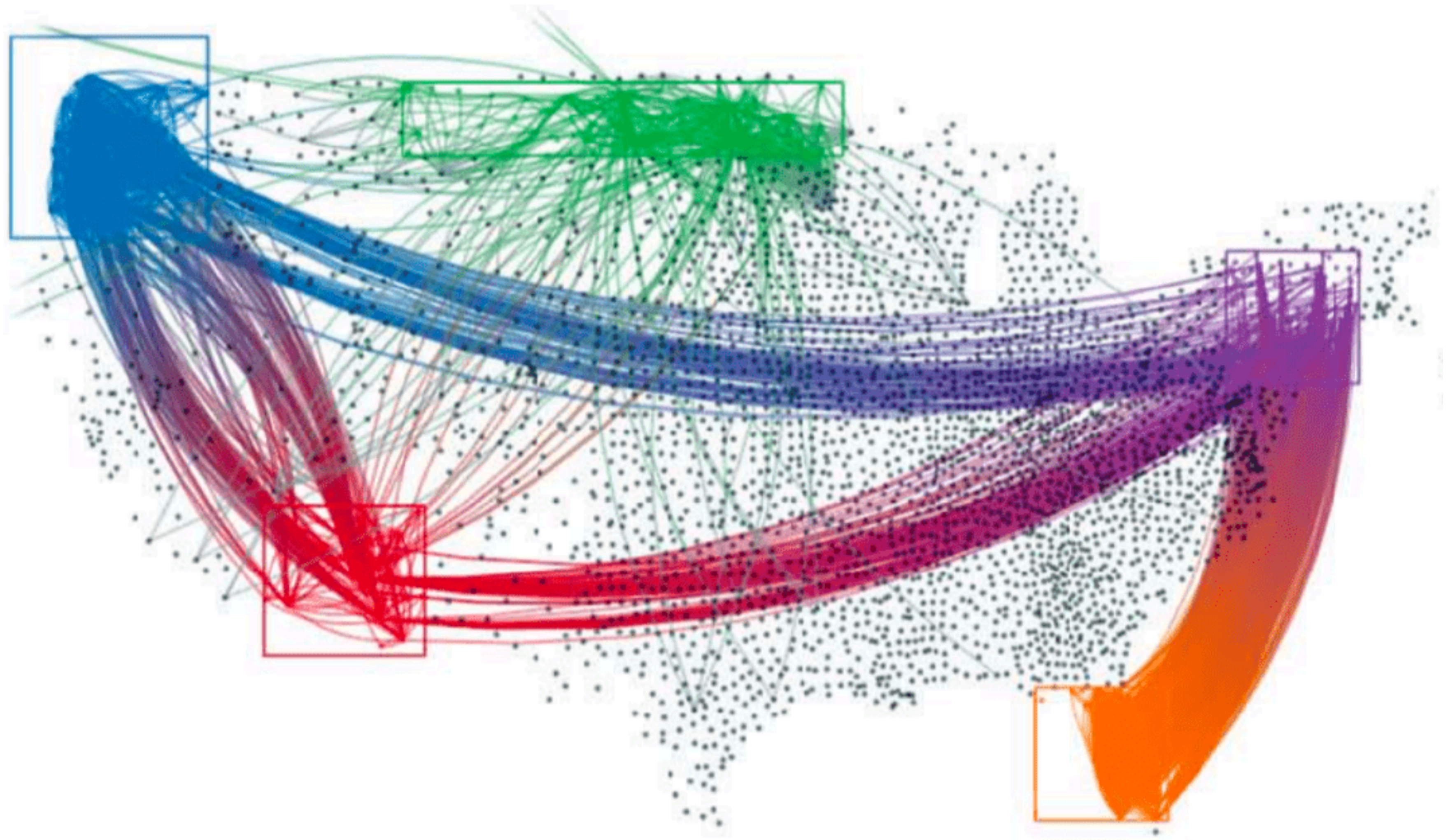
On-Node / On-Edge Encoding

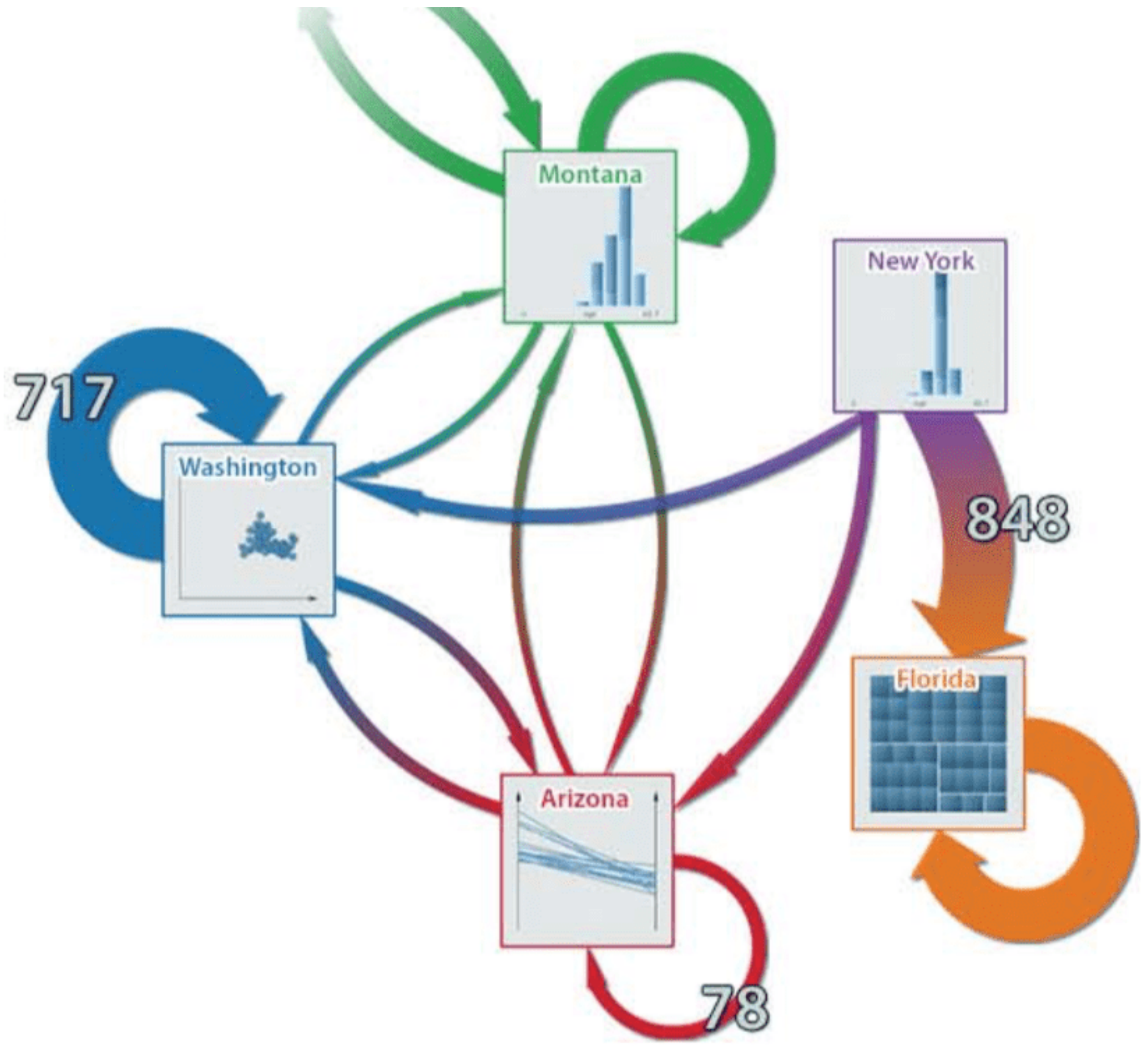


Elzen and Wijk, 2014



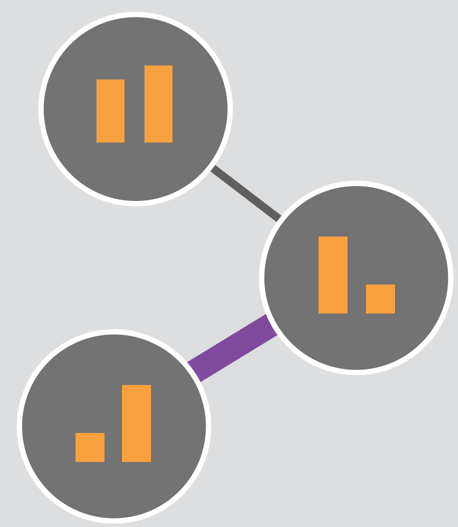
On-Node / On-Edge Encoding



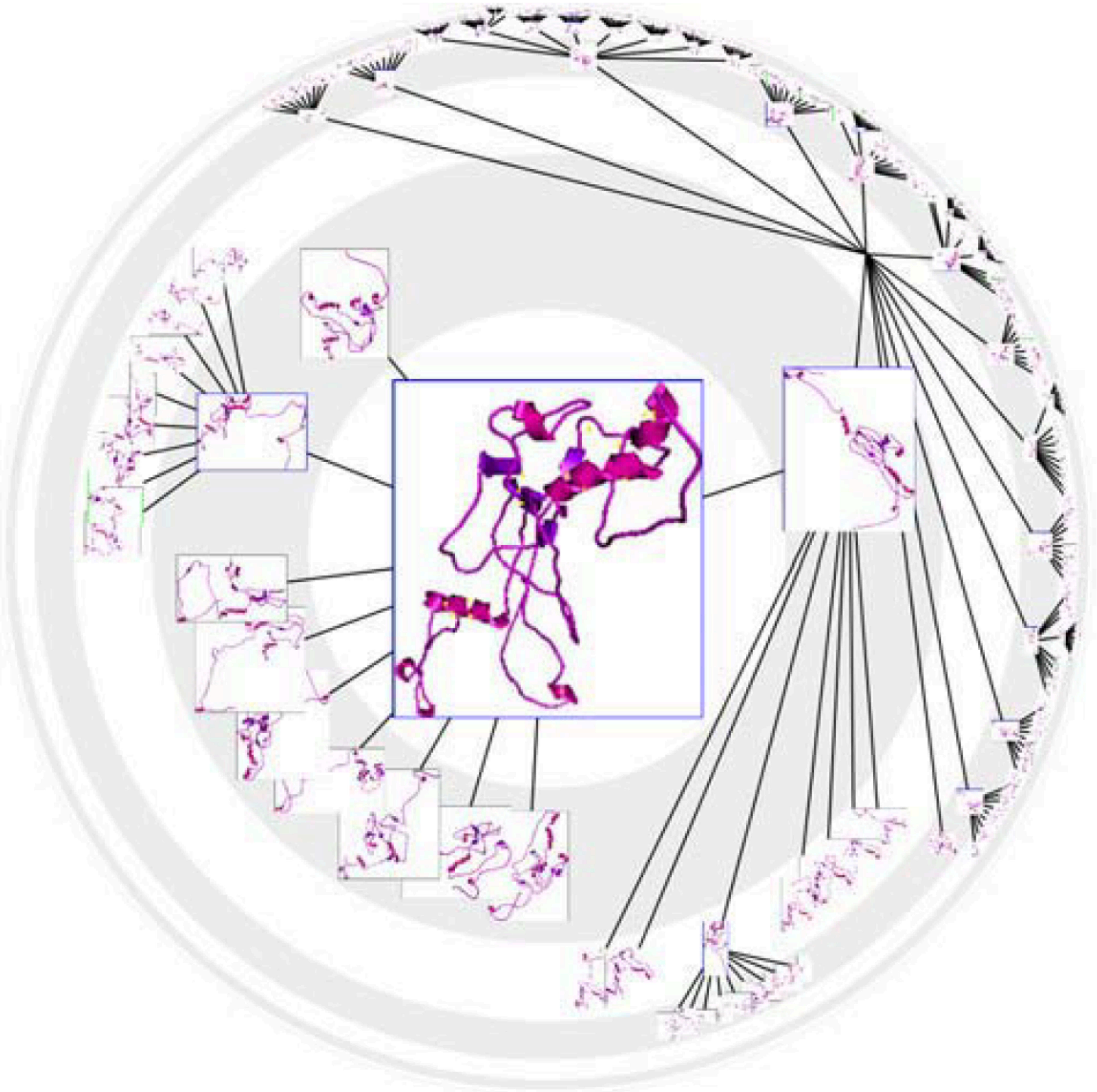


Elzen and Wijk, 2014

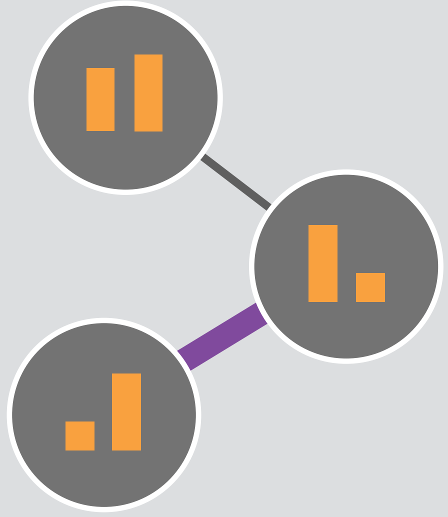
Aggregating Nodes/Edges



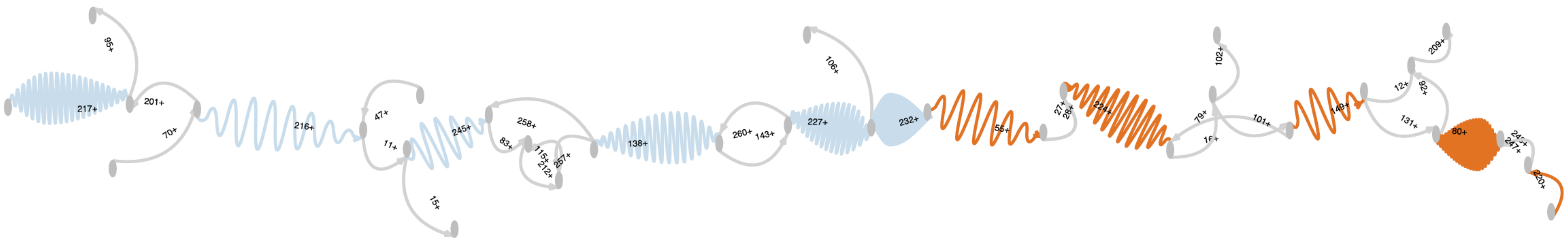
On-Node / On-Edge
Encoding



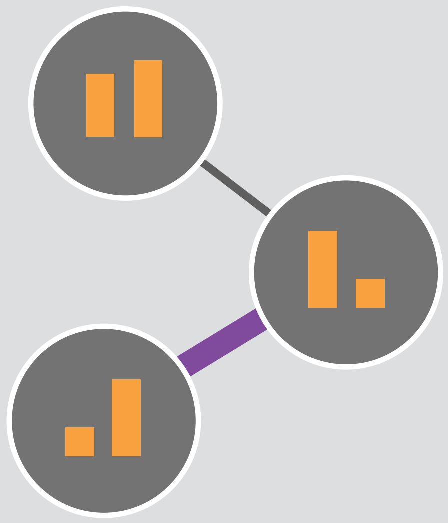
Jankun-Kelly and Ma, 2003



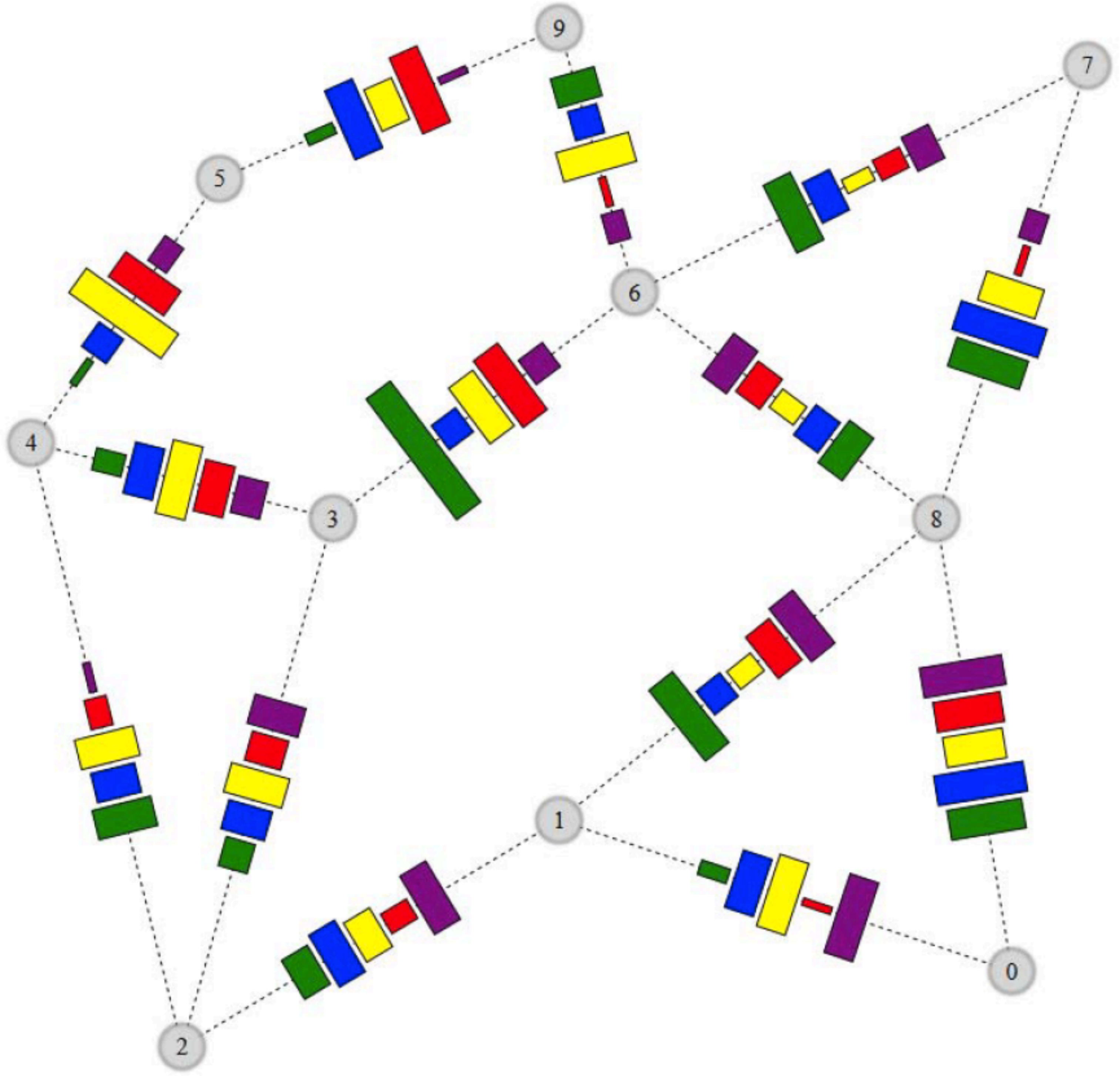
On-Node / On-Edge
Encoding

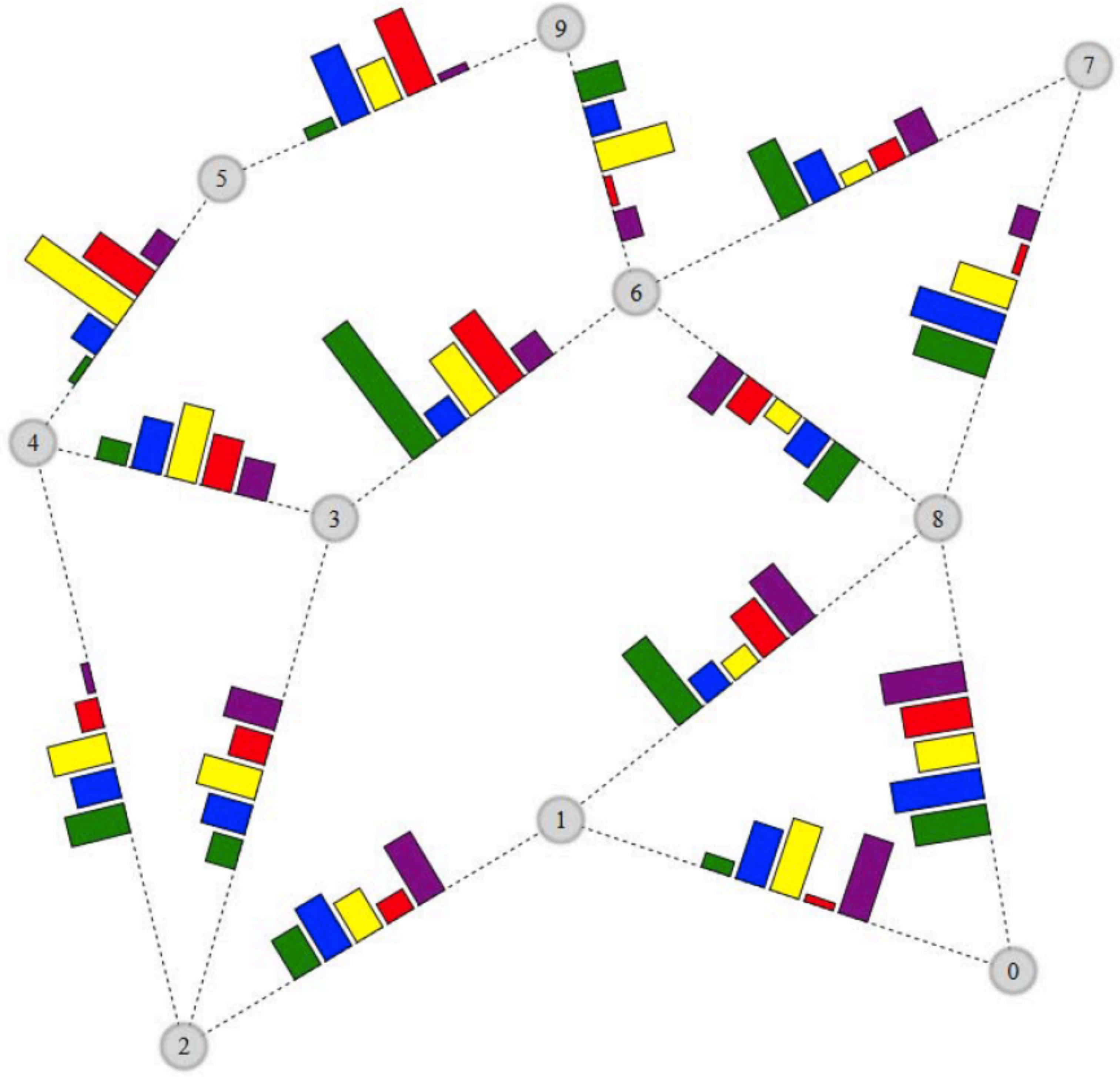


Nielsen, 2009

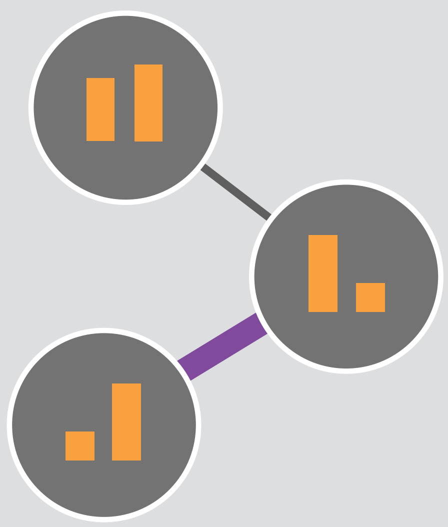


On-Node / On-Edge
Encoding

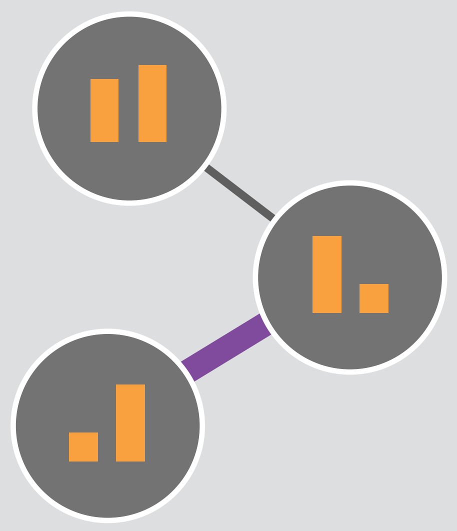




Schöffel et al, 2016



On-Node / On-Edge Encoding



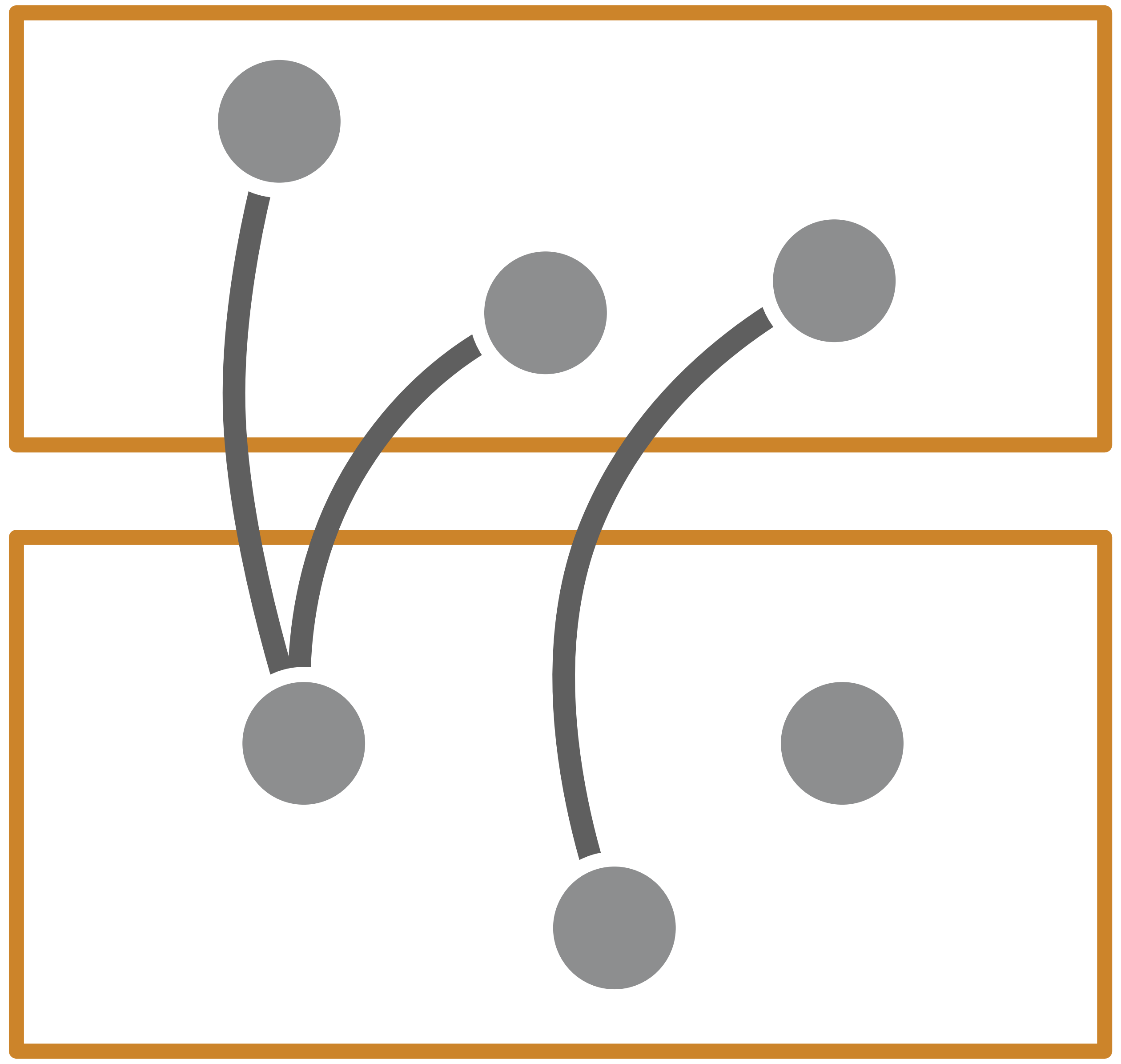
On-Node / On-Edge Encoding

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

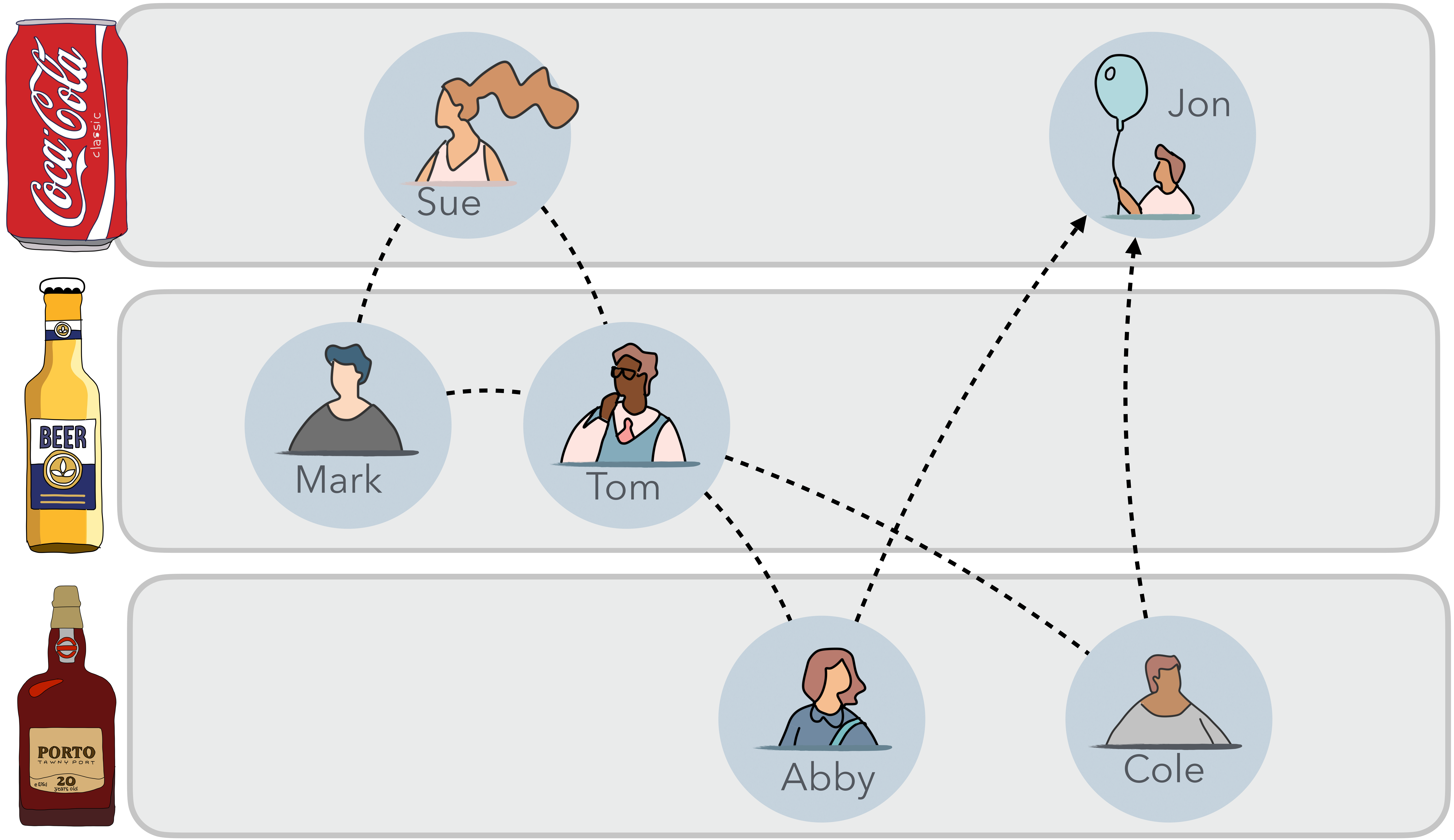



Coca-Cola
classic
BEER
PORTO
TAWNY PORT
20
years old
e 0,75cl

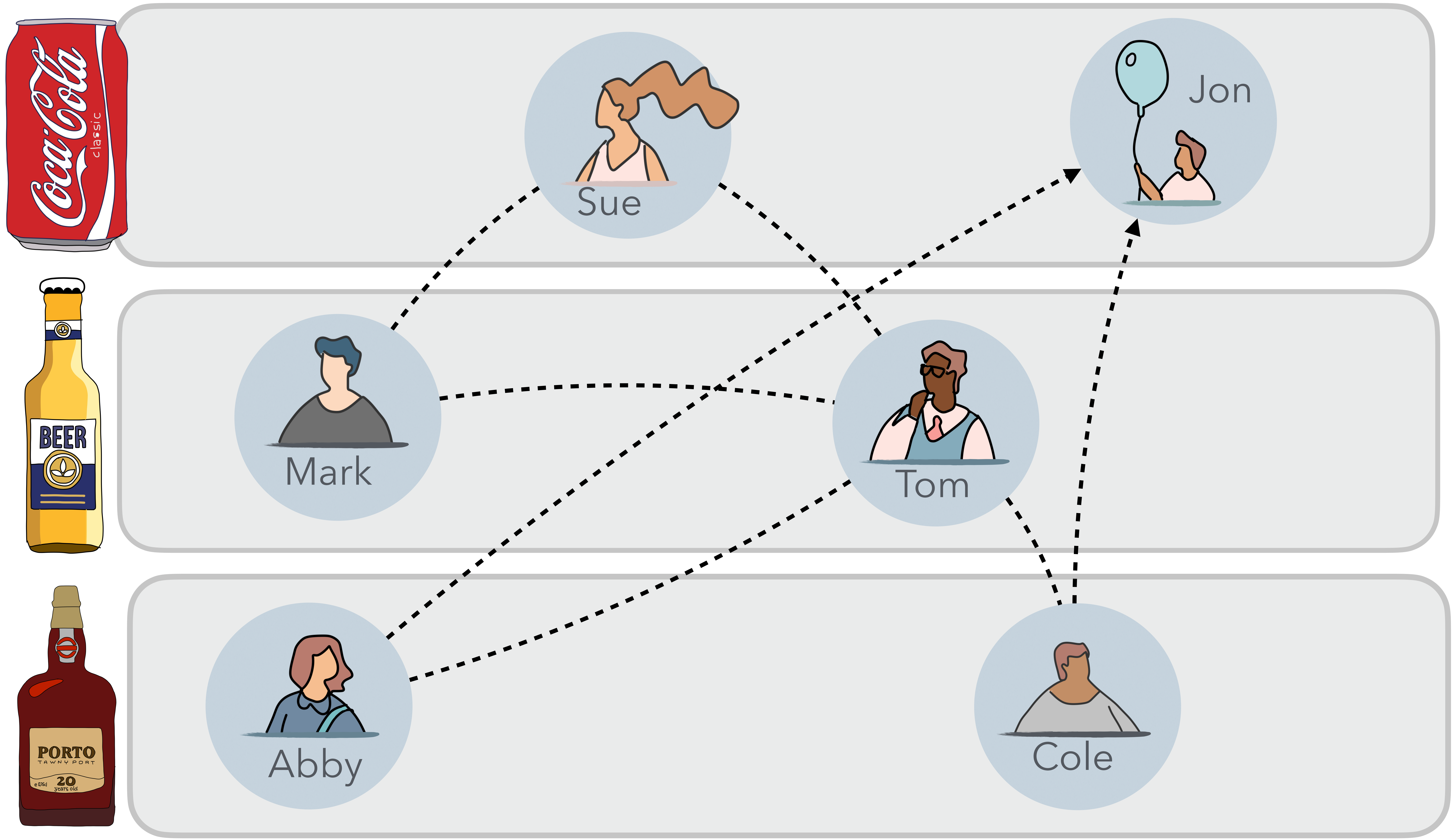

Coca-Cola
classic


BEER

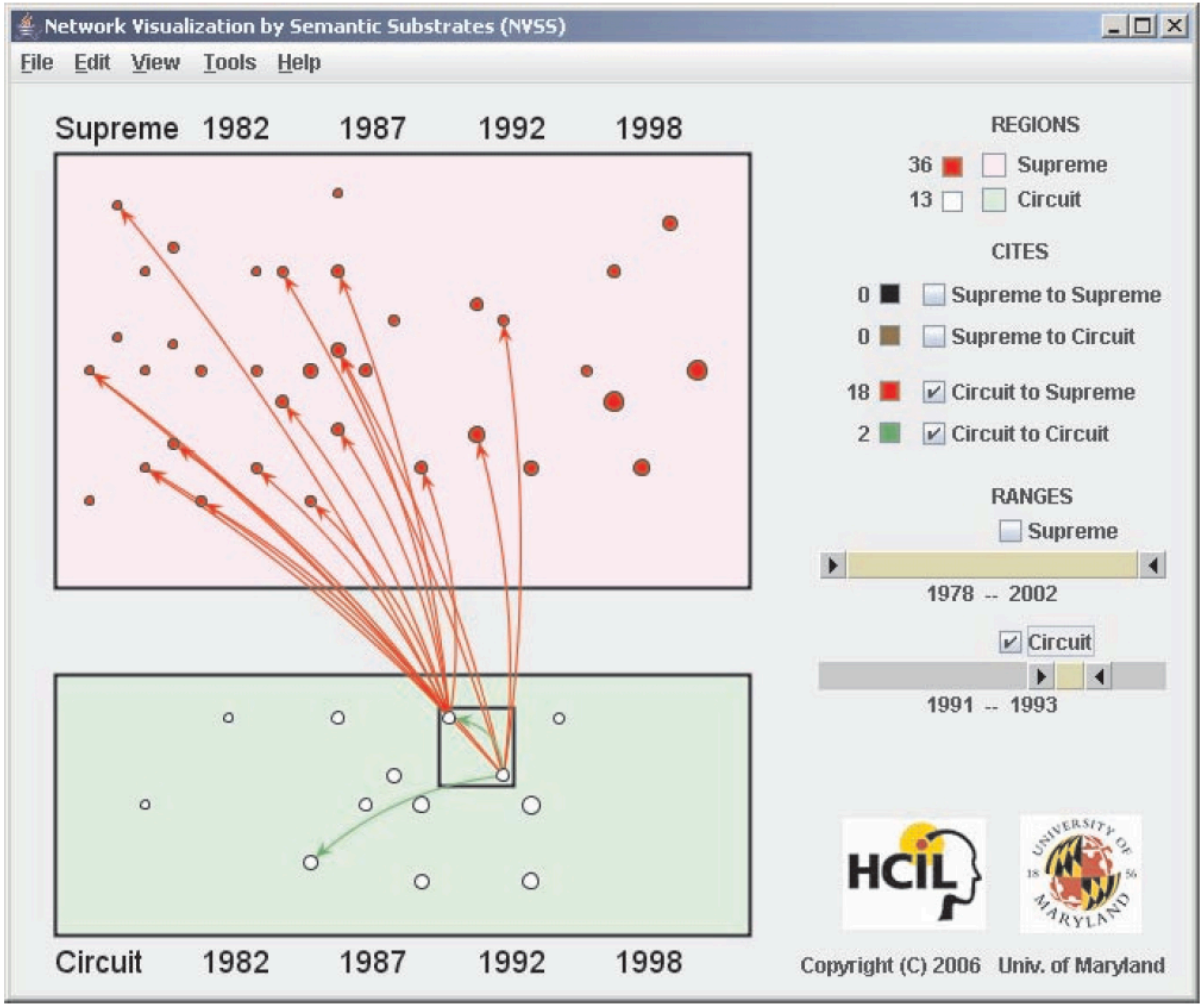

PORTO
TAWNY PORT
20
years old

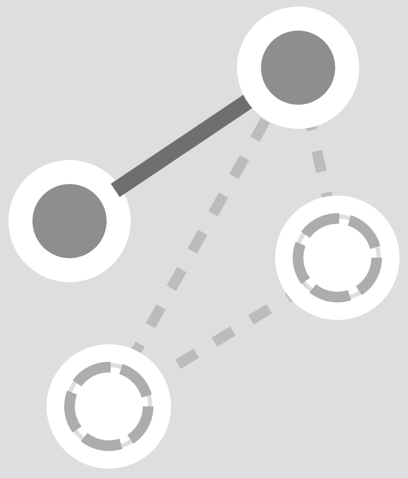


Coca-Cola classic
BEER
PORTO
TAWNY PORT
20 years old
Sue
Jon
Mark
Tom
Abby
Cole

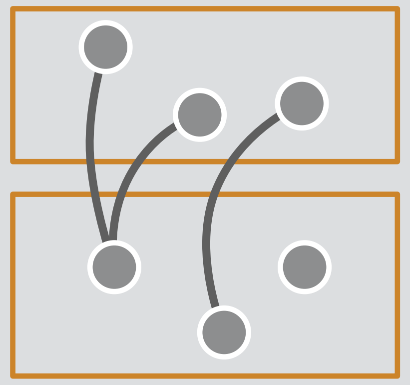

Coca-Cola classic
Sue
Jon
BEER
Mark
Tom
PORTO
TAWNY PORT
20 years old
Abby
Cole

Semantic Substrates *Shneiderman and Aris, 2006*

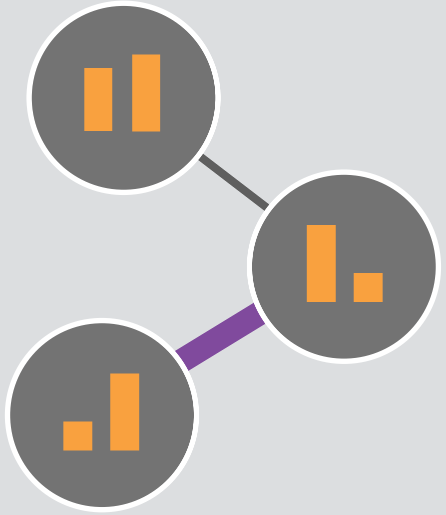




Querying and Filtering

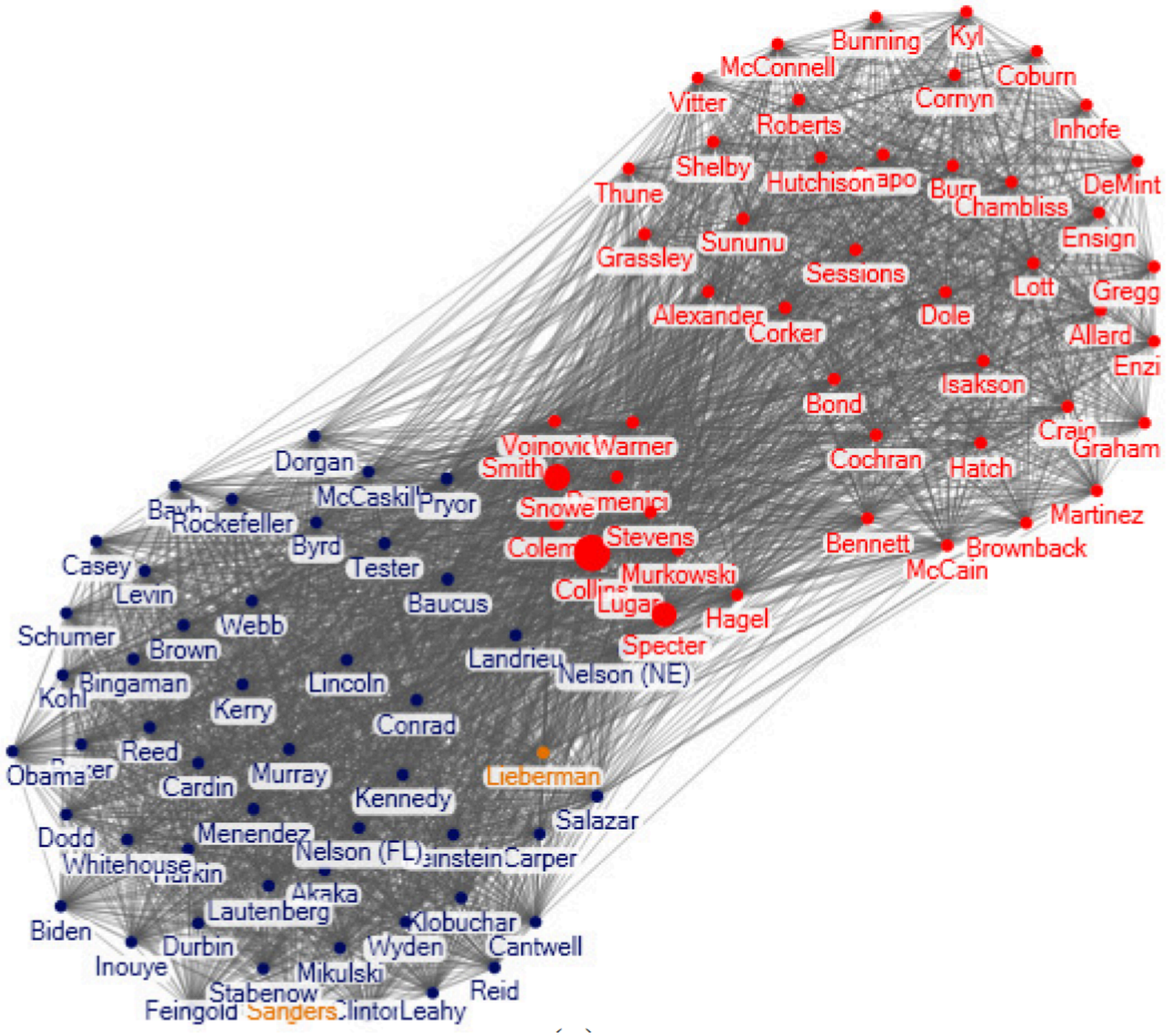


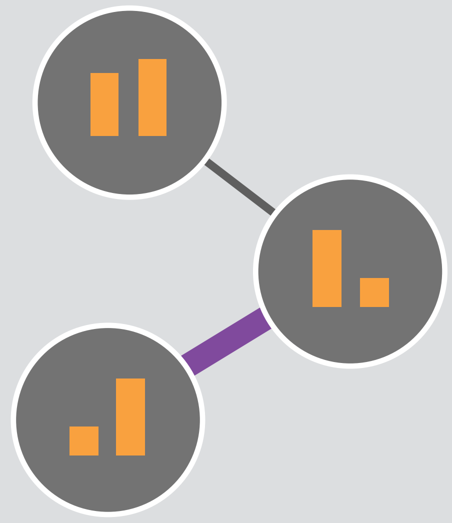
Attribute-Driven Faceting



On-Node / On-Edge Encoding

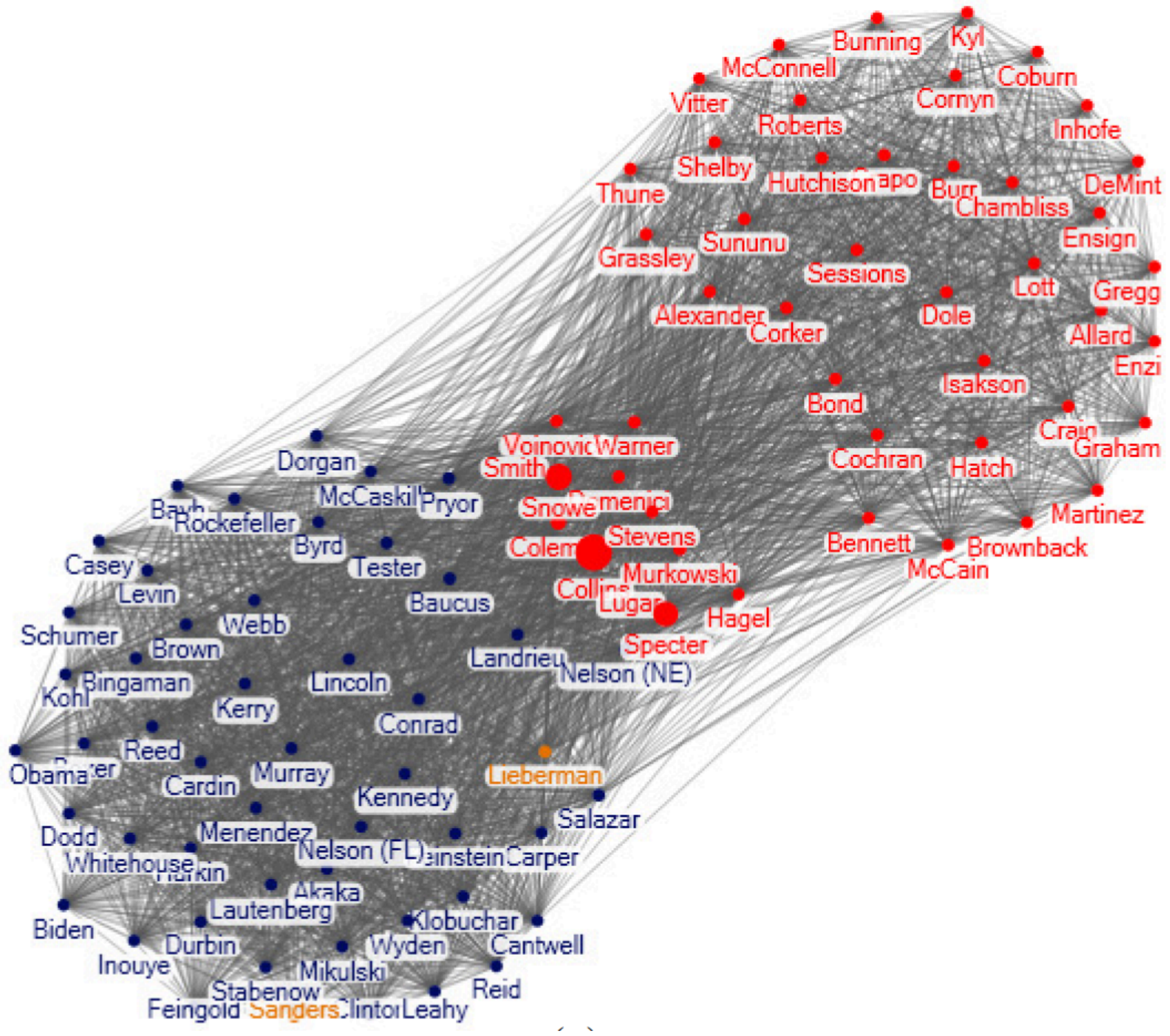
Group-in-a-box *Rodrigues et al. 2011*

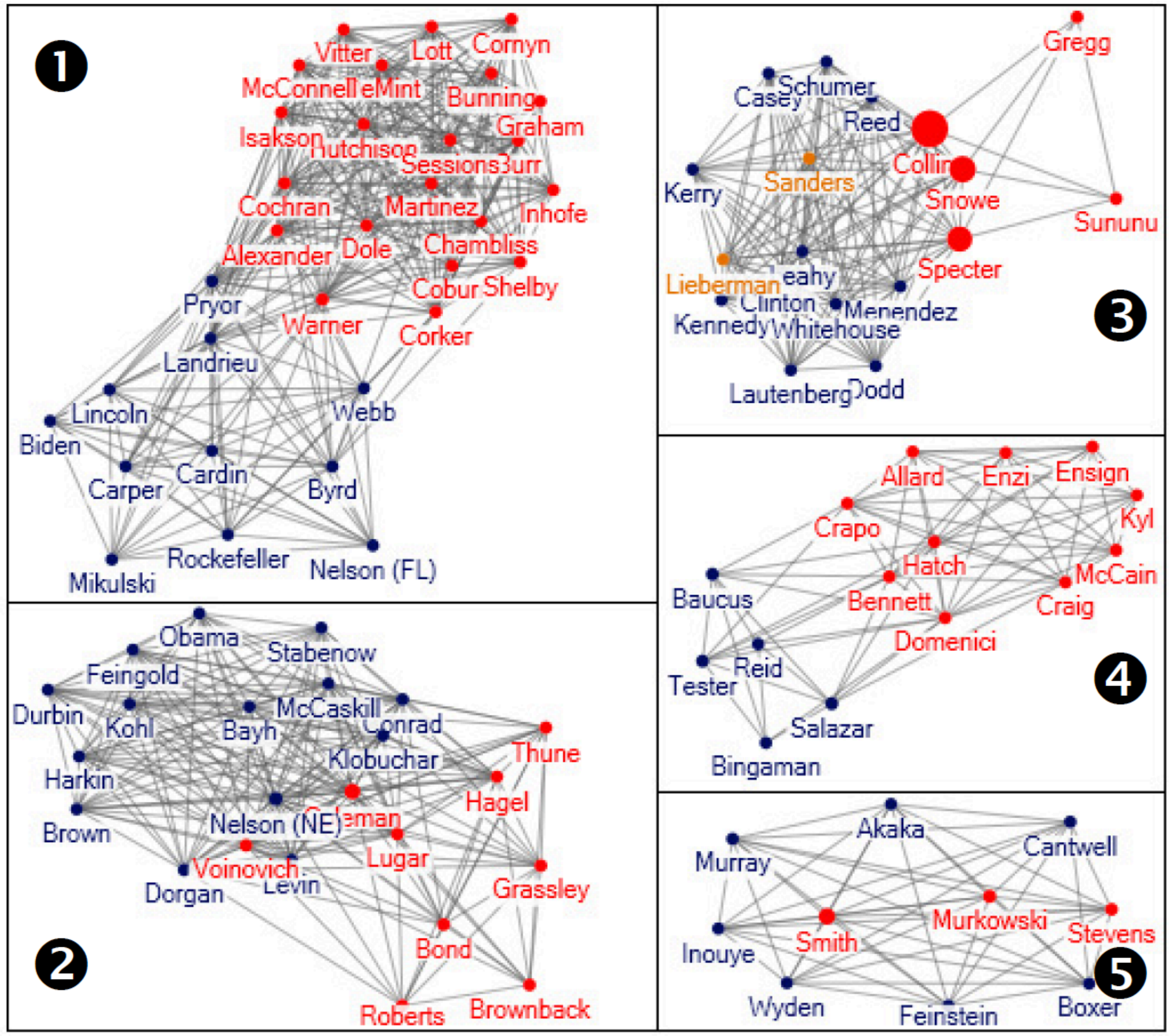


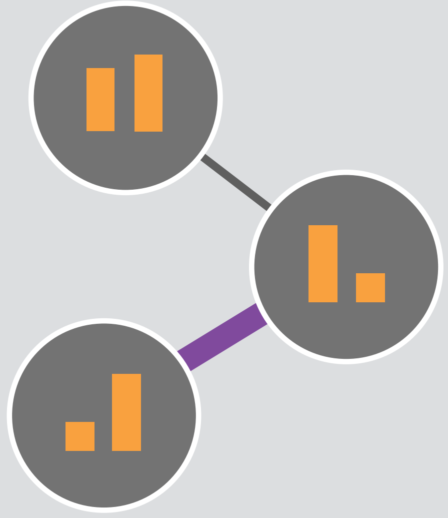


On-Node / On-Edge Encoding

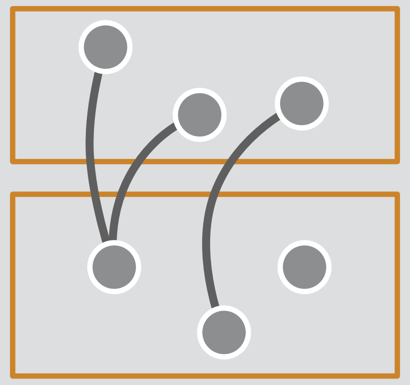
Group-in-a-box *Rodrigues et al. 2011*





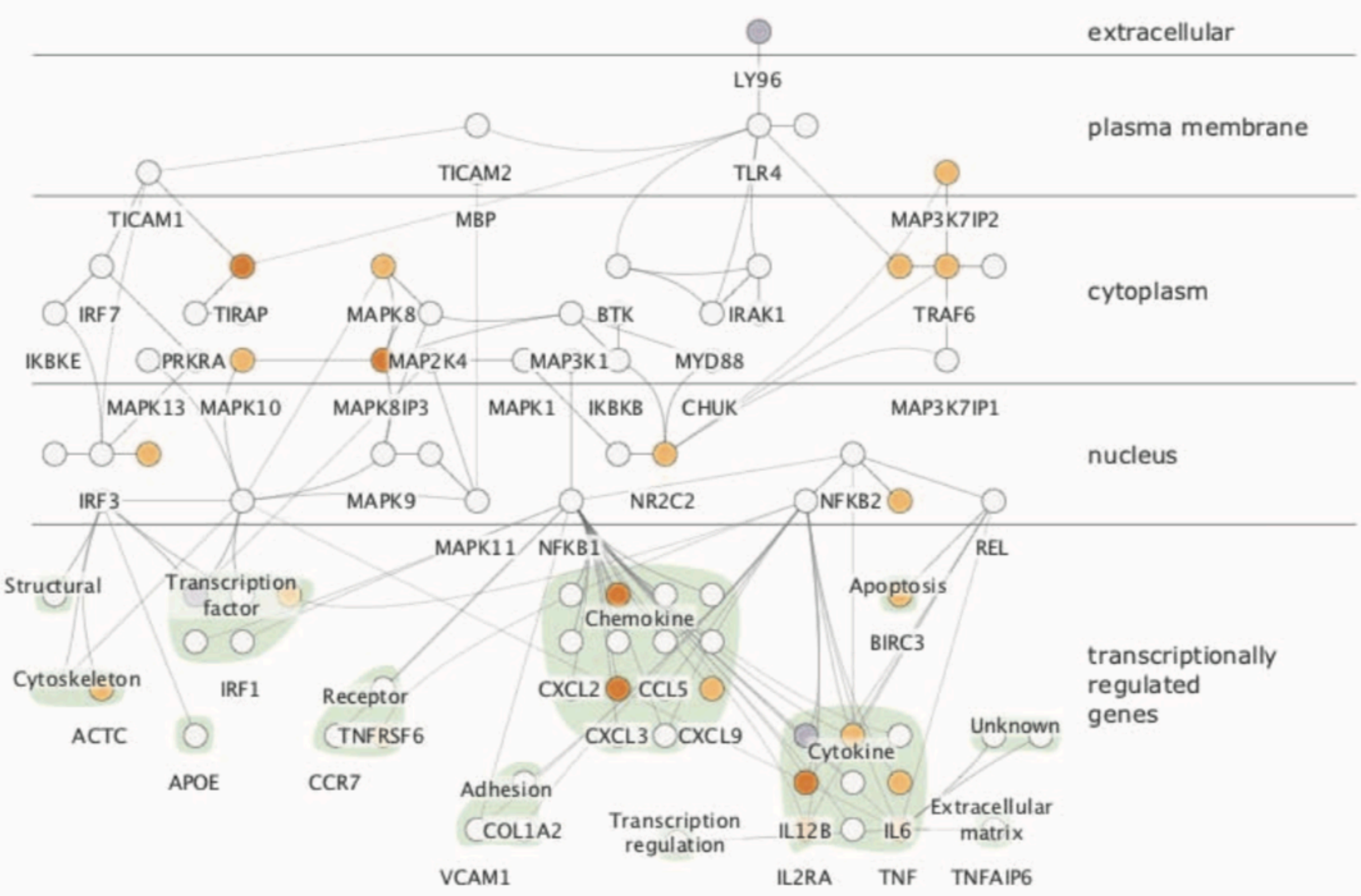


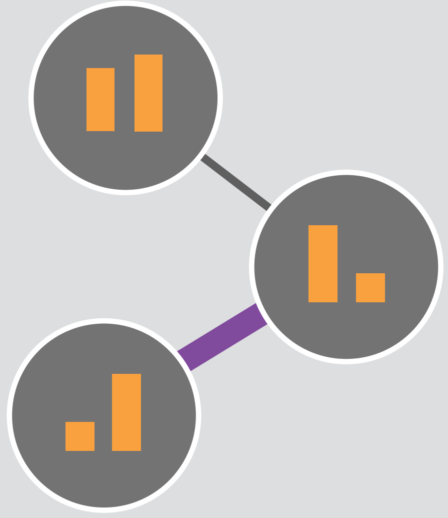
On-Node / On-Edge Encoding



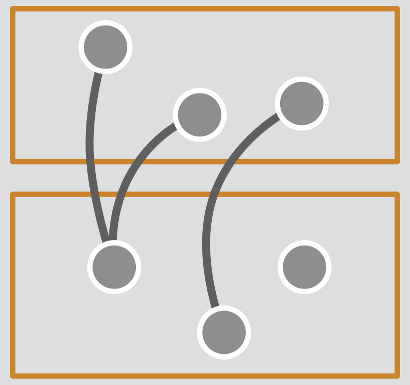
Attribute-Driven Faceting

Cerebral *Barskey et al. 2008*

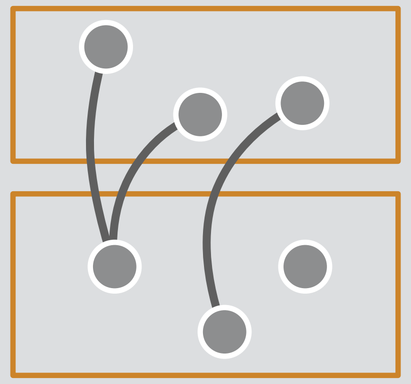




On-Node / On-Edge Encoding



Attribute-Driven Faceting



Attribute-Driven
Faceting

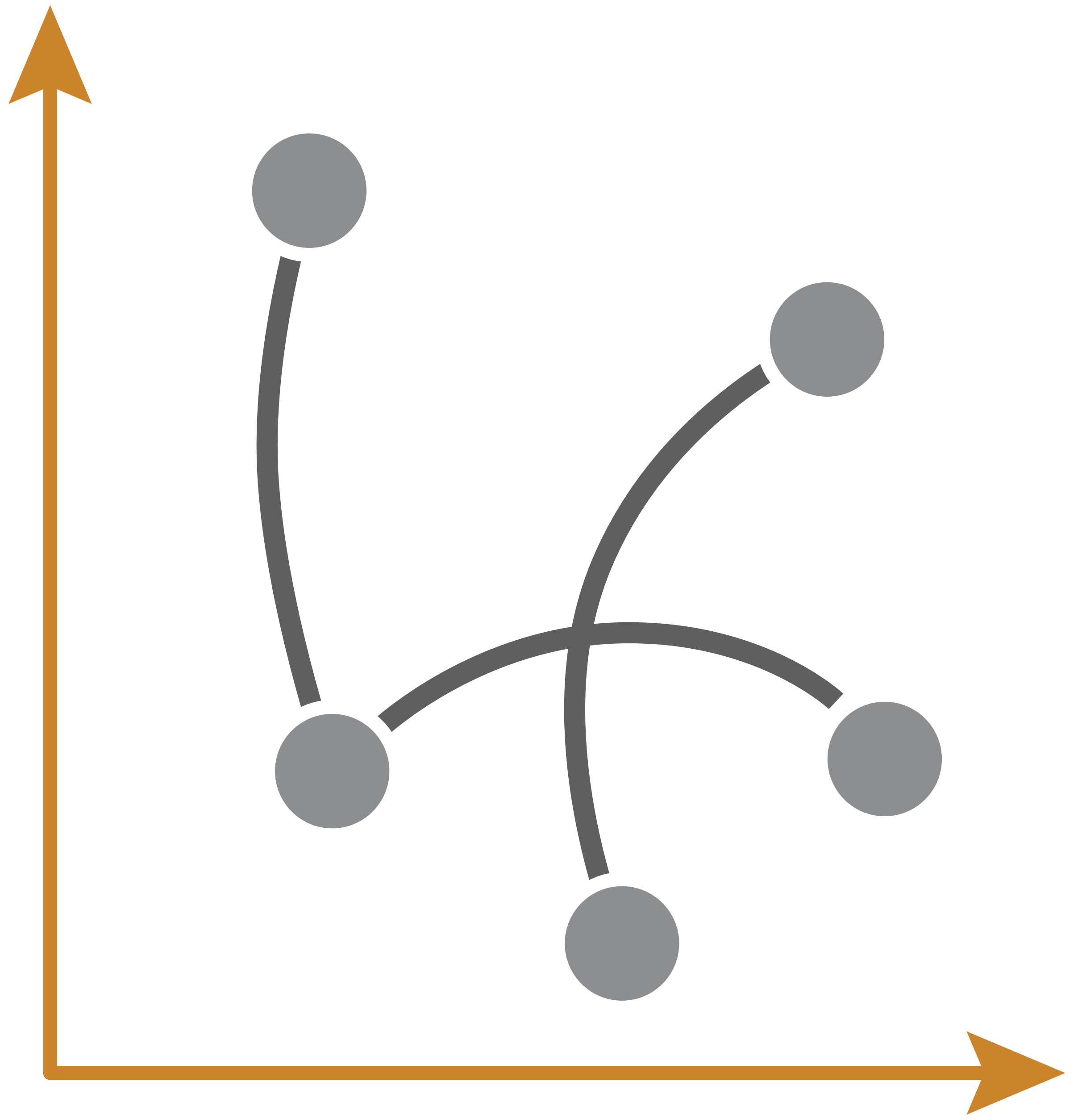
Well suited for networks with different node types or with an important categorical or set-like attribute.

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.

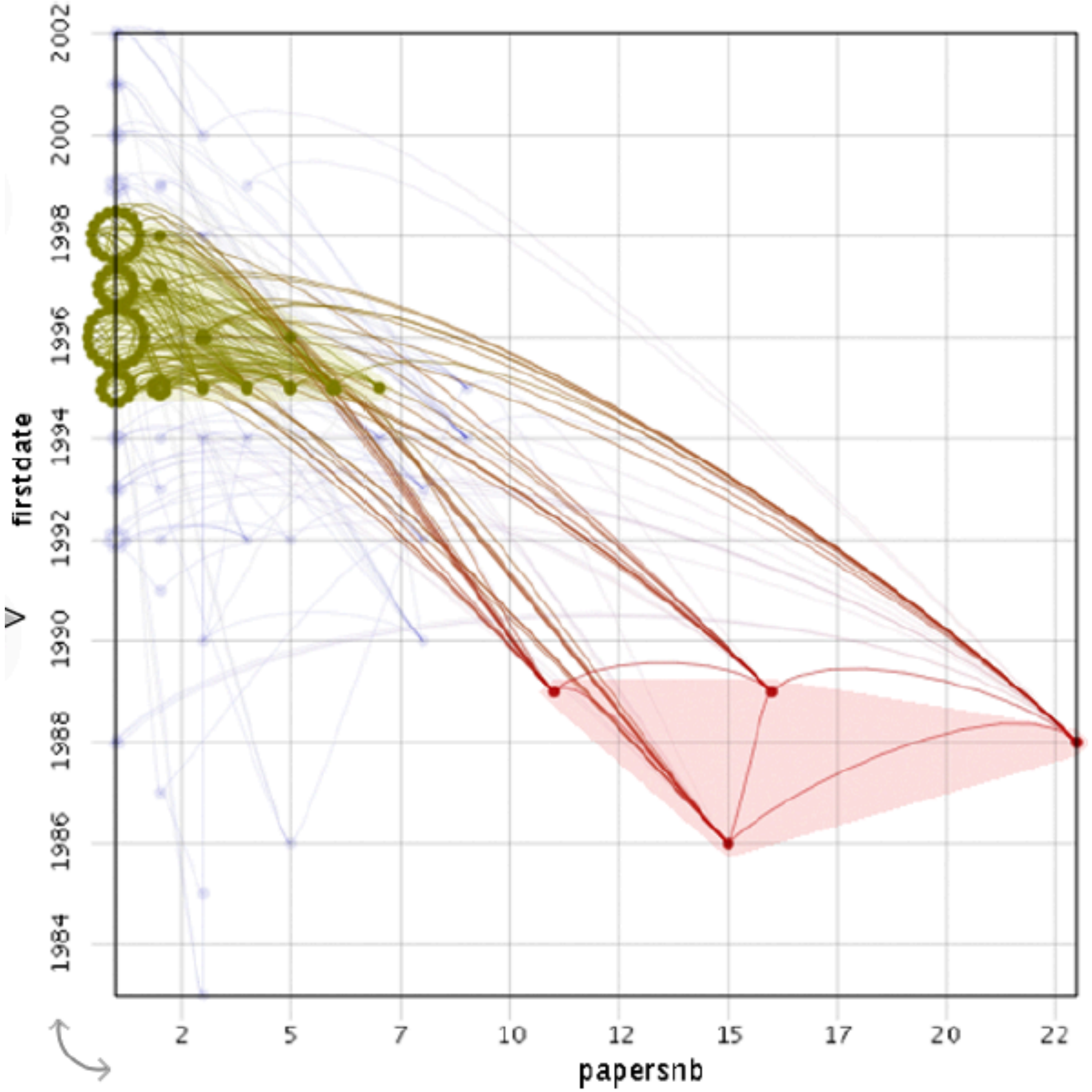
Recommended for networks where nodes can be separated into groups easily and where these groups are central to the analysis

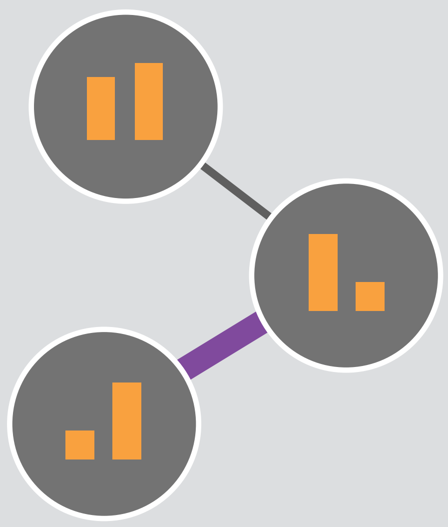
Attribute-Driven Positioning



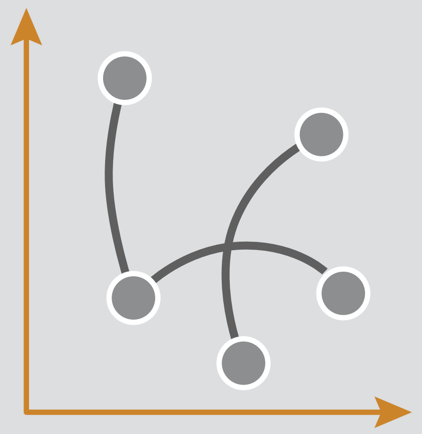

ANCHORAGE
VANCOUVER
EDMONTON
SEATTLE
PORTLAND
SAN FRANCISCO
DENVER
MINNEAPOLIS / ST. PAUL
CHICAGO
KANSAS CITY
DALLAS
TORONTO
CLEVELAND
MONTREAL
BALTIMORE
WASHINGTON D.C.
PHILADELPHIA
NEW YORK
JFK & NEWARK
BOSTON
HALIFAX
TAMPA BAY
ORLANDO
ICELAND
HELSINKI
STOCKHOLM
OSLO
GOTHENBURG
BERGEN
COPENHAGEN
BILLUND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

Graph Dice *Bezerianos et al. 2010*



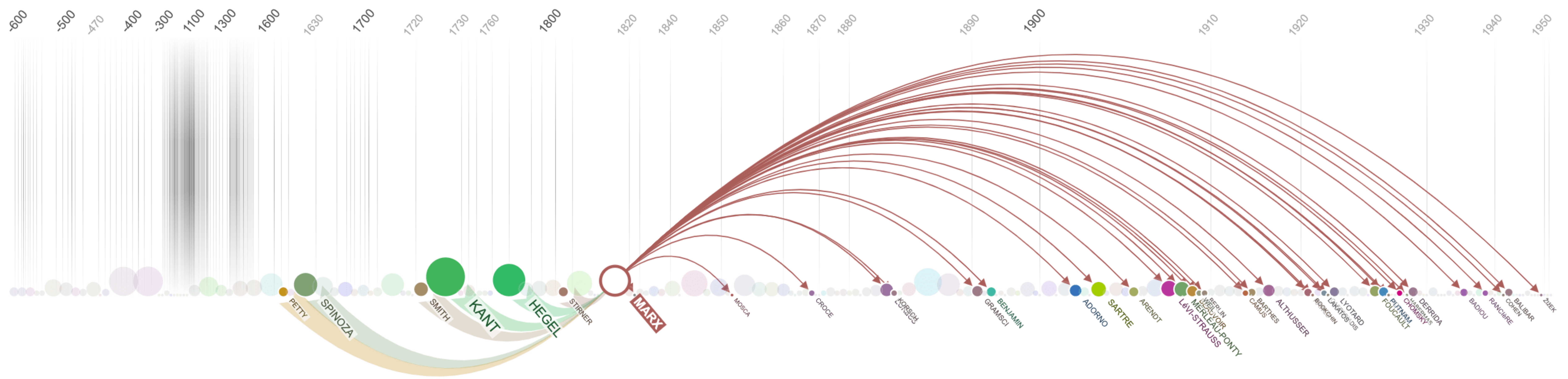


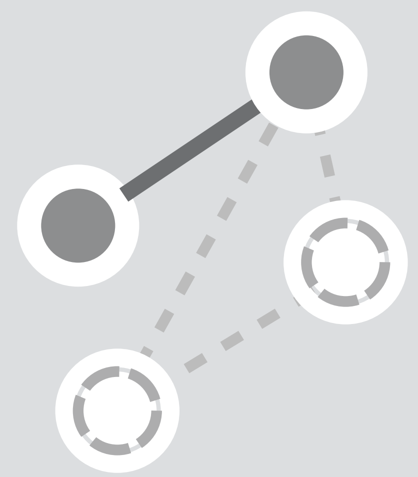
On-Node / On-Edge Encoding



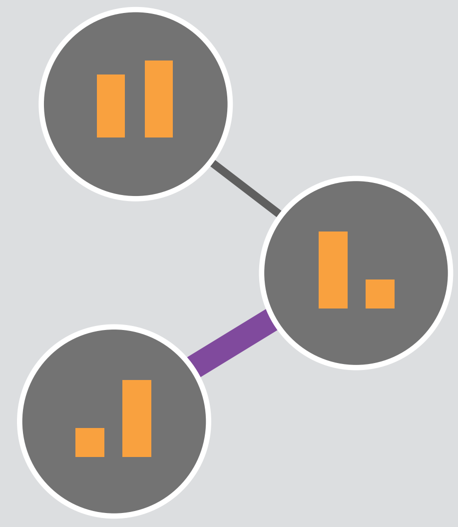
Attribute-Driven Positioning

Edge Map *Dork et al. 2011*

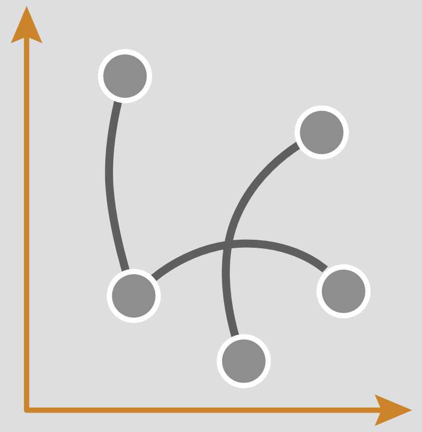




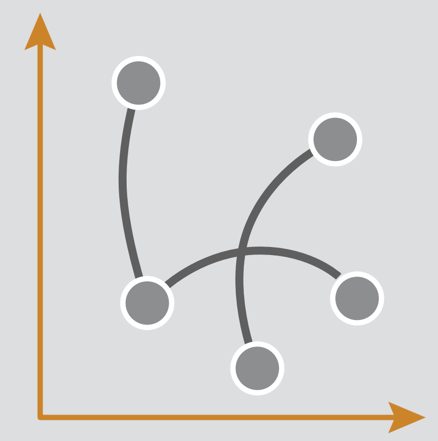
Querying and Filtering



On-Node / On-Edge Encoding



Attribute-Driven Positioning



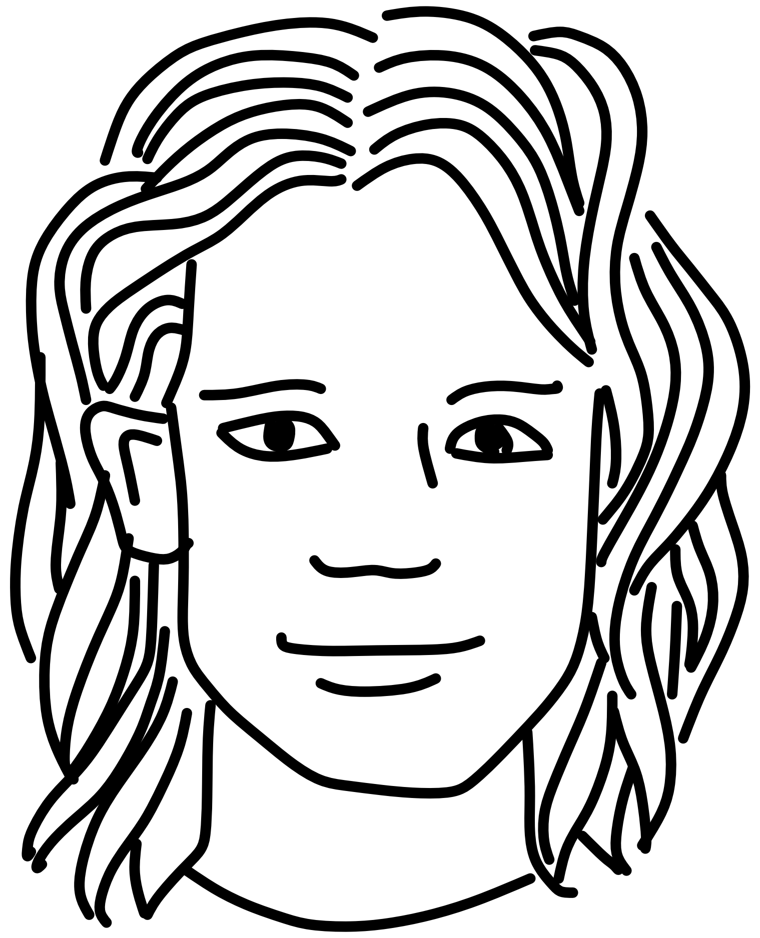
Attribute-Driven Positioning

Well suited for quantitative attributes

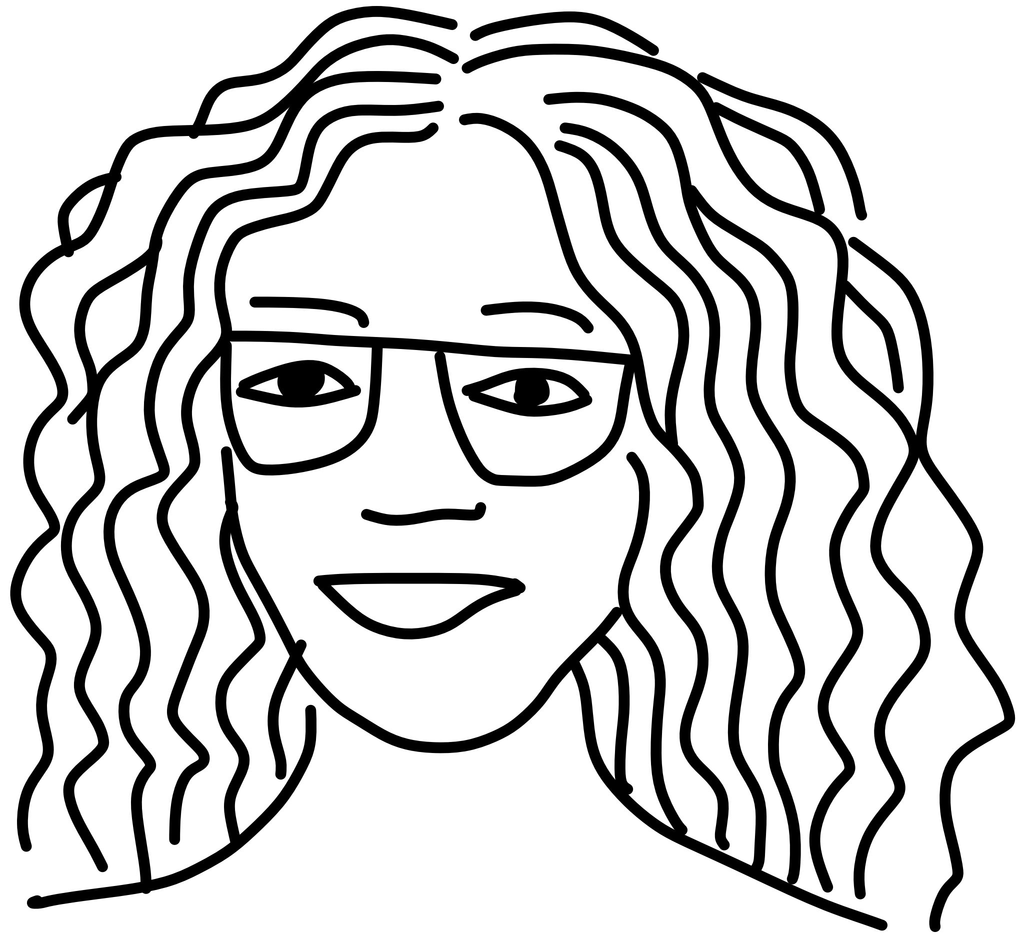
Does not lend itself well to visualizing the topology of the network.

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

Tools and Applications



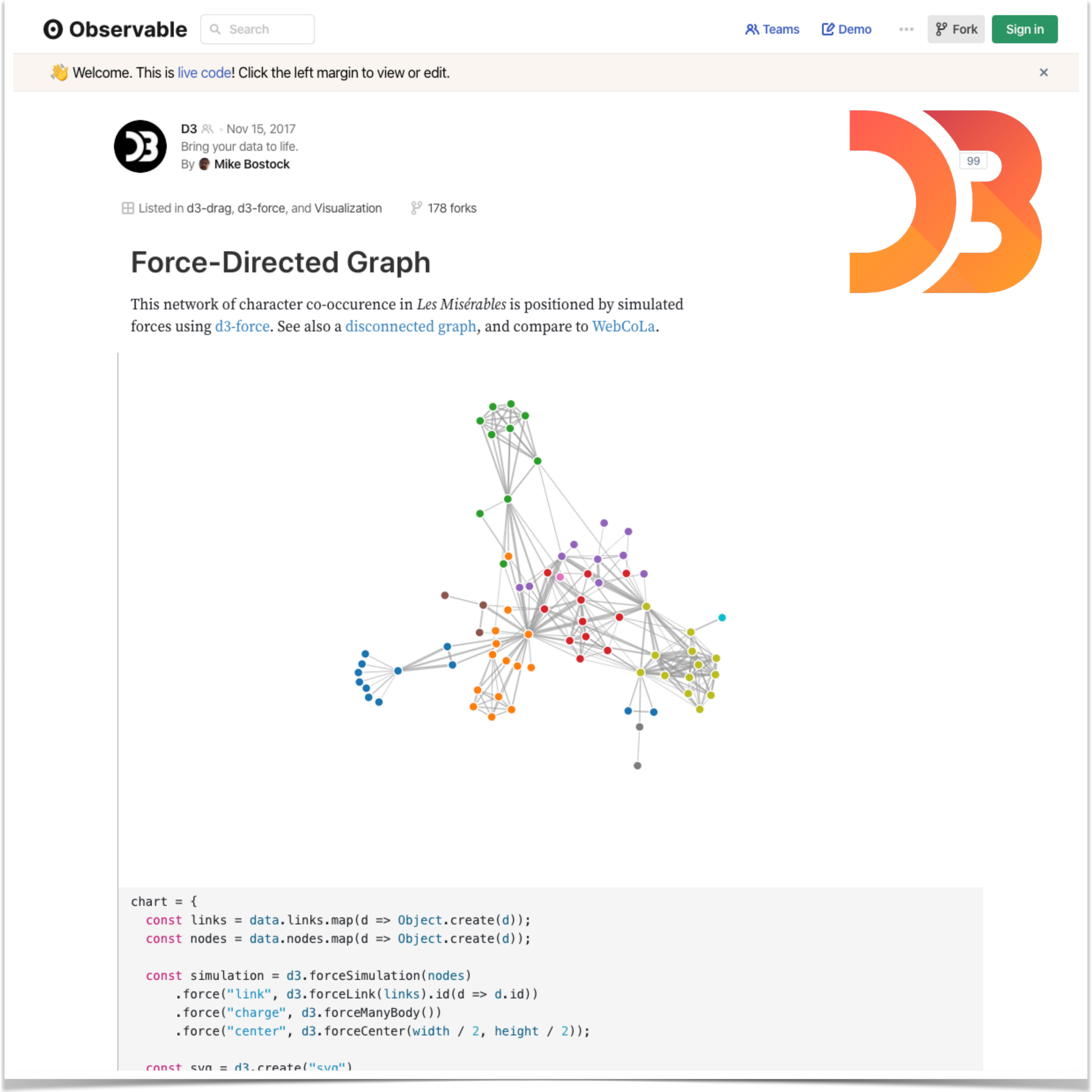
Brad
graphic designer

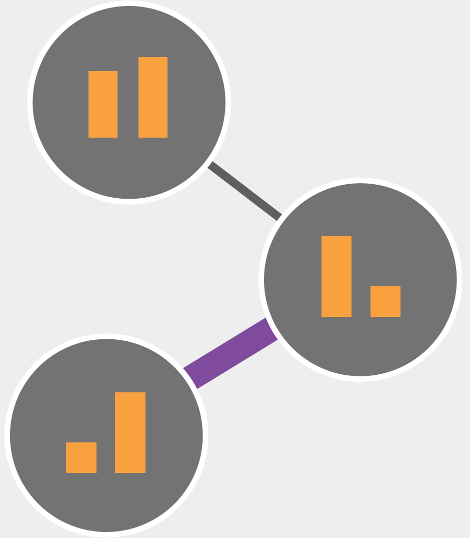


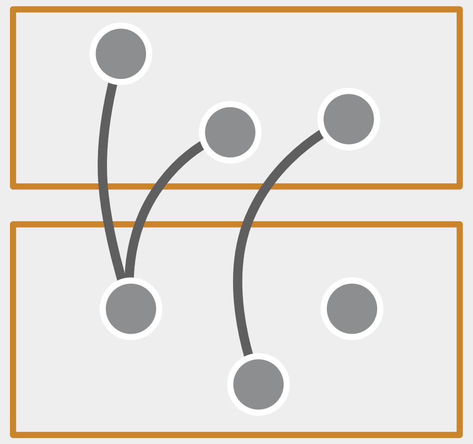
Maya
developer

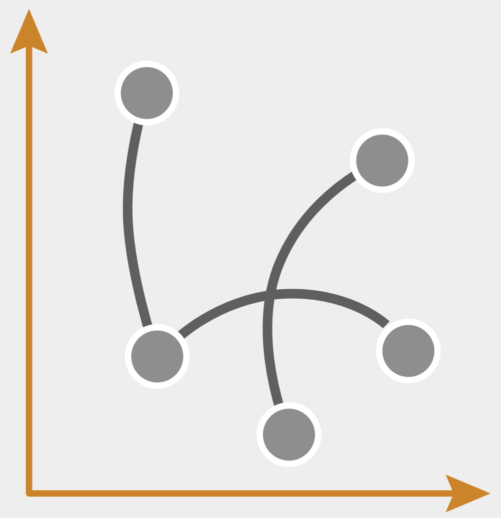
developer

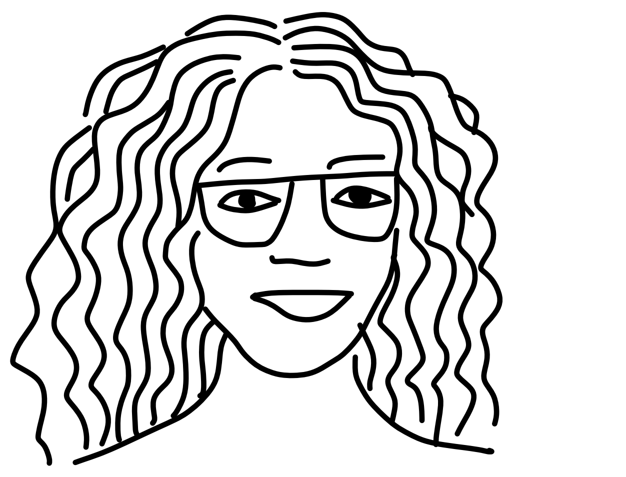
JS











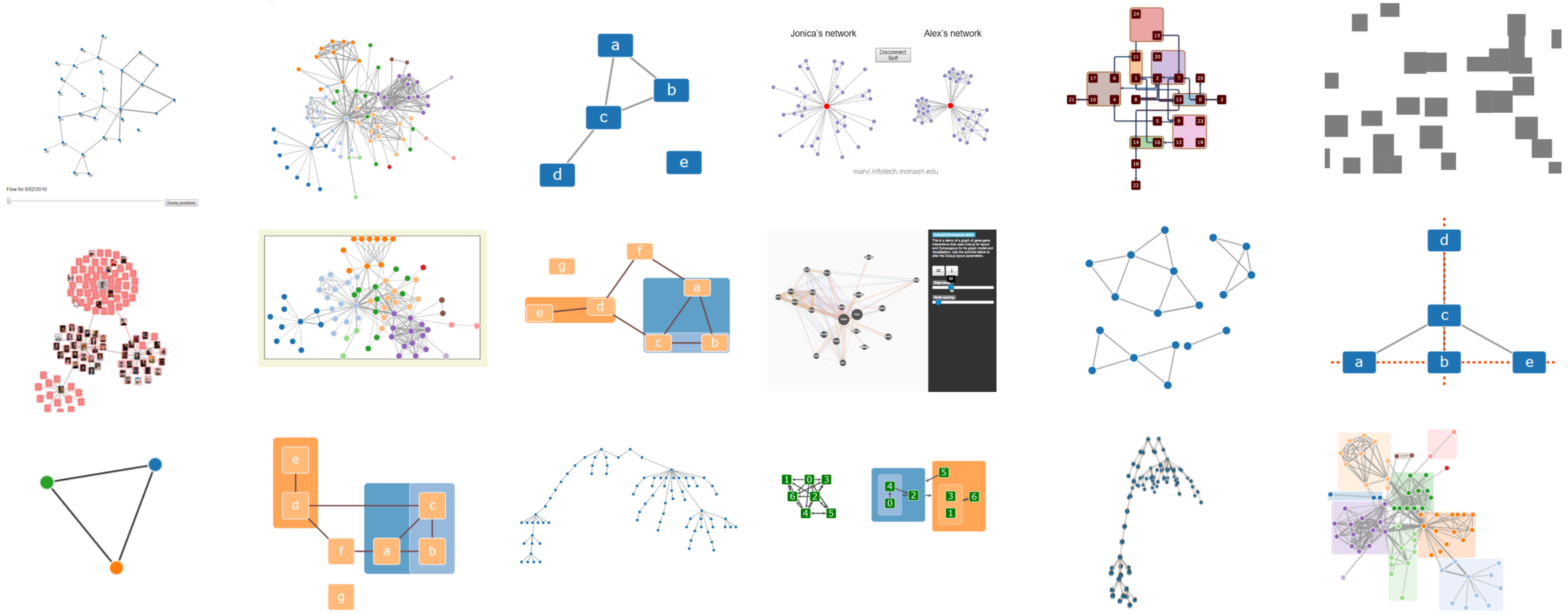
developer

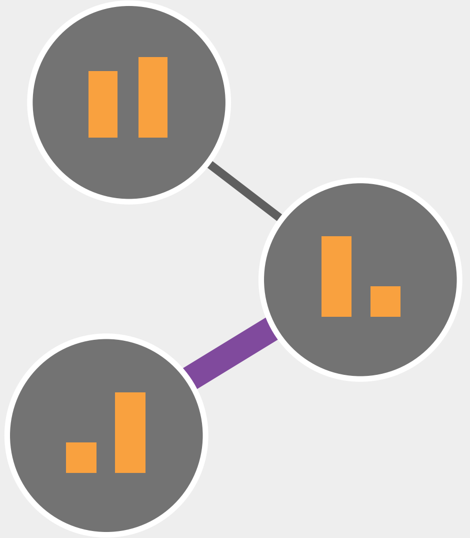
Cola.js (A.K.A. "WebCoLa") is an open-source JavaScript library for arranging your HTML5 documents and diagrams using constraint-based optimization techniques.

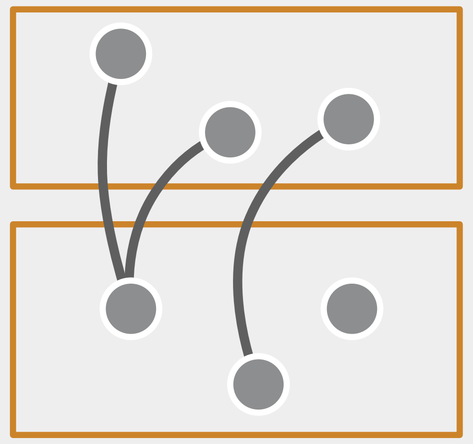
Overview Wiki API Source

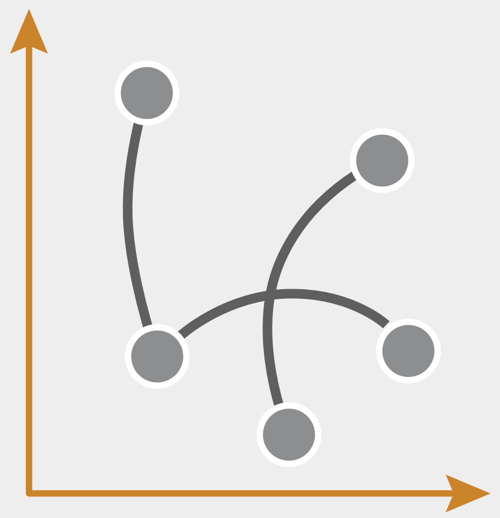
cola.js

Constraint-Based Layout in the Browser









developer

Cytoscape.js

Graph theory (network) library for visualisation and analysis

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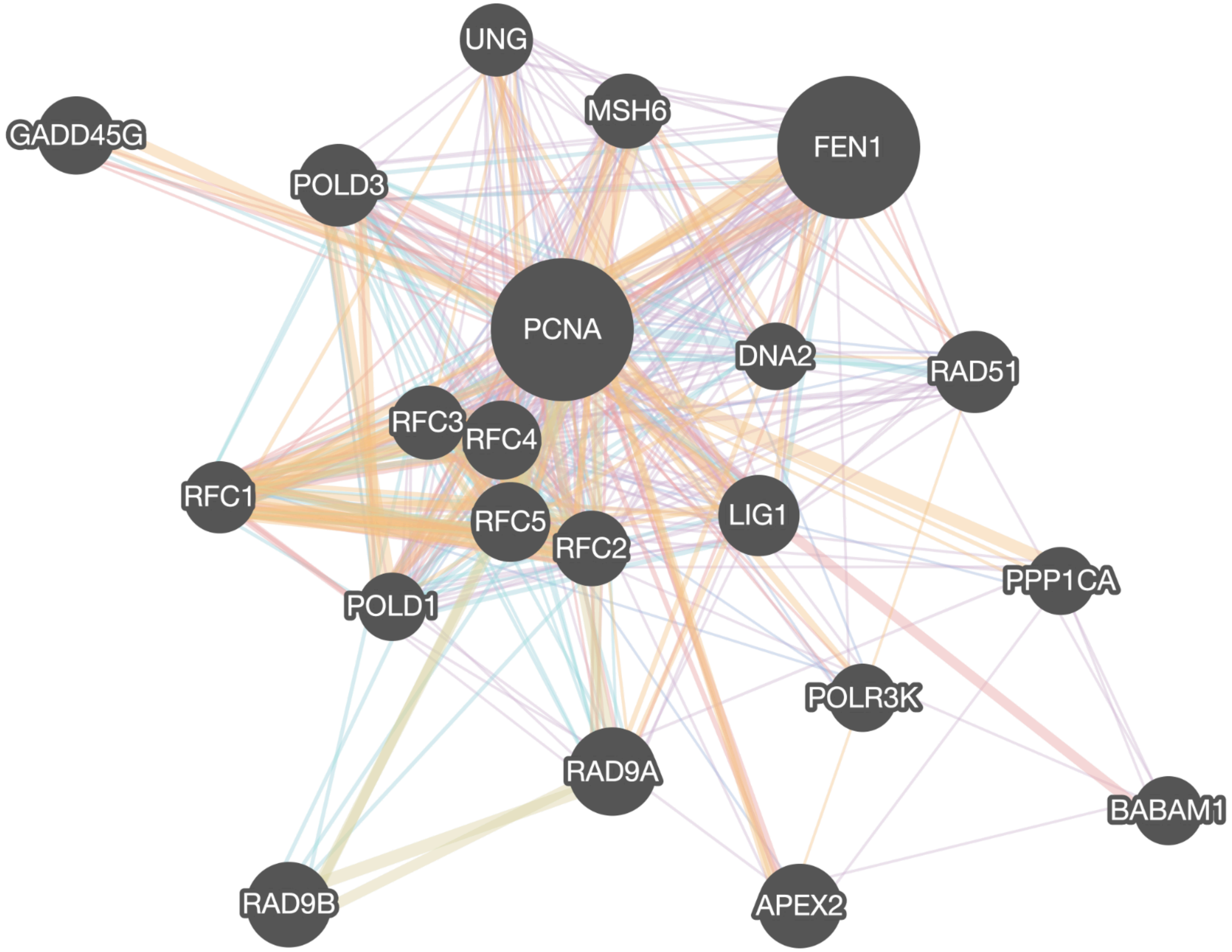
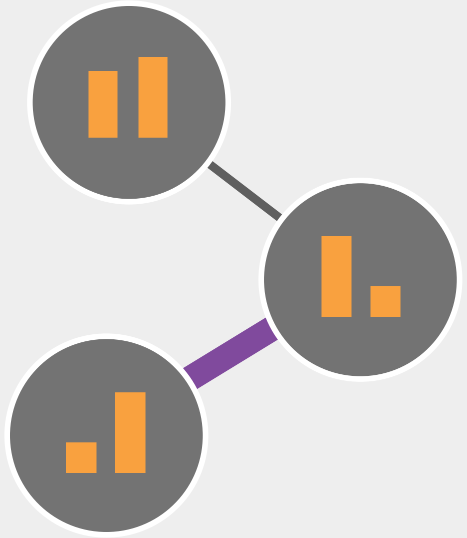
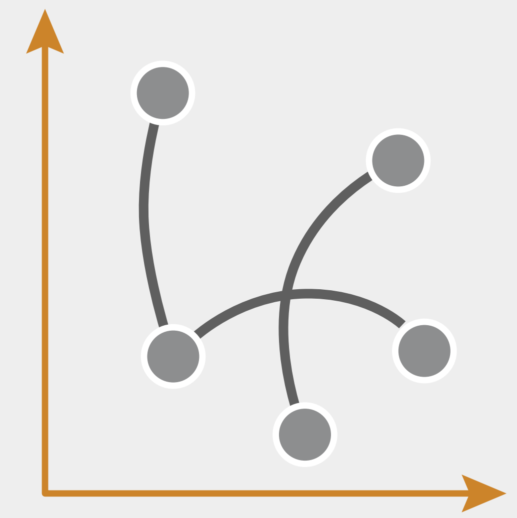
npm installs 100k/month | master branch passing | unstable branch passing | Greenkeeper enabled







developer

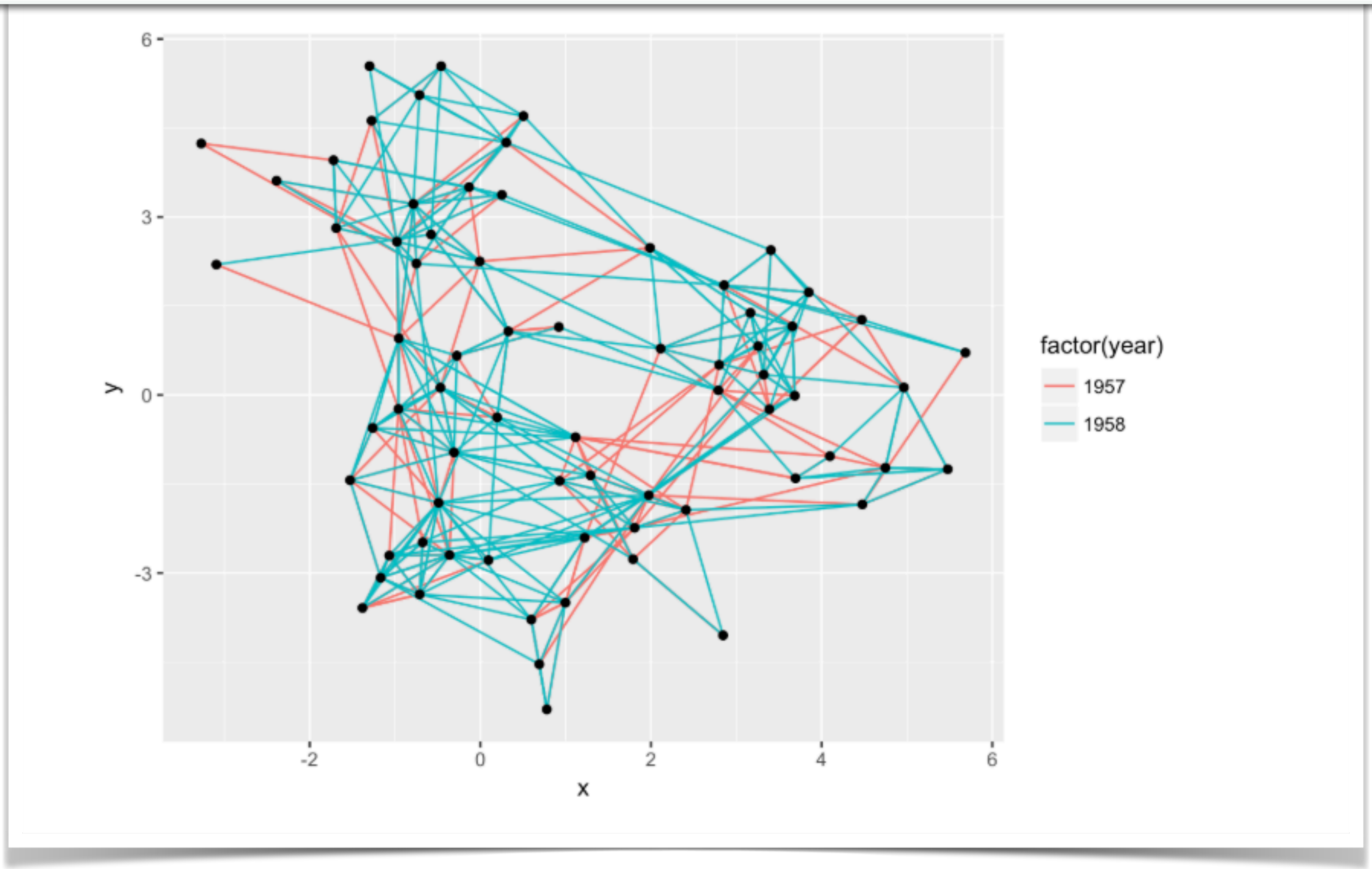
GGRAPH 1.0.2.9999 | Reference | Getting Started | Articles | News

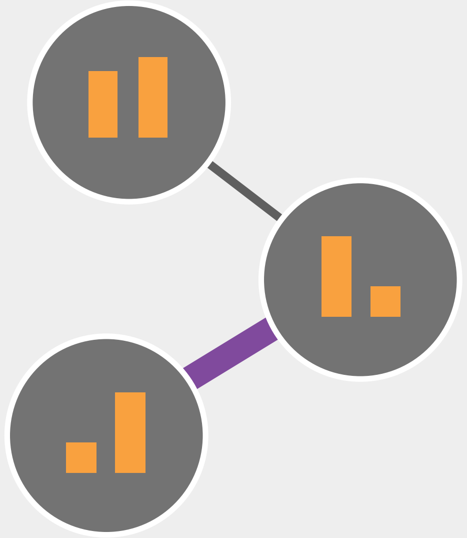
ggraph

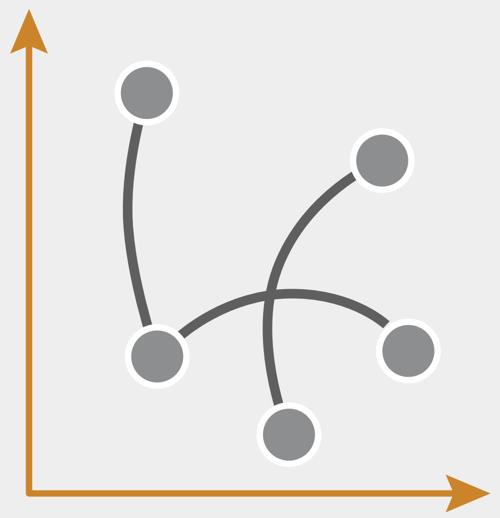
/dʒiː.dʒɪˈrɑːf/ (or g-giraffe)

A grammar of graphics for relational data

ggraph is an extension of `ggplot2` aimed at supporting relational data structures such as networks, graphs, and trees. While it builds upon the foundation of `ggplot2` and its API it comes with its own self-contained set of geoms, facets, etc., as well as adding the concept of *layouts* to the grammar.

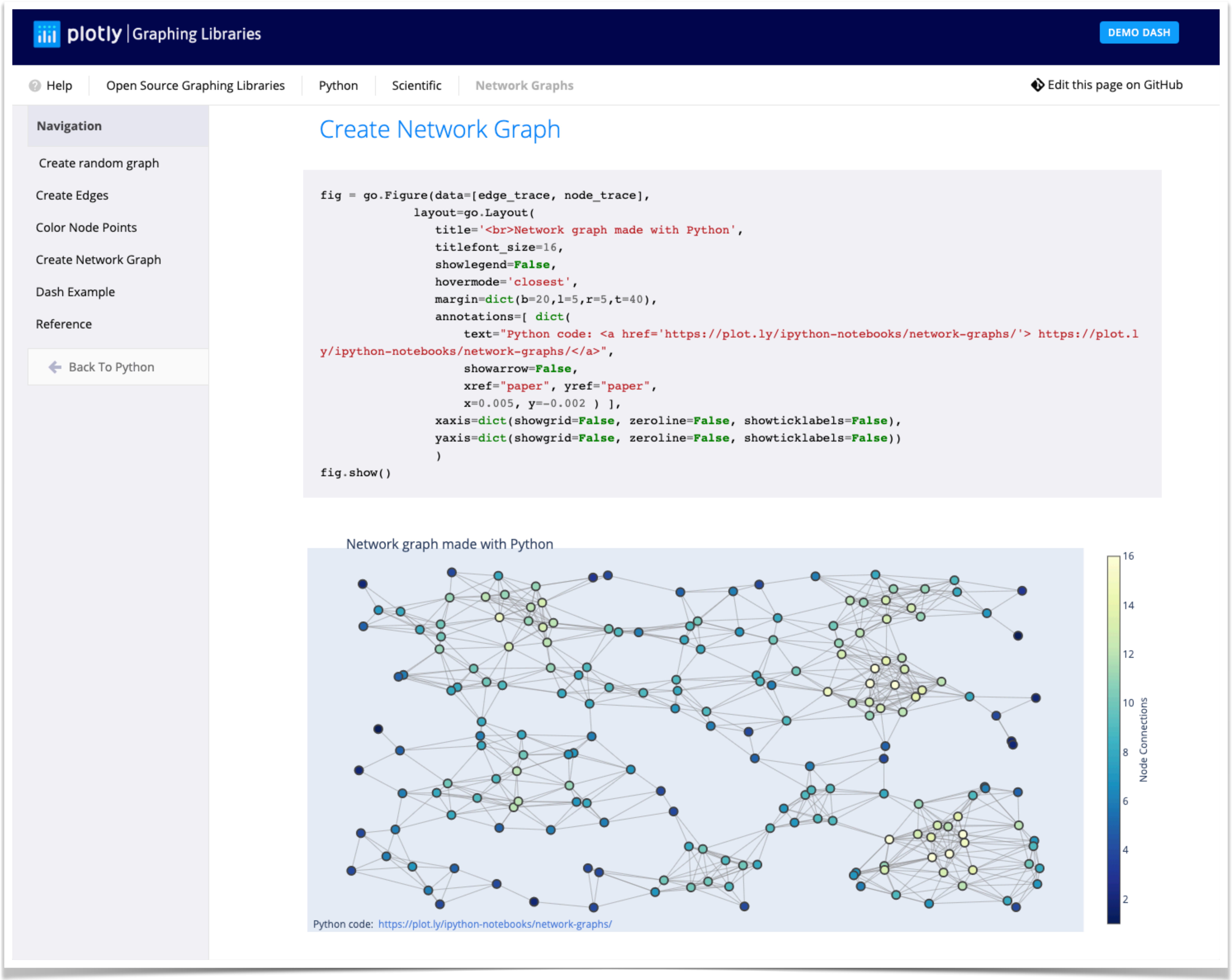


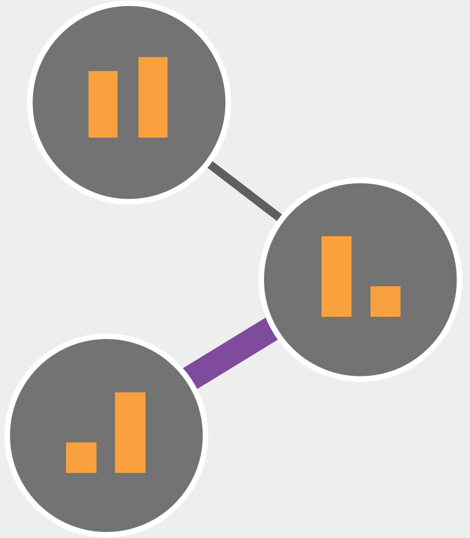


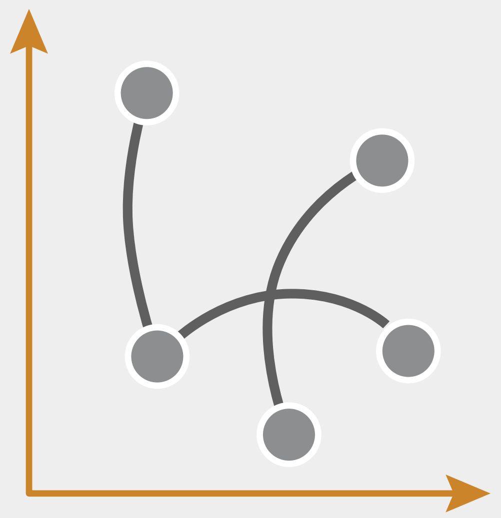


developer

python







developer

python

NetworkX

Stable (notes)

2.3 — April 2019
download | doc | pdf

Latest (notes)

2.4 development
github | doc | pdf

Archive

Contact

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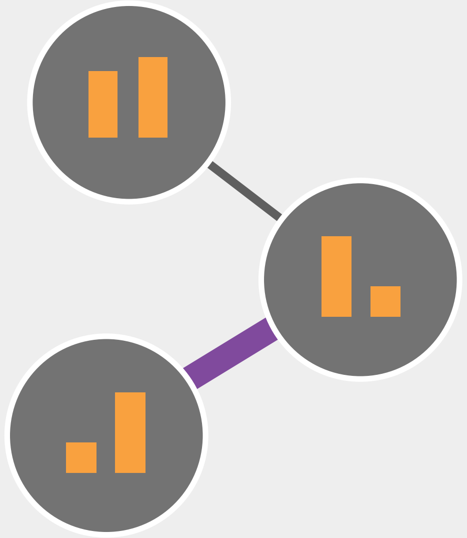
Issue tracker

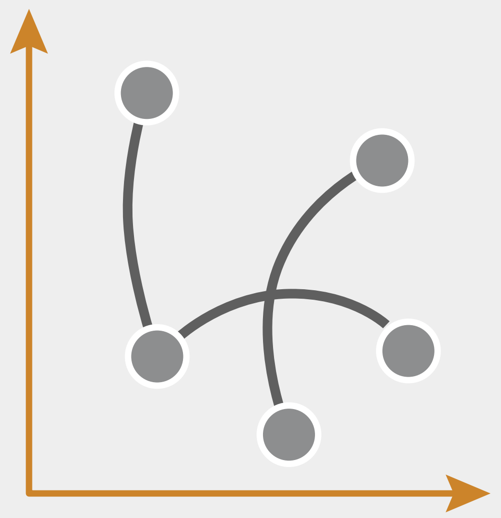
Software for complex networks

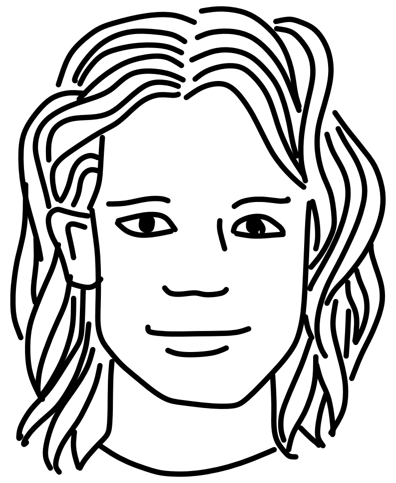
NetworkX is a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks.

Features

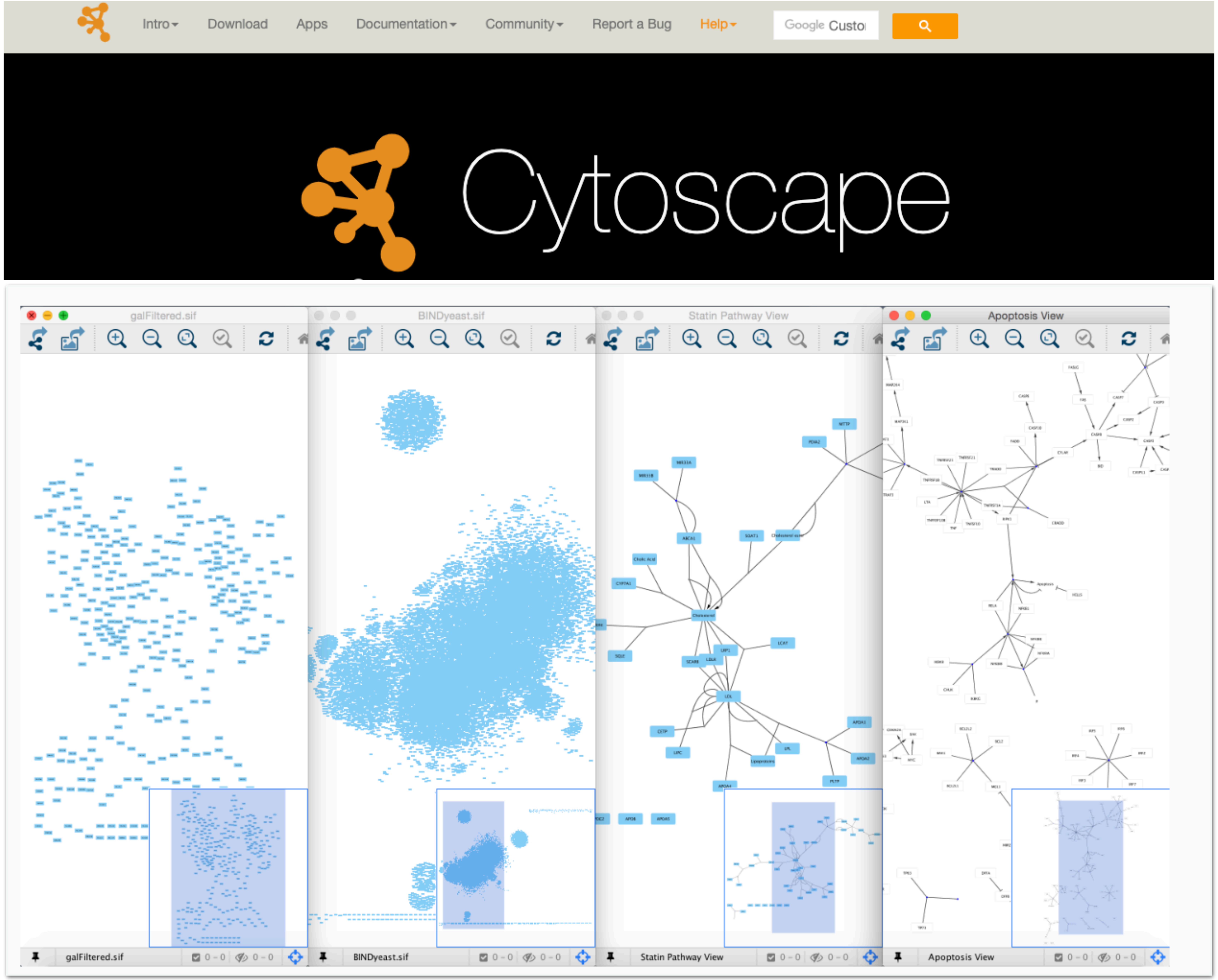
- Data structures for graphs, digraphs, and multigraphs
- Many standard graph algorithms
- Network structure and analysis measures
- Generators for classic graphs, random graphs, and synthetic networks
- Nodes can be "anything" (e.g., text, images, XML records)
- Edges can hold arbitrary data (e.g., weights, time-series)
- Open source 3-clause BSD license
- Well tested with over 90% code coverage
- Additional benefits from Python include fast prototyping, easy to teach, and multi-platform

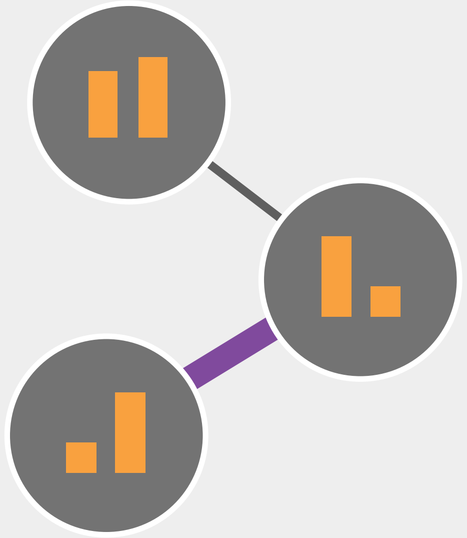


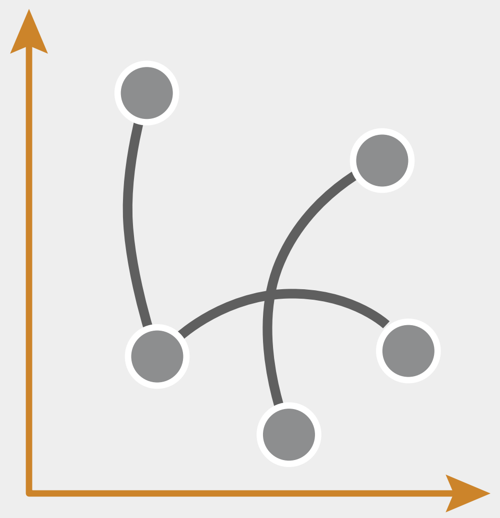


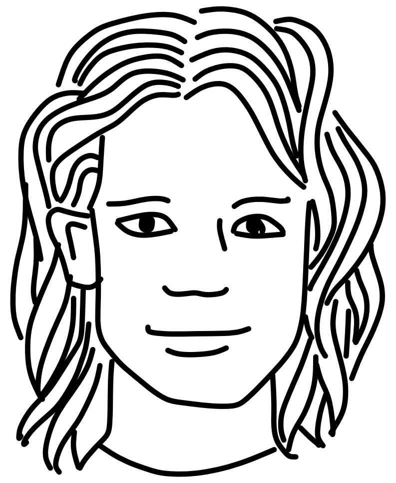


graphic
designer

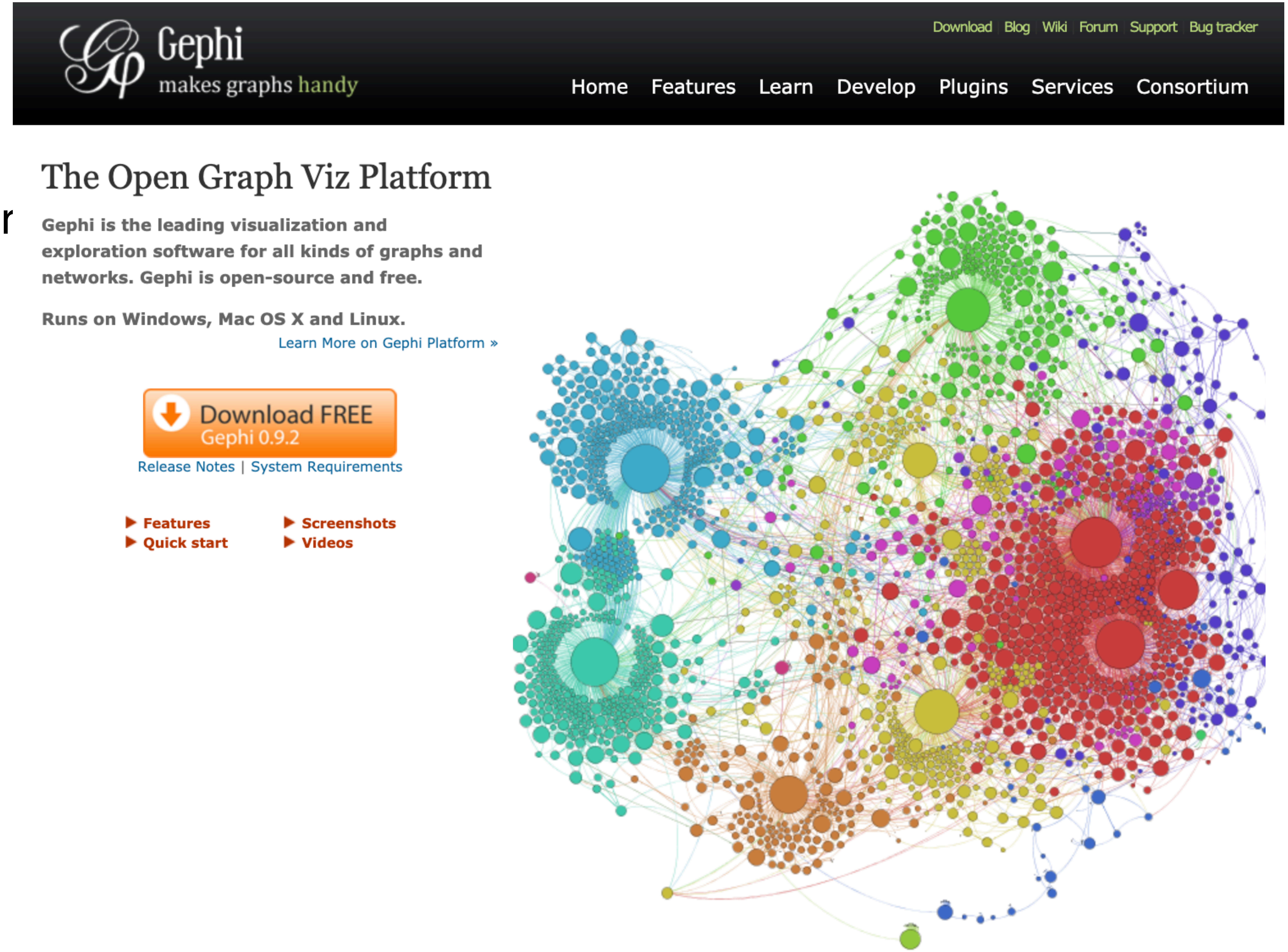


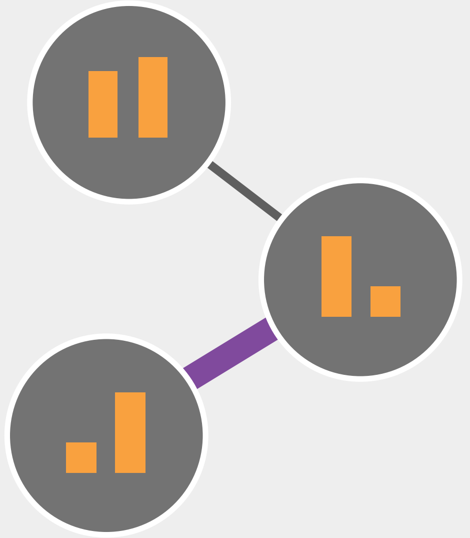


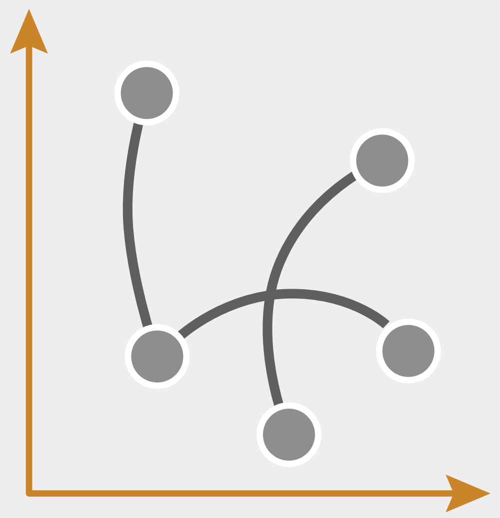


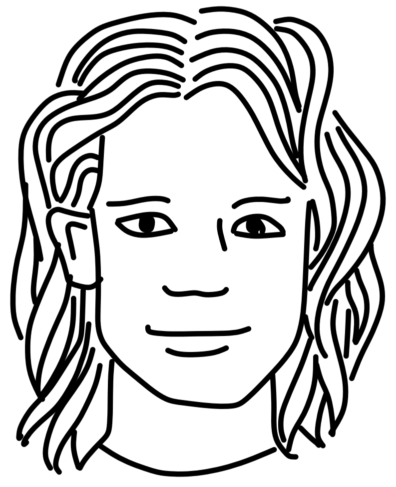


graphic designer



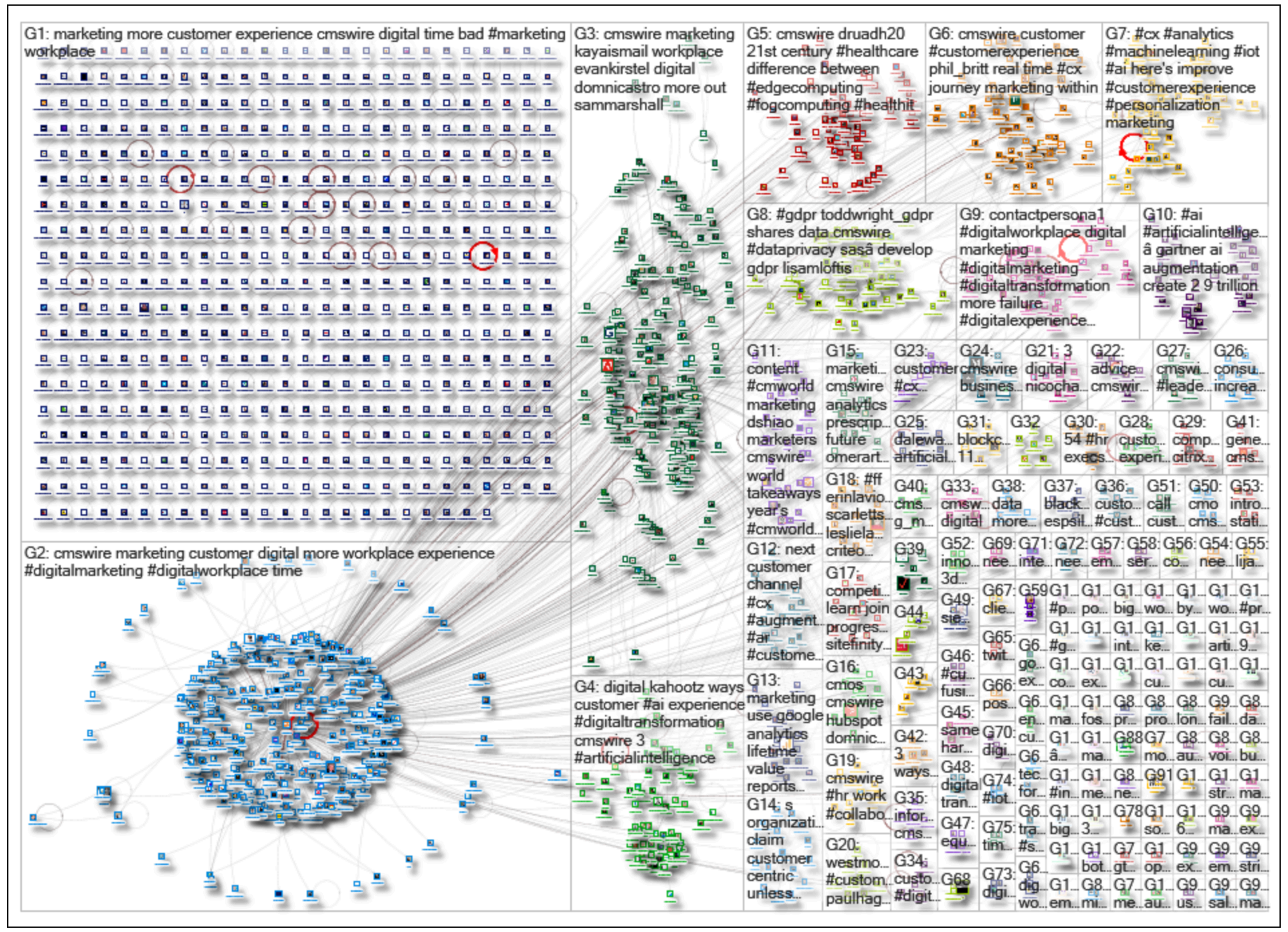


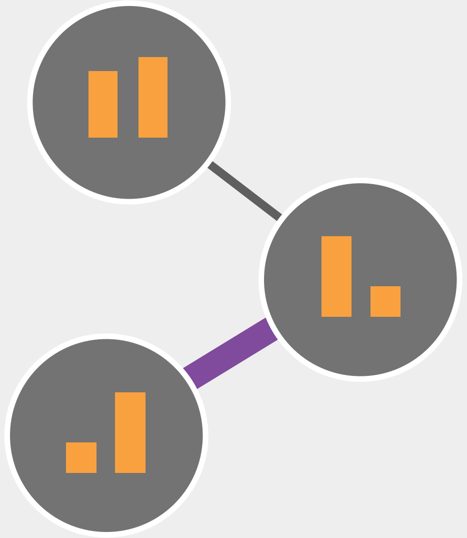


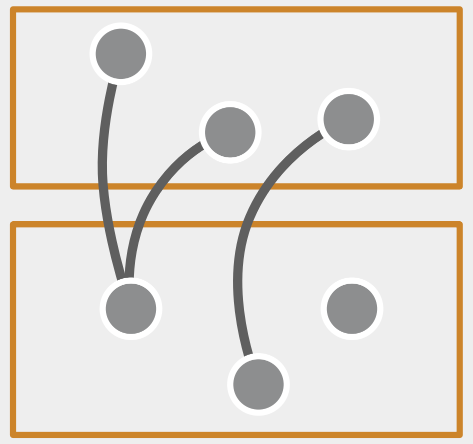


graphic designer

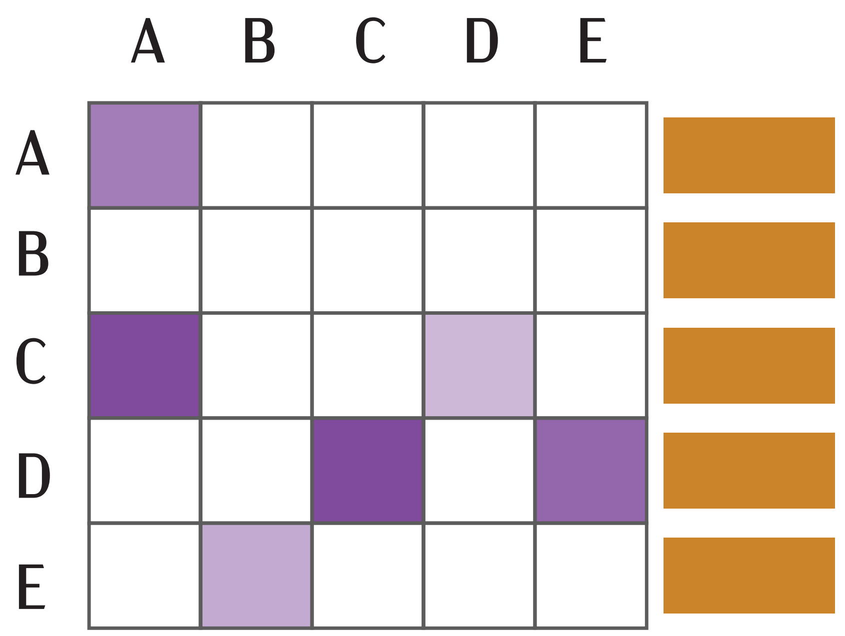
NODE



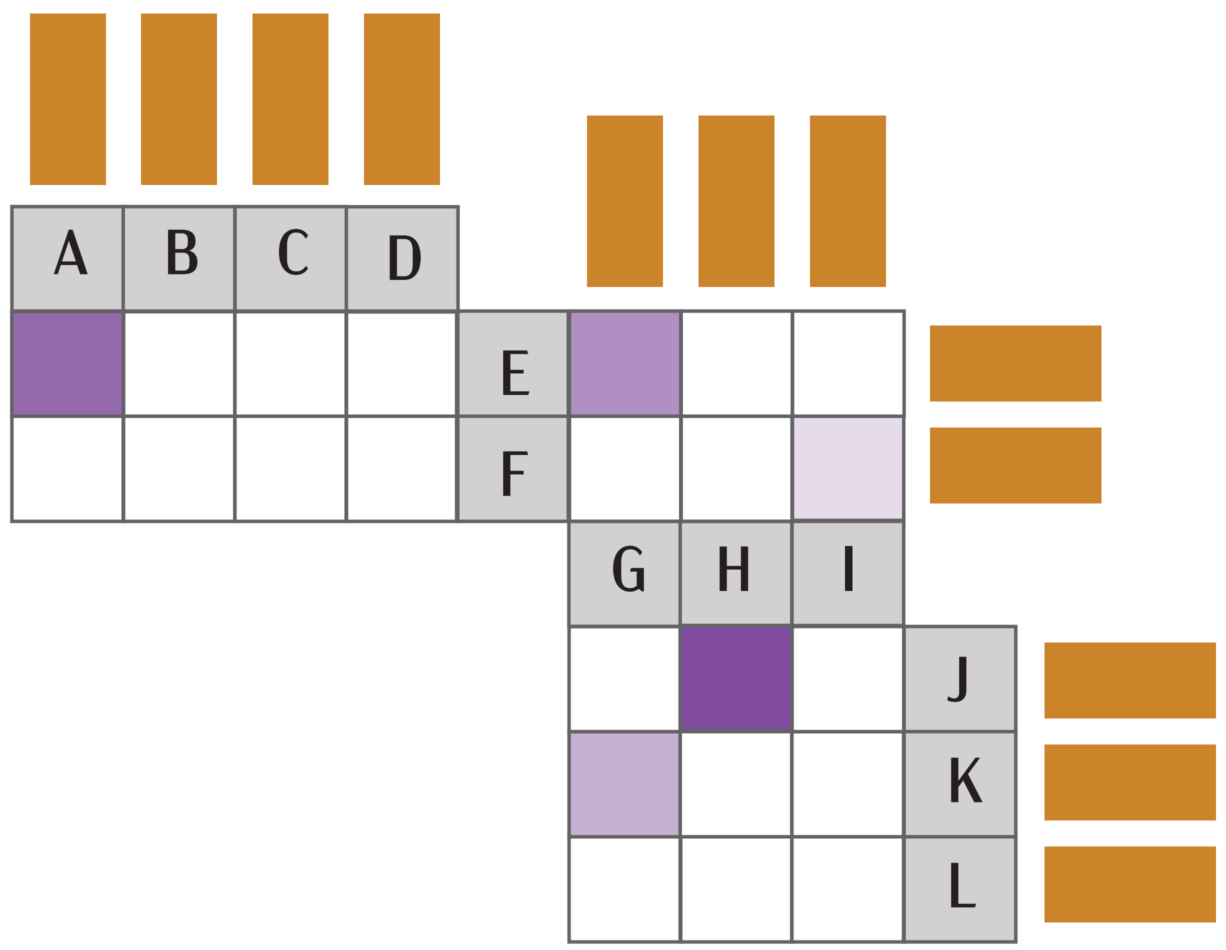




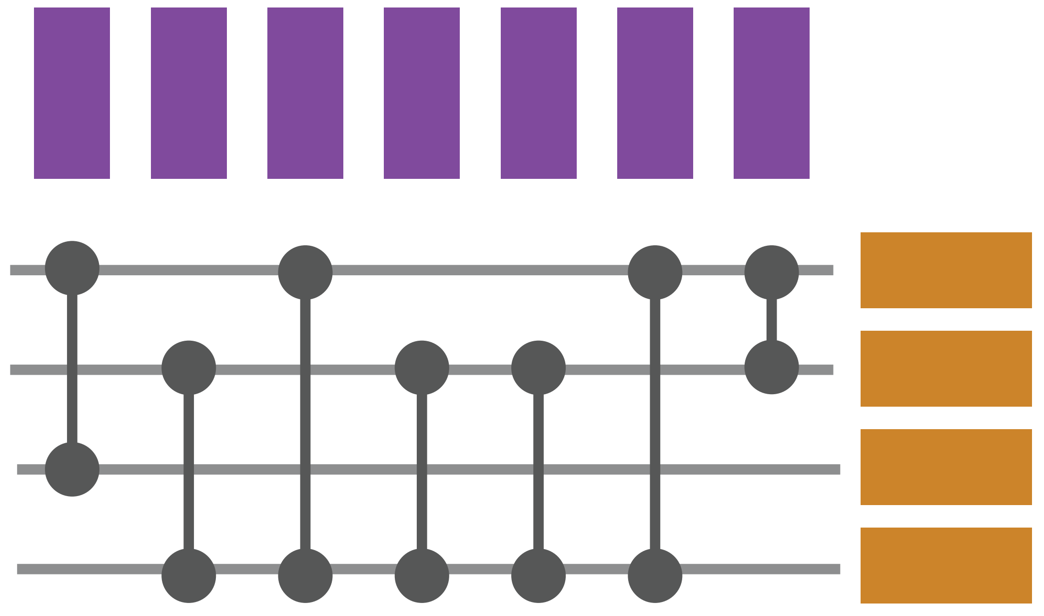
Tabular Layouts



Adjacency Matrix

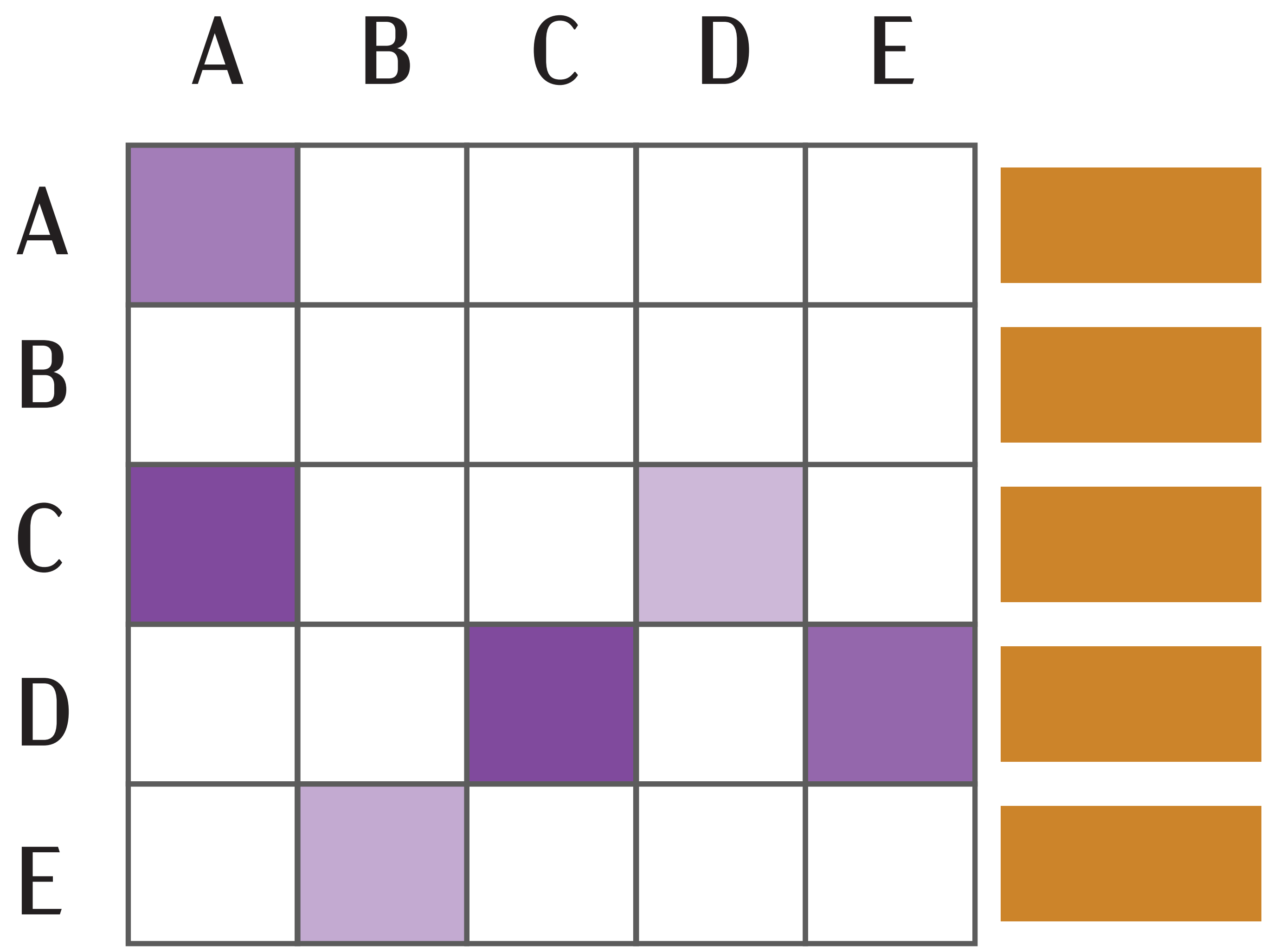


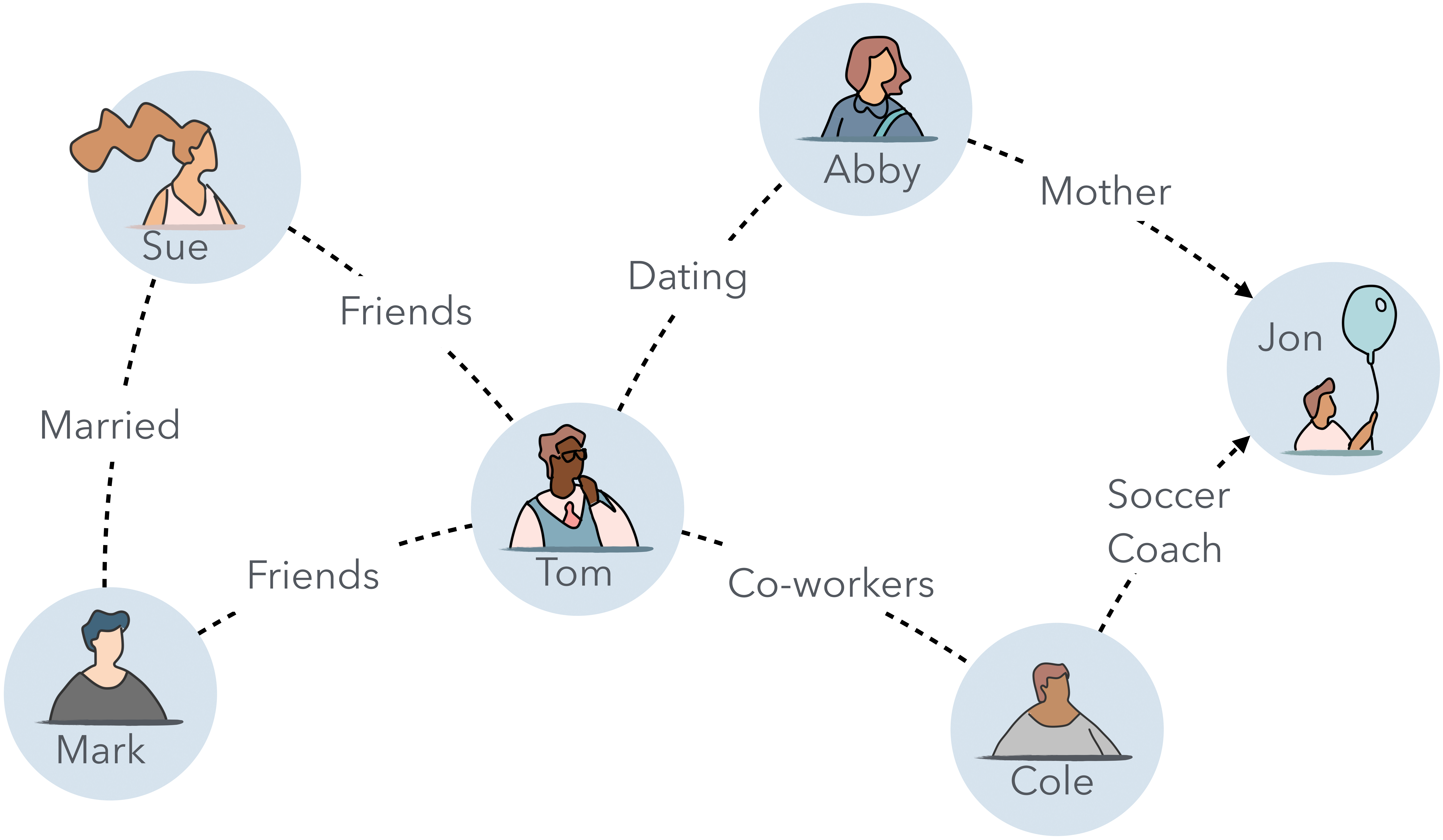
Quilts



BioFabric

Adjacency Matrix

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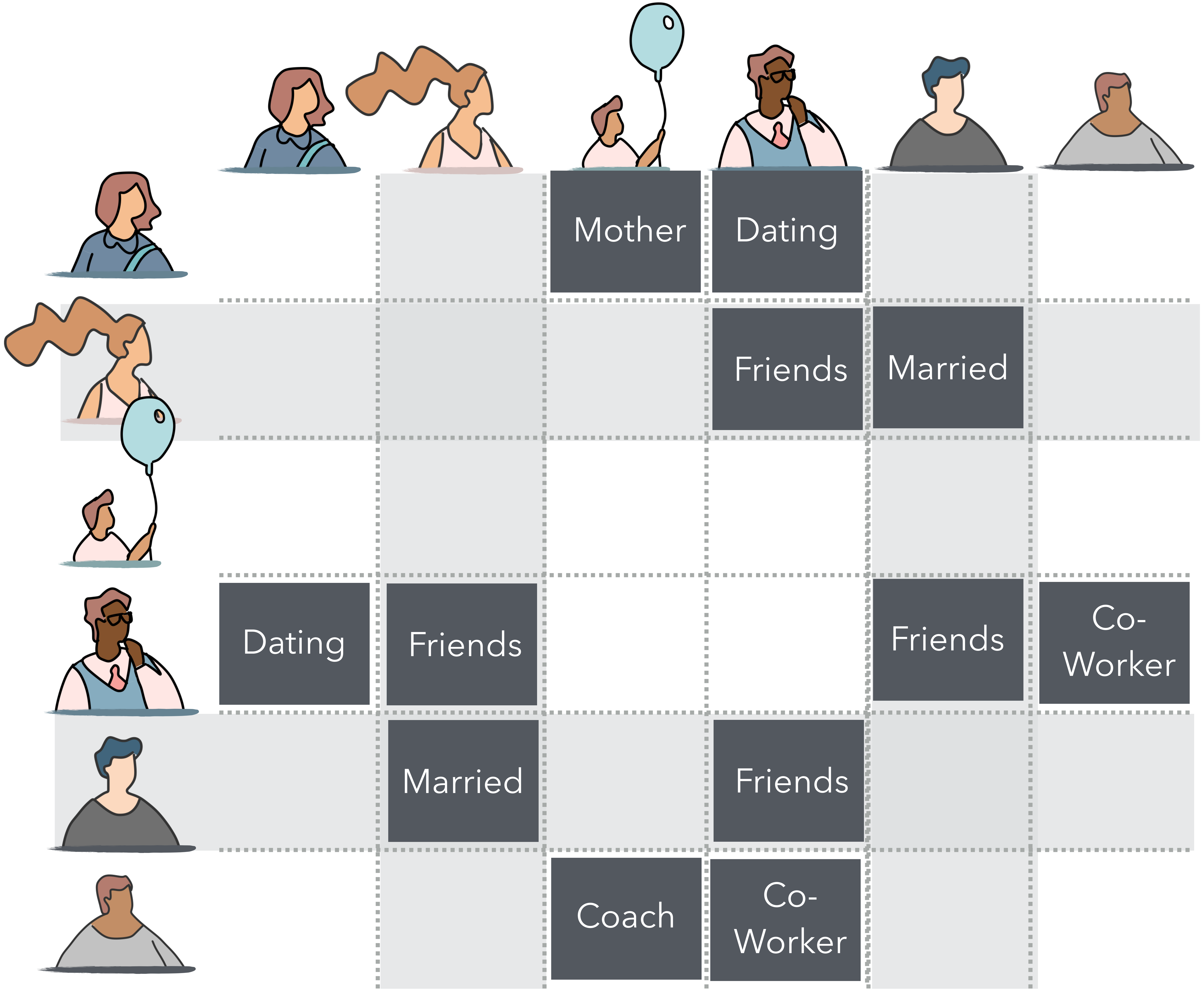
Abby
Mother
Friends
Dating
Jon
Married
Tom
Soccer
Coach
Friends
Co-workers
Mark
Cole



Mother
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Married
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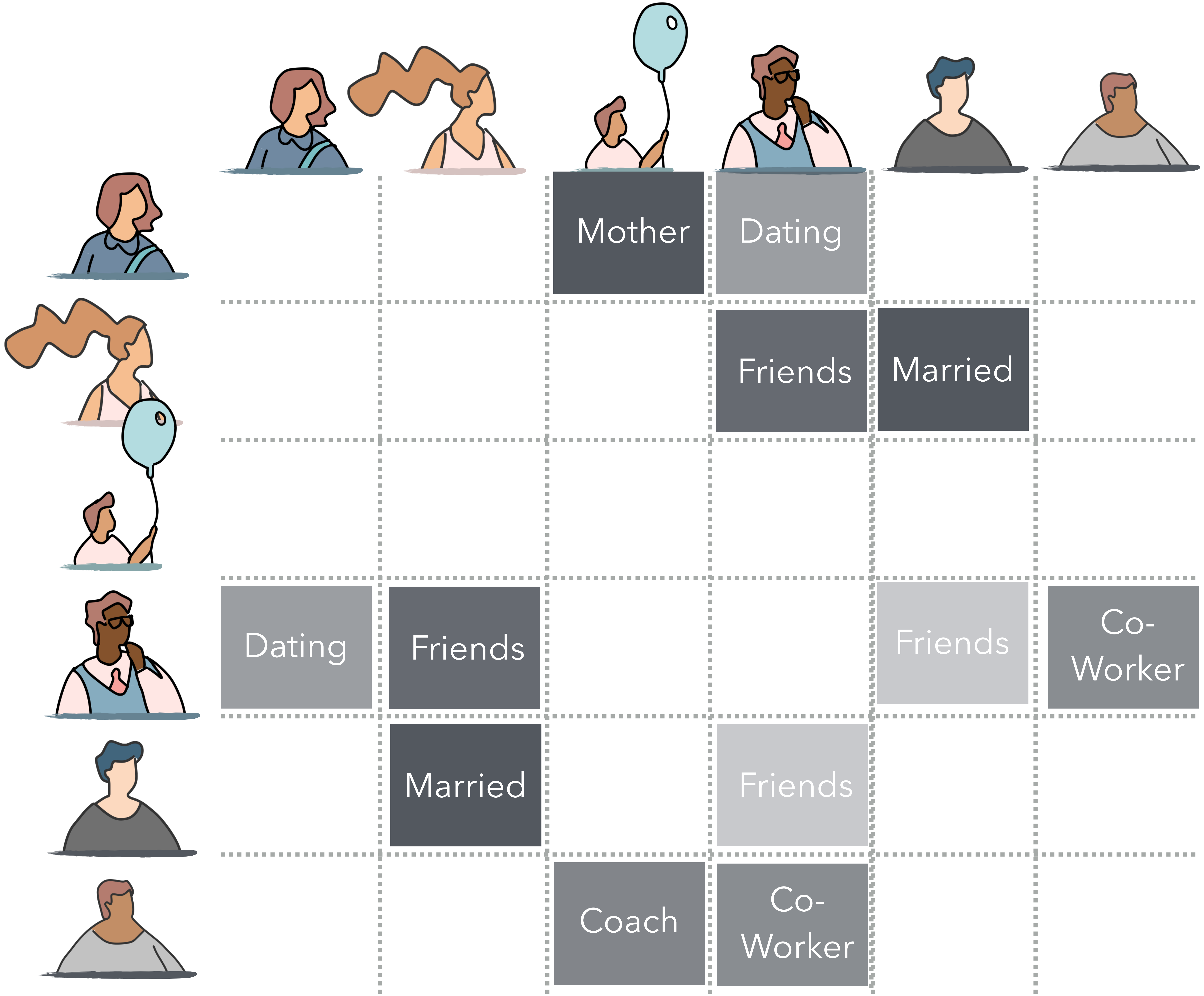
Coach
Co-Worker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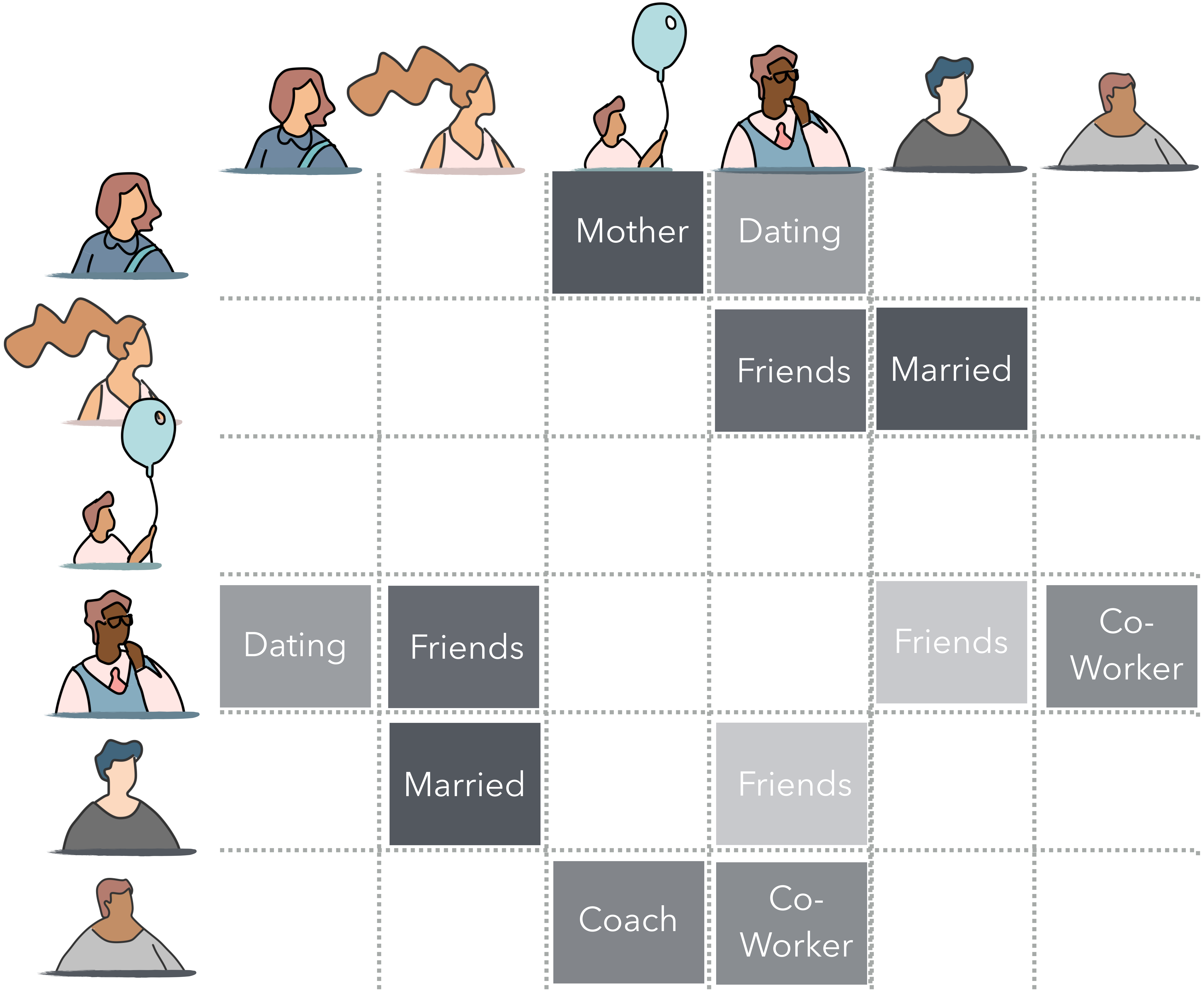
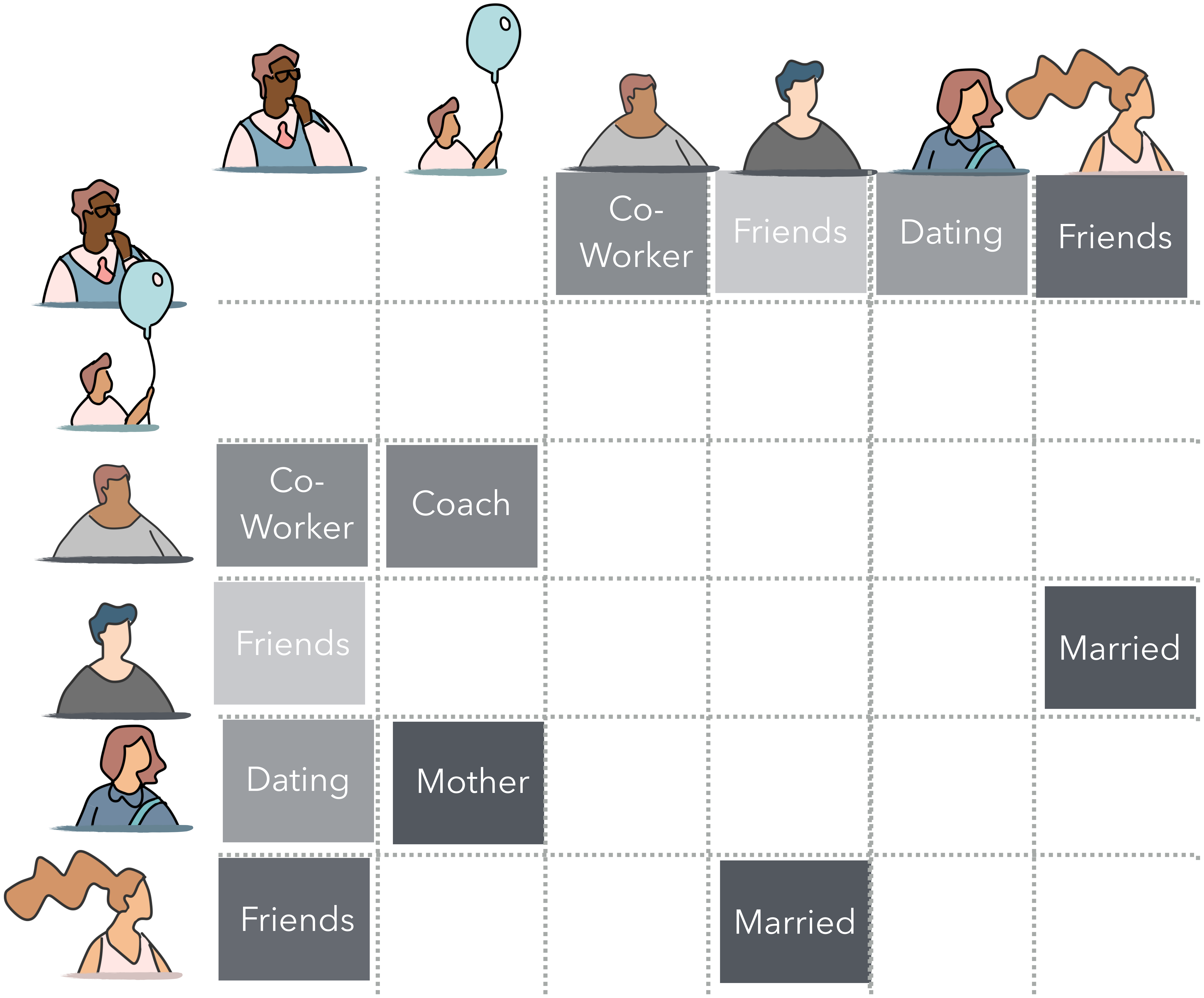
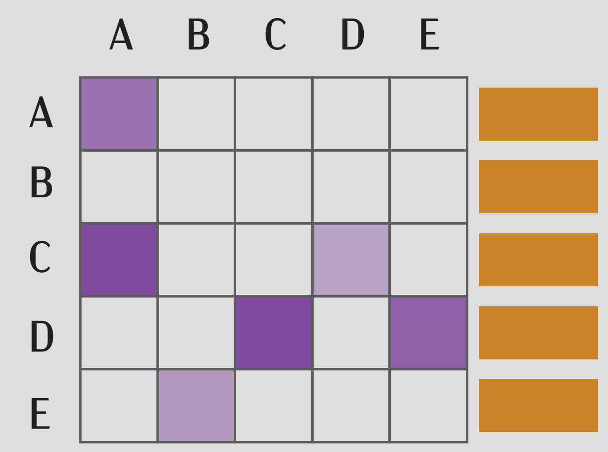


Name	Beverage	Day 1
Abby	Port	1
Sue	Coke	0
Jon	Coke	4
Tom	Beer	5
Mark	Beer	2
Cole	Port	3

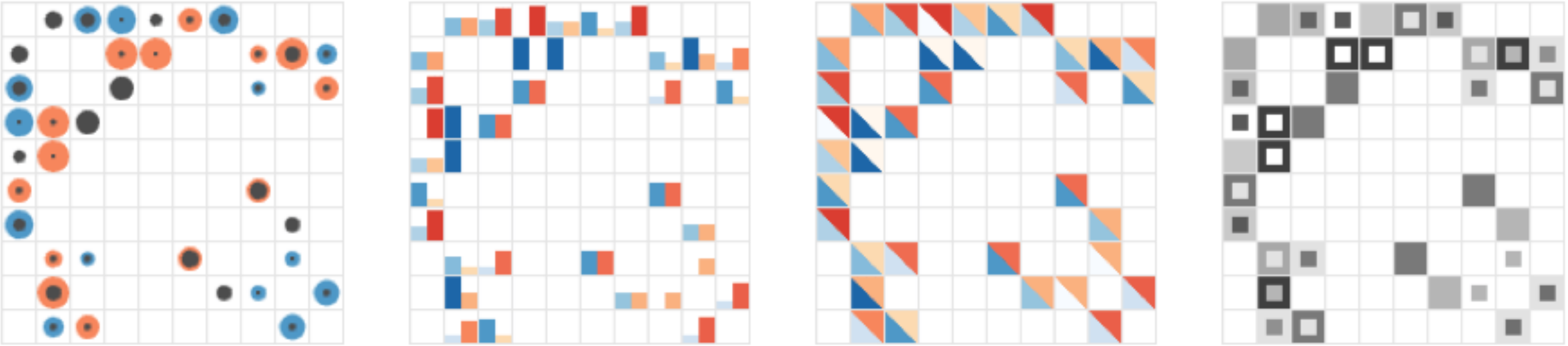


Name	Beverage	Day 1
Tom	Beer	5
Jon	Coke	4
Cole	Port	3
Mark	Beer	2
Abby	Port	1
Sue	Coke	0

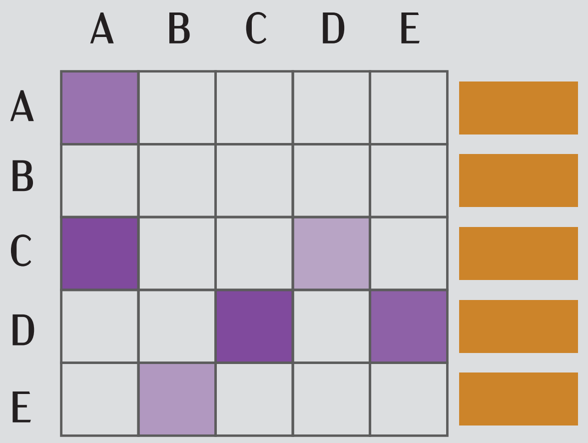
Moritz Stefaner, Musli Ingredient Network. https://truth-and-beauty.net/projects/muesli-ingredient-network



Adjacency Matrix



Alper et al, 2013



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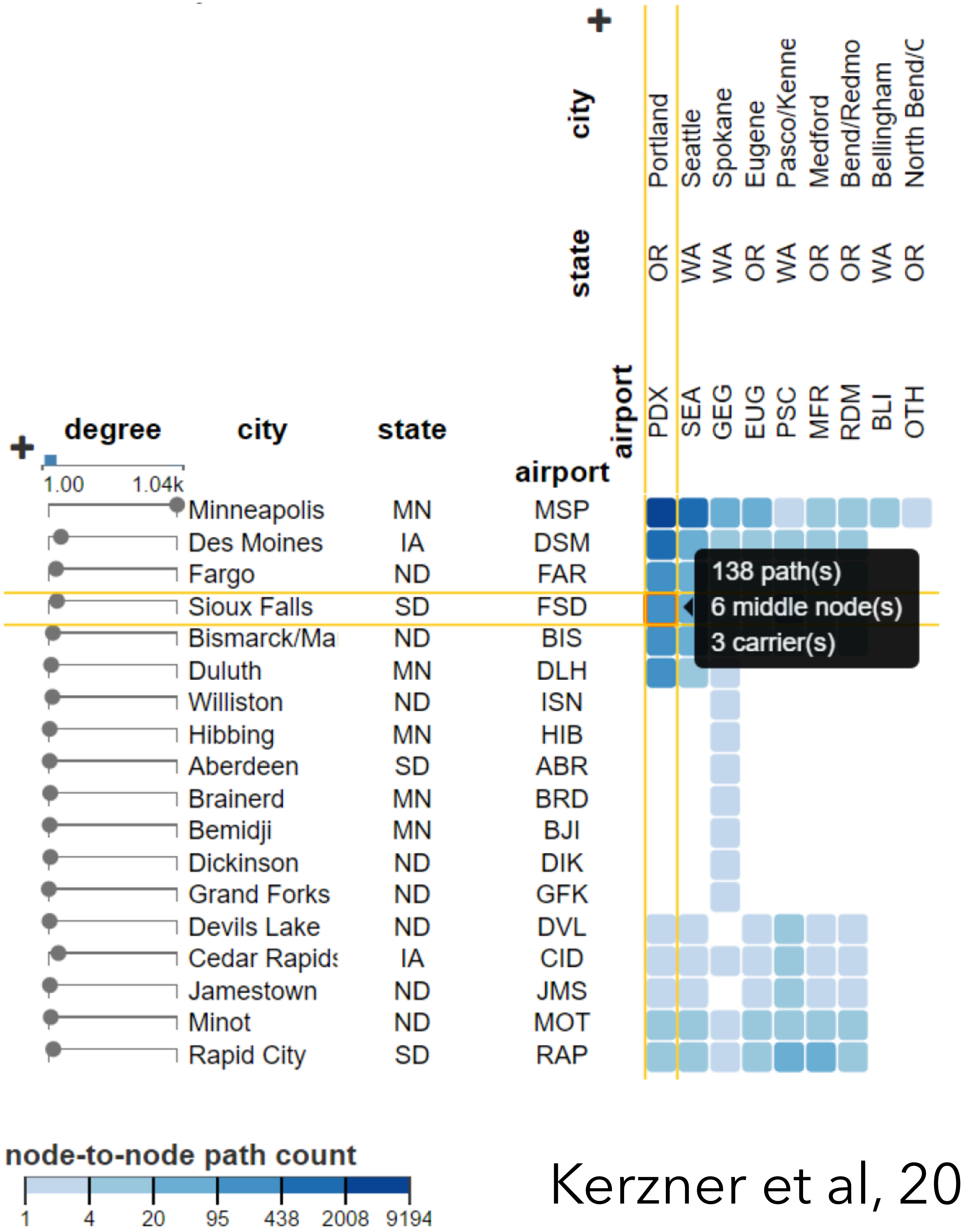
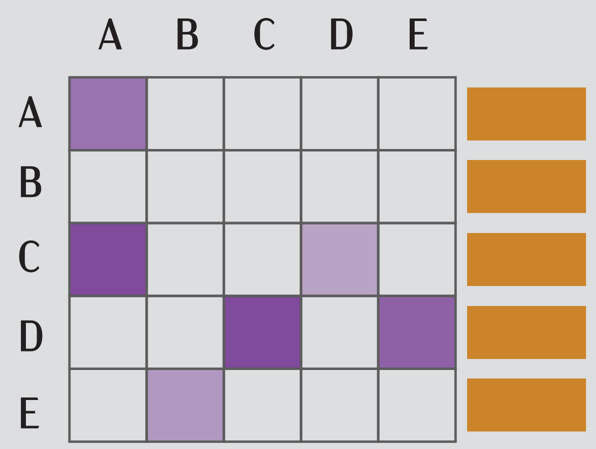


Kerzner et al, 2017



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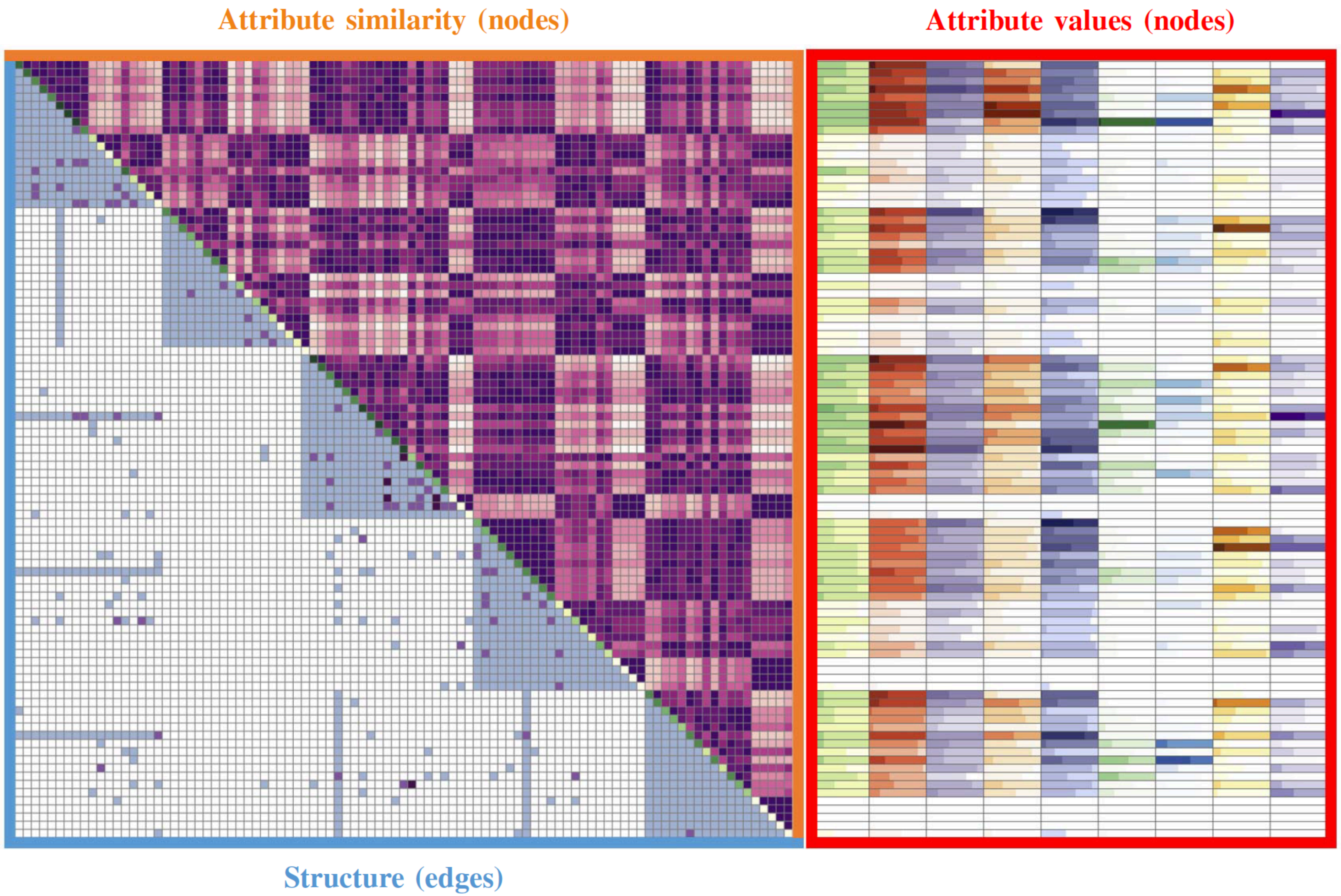
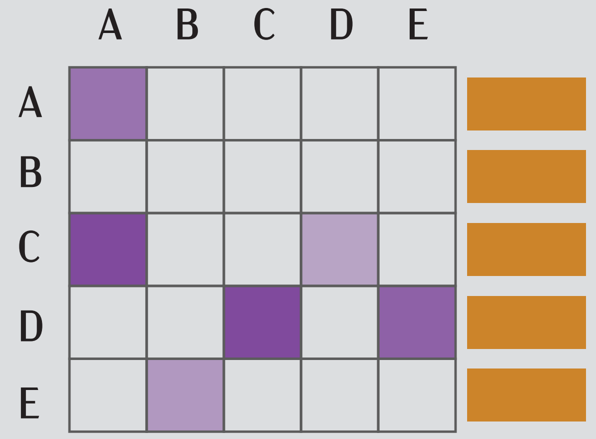
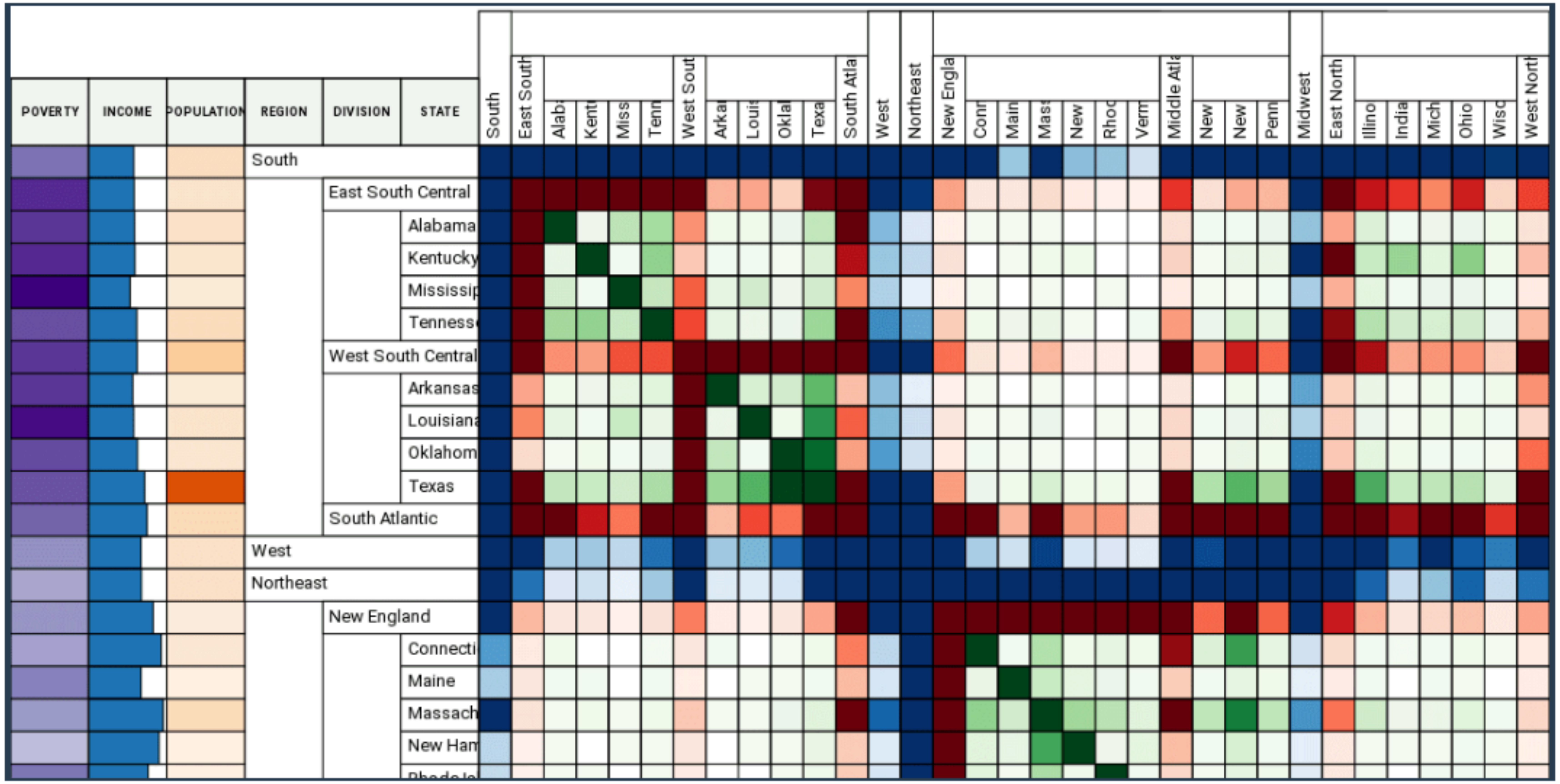
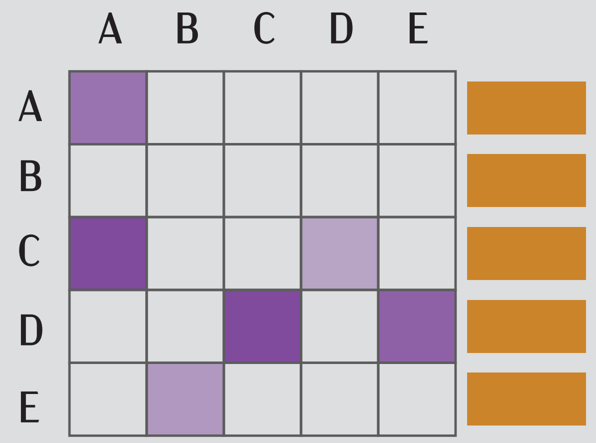




Adjacency Matrix

Berger et al, 2019

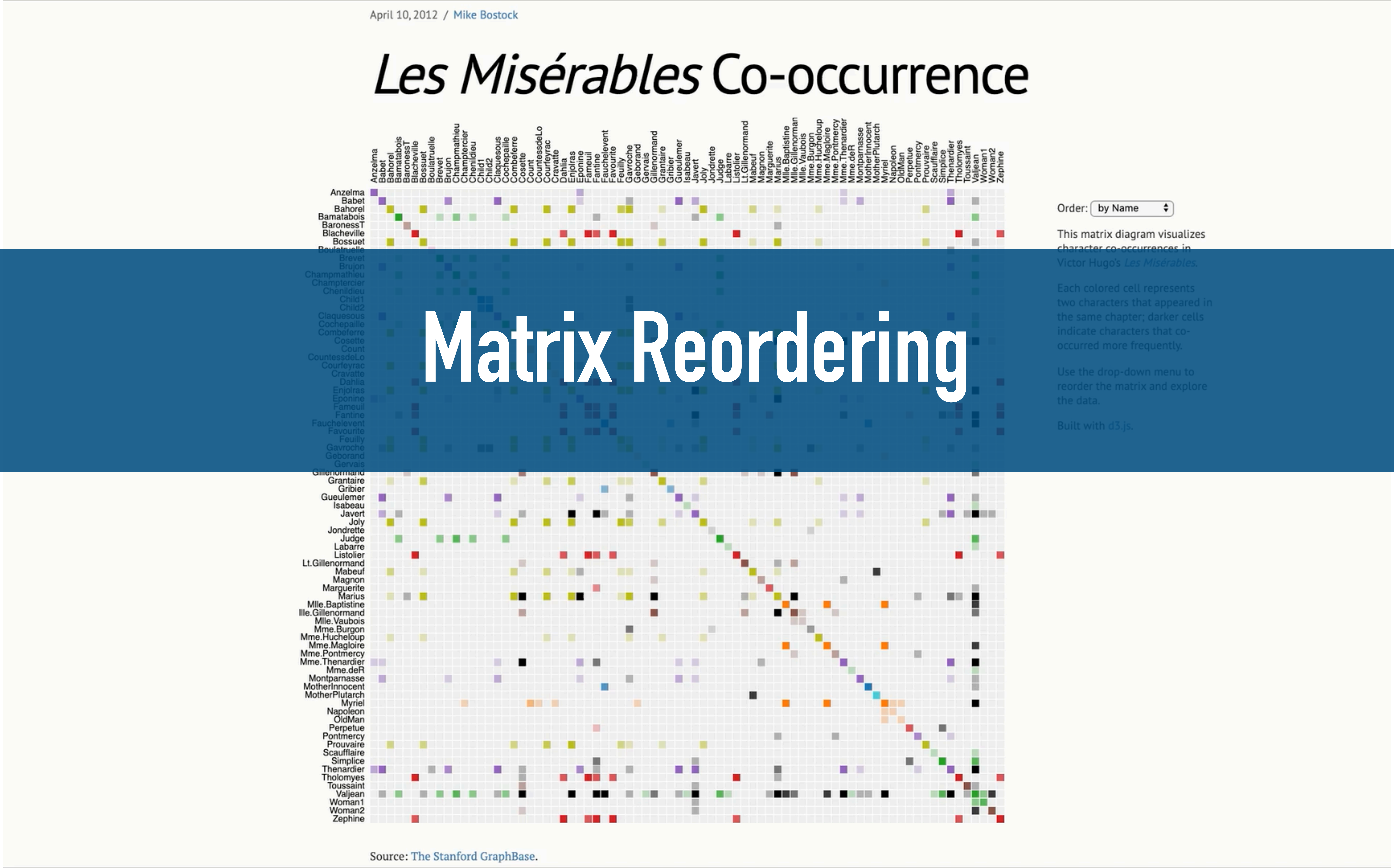


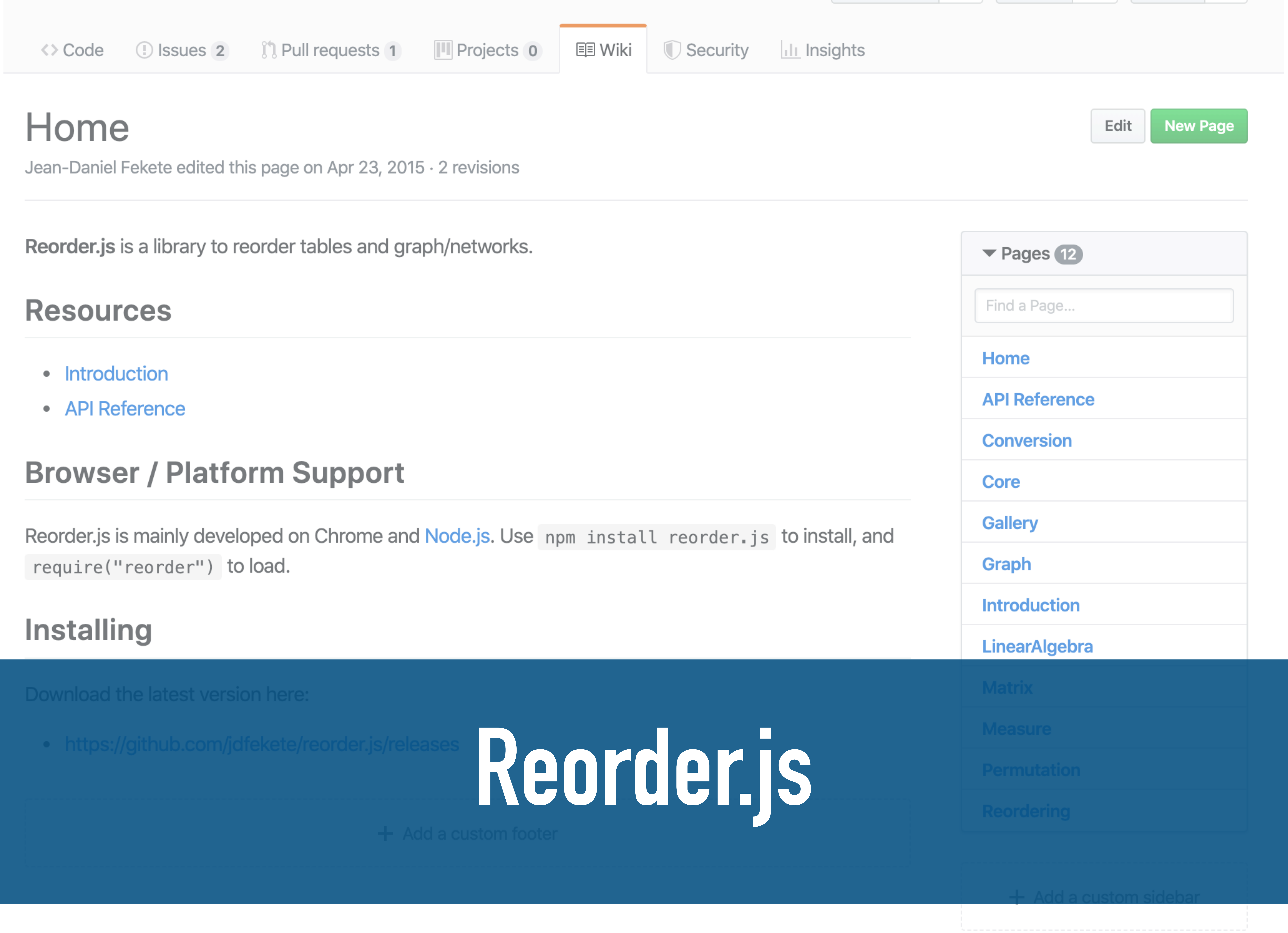


Adjacency Matrix

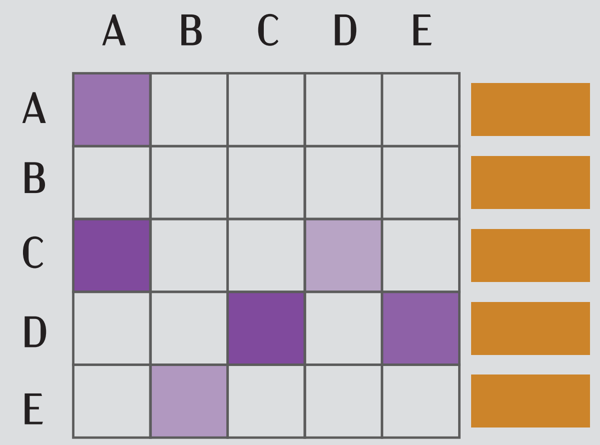
Safarli and Lex, 2019

Matrix Reordering




Code
Issues 2
Pull requests 1
Projects 0
Wiki
Security
Insights
Home
Edit
New Page
Jean-Daniel Fekete edited this page on Apr 23, 2015 · 2 revisions
Reorder.js is a library to reorder tables and graph/networks.
Resources
Introduction
API Reference
Browser / Platform Support
Reorder.js is mainly developed on Chrome and Node.js. Use npm install reorder.js to install, and require("reorder") to load.
Installing
Download the latest version here:
https://github.com/jdfekete/reorder.js/releases
Add a custom footer
Pages 12
Find a Page...
Home
API Reference
Conversion
Core
Gallery
Graph
Introduction
LinearAlgebra
Matrix
Measure
Permutation
Reordering
Add a custom sidebar

Reorder.js



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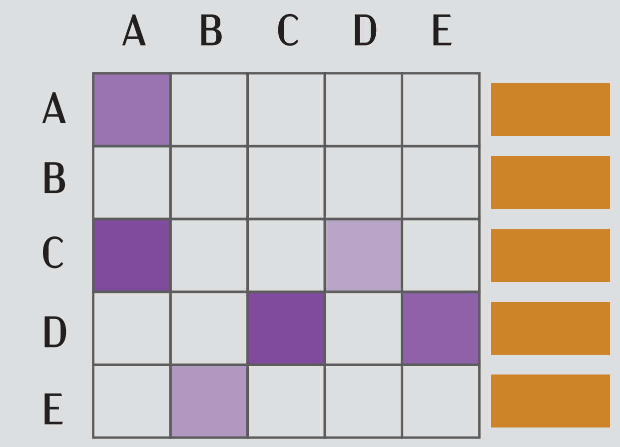


Adjacency
Matrix

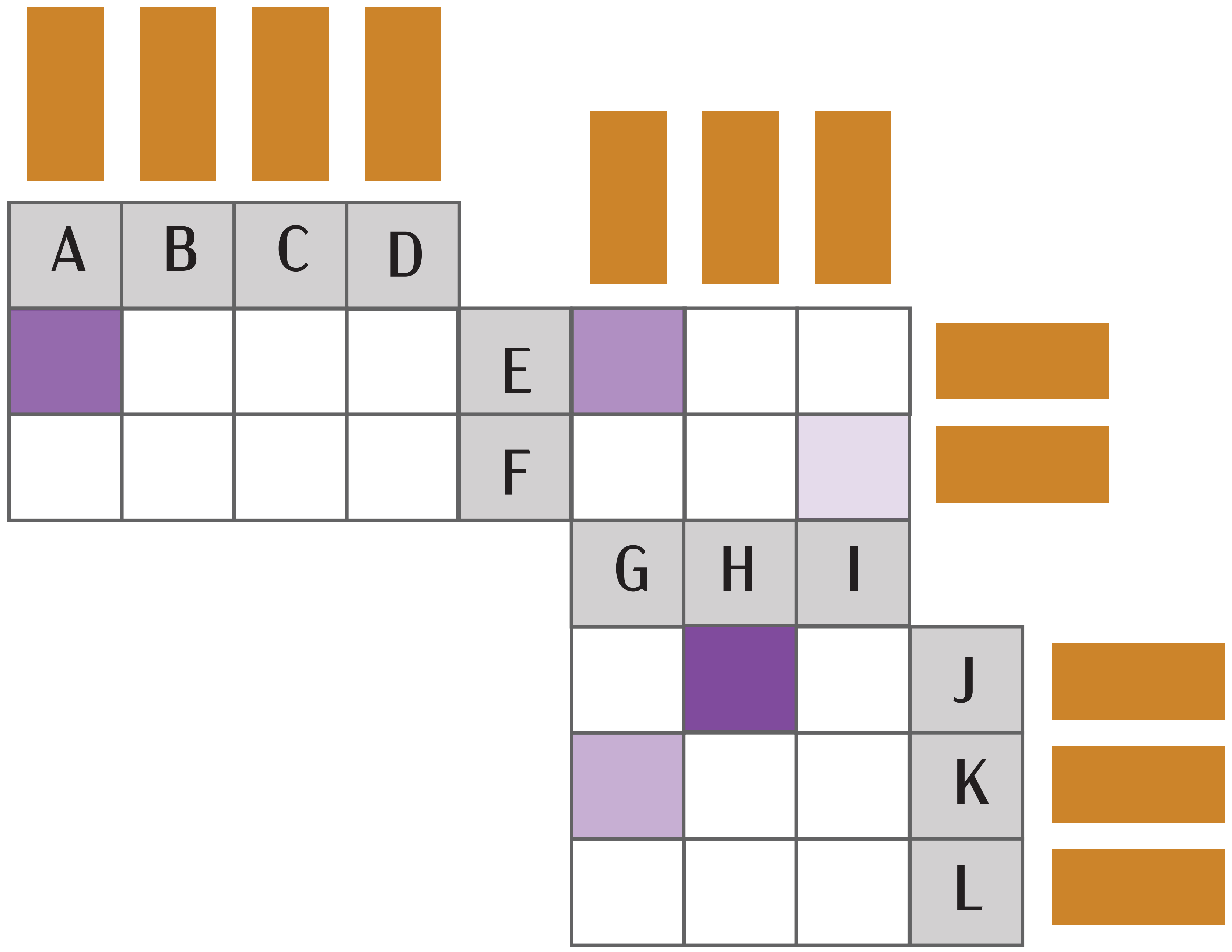
Ideal for dense and completely connected networks

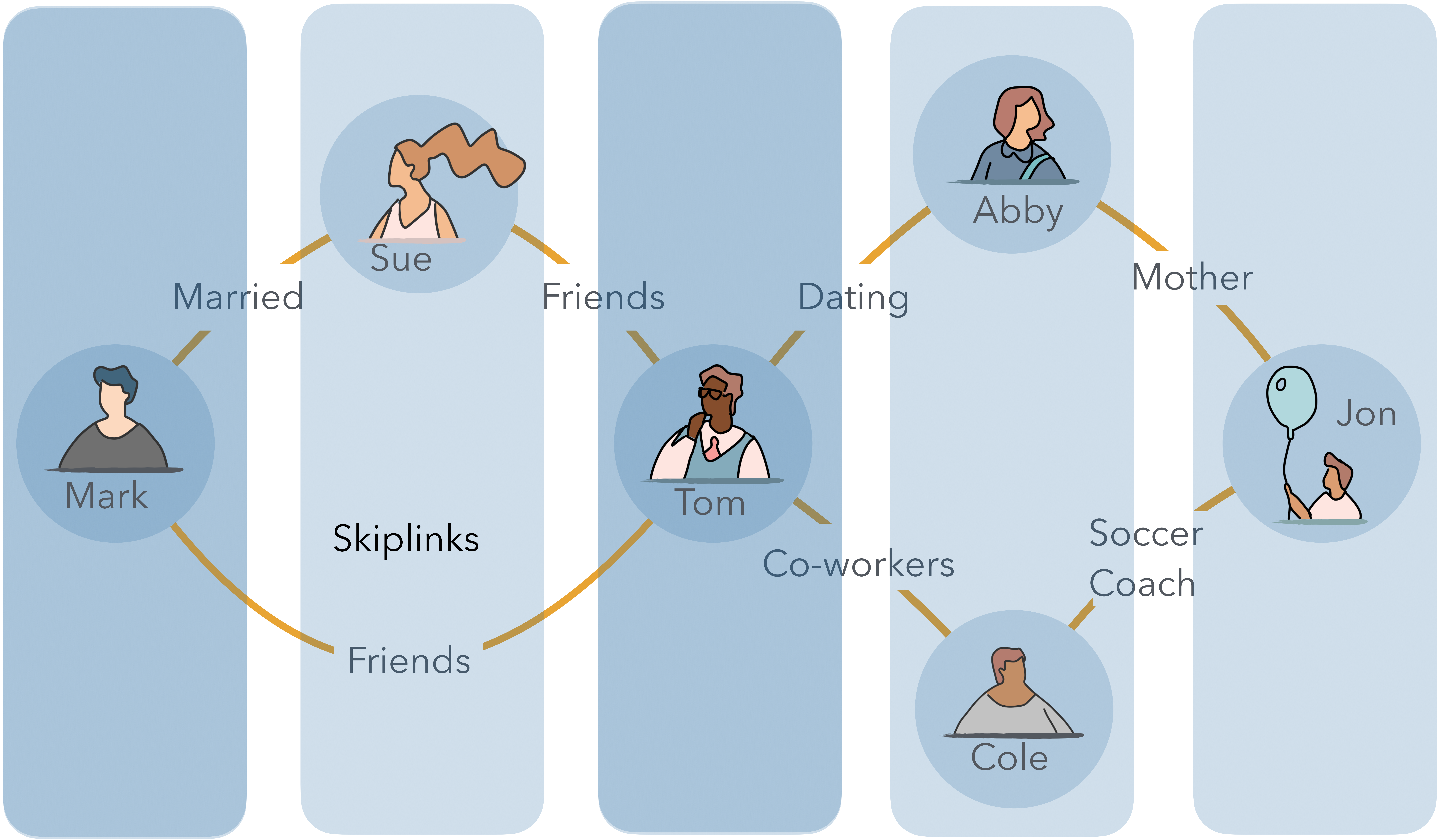
Requires quadratic space with respect to the number of nodes.

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

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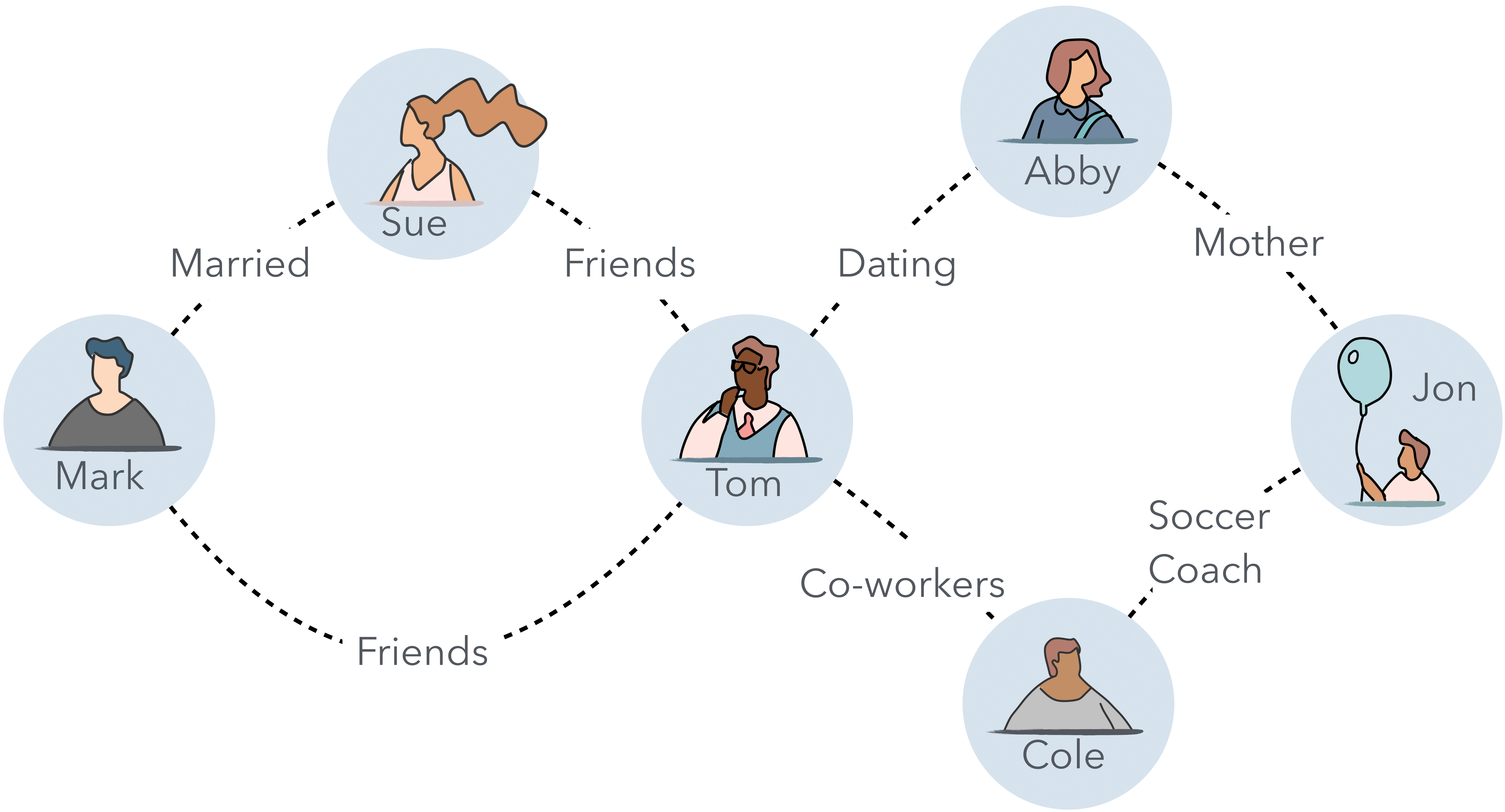
Married
Friends
Dating
Mother
Mark
Tom
Jon
Skiplinks
Co-workers
Soccer Coach
Friends
Cole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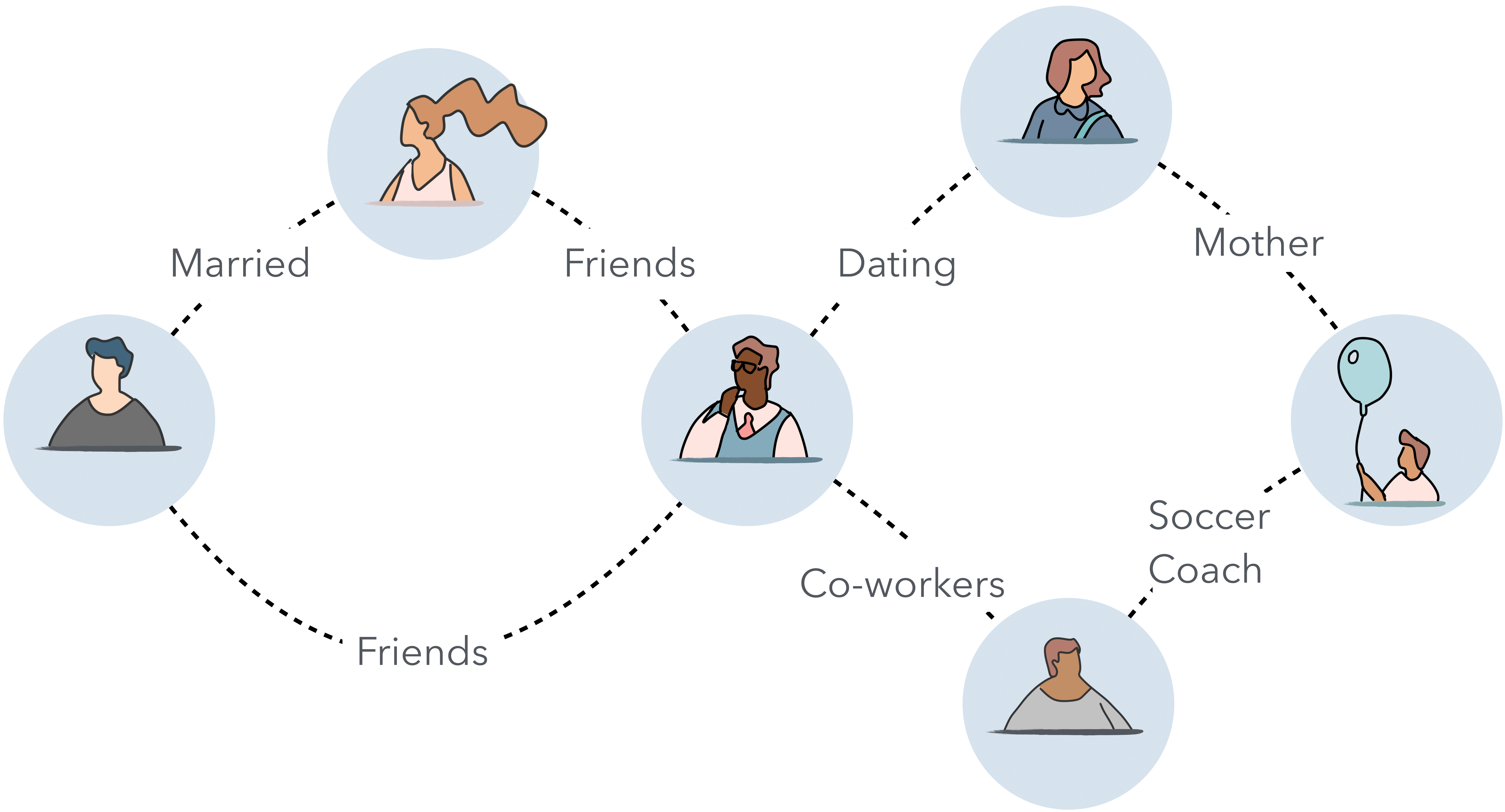
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Co-workers
Soccer
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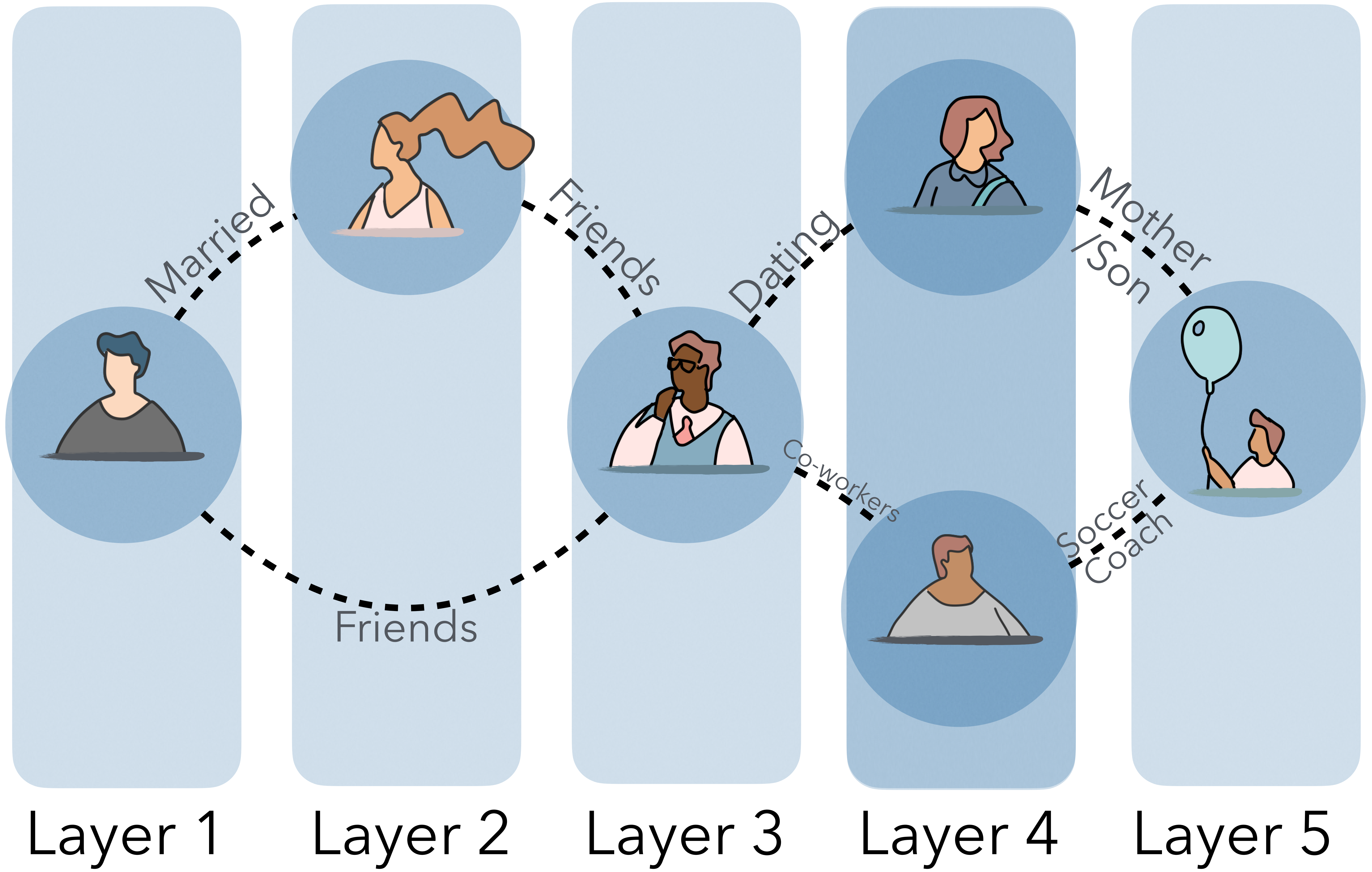
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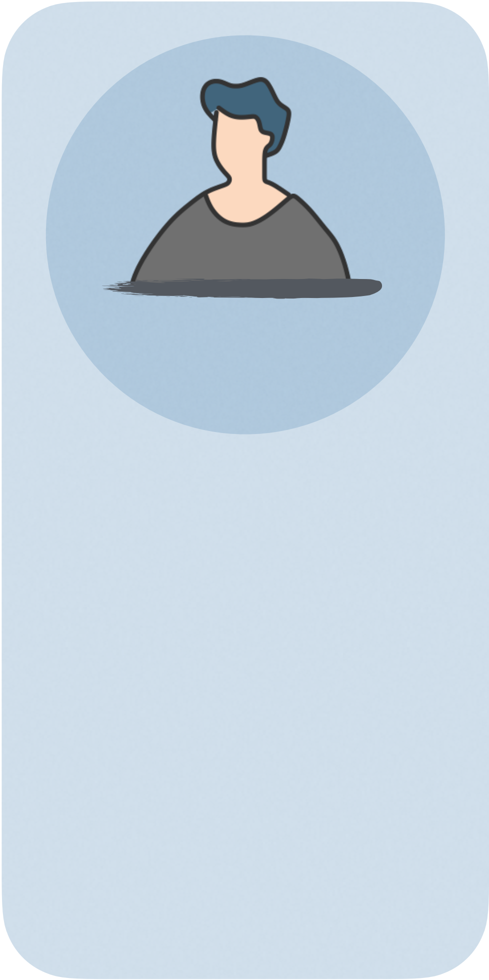
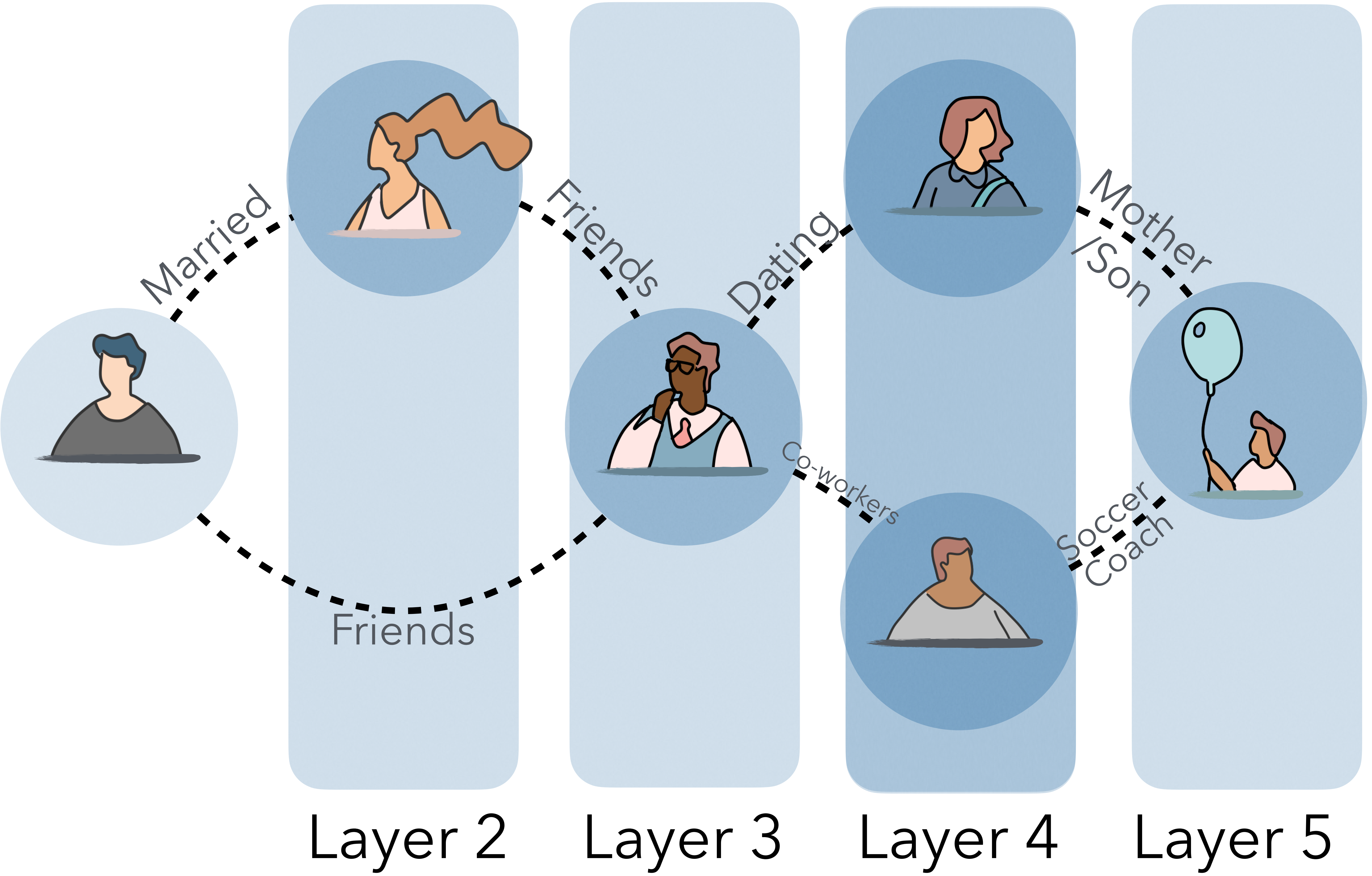
Co-workers
Mother
/Son
Soccer
Coach
Layer 1
Layer 2
Layer 3
Layer 4
Layer 5

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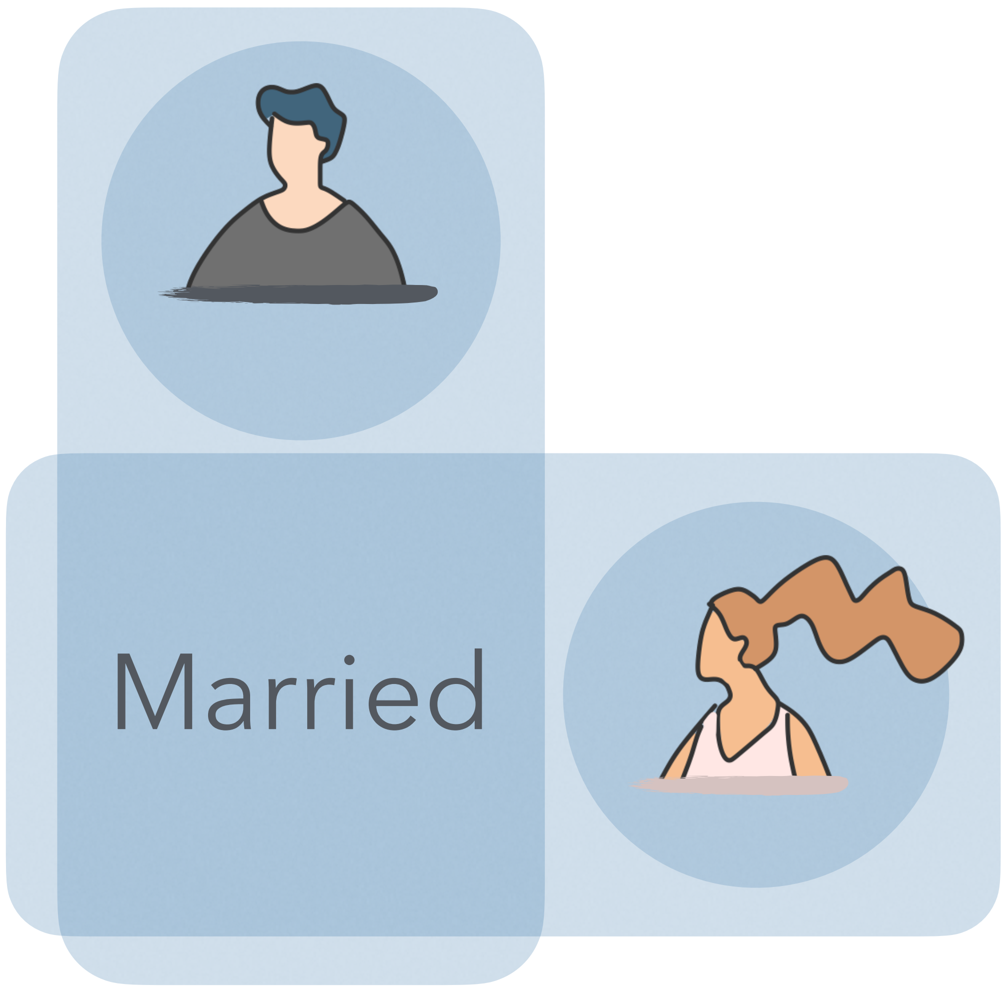
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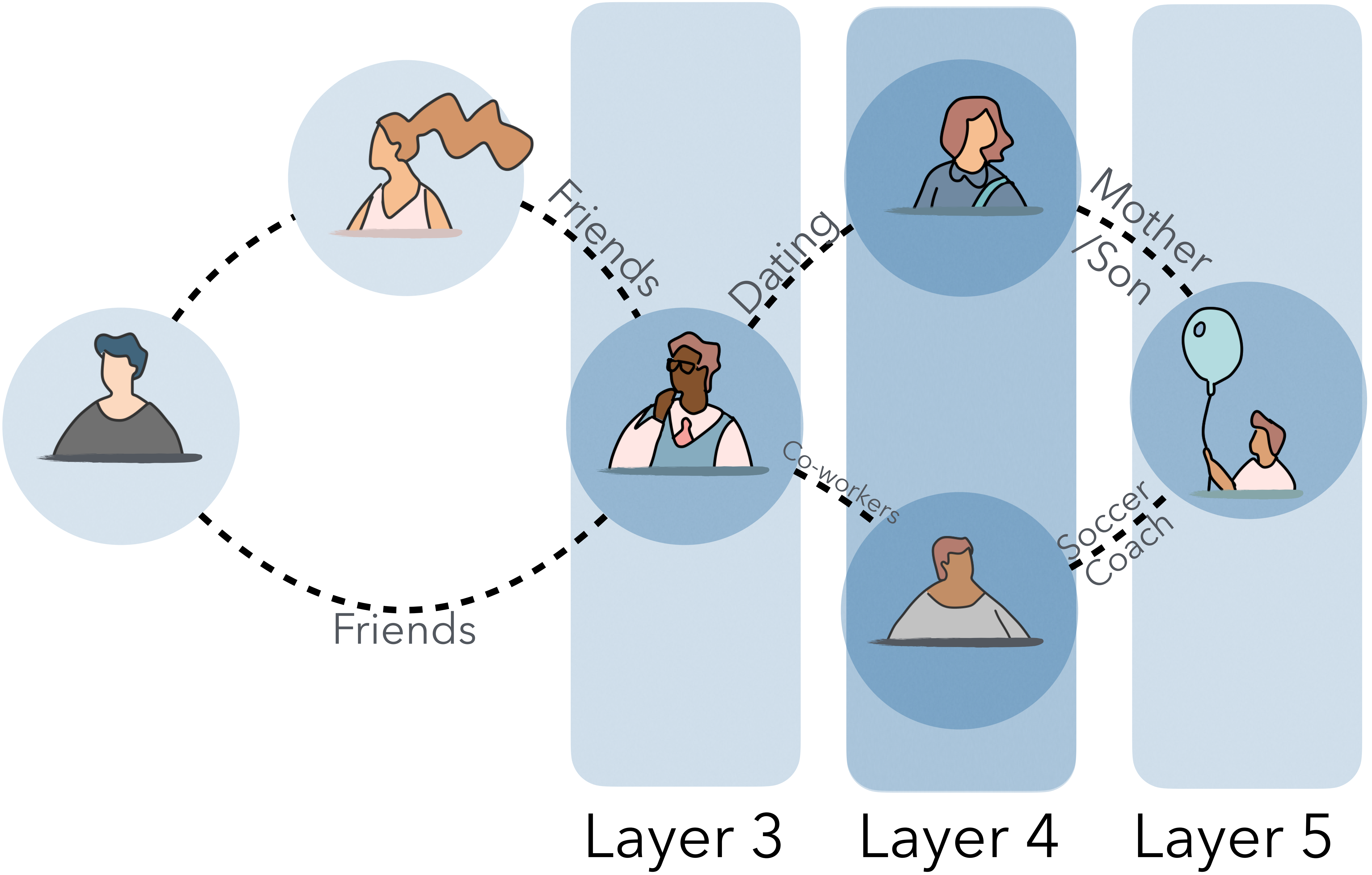
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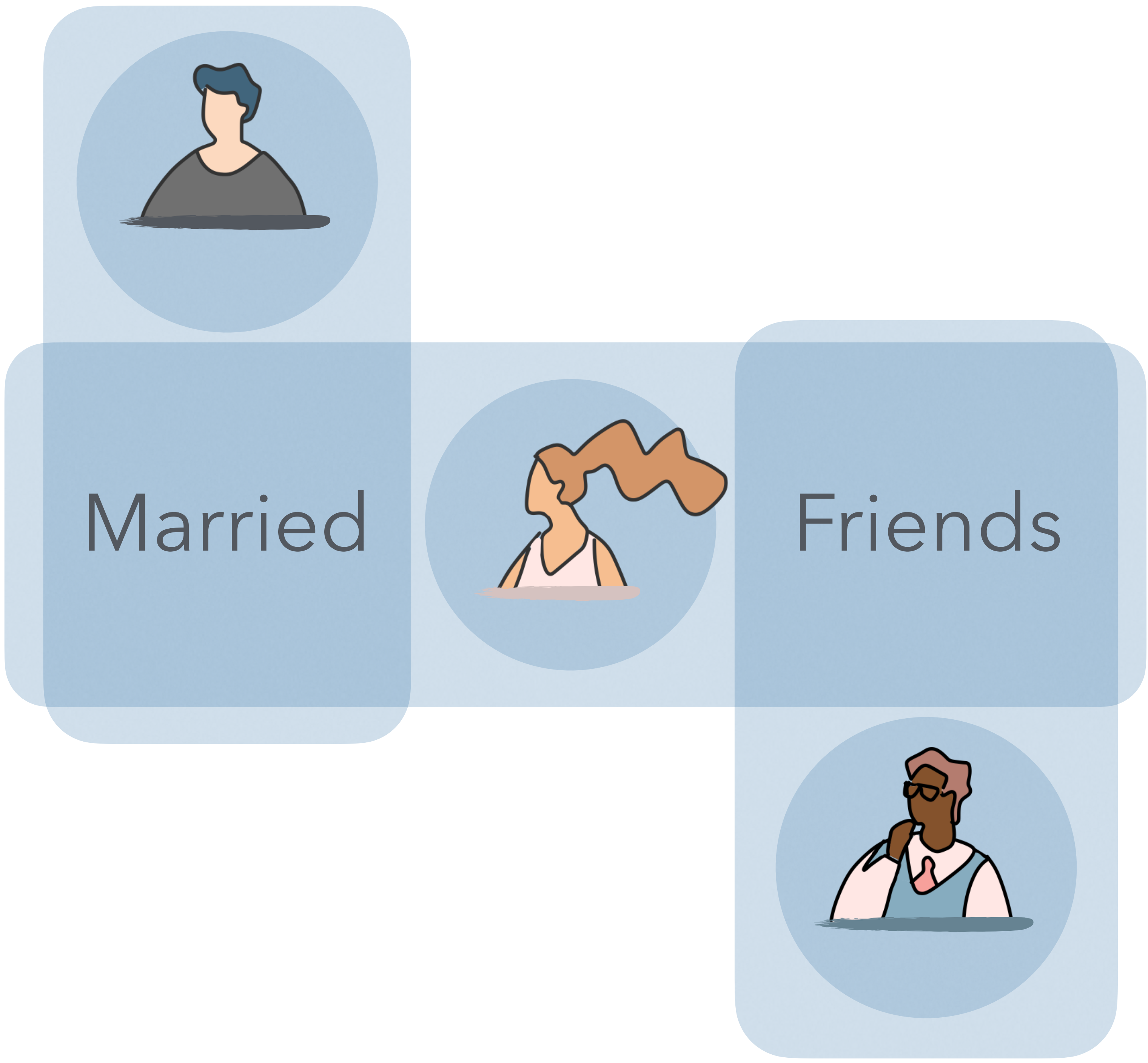
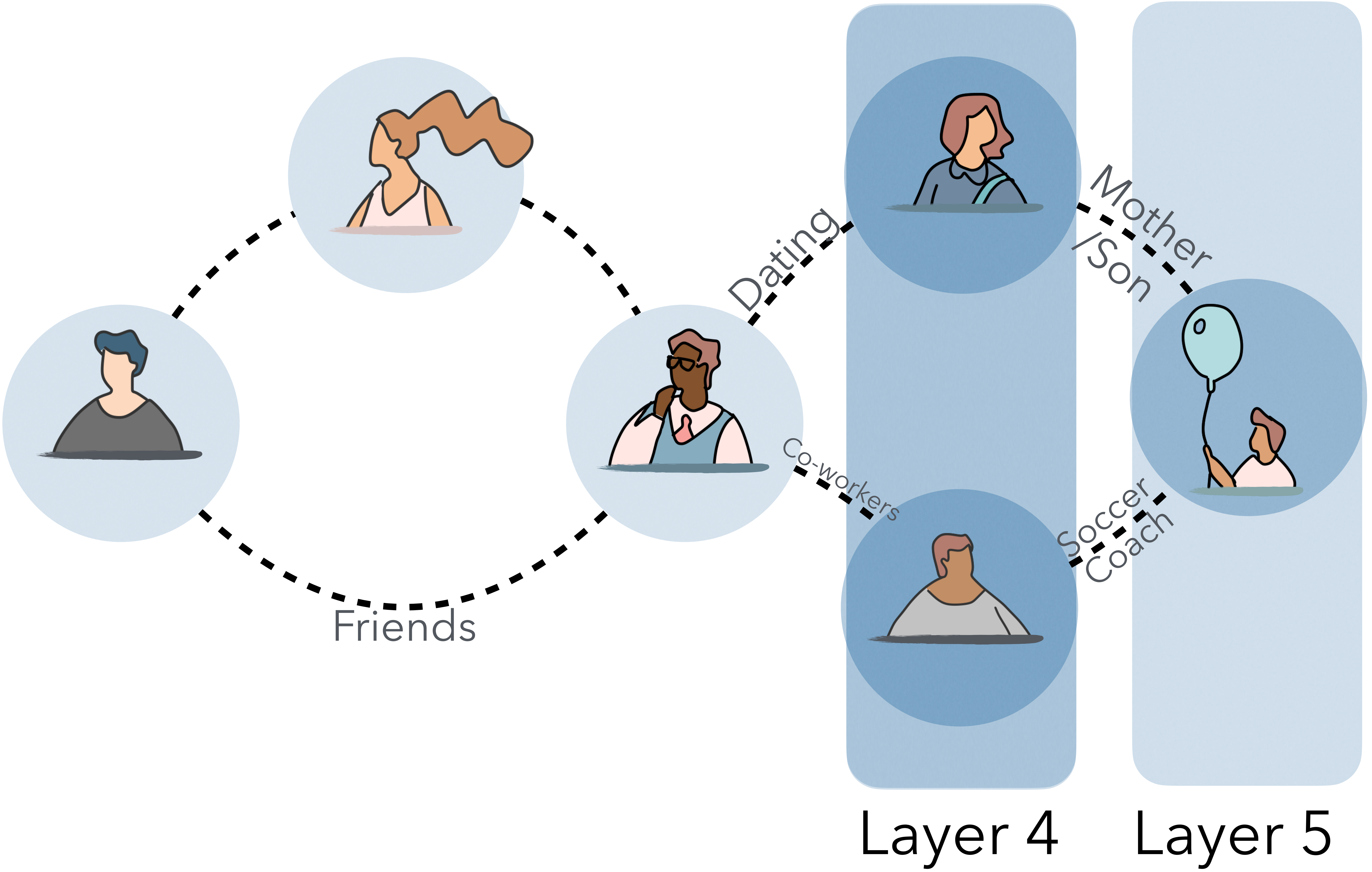
Dating
Co-workers
Mother
/Son
Soccer
Coach
Layer 3
Layer 4
Layer 5


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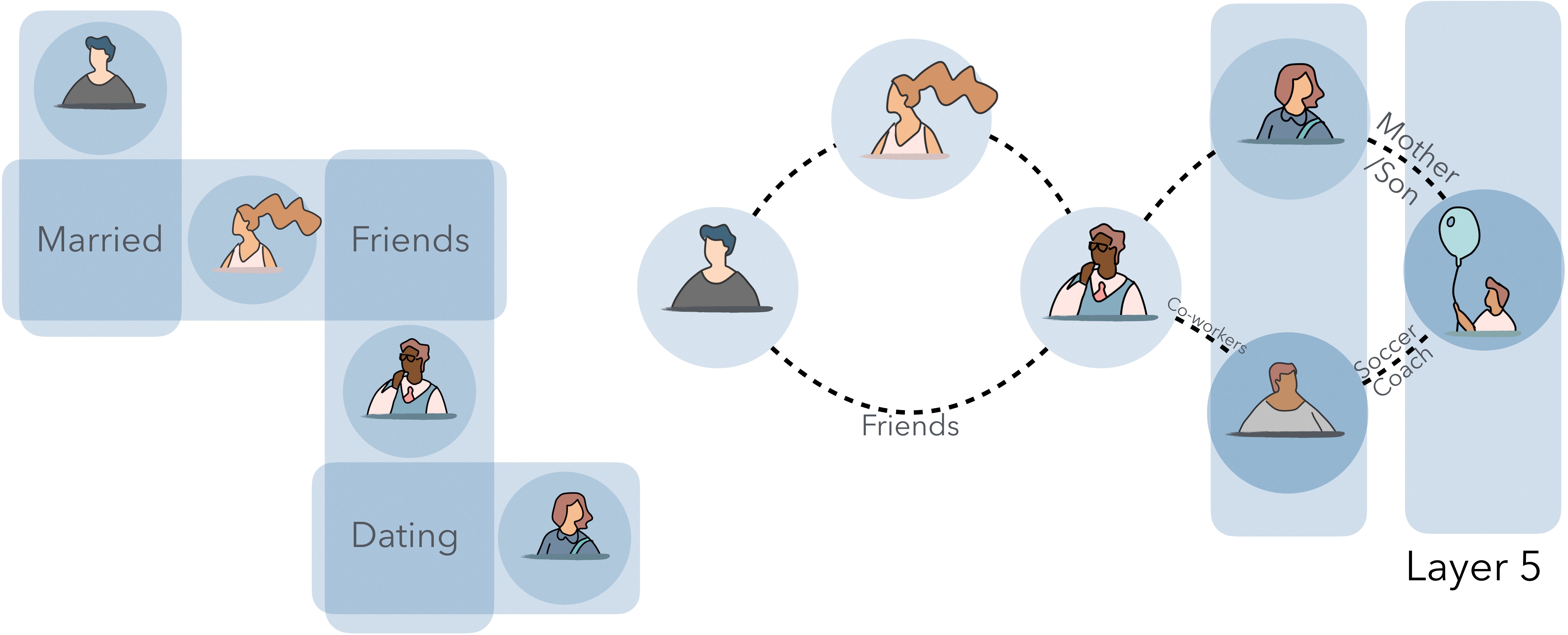
Co-workers
Mother
/Son
Soccer
Coach
Layer 4
Layer 5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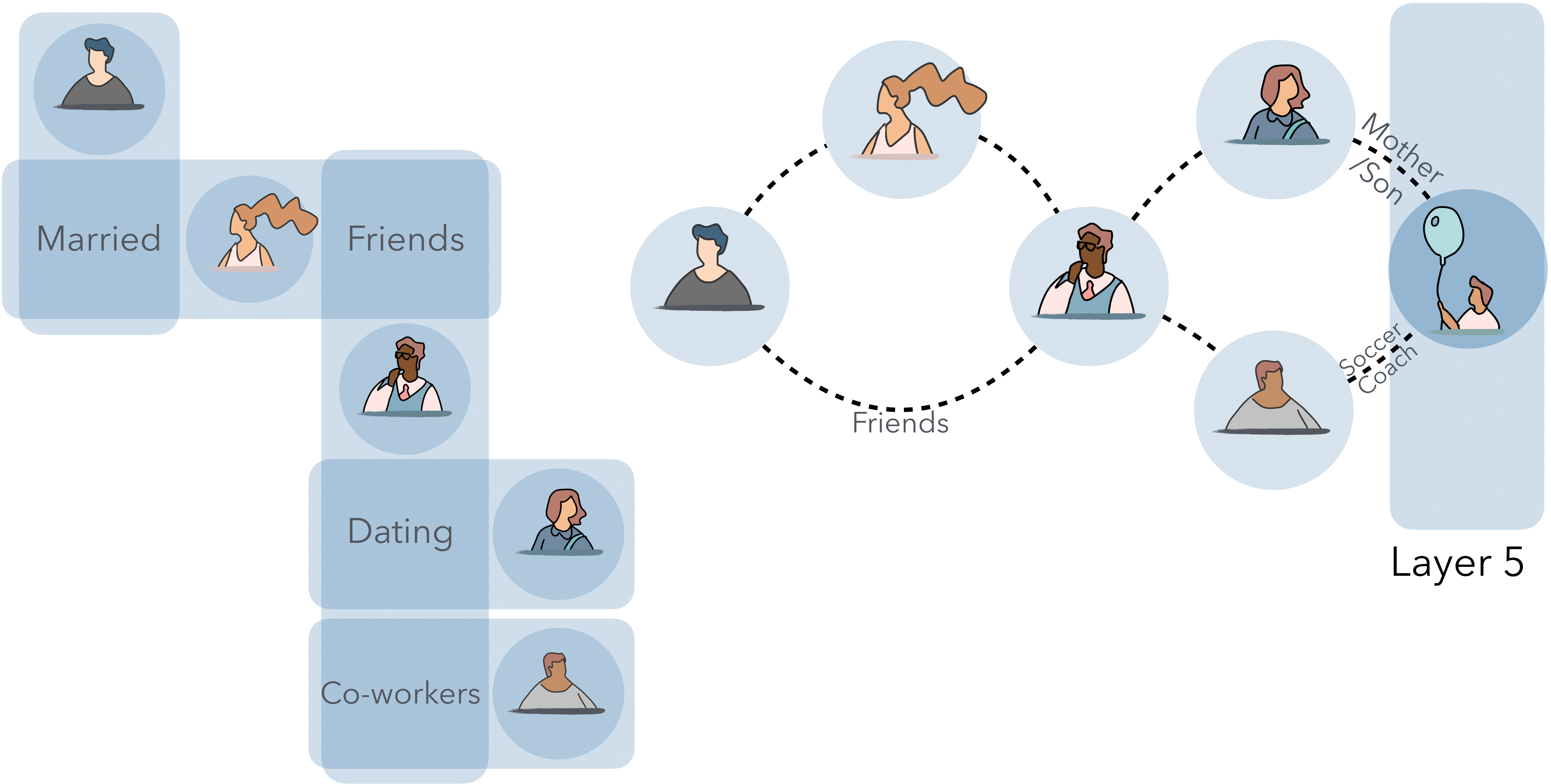
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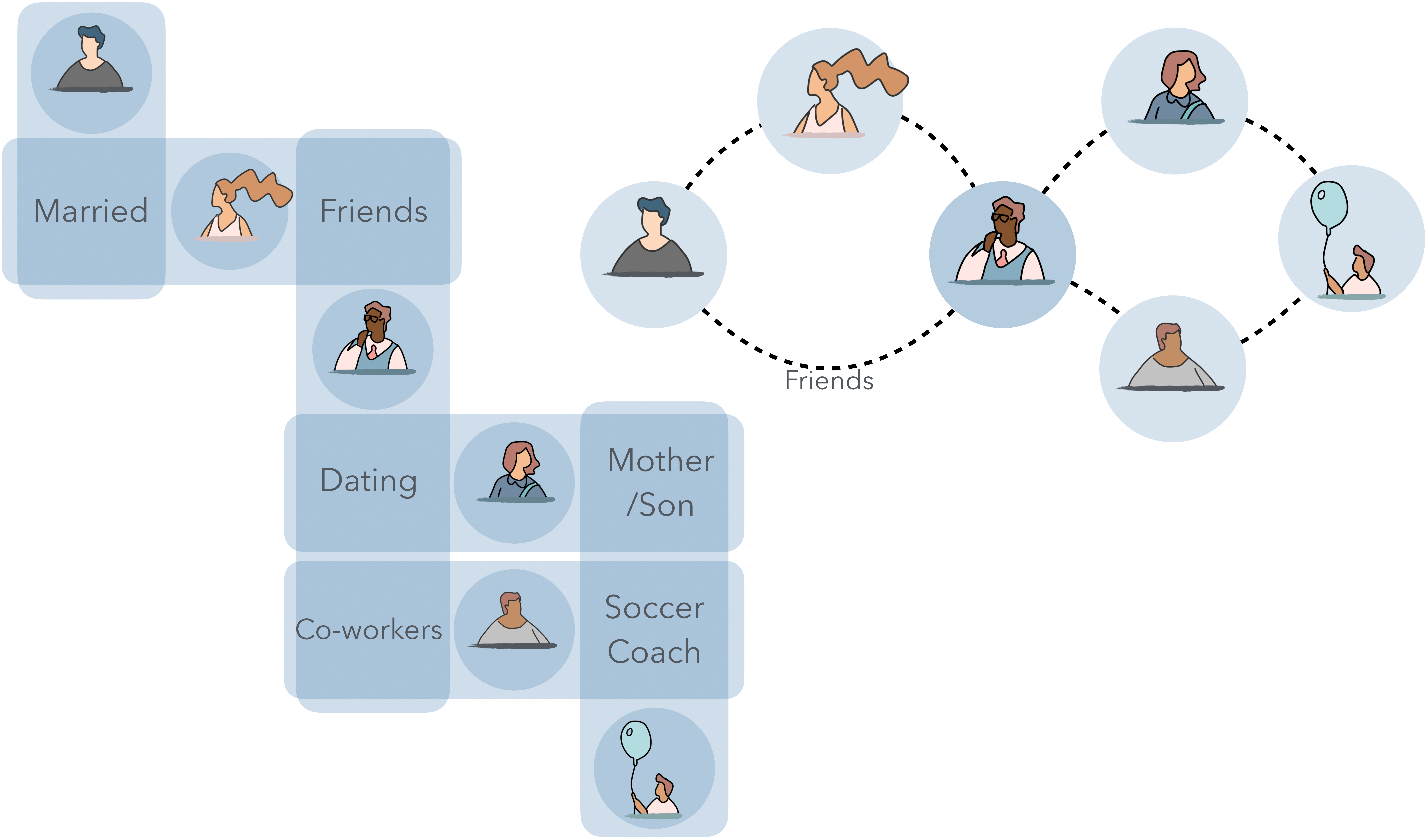
Soccer Coach
Layer 5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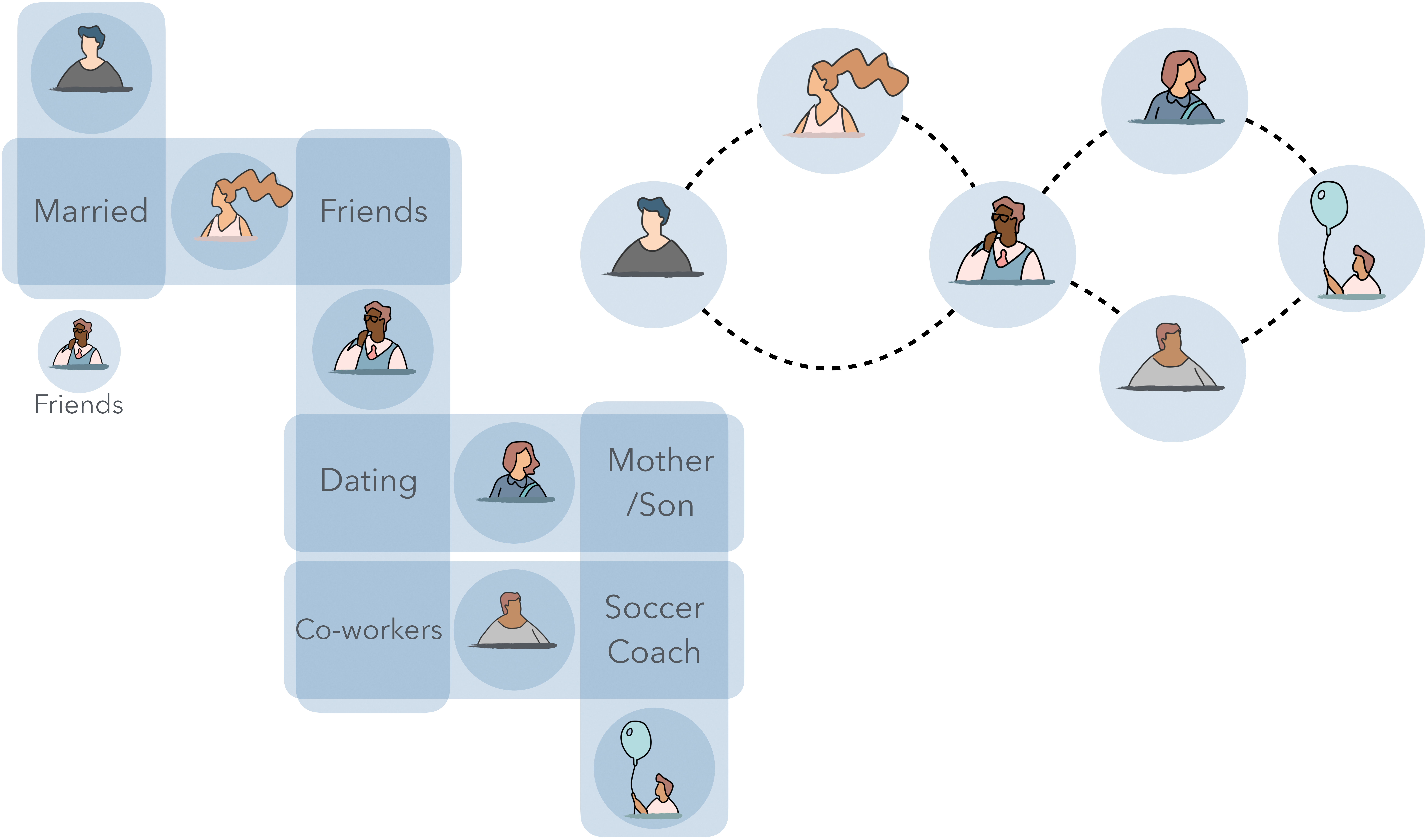
Friends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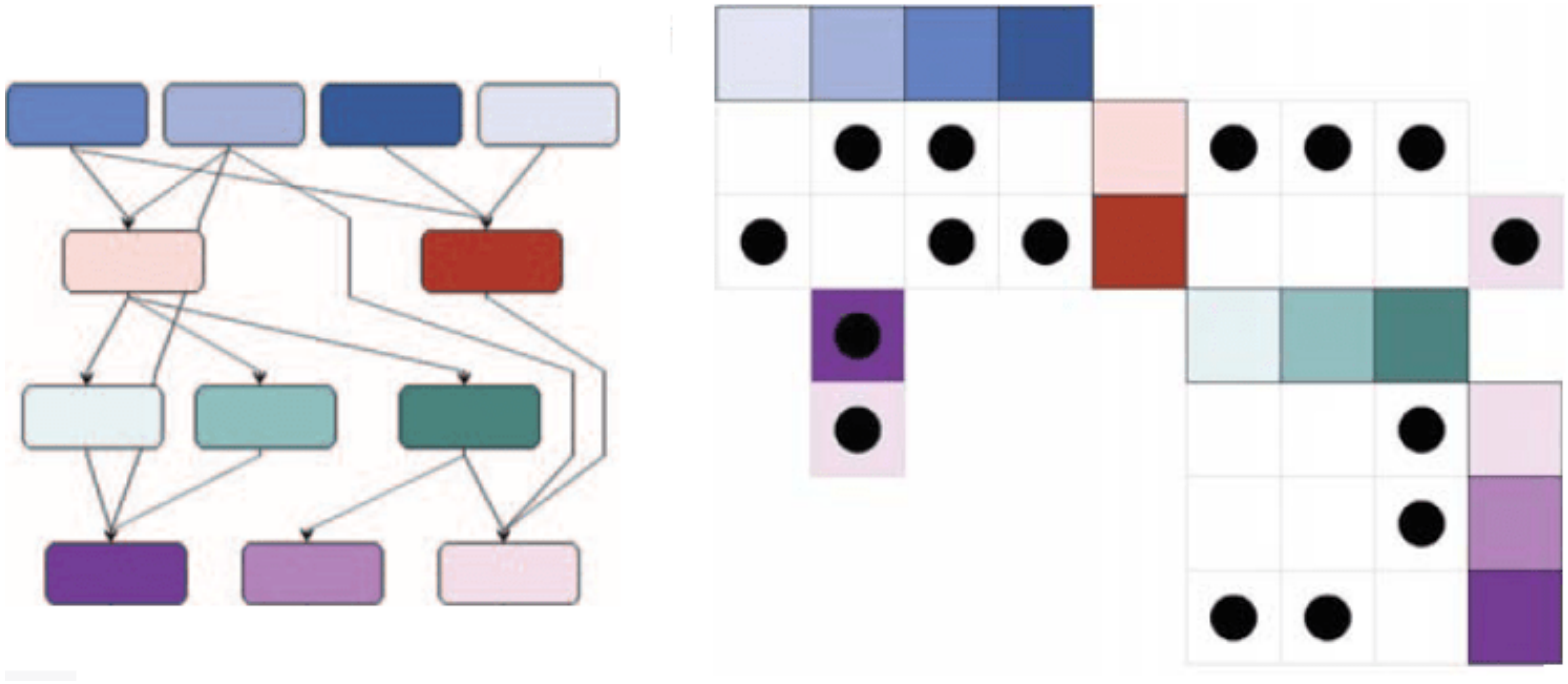
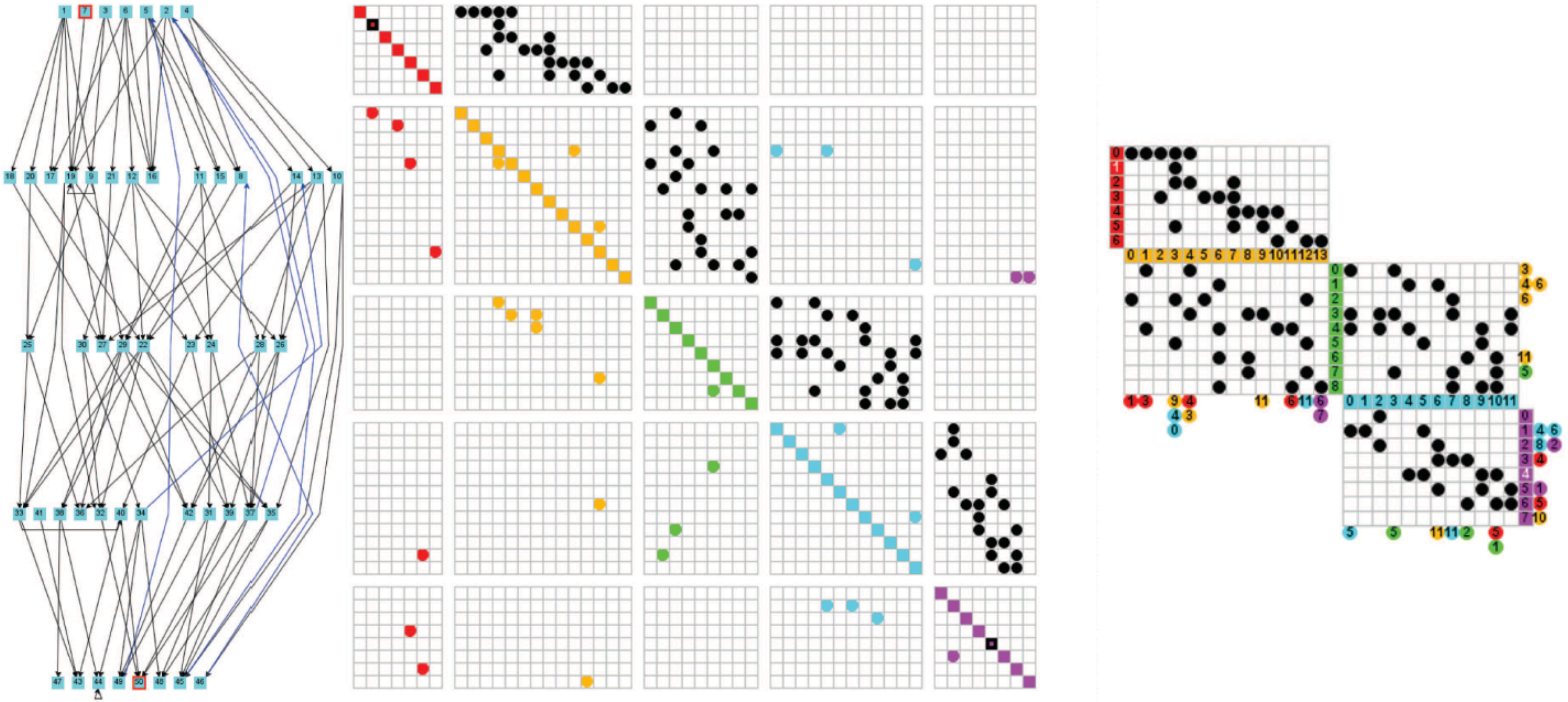
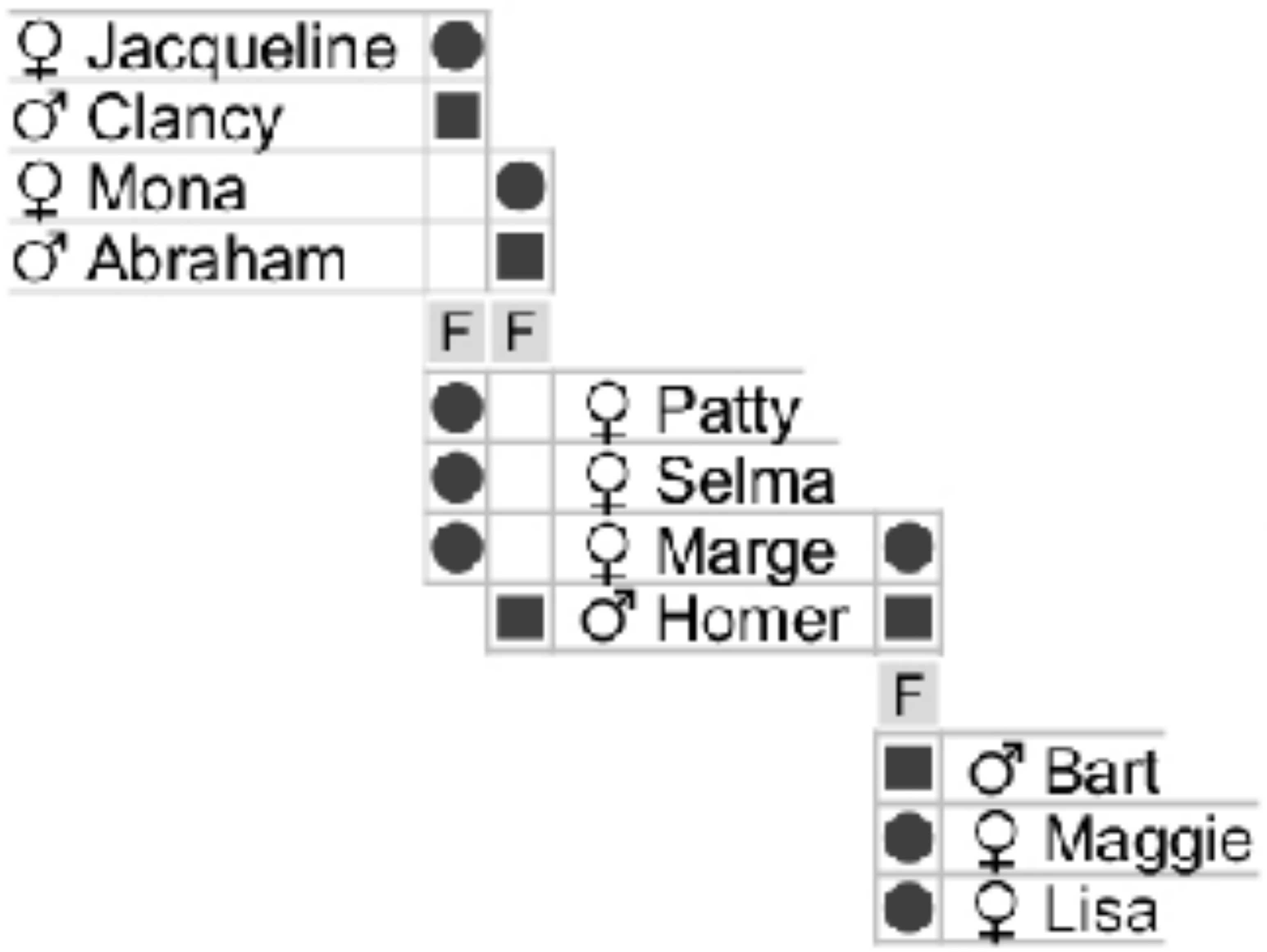
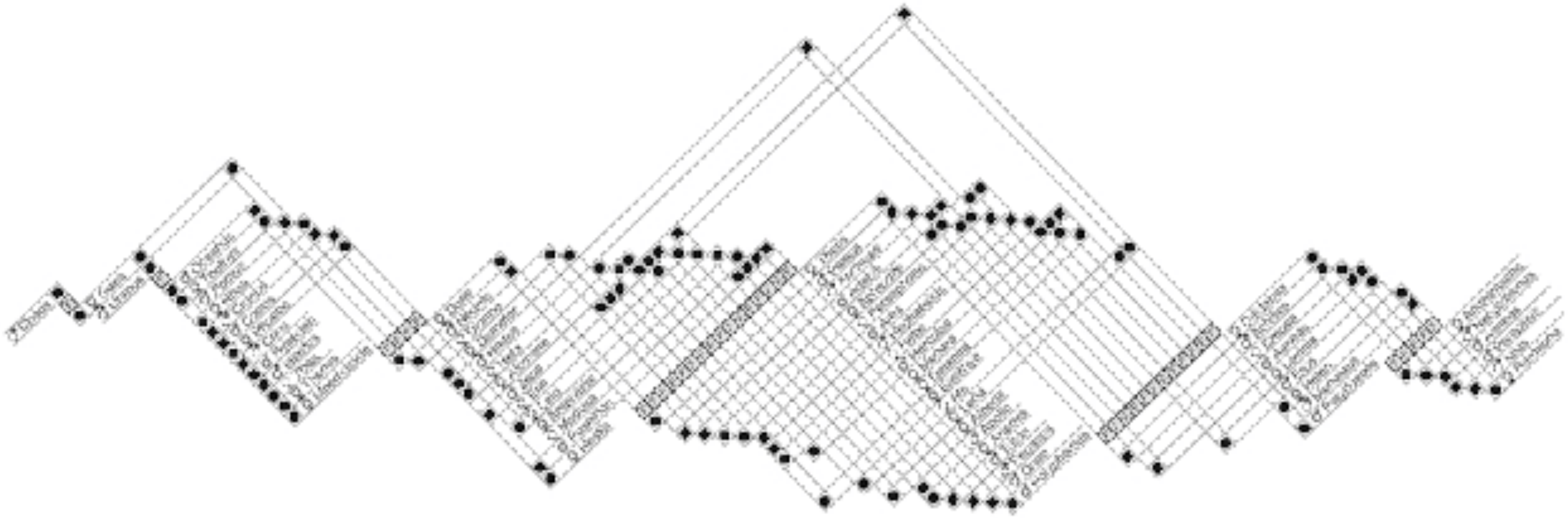






♀ Jacqueline
♂ Clancy
♀ Mona
♂ Abraham
F
F
♀ Patty
♀ Selma
♀ Marge
♂ Homer
F
♂ Bart
♀ Maggie
♀ Lisa

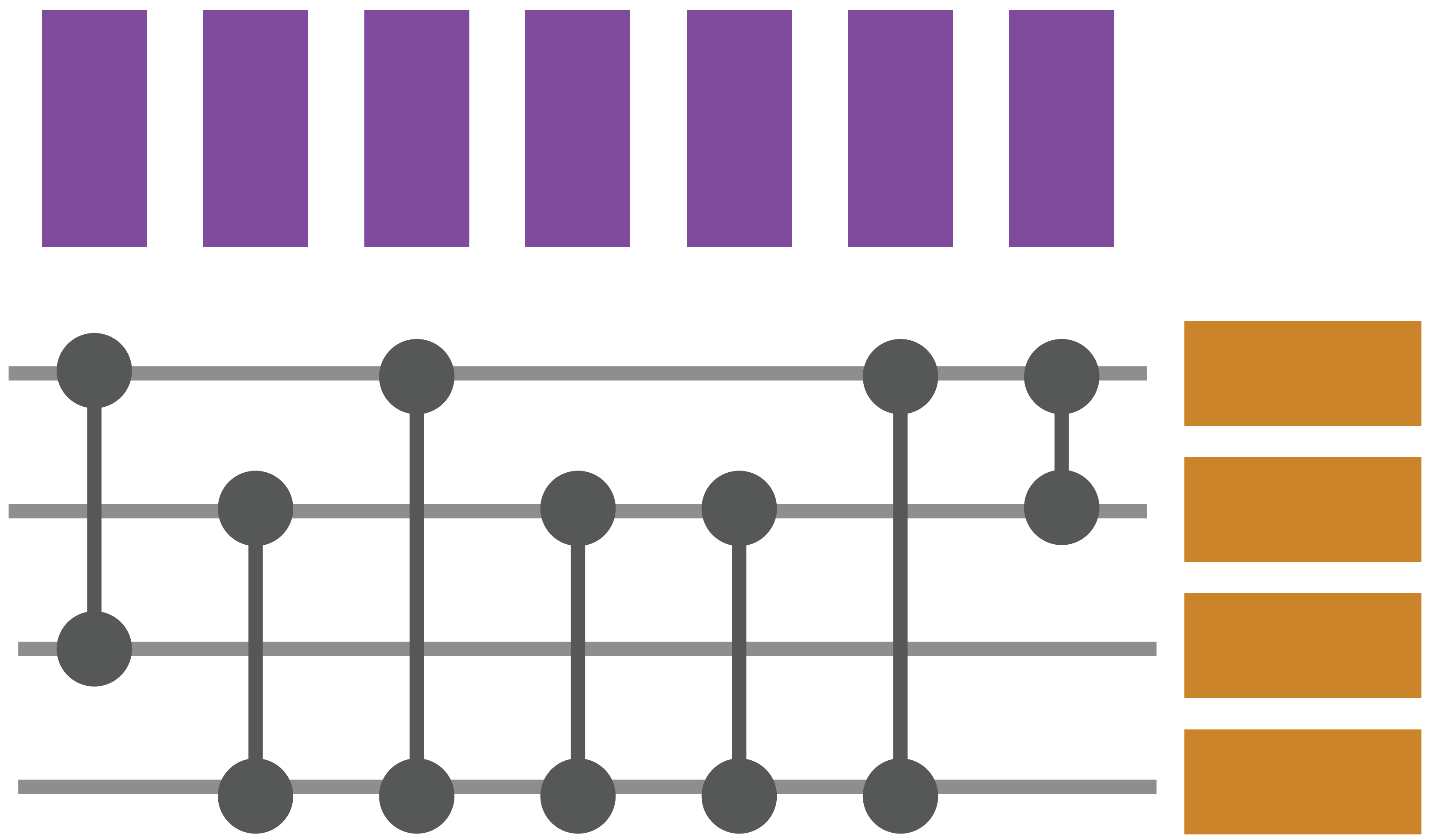


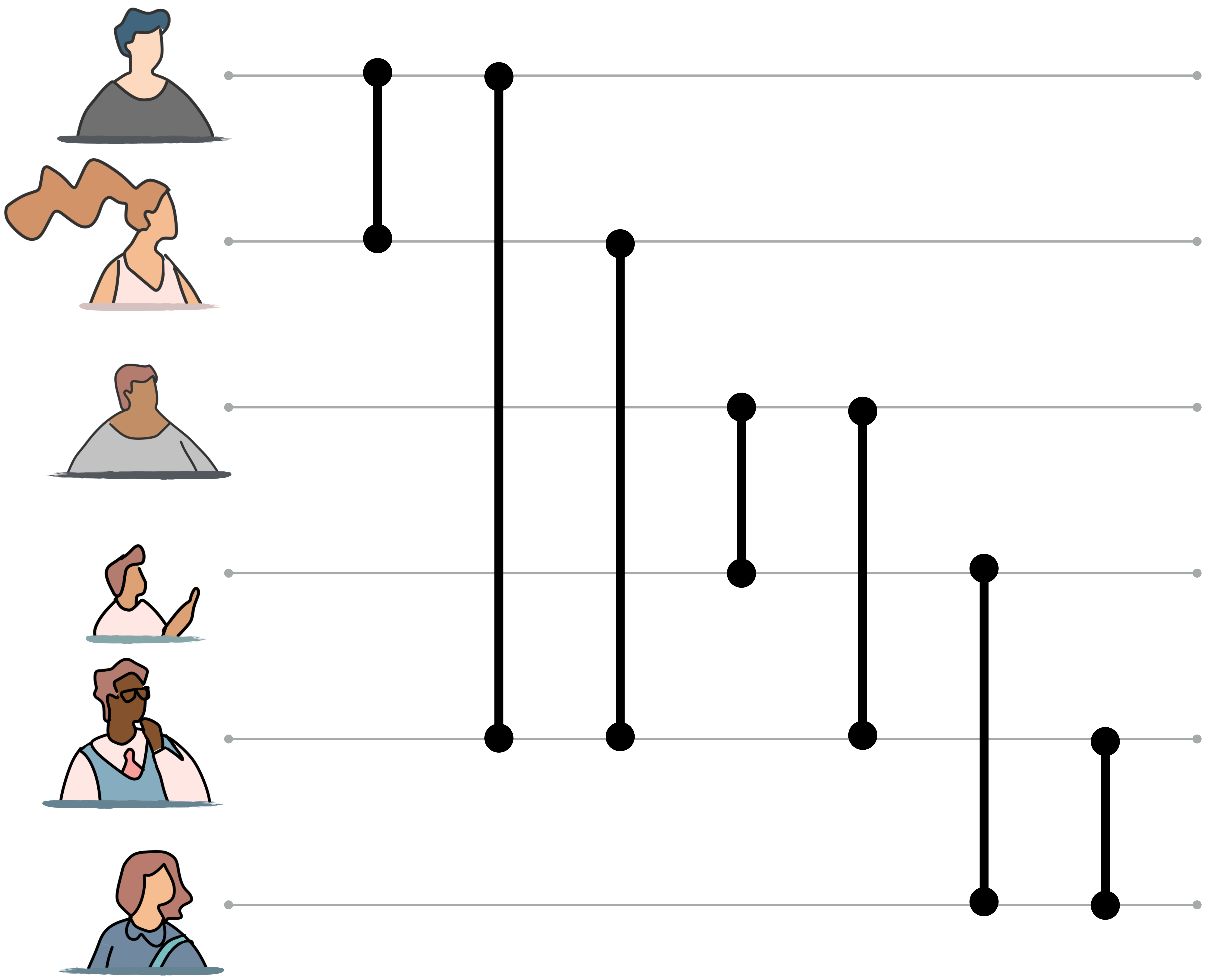
Well suited for layered networks

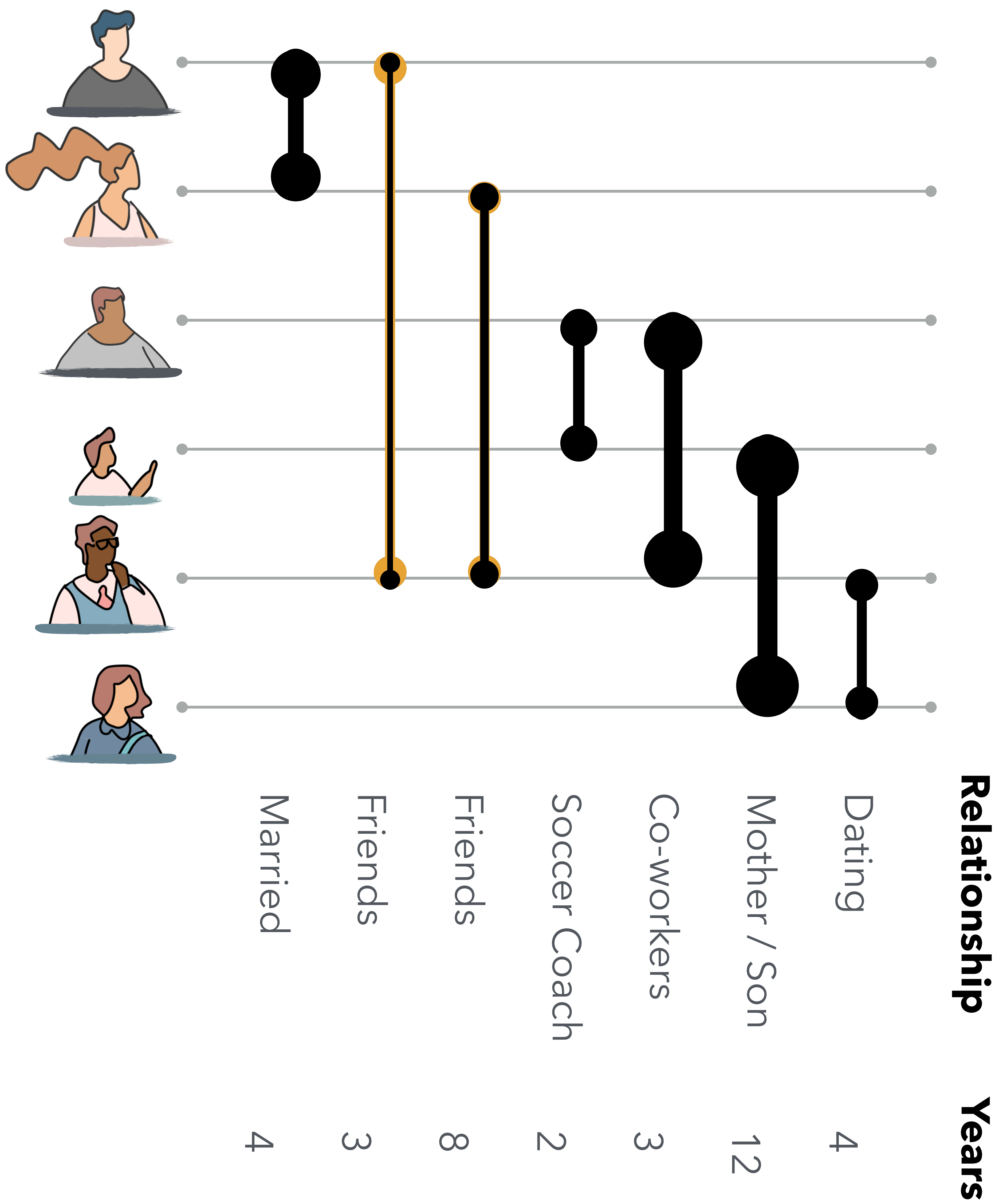
Links between nonconsecutive layers can be problematic to integrate and non-intuitive

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

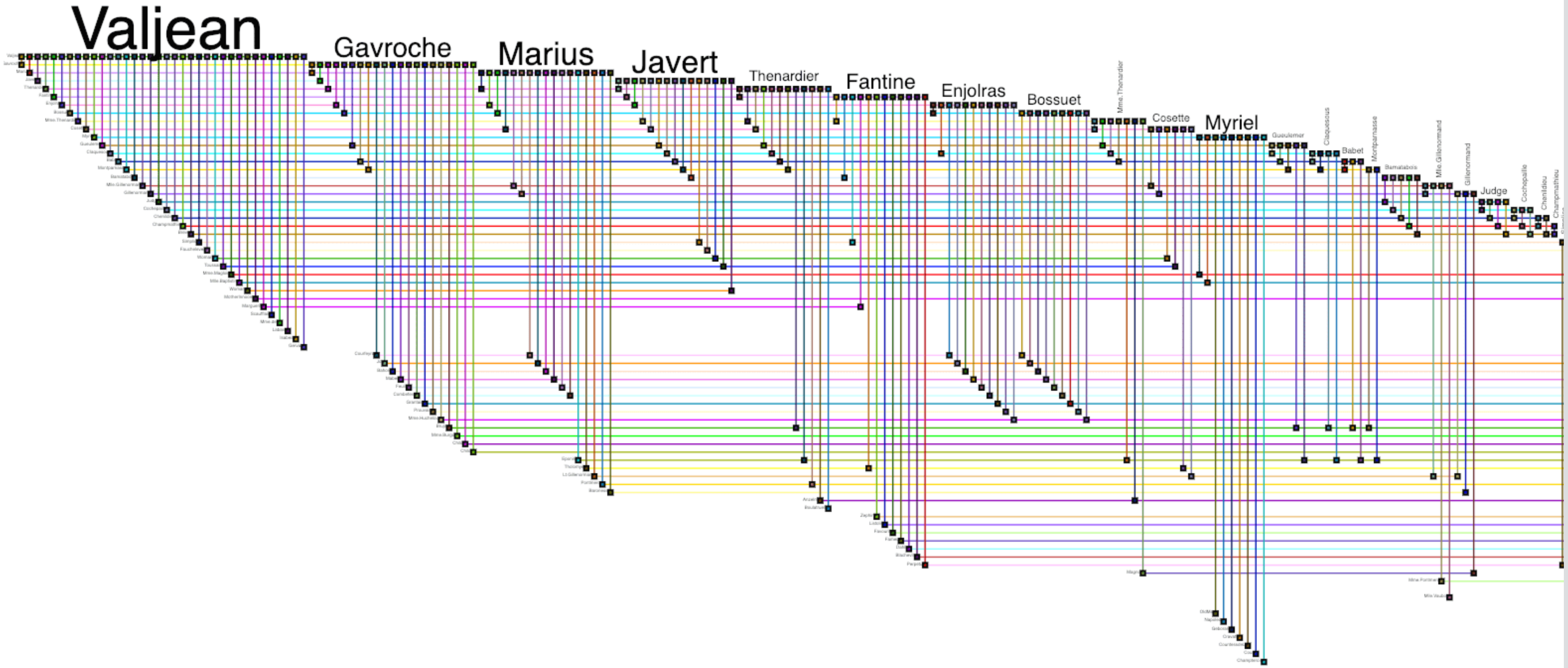
BioFabric



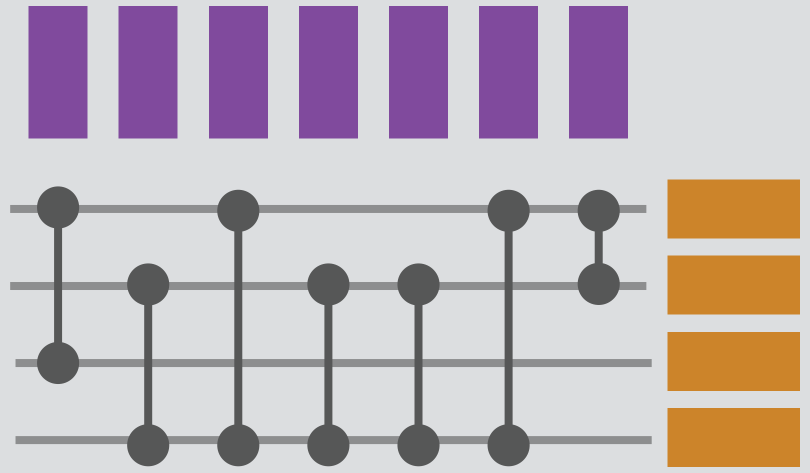




Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

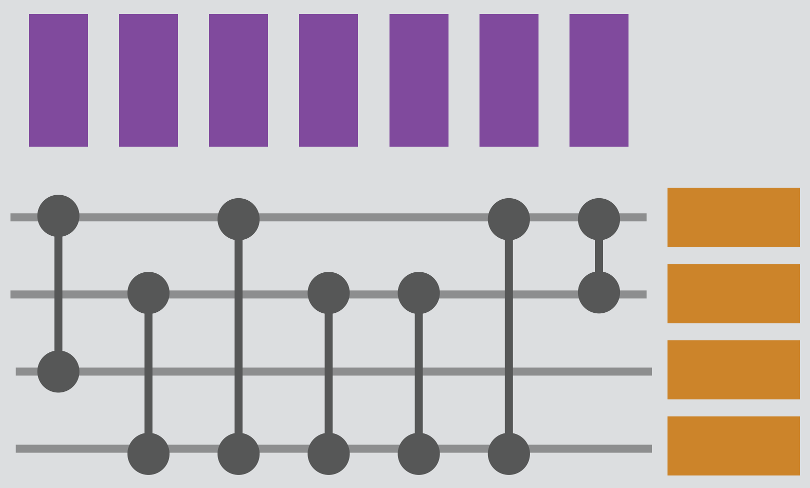


Longabaugh, 2012



BioFabric

BioFabric



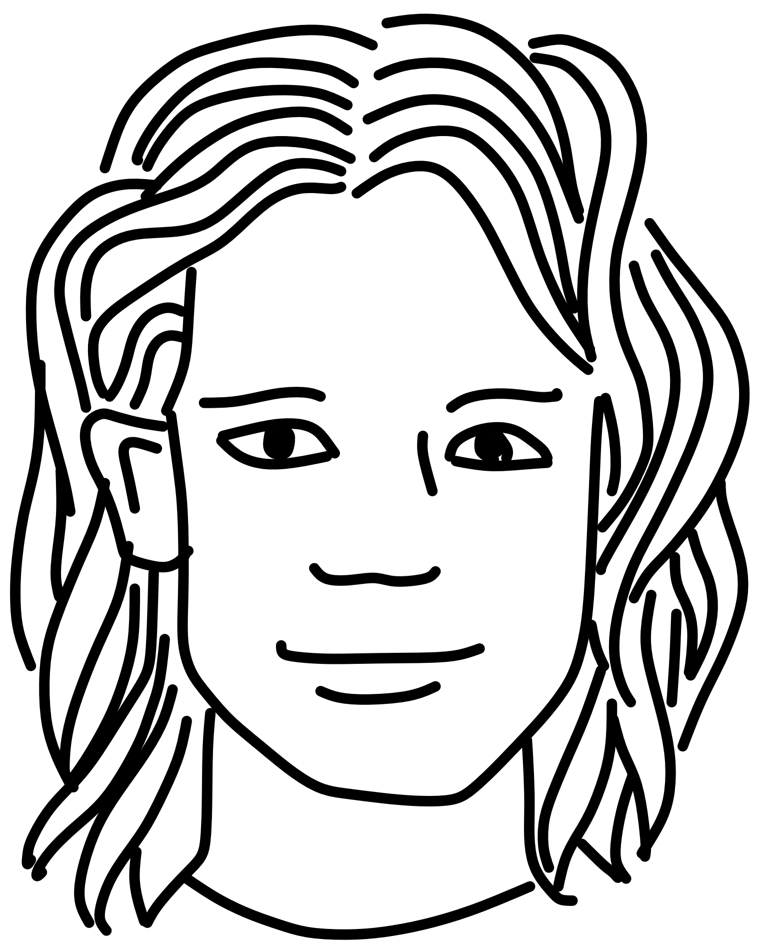
BioFabric

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

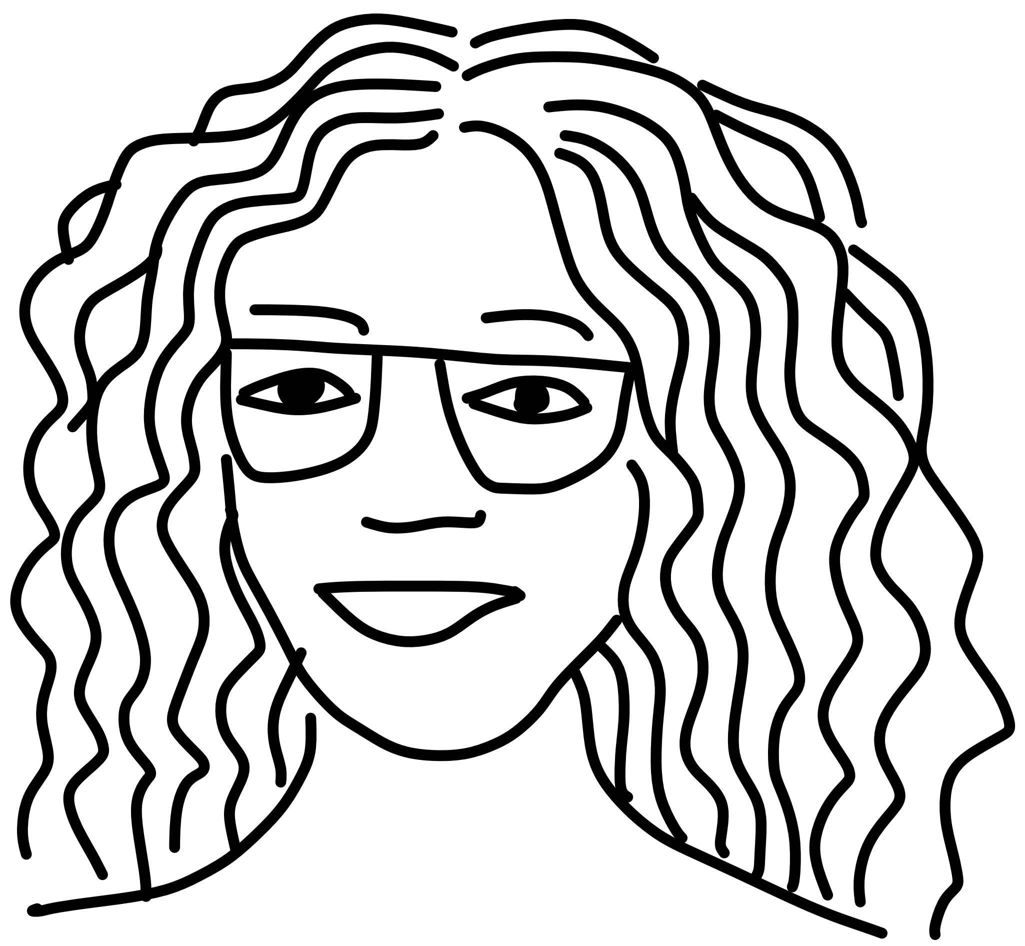
More difficult to discover neighbors and clusters in Biofabric compared to matrices.

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

Tools and Applications

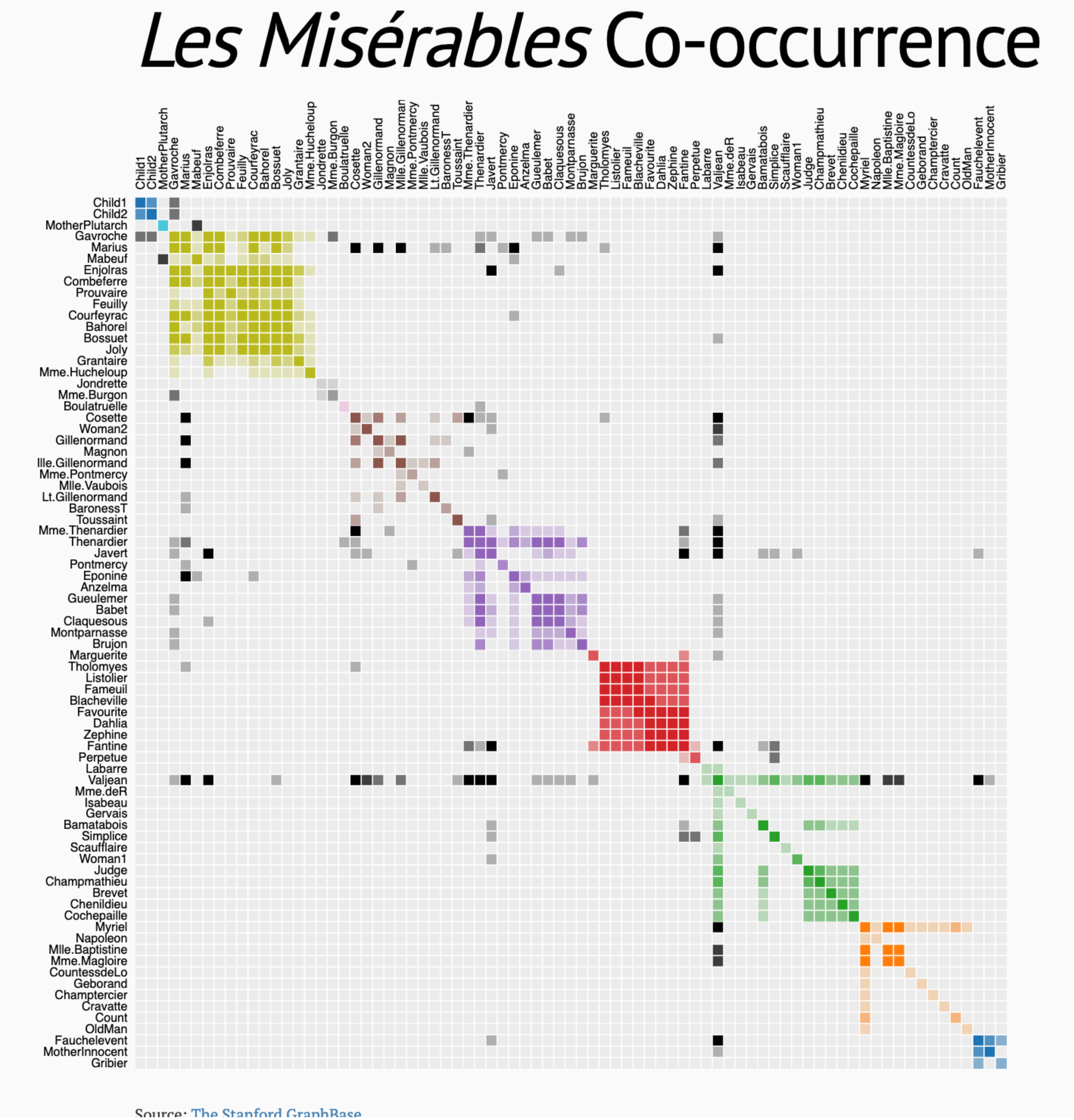


Brad
graphic designer

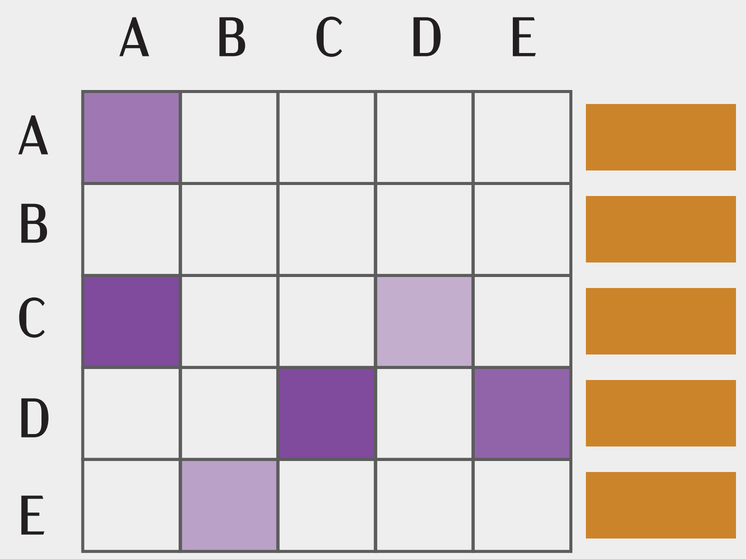


Maya
developer

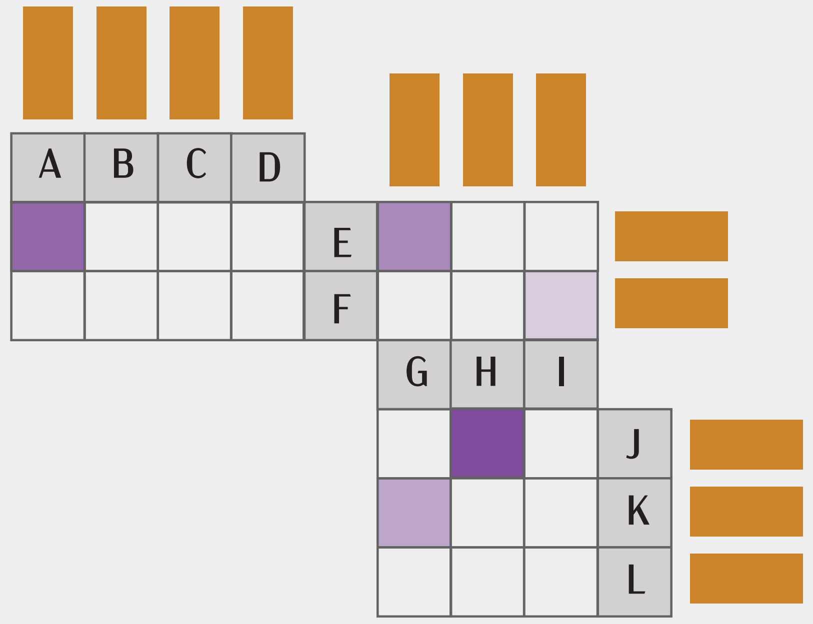
developer



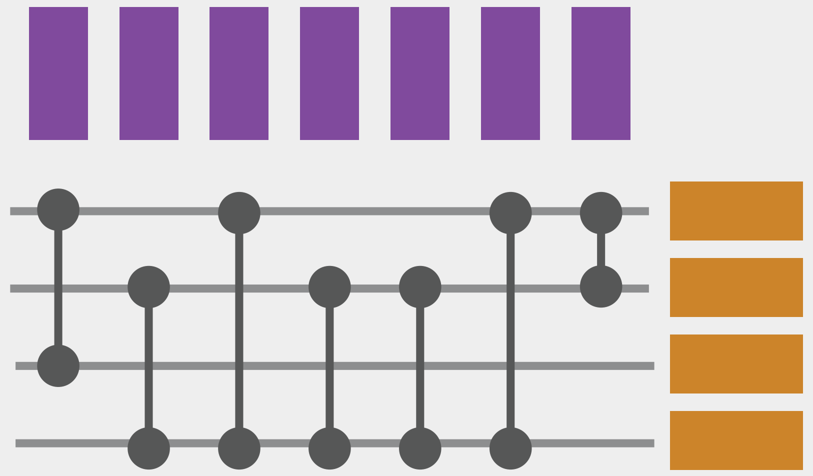
Les Misérables Co-occurrence
Child1
Child2
MotherPlutarch
Gavroche
Marius
Mabeuf
Enjolras
Combeferre
Prouvaire
Feuilly
Courfeyrac
Bahorel
Bossuet
Joly
Grantaire
Mme.Hucheloup
Jondrette
Mme.Burgon
Boulatruelle
Cosette
Woman2
Gillenormand
Magnon
Mlle.Gillenormand
Mme.Pontmercy
Mlle.Vaubois
Lt.Gillenormand
BaronessT
Toussaint
Mme.Thenardier
Thenardier
Javert
Pontmercy
Eponine
Anzelma
Gueulemer
Babet
Claquesous
Montparnasse
Brujon
Marguerite
Tholomyes
Listolier
Fameuil
Blacheville
Favourite
Dahlia
Zephine
Fantine
Perpetue
Labarre
Valjean
Mme.deR
Isabeau
Gervais
Bamatabois
Simplice
Scaufflaire
Woman1
Judge
Champmathieu
Brevet
Chenildieu
Cochepaille
Myriel
Napoleon
Mlle.Baptistine
Mme.Magloire
CountessdeLo
Geborand
Champtercier
Cravatte
Count
OldMan
Fauchelevent
MotherInnocent
Gribier
Source: The Stanford GraphBase



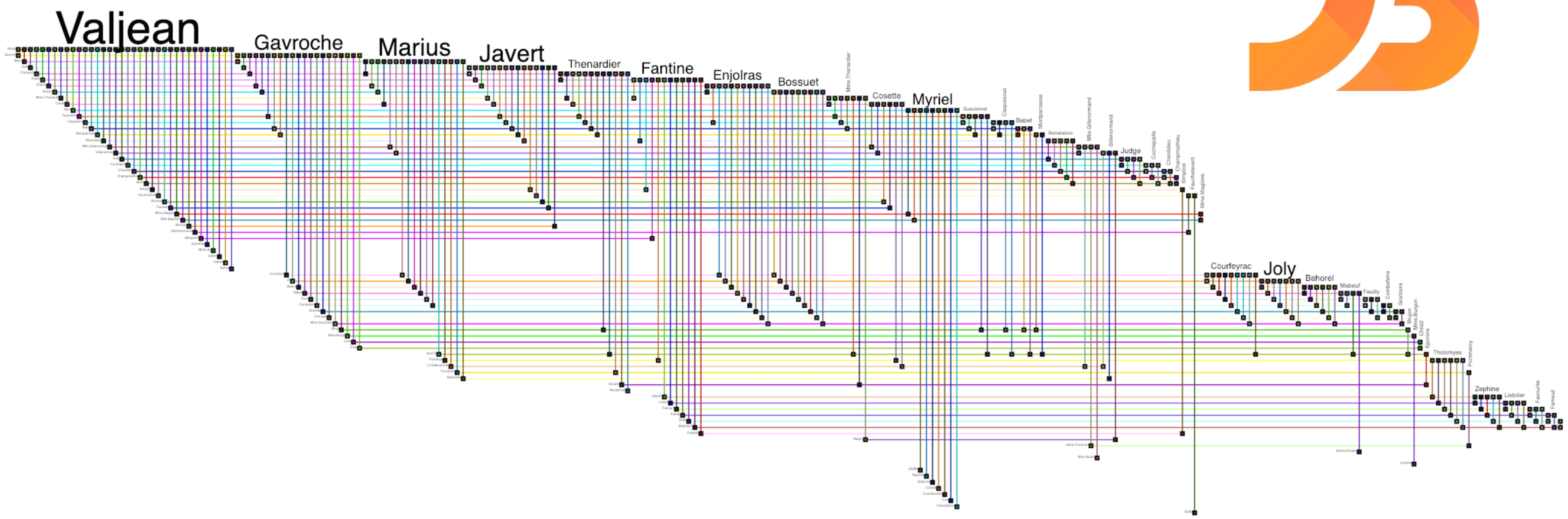
A B C D E
A
B
C
D
E



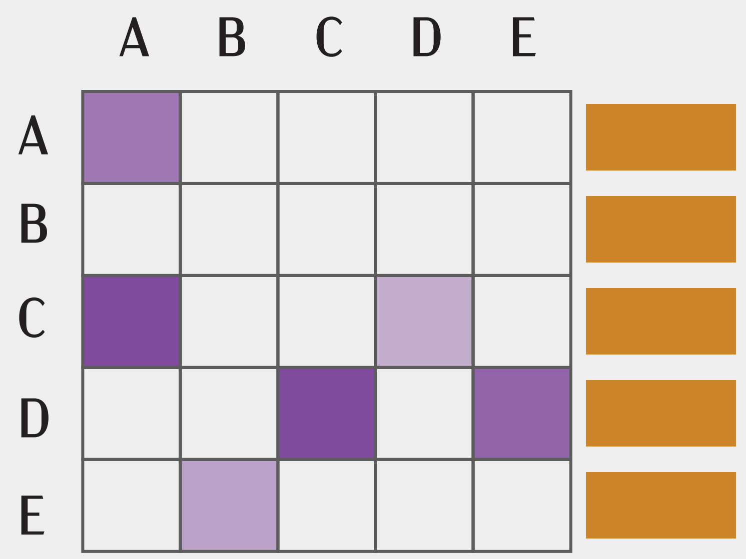
A B C D
E
F
G H I
J
K
L

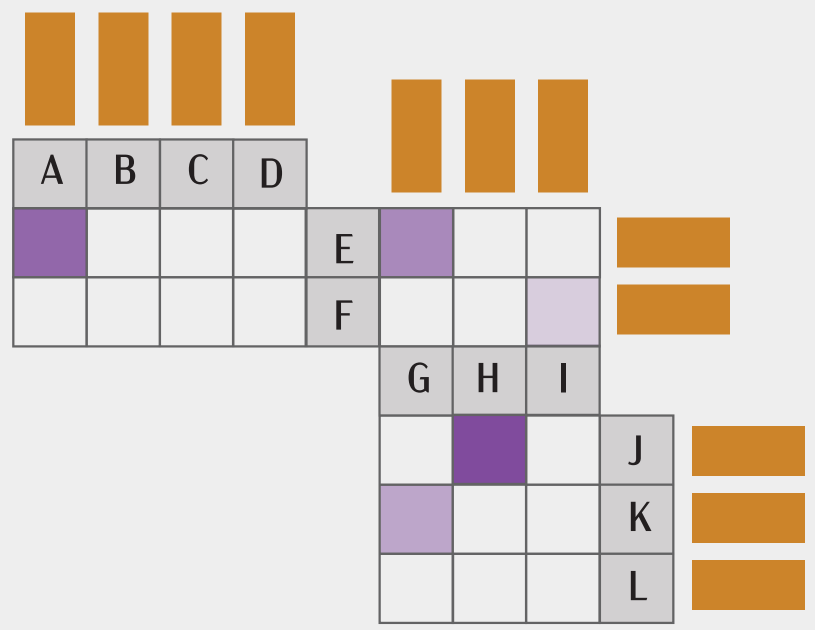


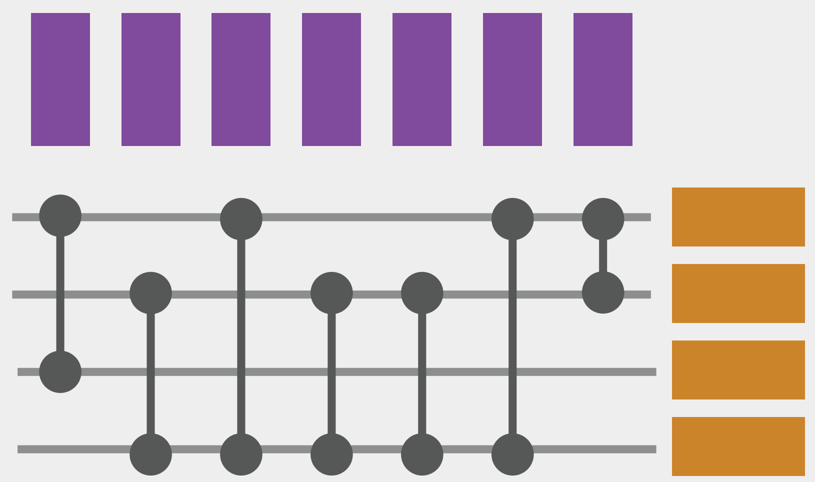
developer

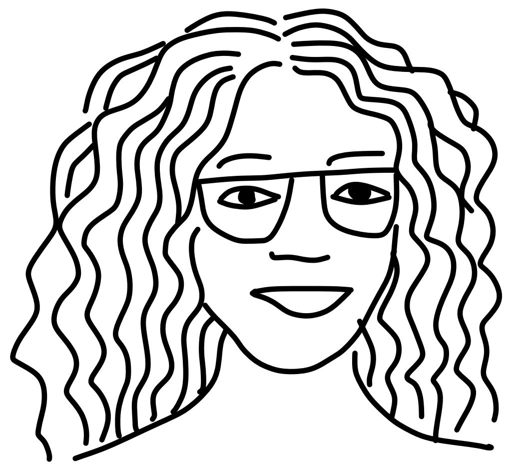


http://www.biofabric.org



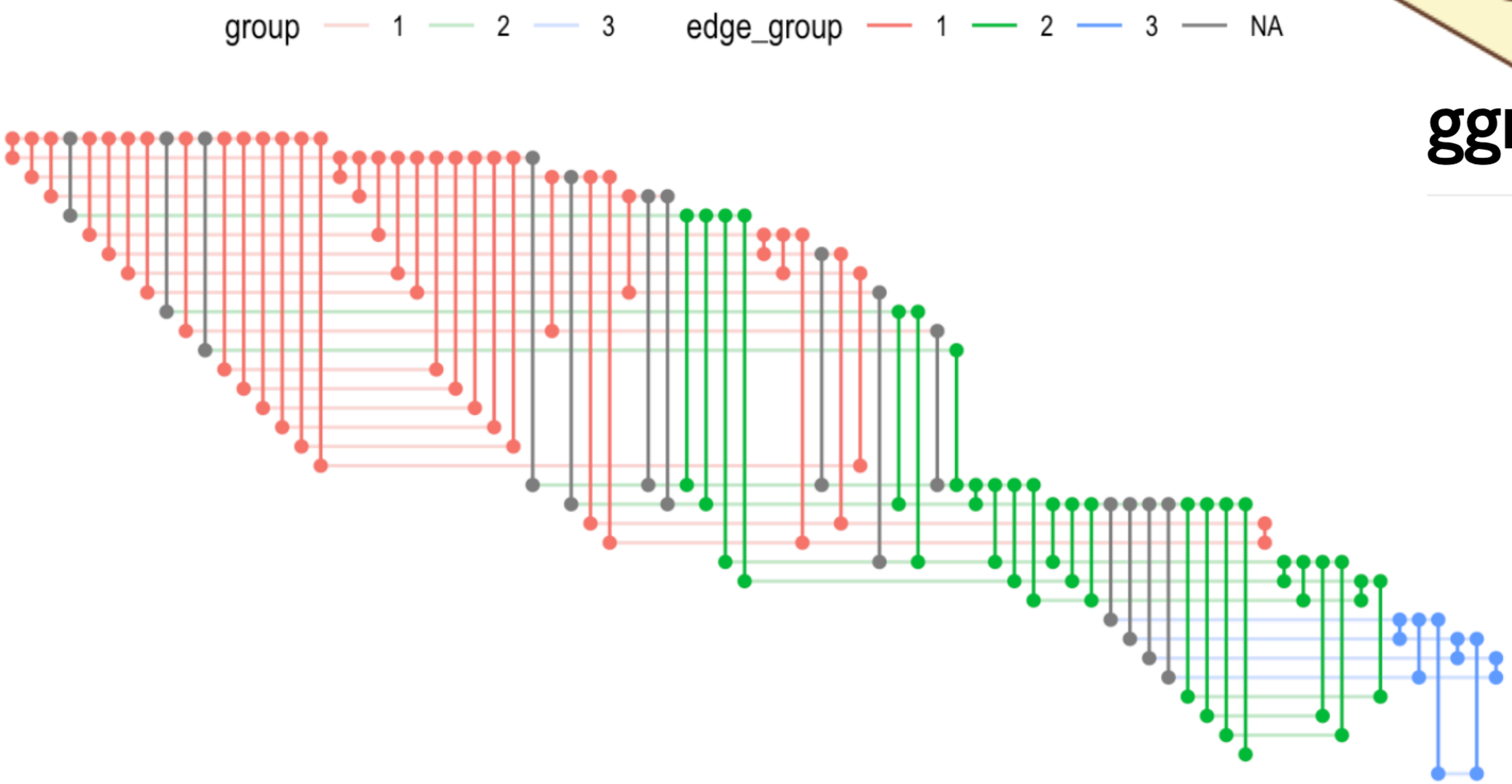


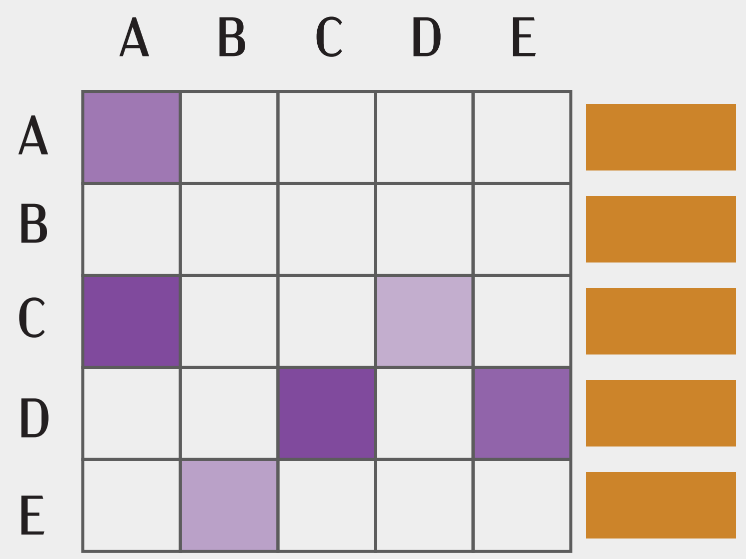


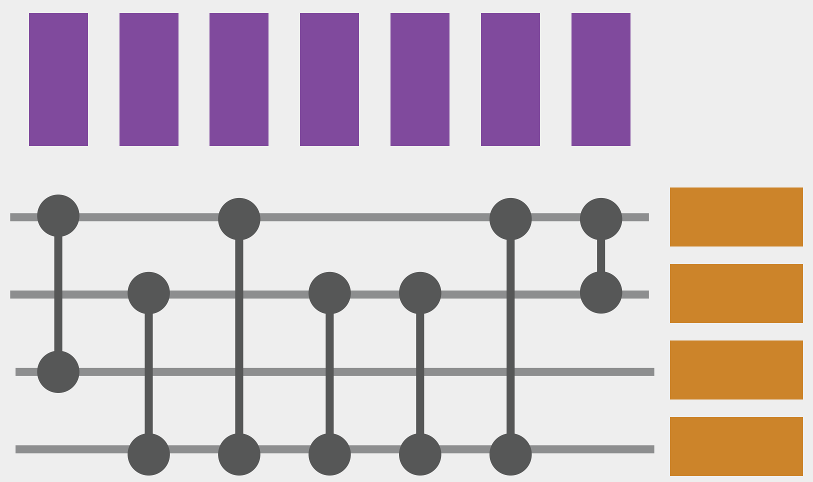


developer

ggraph

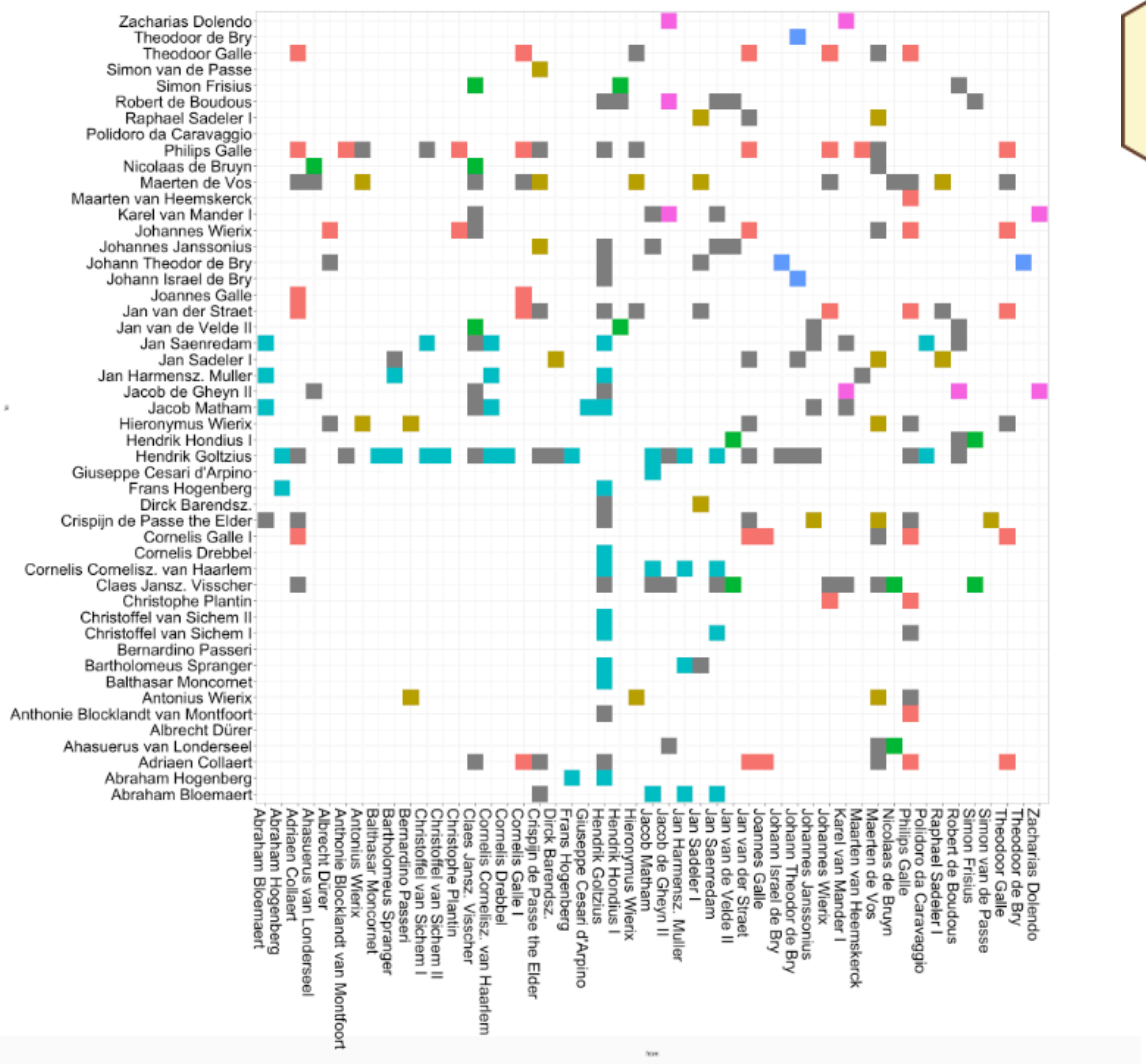




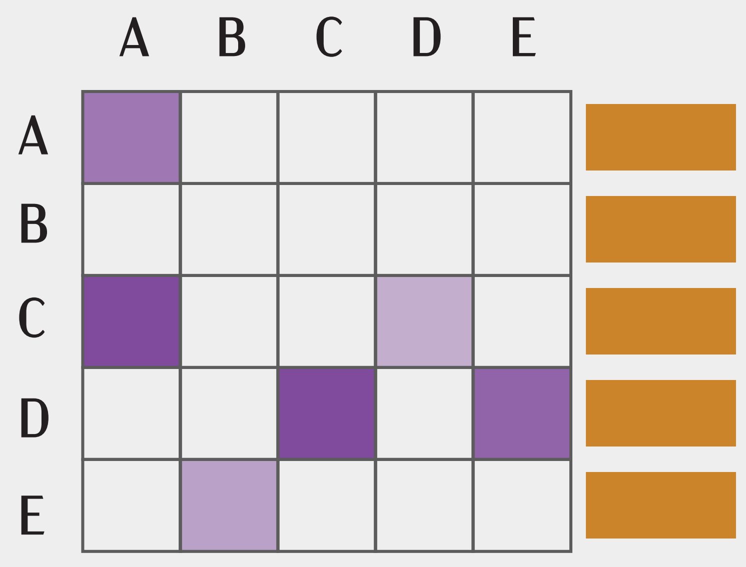


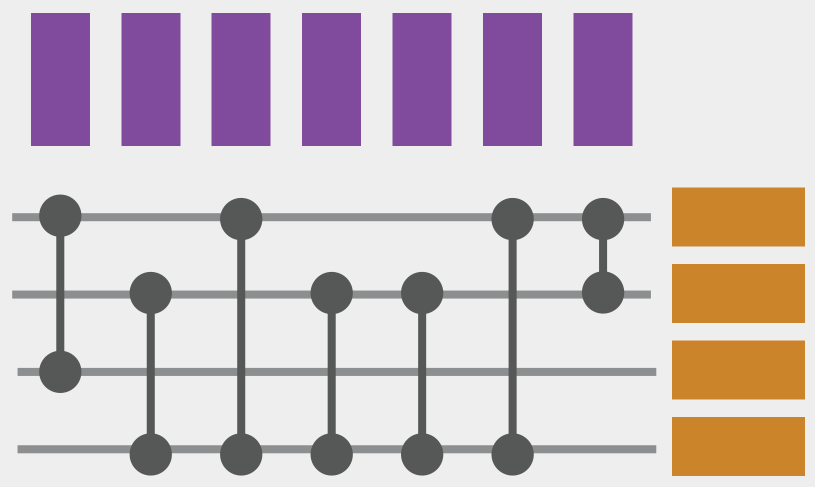
http://www.biofabric.org

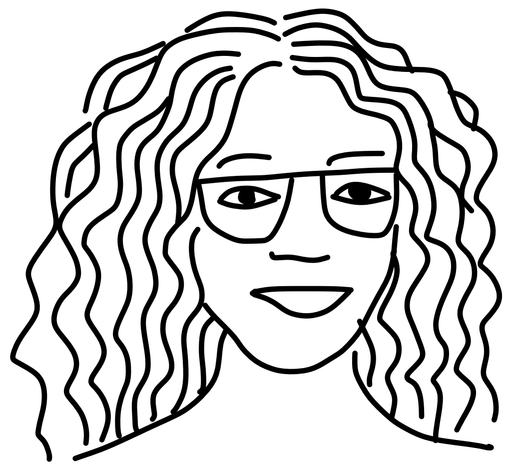
develope



ggraph



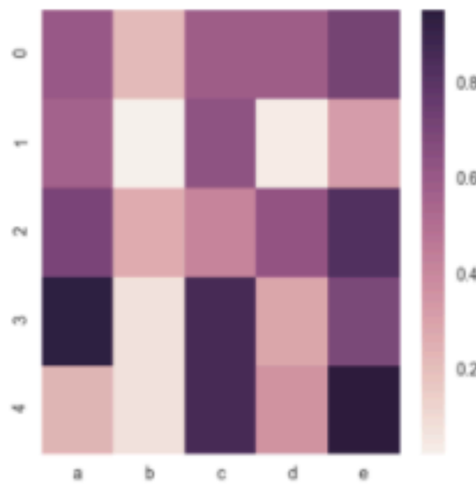




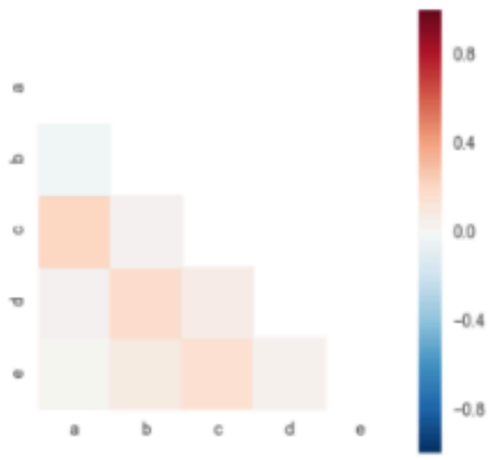
developer

python

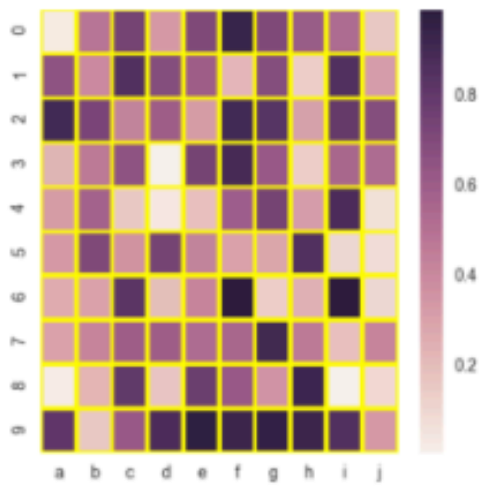
matplotlib



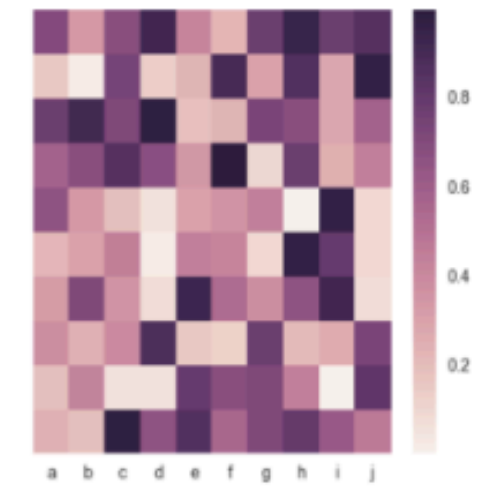
#90 Input format for heatmap



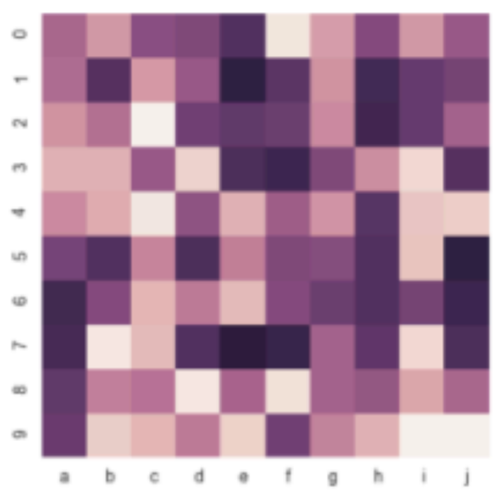
#90 Half heatmap



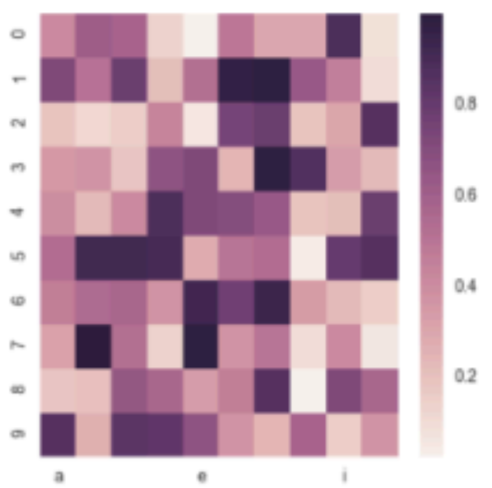
#91 Custom seaborn heatmap



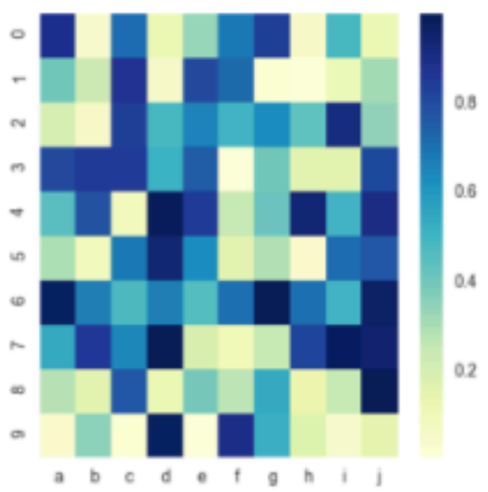
#91 Custom seaborn heatmap



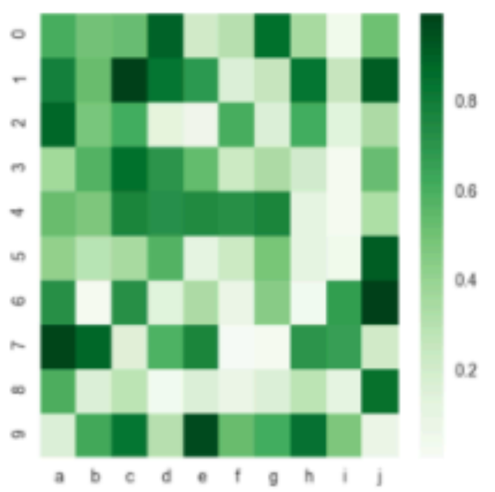
#91 Custom seaborn heatmap



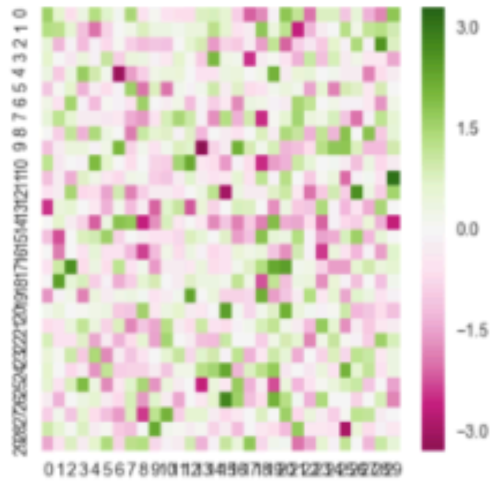
#91 Custom seaborn heatmap



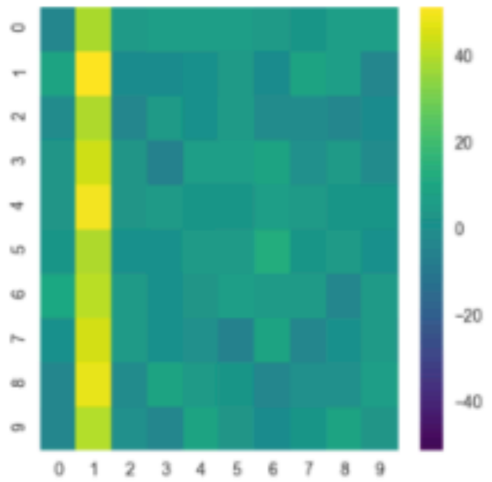
#92 Control heatmap color



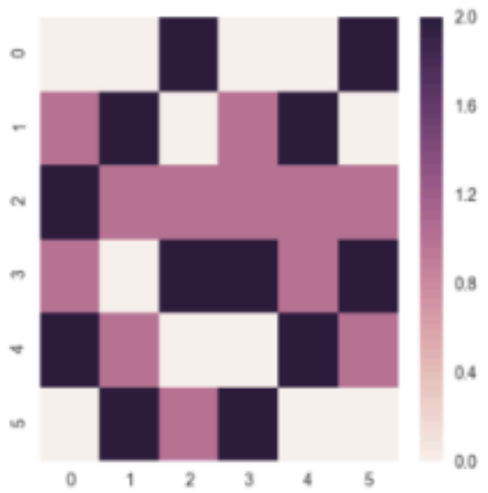
#92 Control heatmap color



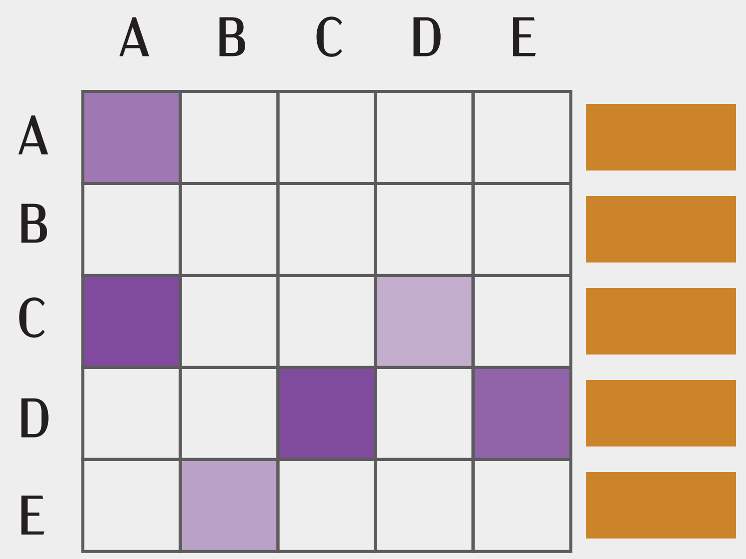
#92 Control heatmap color

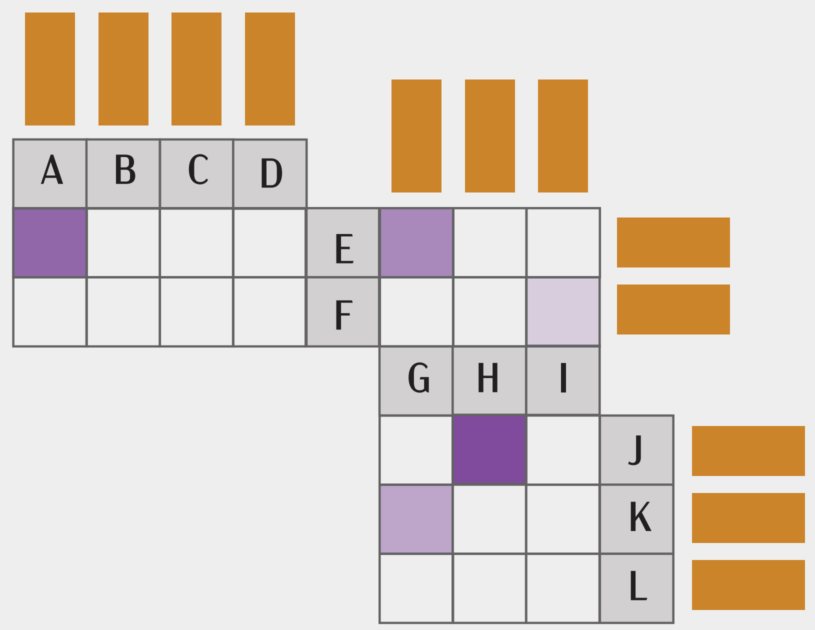


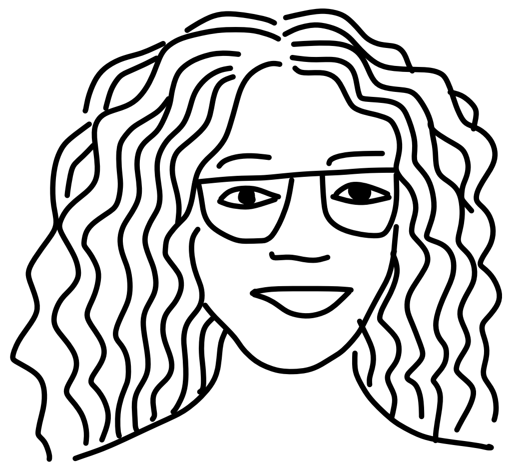
#94 Column normalization on heatmap



#92 Turn your data categorical for heatmap

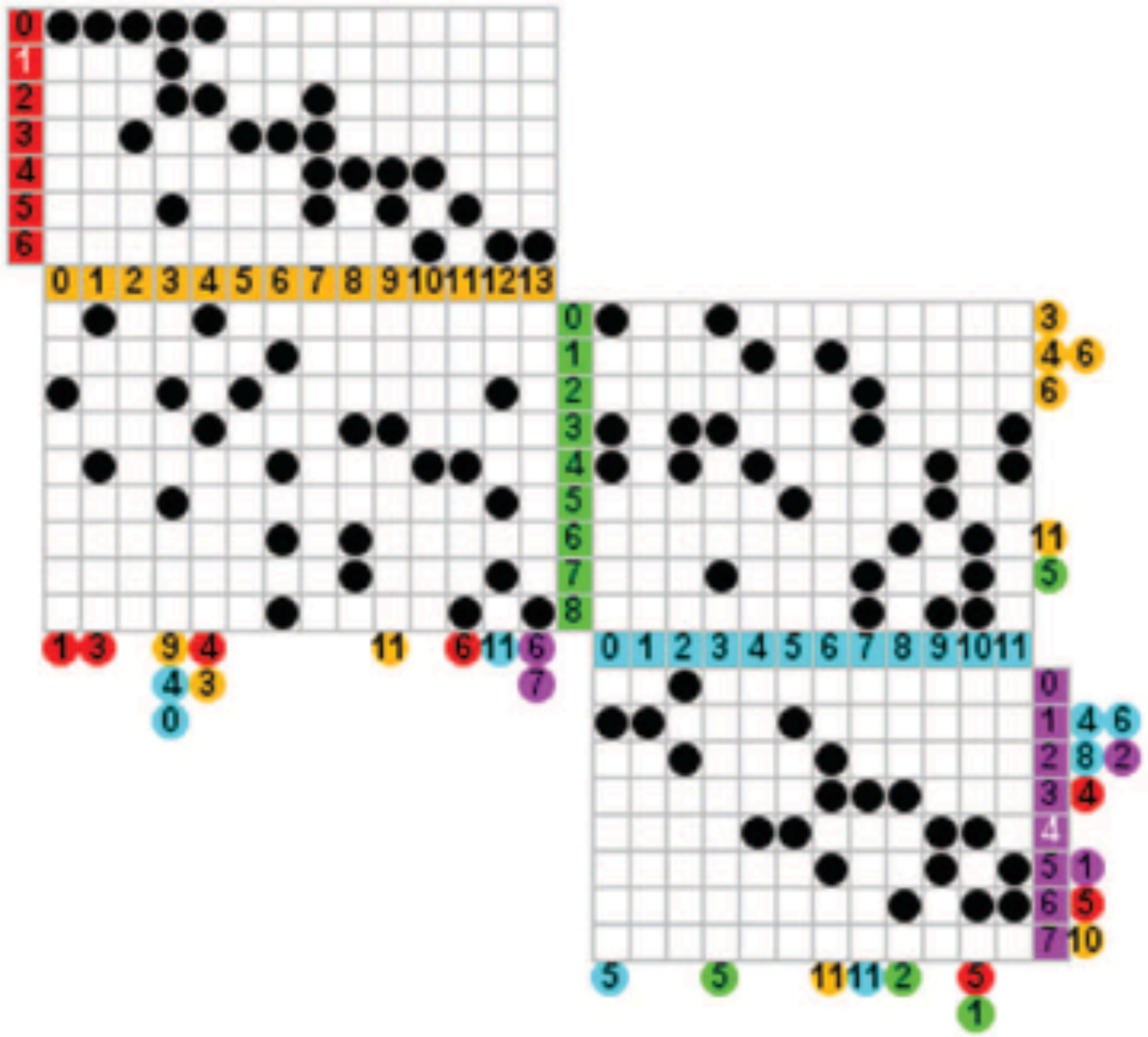


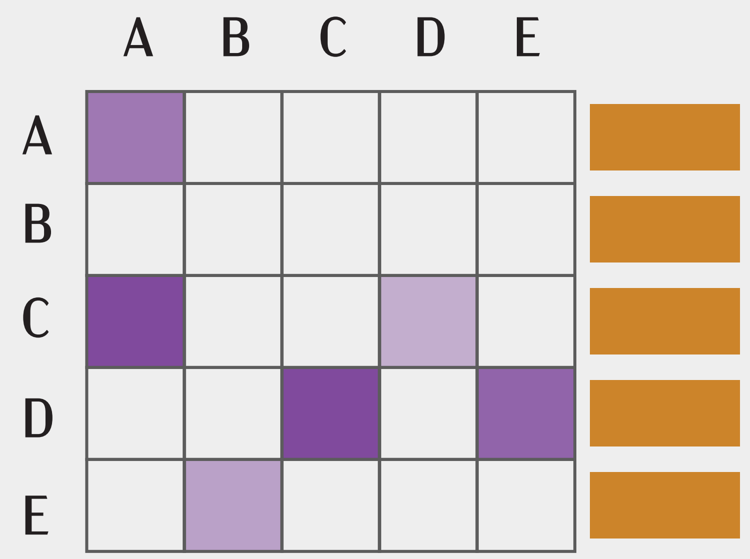


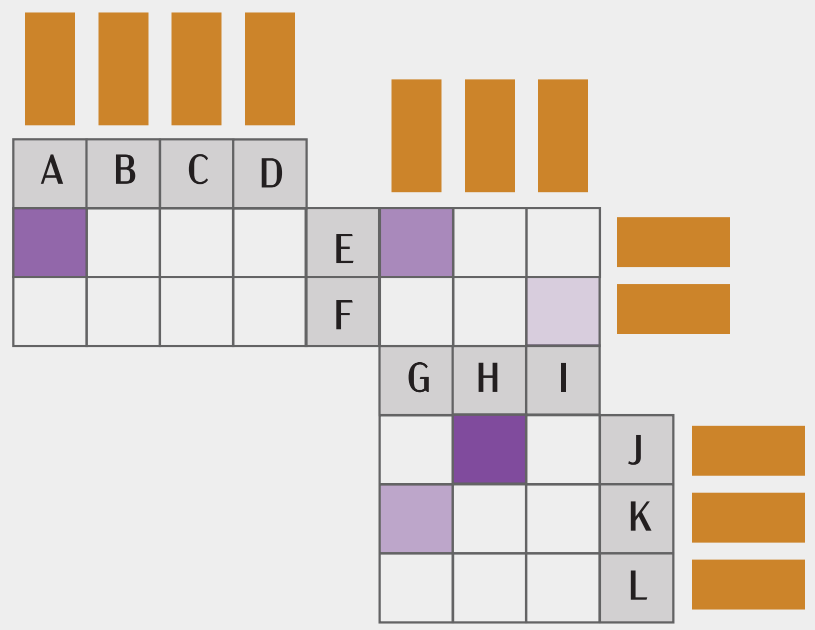


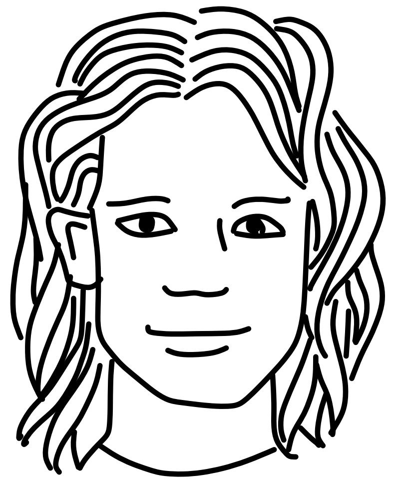
developer

python



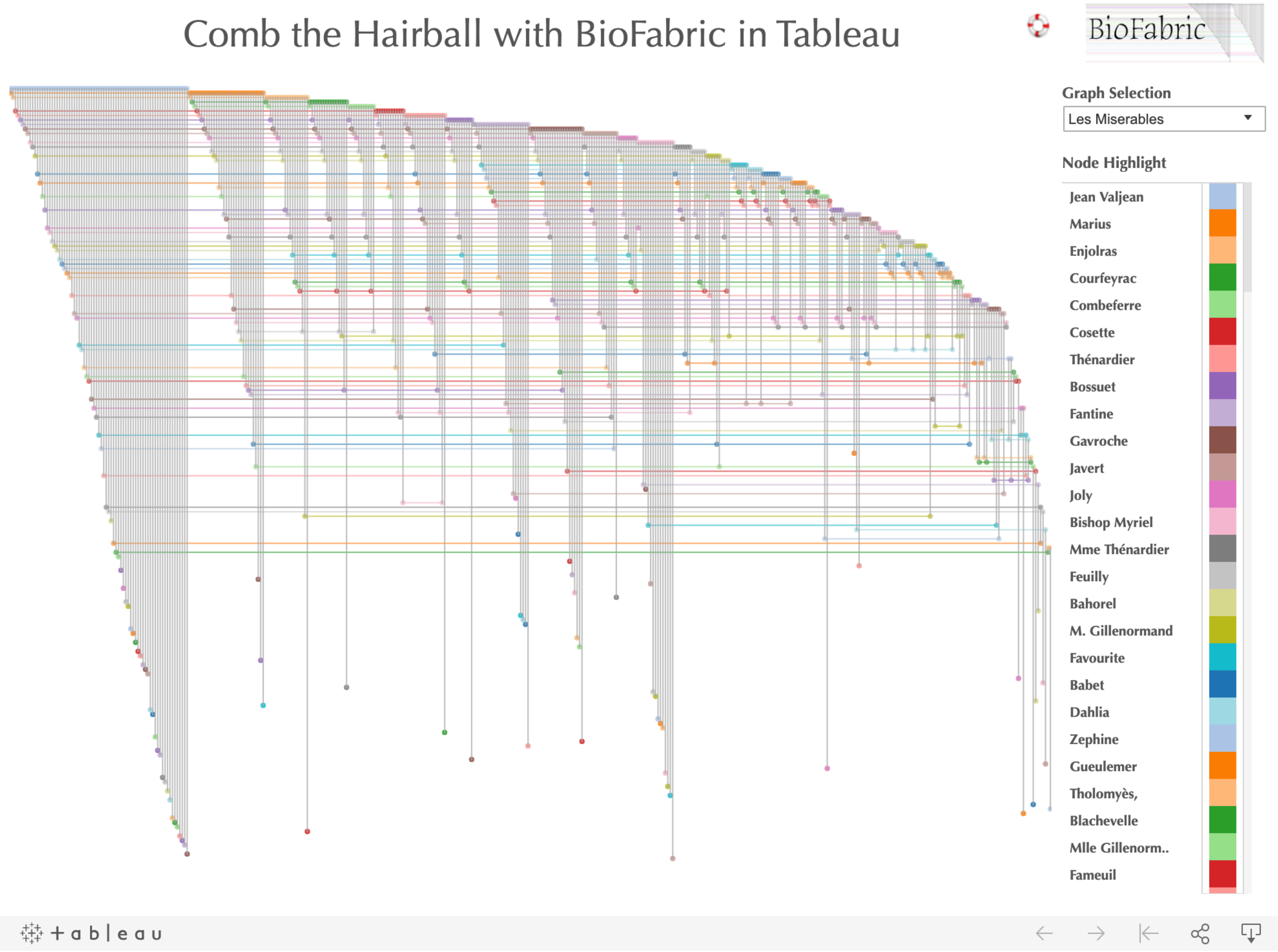


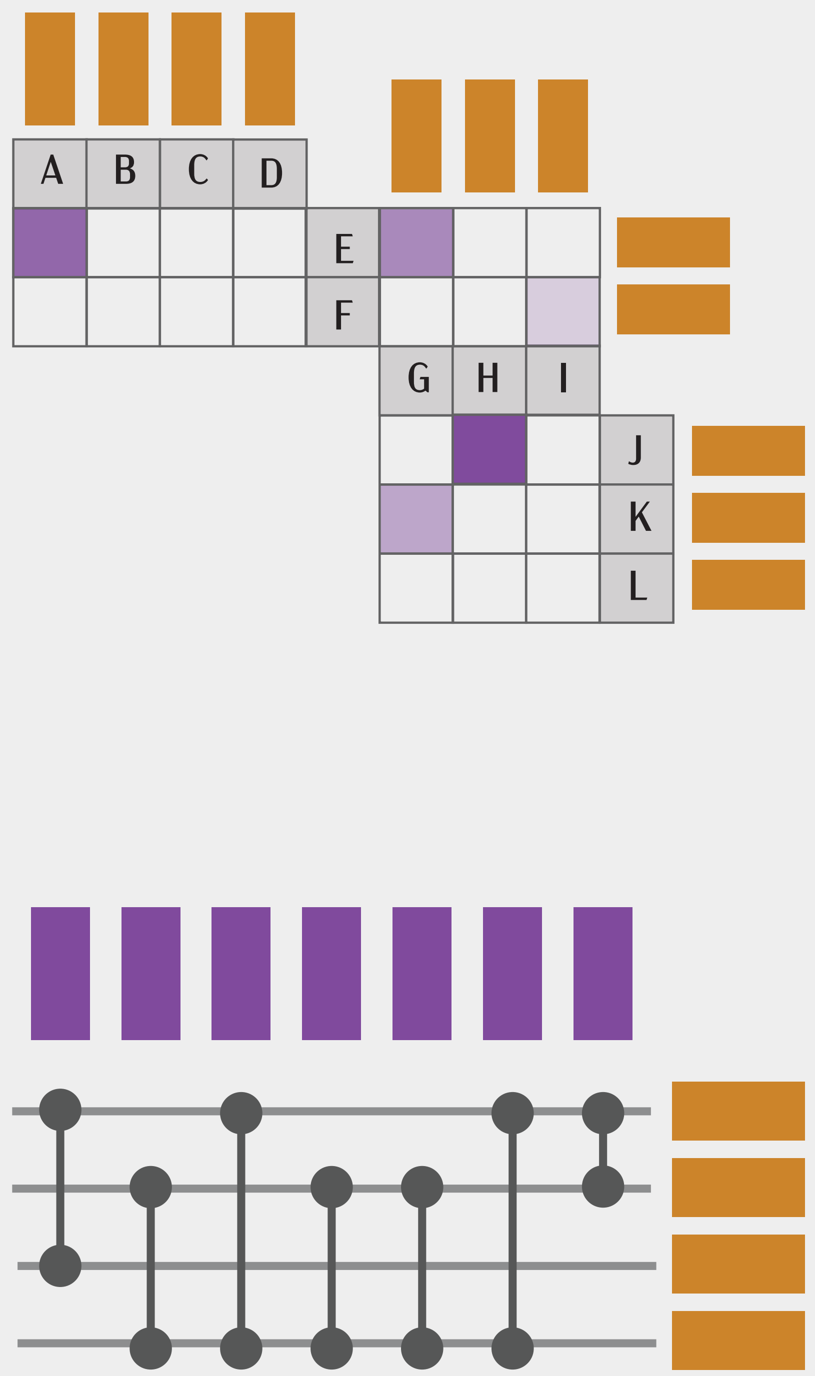


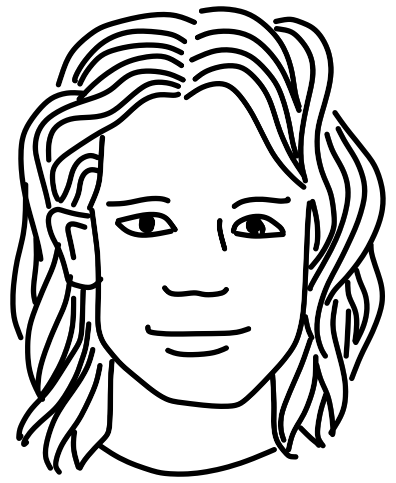


graphic designer

Comb the Hairball with BioFabric in Tableau

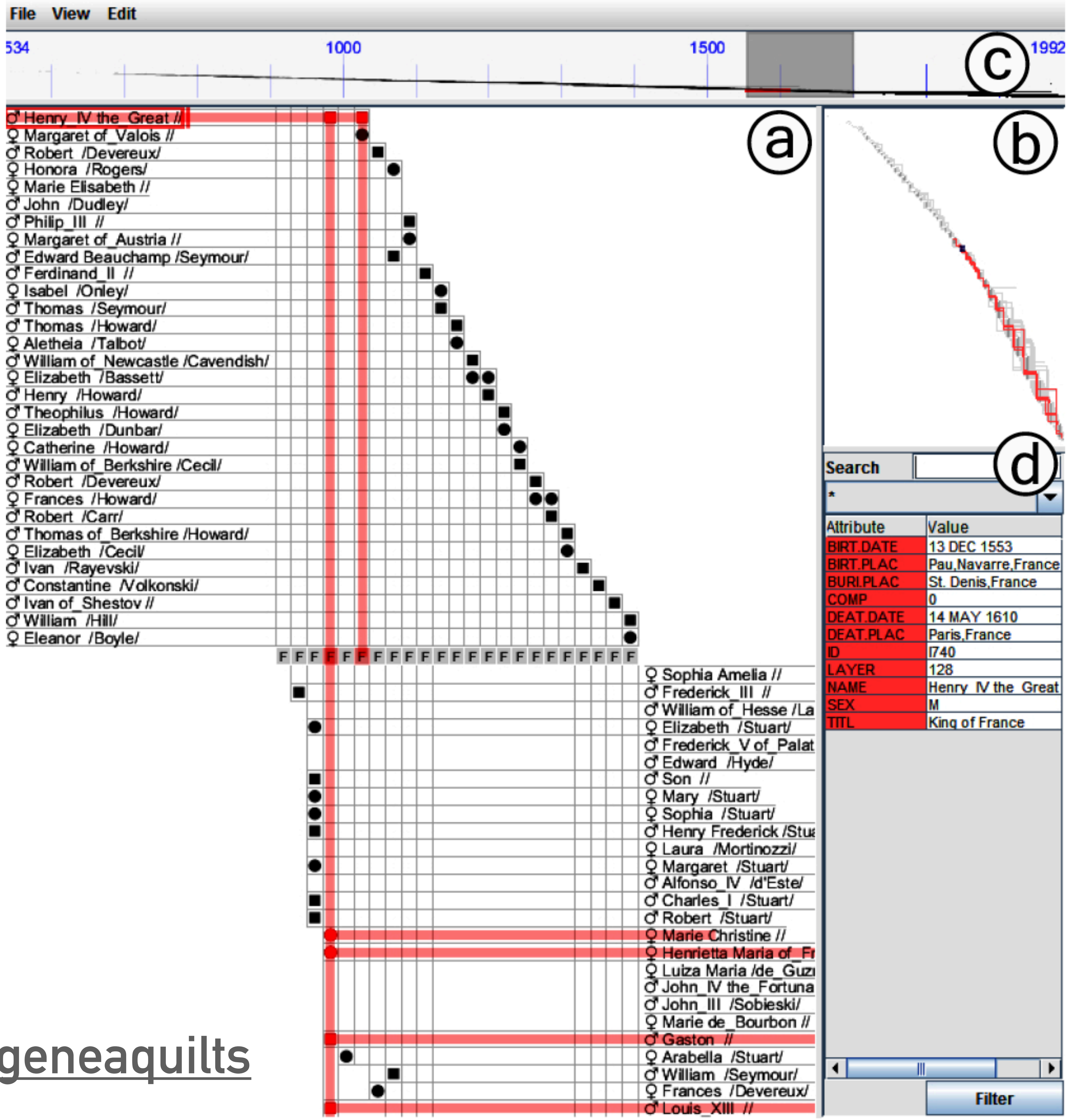




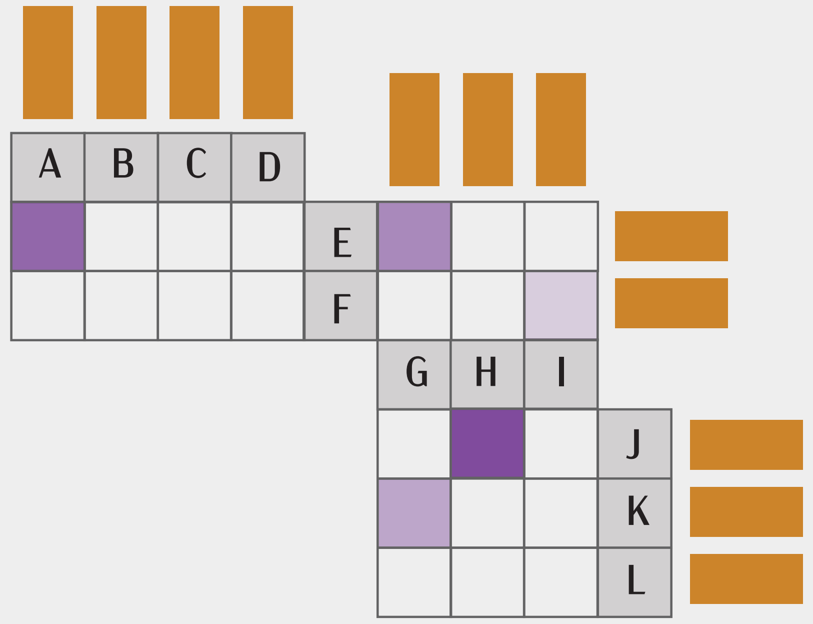


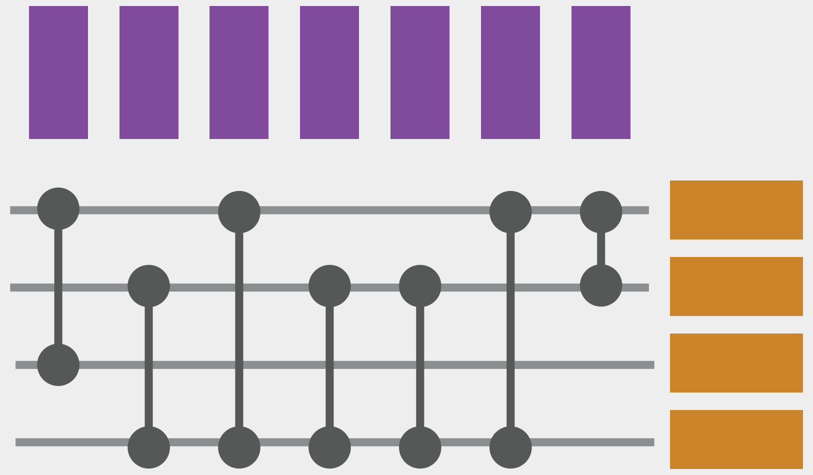
graphic
designer

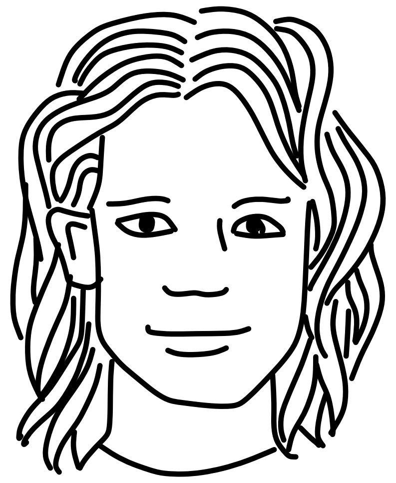
Genea Quilts



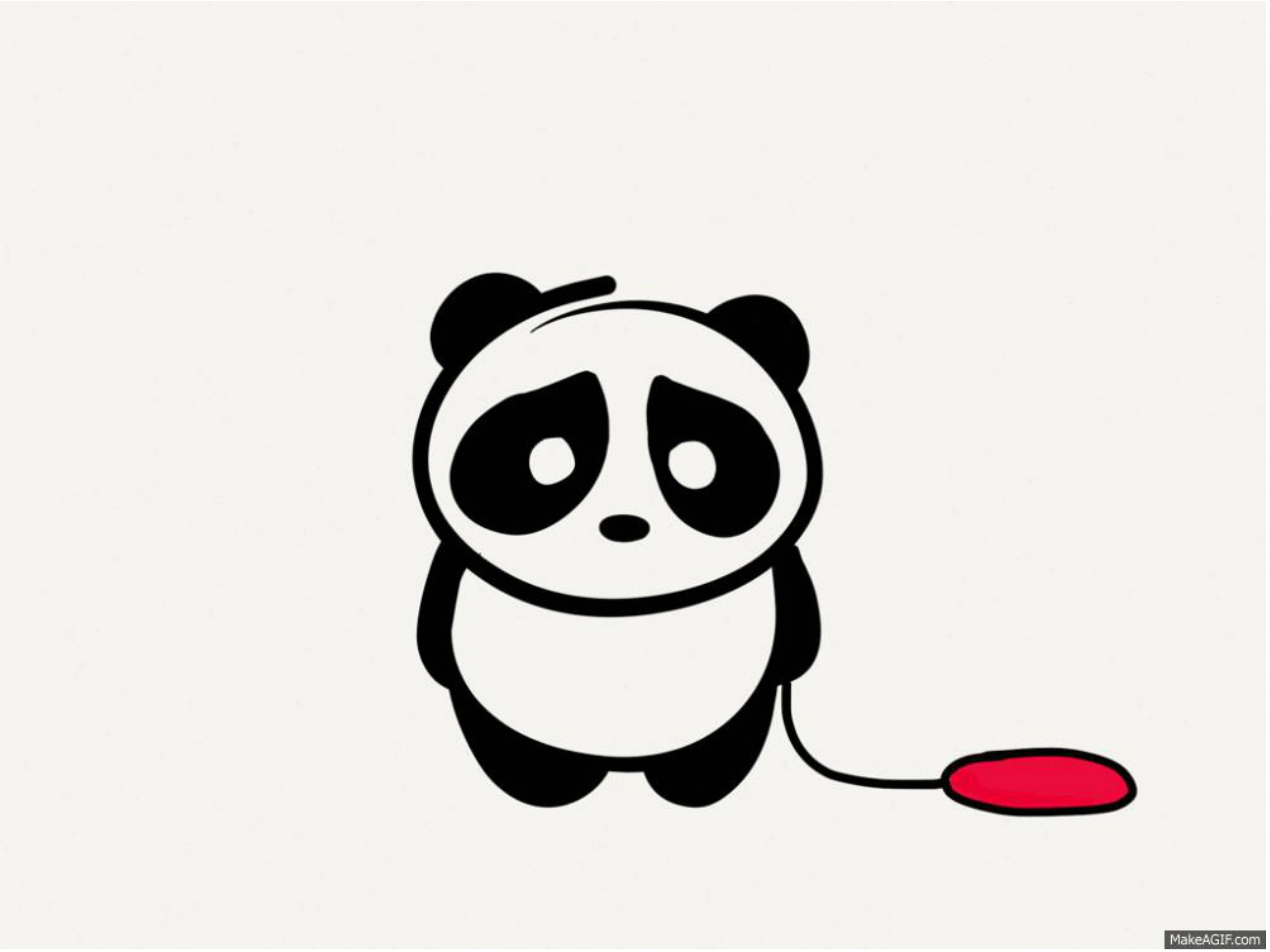
https://aviz.fr/geneaquilts

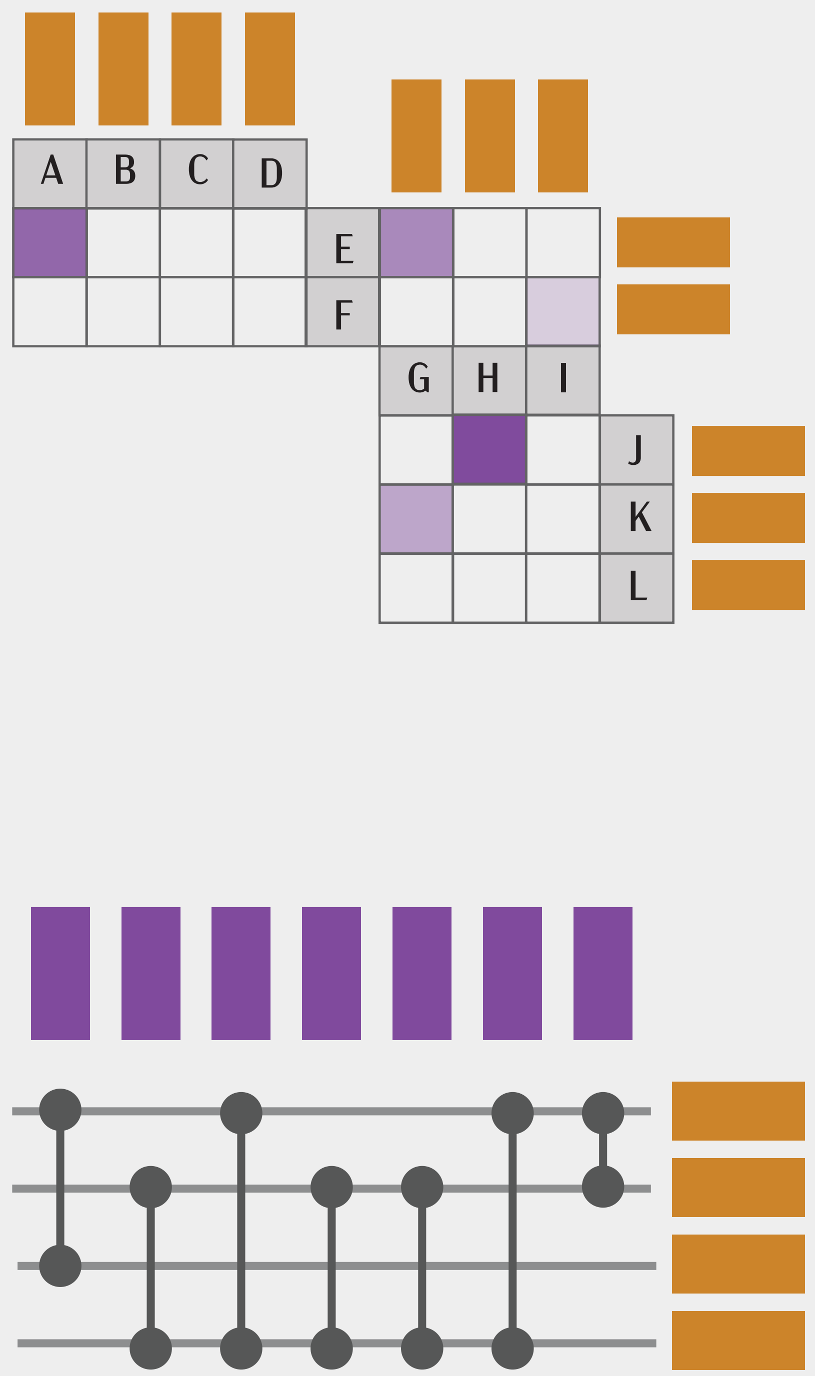






graphic
designer

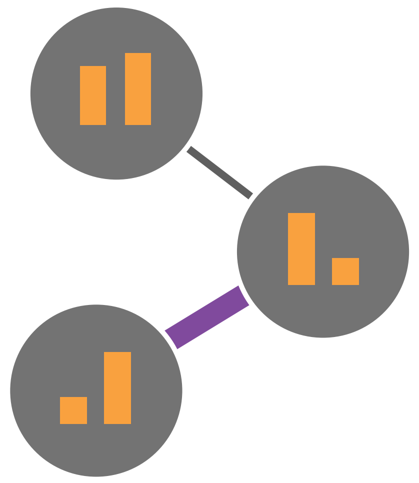




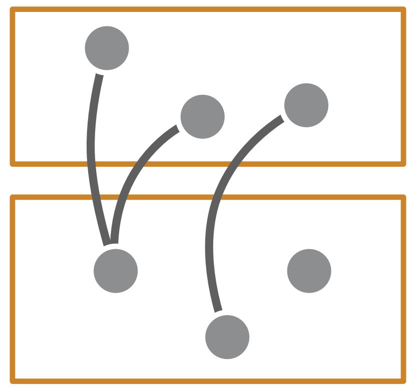
Activity

get your own twitter network @ bit.ly/twitter-network

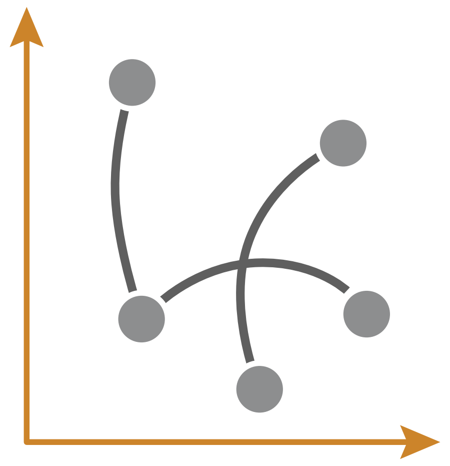
Choose a representation



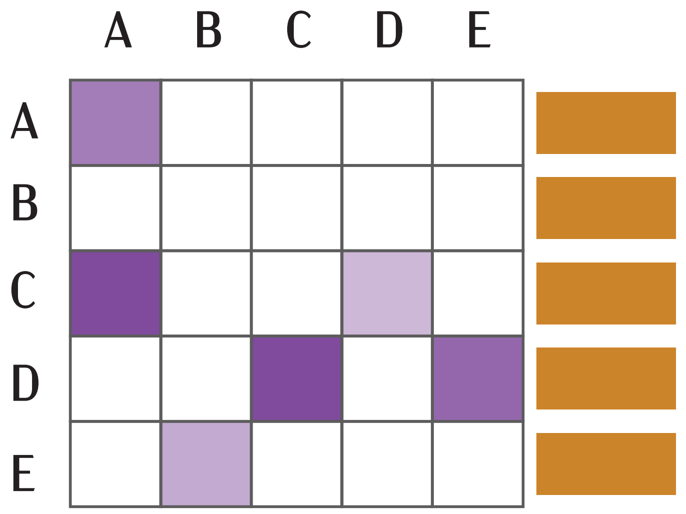
On-Node / On-Edge Encoding



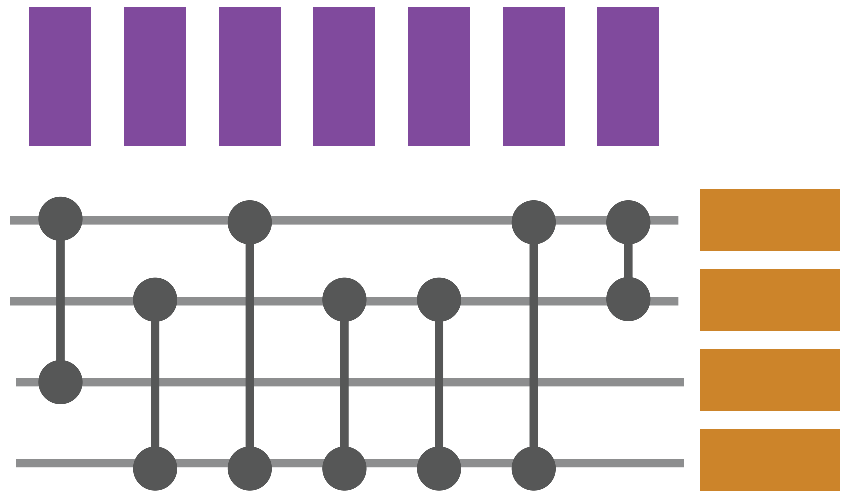
Attribute-Driven Faceting



Attribute-Driven Positioning



Adjacency Matrix



BioFabric

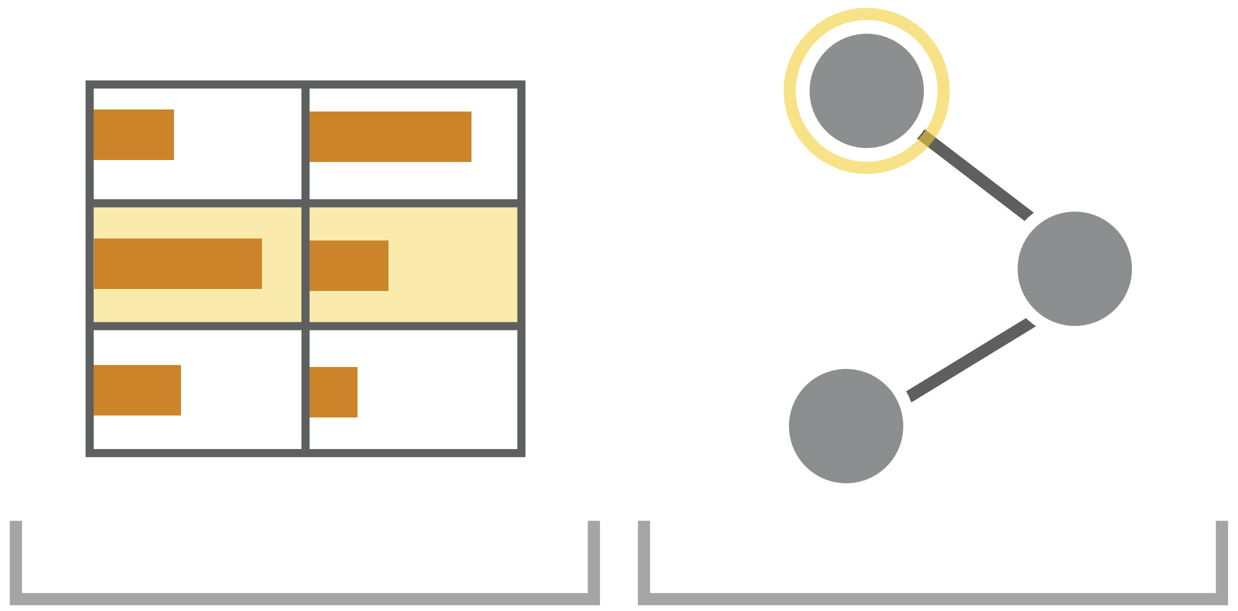
15 minutes

Exchange visualizations with your neighbor and explain your encodings.

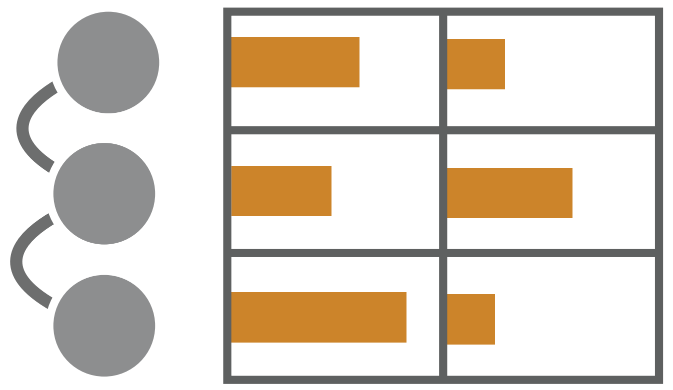
How many tweets does the person who has the most connections in this graph have?

Does the person with the least tweets have more interactions of type retweet or mention?

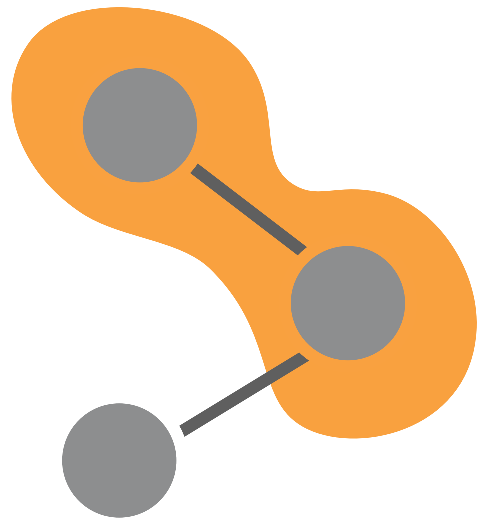
View Operations



Juxtaposed

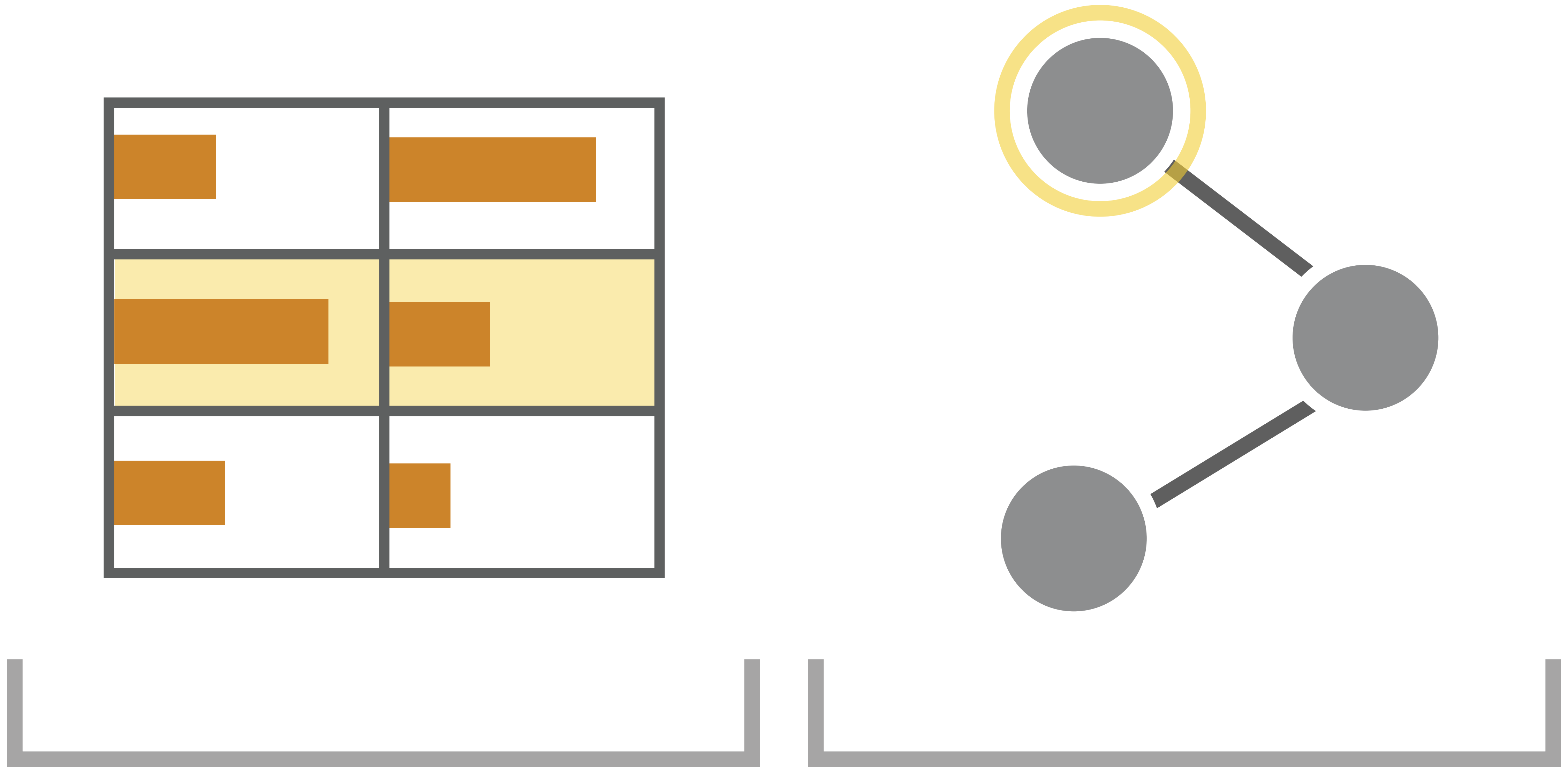


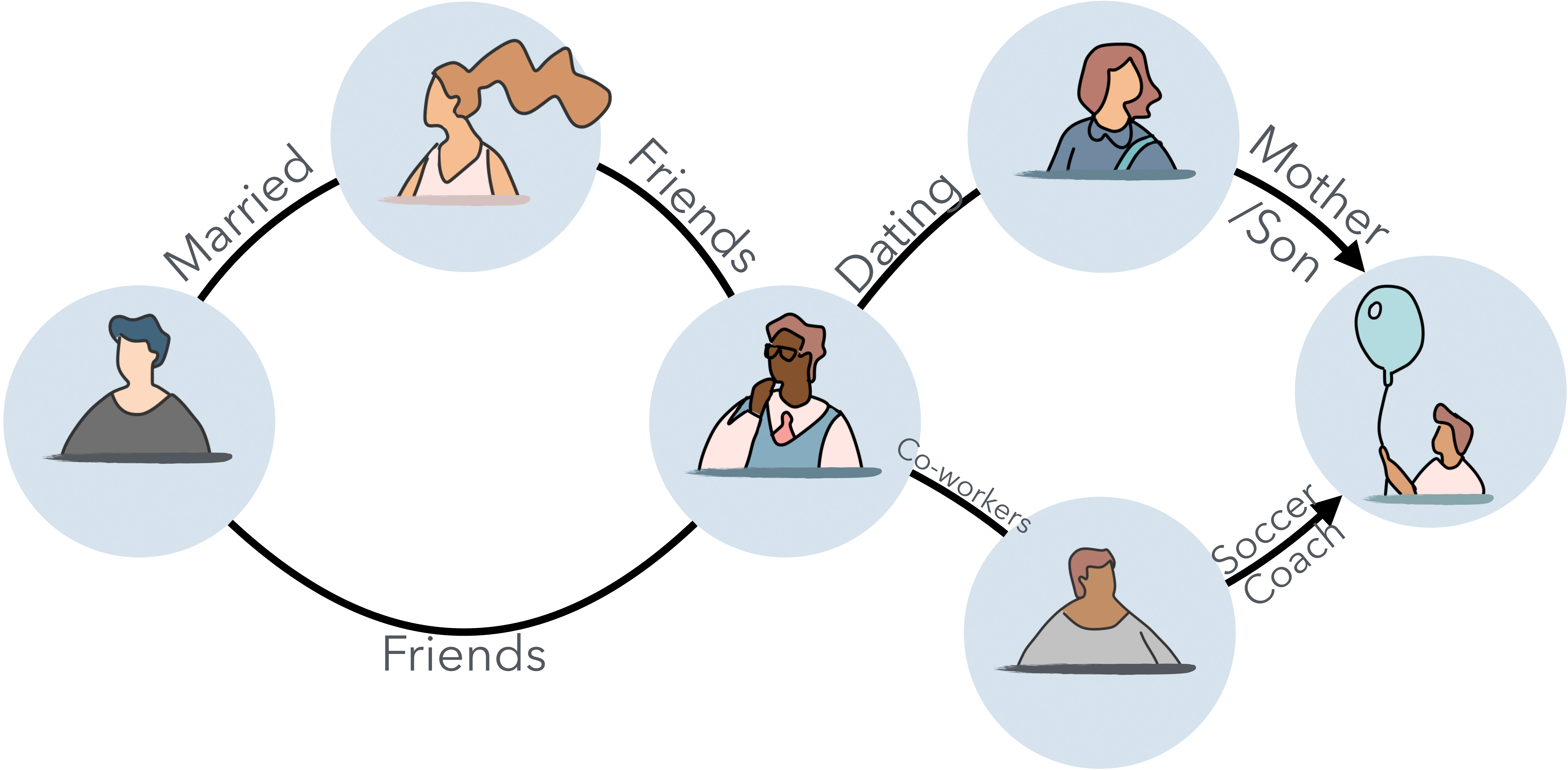
Integrated

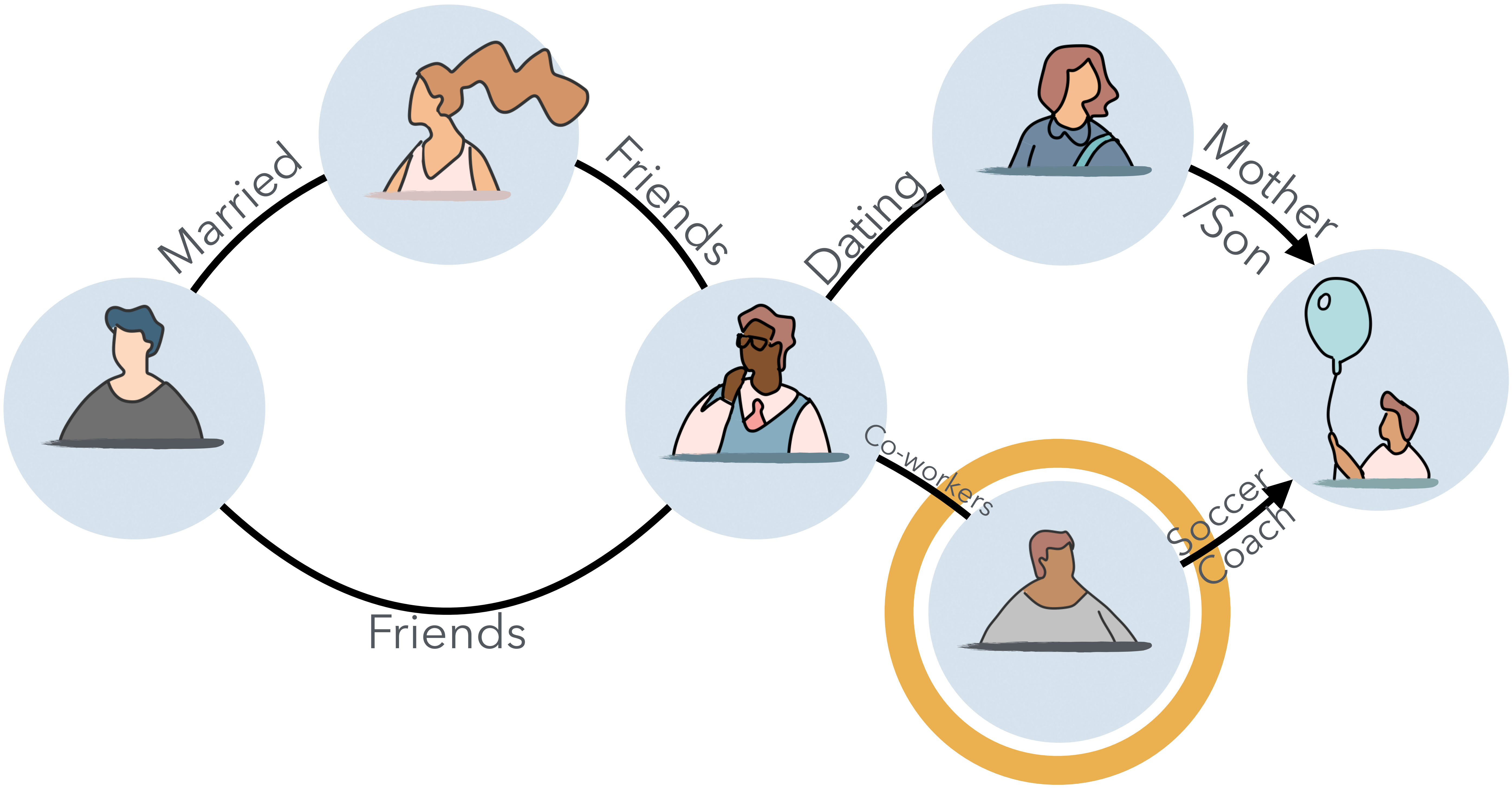


Overloaded

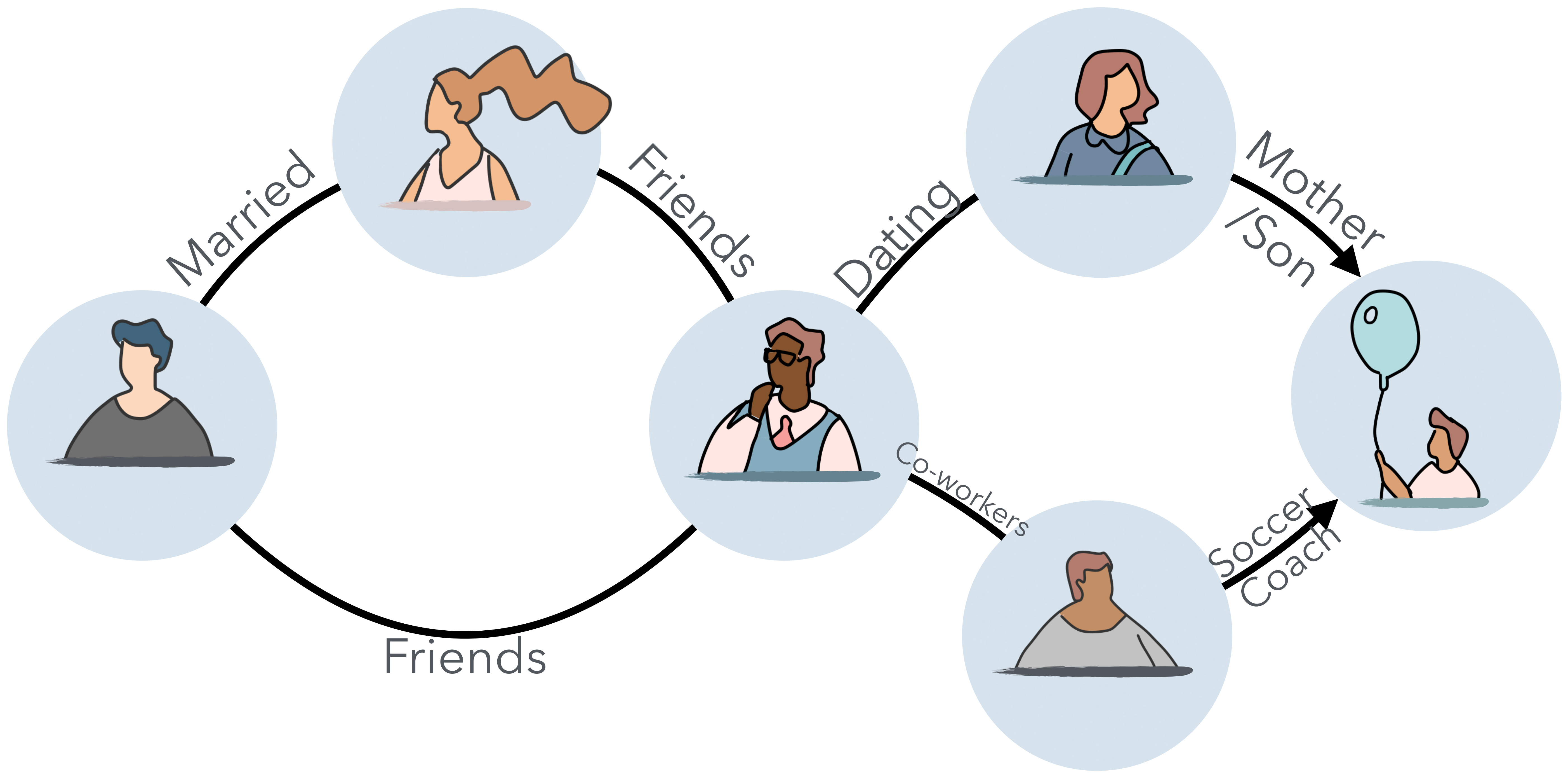
Juxtaposed




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

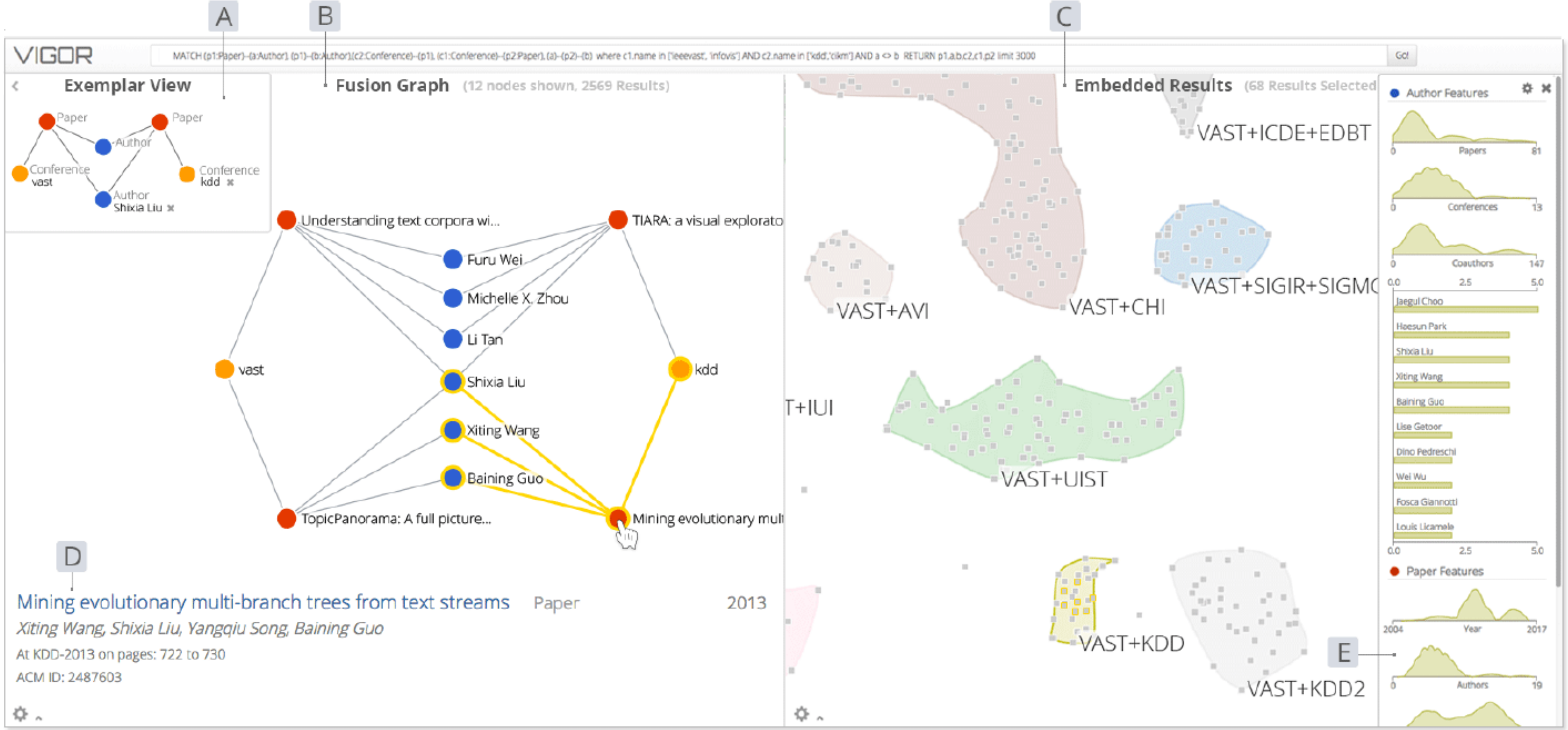


Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

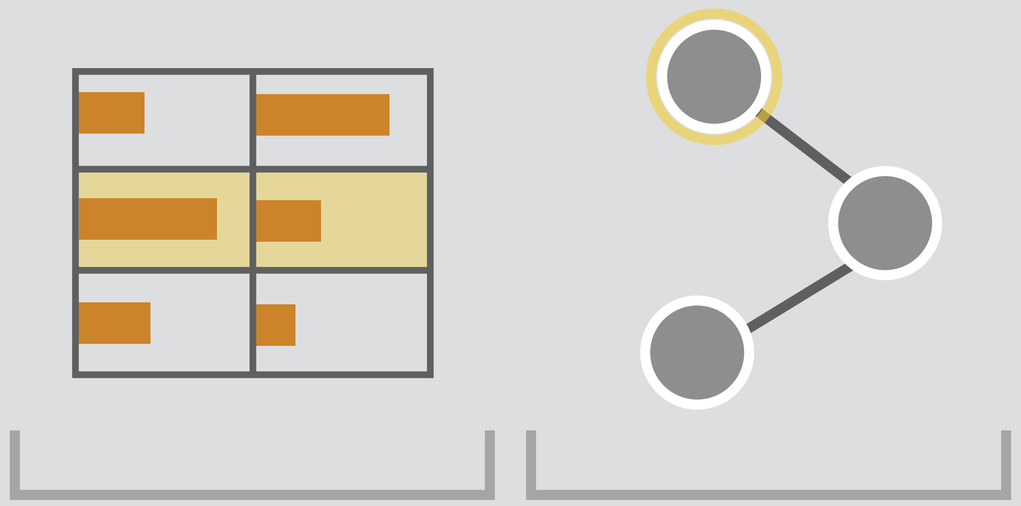


Name	Beverage	Day 1
Mark	Beer	1
Sue	Coke	0
Cole	Port	4
Jon	Coke	5
Tom	Beer	2
Abby	Port	3

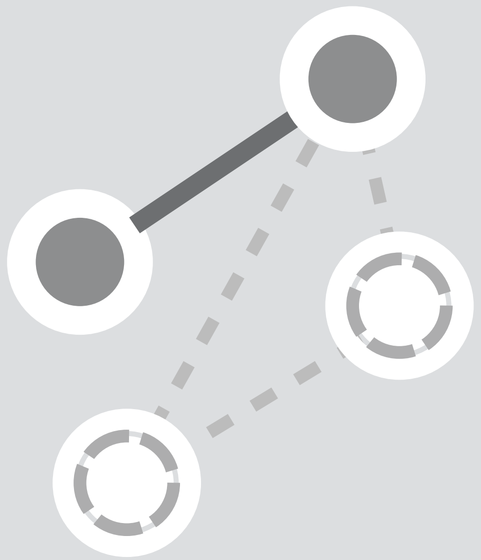
Relationship	Years
Dating	4
Mother / Son	12
Co-workers	3
Soccer Coach	2
Friends	8
Friends	3
Married	4



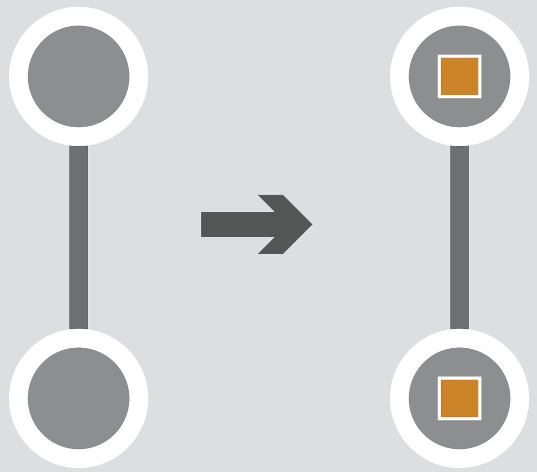
VIGOR *Pienta et al. 2018*



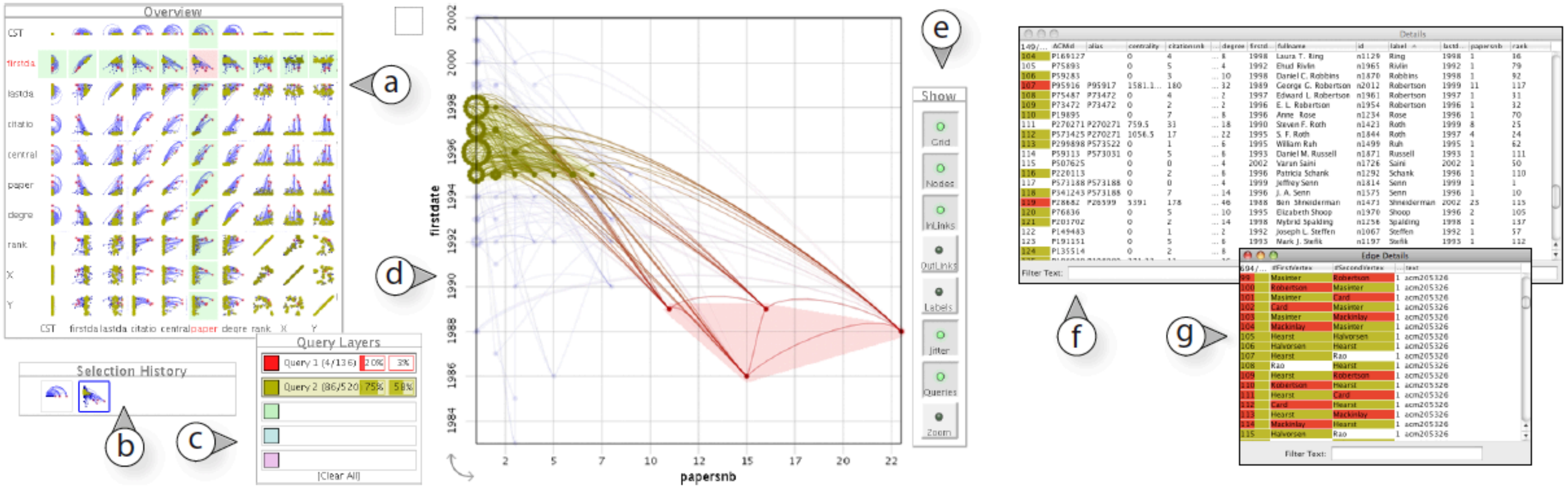
Juxtaposed



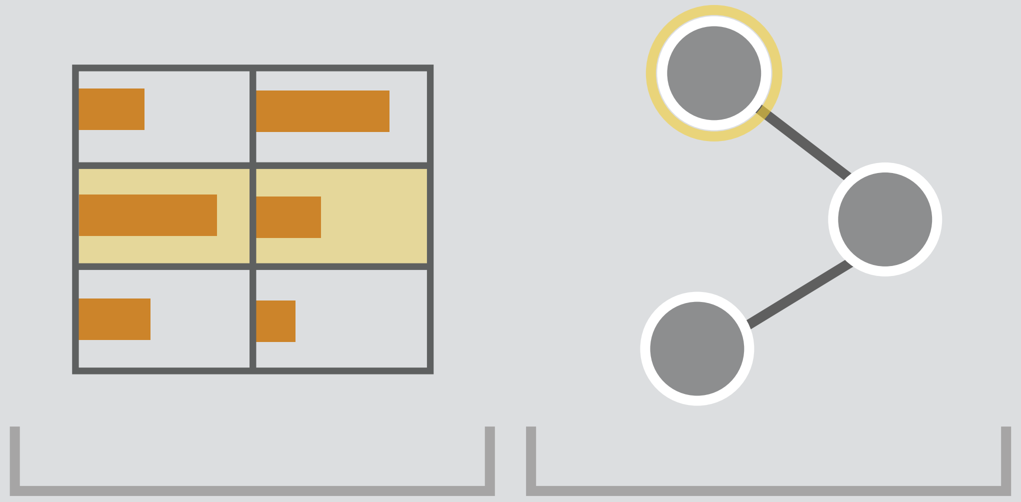
Querying and Filtering



Deriving New Attributes

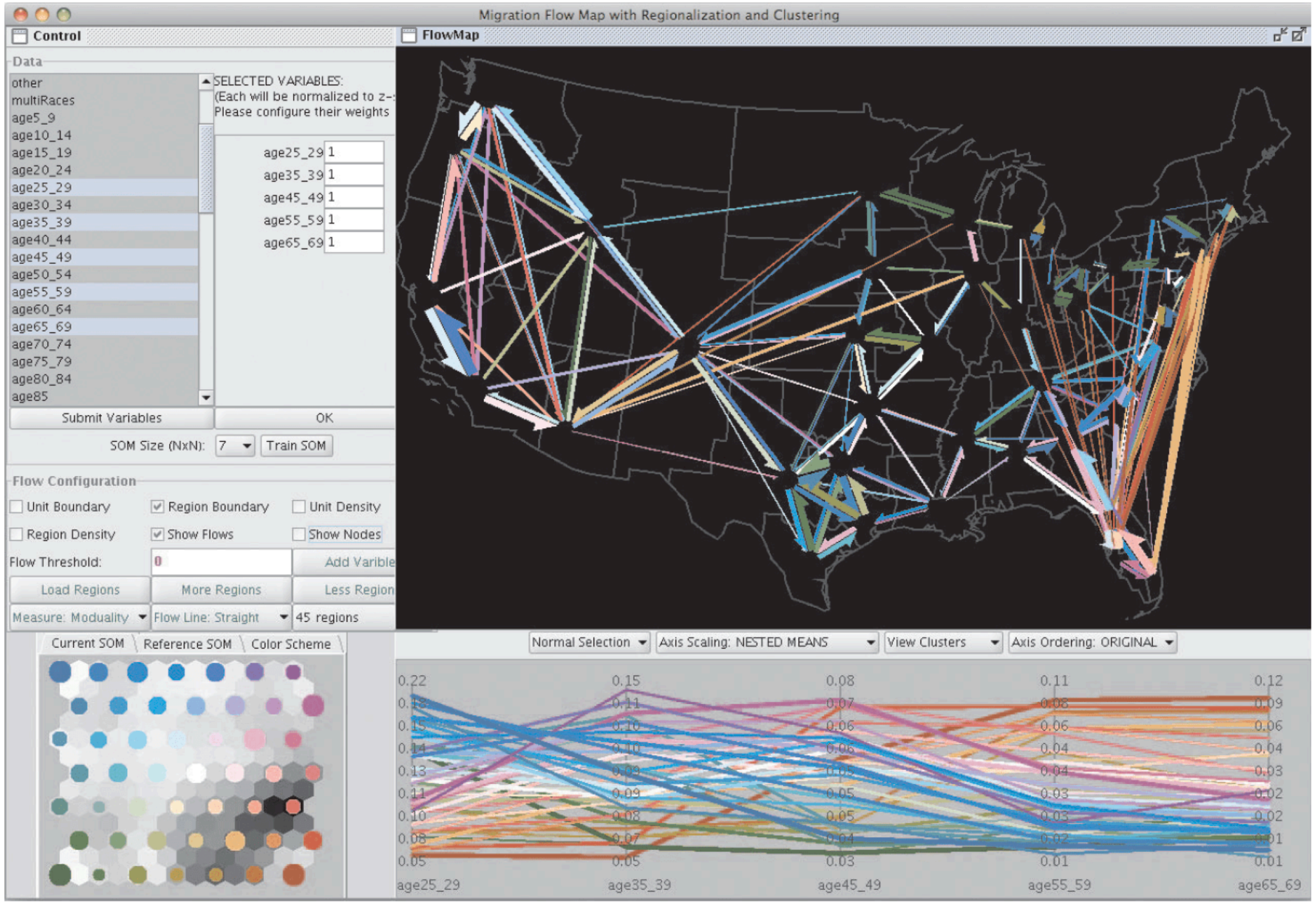


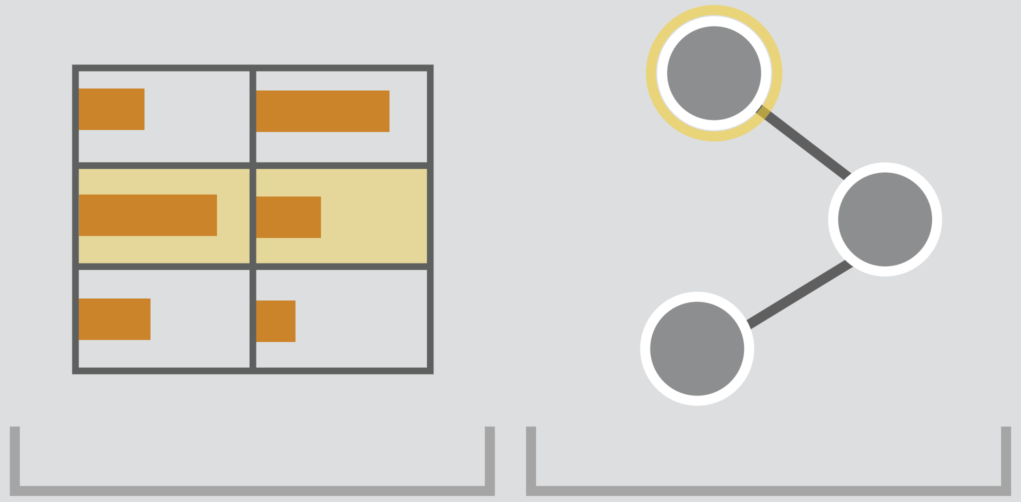
Graph Dice *Bezerianos et al. 2010*



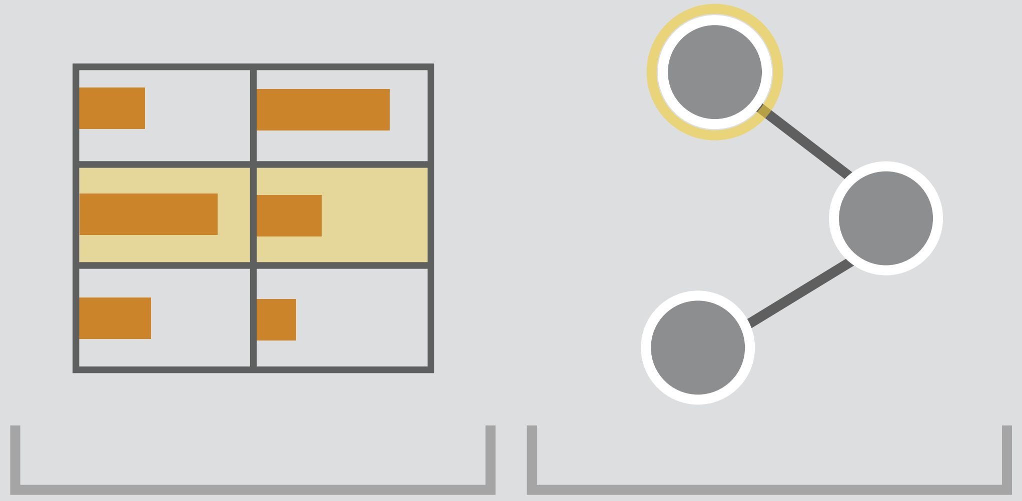
Juxtaposed

Guo, 2009

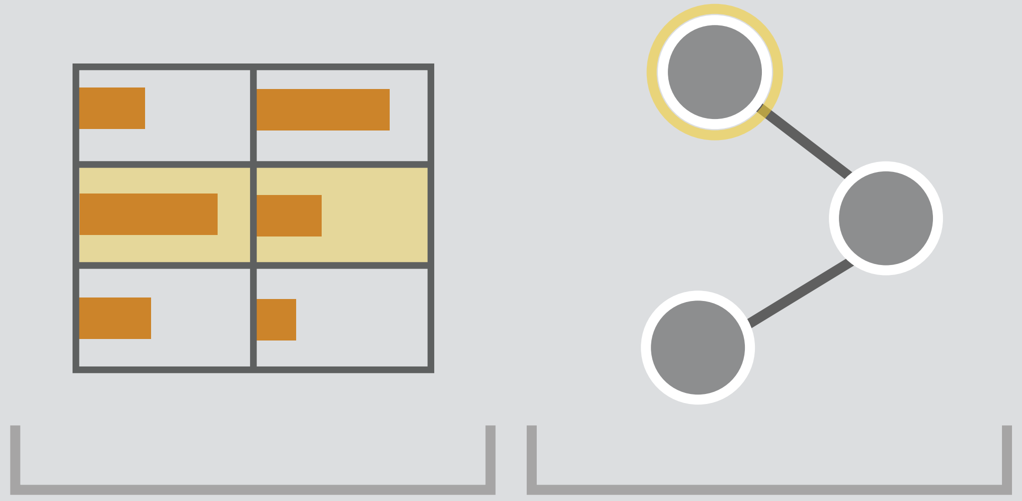




Juxtaposed



Juxtaposed



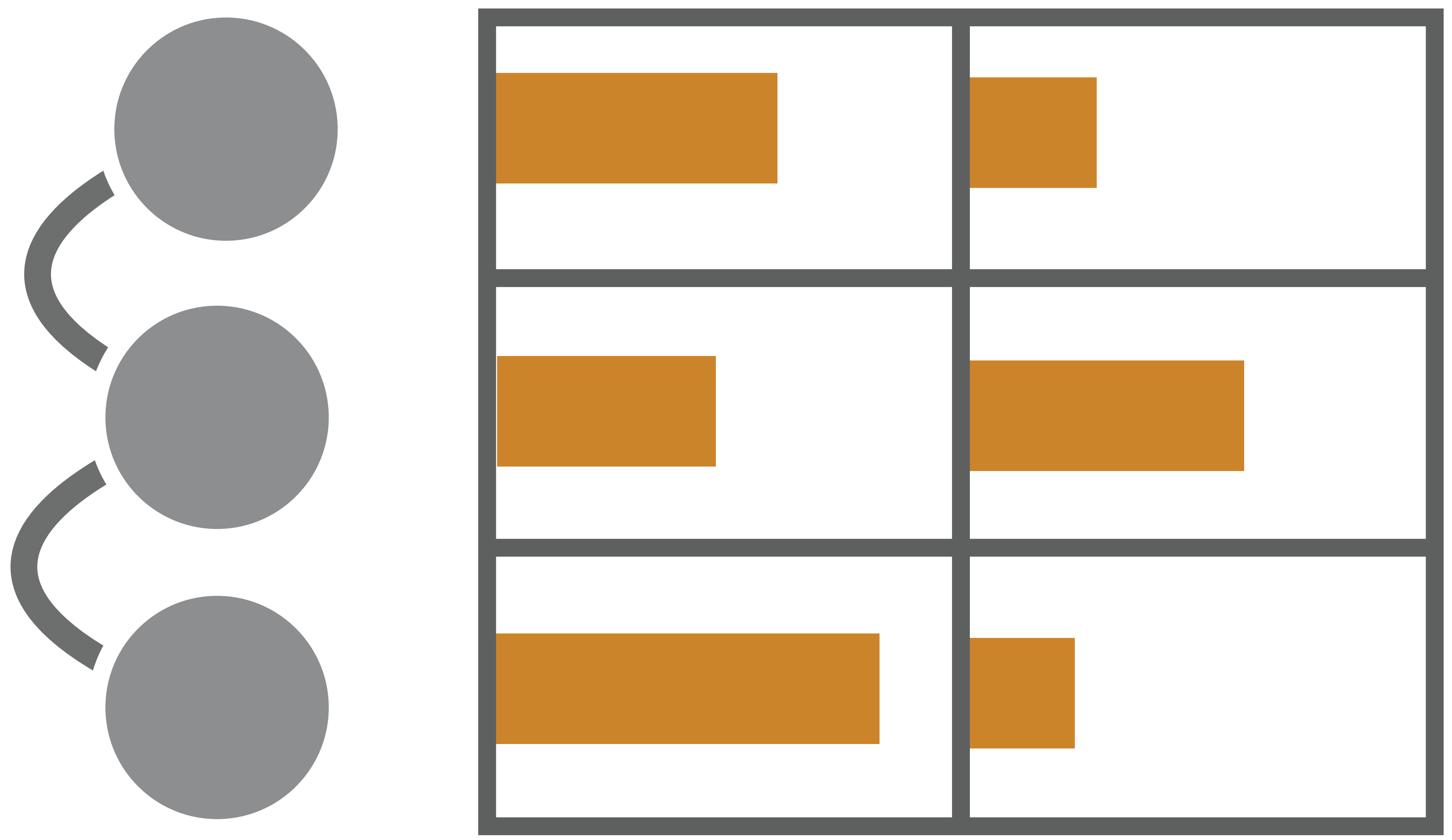
Juxtaposed

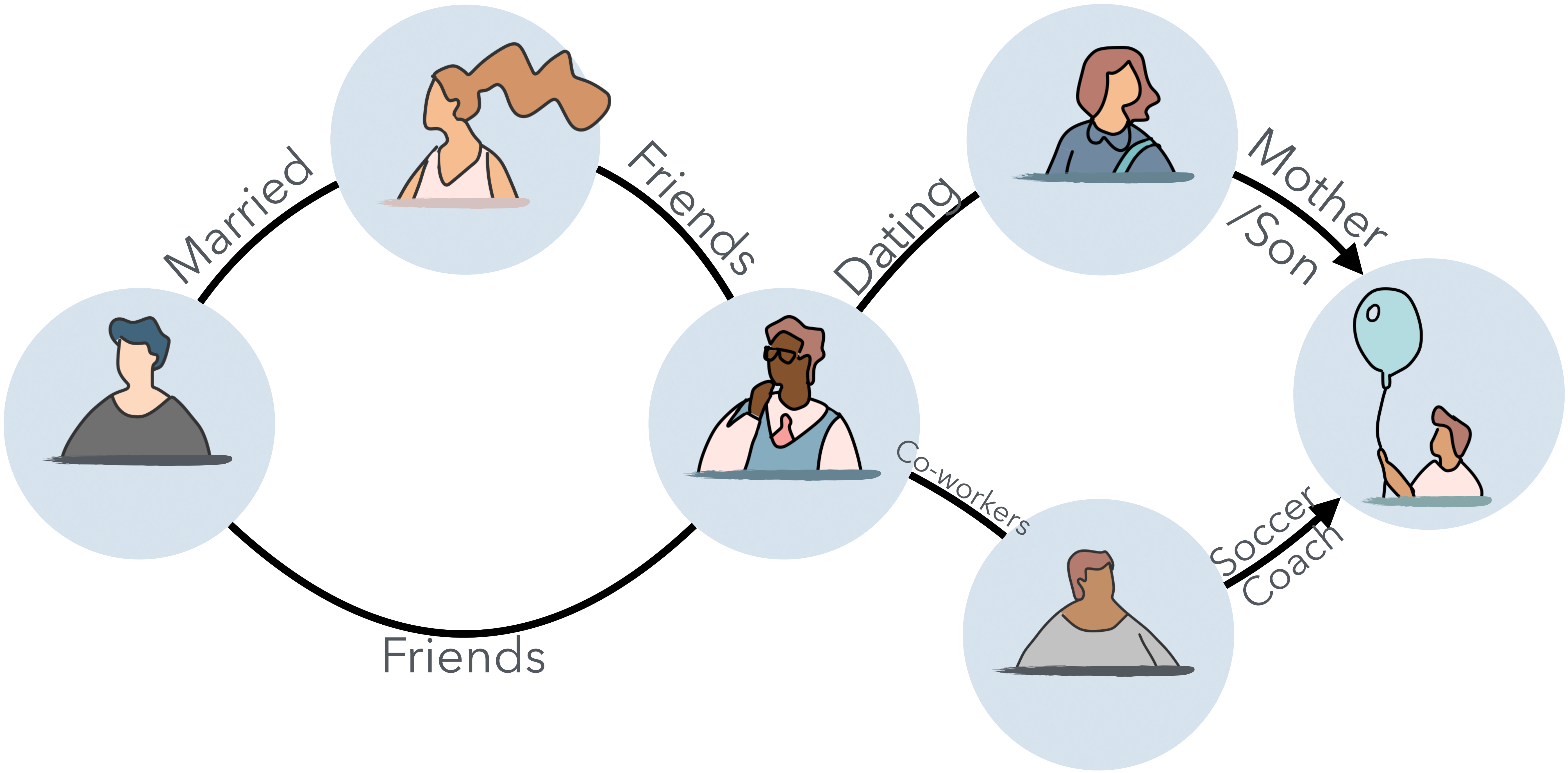
Independent views can optimize for topology and attribute independently.

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

Integrated





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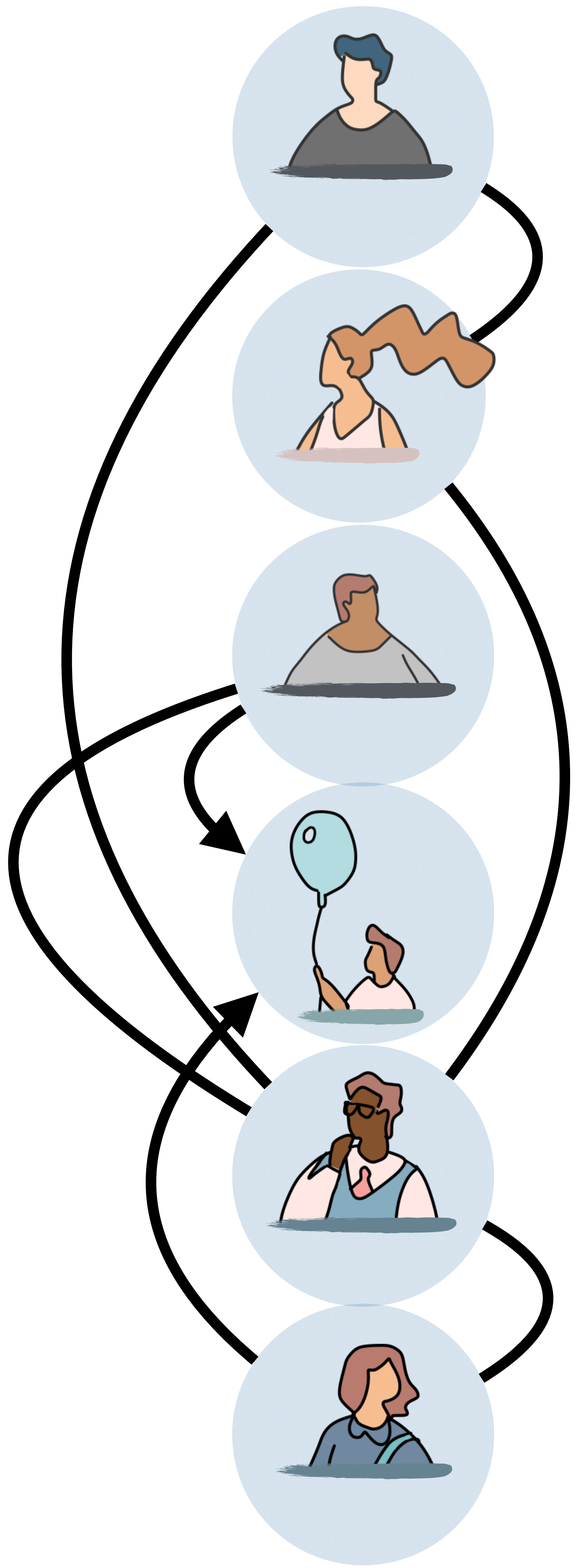

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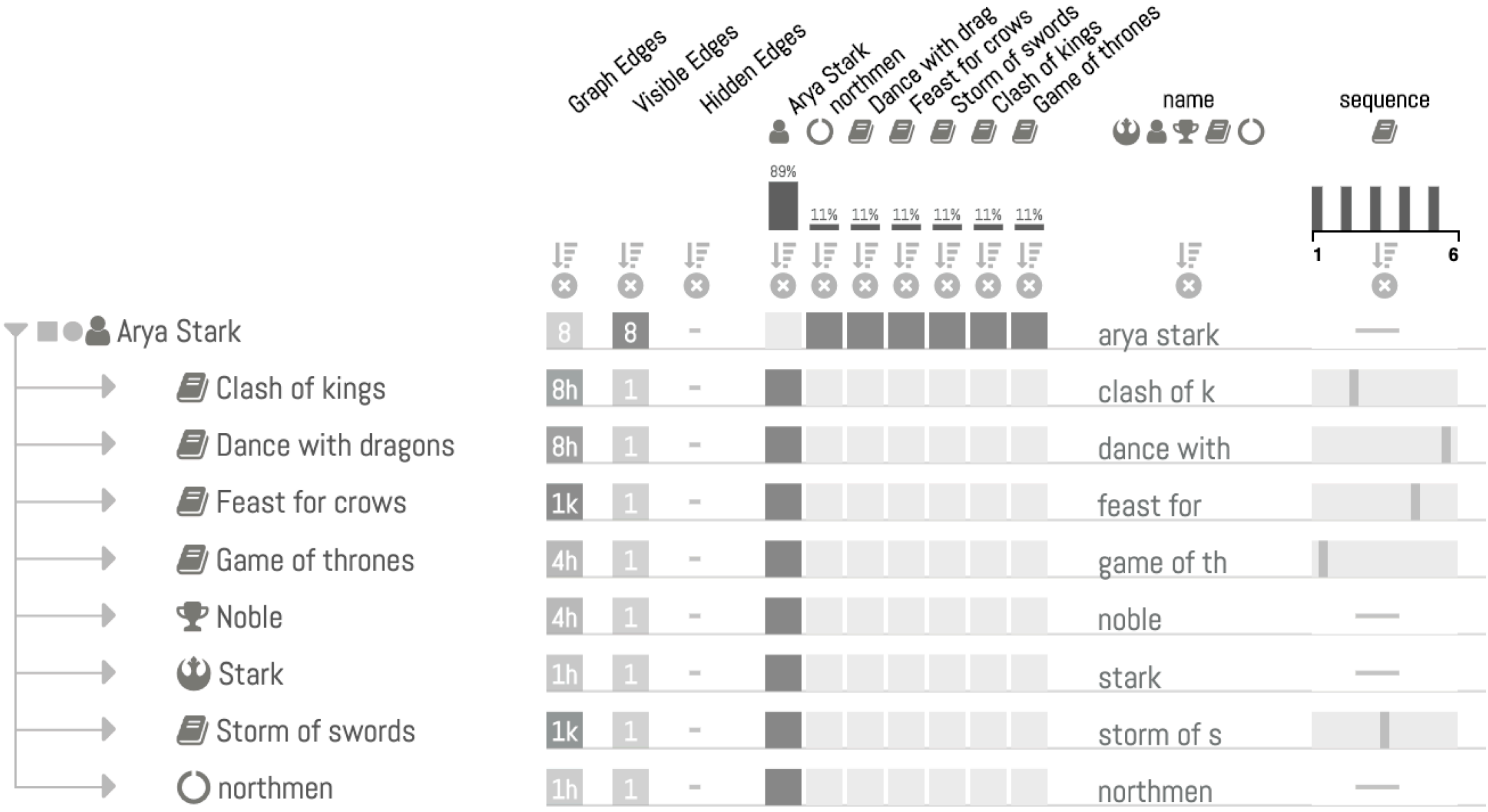
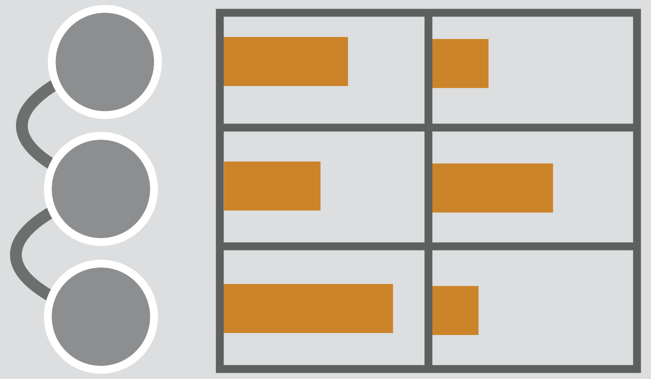
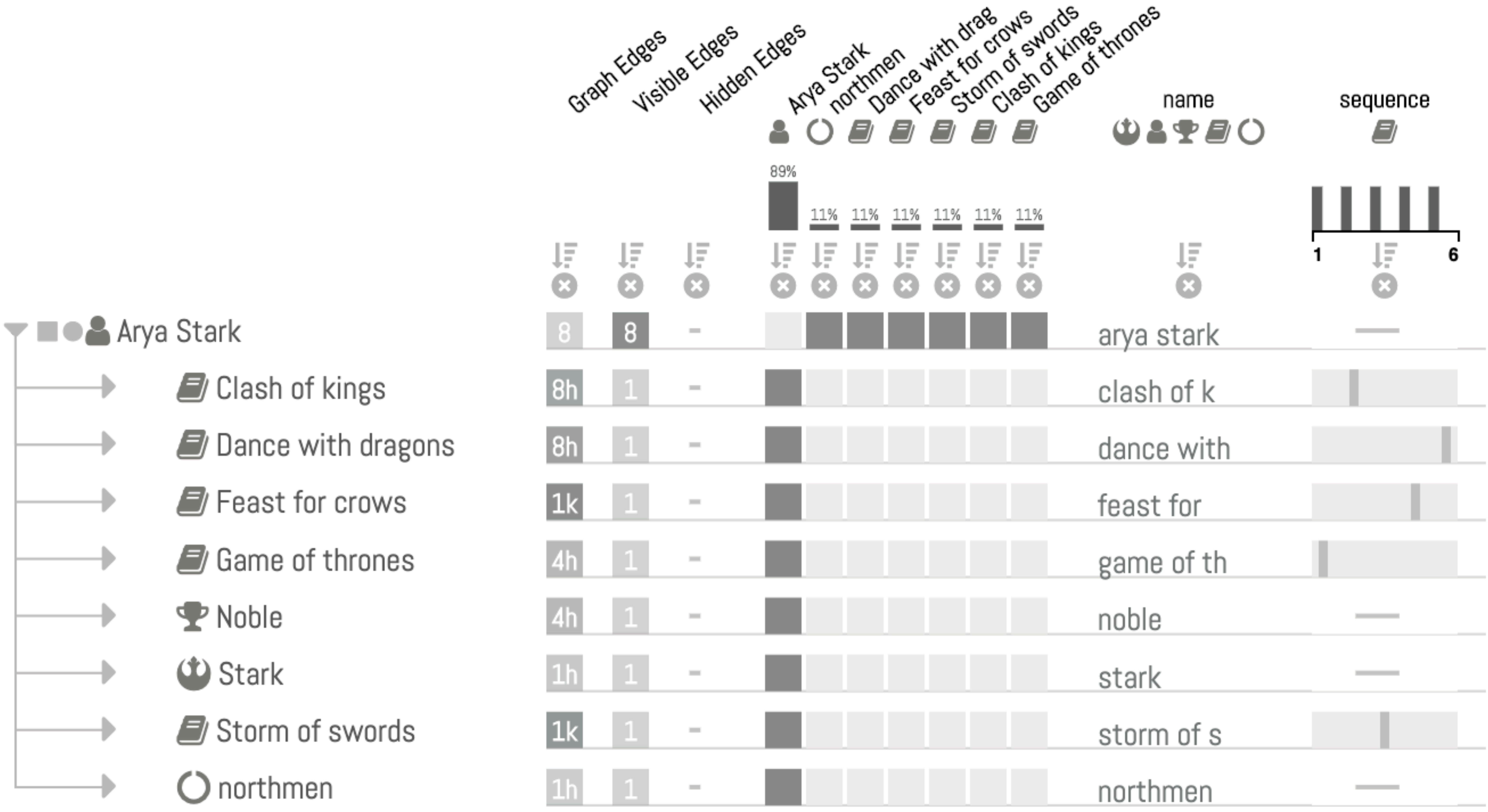


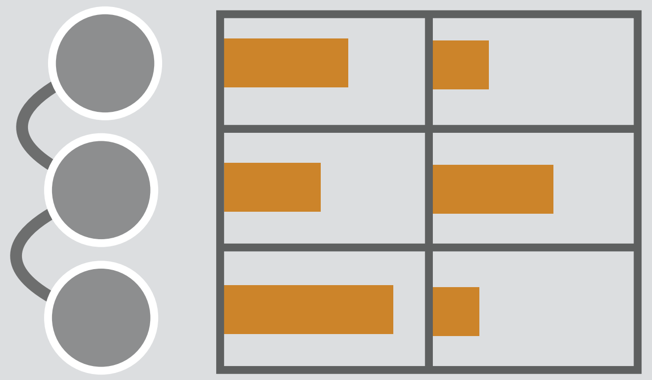
Juniper *Nobre et al. 2018*



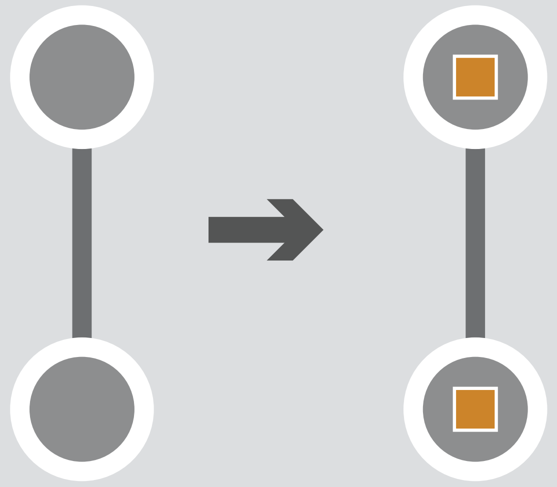
Integrated



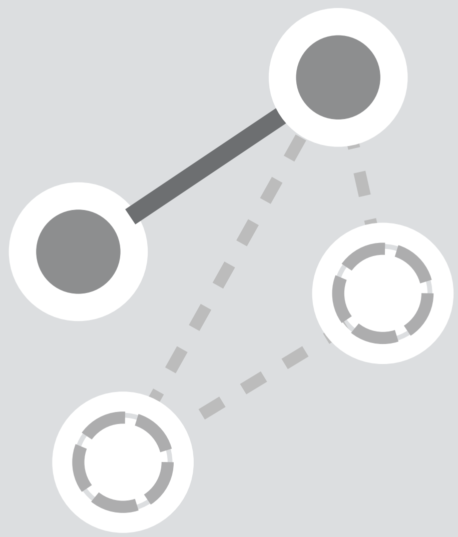
Juniper *Nobre et al. 2018*



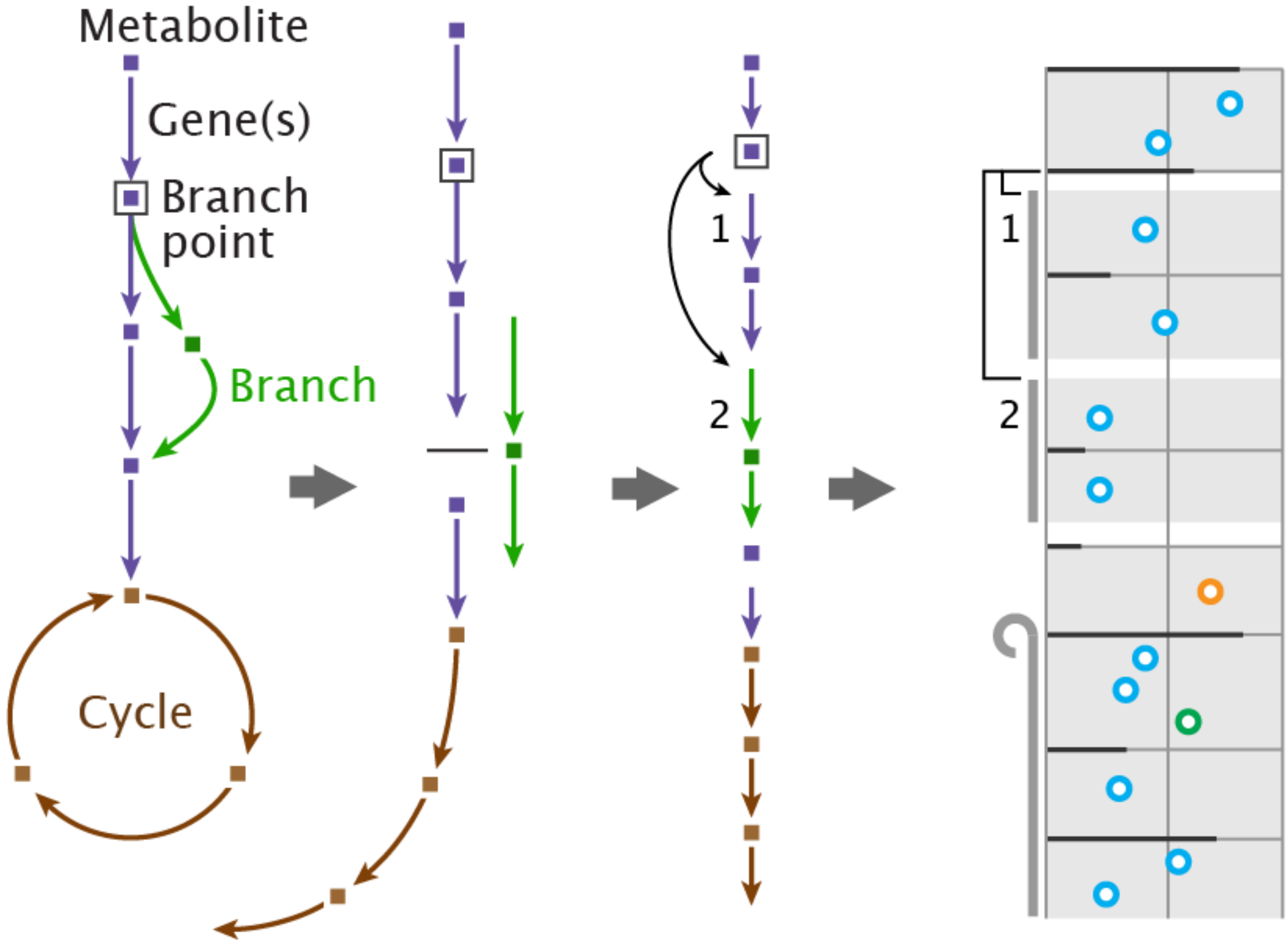
Integrated



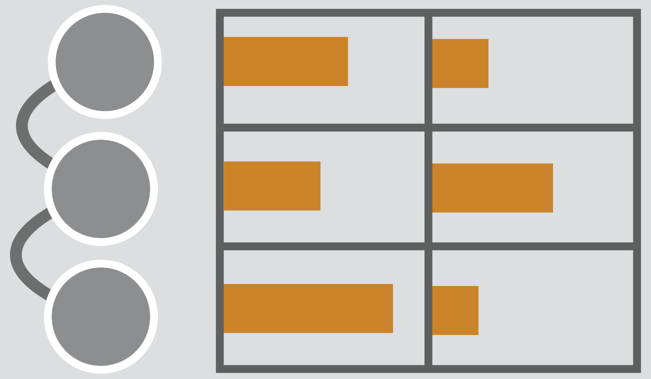
Deriving New Attributes



Querying and Filtering



Pathline Meyer *et al. 2010*



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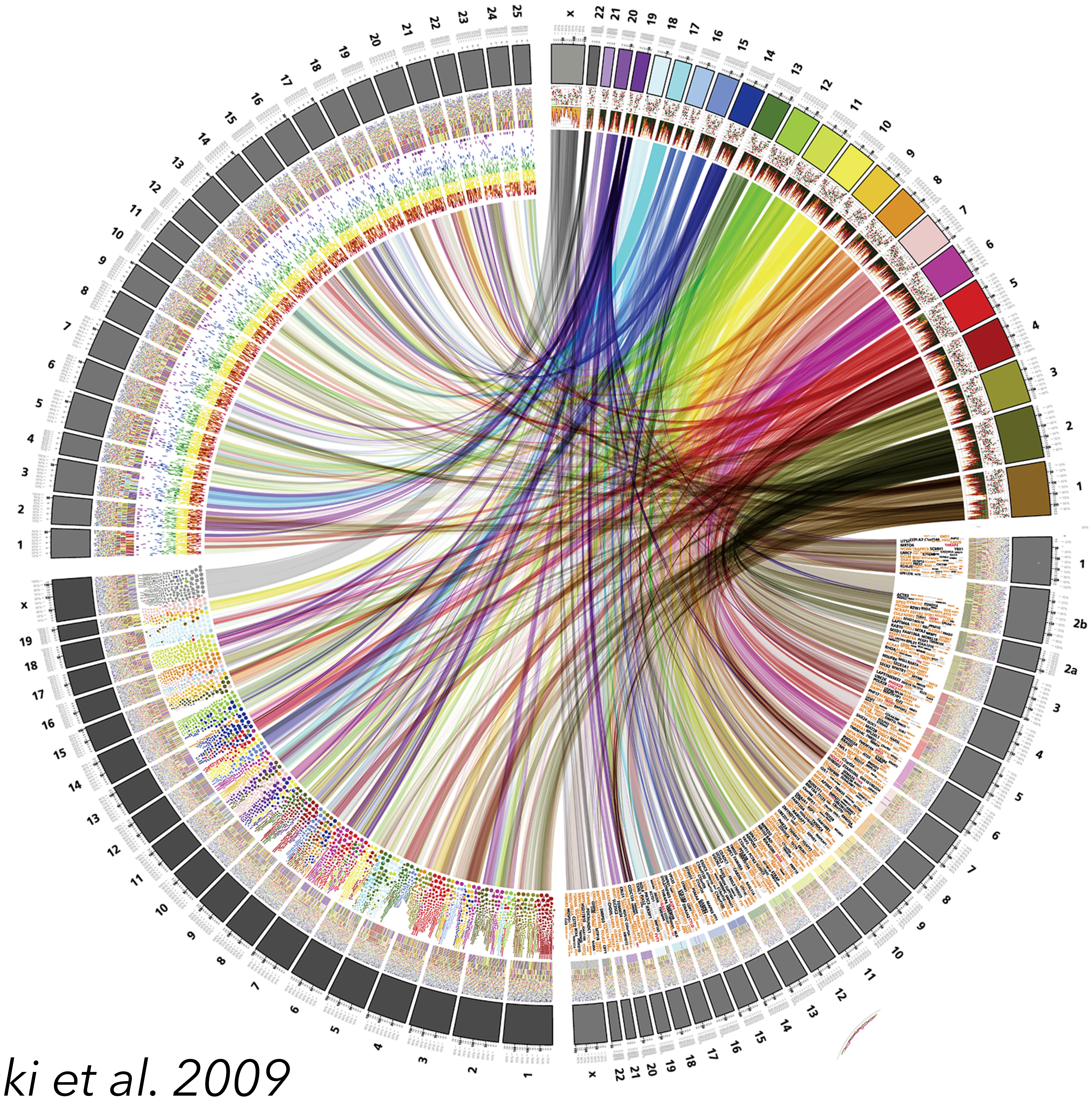
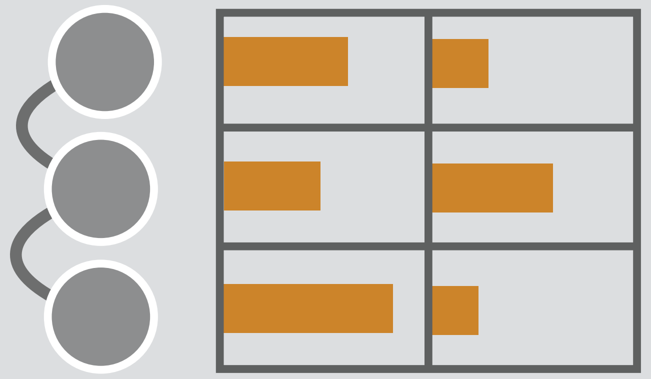


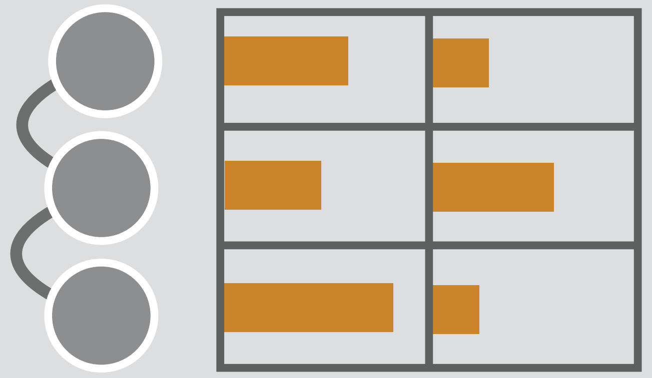


Integrated

Circos

Krzywinski et al. 2009

Integrated



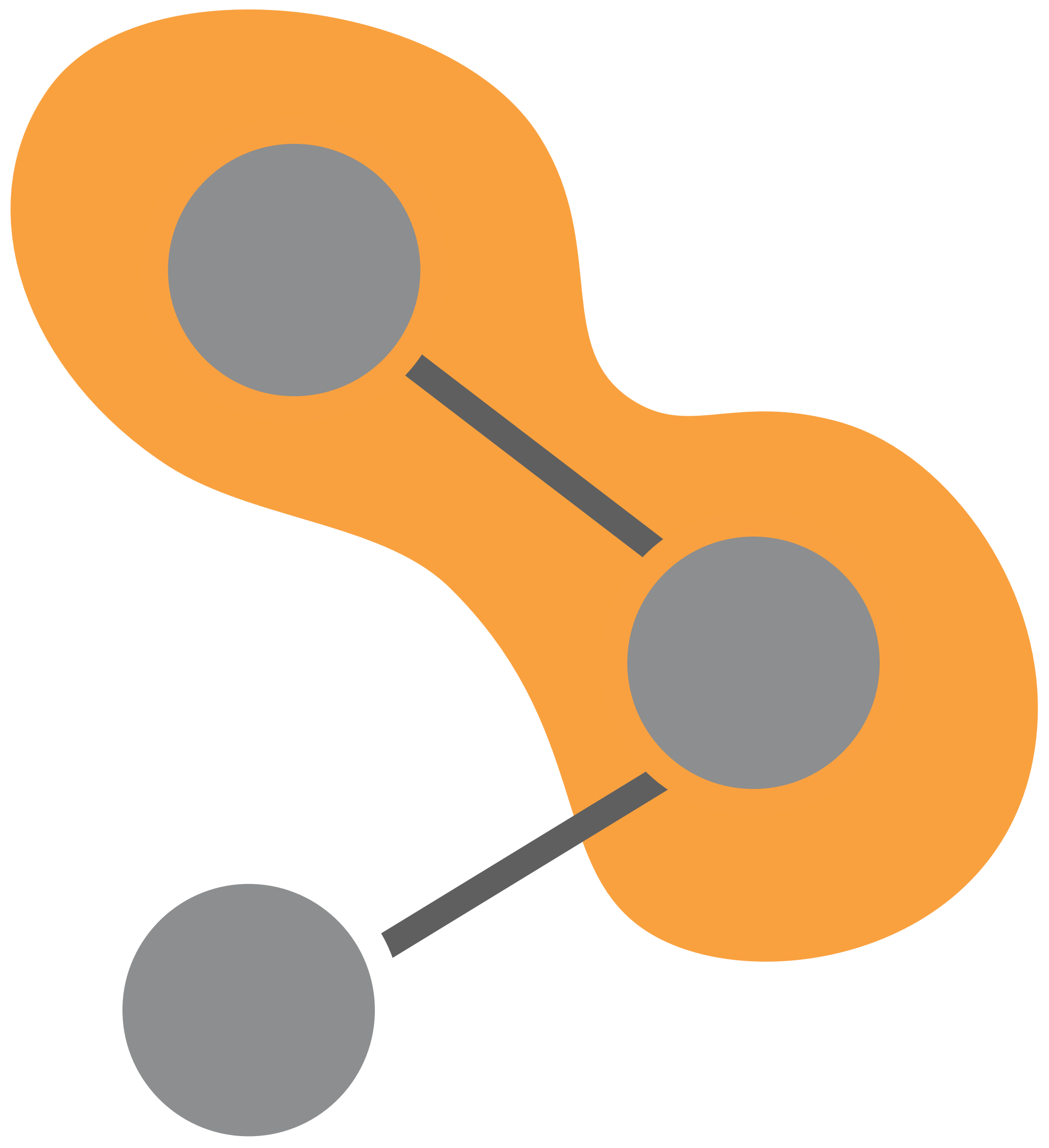
Integrated

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

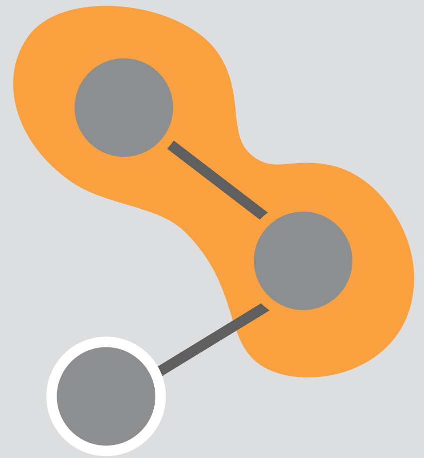
Not suitable for networks that can not be sensibly linearized.

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

Overloaded



GMaps *Gansner et al. 2010*



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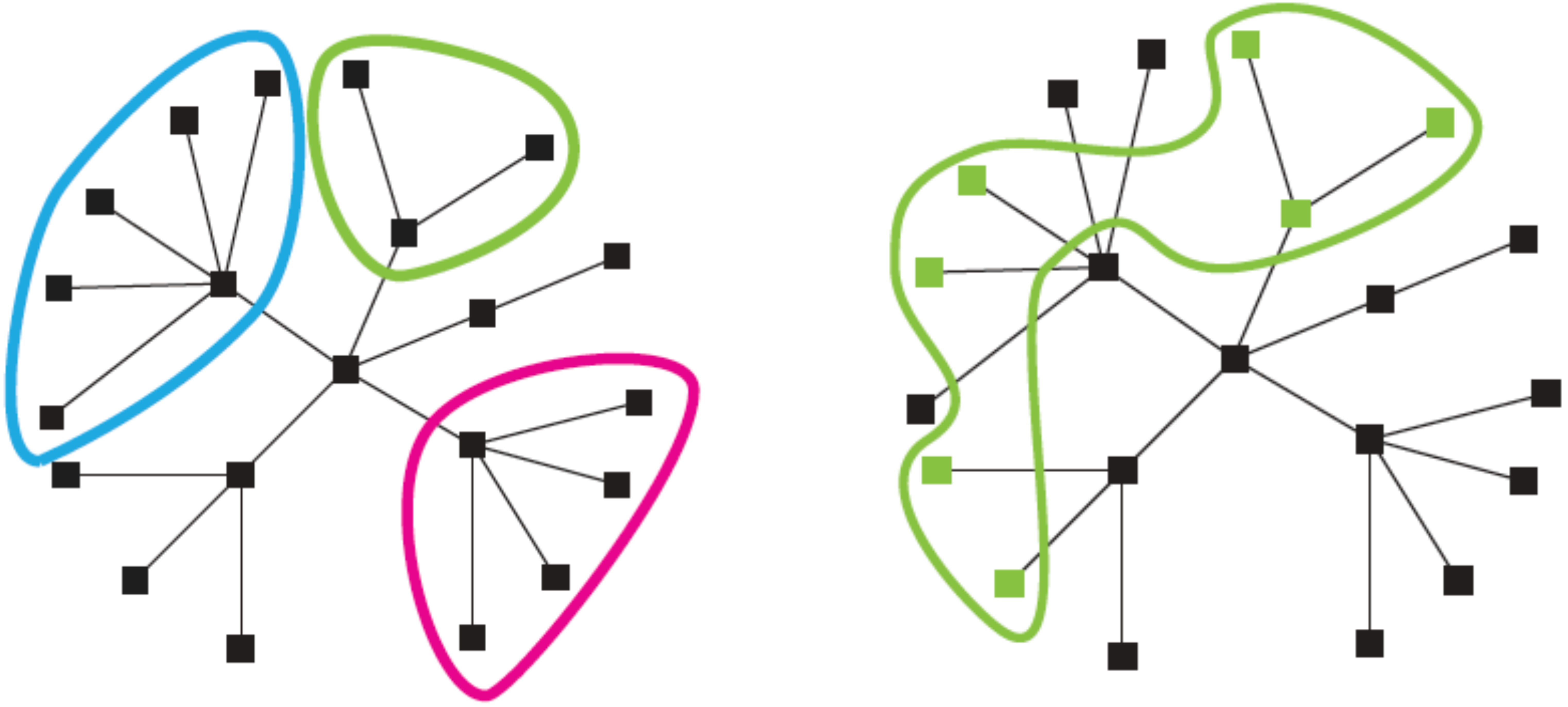
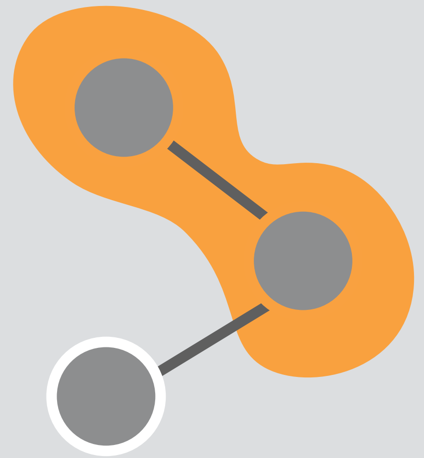


Bubble Sets *Collins et al. 2009*



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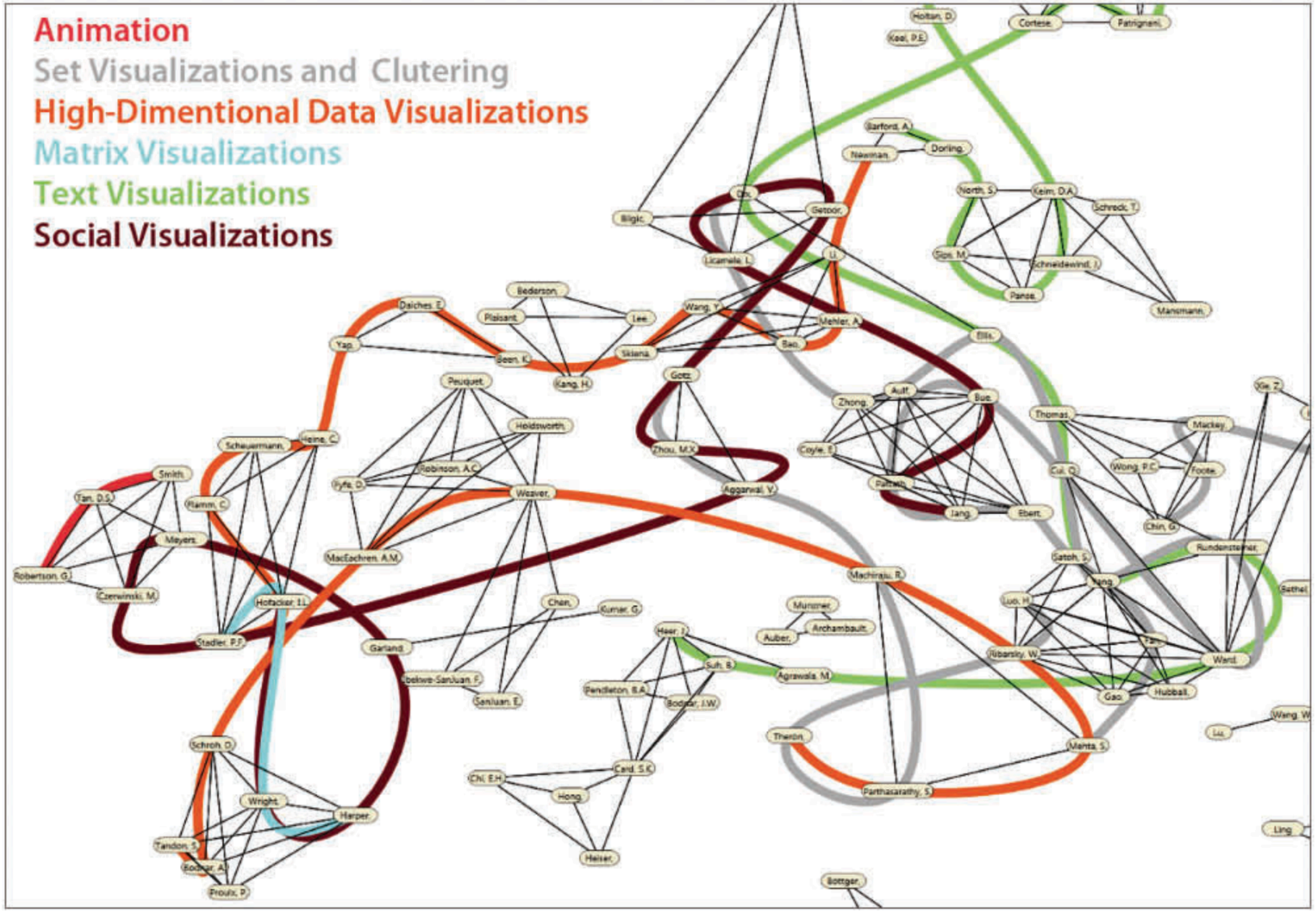
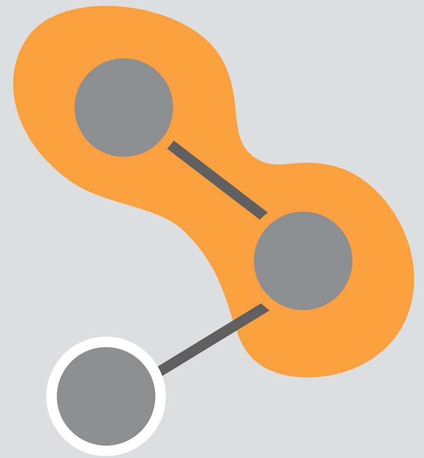


LineSets *Alper et al. 2011*



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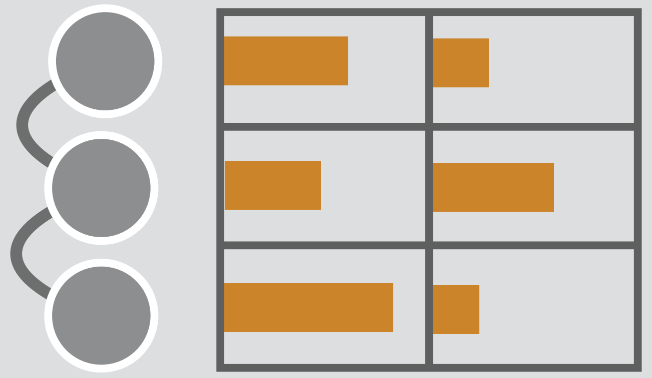
Overloaded



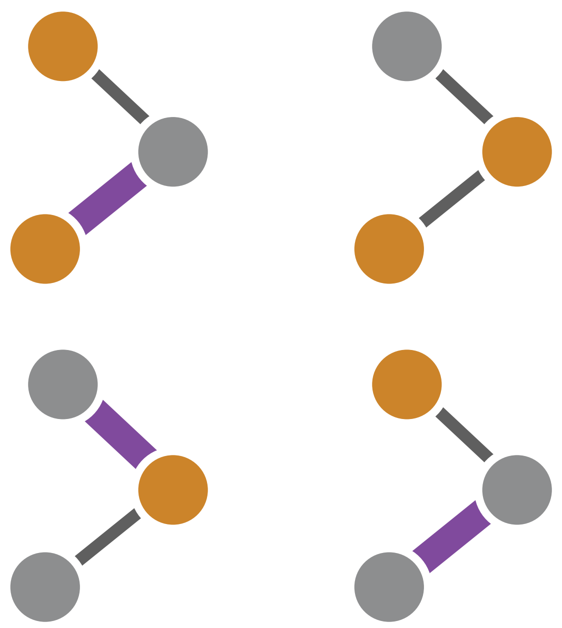
Integrated

good at displaying sets and clusters

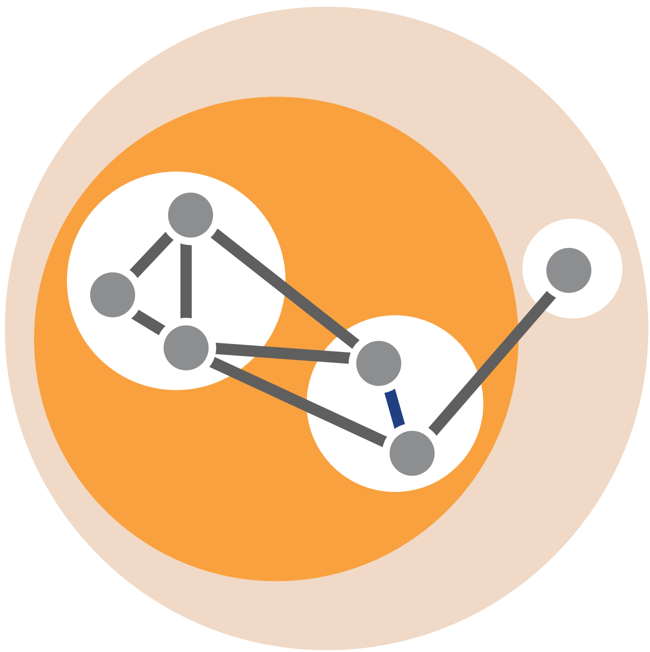
Not suitable for displaying more than one or two attributes at a time.

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

Layout Operations

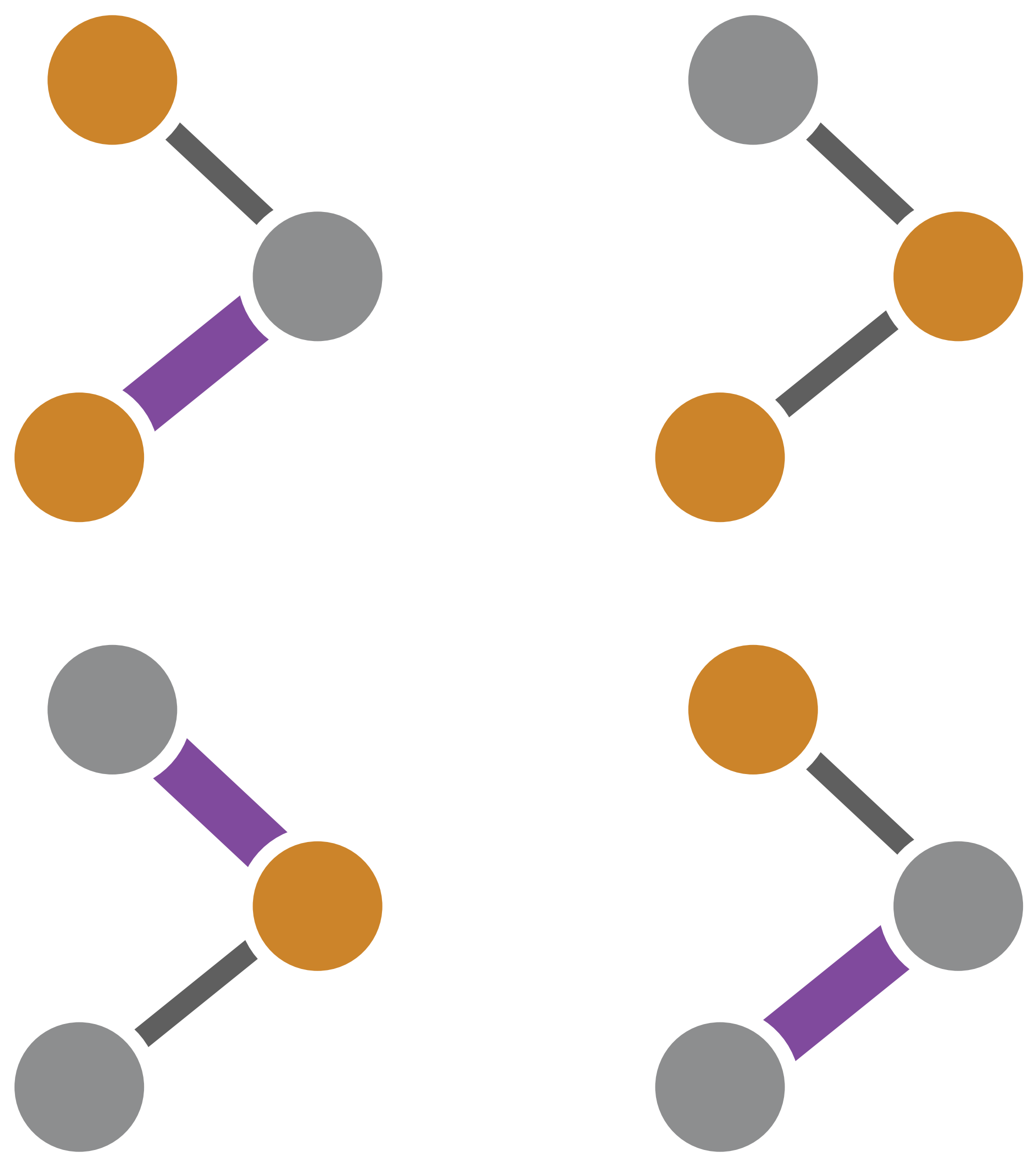


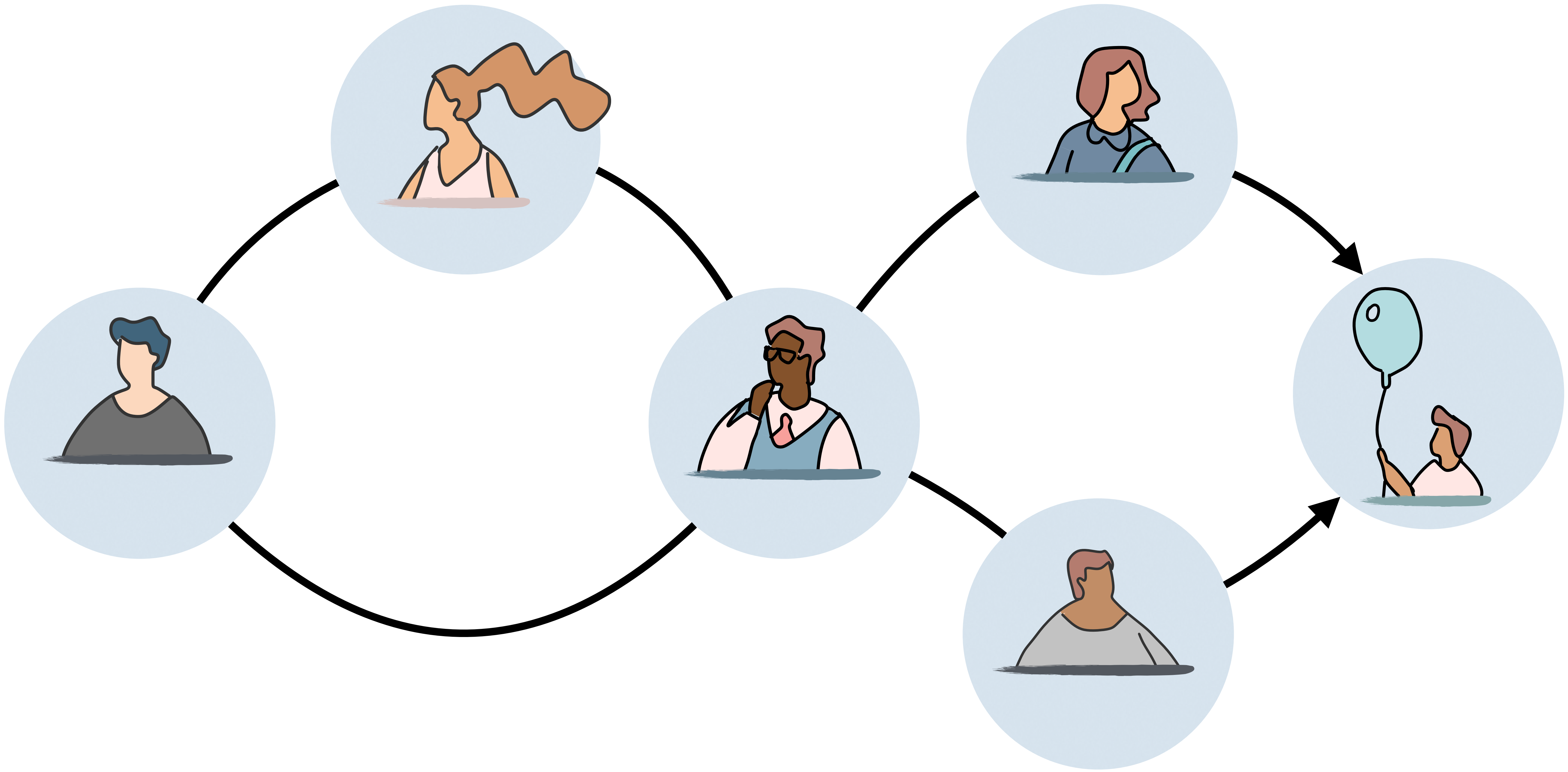
Small Multiples



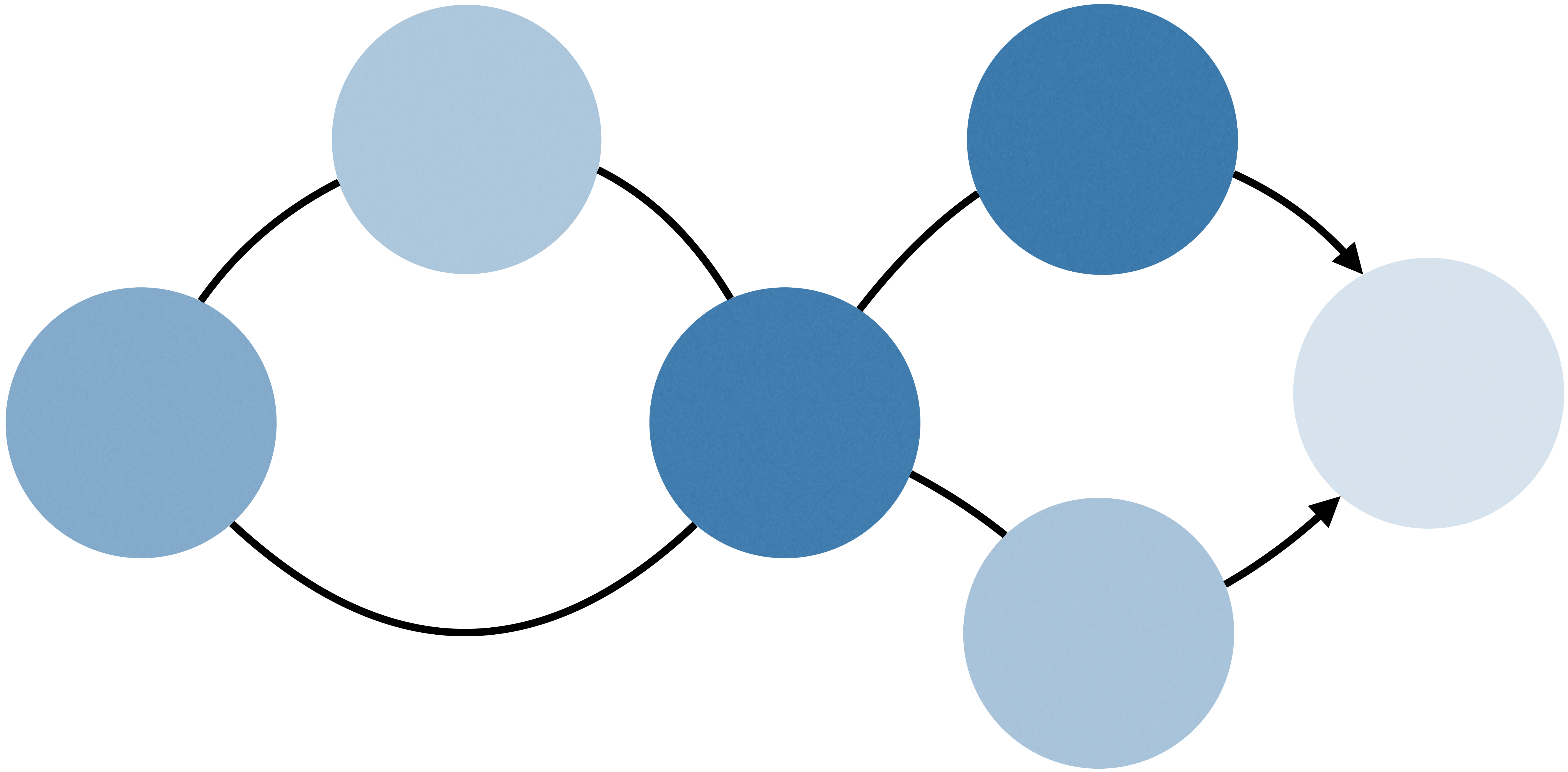
Hybrids

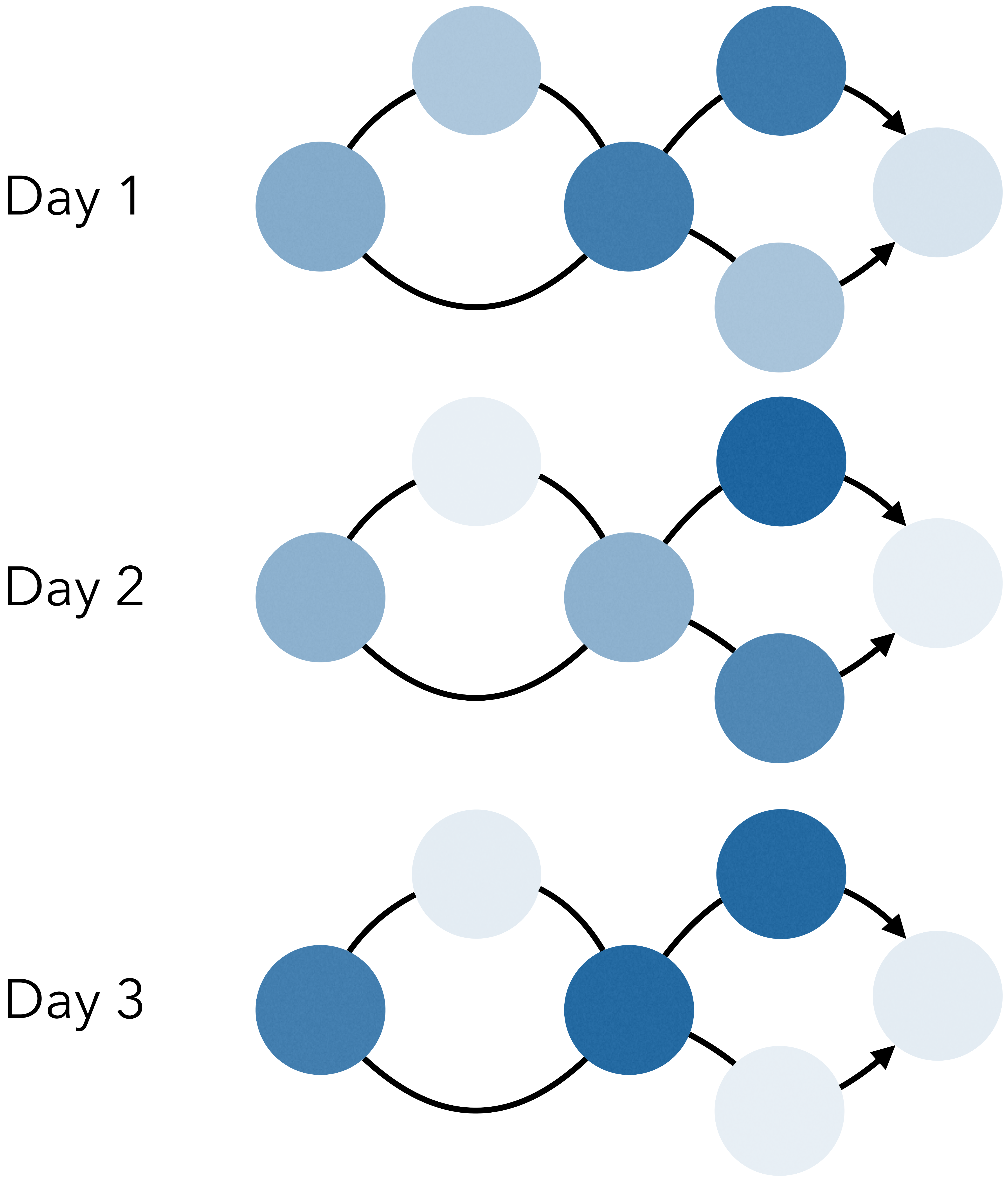
Small Multiples

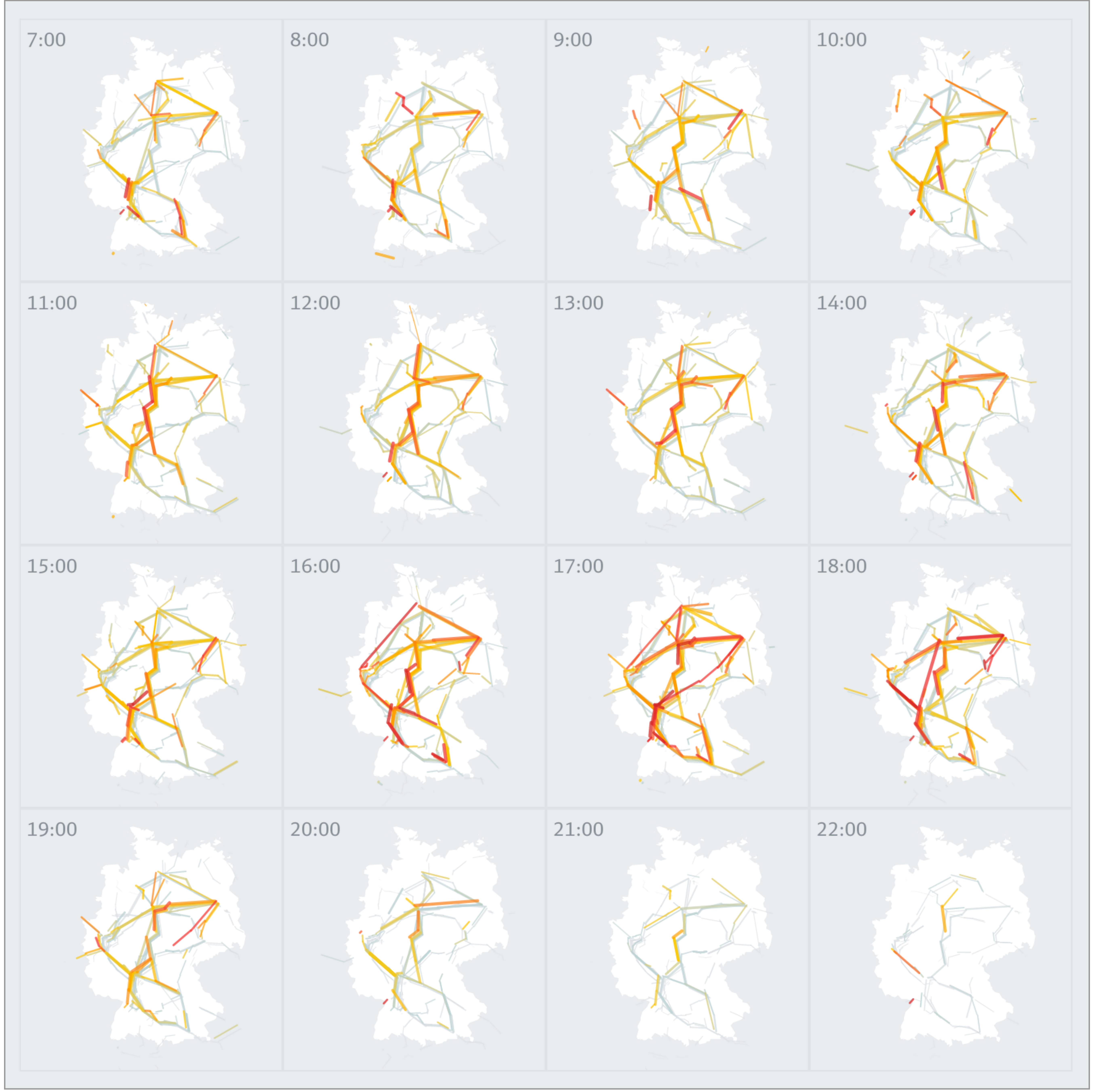


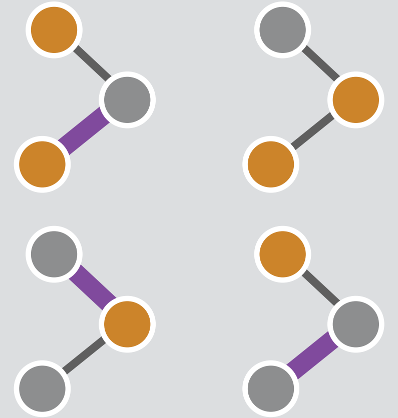


Day 1

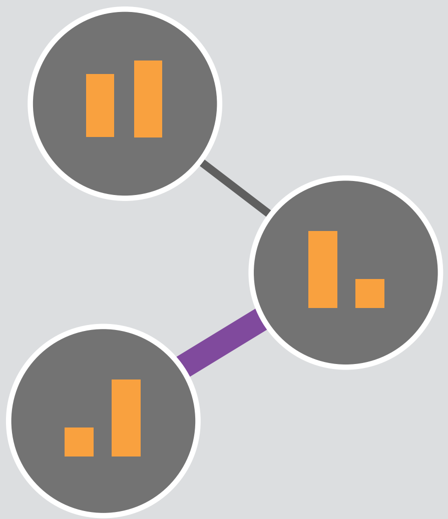



Day 1
Day 2
Day 3



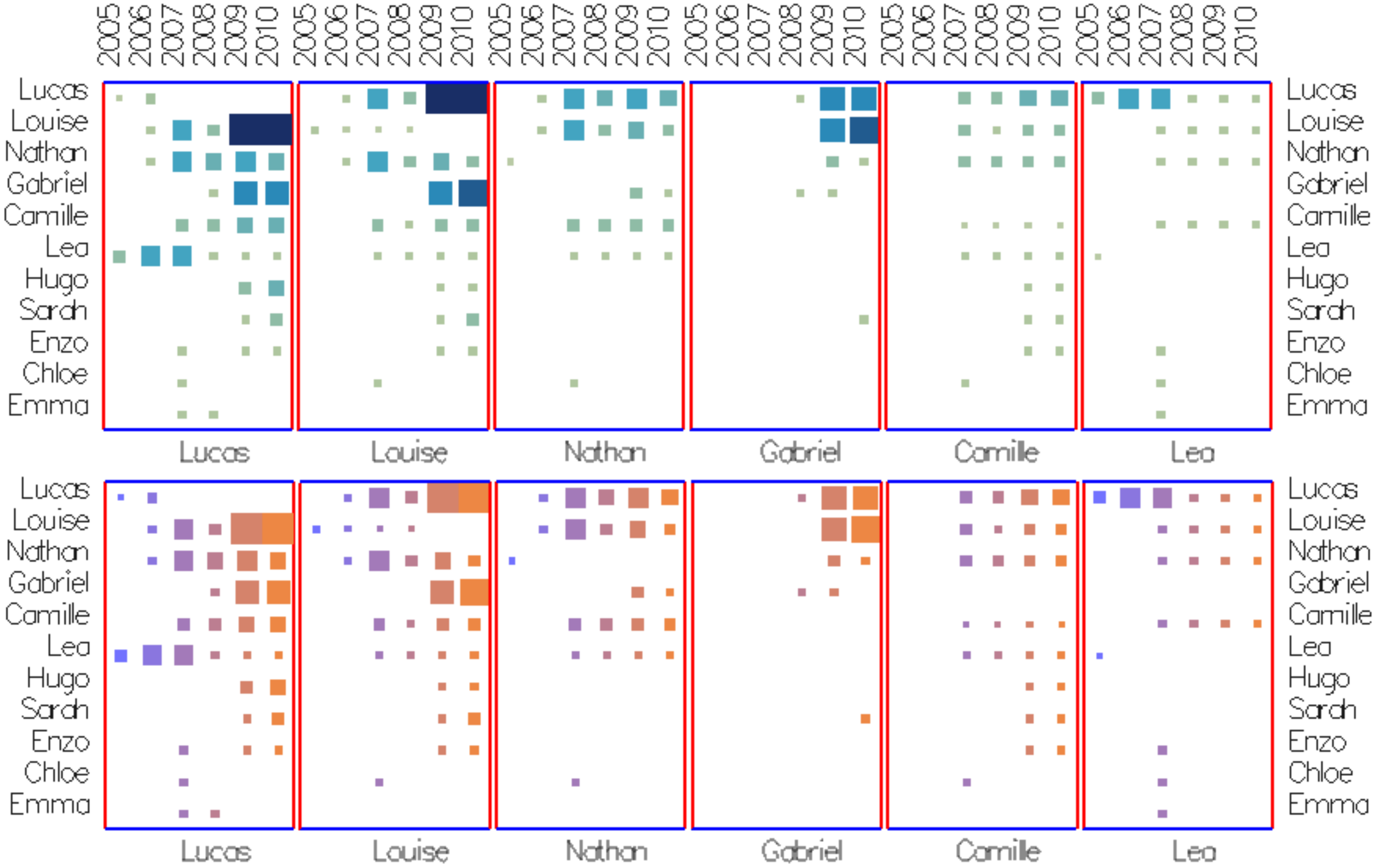


Small Multiples

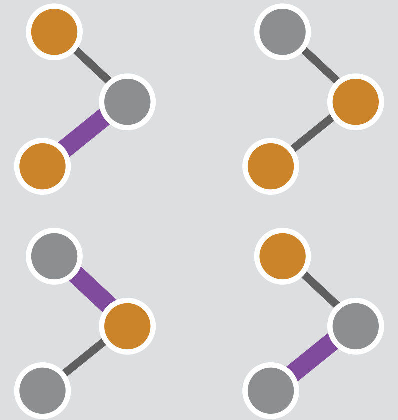


On-Node / On-Edge Encoding

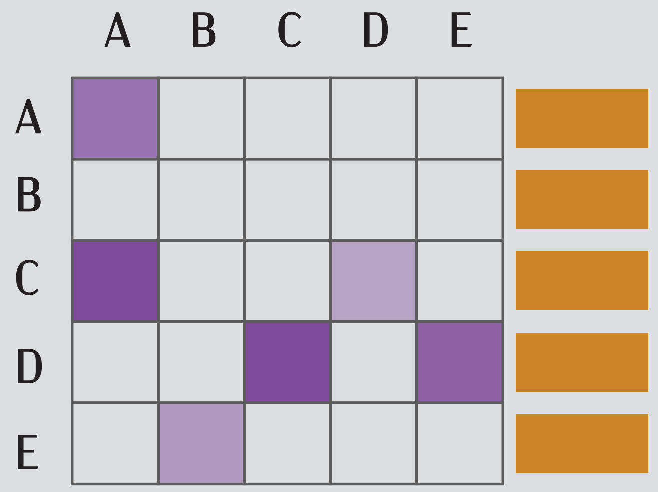
Peakspotting - https://truth-and-beauty.net/projects/peakspotting



Bach et al. 2014

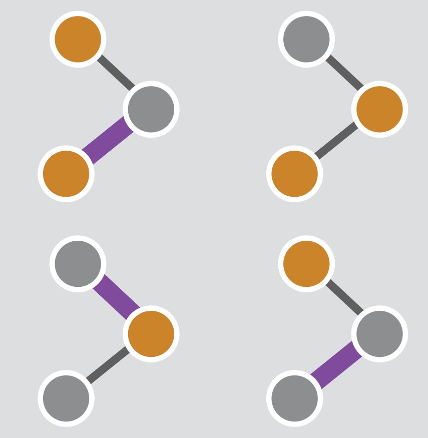


Small Multiples



Adjacency Matrix

Small Multiples



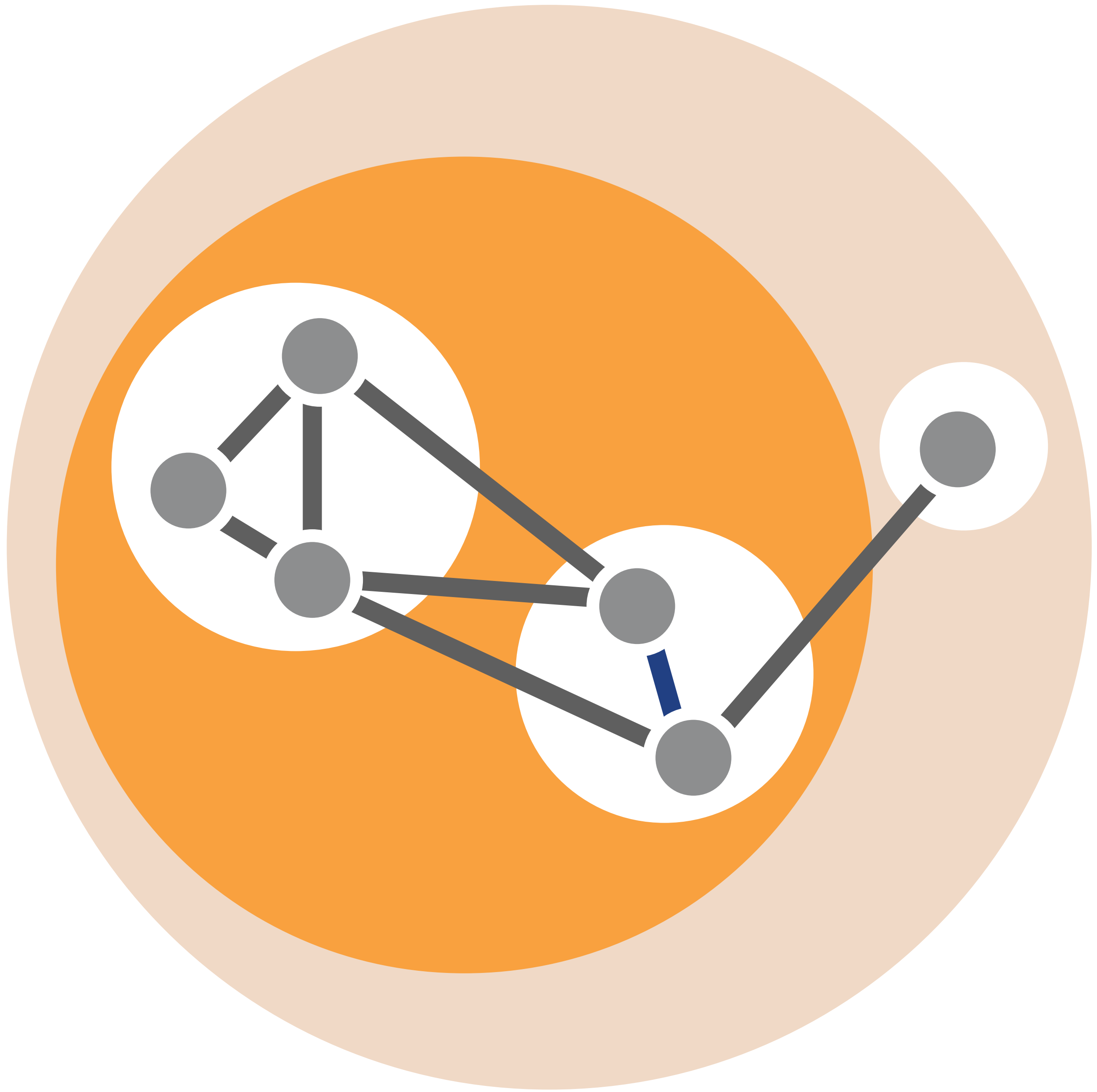
Small Multiples

Common layout facilitates attribute comparisons in specific topological features

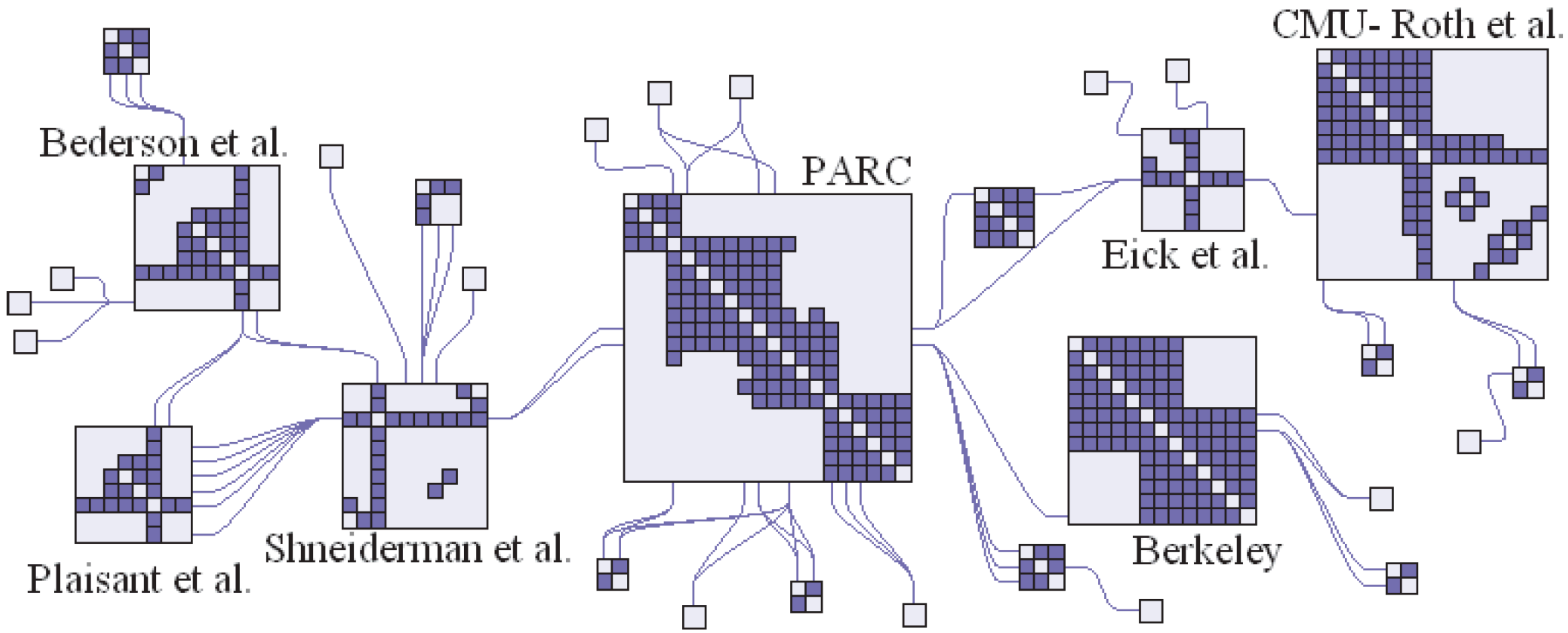
Not ideal for large networks, or tasks on clusters

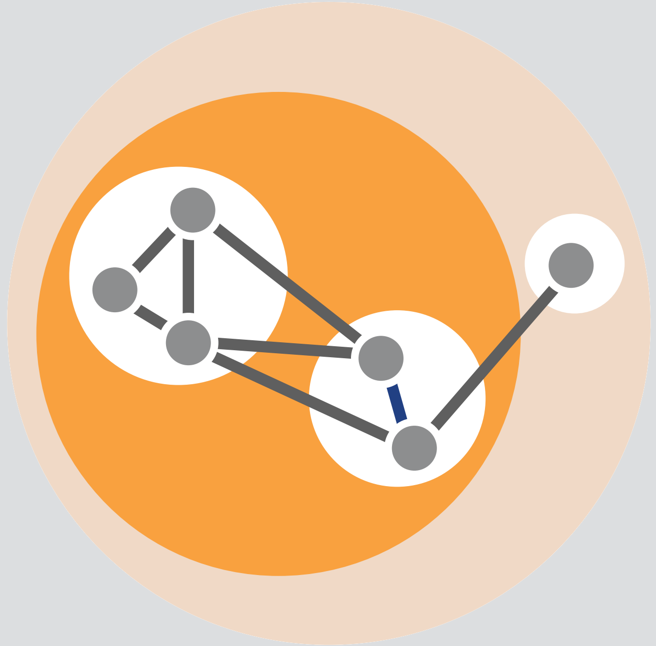
Recommended for small networks where the tasks are focused on attribute comparison

Hybrids



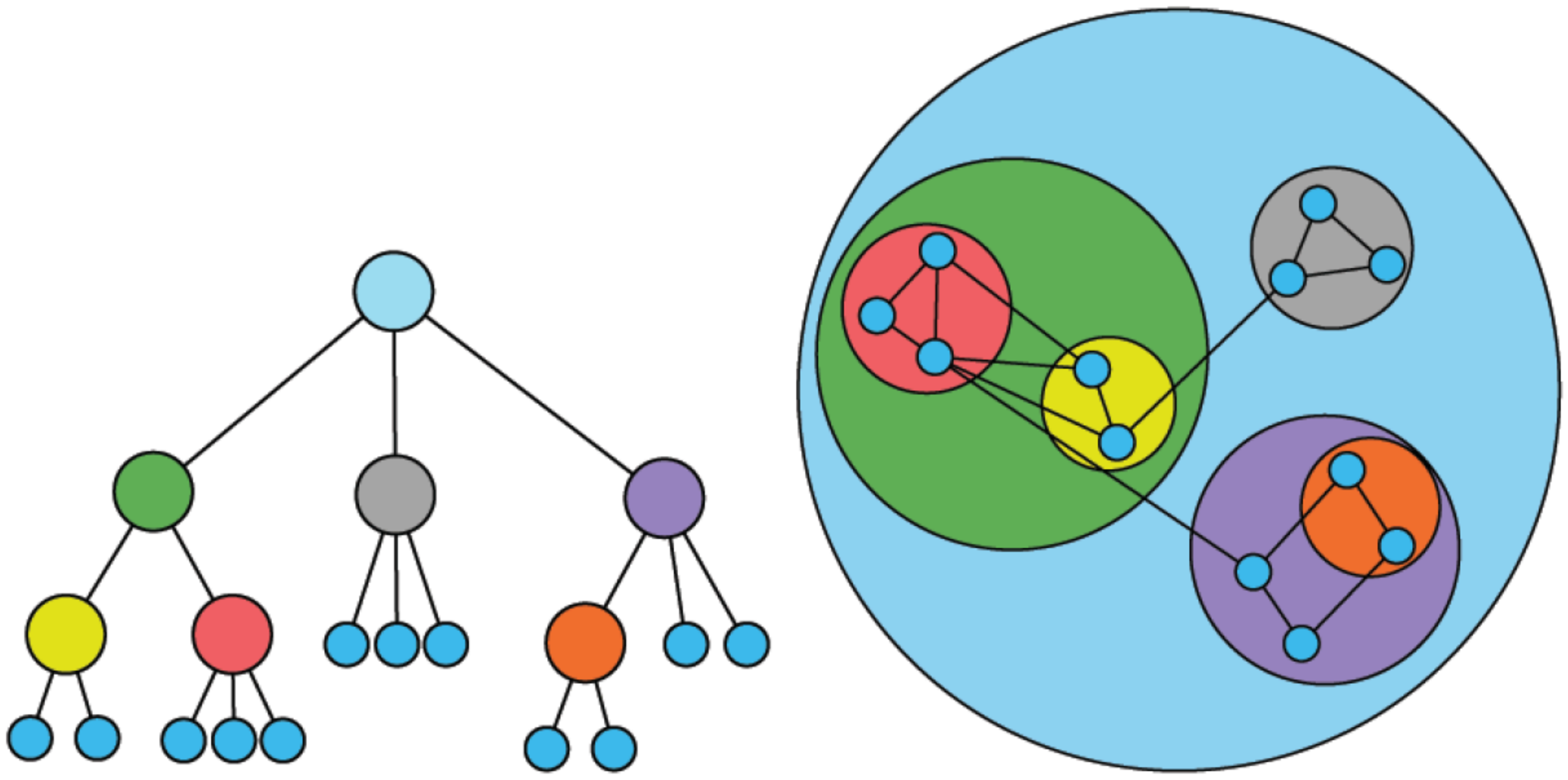
NodeTrix *Henry et al. 2007*

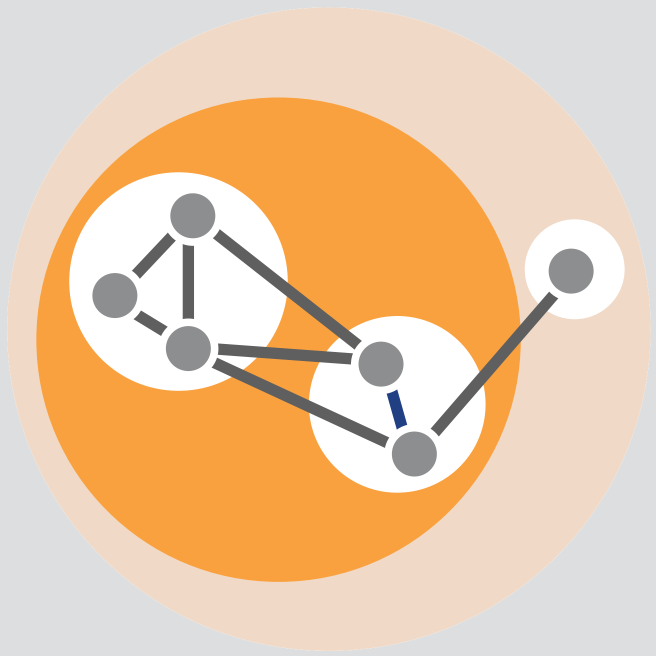




Hybrids

GrouseFlocks *Archambault et al. 2008*





Hybrids

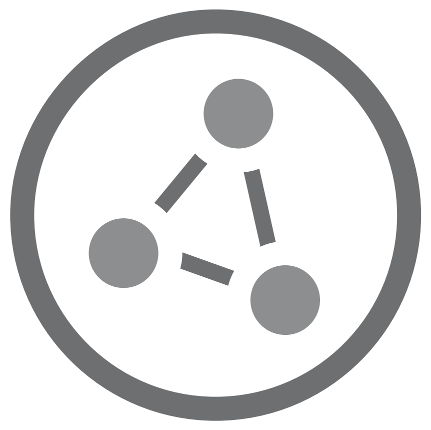
Hybrids

Can be useful for networks with irregular degree distribution

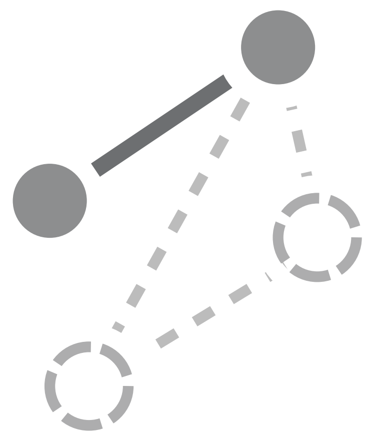
Adds complexity since users must parse different techniques simultaneously.

Recommended for networks with irregular degree distribution and few attributes

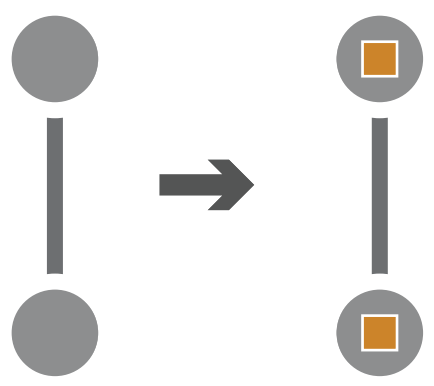
Data Operations



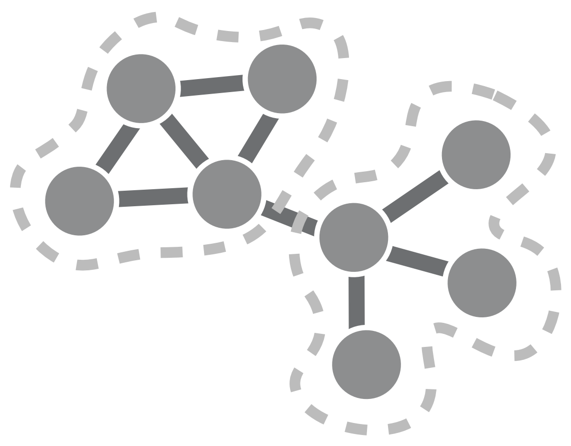
Aggregating Nodes/Edges



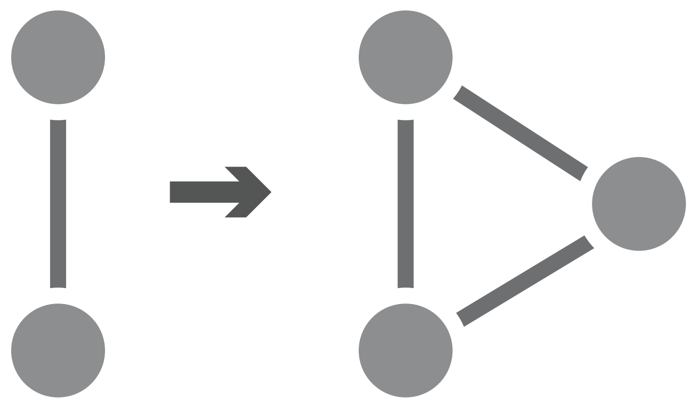
Querying and Filtering



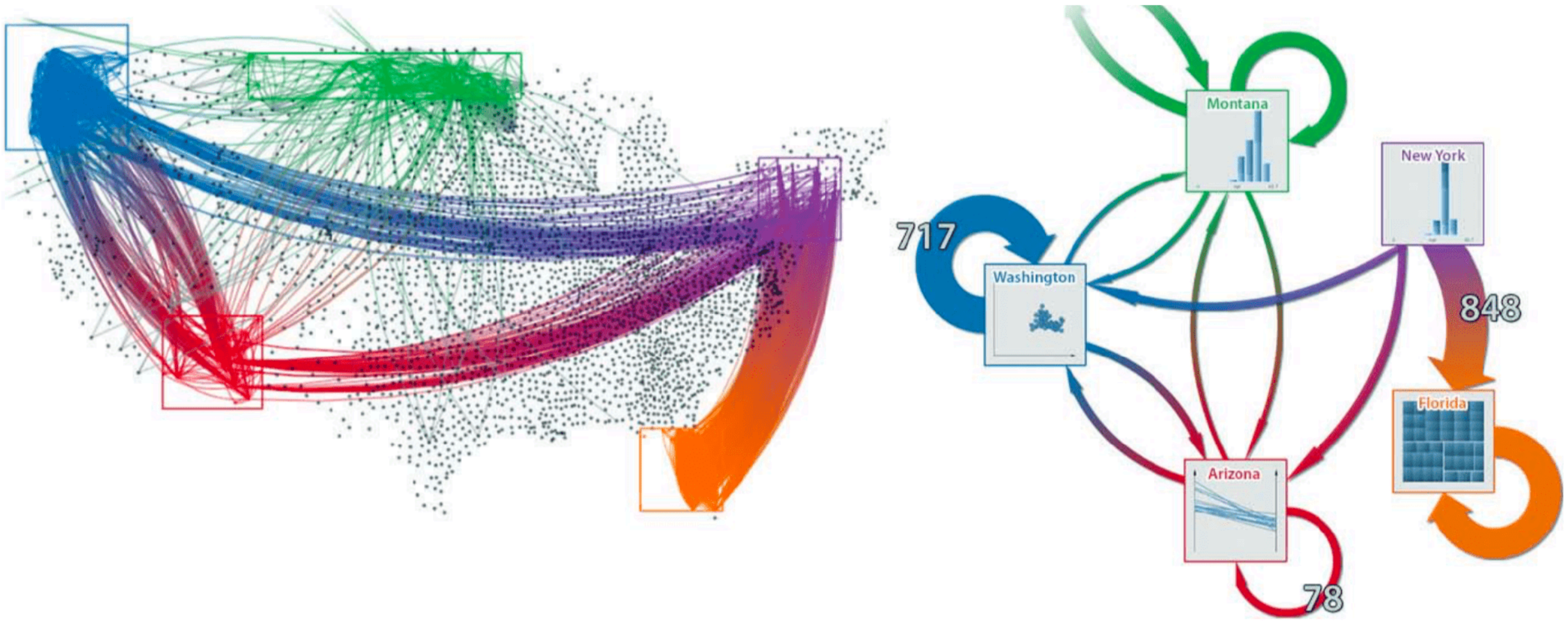
Deriving New Attributes



Clustering

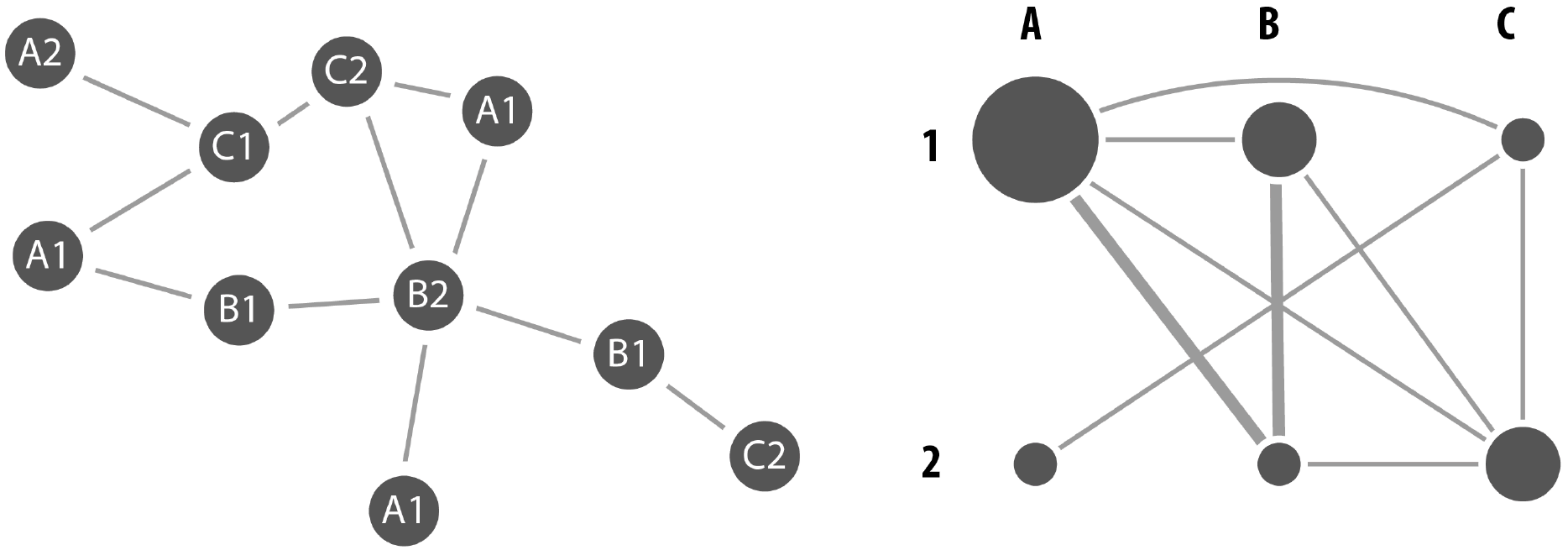


Converting Attributes/Edge to Nodes



Elzen and Wijk, 2014

Aggregating Nodes/Edges

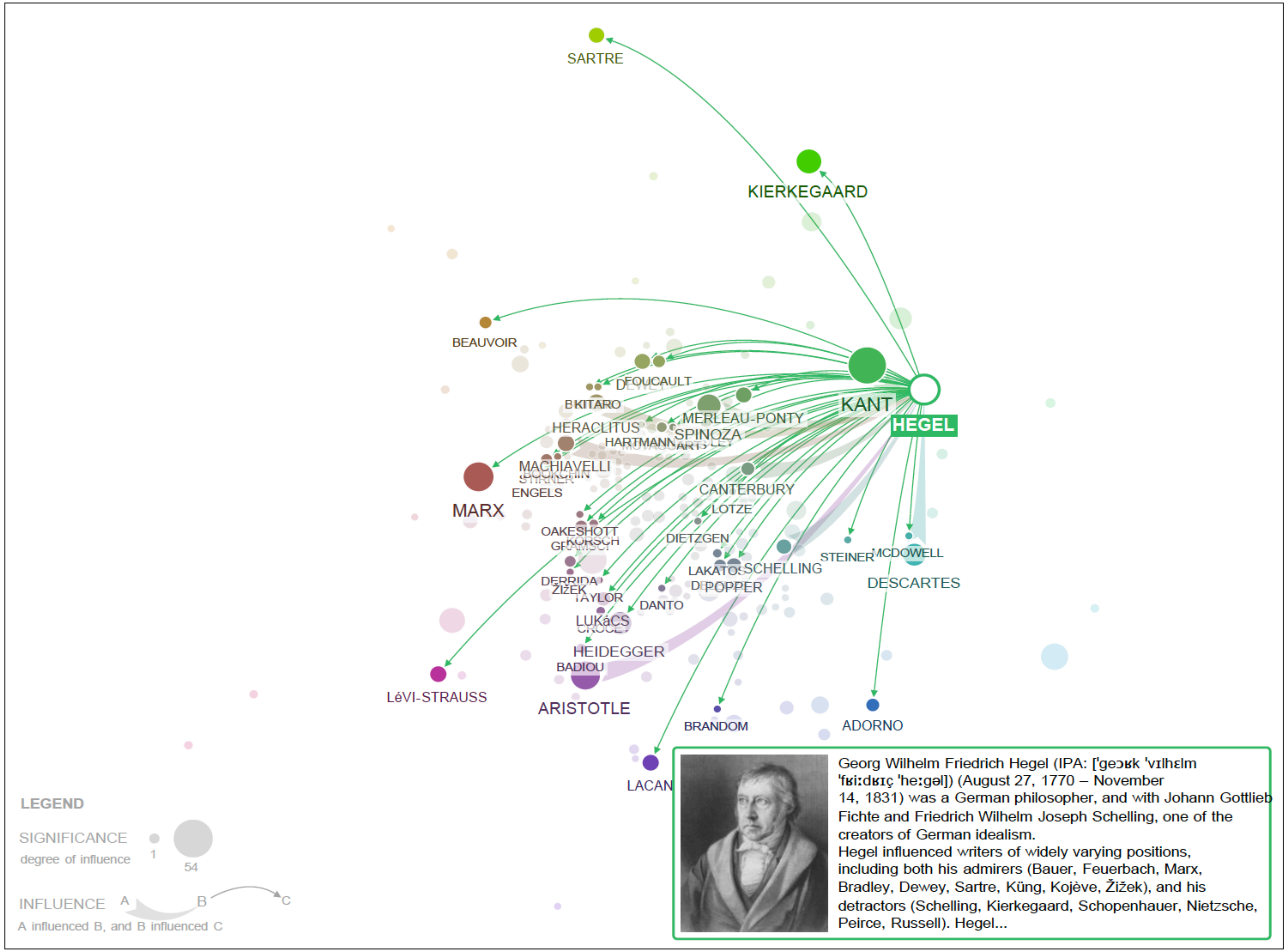


Node-Link Diagram

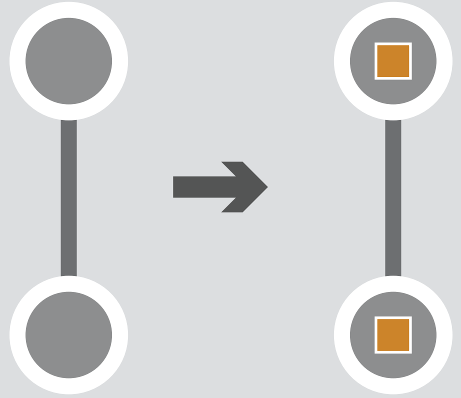
PivotGraph Roll-up

Wattenberg, 2006

Aggregating Nodes/Edges



Edge Map *Dork et al. 2011*



Deriving New Attributes

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/