

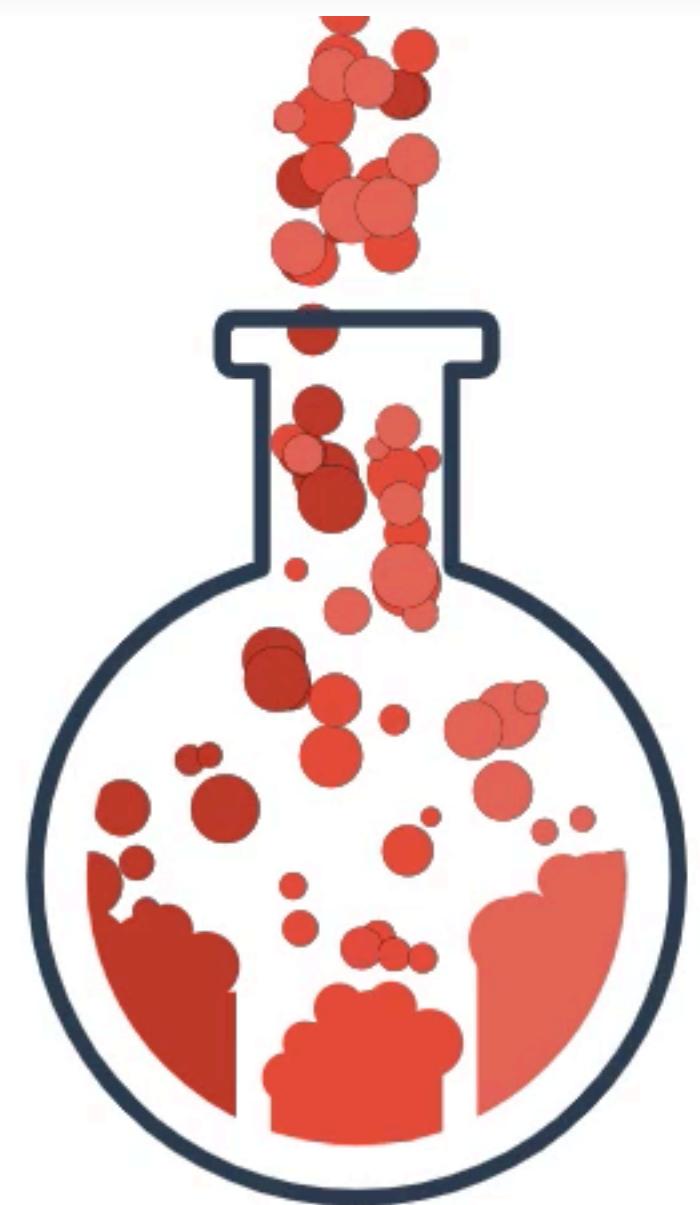
**Alexander Lex**

@alexander\_lex

<http://alexander-lex.net>



# Empirical Evaluation of Complex Interactive Visualization Techniques



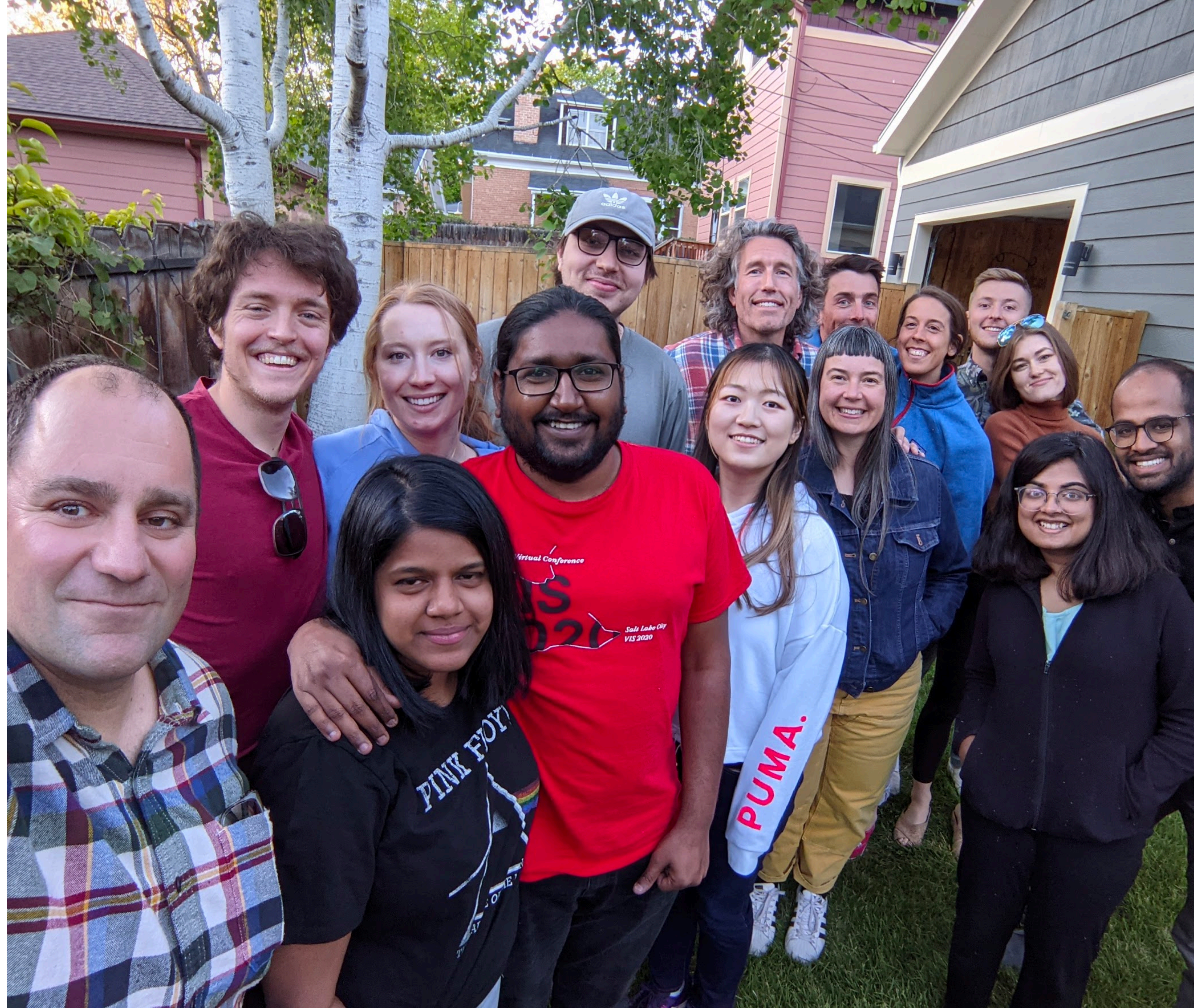
**visualization**  
**design lab**





**visualization**  
**design lab**

<http://vdl.sci.utah.edu/>



# datavisyn

On sabbatical at datavisyn, in Linz

Data visualization solutions for  
pharmaceutical industry

20 people and growing!



Marc Streit, CEO



Dominic Giradi, CPO



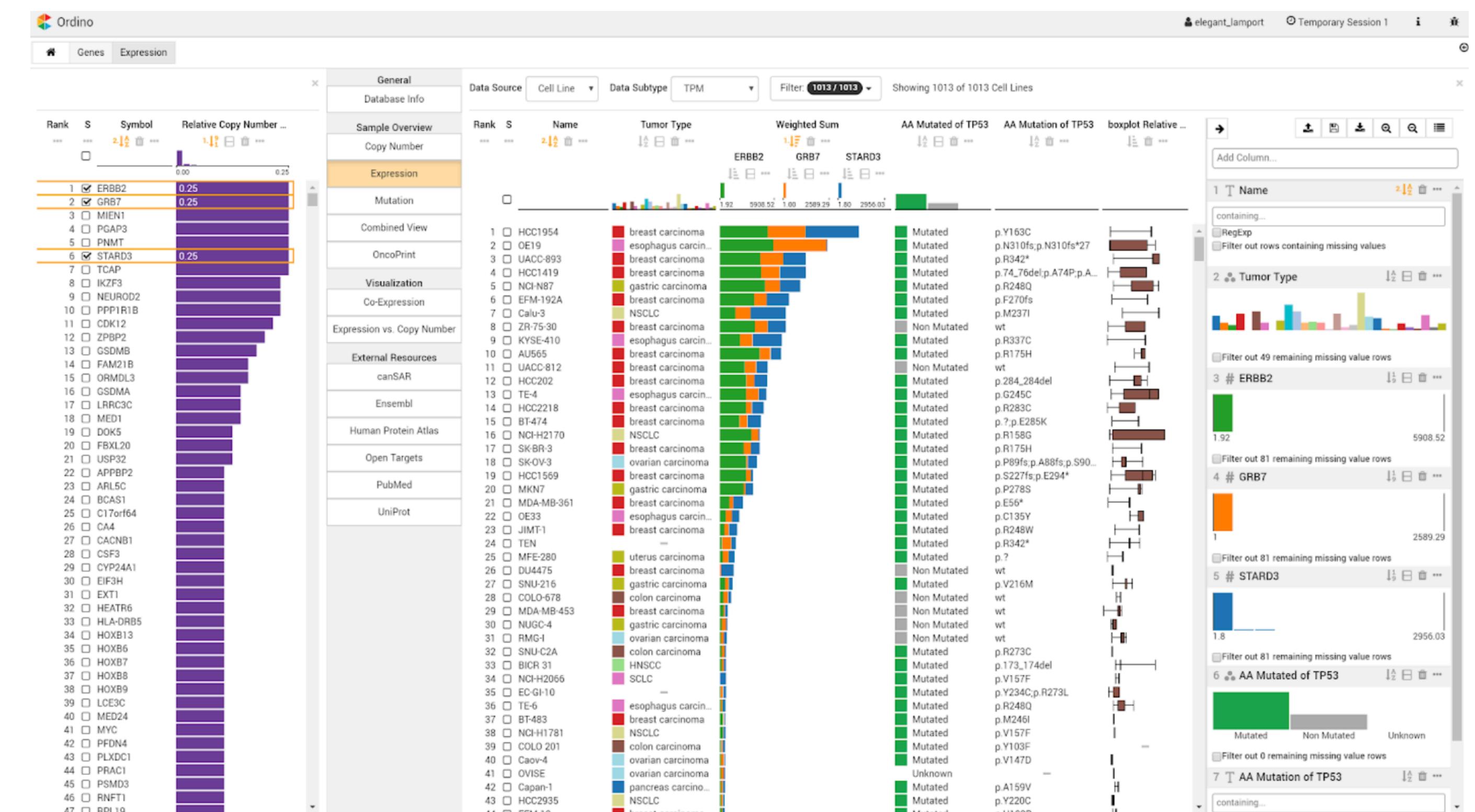
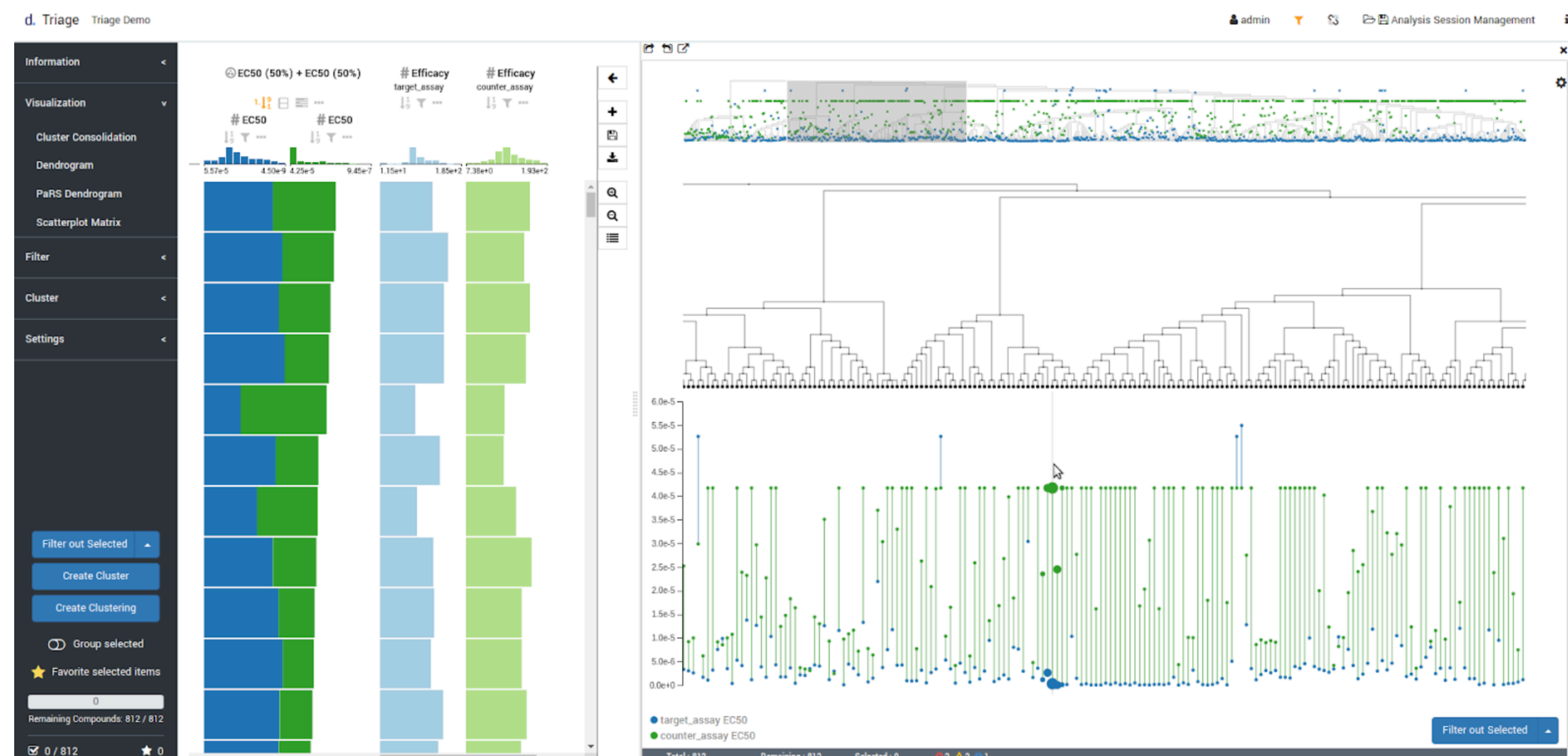
Alexander Lex



Nils Gehlenborg



Samuel Gratzl



**visualization**

**The purpose of computing is insight,  
not numbers.**

**pictures**

**[Card, Mackinlay, Shneiderman]**

**[Richard Wesley Hamming]**

**Banana** *M. acuminata*

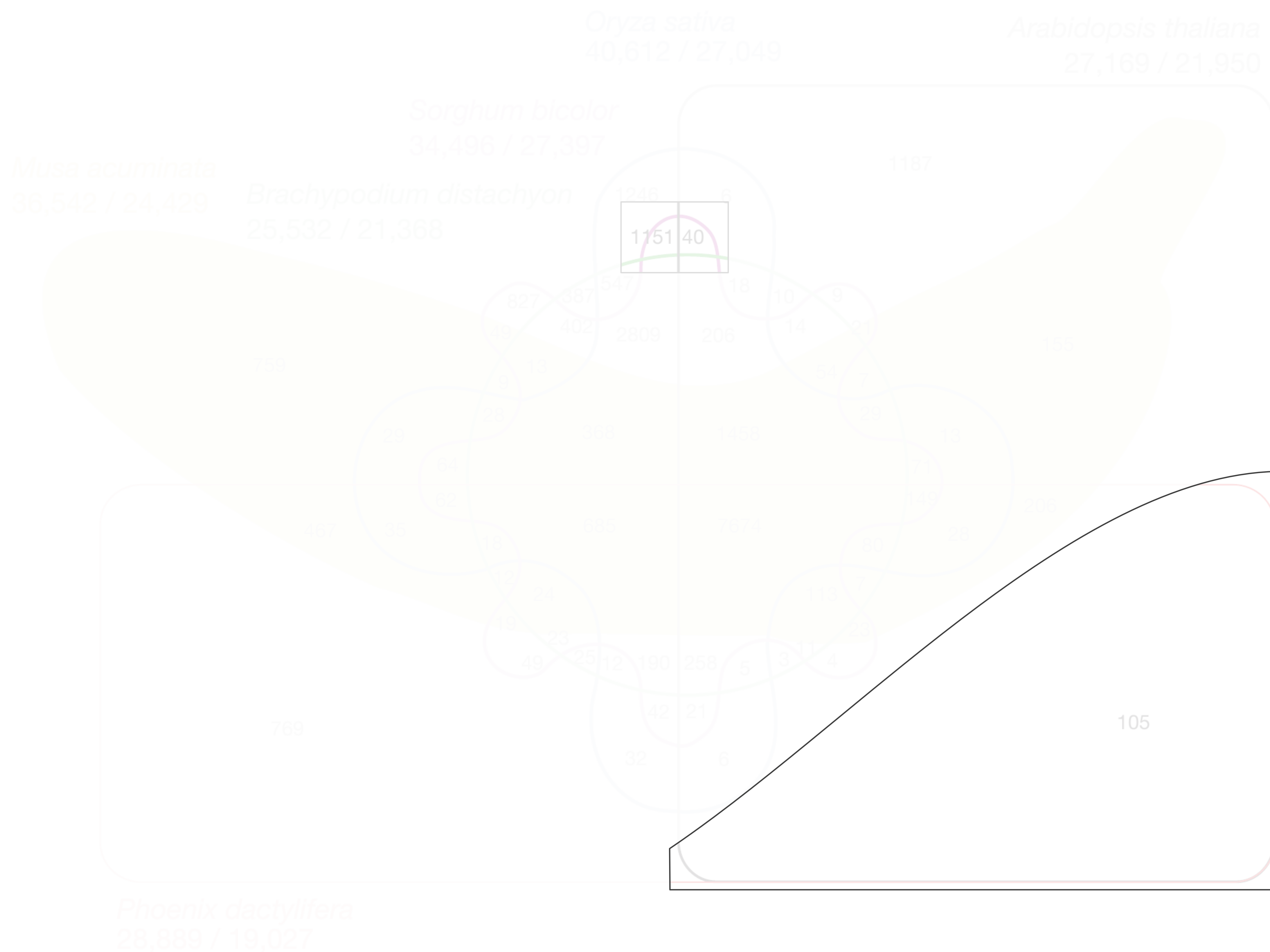
**Date** *P. dactylifera*

**Cress** *Arabidopsis thaliana*

**Rice** *Oryza sativa*

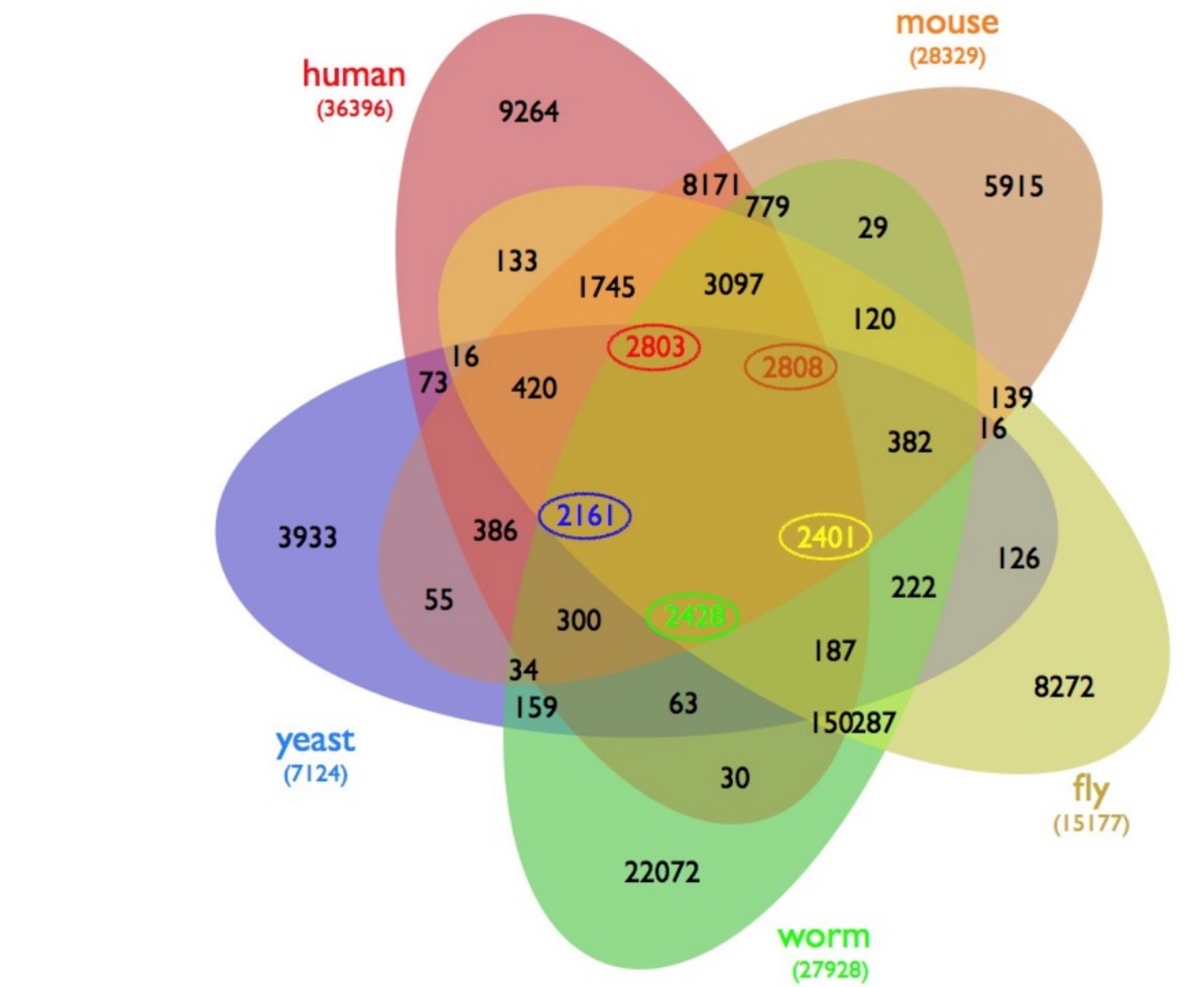
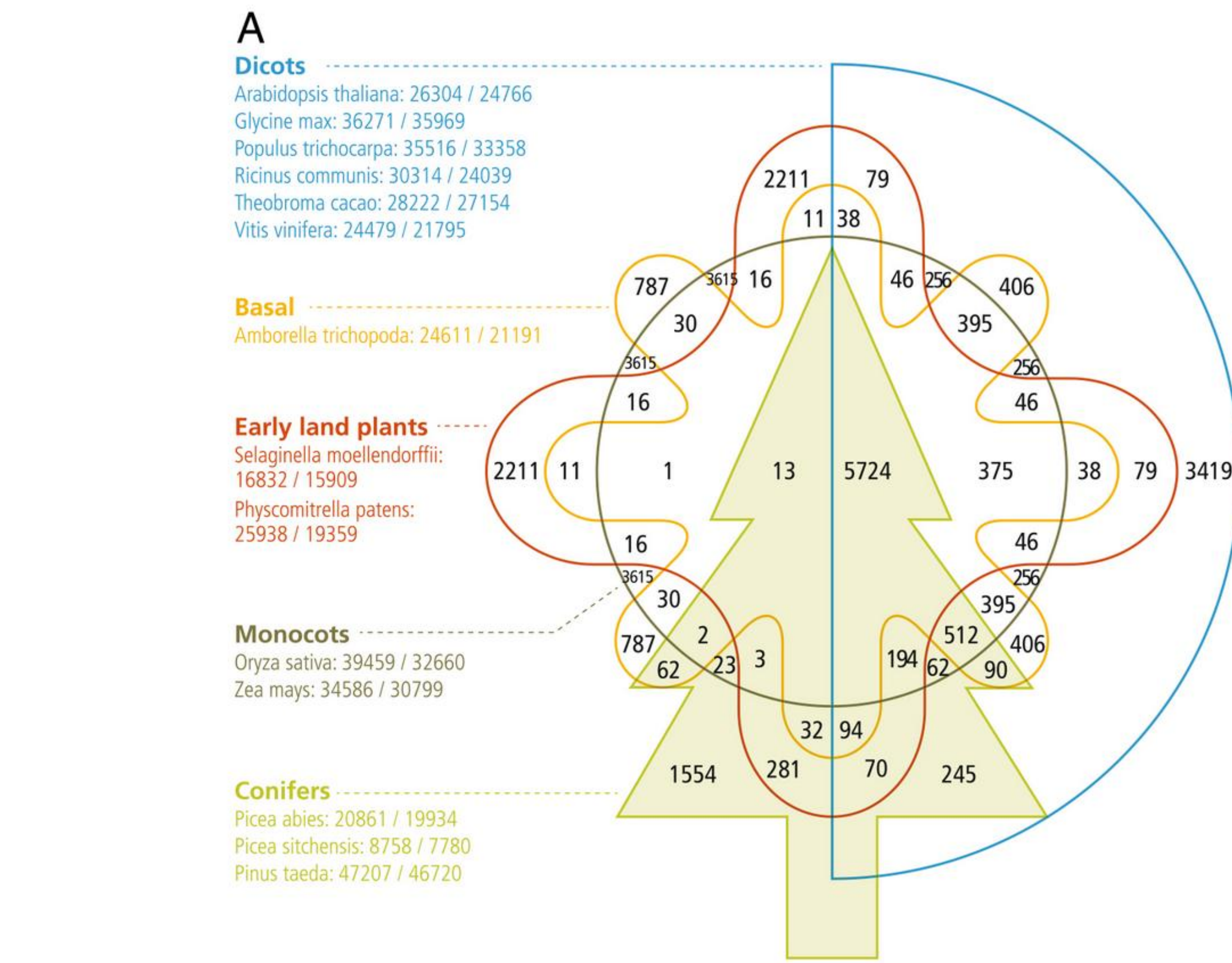
**Sorghum** *Sorghum bicolor*

**Brome** *Brachypodium distachyon*

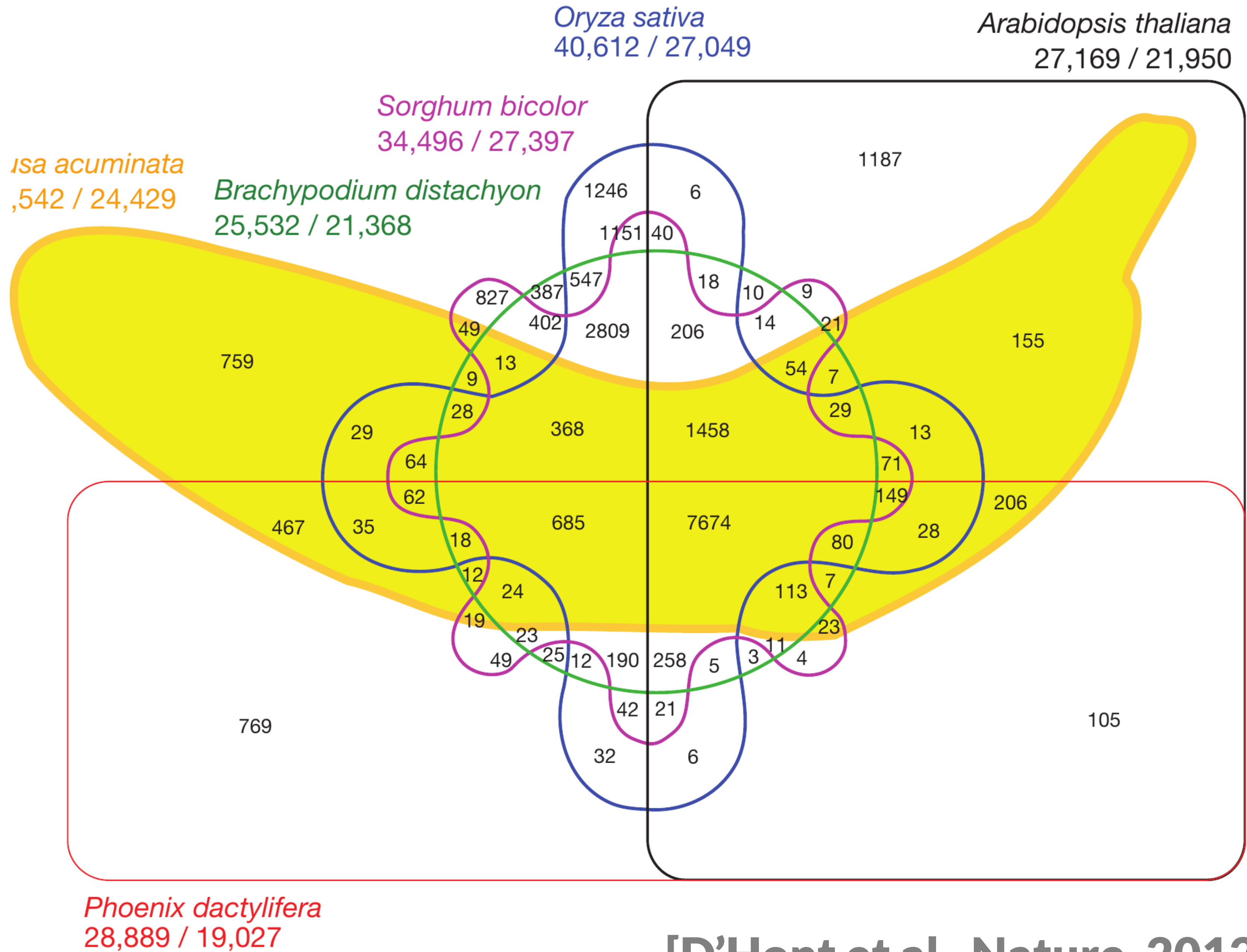


[D'Hont et al., Nature, 2012]

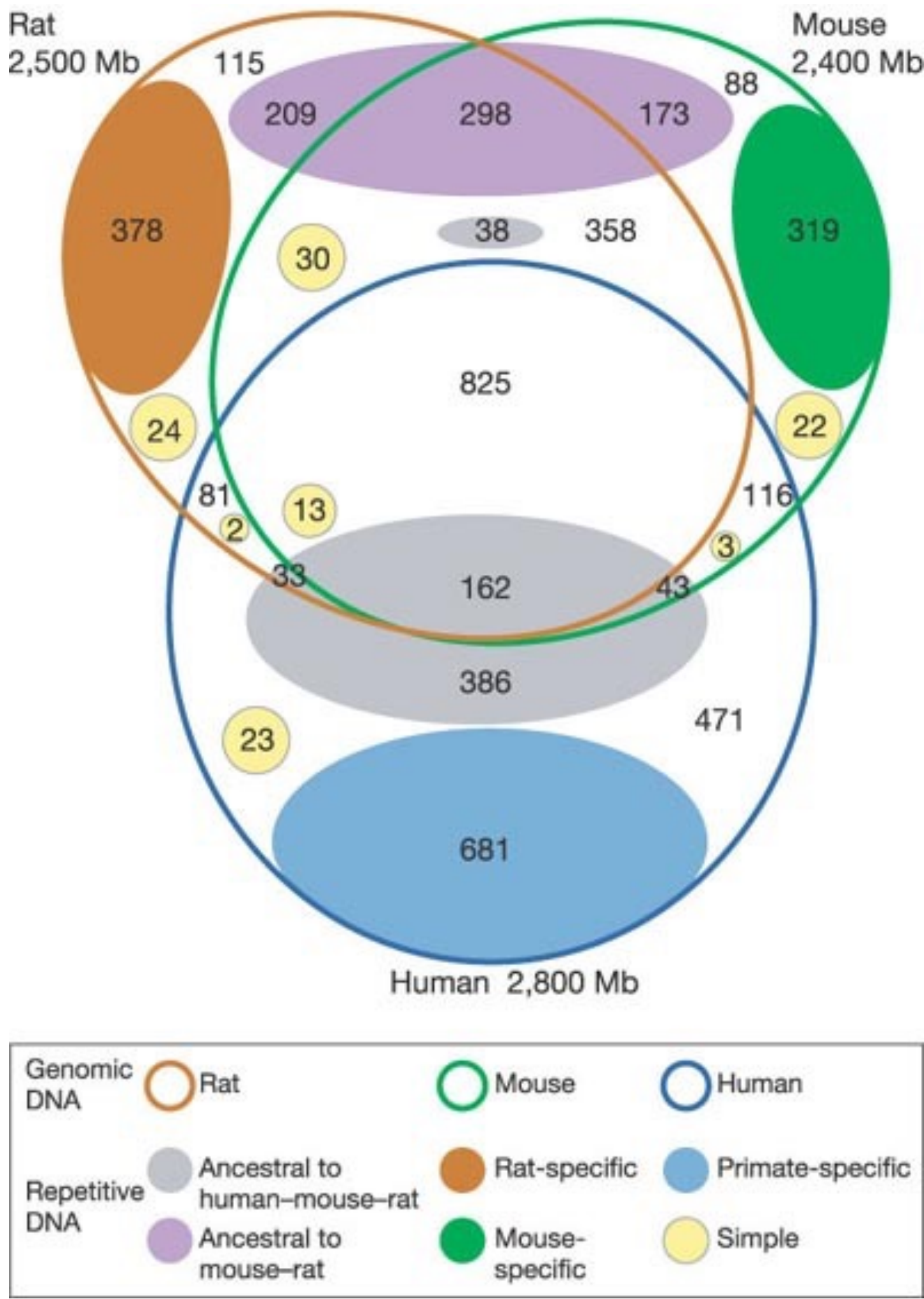
[Neale et al., BMC Genome Biology, 2014]



[Wiles et al., BMC Systems Biology]

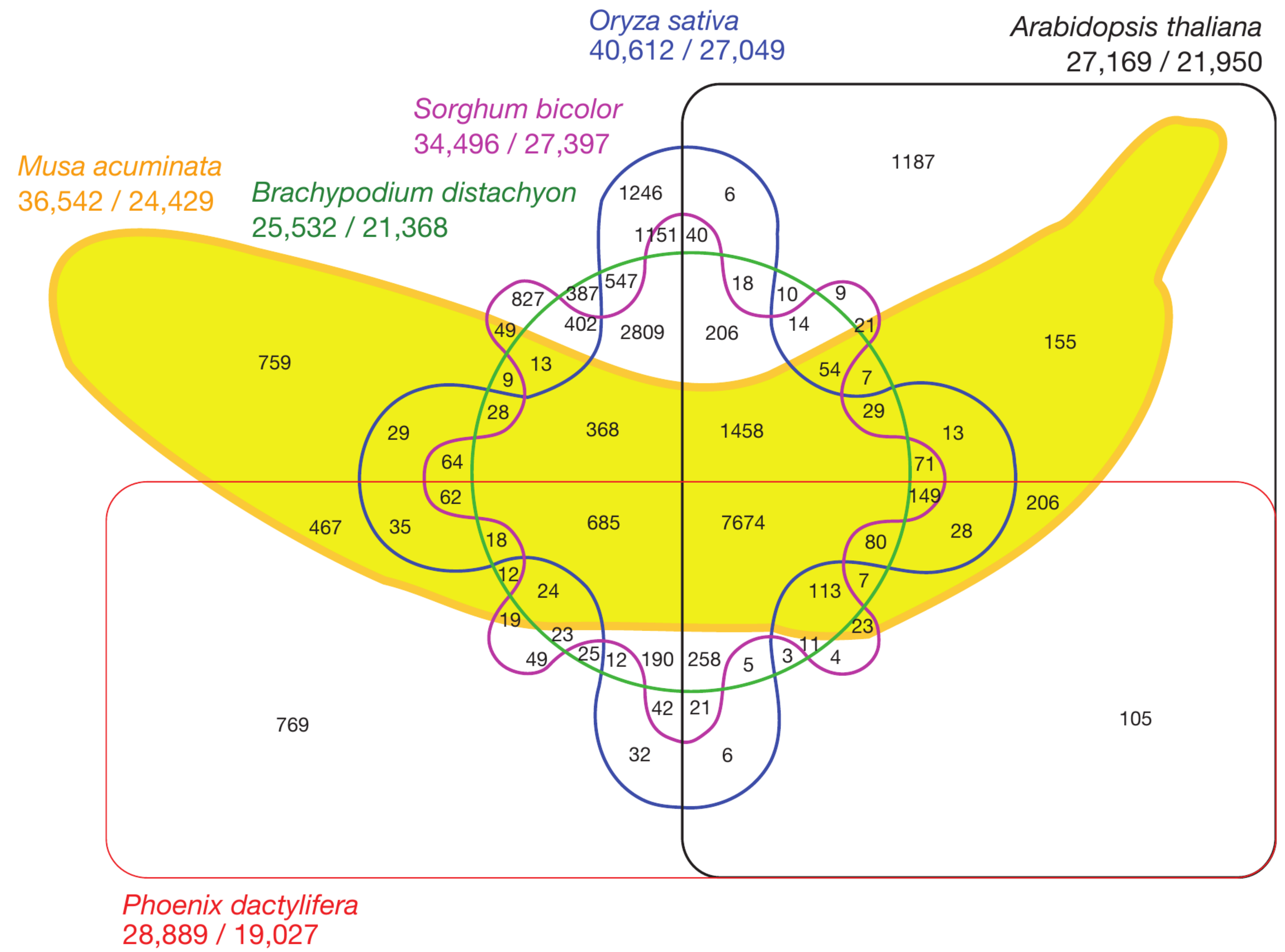


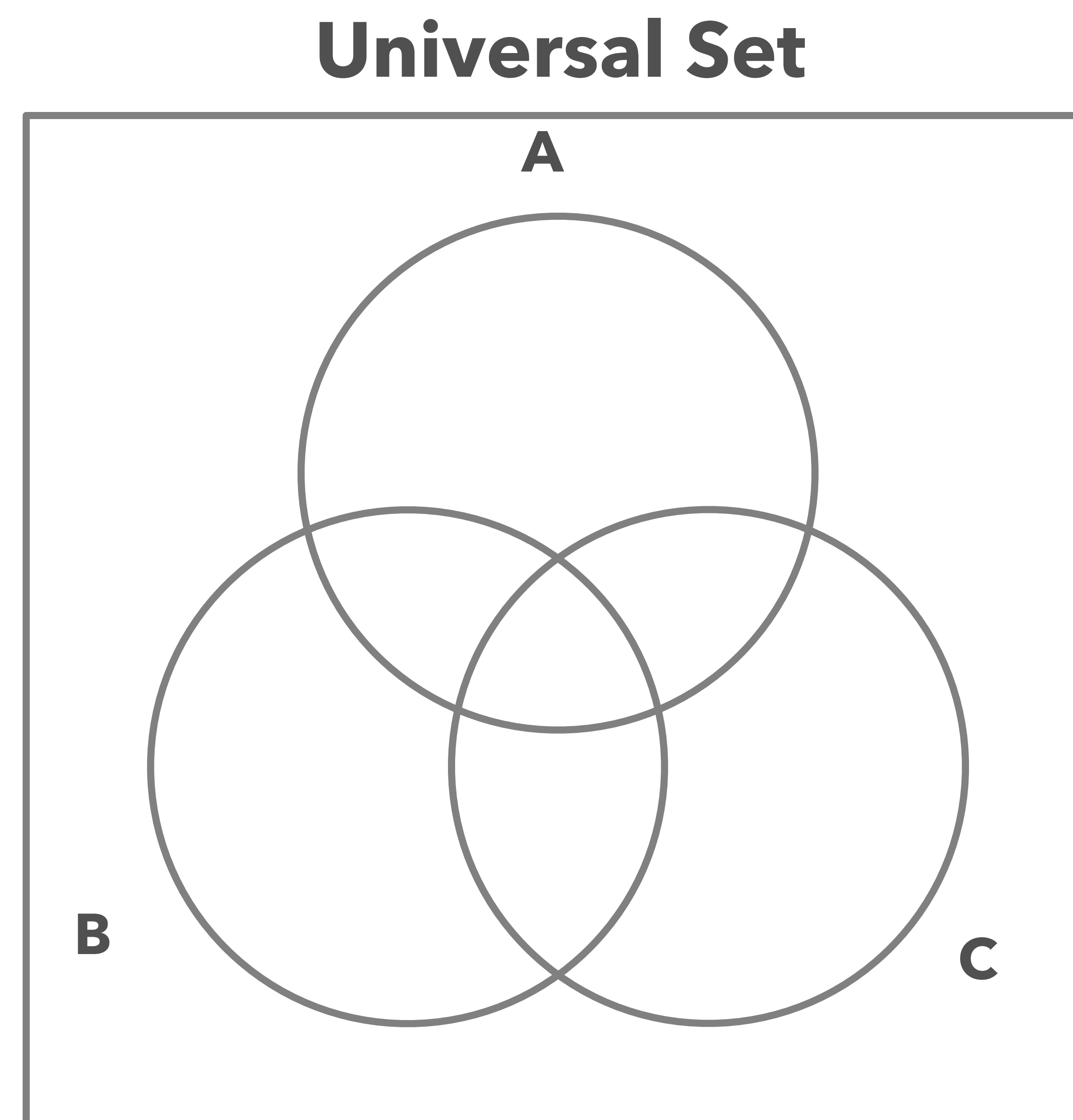
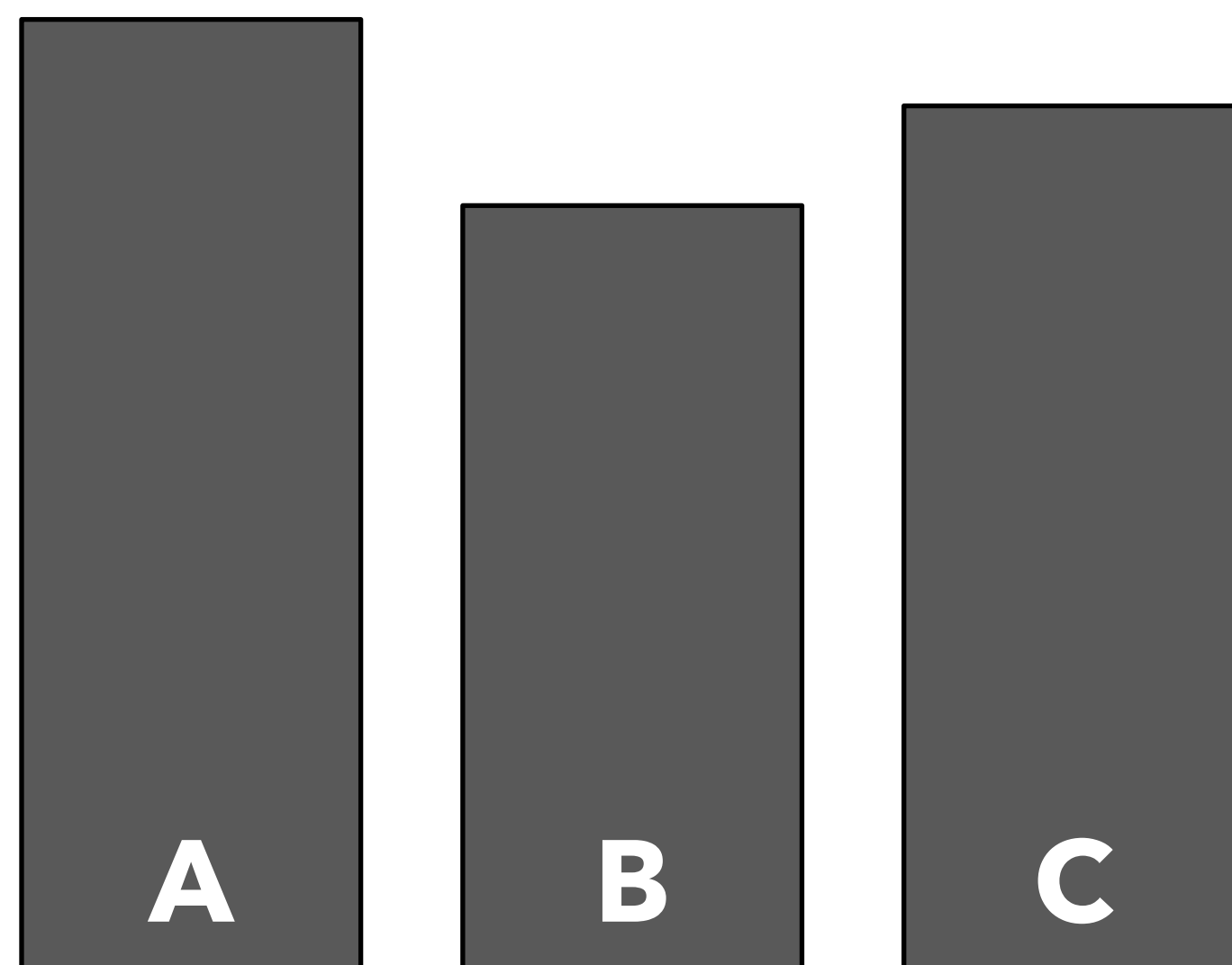
[D'Hont et al., Nature, 2012]

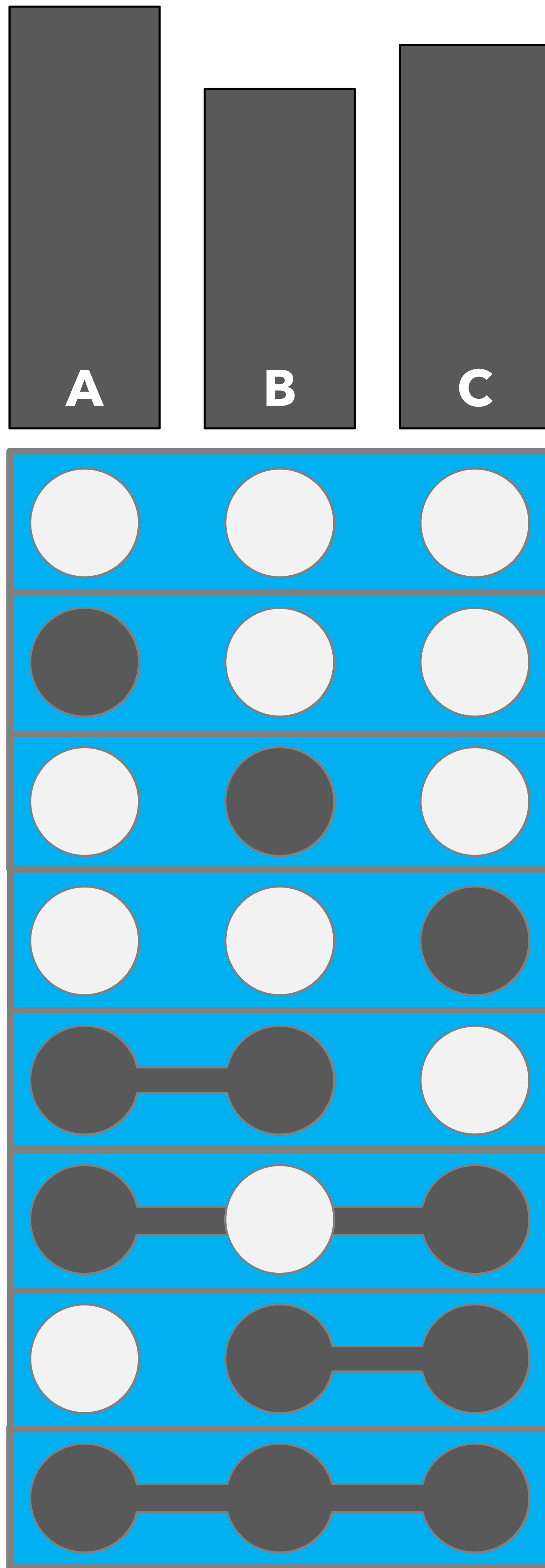


[Gibbs et al., Nature, 2004]

SO CAN WE DO  
BETTER?





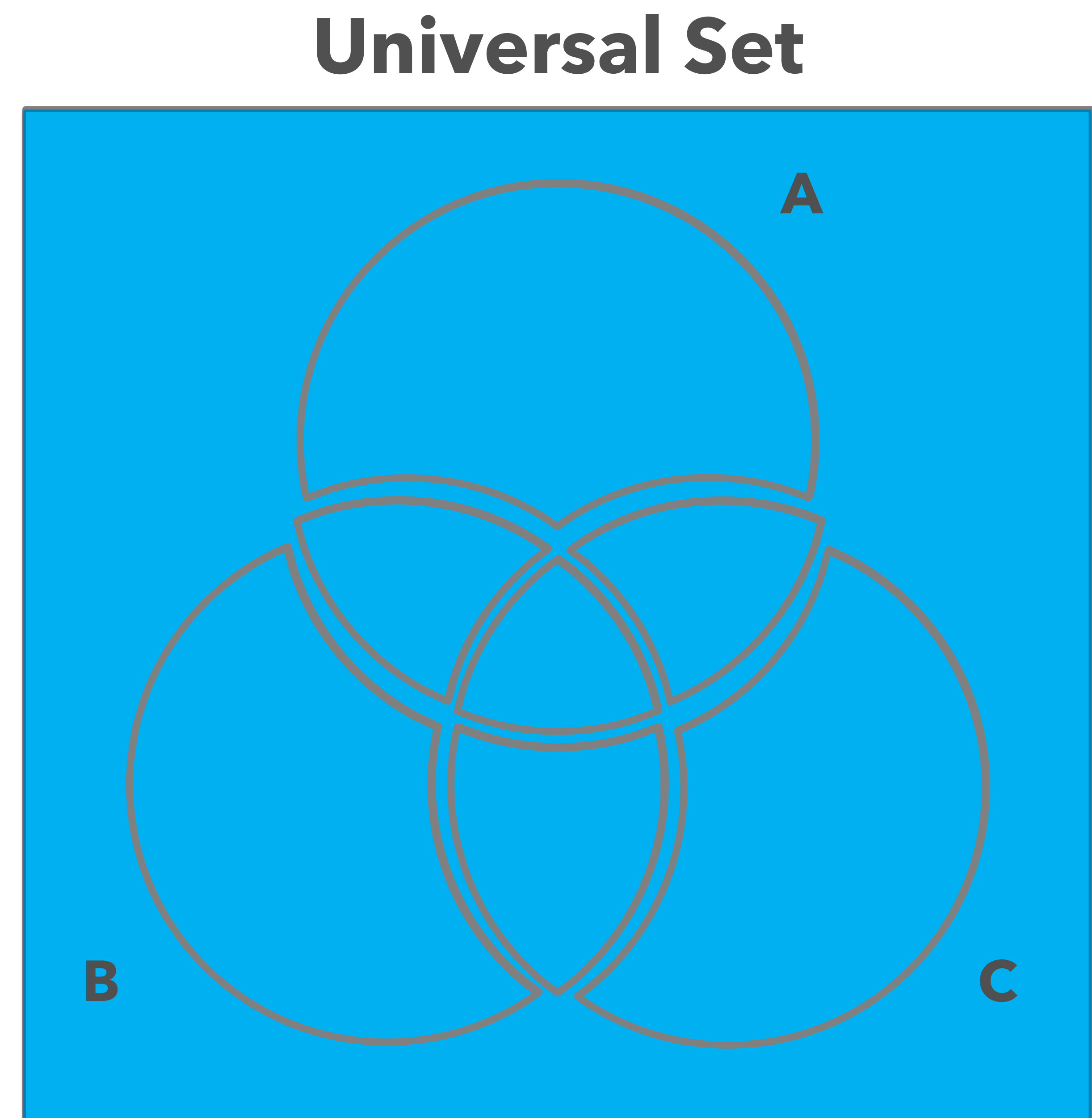


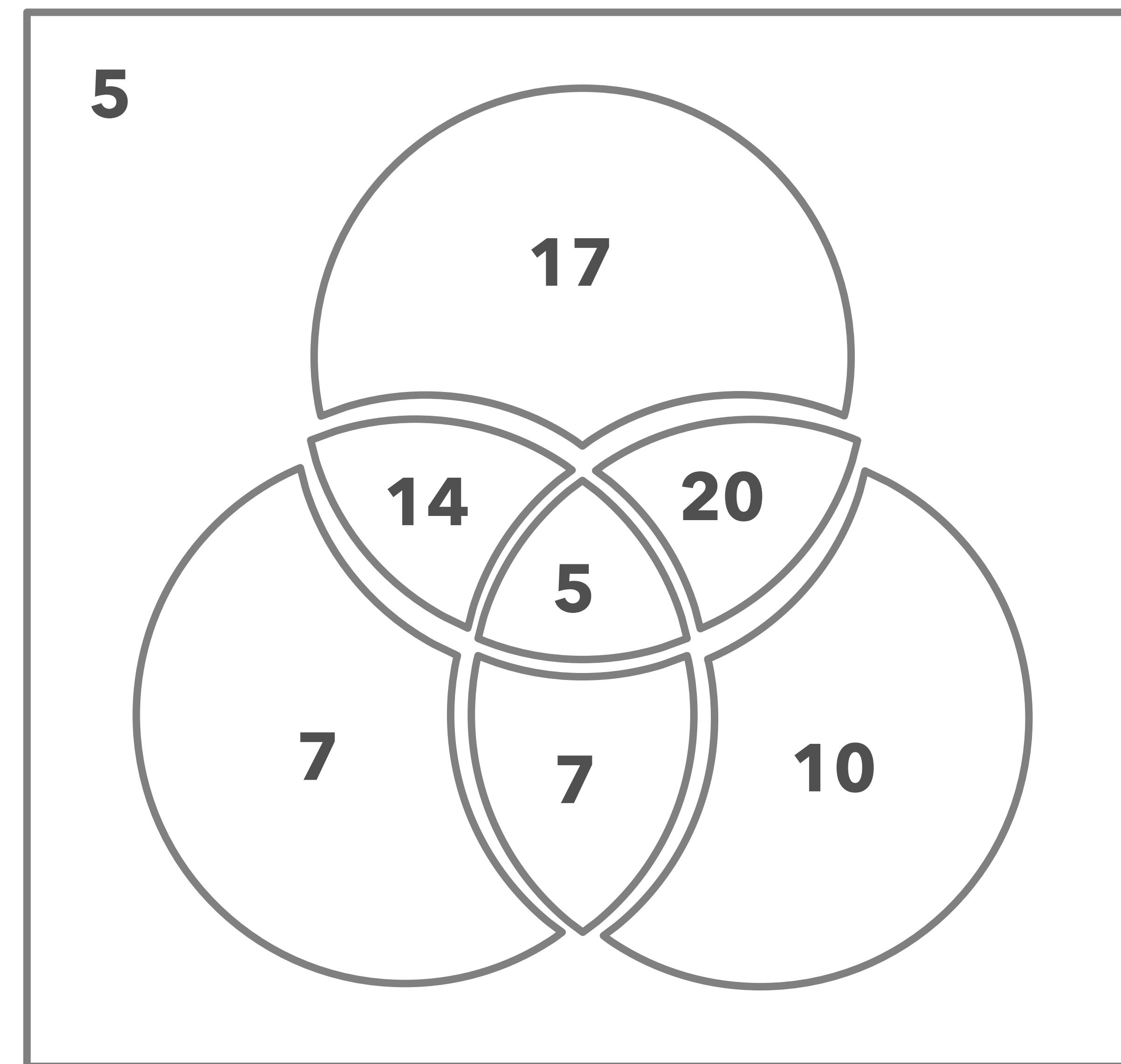
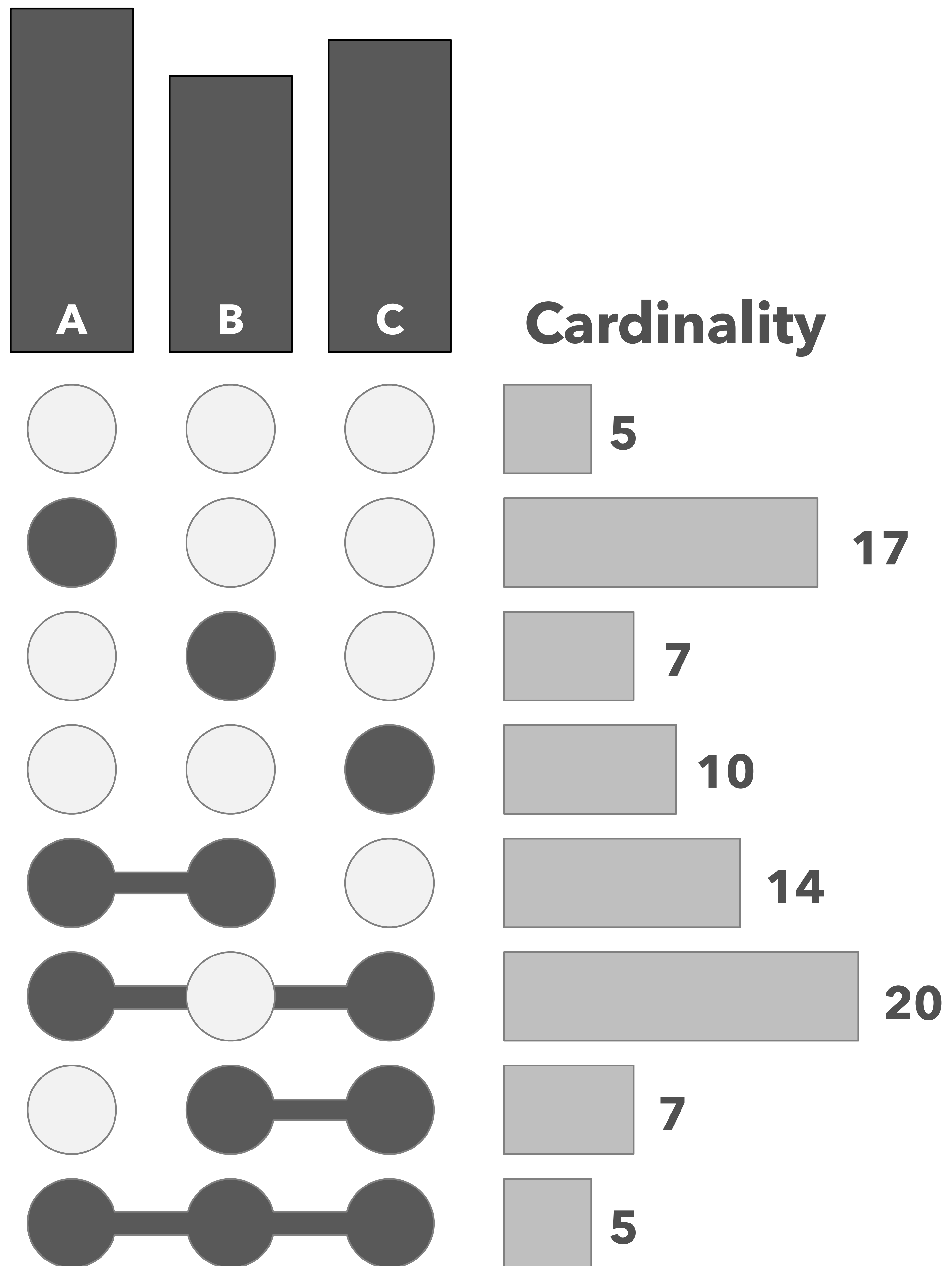
●

Must

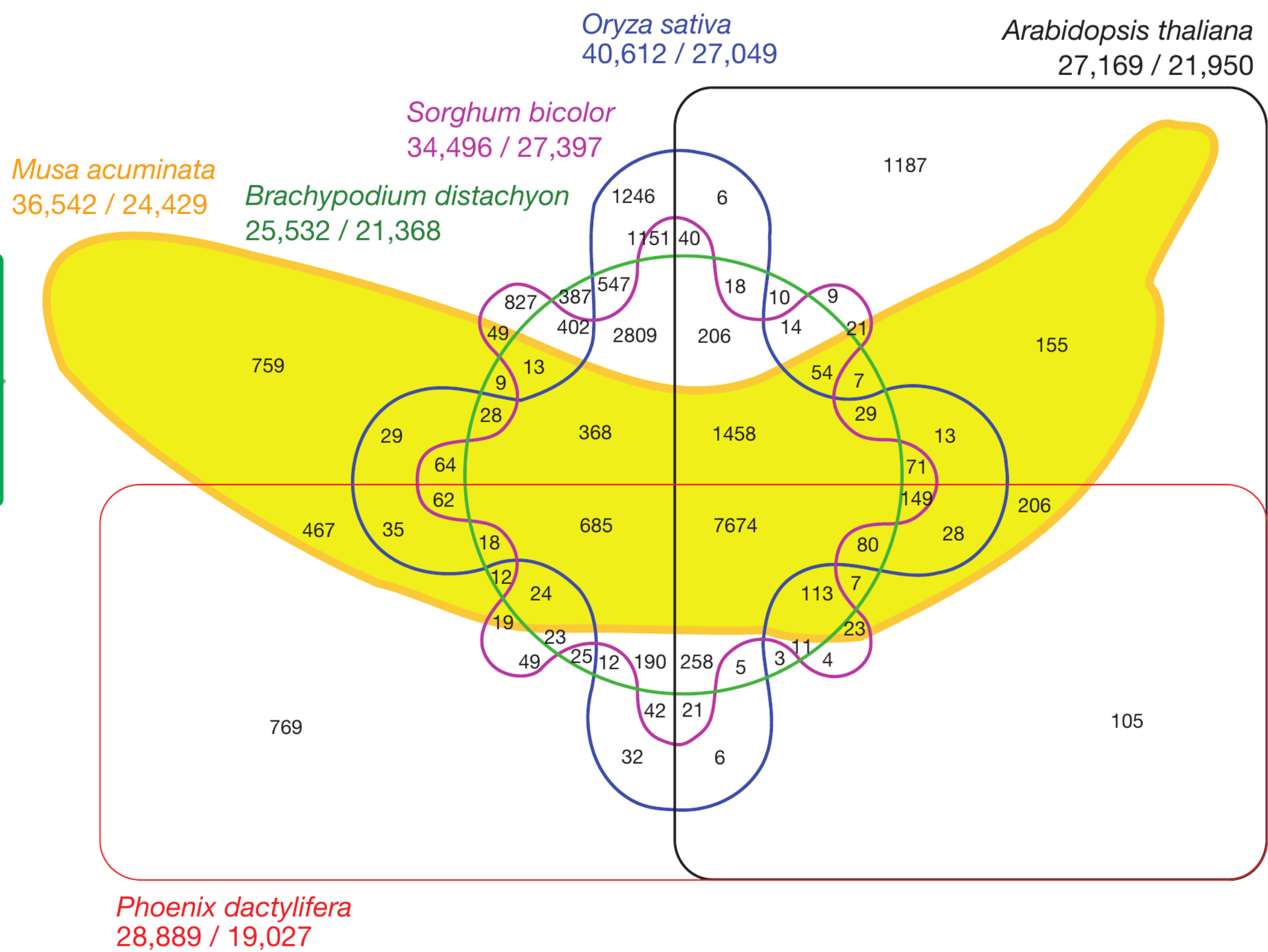
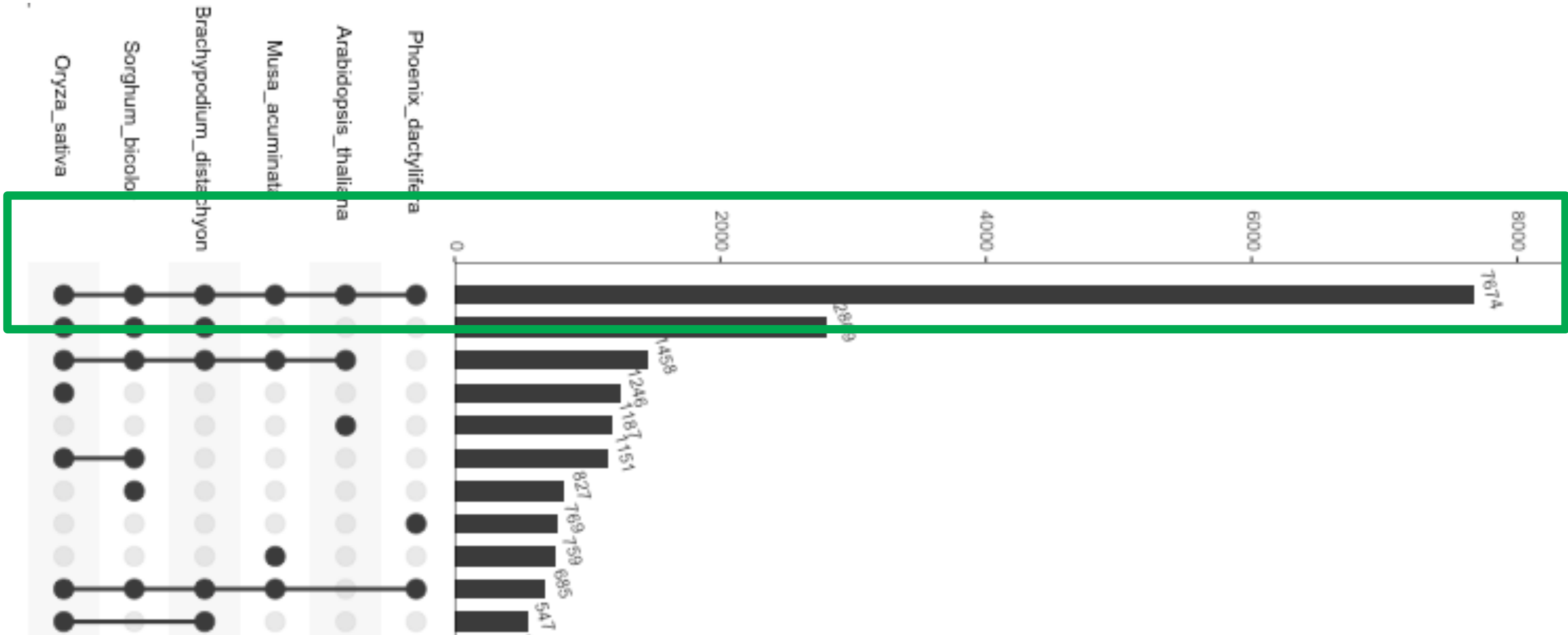
○

Must Not



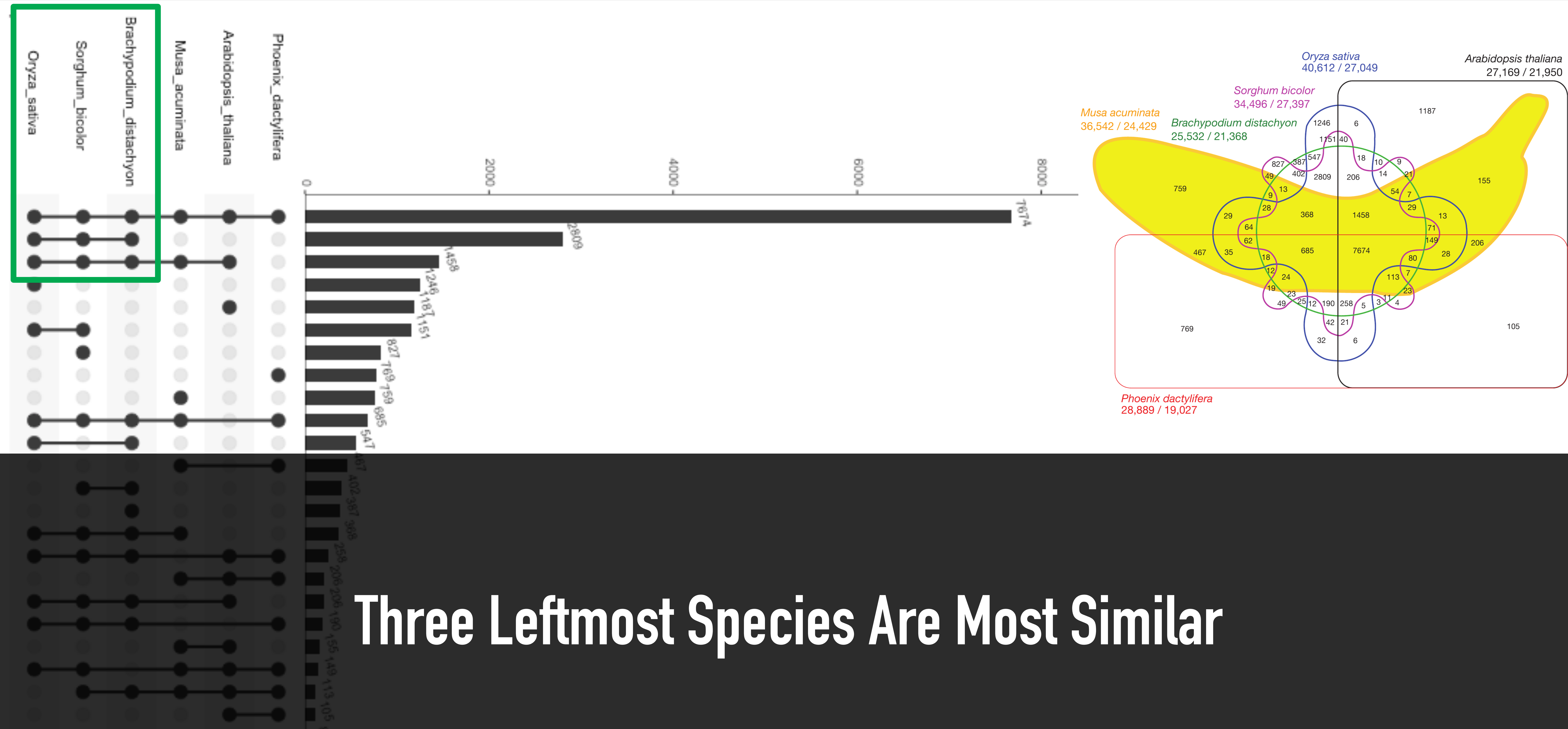


# THE BANANA CHART REDESIGNED: UPSET



Largest Intersection Includes All Sets

# THE BANANA CHART REDESIGNED: UPSET



# THE BANANA CHART REDESIGNED: UPSET



Rightmost species is most different

First, aggregate by  
Don't Aggregate

Then, aggregate by  
Don't Aggregate

Sort by

- Degree
- Cardinality
- Deviation

Aggregates

Collapse All  
Expand All

Row Height

Large

Data

Min Degree:

0

Max Degree:

5

Hide Empty Intersections

Dataset Information

Name: Movies Genres

# Sets: 17

# Attributes: 6

# Elements: 3883

Author: grouplens

Description:

MovieLens ratings dataset, curated and filtered by Alsallakh.

Source:

http://grouplens.org/d..

Set Selection

0 - 11

Batch Add Sets

Sort Sets

Drama Thriller Romance Horror SciFi War Musical Mystery Fantasy Western Noir

0 1000 2000 3000 3883

Cardinality

Deviation

Release Date

Average Rating

Times Watched

+ Query

Adventure Children Comedy Crime

0 100 200 300 400 500

-10% -5% 0% 5% 10%

1,950 2,000

2 4

0 2,000

1777

1003

283

131

123

101

85

78

66

62

38

38

24

13

13

13

9

7

5

4

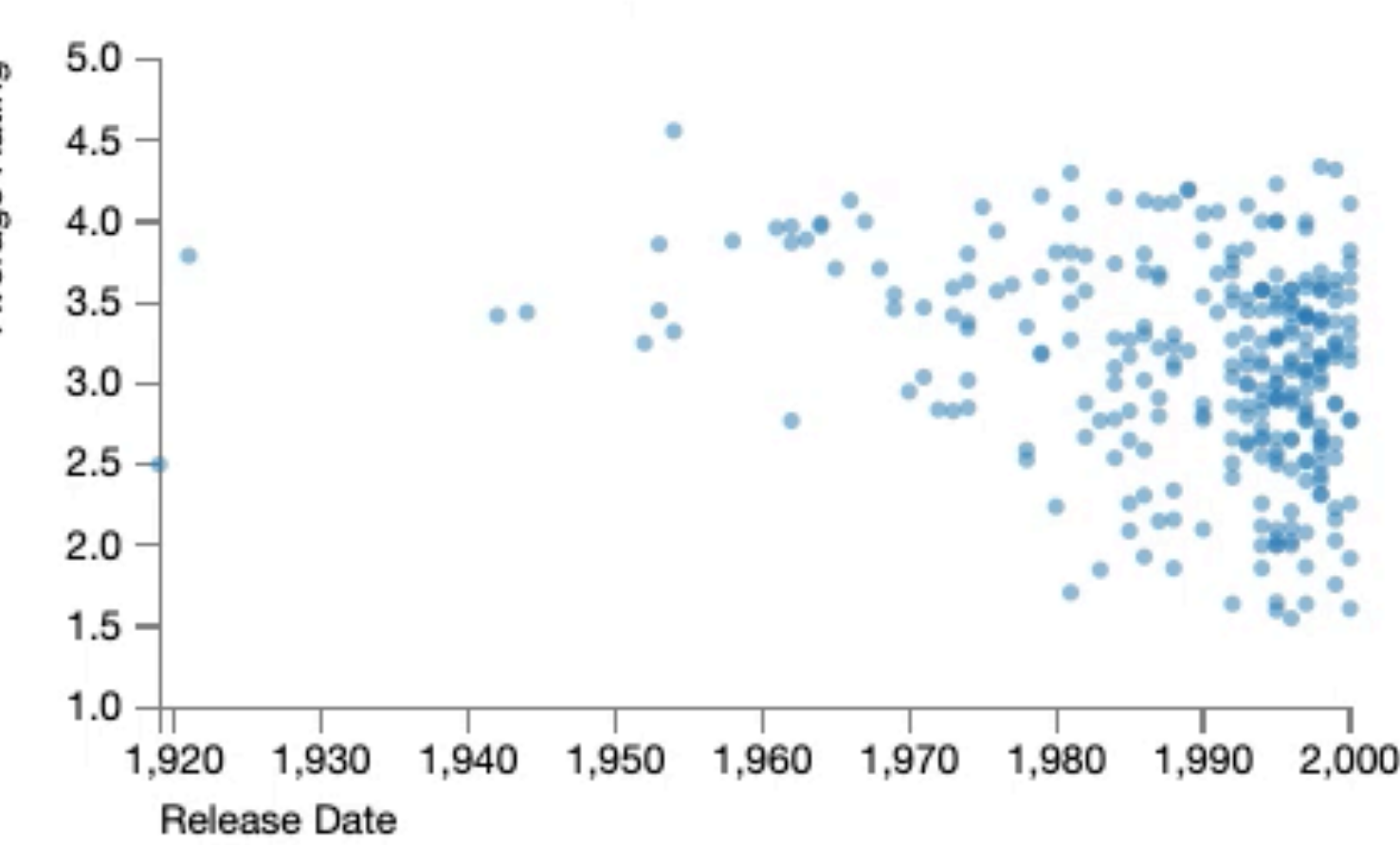
4

3

2

1

Element Visualizations



+ Scatterplot

Element Queries

283

+

Query Filters

Subset | Sets

● ○ ○ ○ ○ ○

+ Name Contains

Query Results

Name	Release Date	Average Rating	Times Watched	Set Count
Sudden Death (1995)	1995	2.66	102	1
Money Train (1995)	1995	2.54	160	1
Guardian Angel (1994)	1994	3.5801	0	3
Fair Game (1995)	1995	2.1	96	1
Nick of Time (1995)	1995	3.07	229	2
Broken Arrow (1996)	1996	2.88	638	2
Shopping (1994)	1994	2	6	2
Braveheart (1995)	1995	4.23	2443	3
Target (1995)	1995	4	1	2

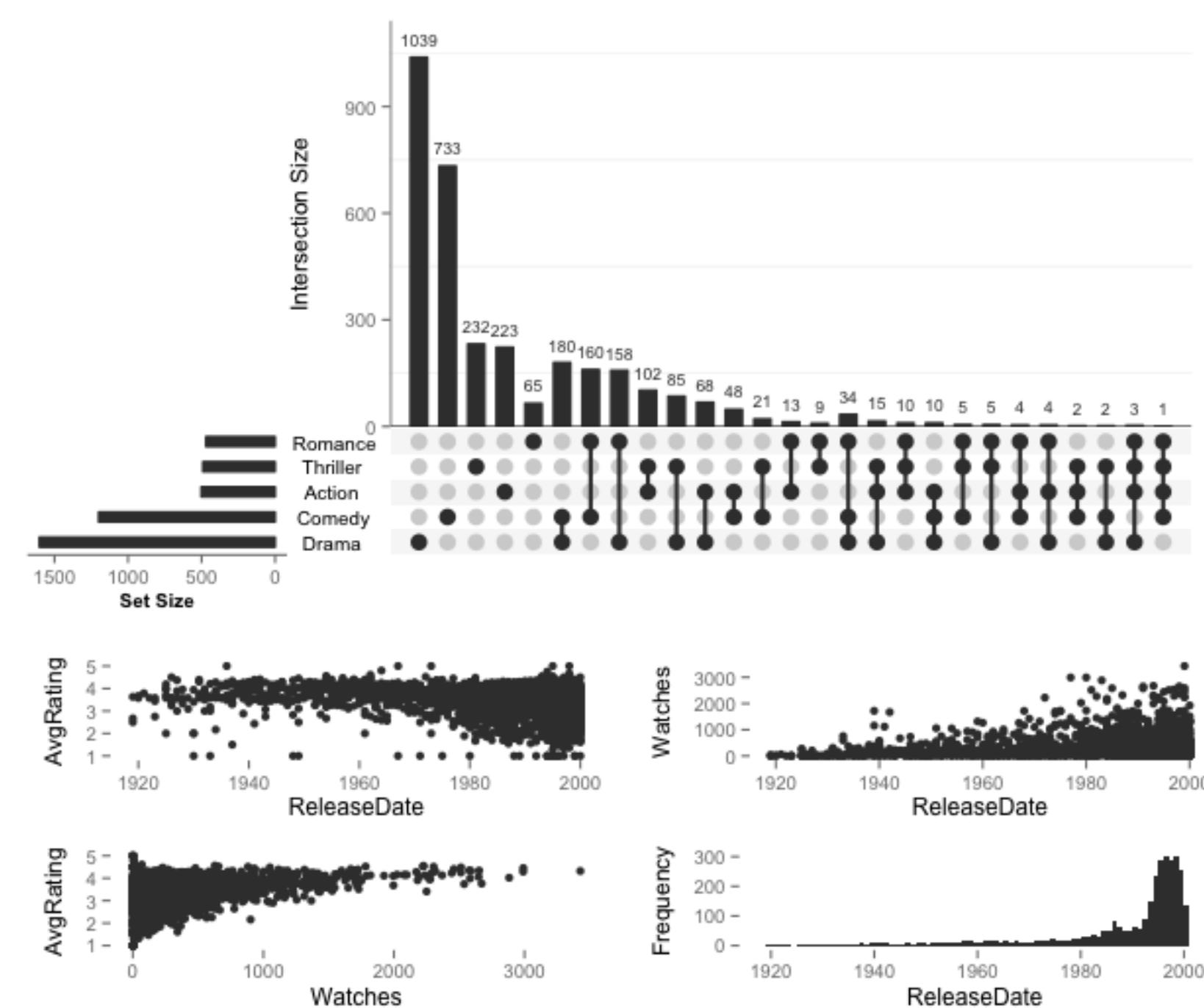
# COMMUNITY IMPACT

The canonical way to show set data with  $> 3$  sets

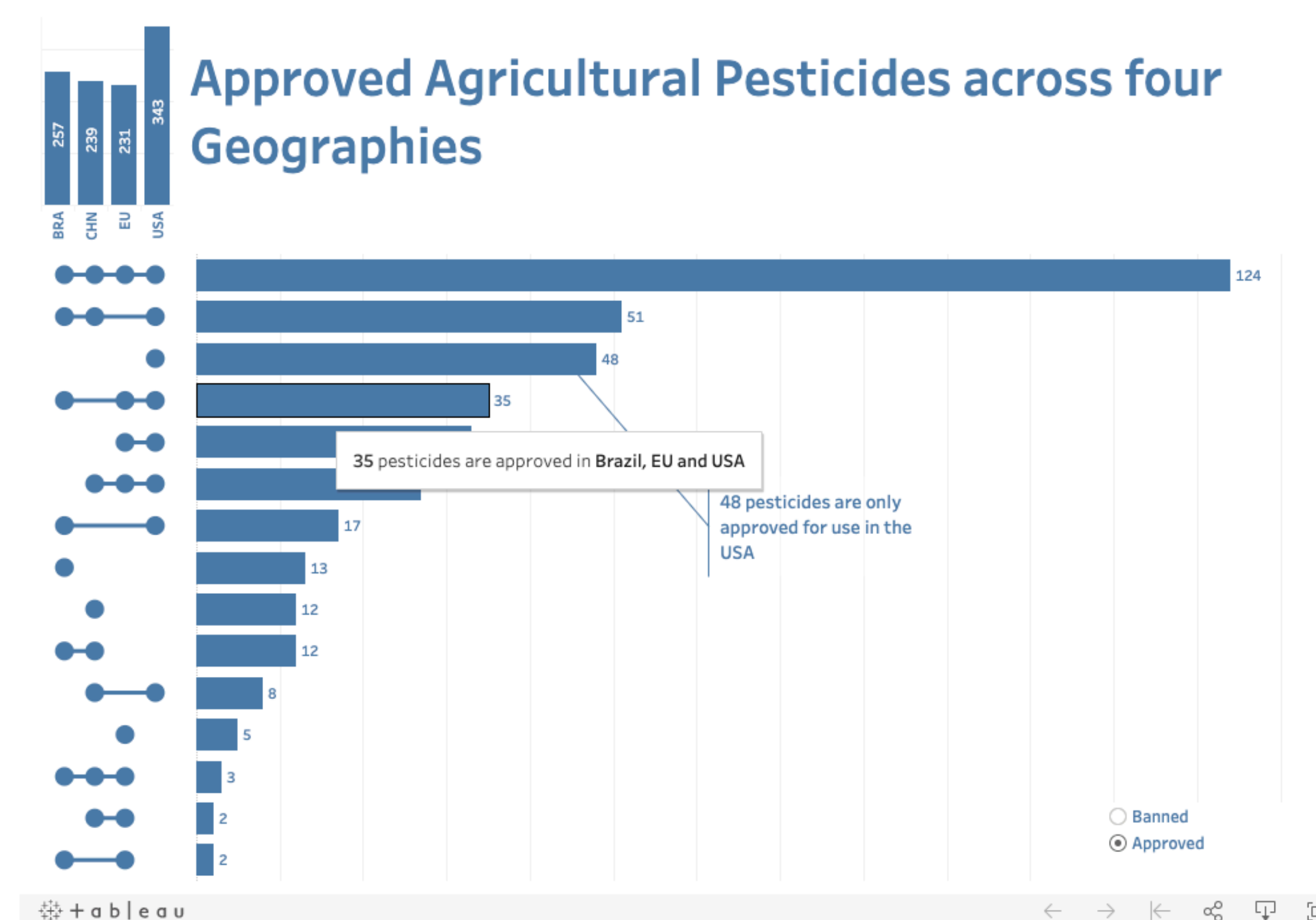
Second-most cited VIS paper of the last decade

$> 11$  implementations in various languages

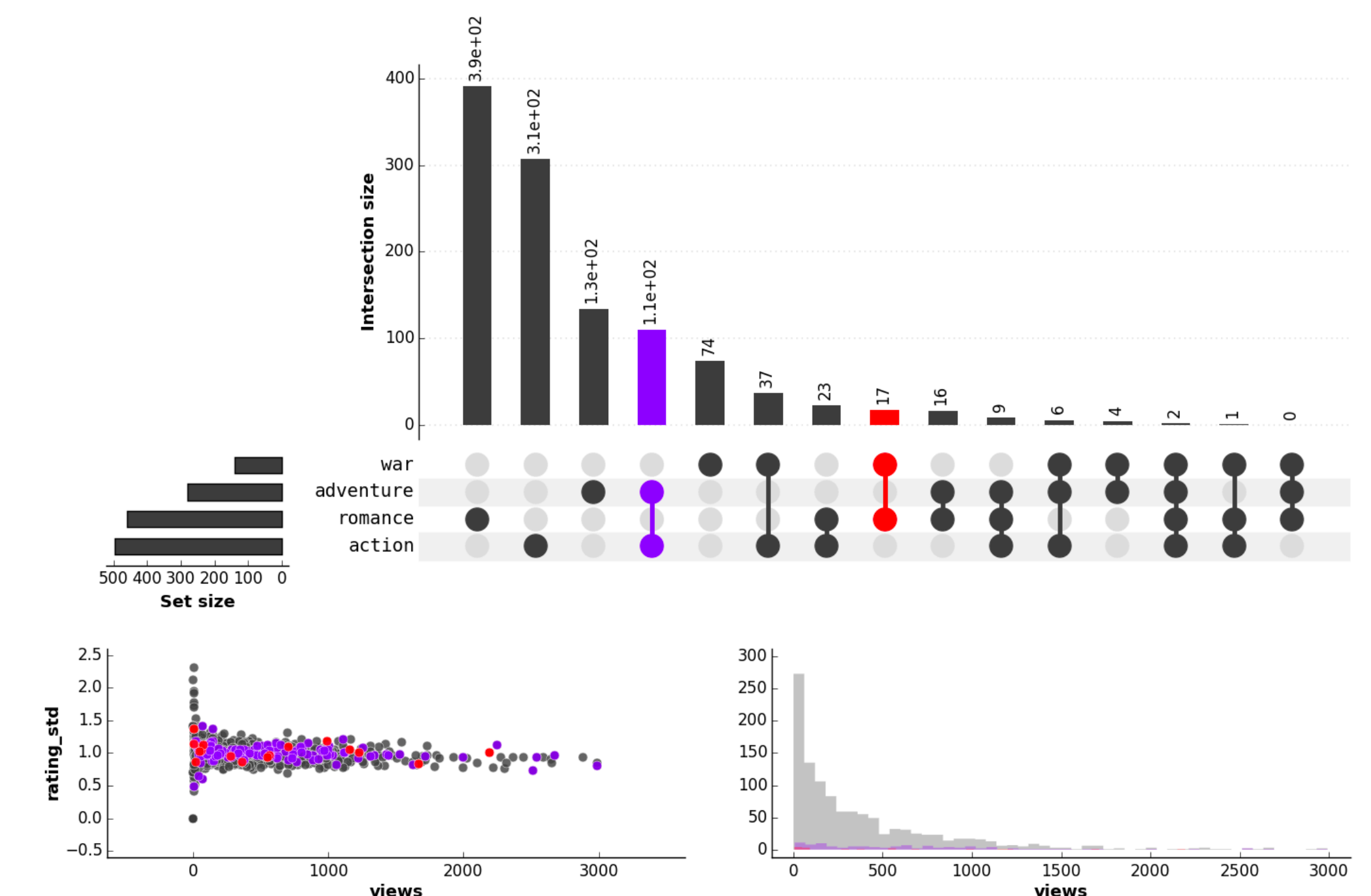
See <https://upset.app>



R



Tableau



Python

# RESEARCH AREAS

## TECHNICAL CONTRIBUTIONS

**Novel Visualization  
Techniques**

**Visualization Process  
Innovations**

**Data Wrangling  
Methods**

## DOMAIN DRIVEN TECHNIQUES

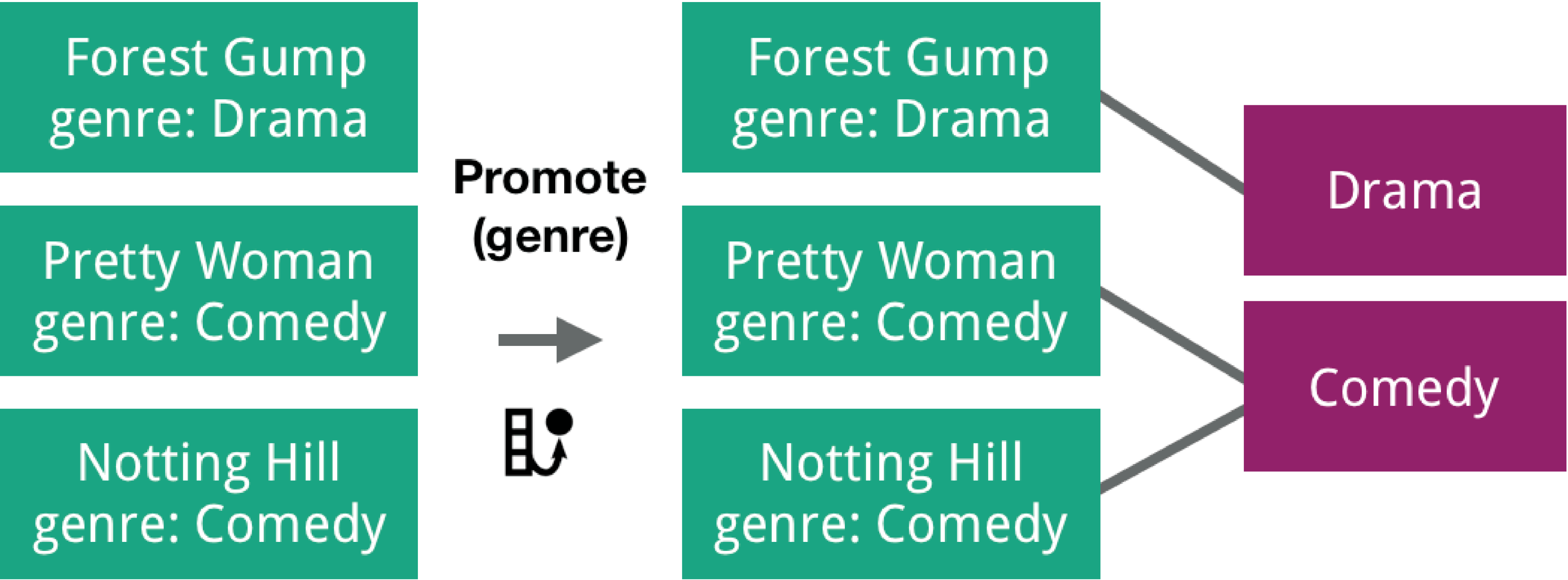
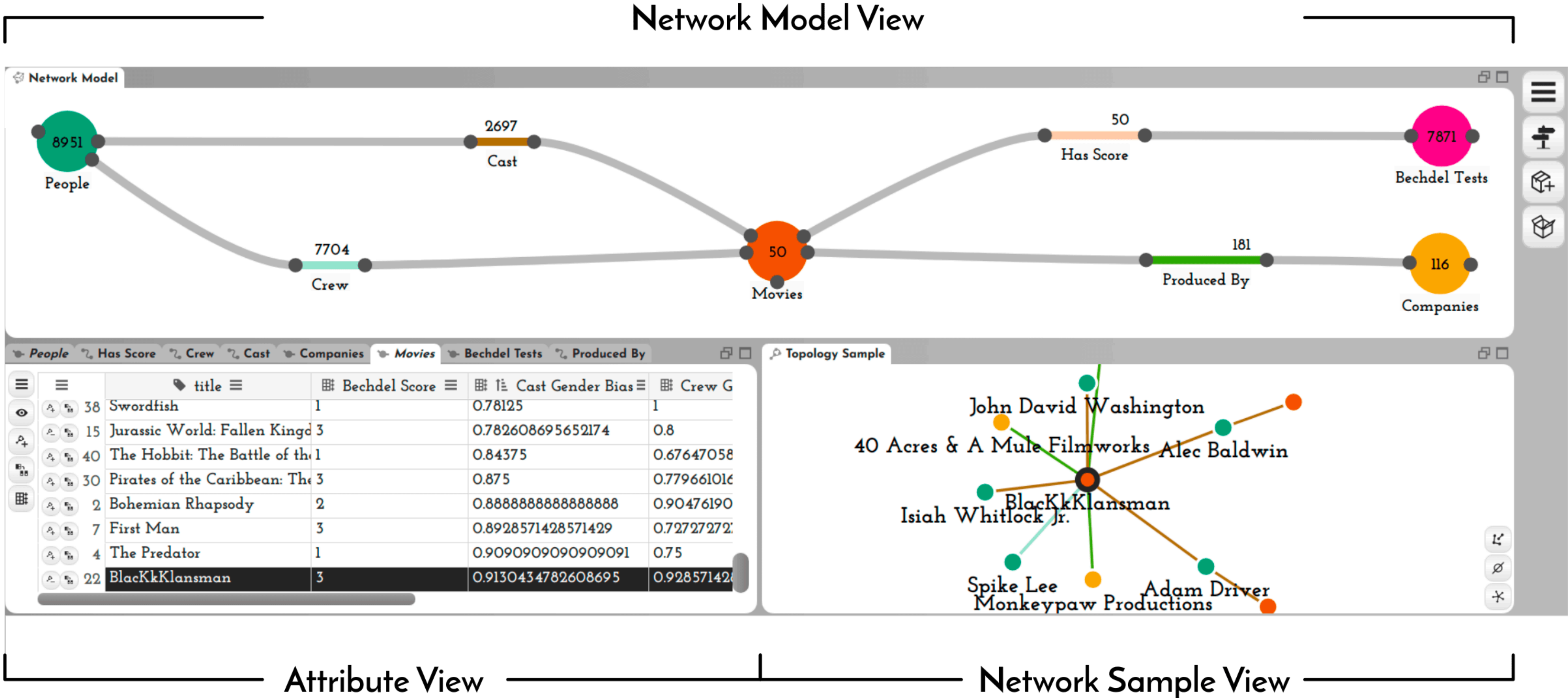
**Tailored Methods  
and Systems for High  
Impact Science  
Problems**

## EMPIRICAL & THEORETICAL WORK

**Evaluation  
Methodology**

**Design Spaces /  
Taxonomies**

Data Wrangling  
Methods



## TECHNICAL CONTRIBUTIONS

**Data Wrangling  
Methods**

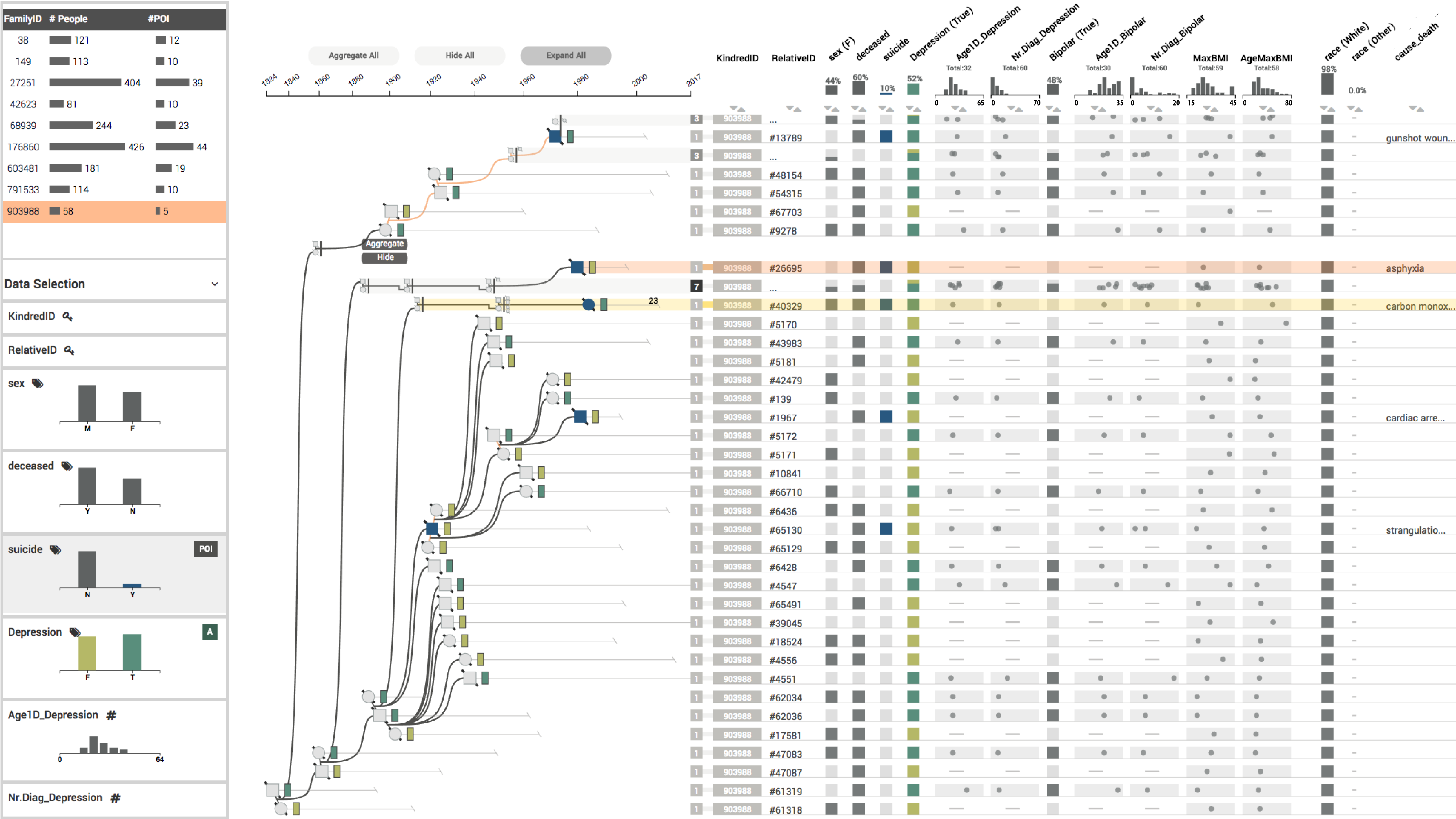
## DOMAIN DRIVEN TECHNIQUES

**Tailored Methods  
and Systems for High  
Impact Science  
Problems**

DOMAIN DRIVEN TECHNIQUES

Tailored Methods  
and Systems for High  
Impact Science  
Problems

Genealogies for Clinical Data Analysis



## DOMAIN DRIVEN TECHNIQUES

**Tailored Methods  
and Systems for High  
Impact Science  
Problems**

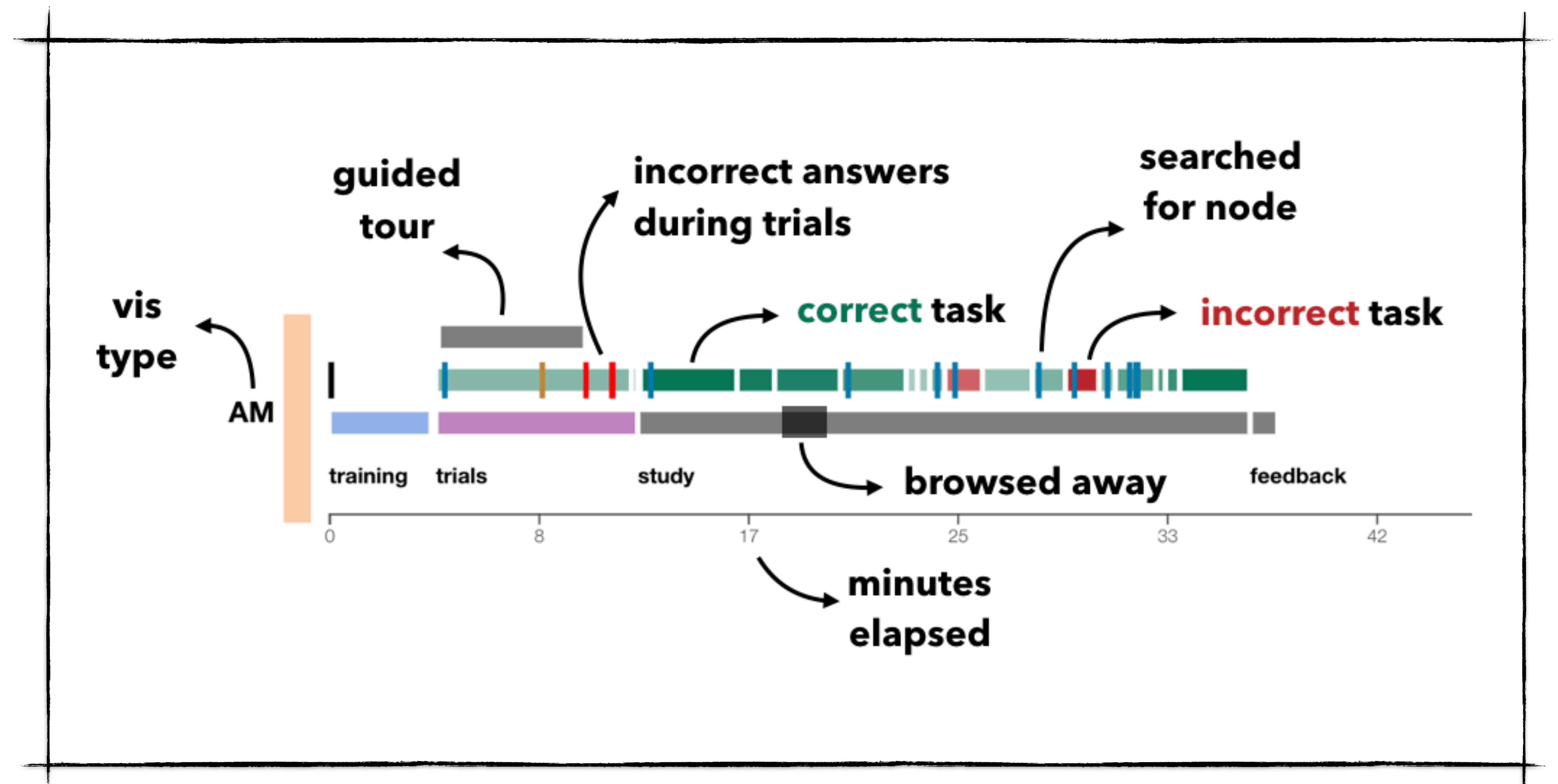
## EMPIRICAL & THEORETICAL WORK

**Evaluation  
Methodology**

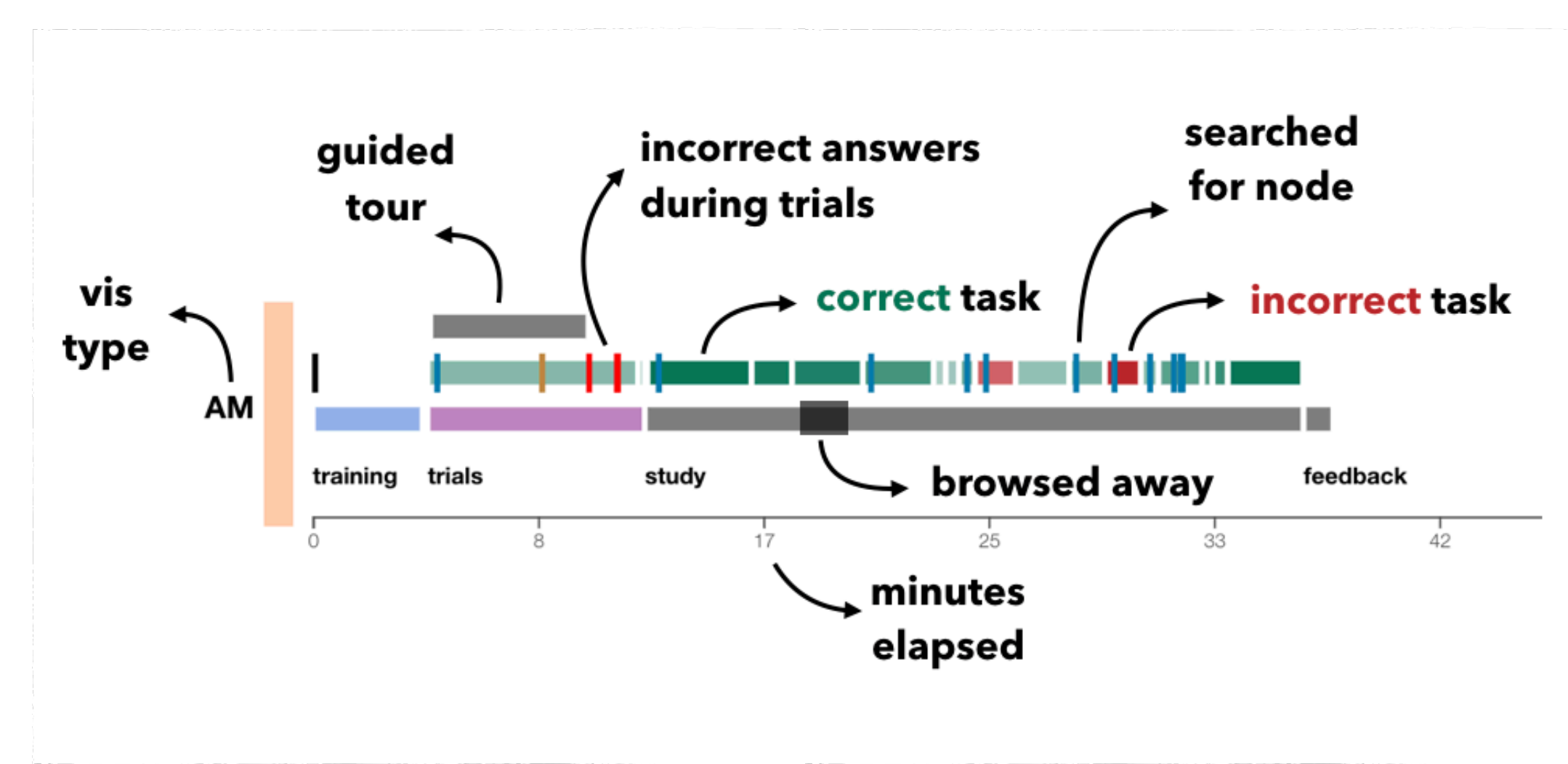
**Design Spaces /  
Taxonomies**

## Evaluation Methodology

## Design Spaces / Taxonomies

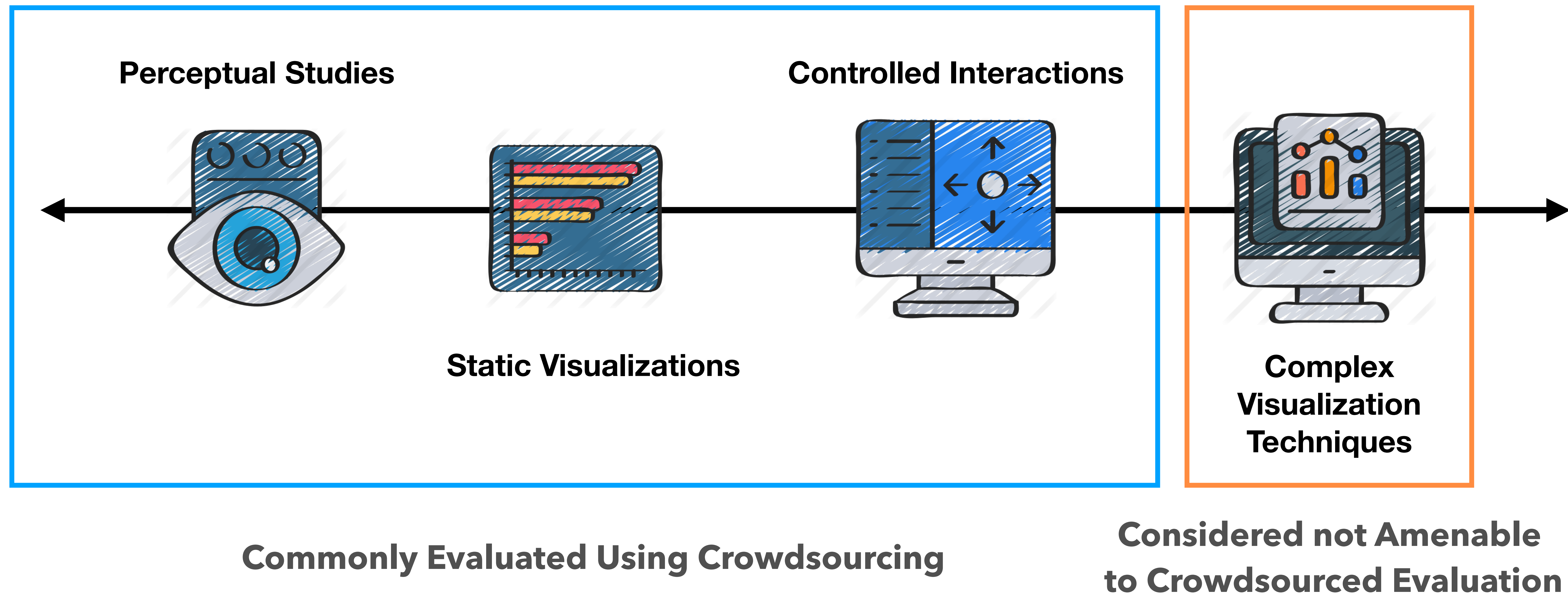


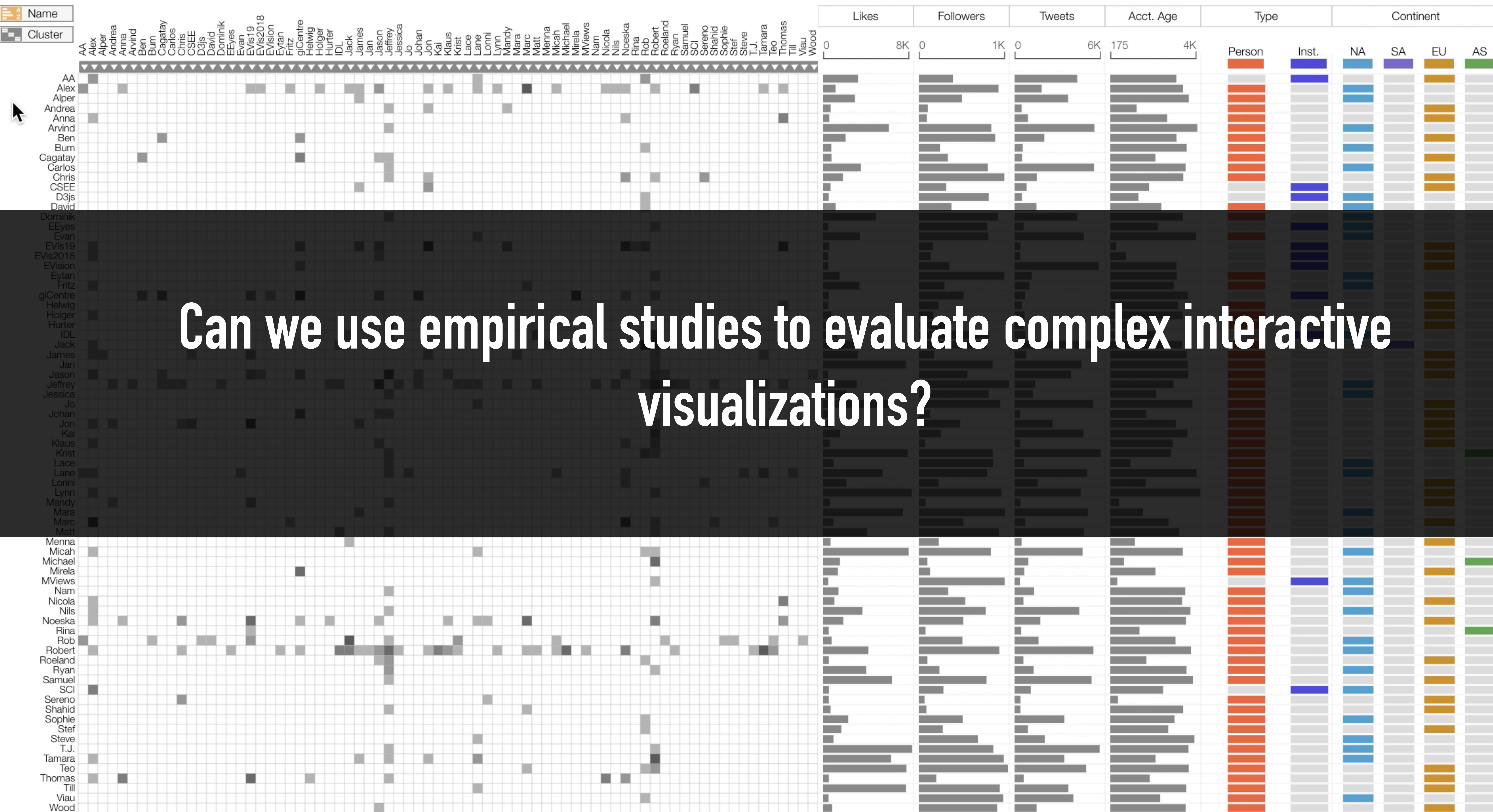
## Evaluating Complex Systems



## Empirically Evaluating Complex Interactive Visualization Techniques

Carolina Nobre, Dylan Wootton, Lane Harrison

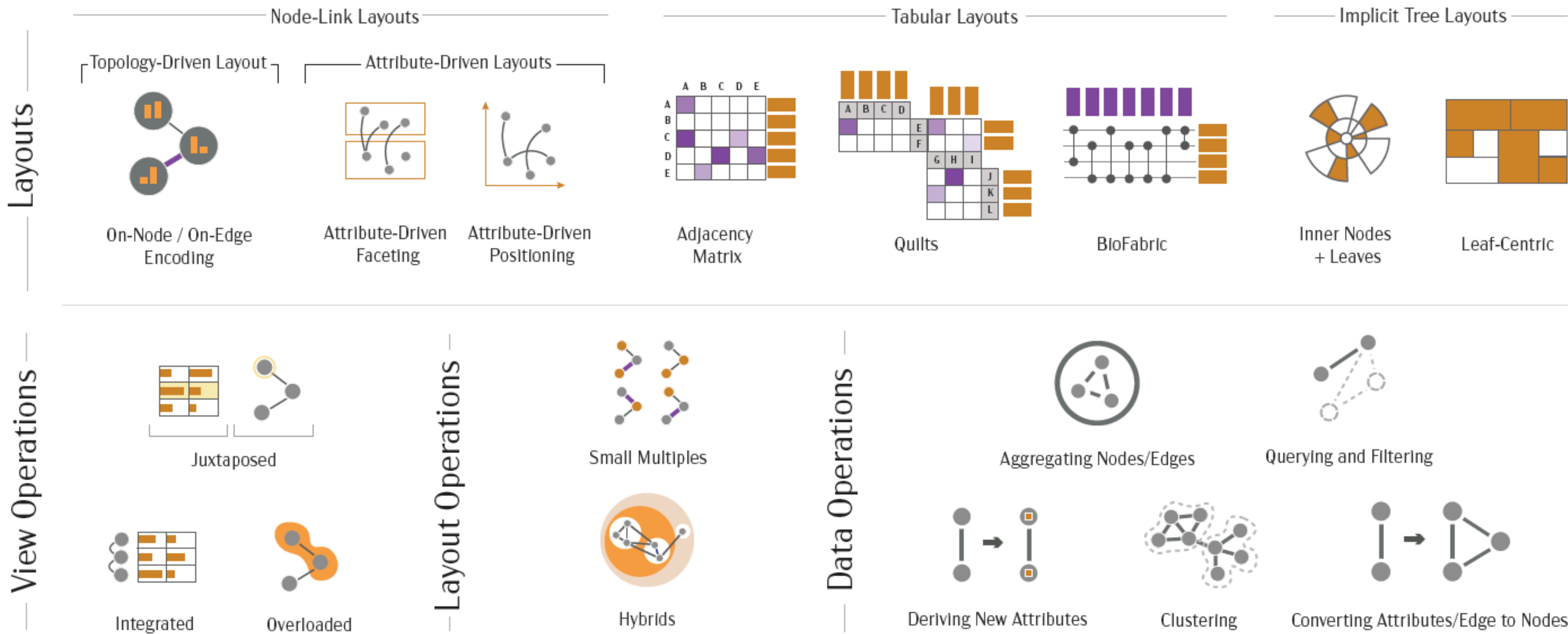




# The State of the Art in Visualizing Multivariate Networks

C. Nobre<sup>1</sup>, M. Meyer<sup>1</sup>, M. Streit<sup>2</sup>, and A. Lex<sup>1</sup>

<sup>1</sup>University of Utah, Utah, USA  
<sup>2</sup>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).

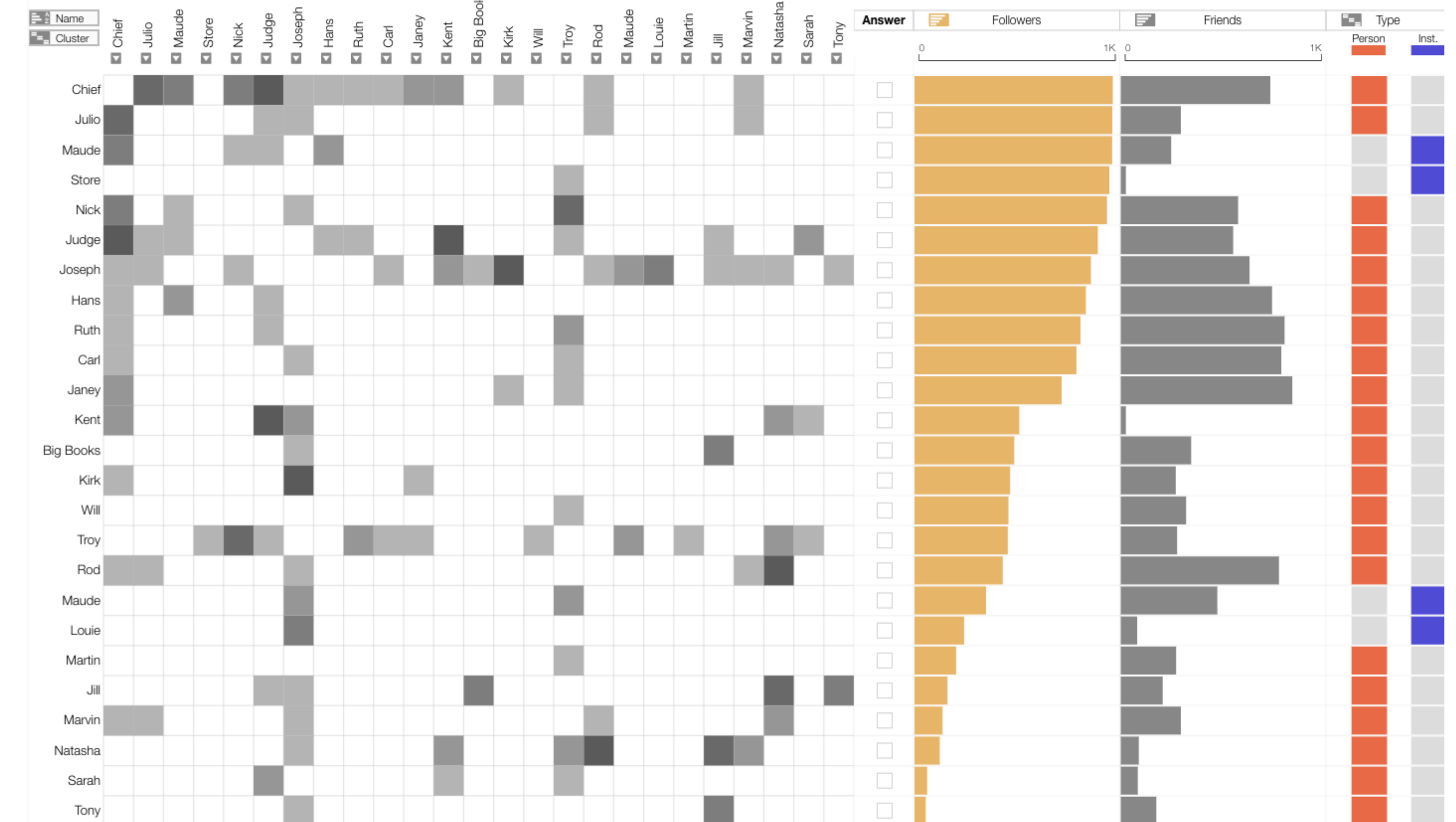
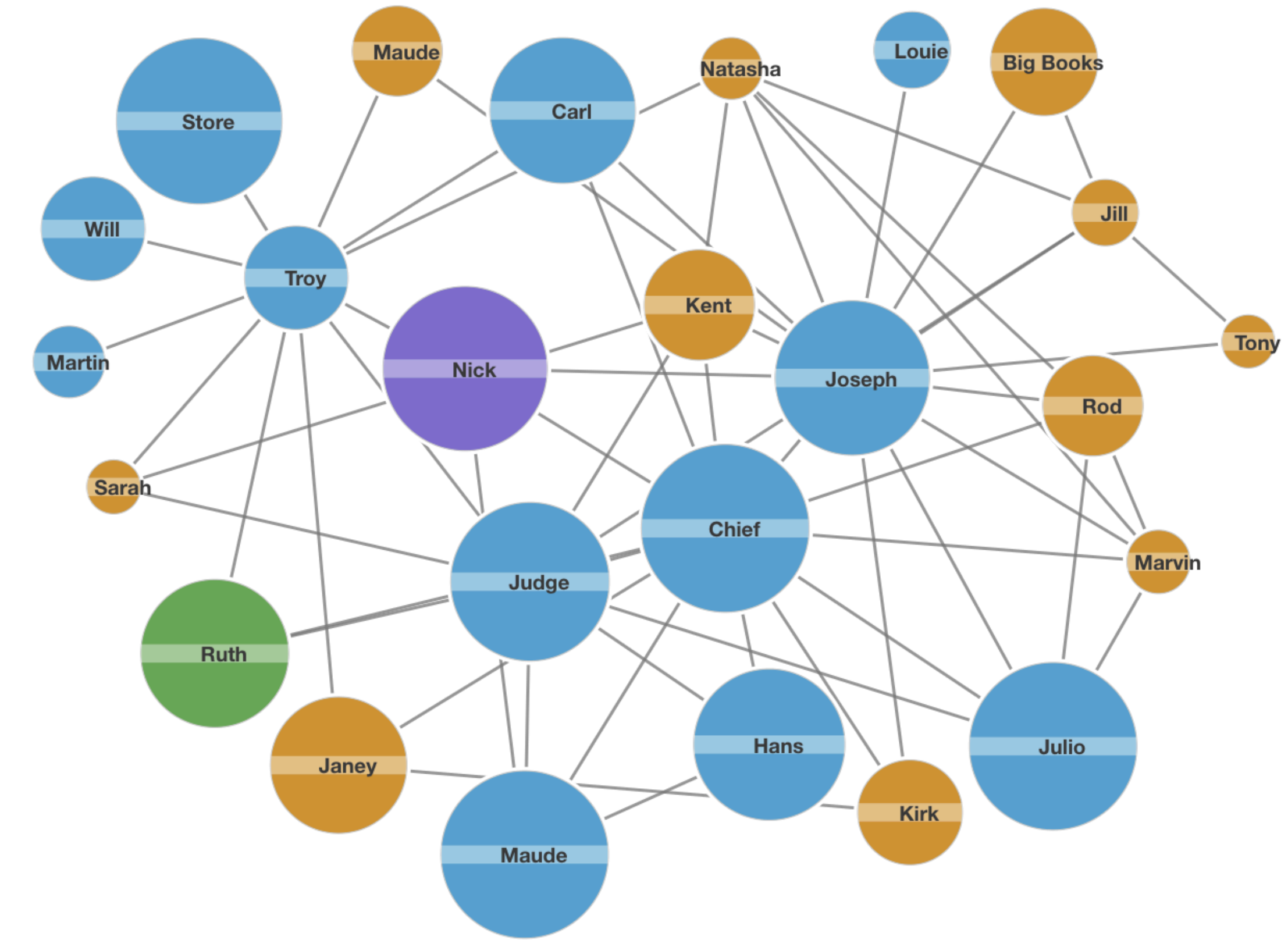
## Abstract

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 still a relatively new area, and the terminology of the network visualization field is not as well established as in other fields. In this state-of-the-art report, we survey 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.

# Which is better for which task?

# CHALLENGE CONFOUNDERS

# HOW CAN WE MAKE SURE THAT WHAT WE TEST IS WHAT WE CARE ABOUT?



DESIGN BASED ON EXISTING  
GUIDELINES AND KNOWLEDGE

VALIDATED & REFINE DESIGN  
BASED ON EXPERT HEURISTIC  
EVALUATION

## Nested Bars/Glyphs



27. **Embedded colored glyphs are well suited to encode multiple categorical attributes.**  
Mark only one oval.

[illegible]

CHALLENGE  
SCALE  
NEED STATISTICAL POWER  
HOW CAN WE DO THIS IN A  
CROWDSOURCED SETTING?

## Quickly find research participants you can trust.

Launch your study to tens of thousands of trusted participants in minutes. Recruit niche or representative samples on-demand. Prolific builds the most powerful and flexible tools for online research. Sign up for free.

### Research

Collect high quality responses from people around the world within minutes. [Learn more](#)

[SIGN UP TO RESEARCH](#)

### Participate

Take part in engaging research, earn cash, and help improve human knowledge. [Learn more](#)

[SIGN UP TO PARTICIPATE](#)



**Find any research participant, anywhere in the world**

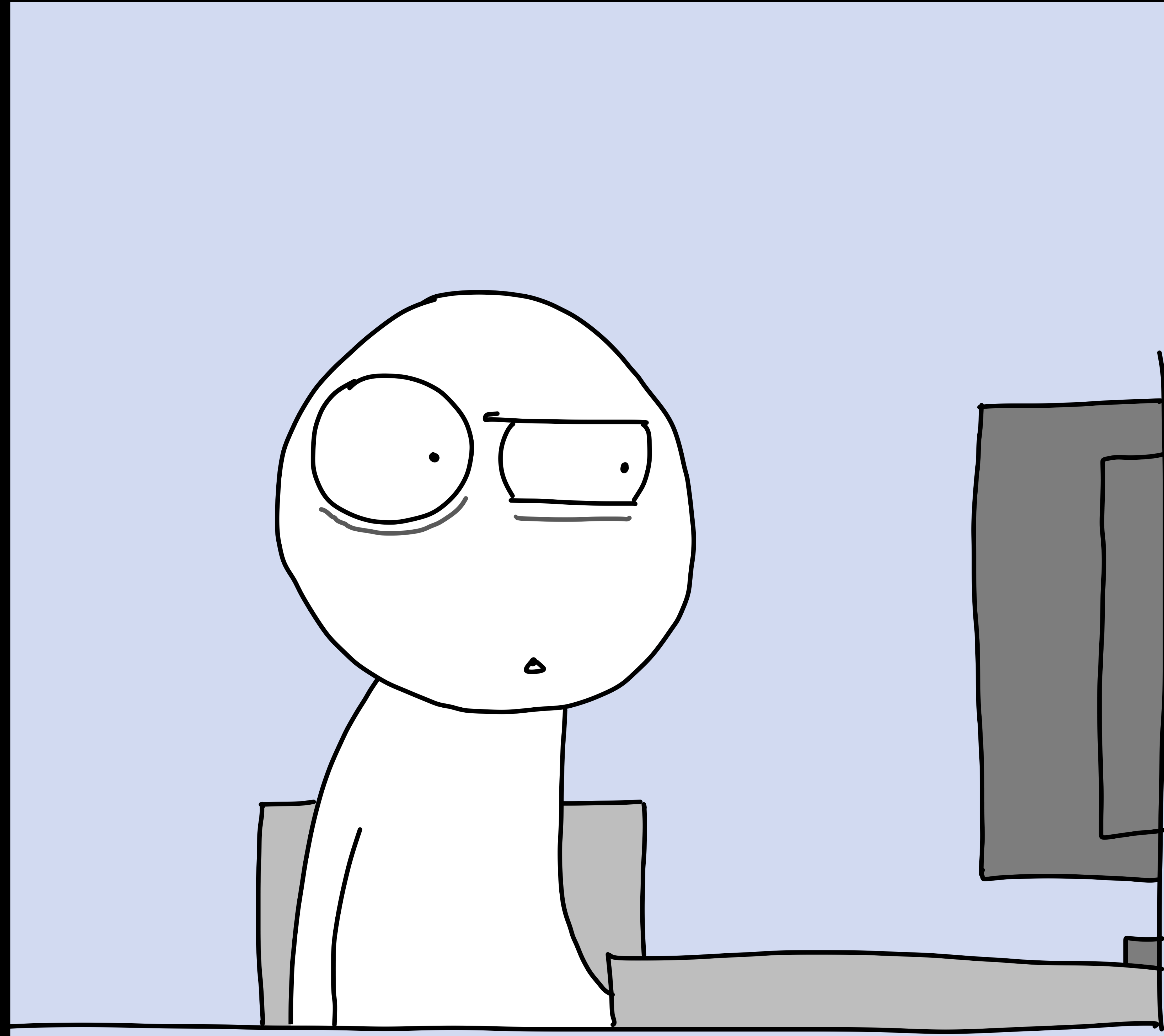
Our participant pool is profiled, high quality and fast. The average study is completed in under 2 hours. Filter particip

**WHAT DID I JUST SEE?**

**CHALLENGE**

# NOVICE USERS

NOVICE USERS DON'T KNOW  
ABOUT ADVANCED  
VISUALIZATIONS

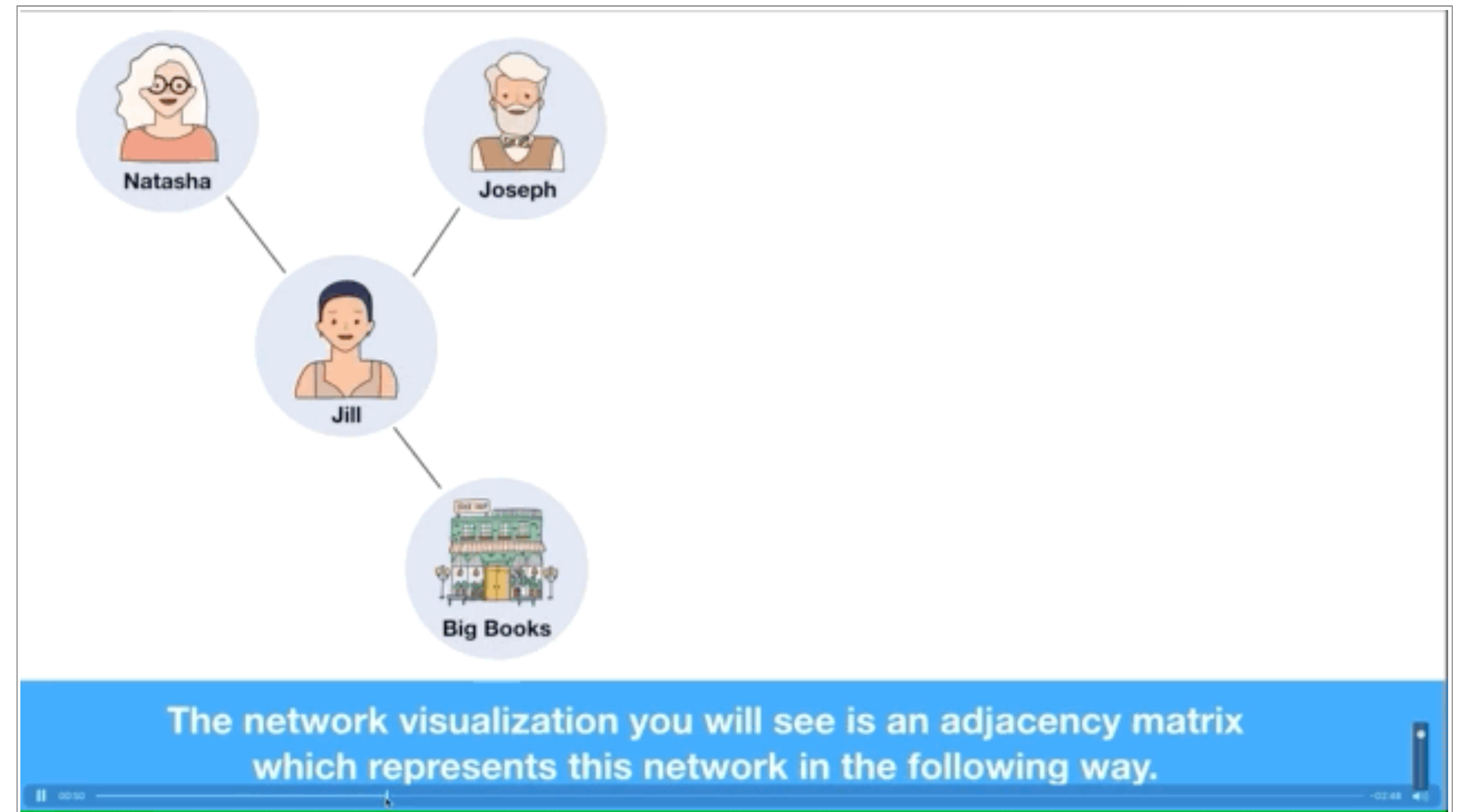


# Passive Training

SOLUTION

## NOVICE USERS

TRAINING CAN GIVE USERS THE  
EXPERTISE NECESSARY TO  
COMPLETE THE TASKS.



SOLUTION

# NOVICE USERS

TRAINING CAN GIVE USERS THE  
EXPERTISE NECESSARY TO  
COMPLETE THE TASKS.

# Active Training



CHALLENGE

# INCENTIVES

HOW CAN WE GET USERS  
TO TRY HARD

AND

TO PARTICIPATE IN AN EXPERIMENT  
THAT TAKES ~1H



SOLUTION

# INCENTIVES

AN INTERESTING PROBLEM

MONEY

Multivariate Network Exploration - Link

COMPLETEDACTION

100%

26 Aug 2019, 21:04

Published

\$15.67/hr

Average reward per hour

73,947 of 86,264

Eligible Participants

150/150

Submissions Progress

Approve all

Message all

Bonus payment

Find by ID...

More

<input type="checkbox"/>	PARTICIPANT ID	STARTED	TIME TAKEN	STUDY CODE	STATUS			
<input type="checkbox"/>	5d64894fa174790001c3845b	26 Aug 2019, 21:13	N/A		RETURNED			
<input type="checkbox"/>	5d6495352721a700192dd040	26 Aug 2019, 21:18	N/A		RETURNED			
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<input type="checkbox"/>	5d64759fedf23500018f9334	26 Aug 2019, 21:24	00:32:18	HX615JBC	APPROVED			
<input type="checkbox"/>	5d64939d0d4a200001d27315	26 Aug 2019, 21:25	N/A		TIMED-OUT			
<input type="checkbox"/>	5c9e41603bd25f001bdcf950	26 Aug 2019, 21:35	N/A		RETURNED			
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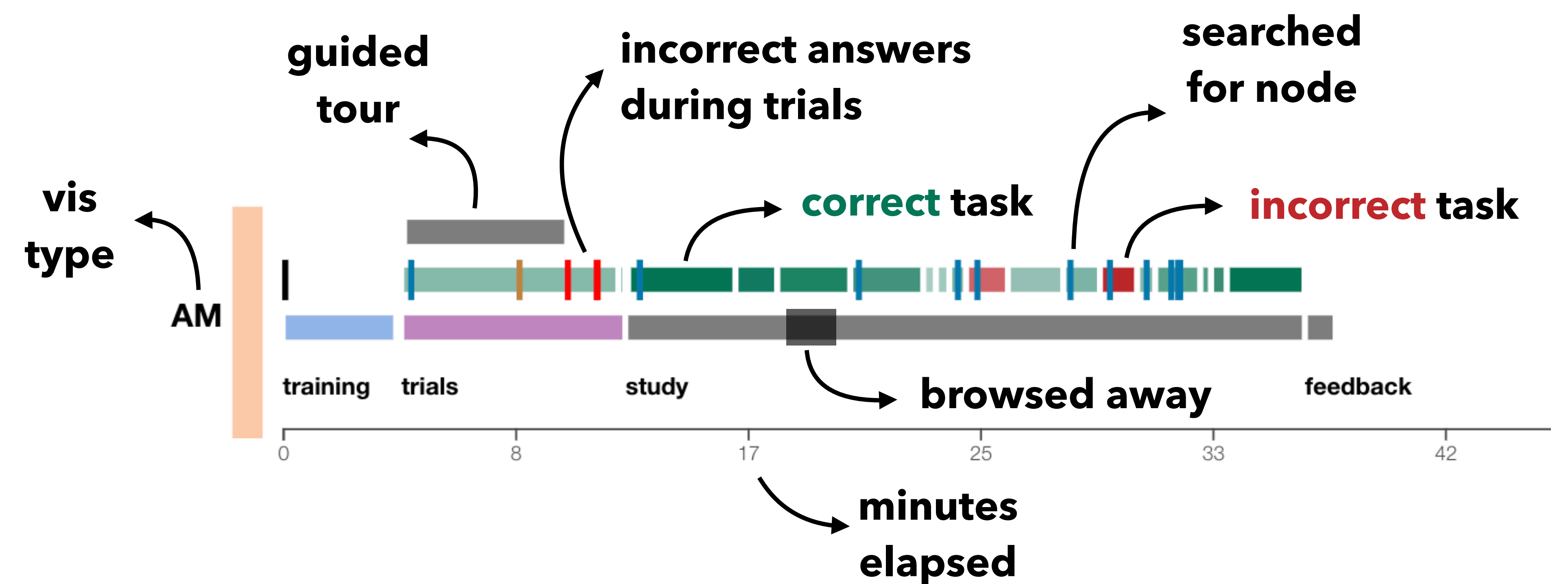
~ \$ 4,500 in 2h

# VALIDATION

HOW CAN WE MAKE SURE  
THIS ALL WORKS?

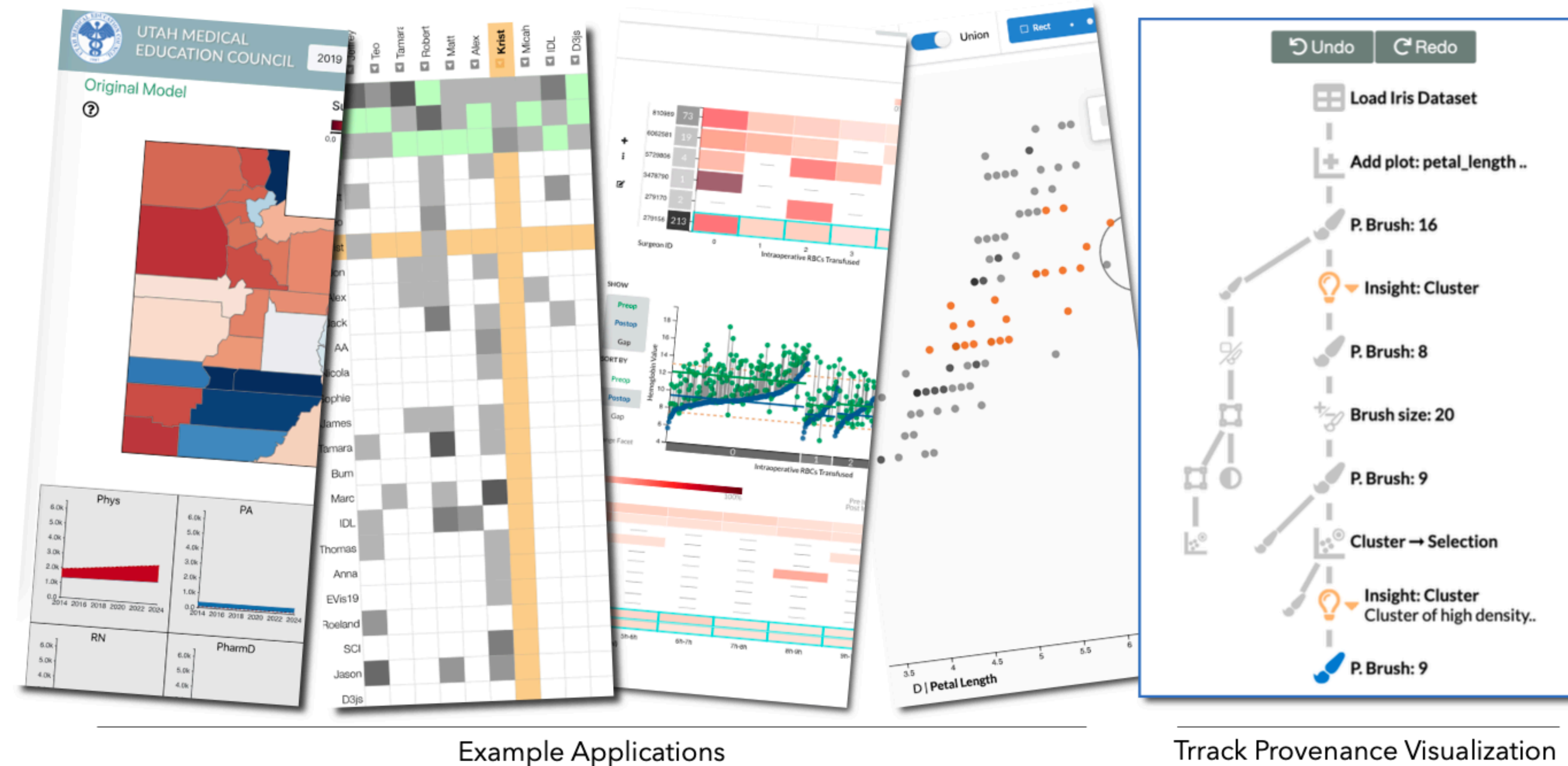
DETAILED PROVENANCE TRACKING

MULTIPLE PILOTS



# TRRACK

## A library for reproducible tracking



Tracks “differential state”

Tracks 2 levels:

Application State

Study Metadata (responses, etc.)

<https://vdl.sci.utah.edu/trrack/>

[VIS Short 2020]

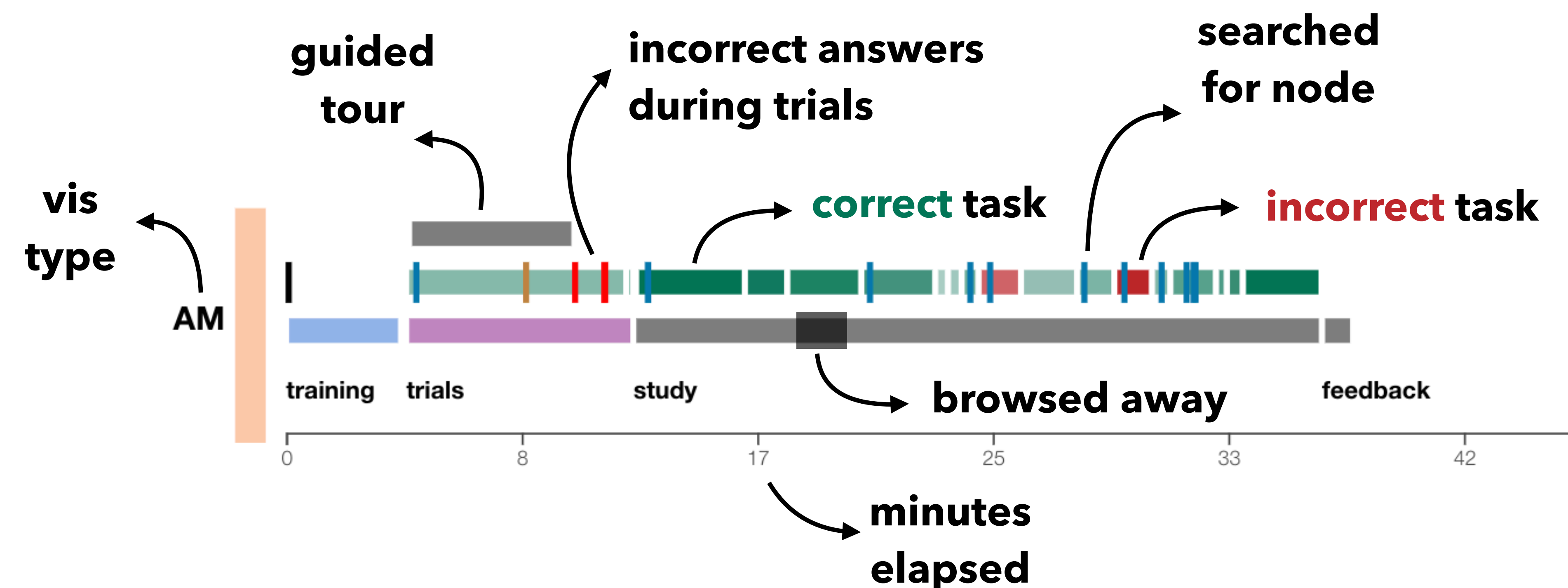
# PROVENANCE TRACKING

**Allows a full re-hydrate of every analysis session**

**Great for debugging pilots - what went wrong for this person?**

**Great for detailed analysis**

**Provenance data vis to spot problems e.g. with tasks**

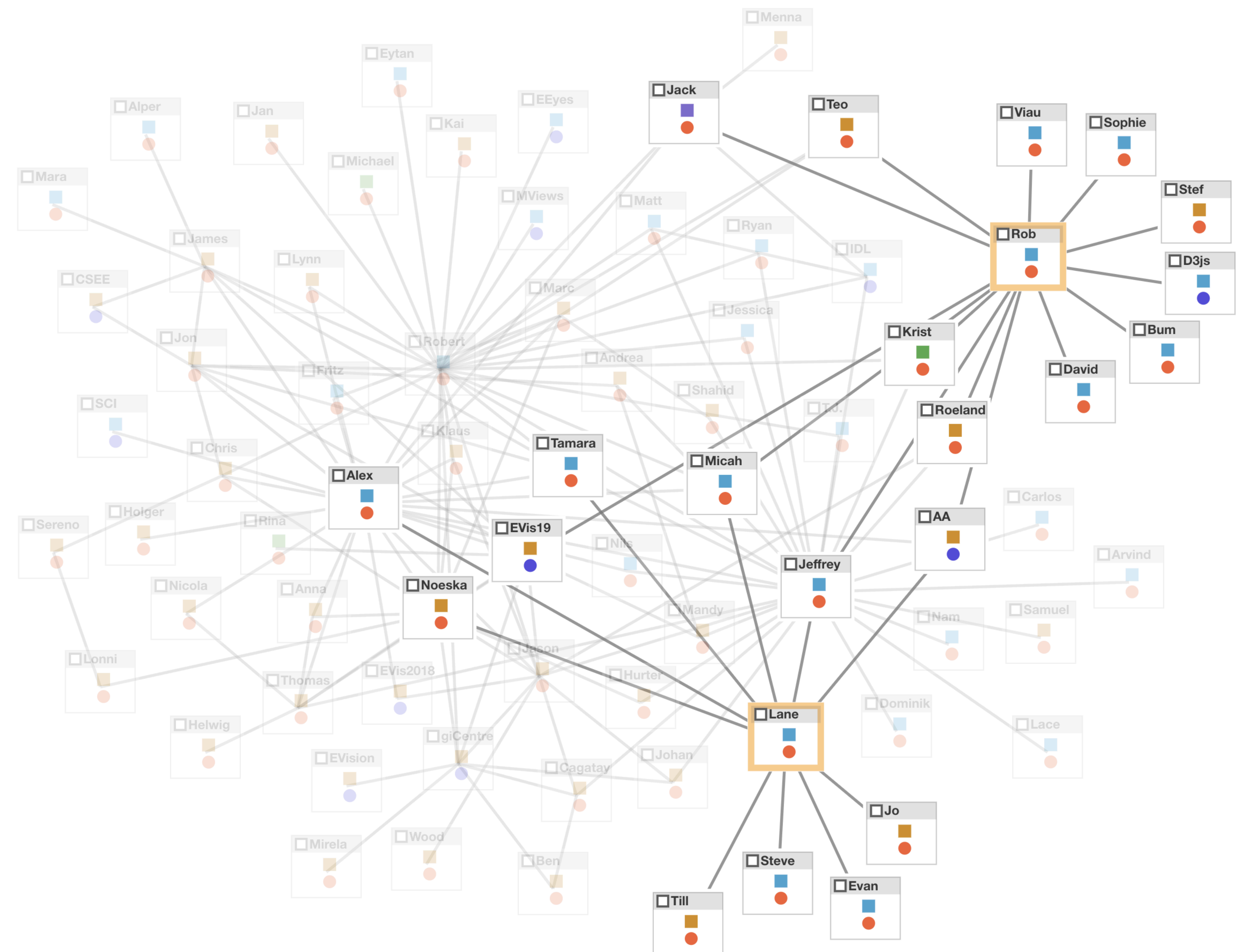


# SELECTED RESULTS

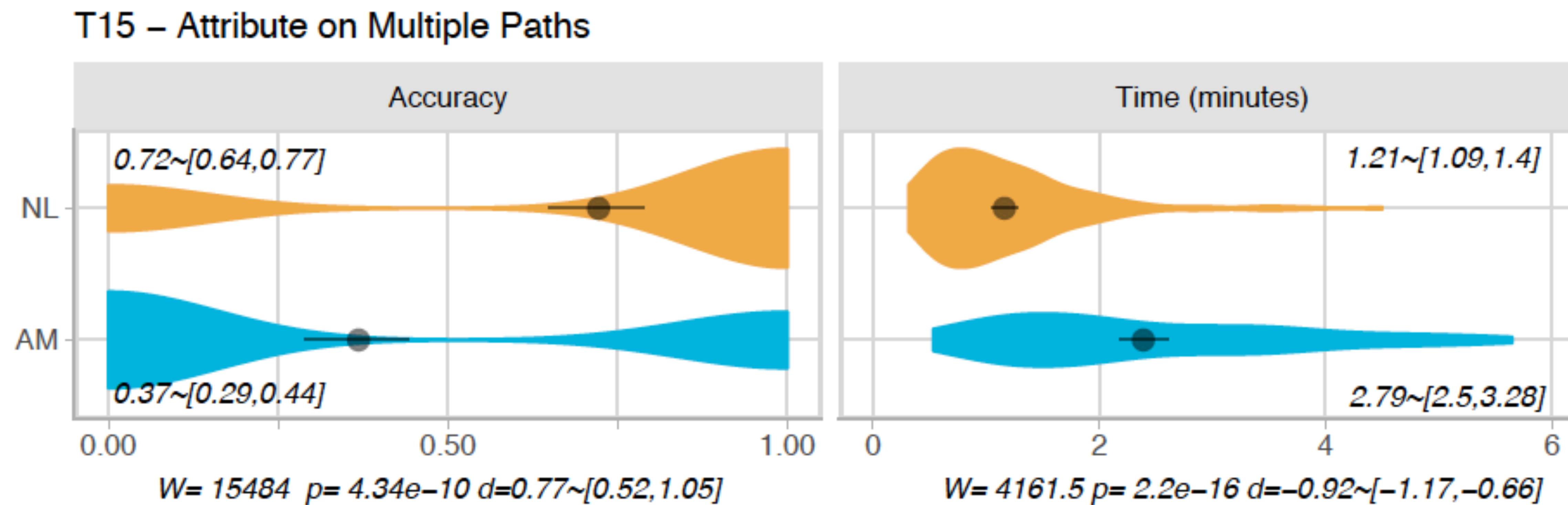
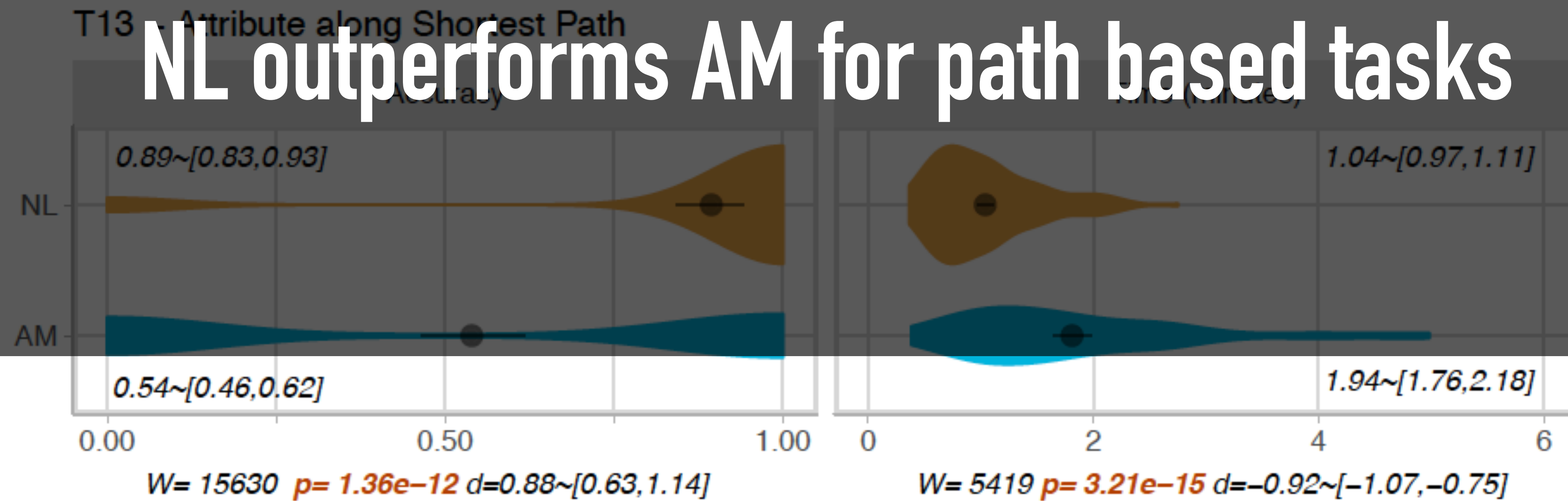


# PATHS

Is NL or AM better for  
Path Tasks?



# NL outperforms AM for path based tasks



**What types of insight do NL and AM representations support?**

The figure is a data visualization titled "ATTRIBUTE OVERVIEW". It is divided into two main sections: a heatmap on the left and a bar chart on the right.

**Heatmap Section:**

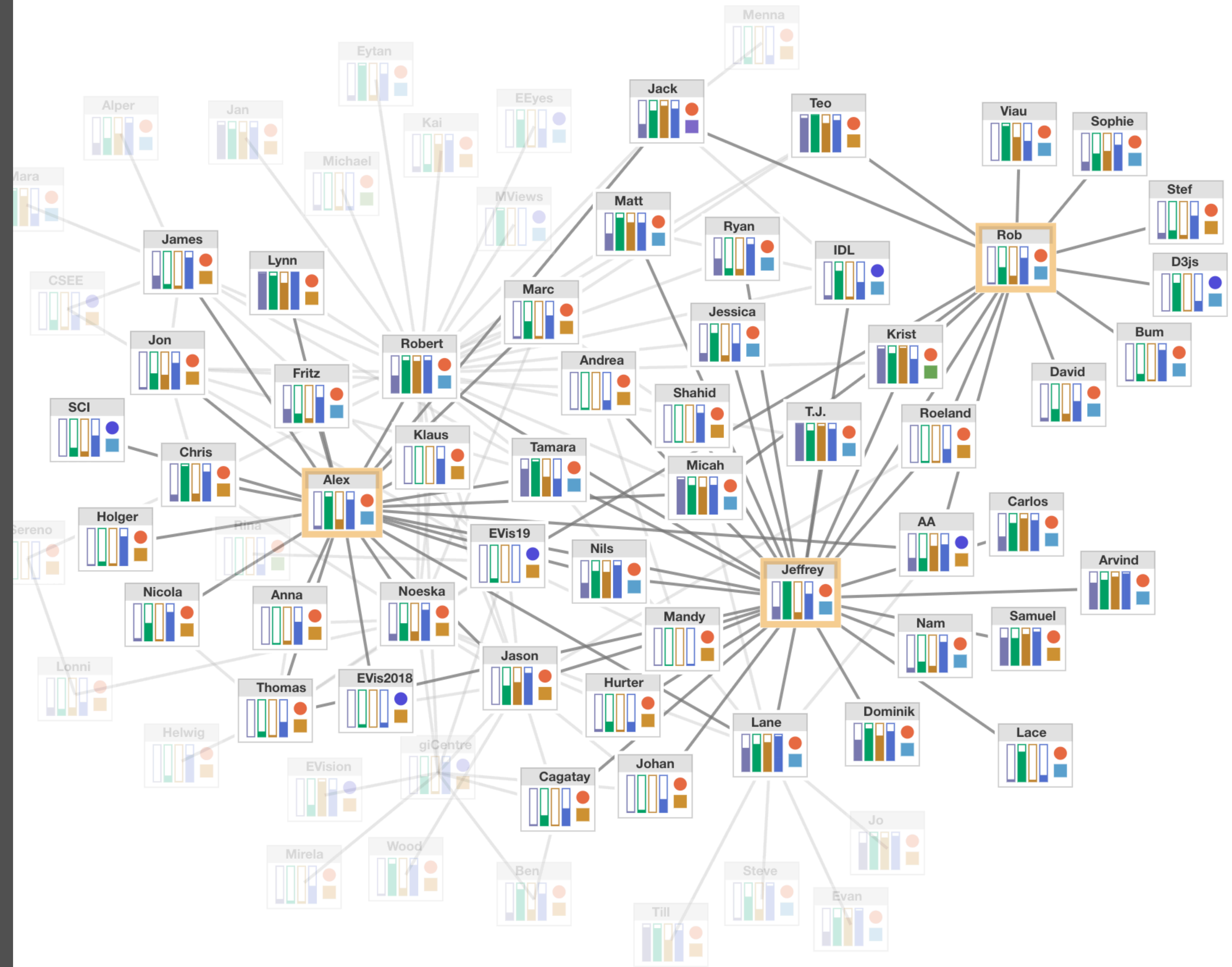
- Y-axis:** Lists 50 account names, including Krist T.J., EVision, Arvind, Carlos, Robert, Jack, Jo, Samuel, Mara, Lane, Teo, Matt, Evan, Kai, Micah, Jan, Lynn, Nils, AA, Dominik, Viau, Jason, Till, Alper, Sophie, Tamara, Jon, Steve, Ben, Alex, Noeska, Rob, Lonni, Chris, Wood, David, Jeffrey, Nam, Ryan, Jessica, Eytan, SCI, Fritz, Michael, Anna, Stef, CSEE, James, IDL, Marc, giCentre, Holger, Mirela, Lace, Thomas, EEyes, Hurter, Nicola, Roeland, Bum, Cagatay, D3js, Helwig, Andrea, Menna, Rina, Sereno, EVis19, Mandy, Shahid, Johan, Klaus, EVis2018, and MViews.
- X-axis:** Lists 50 attributes, including Name, Cluster, Likes, Followers, Tweets, Acct. Age, Type, and Continent.
- Legend:** Located at the top left, showing color-coded boxes for Name (dark grey), Cluster (light grey), Likes (dark grey), Followers (light grey), Tweets (dark grey), Acct. Age (light grey), Type (dark grey), and Continent (light grey).
- Text:** A large white text overlay reads "ATTRIBUTE OVERVIEW". Below it, a green text overlay reads "INSTITUTIONS HAVE MUCH FEWER TWEETS IN GENERAL THAN PERSON ACCOUNTS".

**Bar Chart Section:**

- Y-axis:** Same 50 account names as the heatmap.
- X-axis:** Engagement metrics: Likes (0 to 8K), Followers (0 to 1K), Tweets (0 to 6K), Acct. Age (175 to 4K), Type (Person, Inst.), and Continent (NA, SA, EU, AS).
- Legend:** Located at the top right, showing color-coded boxes for Likes (dark grey), Followers (light grey), Tweets (dark grey), Acct. Age (light grey), Type (dark grey), and Continent (light grey).

# TOPOLOGY-ATTRIBUTE

*"IT DOES SEEM A BIT ODD THAT  
JEFFREY ALEX AND ROB HAVE SUCH  
LARGE NETWORKS WITH THEIR  
LOWER THEN AVERAGE TWEETING."*



# RECAP

CAN WE DO QUANTITATIVE  
EVALUATION WITH COMPLEX  
SYSTEMS?

## Yes We Can!

- Picking the right techniques
- Evidence-based design
- Design validation
- Careful training
- Good compensation
- Interesting Tasks

**Pushing the boundary** of what can be  
evaluated using crowdsourcing

## CAVEATS / THOUGHTS

**Should this be the new gold standard to evaluate systems?**

**NO!**

**Needs established techniques**

**Needs specifically designed and instrumented systems**

**Our instrumentation can be used broadly**

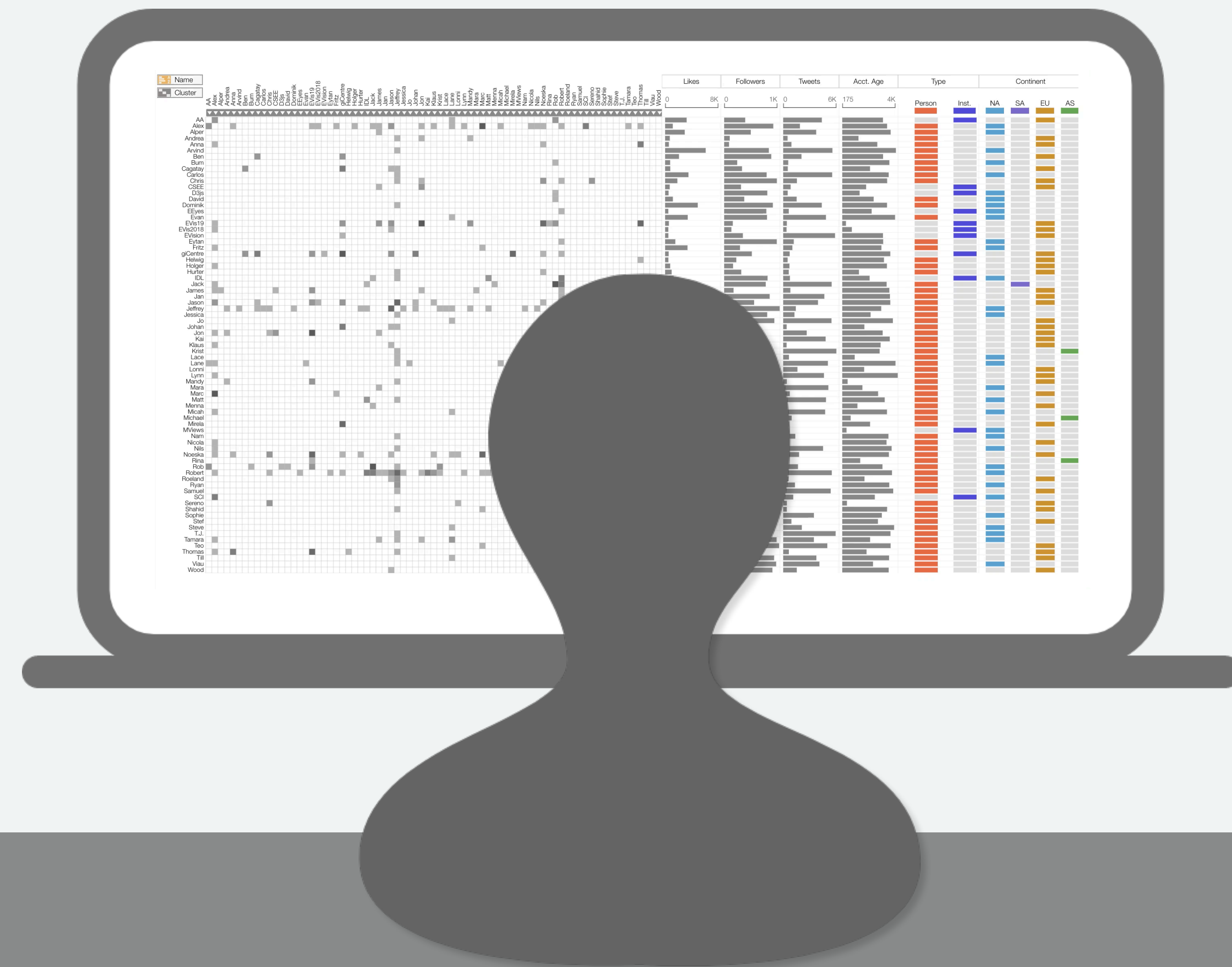
# ADVANCED ANALYSIS OF STUDY DATA

# **INSTRUMENTED STUDIES**

**What else can we do with this rich data?**

**Do different analysis strategies result in different results?**

Participant A



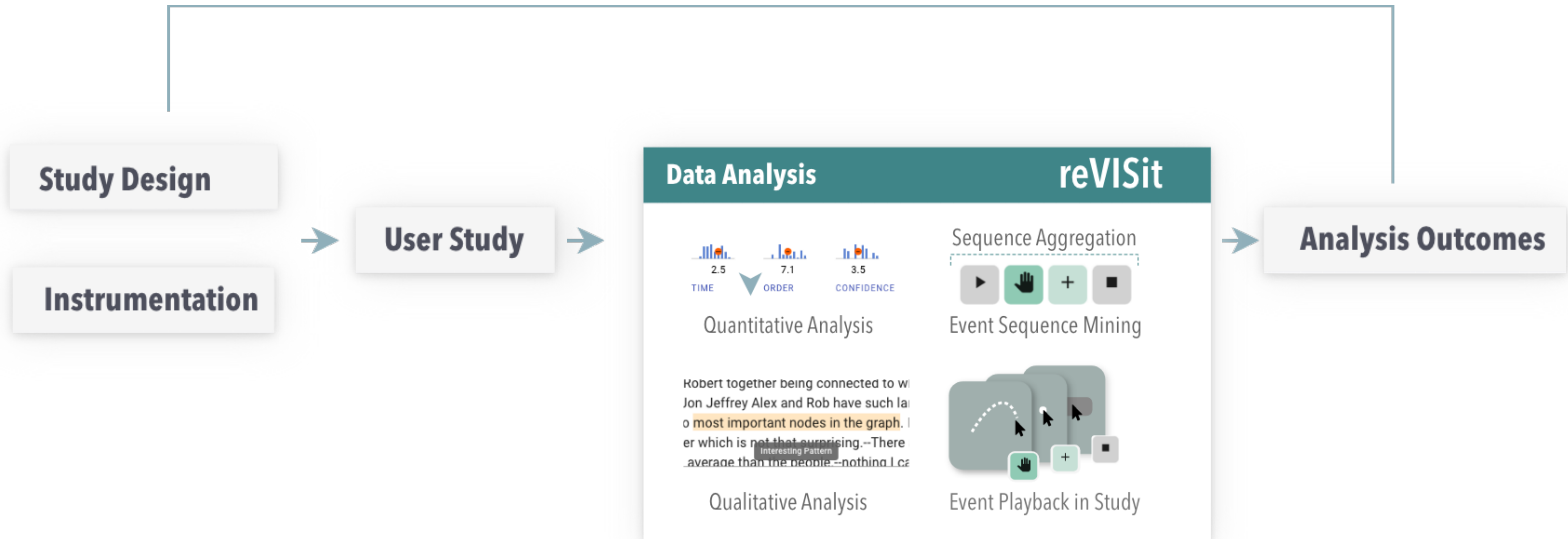
Participant B



How do **analysis strategies** impact **user performance** when using interactive visualizations?



## Pilot Iterations



## Data Analysis

reVISit

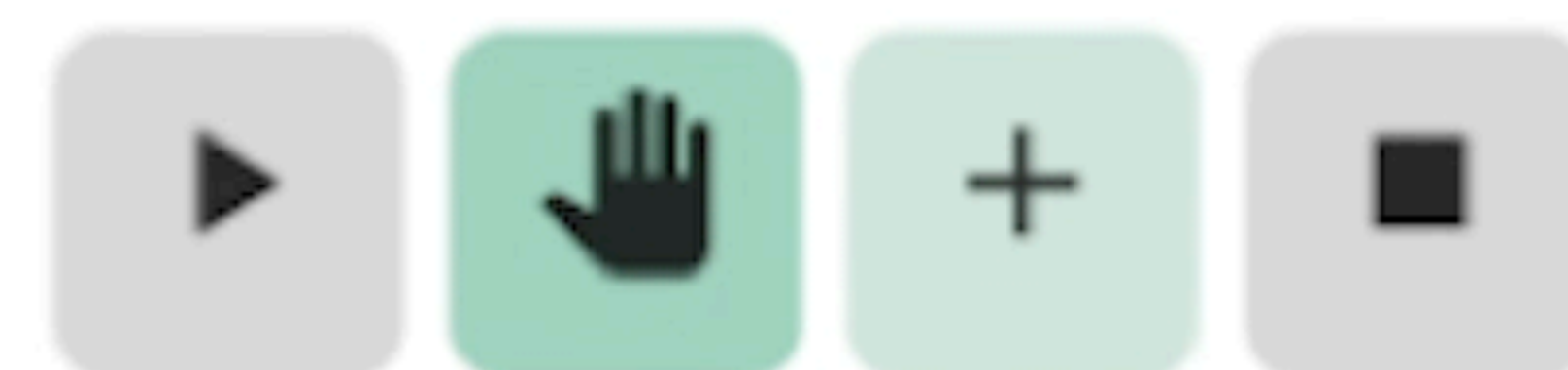


### Quantitative Analysis

Robert together being connected to w  
Jon Jeffrey Alex and Rob have such la  
o most important nodes in the graph. I  
er which is not that surprising.--There  
average than the people.--nothing I ca

### Qualitative Analysis

### Sequence Aggregation



### Event Sequence Mining



### Event Playback in Study

Ana

# FUTURE WORK: BETTER SCAFFOLDING FOR STUDIES

## reVISit: Scalable Empirical Evaluation of Interactive Visualizations

### Community Input

Collaborators  
Core Community

Community Workshops  
Broader Community

### User Services and Resources

Documentation / Examples   Replications   Community Engagement

----- ↓ ----- **Inform Software Development** ----- ↓ -----   **Synergistic Activities** ----- ↓ ↑ -----

### Core Infrastructure: Software Components

— ● New Component — ● Prototype — ● Robust —

#### Aim 1: Study Infrastructure and Multilevel Instrumentation

Study Scaffolding   Integration with Crowdsourcing Platforms

Component Registry   Capturing Insights / Rationale

Provenance Tracking   Designing Trainings

#### Aim 2: Data Transformation and Visualization Methods

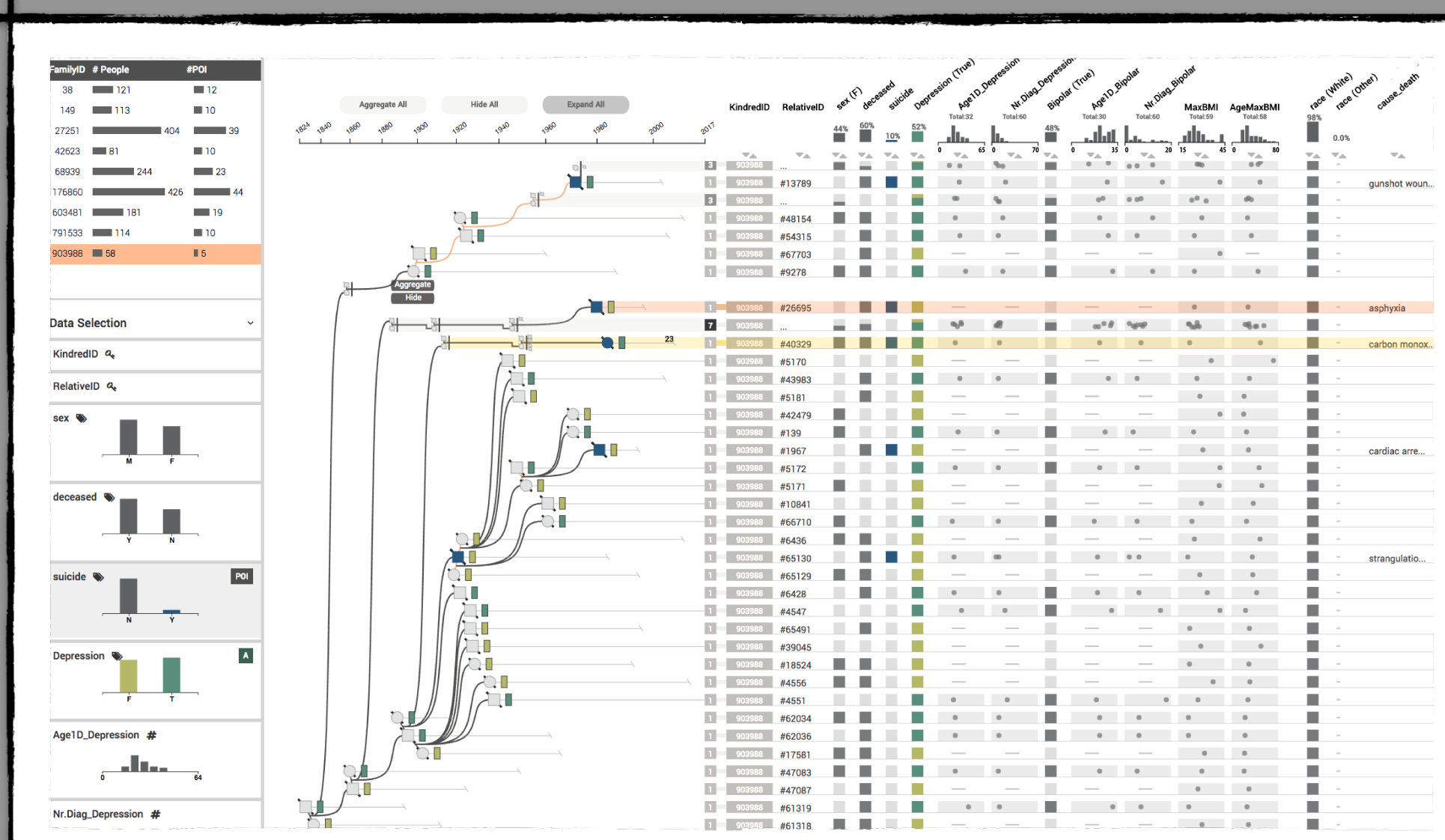
Data Transformation   Event Sequence Visualization

Trials Visualization   Study Results Visualization

Study Replay Interface   Qualitative Coding Tools

# DOMAIN DRIVEN TECHNIQUES

# Clinical Genealogies



# LINEAGE:

# VISUALIZING CLINICAL DATA IN GENEALOGY GRAPHS

**Carolina Nobre, Nils Gehlenborg, Hilary Coon, Alexander Lex**

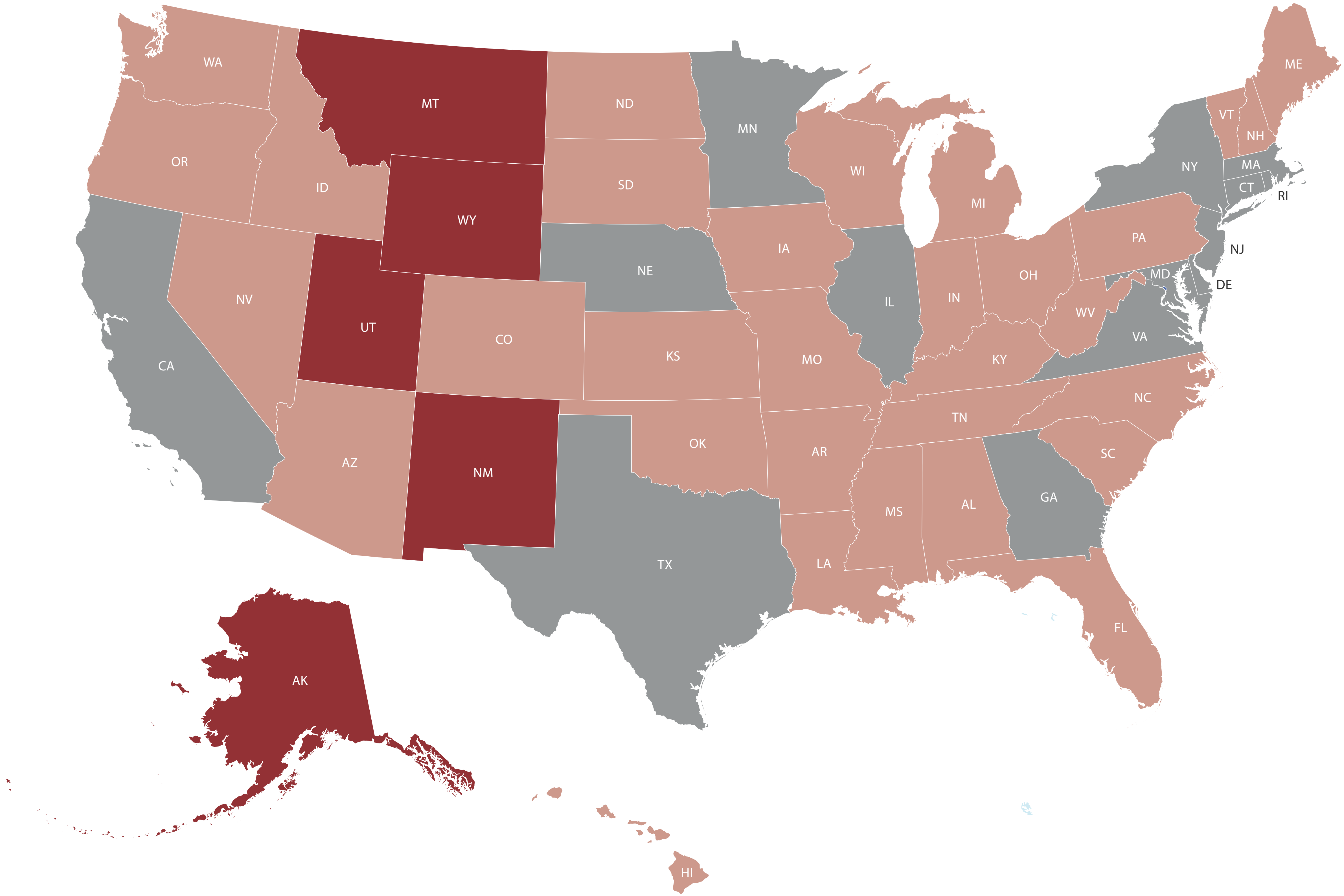


THE WORLD HEALTH  
ORGANIZATION ESTIMATES  
**ONE PERSON DIES OF  
SUICIDE EVERY 40 SECONDS**

**SUICIDE IS THE SECOND LEADING CAUSE OF DEATH**  
**IN YOUTHS BETWEEN 15 AND 29 YEARS OLD**

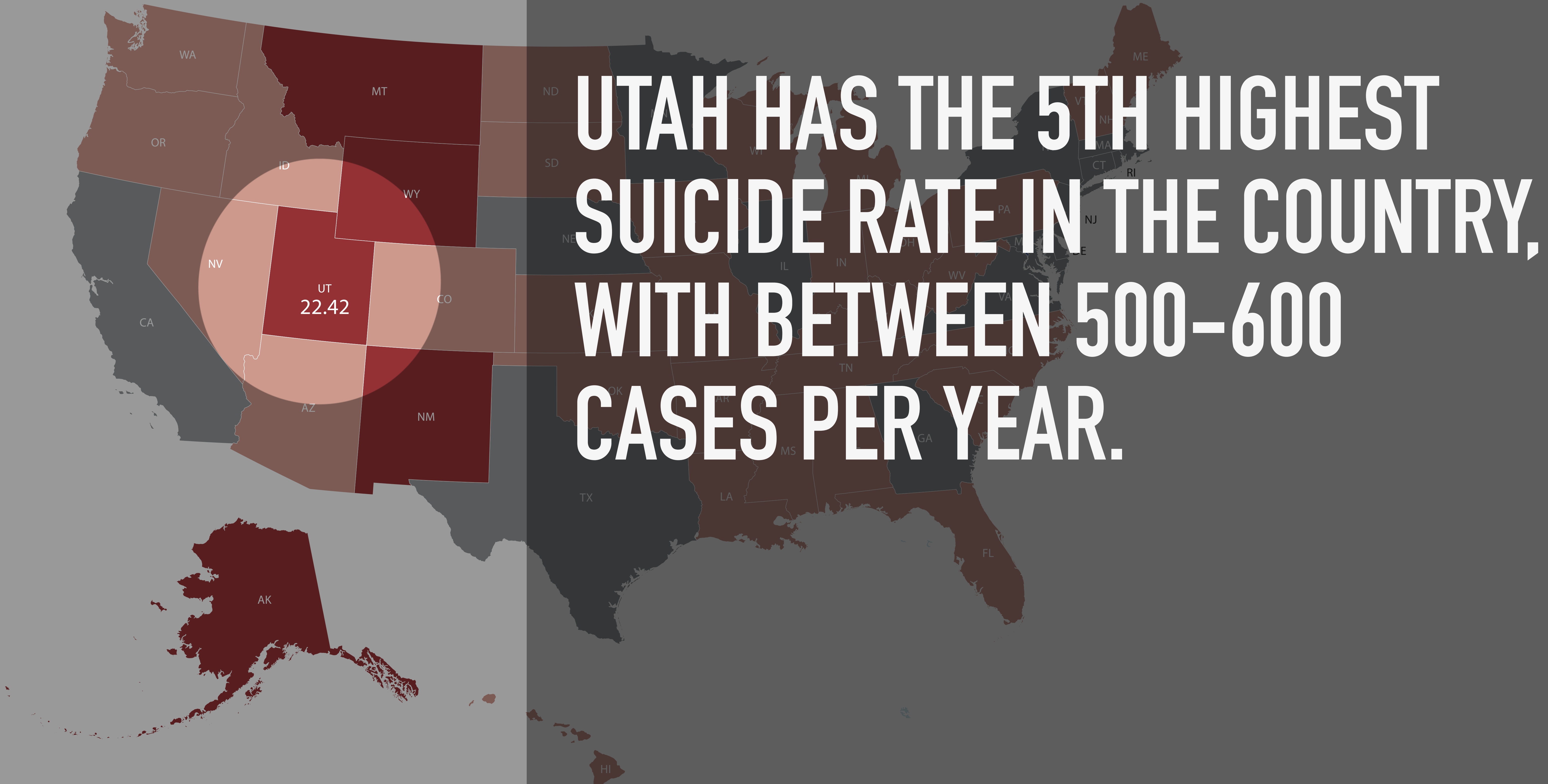
AVERAGE SUICIDE RATE BY STATE  
(National average 13.26 per 100,000)

- Top 5 states  
with the highest  
suicide rates
- States with suicide  
rates above the  
national average
- States with suicide  
rates below the  
national average



AVERAGE SUICIDE RATE BY STATE  
(National average 13.26 per 100,000)

- Top 5 states with the highest suicide rates
- States with suicide rates above the national average
- States with suicide rates below the national average





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Vol. 181, No. 5  
DOI: 10.1093/aje/kwu341  
Advance Access publication:  
February 10, 2015

## Original Contribution

### Acute Air Pollution Exposure and Risk of Suicide Completion

OPEN

Citation: Transl Psychiatry (2013) 3, e325; doi:10.1038/tp.2013.100  
© 2013 Macmillan Publishers Limited All rights reserved 2158-3188/13  
[www.nature.com/tp](http://www.nature.com/tp)



er, Hilary Coon, Douglas Gray, Phillip Wilson,  
nshaw

Department of Psychiatry, School of Medicine, University of Utah, 650 Komas Drive, Suite 206,  
@hsc.utah.edu).

for publication August 11, 2014.

## ORIGINAL ARTICLE

### Genetic risk factors in two Utah pedigrees at high risk for suicide

H Coon<sup>1</sup>, T Darlington<sup>1</sup>, R Pimentel<sup>2</sup>, KR Smith<sup>2,3</sup>, CD Huff<sup>4</sup>, H Hu<sup>4</sup>, L Jerominski<sup>1</sup>, J Hansen<sup>1</sup>, M Klein<sup>5</sup>, WB Callor<sup>6</sup>, J Byrd<sup>6</sup>, A Bakian<sup>1</sup>,  
SE Crowell<sup>1,7</sup>, WM McMahon<sup>1</sup>, V Rajamanickam<sup>8</sup>, NJ Camp<sup>8</sup>, E McGlade<sup>1,9</sup>, D Yurgelun-Todd<sup>1,9</sup>, T Grey<sup>6</sup> and D Gray<sup>1,9</sup>

We have used unique population-based data res  
over twice that expected from demographically  
two high-risk pedigrees. In the first of these (ped  
death was 30.95. In the second (pedigree 5), 7/5  
decedents in pedigree 12 and nine in pedigree  
analyzed using the Variant Annotation, Analysis,  
functional impact of the DNA variation, aggrega  
prioritized variants that were: (1) shared across  
(3)  $\leq 5\%$  in genotyping data from 398 other Ut  
from 1358 controls and/or in dbSNP. Results inc  
FAM38A and HRCT1 for pedigree 5). Other gene

## The Role of Social Isolation in Suicide

Deborah L. Trout M.A.

First published: Spring 1980 | <https://doi-org.ezproxy.lib.utah.edu/10.1111/j.1943-278X.1980.tb00693.x>  
| Cited by: 95

The author wishes to thank Dr. Charles Neuringer for his assistance with the preparation of this manuscript.

# MOTIVATION & DATA

Understand **Complex Conditions**

Discover **Genetic Risk Factors**

## **Dataset:**

118k people, 19k suicide cases, ~2k  
with genomic data, 550 families

Based on **Utah Population Database**

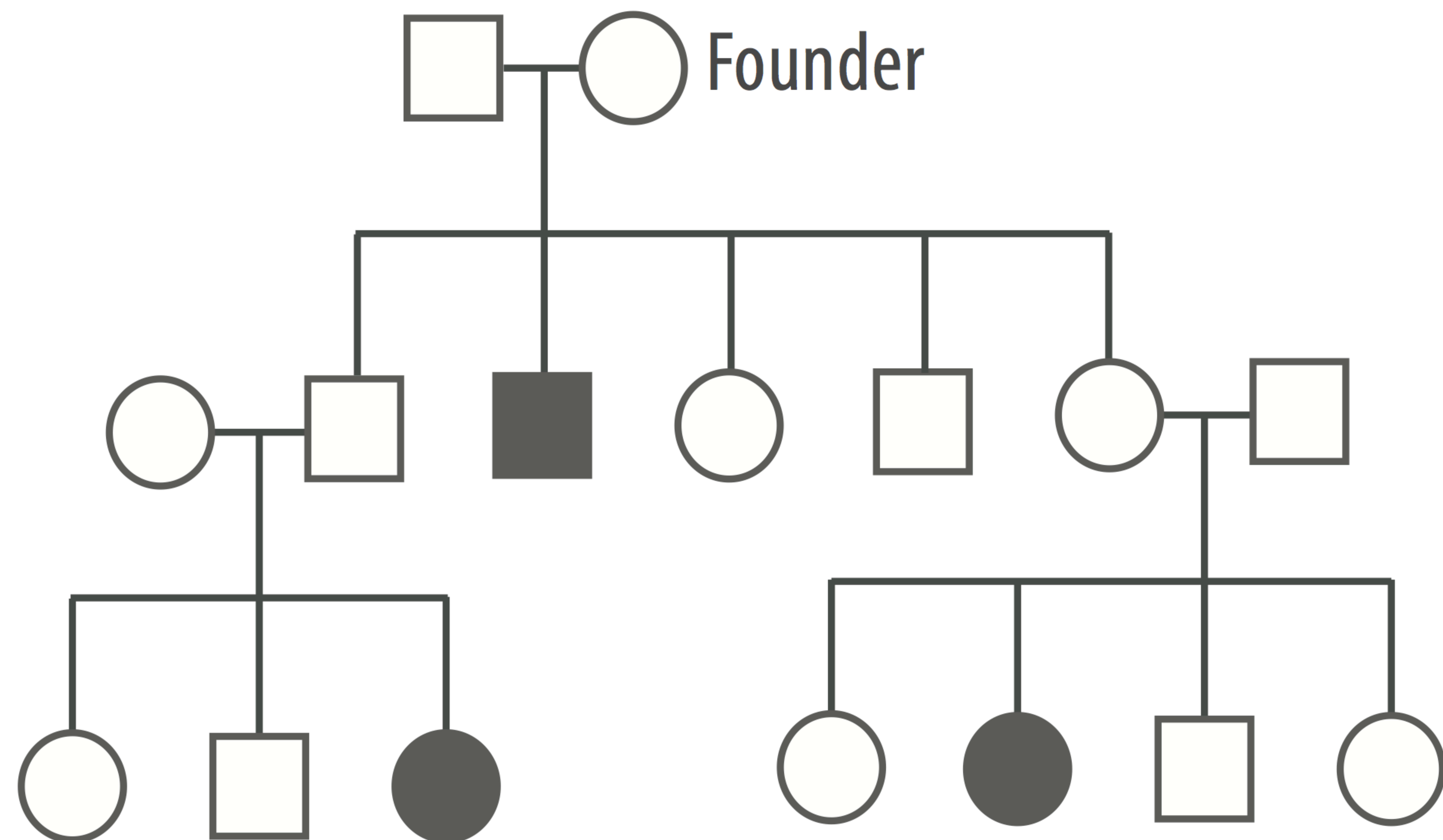
## SPECIFIC GOALS

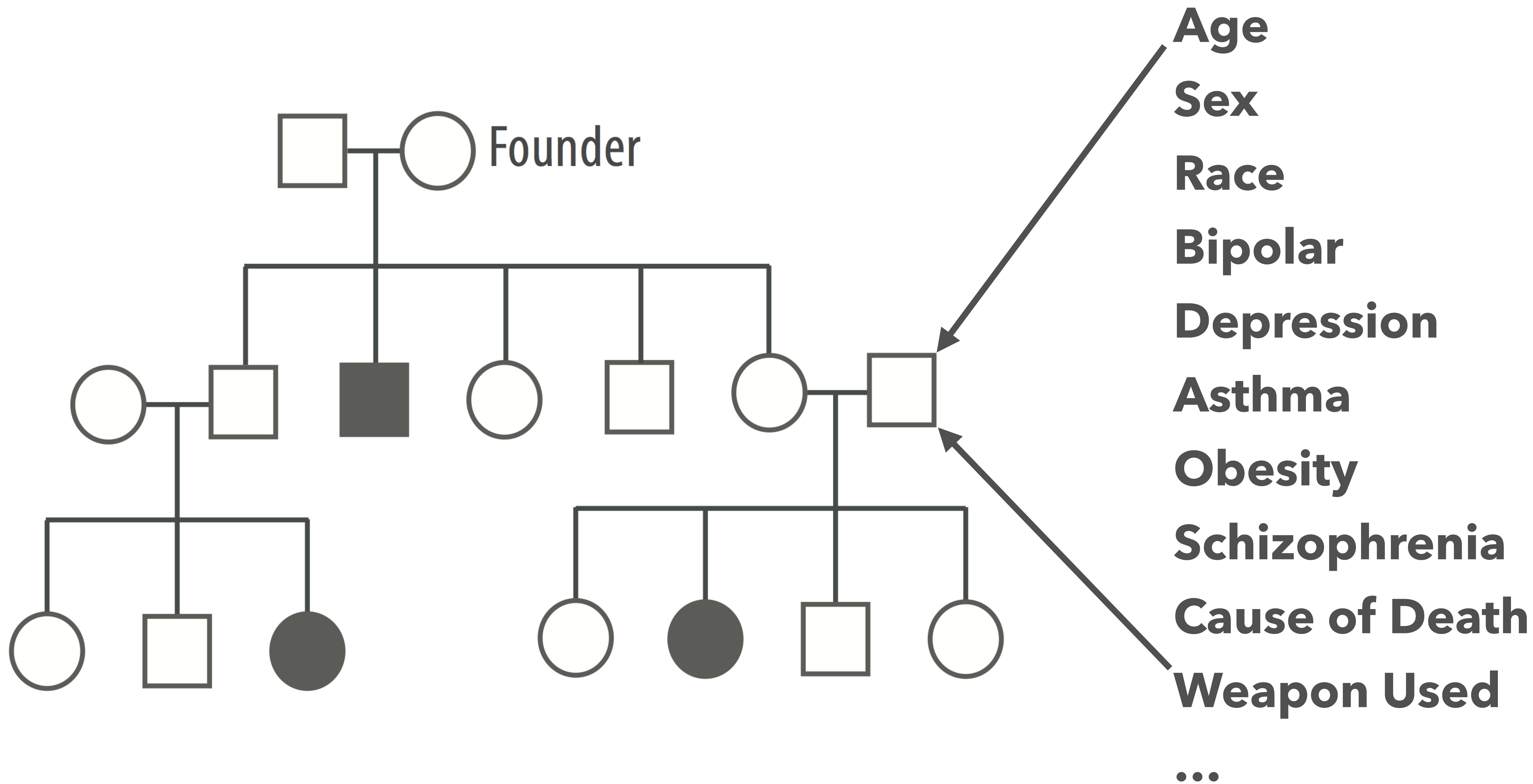
**Find familial cases that also have an “interesting” phenotype**

e.g., predominantly female, associated with rare psychiatric disease, etc.

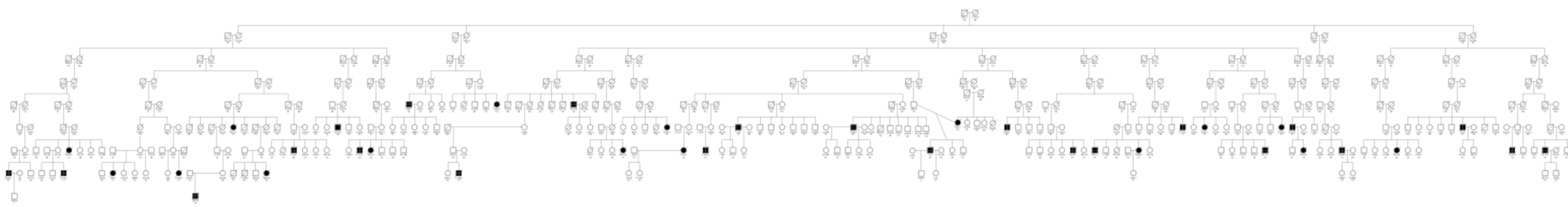
**Prioritize those cases for analysis of shared genomic sequences**

**Proofread the Data!**

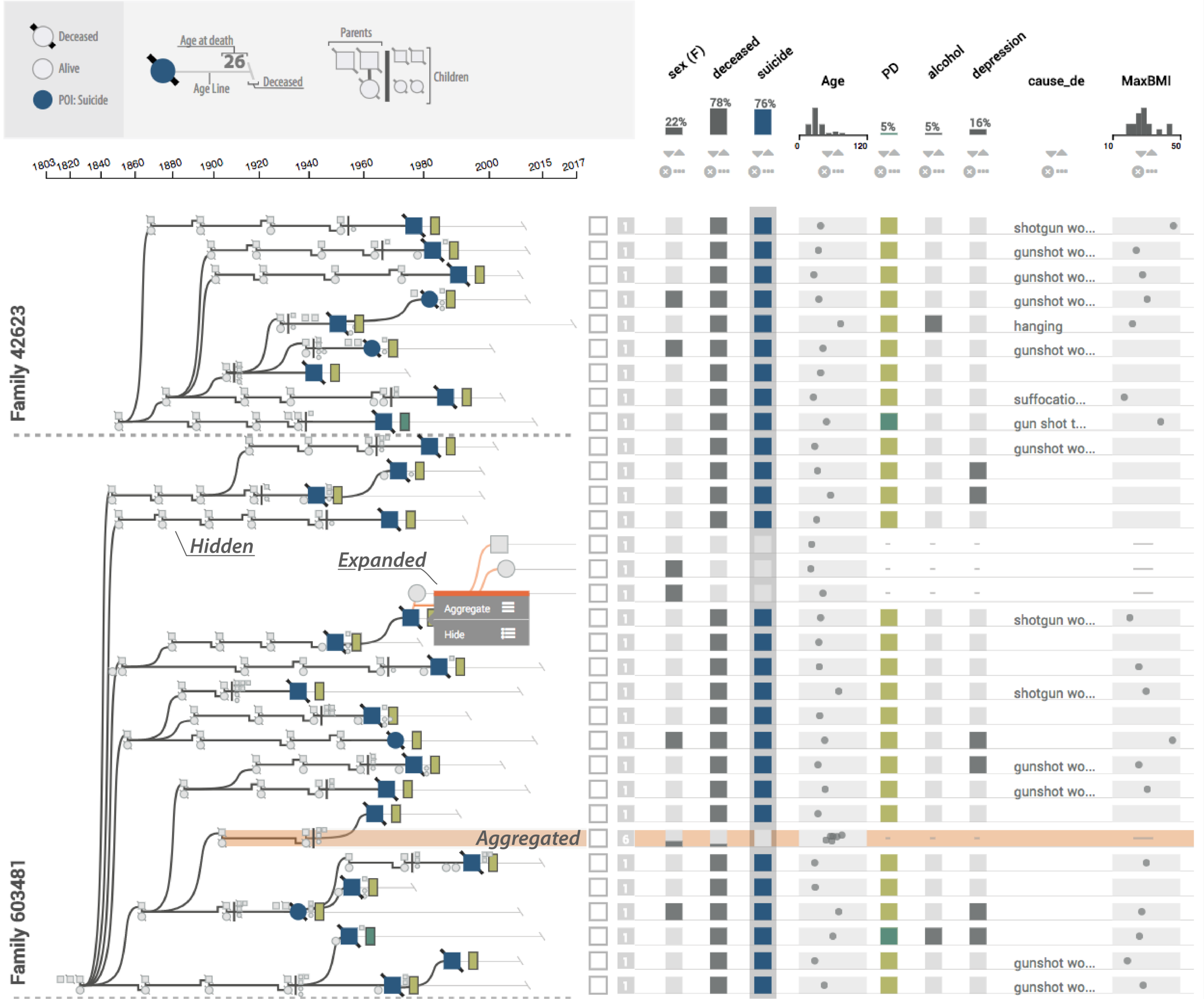




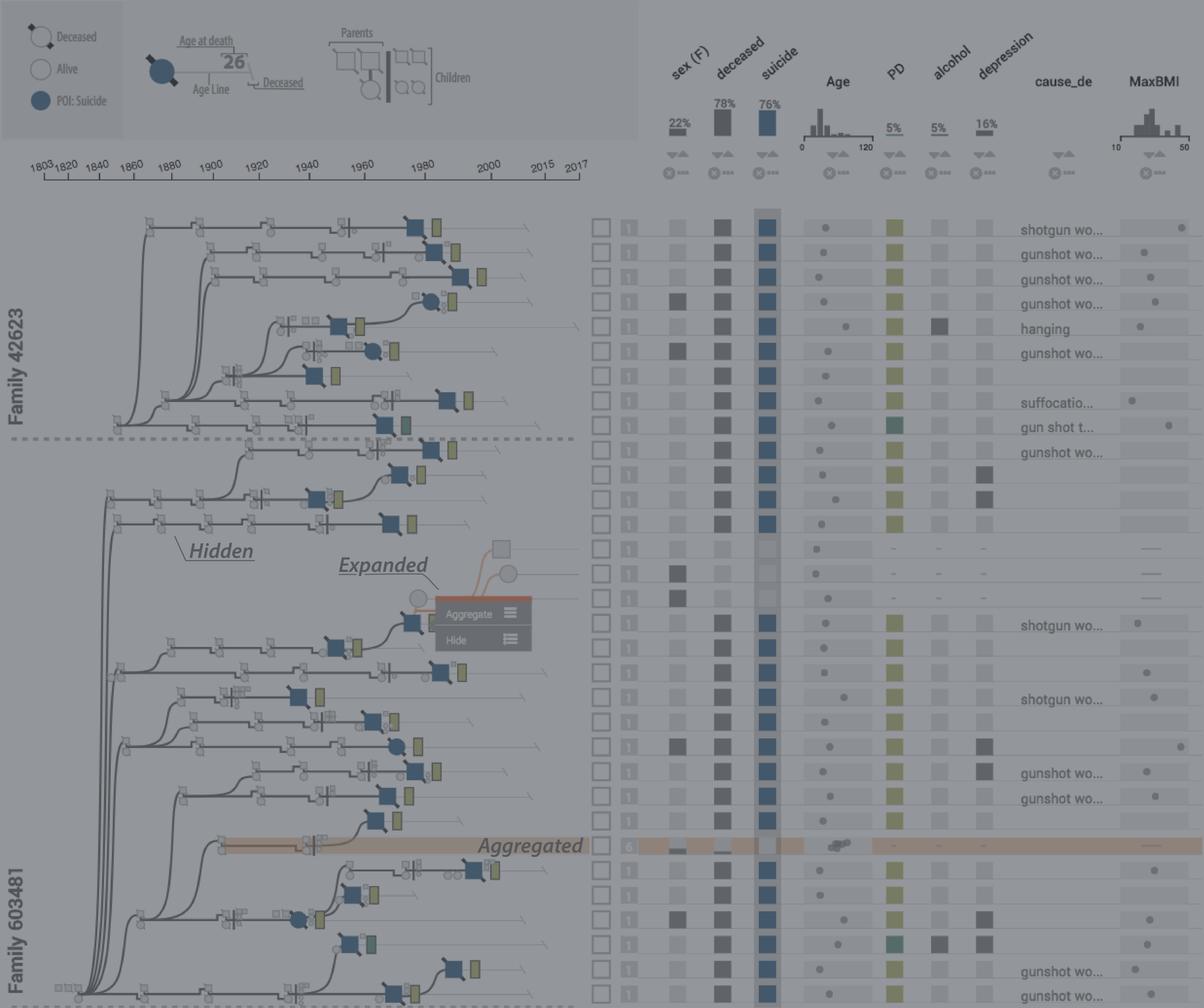
# GENEALOGY WITH ~400 MEMBERS RENDERED WITH PROGENY



Family Selector			Expand
ID	#People	#POI	
42623	88	10 (11.4%)	
603481	192	19 (9.9%)	
563221	215	20 (9.3%)	
564118	150	14 (9.3%)	
564323	1164	36 (3.1%)	
564569	243	21 (8.6%)	
565350	268	23 (8.6%)	
565984	92	9 (9.8%)	
567427	169	15 (8.9%)	
568085	1624	58 (3.6%)	
568132	74	7 (9.5%)	
569170	148	14 (9.5%)	
569543	197	19 (9.6%)	
570128	346	30 (8.7%)	
570915	246	23 (9.3%)	
571227	227	20 (8.8%)	
572059	406	32 (7.9%)	
572163	339	15 (4.4%)	
572218	384	16 (4.2%)	
572324	750	25 (3.3%)	
572326	750	25 (3.3%)	
572932	245	20 (8.2%)	
573378	239	21 (8.8%)	
575370	134	11 (8.2%)	
576442	185	15 (8.1%)	



Family Selector			Expand
ID	#People	#POI	
42623	88	10 (11.4%)	
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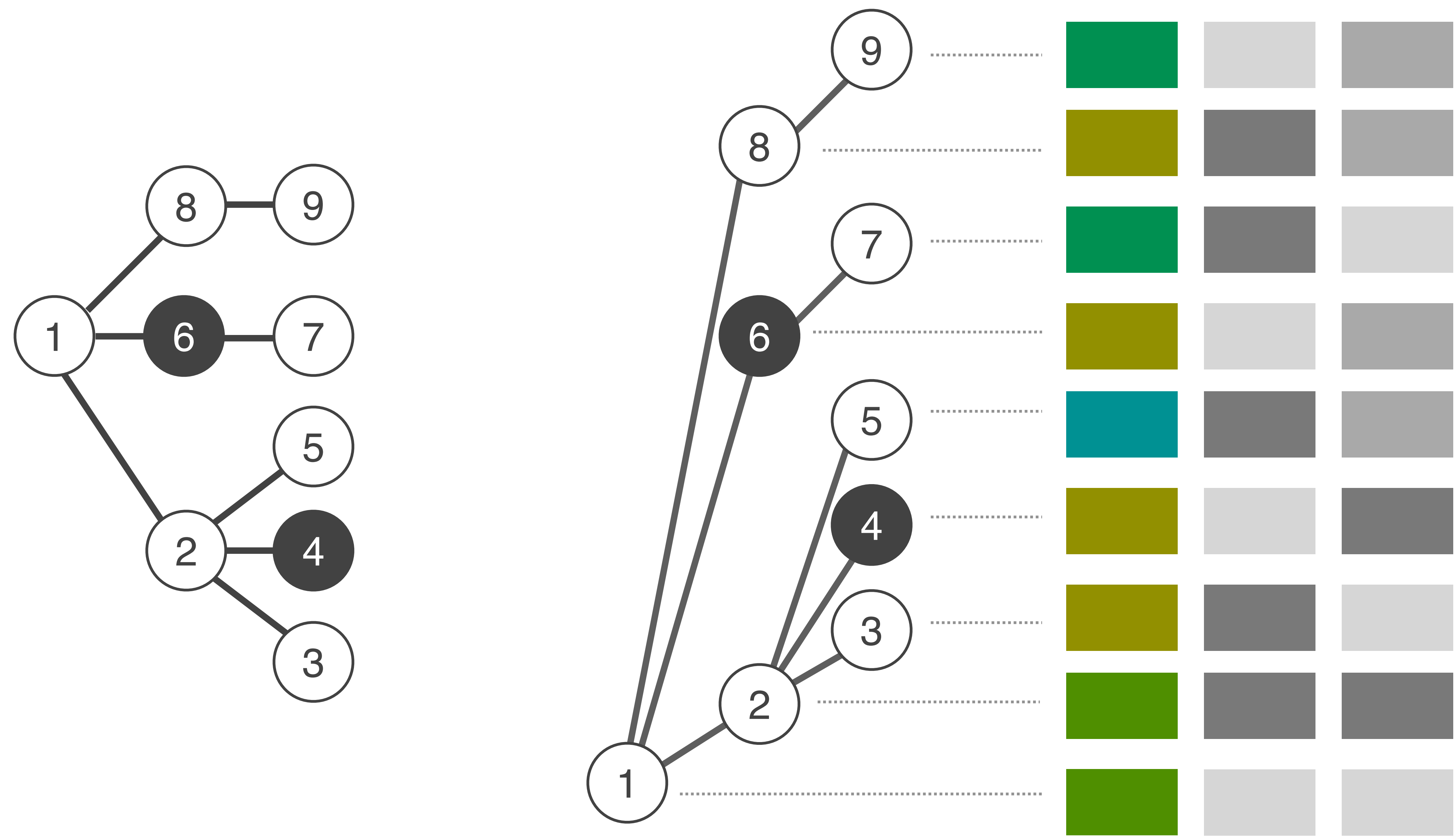


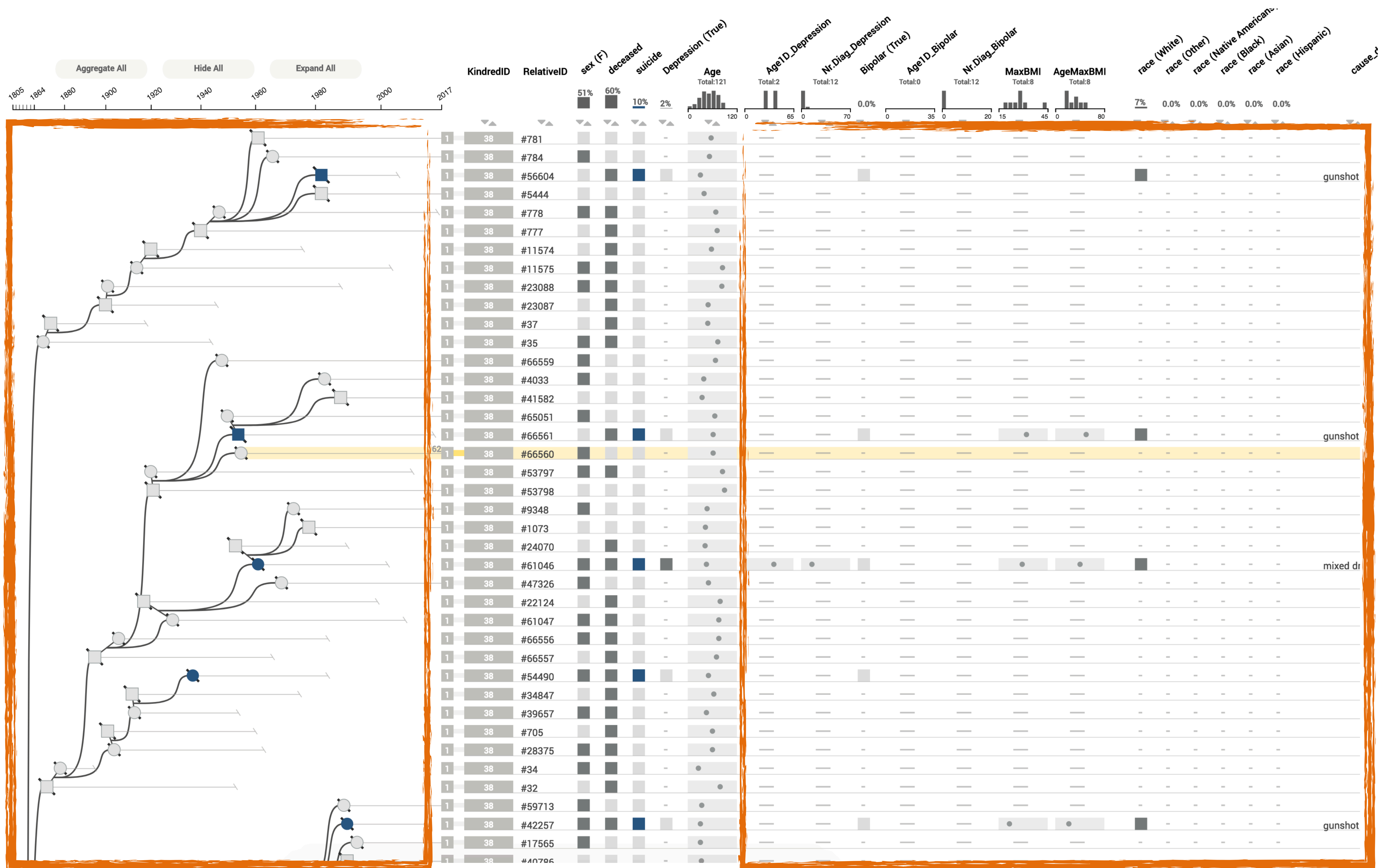
Family Selector





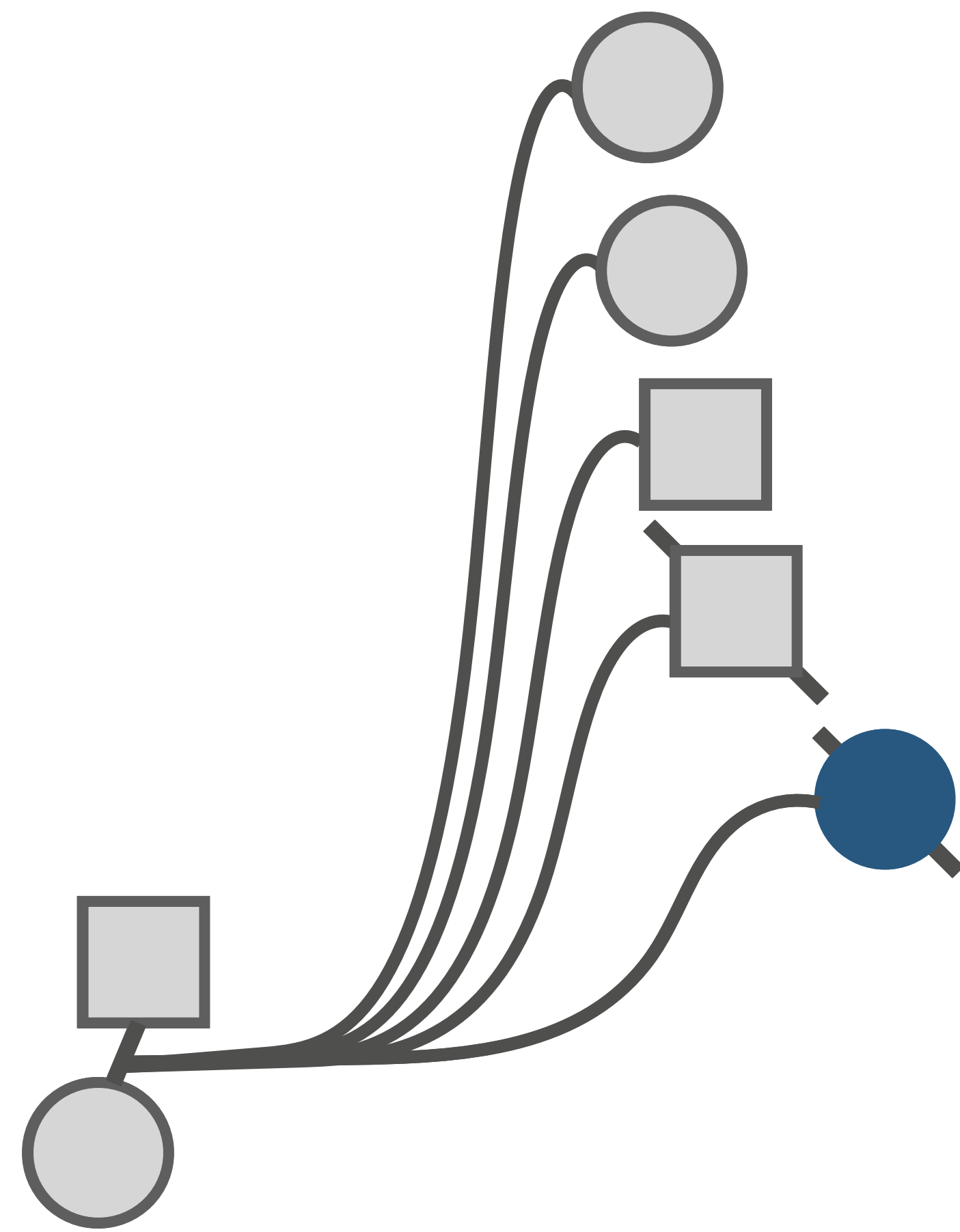
# LINEARIZING

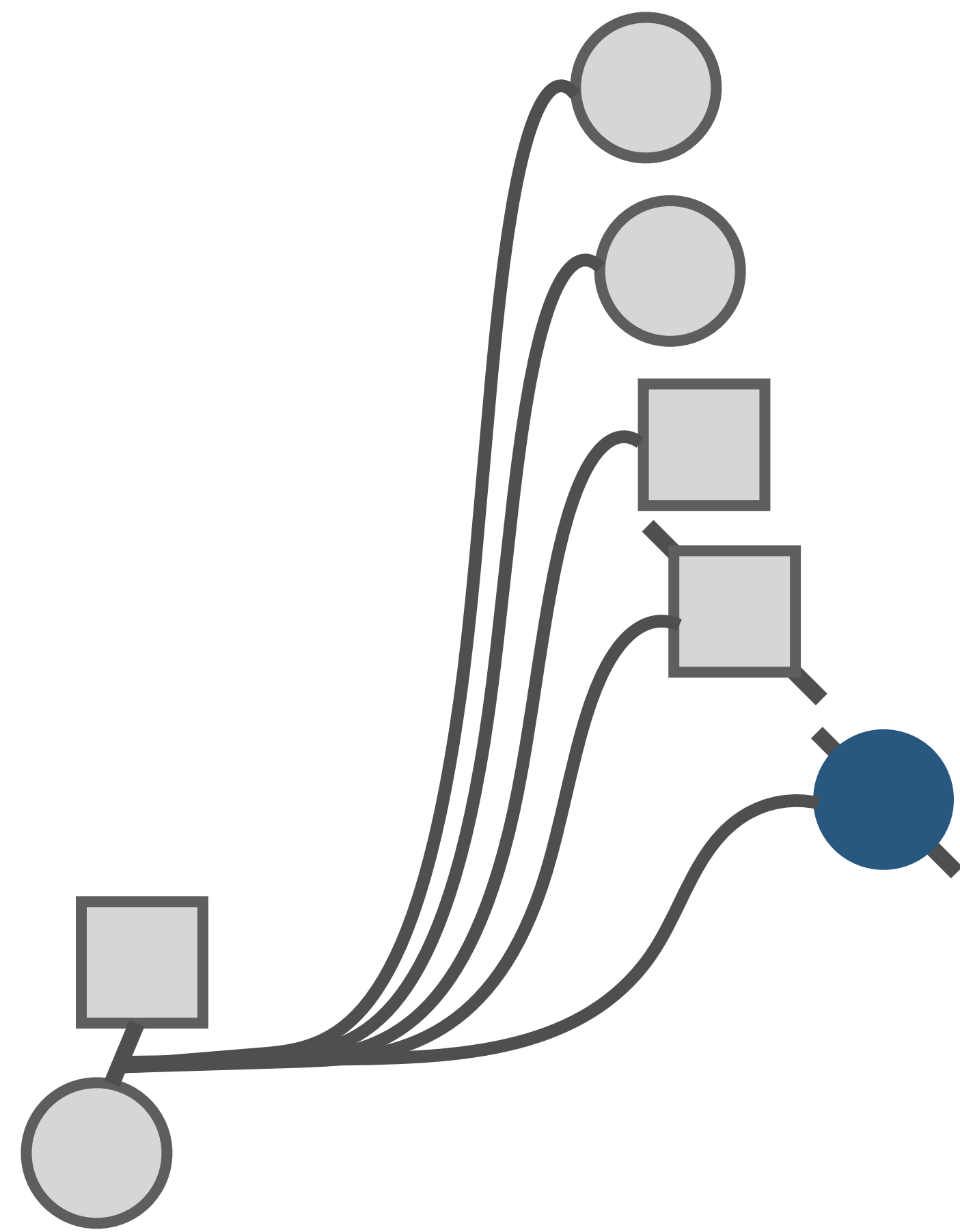


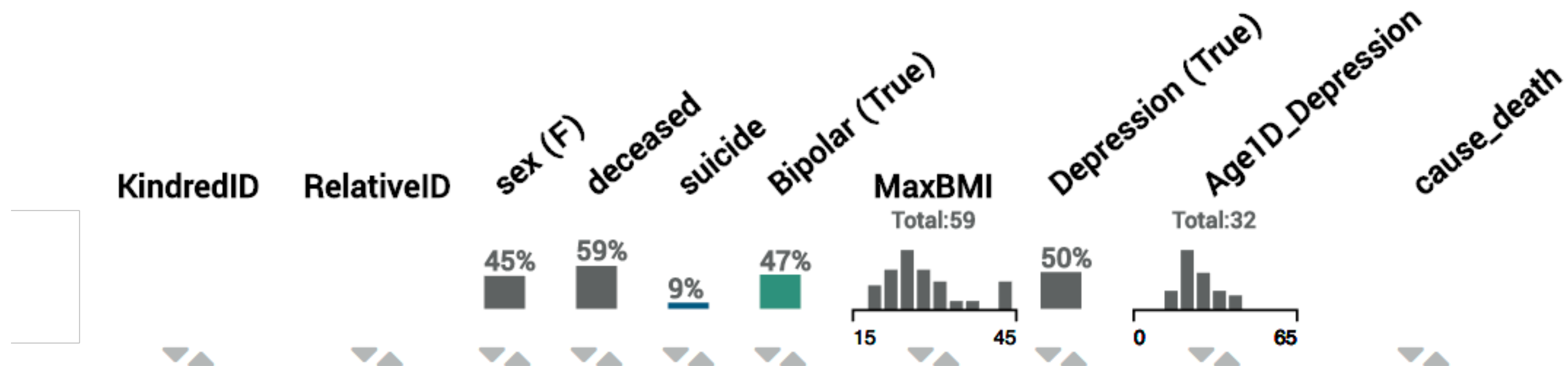


Can't show many people

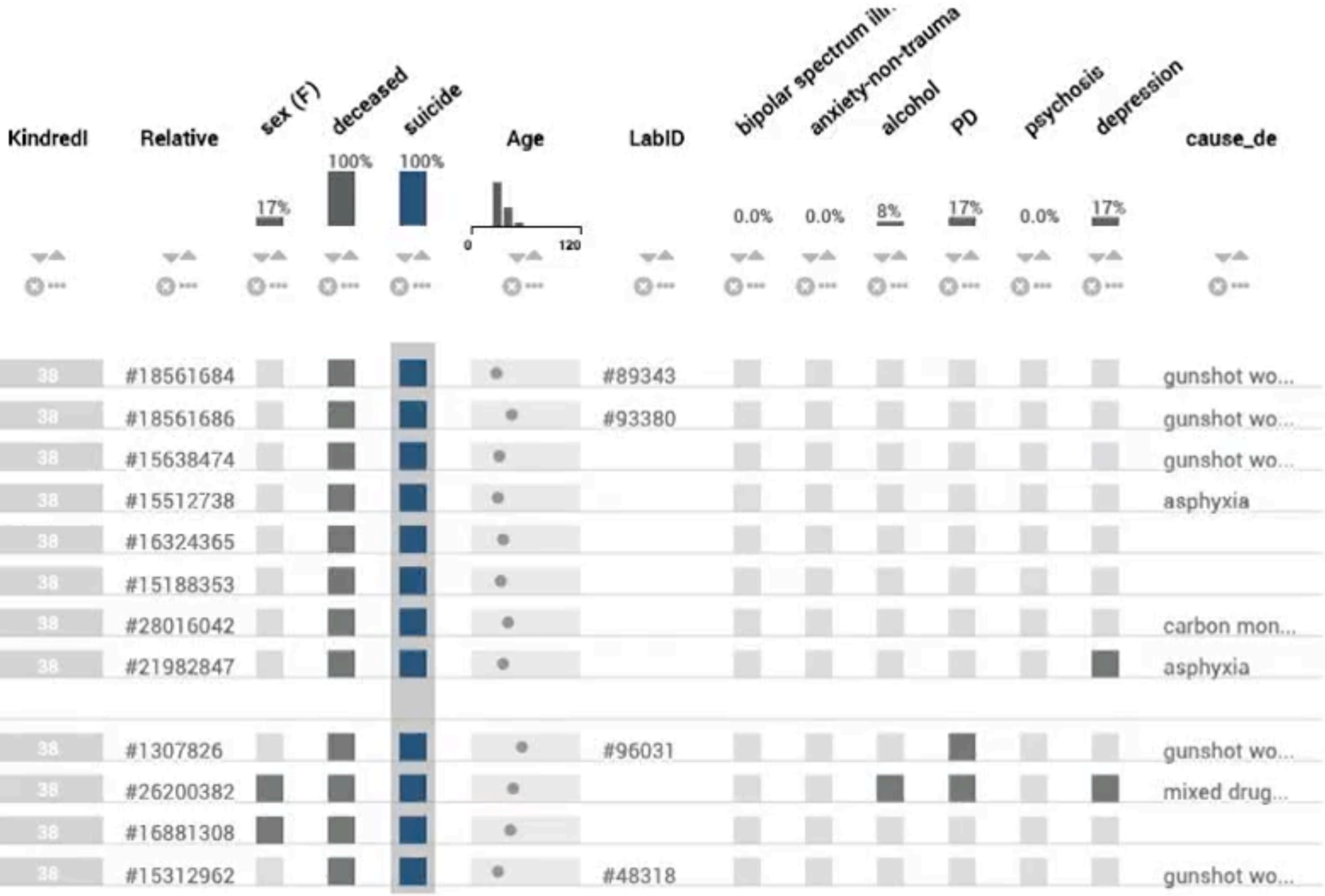
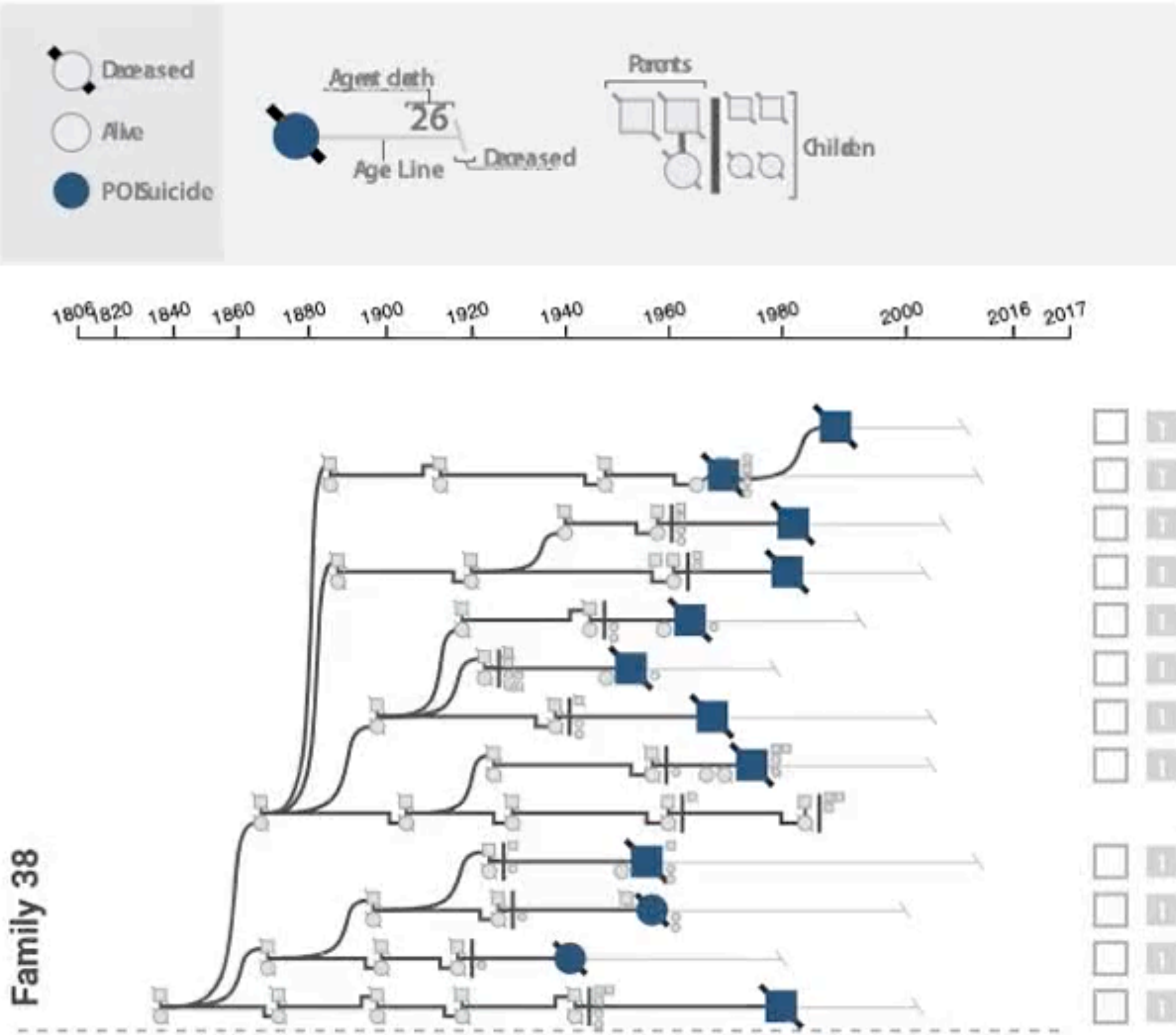
Lots of missing data







Family Selector			Expand
ID	#People	#POI	
38	129	12 (9.3%)	
38	129	12 (9.3%)	
149	122	10 (8.2%)	
212	368	35 (9.5%)	
234	145	13 (9%)	
331	389	19 (4.9%)	
490	277	25 (9%)	
709	285	28 (9.8%)	
1253	245	23 (9.4%)	
1474	237	18 (7.6%)	
1627	171	17 (9.9%)	
1787	768	29 (3.8%)	
1843	218	18 (8.3%)	
1881	196	19 (9.7%)	
2053	322	31 (9.6%)	
2082	209	21 (10%)	
2117	190	17 (8.9%)	
2194	164	13 (7.9%)	
2208	162	13 (8%)	
2563	157	15 (9.6%)	
2749	230	19 (8.3%)	
2902	224	17 (7.6%)	
3222	191	20 (10.5%)	
3841	313	15 (4.8%)	
3933	198	8 (4%)	



## **USAGE & FUTURE WORK**

**Currently used by team of Psychiatry researchers on a daily basis**

**Widespread interest from other labs working with UPDB data**

**Integration of other data types**

Geospatial, Environmental, Genomic

**Alexander Lex**

@alexander\_lex

<http://alexander-lex.net>



Thanks to: **Carolina Nobre, Dylan Wootton, Kiran Gadhave, Zach Cutler**, Marc Streit, Jochen Görtler, Oliver Deussen, Miriah Meyer, Jeff Phillips, Samuel Gratzl, Holger Stitz, Nils Gehlenborg, Hendrik Strobelt, Romain Vuillemot, Hanspeter Pfister, and many others!



**visualization**  
**design lab**

