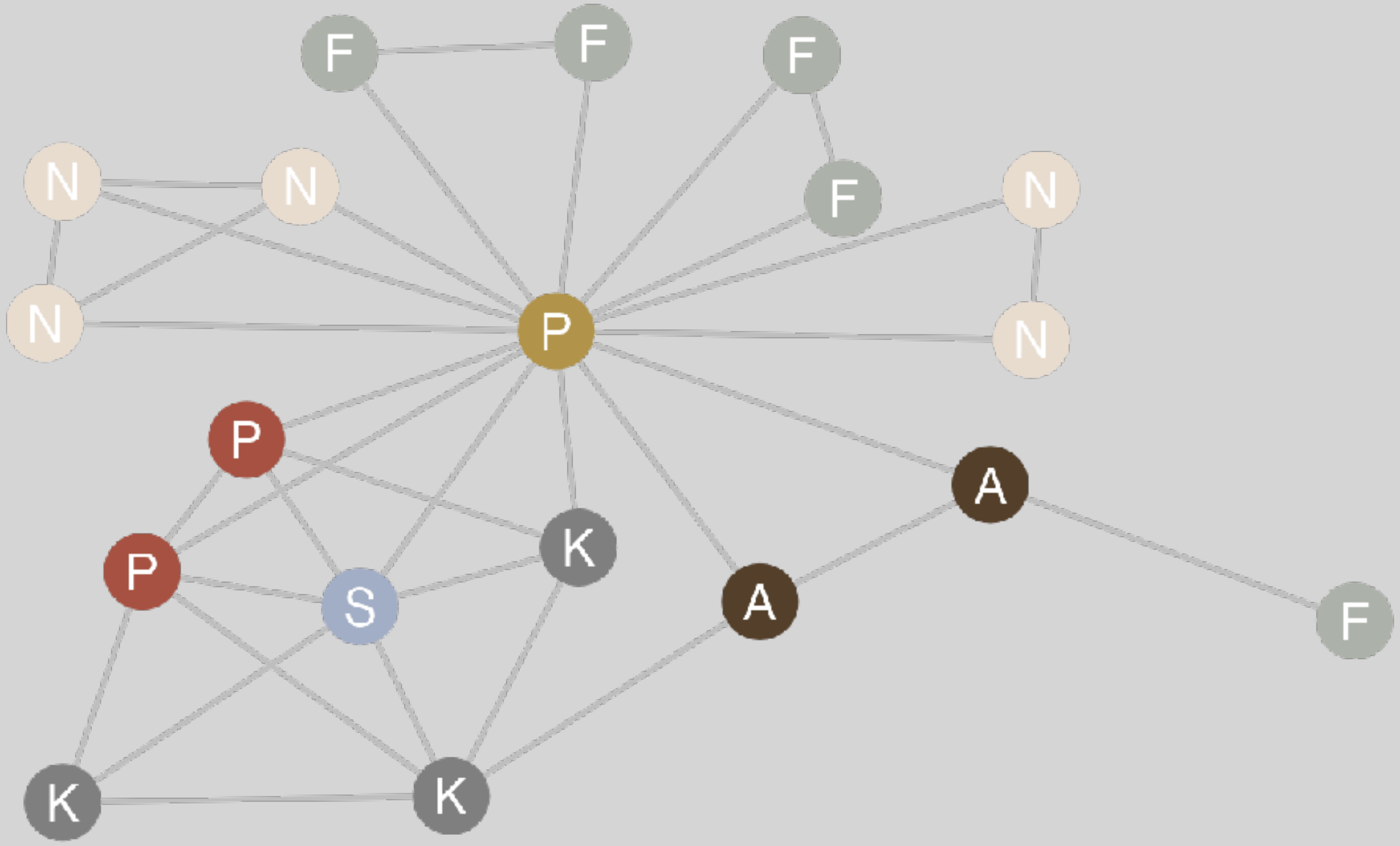
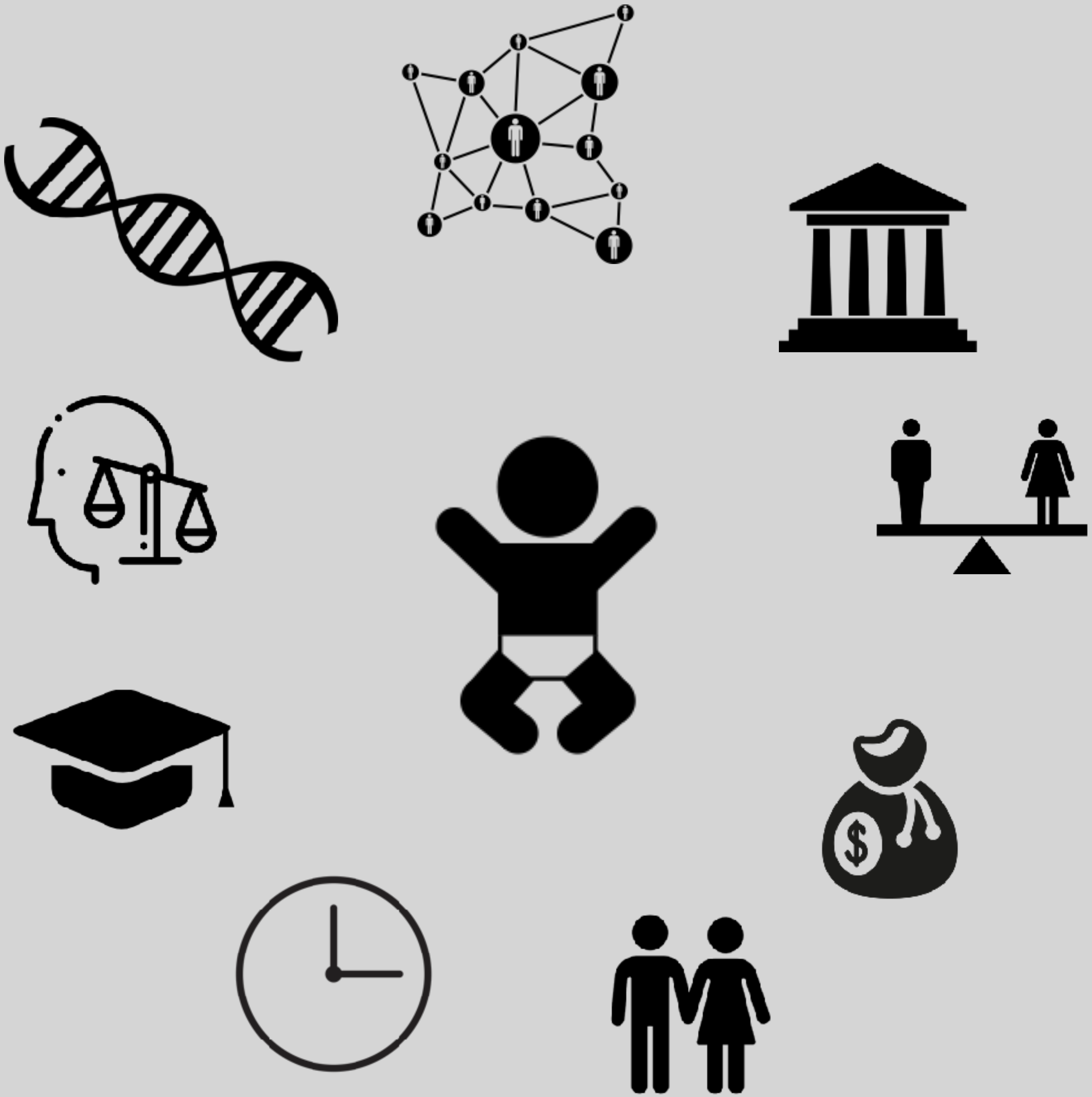
Predicting fertility outcomes with networks



gert stulp - gertstulp.com



variables explain little

Fewer births because of study and flexwork?

“ total effect on fertility … rather small

surprising patterns

incomparable results

non-replicable results

Replication Crisis

PSYCHOLOGY

Estimating the reproducibility of psychological science

Open Science Collaboration*

ROYAL SOCIETY OPEN SCIENCE

rsos.royalsocietypublishing.org

Research

CrossMark
click for updates

Cite this article: Smaldino PE, McElreath R. 2016 The natural selection of bad science.

The natural selection of bad science

Paul E. Smaldino[1] and Richard McElreath[2]

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[2]Department of Human Behavior, Ecology, and Culture, Max Planck Institute for Evolutionary Anthropology, Leipzig, Germany

PES, 0000-0002-7133-5620; RME, 0000

Check for updates

aps
ASSOCIATION FOR PSYCHOLOGICAL SCIENCE

General Article

False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant

Psychological Science
22(11) 1359–1366

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DOI: 10.1177/0956797611417632
http://pss.sagepub.com
SAGE

Joseph P. Simmons[1], Leif D. Nelson[2], and Uri Simonsohn[1]
[1]The Wharton School, University of Pennsylvania, and [2]Haas School of Business, University of California, Berkeley

Crisis in Family Sociology

Reasons unlikely

- ✓ *Strong methods*
- ✓ *Strong focus on representative data*
- ✓ *Less measurement error*
- ✓ *Open data*
- ✓ *Large N*
- ✓ *Often descriptive*

Reasons not unlikely

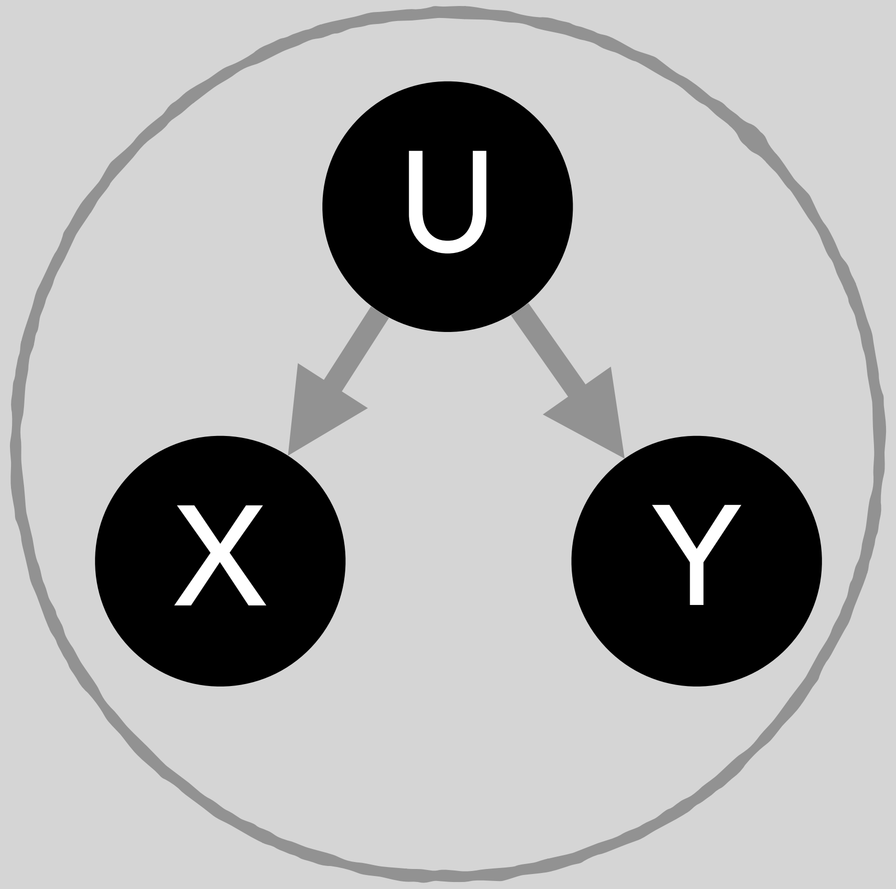
- ✗ *Non-experimental*
- ✗ *Correlational, but little causal inference*
- ✗ *Large N, yet star gazing*
- ✗ *Controlling at will*
- ✗ *Long reign linearity*

Overcoming the Crisis


theory


measurement


incentives



causal inference


prediction

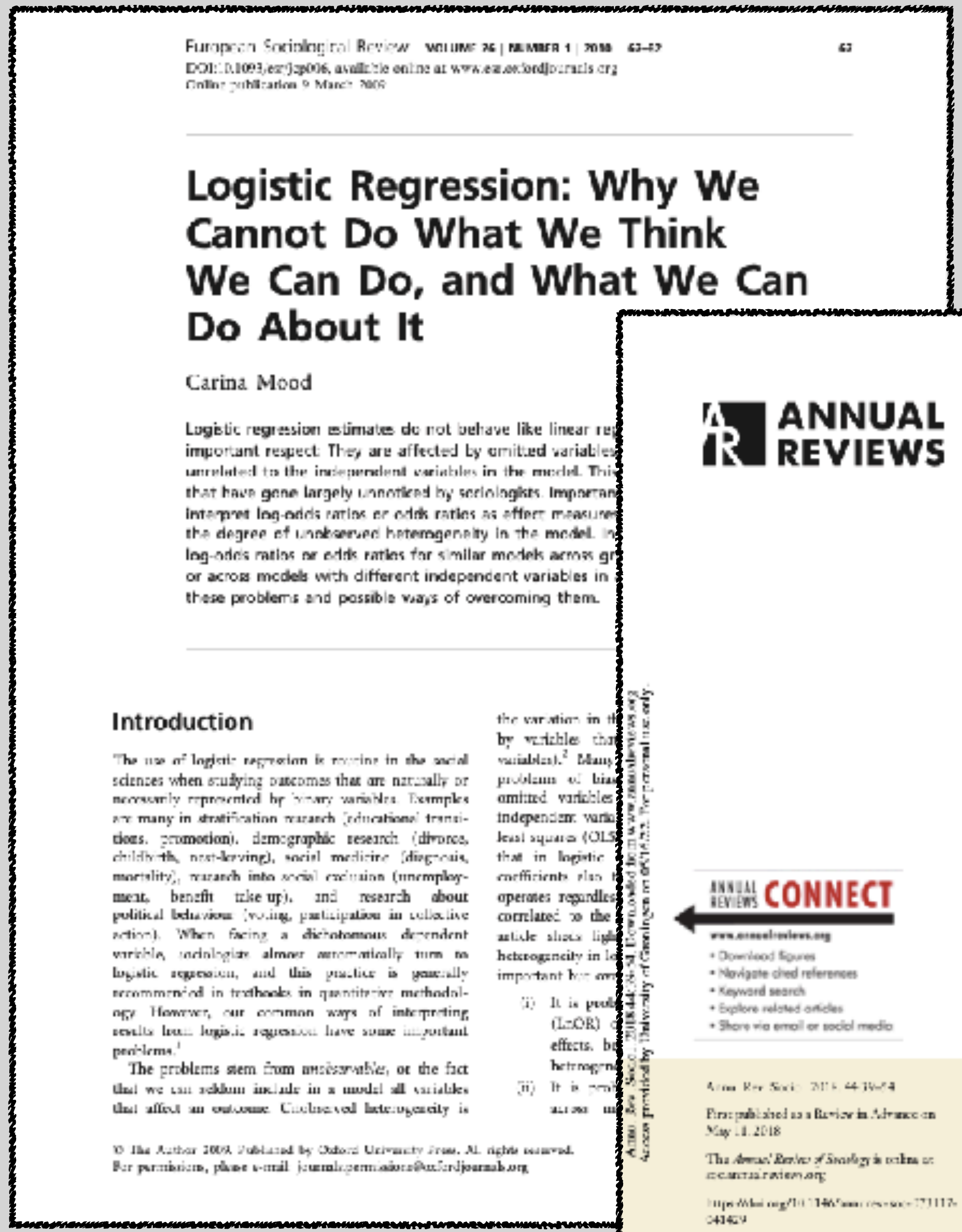
a shift towards **prediction** leads to a more reliable and useful social science

out-of-sample predictive ability:

clear measure of effect size

out-of-sample predictive ability

- is easy(ier) to understand
- can be compared across analytical techniques
- can be compared across models
- is less gameable


European Sociological Review

Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It

Carina Mood

Introduction


ANNUAL REVIEWS

Annual Review of Sociology

Interpreting and Understanding Logits, Probits, and Other Nonlinear Probability Models

Richard Breen, Kristian Bernt Karlson, and Anders Holm

ANNUAL REVIEWS CONNECT

Keywords

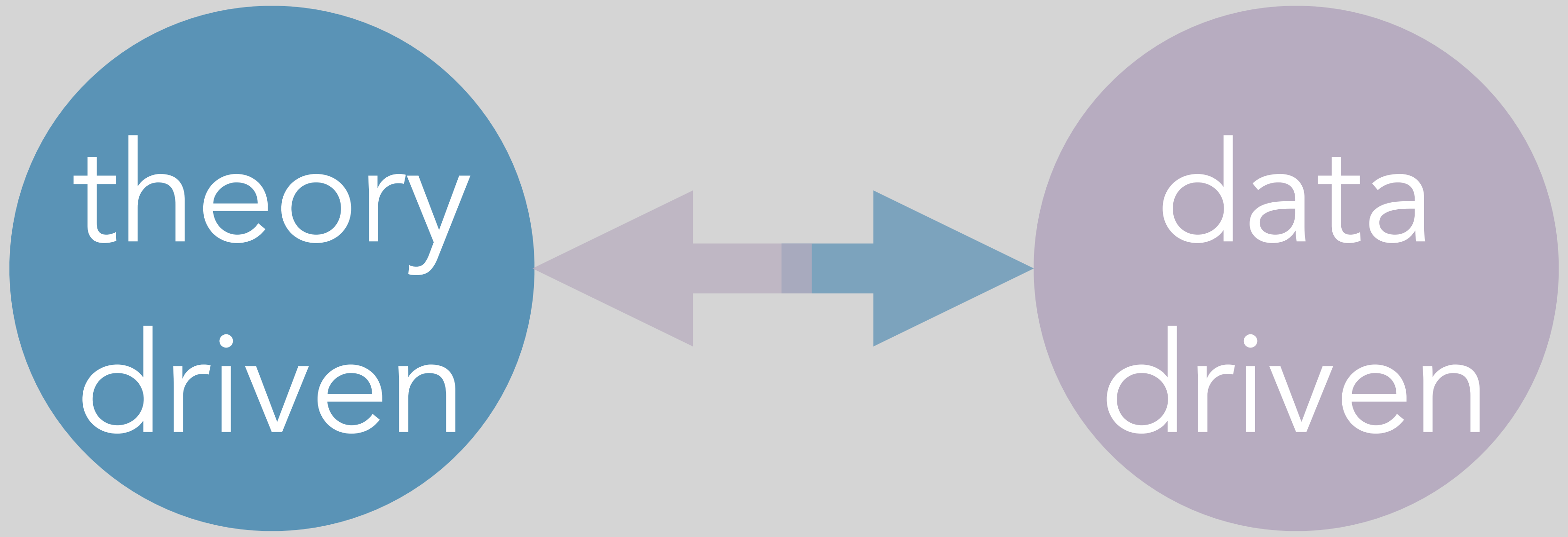
logit, probit, KHB method, Y-standardization, marginal effects, linear probability model, mediation

Abstract

a shift towards **prediction** leads to a more reliable and useful social science

out-of-sample predictive ability:

clear measure of effect size

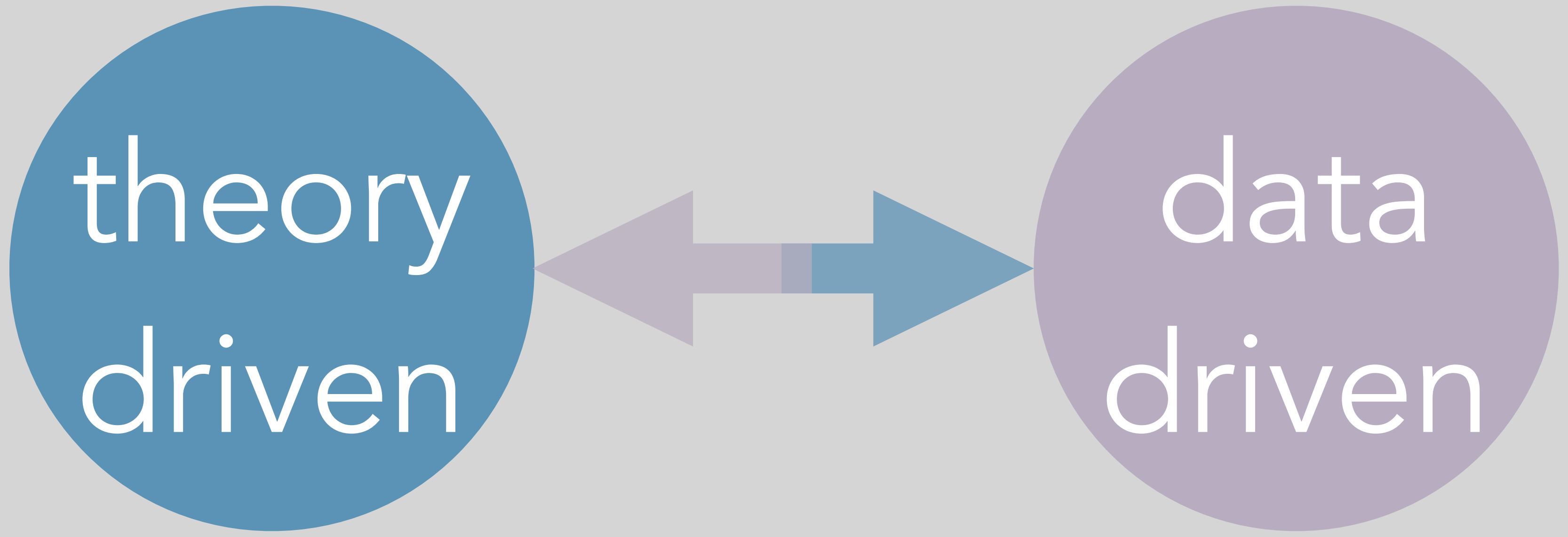


facilitates dialogue theory- and data-driven models

a shift towards **prediction** leads to a more reliable and useful social science

out-of-sample predictive ability:

clear measure of effect size



facilitates dialogue theory- and data-driven models

measure of distance theory and practice

out-of-sample predictive ability is a measure of how useful our theory is in the real world

Articles

Journal of Peace Research

Journal of Peace Research
47(4) 363–375

DOI: 10.1177/0022343309356491
jpr.sagepub.com
SAGE

The perils of policy by p-value: Predicting civil conflicts

Michael D Ward

Department of Political Science, Duke University

Brian D Greenhill

Department of Political Science, University of Washington

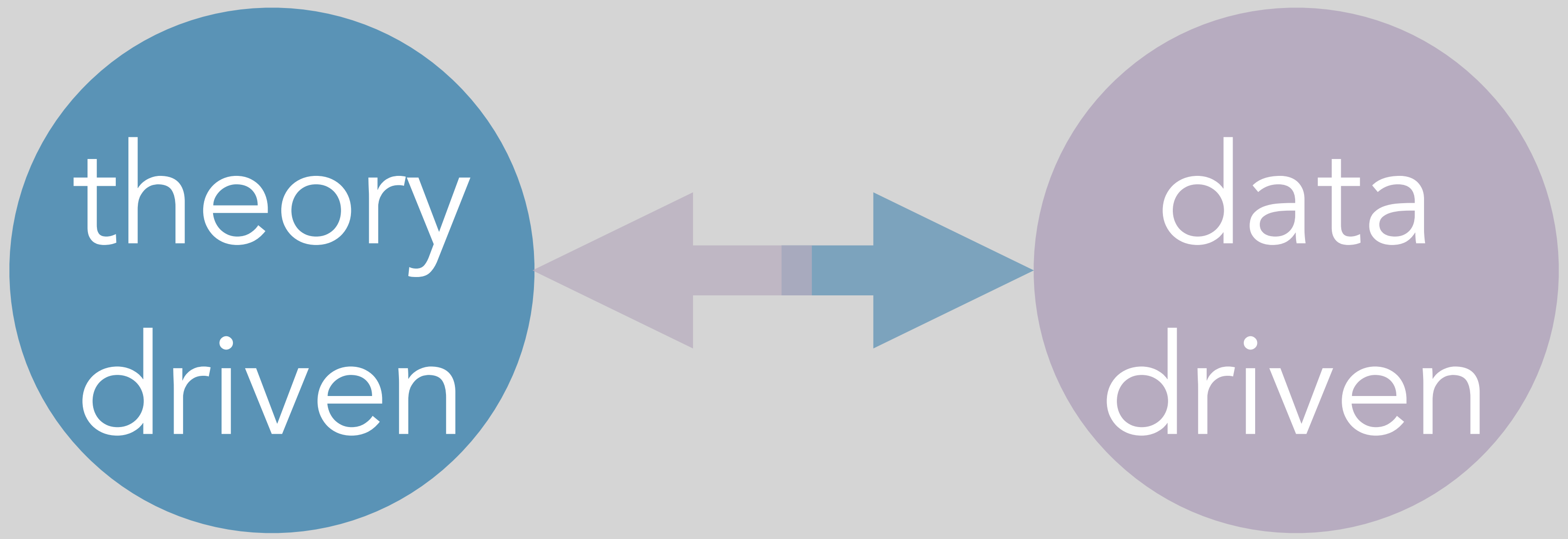
Kristin M Bakke

Department of Political Science, University College London

a shift towards **prediction** leads to a more reliable and useful social science

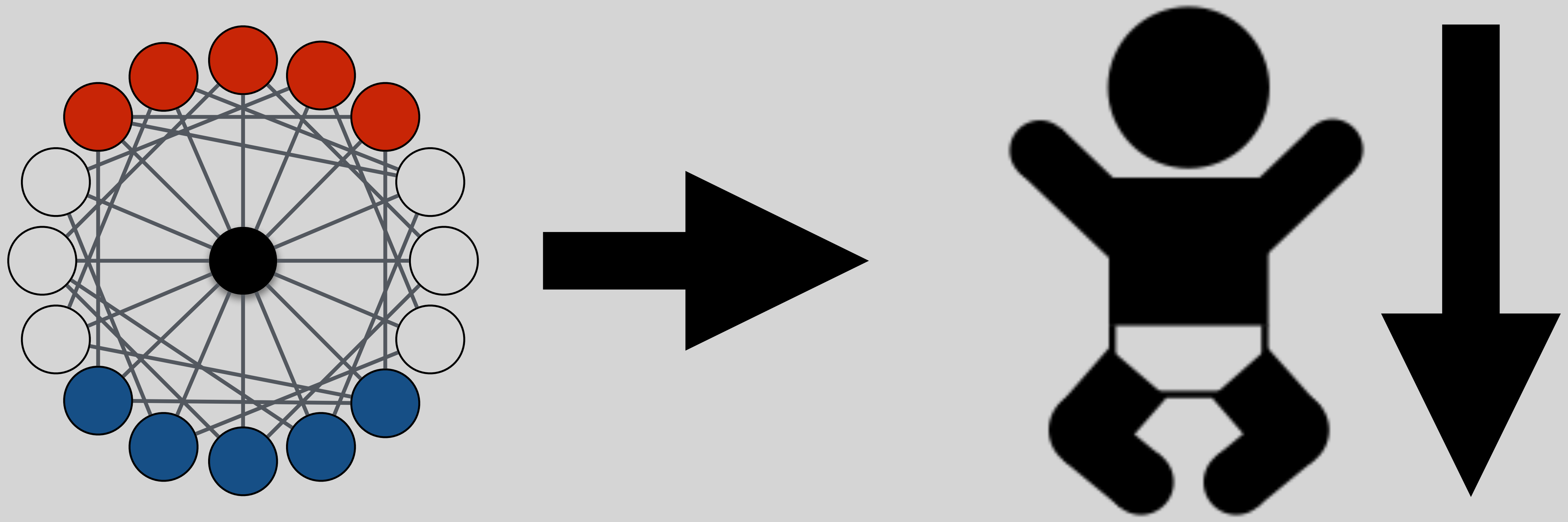
out-of-sample predictive ability:

clear measure of effect size



facilitates dialogue theory- and data-driven models

measure of distance theory and practice



PreFer
1|0
Predicting Fertility data challenge

PreFer

Predicting Fertility data challenge

theory- and data-driven teams

engage in common task

using common data

and common metric

Low predictability

Measuring the predictability of life outcomes with a scientific mass collaboration

Matthew J. Salganik[a,1], Ian Lundberg[a], Alexander T. Kindel[a], Caitlin E. Ahearn[b], Khaled Al-Ghoneim[c], Abdullah Almaatouq[d,e], Drew M. Altschul[f], Jennie E. Brand[b,g], Nicole Bohme Carnegie[h], Ryan James Compton[i], Debanjan Datta[j], Thomas Davidson[k], Anna Filippova[l], Connor Gilroy[m], Brian J. Goode[n], Eaman Jahani[o], Ridhi Kashyap[p,q,r], Antje Kirchner[s], Stephen McKay[t], Allison C. Morgan[u], Alex Pentland[e], Kivan Polimis[v], Louis Raes[w], Daniel E. Rigobon[x], Claudia V. Roberts[y], Diana M. Stanescu[z], Yoshihiko Suhara[e], Adaner Usmani[aa], Erik H. Wang[z], Muna Adem[bb], Abdulla Alhajri[cc], Bedoor AlShebli[dd], Redwane Amin[ee], Ryan B. Amos[y], Lisa P. Argyle[ff], Livia Baer-Bositis[gg], Moritz Büchi[hh], Bo-Ryehn Chung[ii], William Eggert[jj], Gregory Faletto[kk], Zhilin Fan[ll], Jeremy Freese[gg], Tejomay Gadgil[mm], Josh Gagné[gg], Yue Gao[nn], Andrew Halpern-Manners[bb], Sonia P. Hashim[y], Sonia Hausen[gg], Guanhua He[oo], Kimberly Higuera[gg], Bernie Hogan[pp], Ilana M. Horwitz[qq], Lisa M. Hummel[gg], Naman Jain[x], Kun Jin[rr], David Jurgens[ss], Patrick Kaminski[bb,tt], Areg Karapetyan[uu,vv], E. H. Kim[gg], Ben Leizman[y], Naijia Liu[z], Malte Möser[y], Andrew E. Mack[z], Mayank Mahajan[y], Noah Mandell[ww], Helge Marahrens[bb], Diana Mercado-Garcia[qq], Viola Mocz[xx], Katariina Mueller-Gastell[gg], Ahmed Musse[yy], Qiankun Niu[ee], William Nowak[zz], Hamidreza Omidvar[aaa], Andrew Or[y], Karen Ouyang[y], Katy M. Pinto[bbb], Ethan Porter[ccc], Kristin E. Porter[ddd], Crystal Qian[y], Tamkinat Rauf[gg], Anahit Sargsyan[eee], Thomas Schaffner[y], Landon Schnabel[gg], Bryan Schonfeld[z], Ben Sender[fff], Jonathan D. Tang[y], Emma Tsurkov[gg], Austin van Loon[gg], Onur Varol[ggg,hhh], Xiafei Wang[iii], Zhi Wang[hhh,jjj], Julia Wang[y], Flora Wang[fff], Samantha Weissman[y], Kirstie Whitaker[kkk,lll], Maria K. Wolters[mmm], Wei Lee Woon[nnn], James Wu[ooo], Catherine Wu[y], Kengran Yang[aaa], Jingwen Yin[ll], Bingyu Zhao[ppp], Chenyun Zhu[ll], Jeanne Brooks-Gunn[qqq,rrr], Barbara E. Engelhardt[y,ii], Moritz Hardt[sss], Dean Knox[z], Karen Levy[ttt], Arvind Narayanan[y], Brandon M. Stewart[a], Duncan J. Watts[uuu,vvv,www], and Sara McLanahan[a,1]

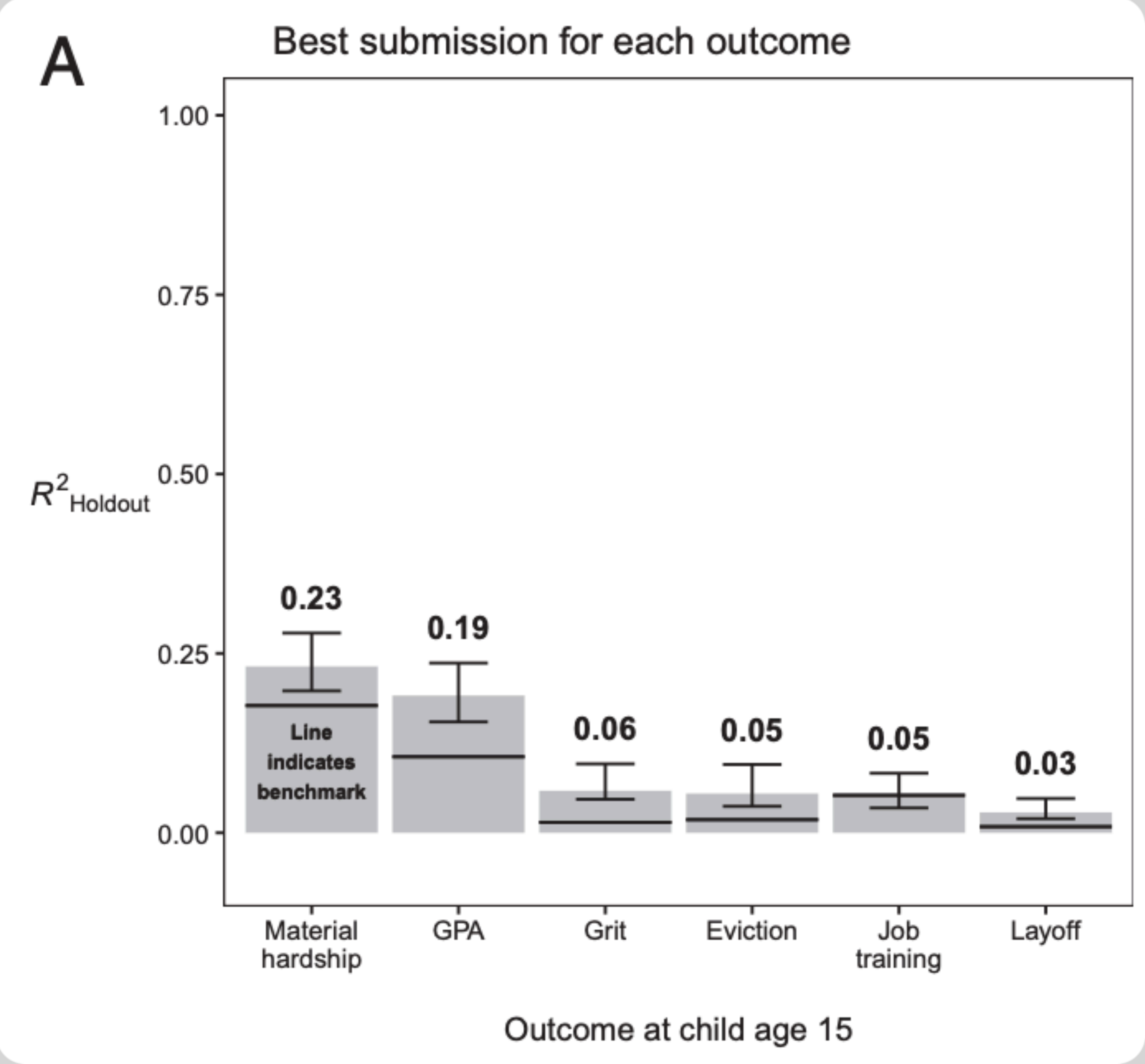
***data challenge*:**

predicting life outcomes

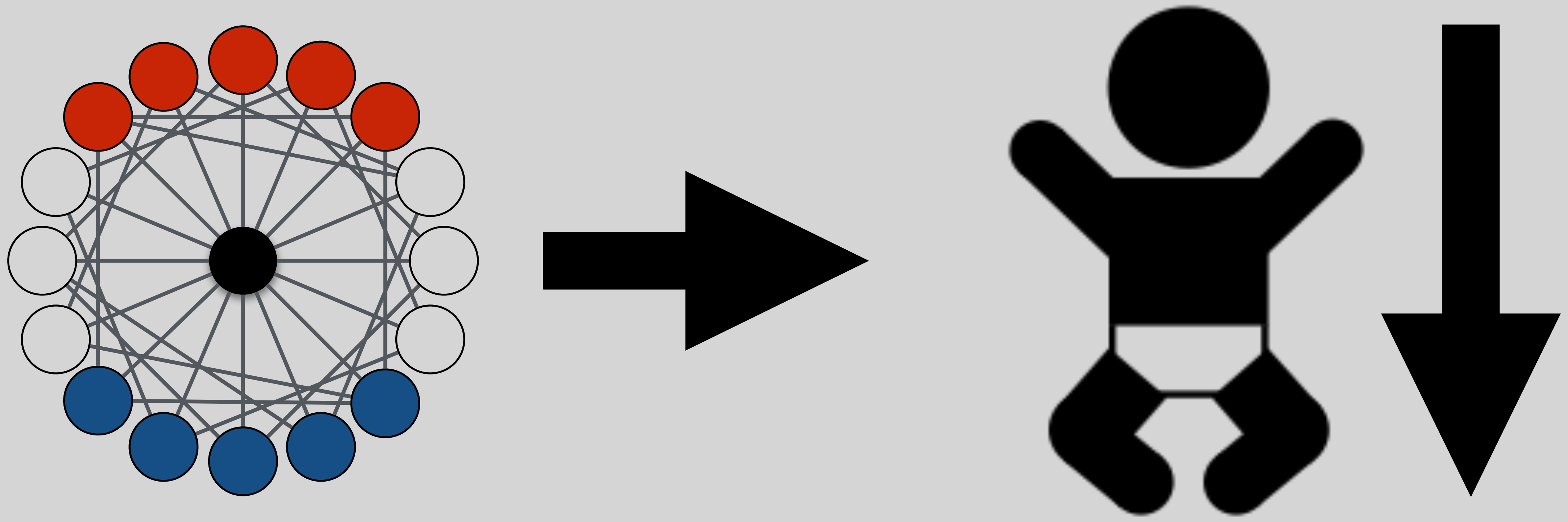
based on ~6000 variables

by 160 teams

both theory- & data-driven

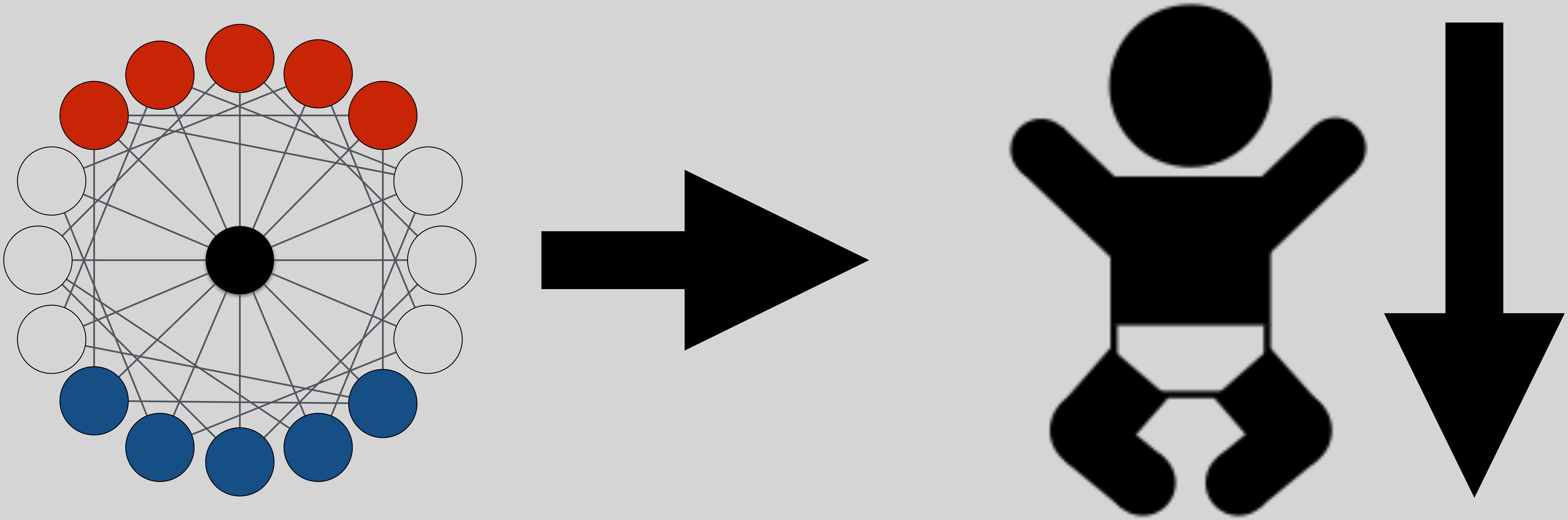


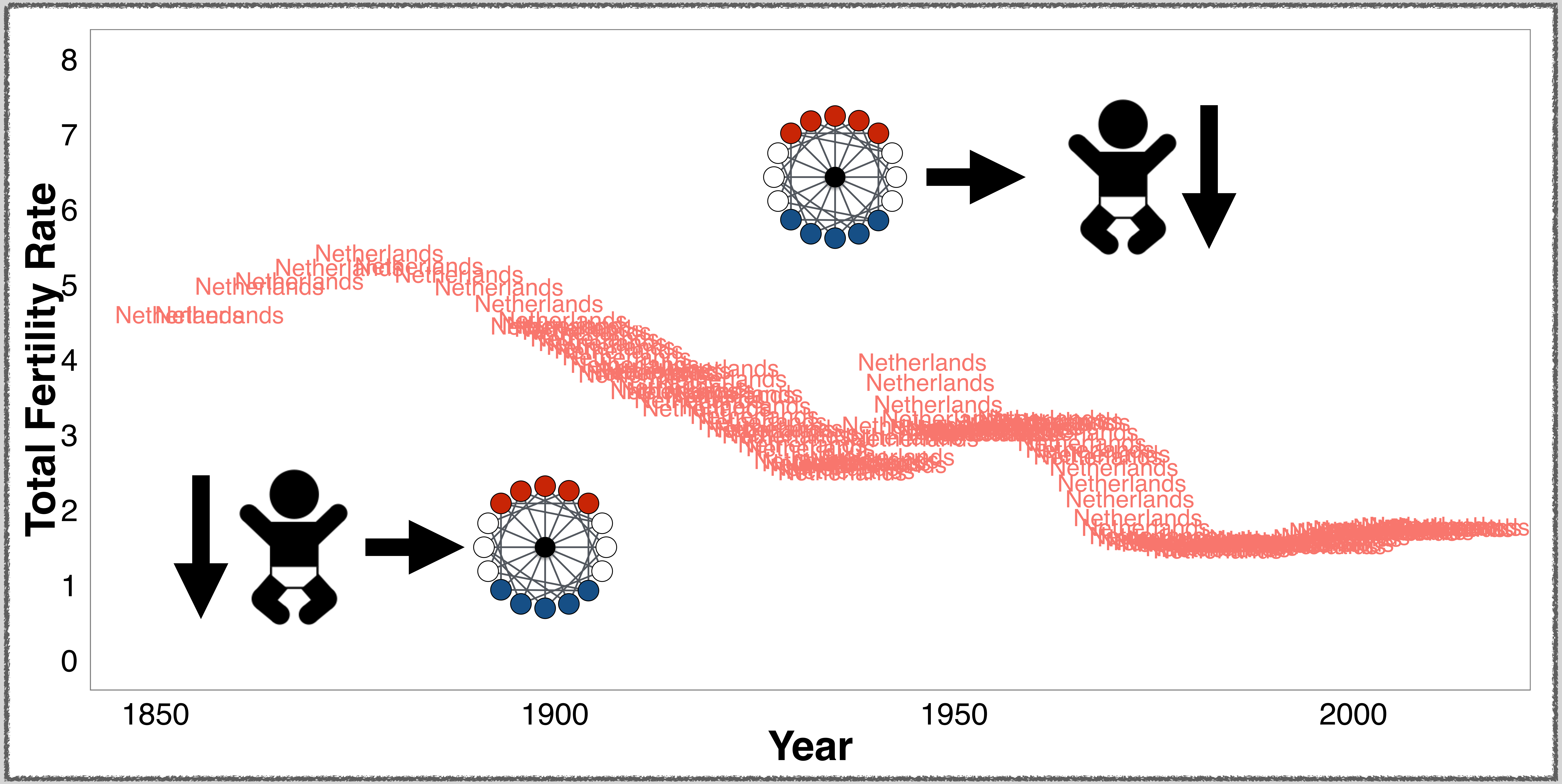
Social scientists studying the life course must find a way to reconcile a widespread belief that understanding has been generated by these data—as demonstrated by more than 750 published journal articles using the Fragile Families data with the fact that the very same data could not yield accurate predictions of these important outcomes.



PreFer

Predicting Fertility data challenge

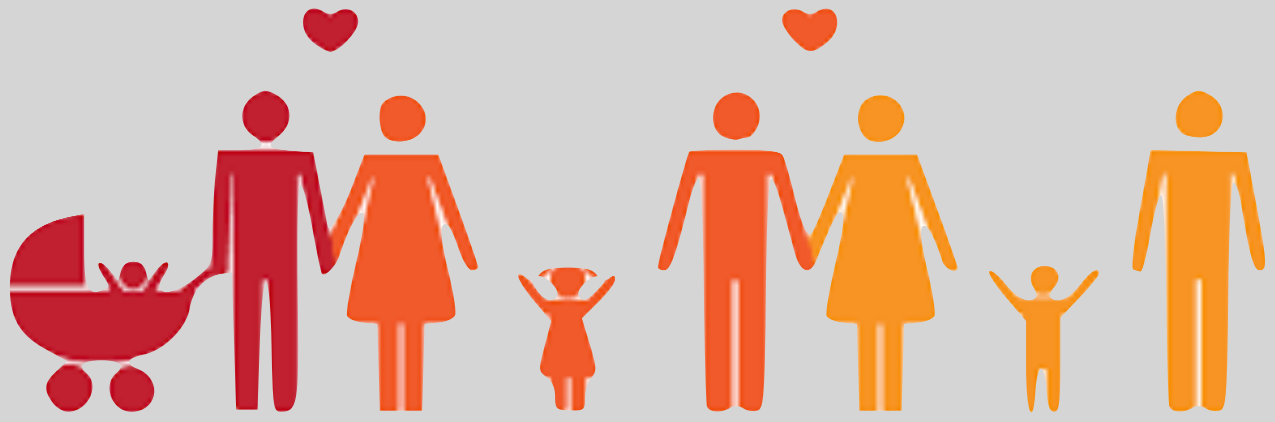




Total Fertility Rate
Year
0
1
2
3
4
5
6
7
8
1850
1900
1950
2000
Netherlands

FROM
EXTENDED
KIN
NETWORKS

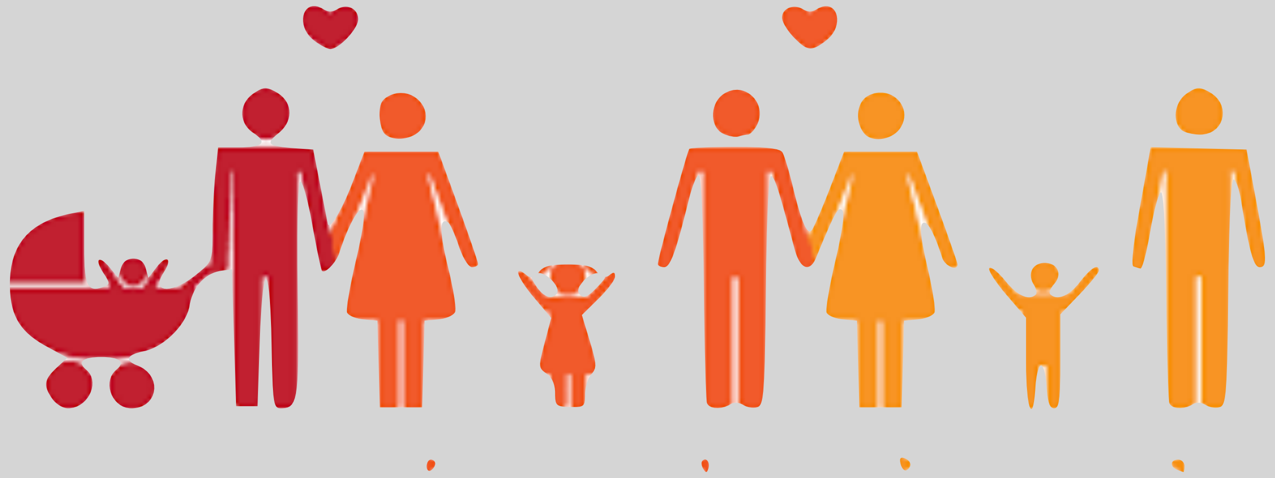
TO
IMPORTANCE
OF NUCLEAR
FAMILY



TO
A DIVERSITY
OF
FAMILIES

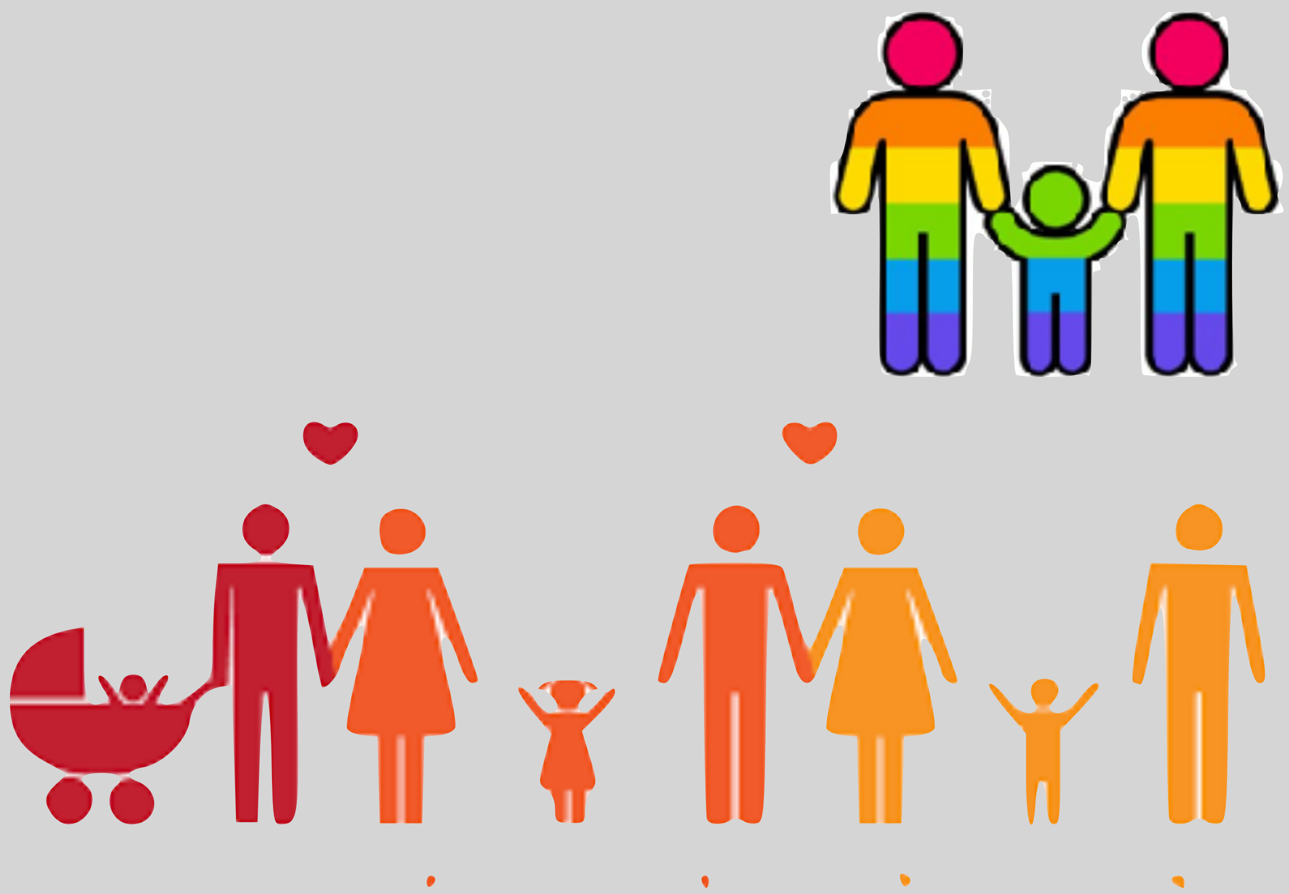
FROM
EXTENDED
KIN
NETWORKS

TO
IMPORTANCE
OF NUCLEAR
FAMILY



TO
A DIVERSITY
OF
FAMILIES

worries about social cohesion and
the general demise of civilisation



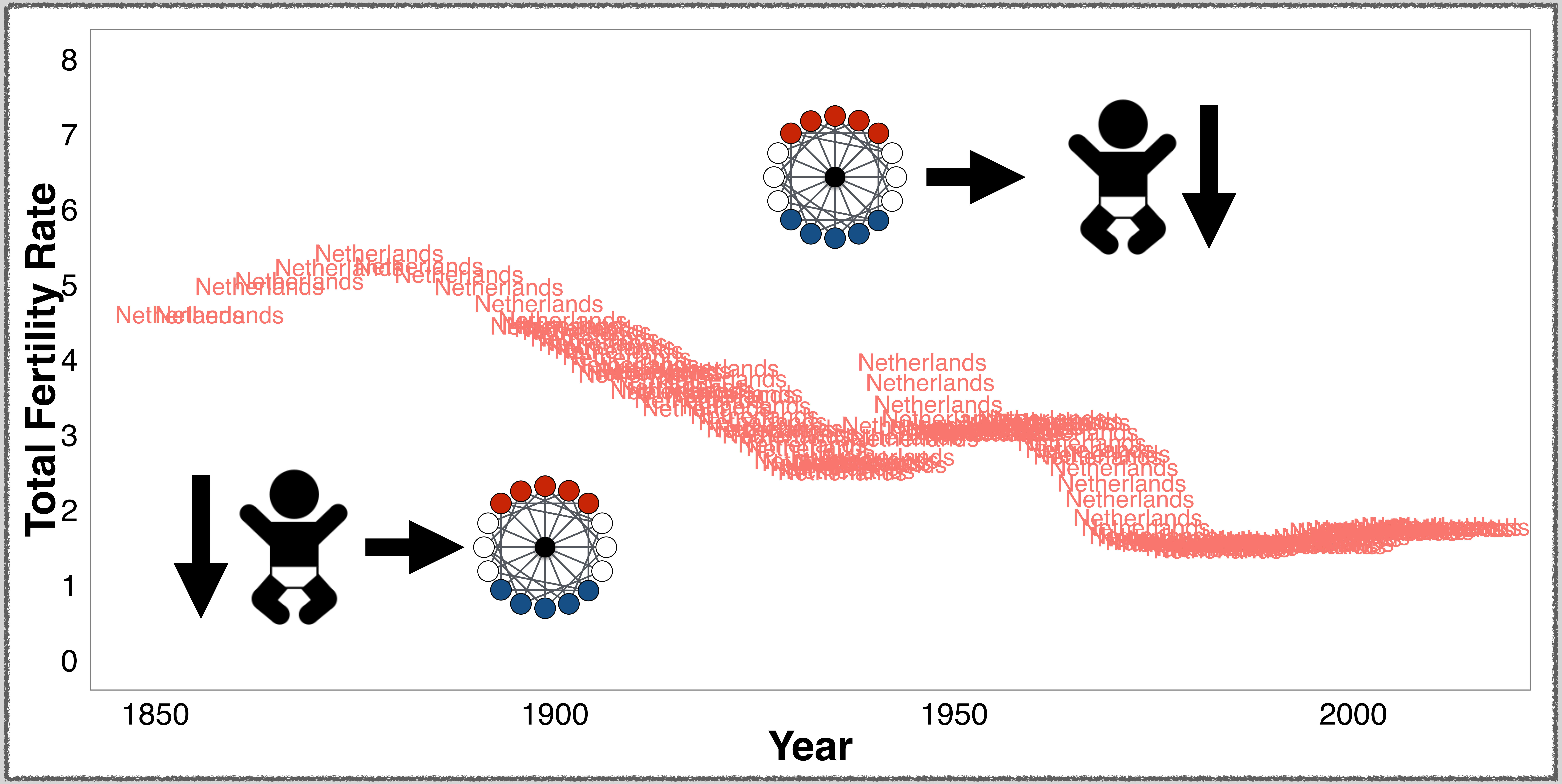
FROM
EXTENDED
KIN
NETWORKS

CUSTOM
AND
LAWS

TO
IMPORTANCE
OF NUCLEAR
FAMILY

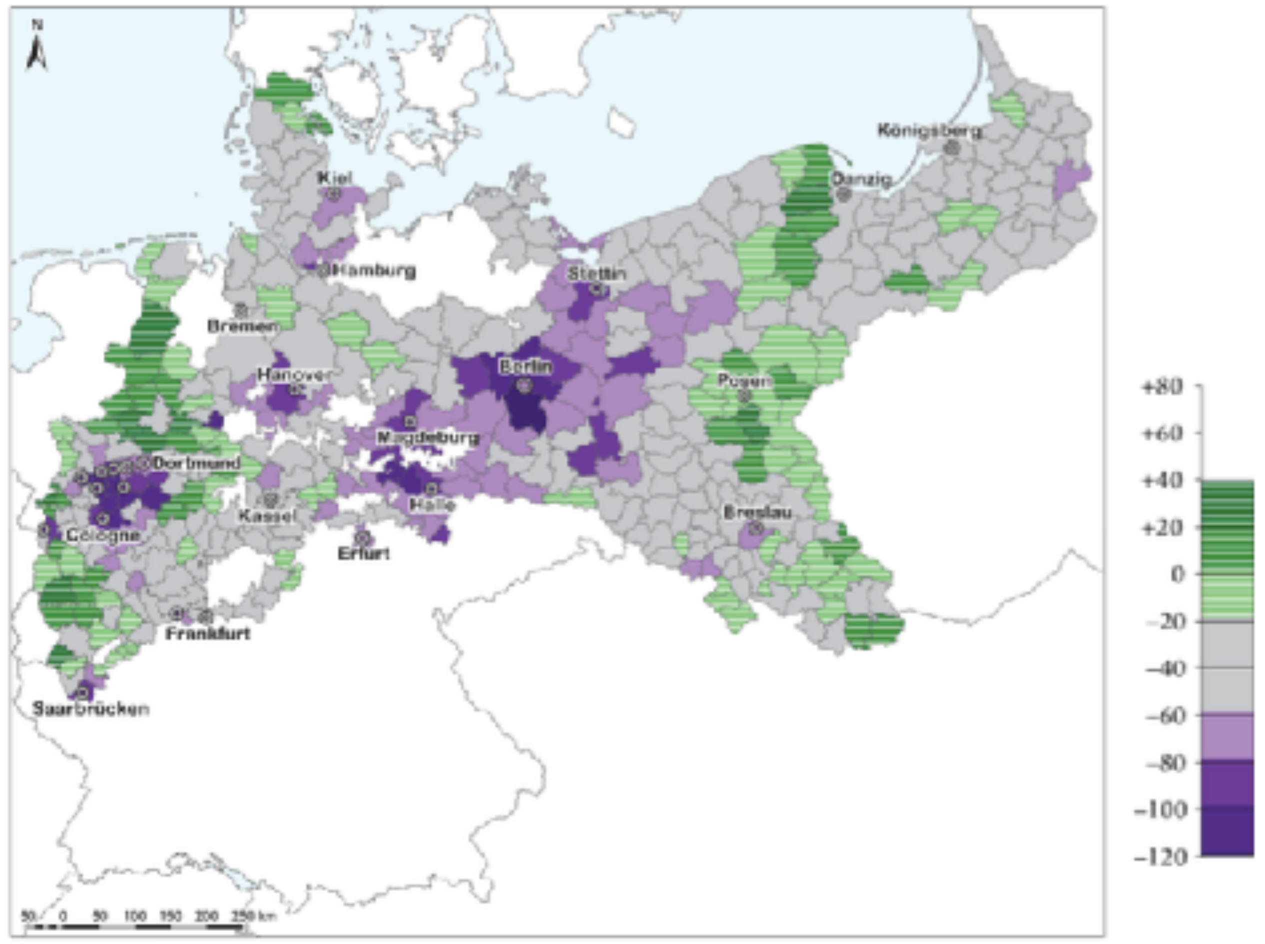
love
and
affection

TO
A DIVERSITY
OF
FAMILIES



Total Fertility Rate
8
7
6
5
4
3
2
1
0
1850
1900
1950
2000
Year
Netherlands

historical
data



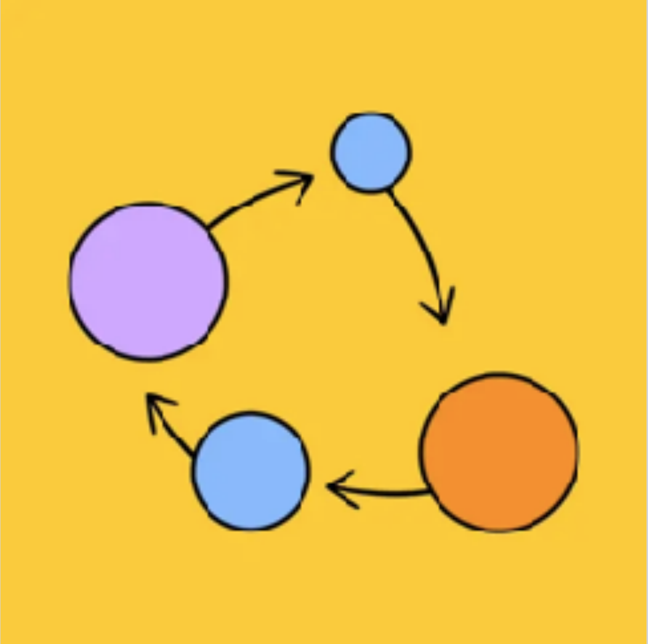
Spatial Analysis of the Causes of Fertility Decline in Prussia
JOSHUA R. GOLDSTEIN
SEBASTIAN KLÜSENER

convenience
samples

Does Fertility Behavior Spread among Friends?
Nicoletta Balbo[a] and Nicola Barban[b]

causal
design

Family, Firms, and Fertility: A Study of Social Interaction Effects
Zafer Buyukkececi[1] · Thomas Leopold[2] · Ruben van Gaalen[3] · Henriette Engelhardt[4]

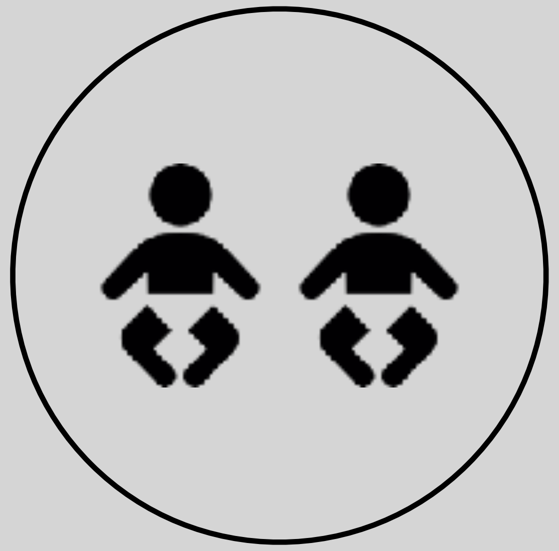


qualitative
studies

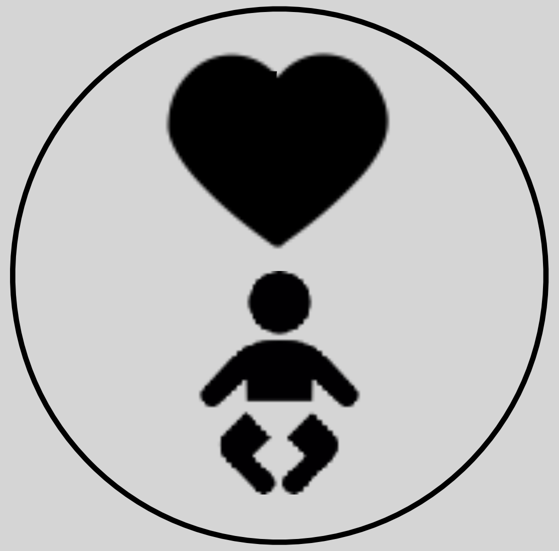
Channels of social influence on reproduction
LAURA BERNARDI

social learning
social contagion
social pressure
social support

social learning

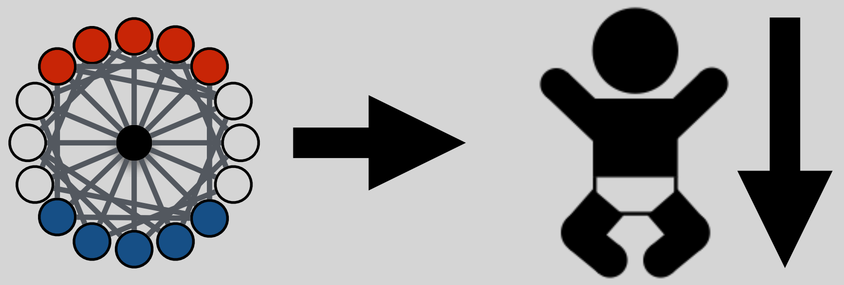


social contagion



social support

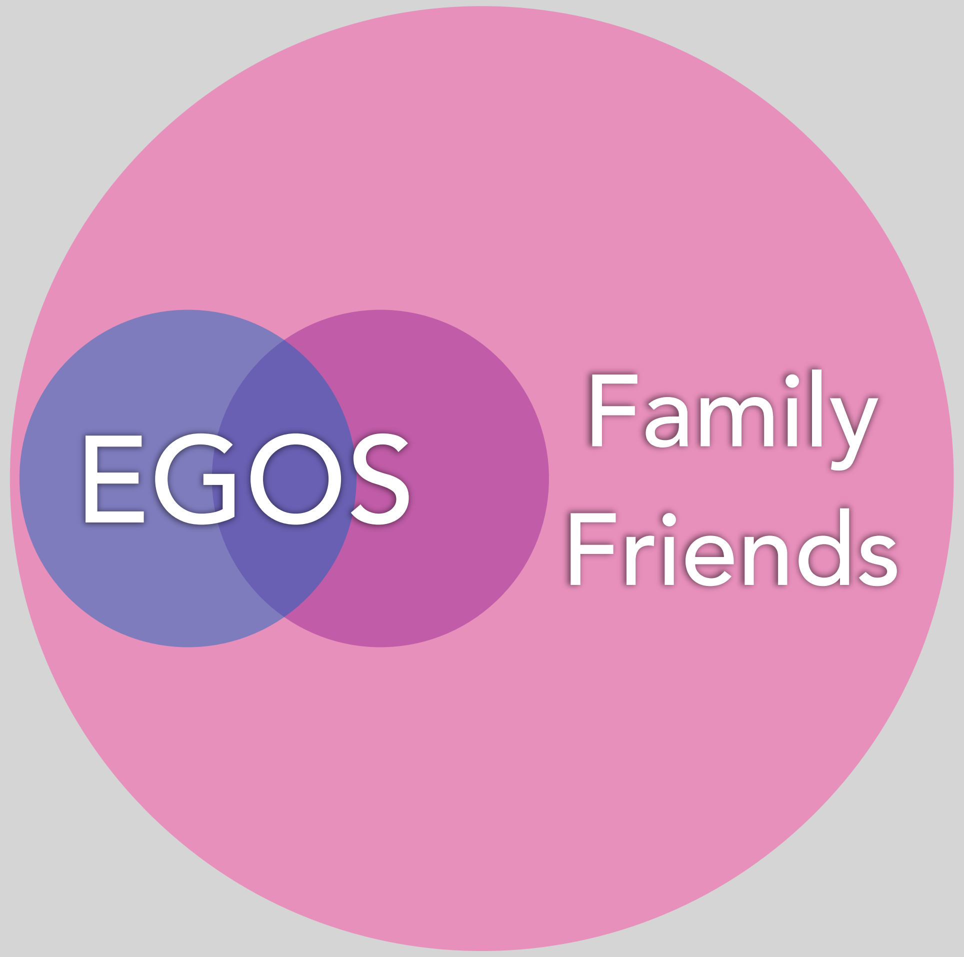
social pressure

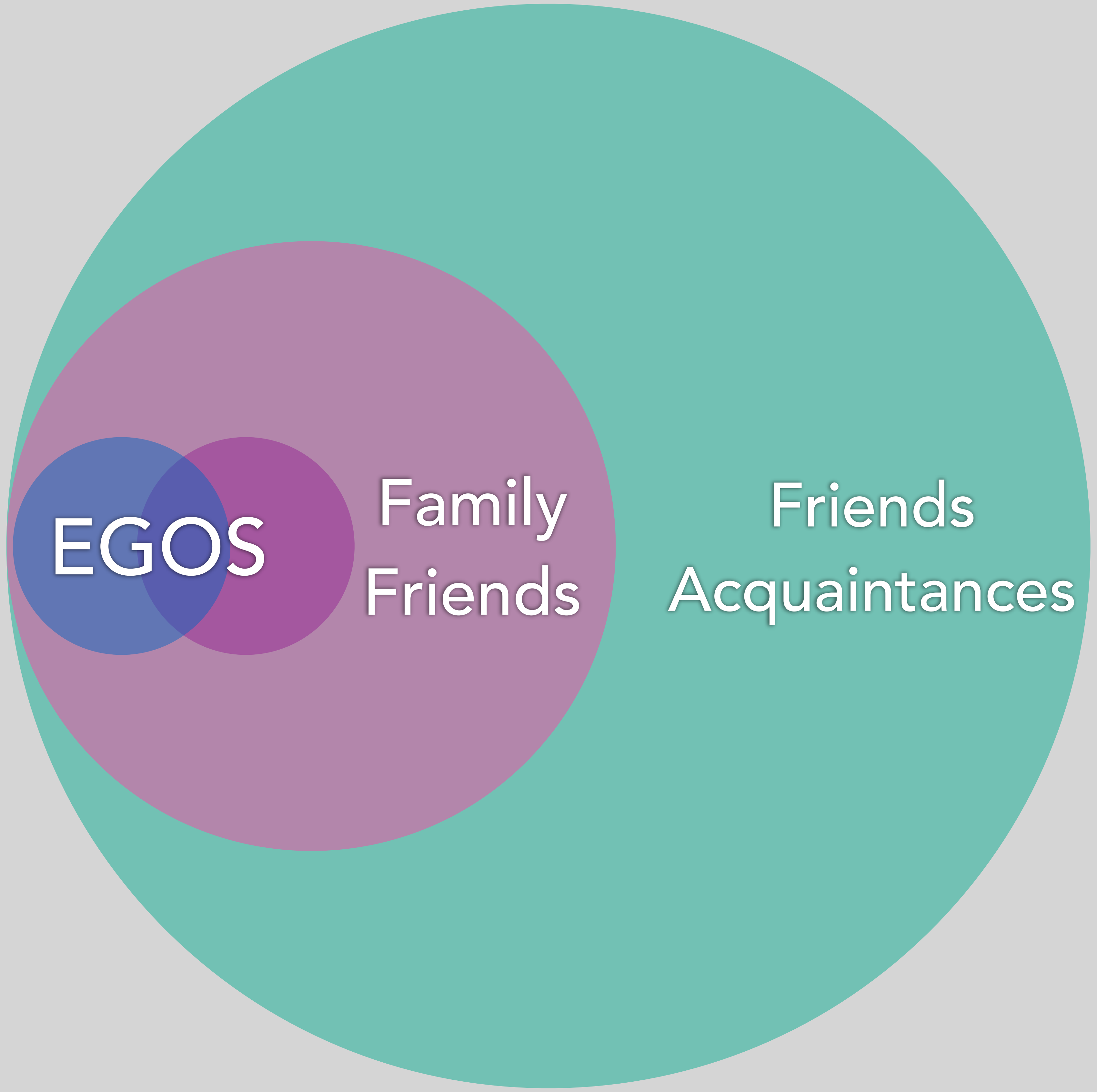


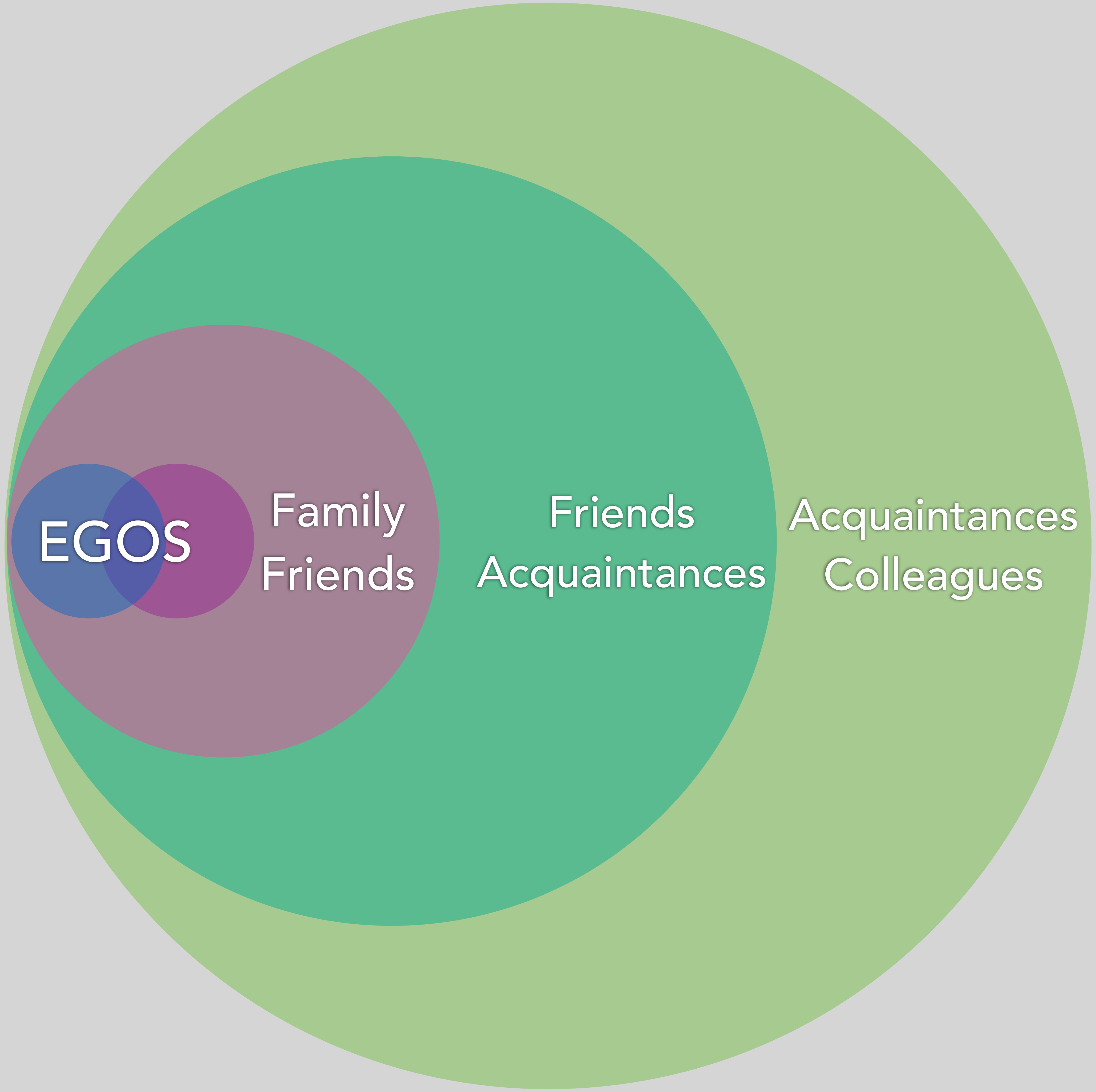
quantifying social influences
on fertility behaviour
using personal network data

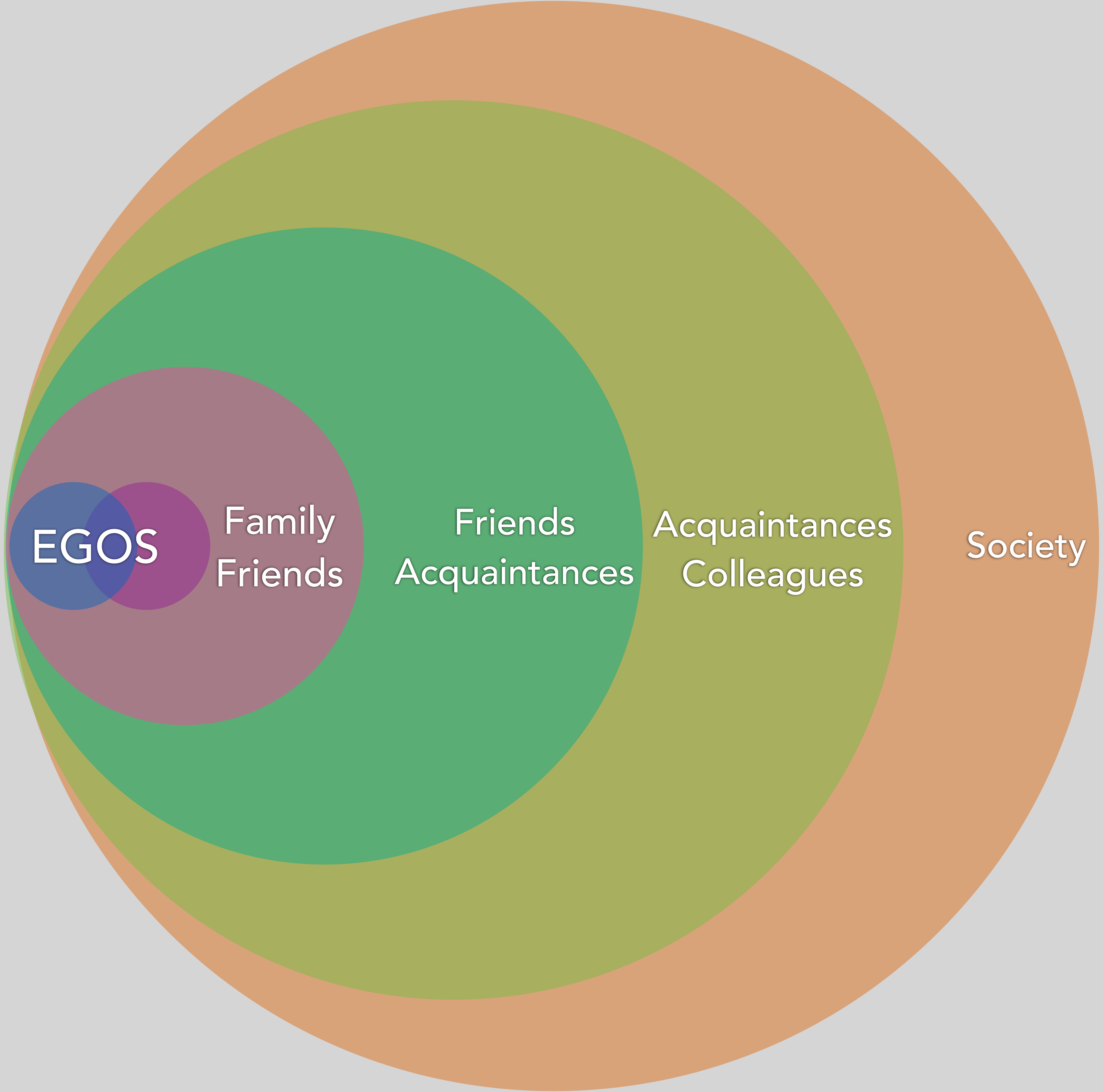

EGO

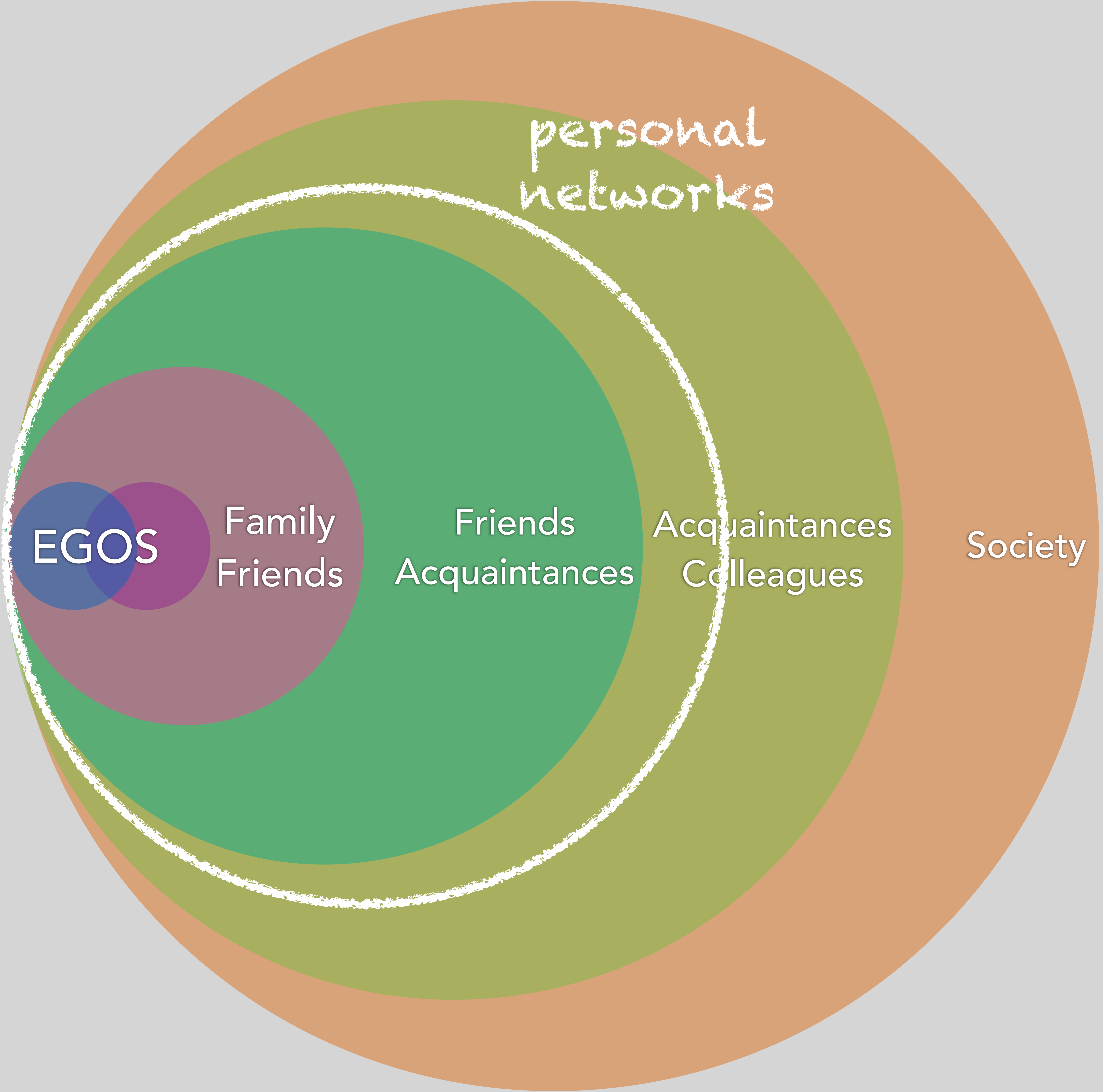
EGOS


EGOS
Family
Friends


EGOS
Family
Friends
Friends
Acquaintances

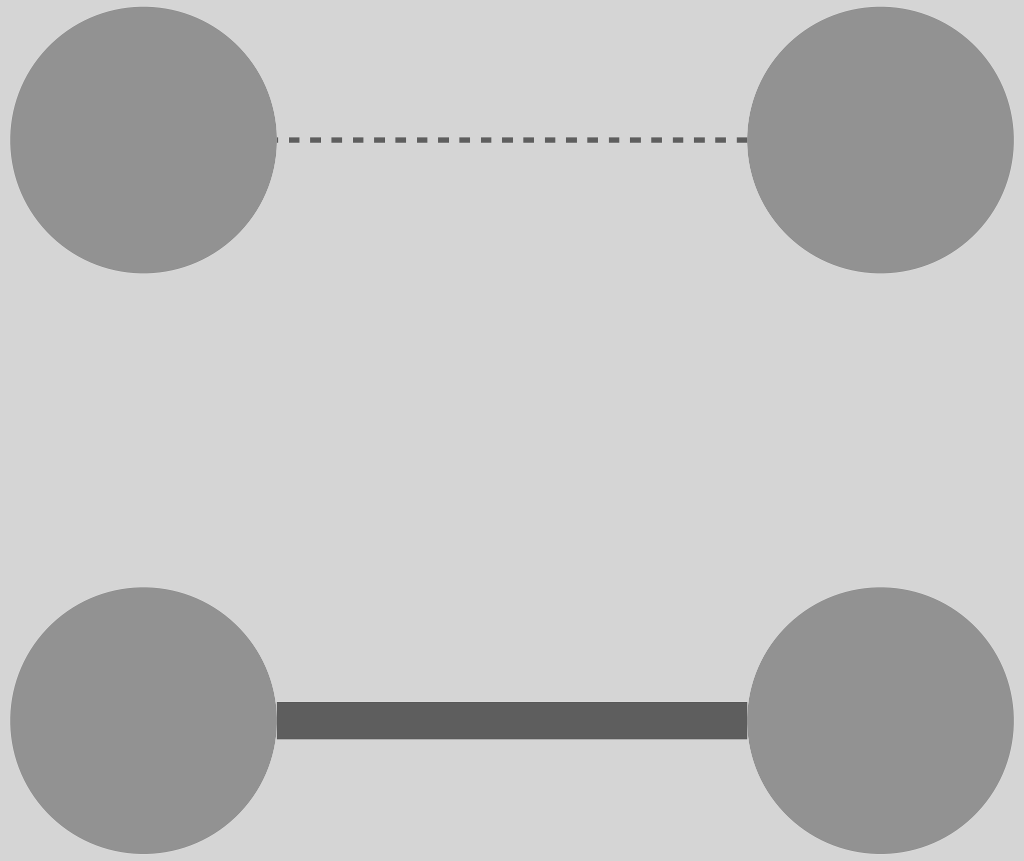

EGOS
Family
Friends
Friends
Acquaintances
Acquaintances
Colleagues


EGOS
Family
Friends
Friends
Acquaintances
Acquaintances
Colleagues
Society


personal
networks
EGOS
Family
Friends
Friends
Acquaintances
Acquaintances
Colleagues
Society

Personal Networks

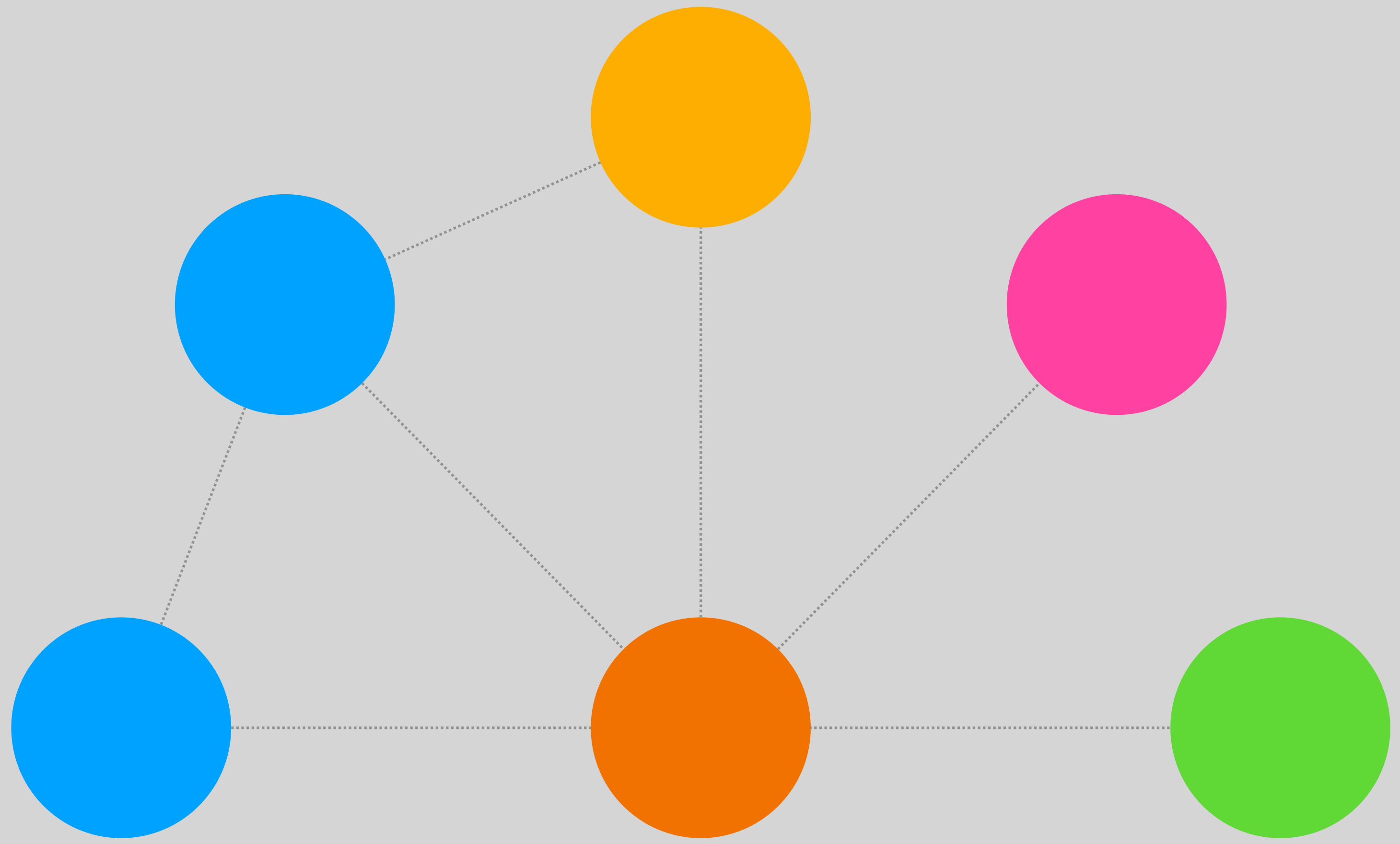
tie (strength)



strong tie, more support/pressure

e.g., quality of relation with parent

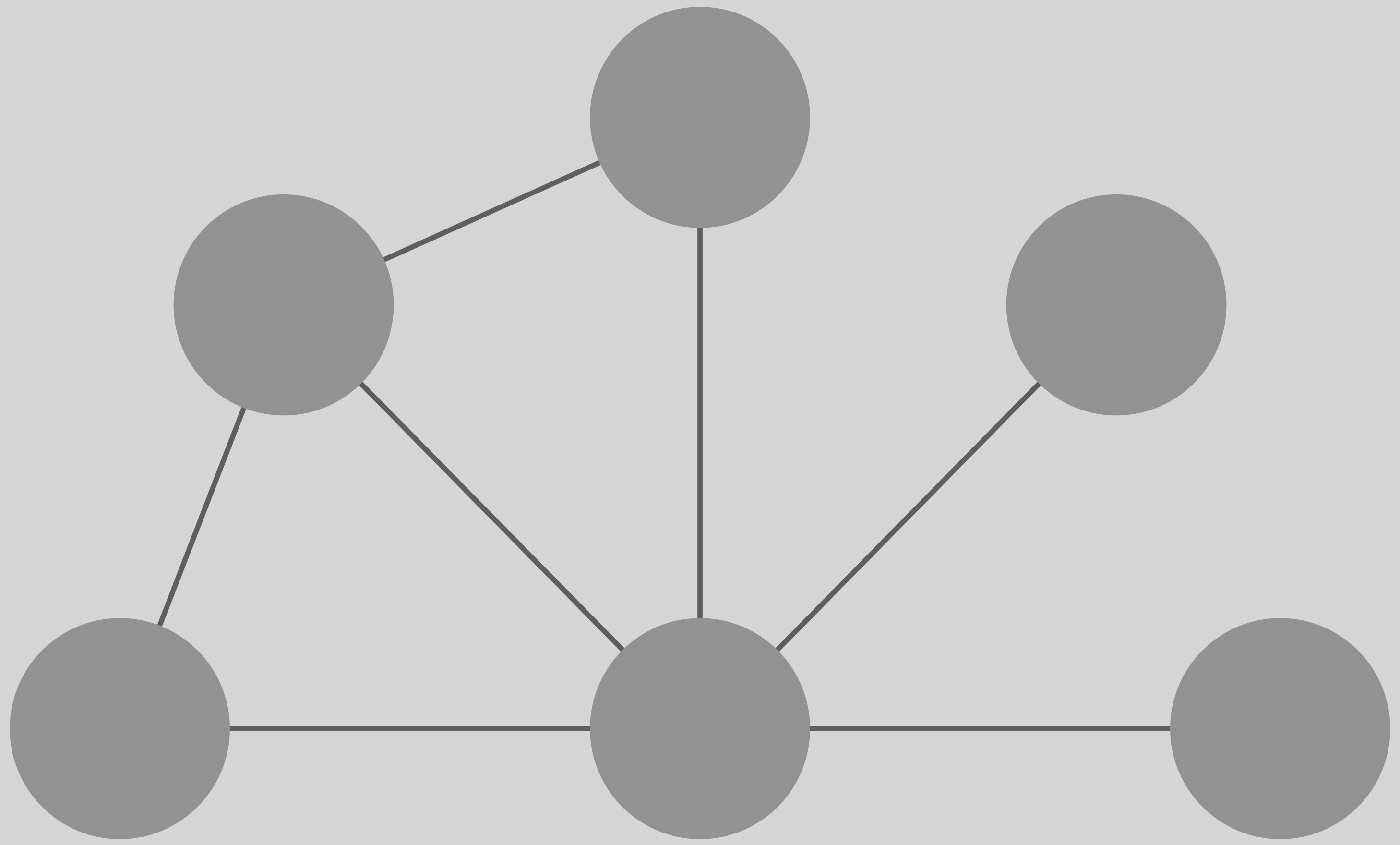
composition



support network, diversity in ideas

e.g., # kin, # friends, # can help

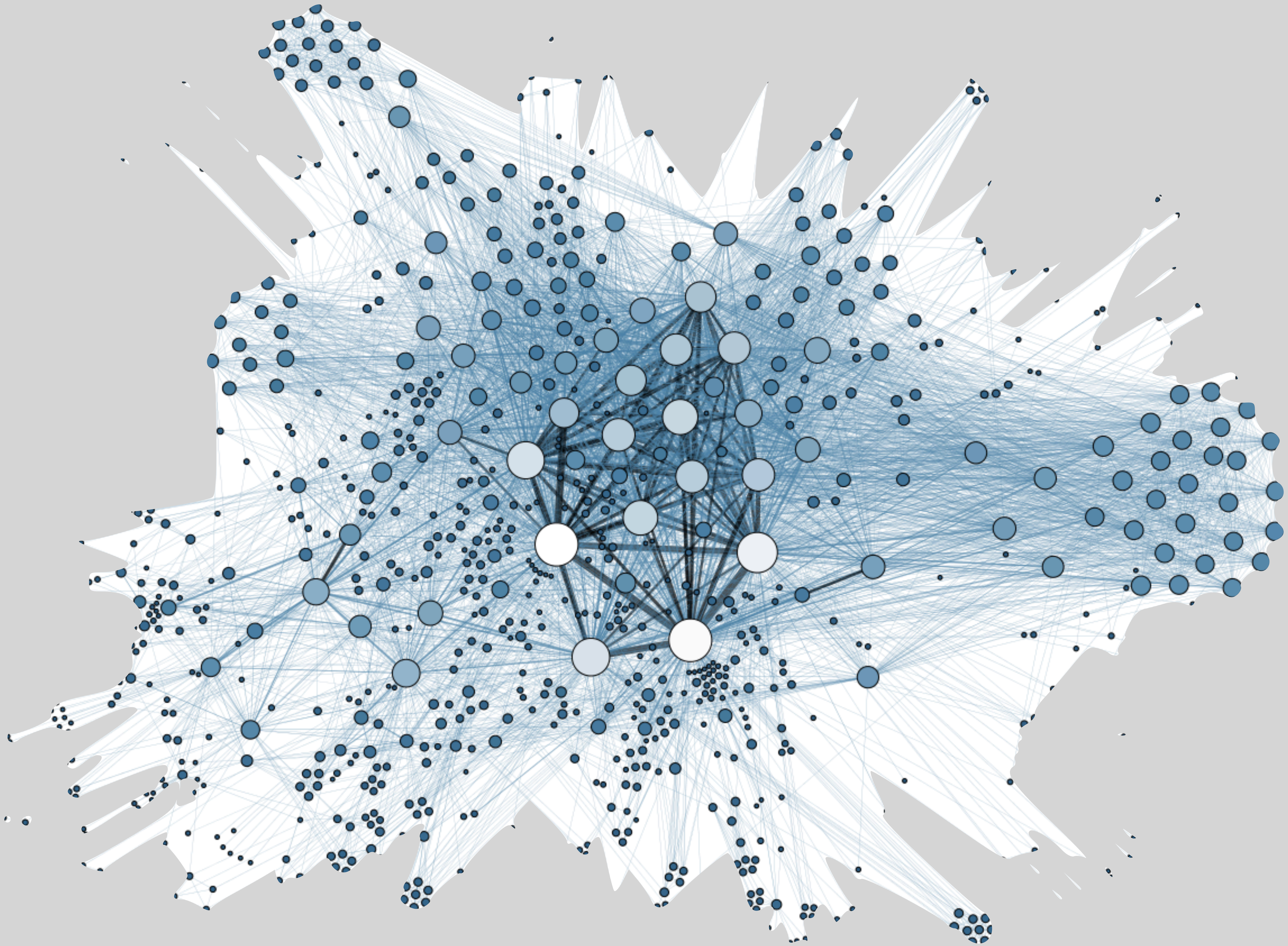
structure



reinforcing norms, flow information

e.g., density, # cliques

Network size



weak ties

structure

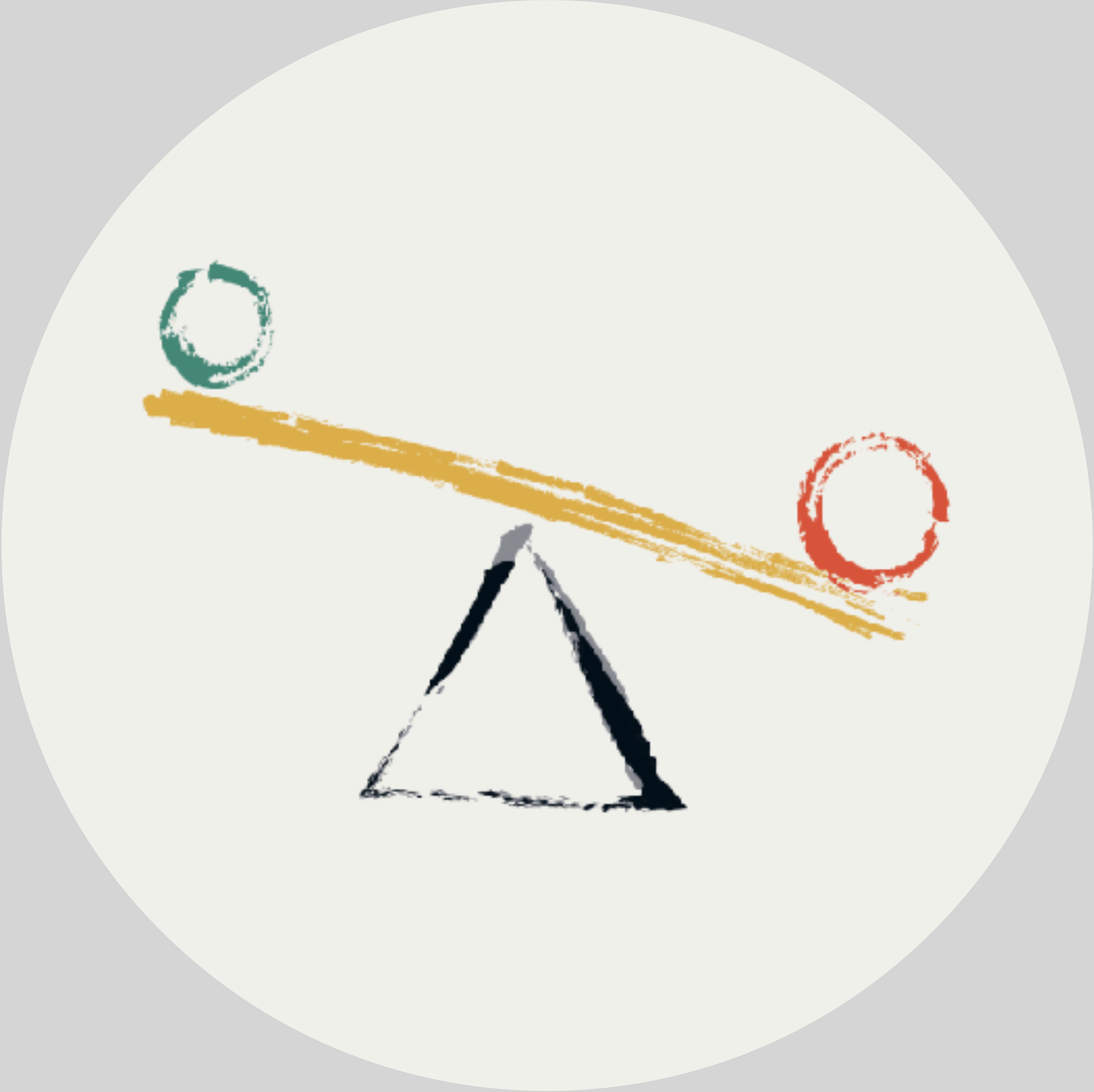
The Right Answer is 25

scientific interest

weak ties

network structure

network composition



respondent burden

time

boredom

poor(er) response

Methodology

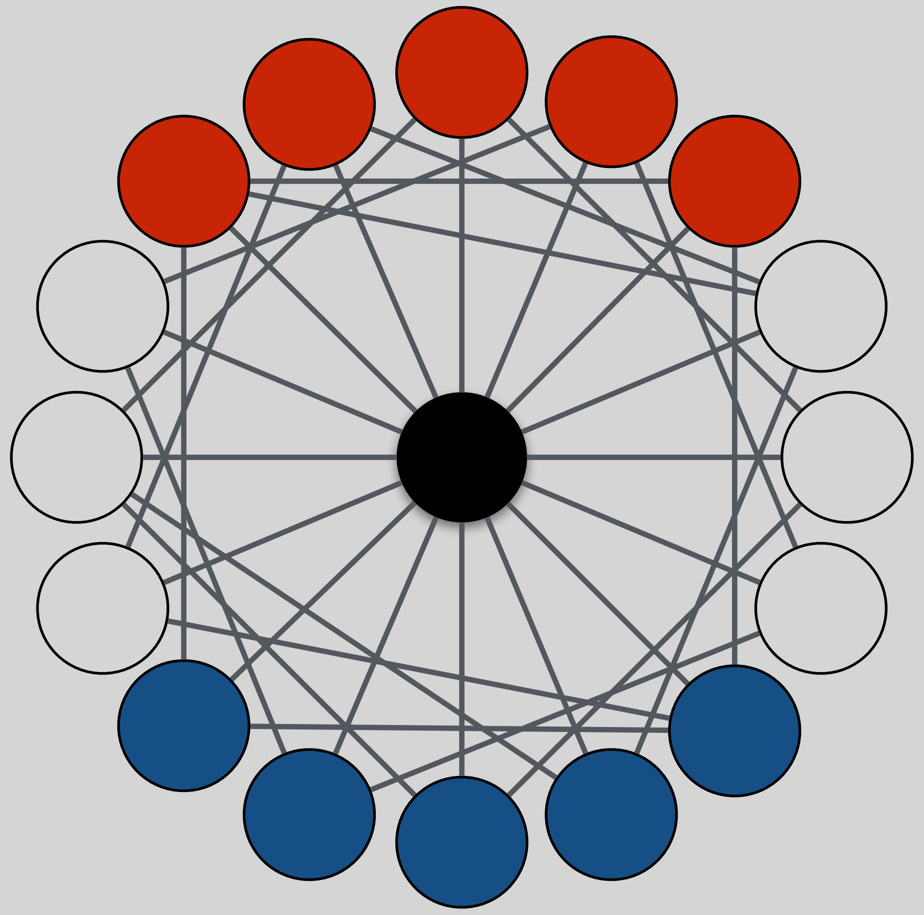
Longitudinal Internet Studies for the Social sciences

~750 women
age: 18 - 40

Ego

Age
Education
Income
Partnership status
Children
Detailed fertility preferences

Alters (25)



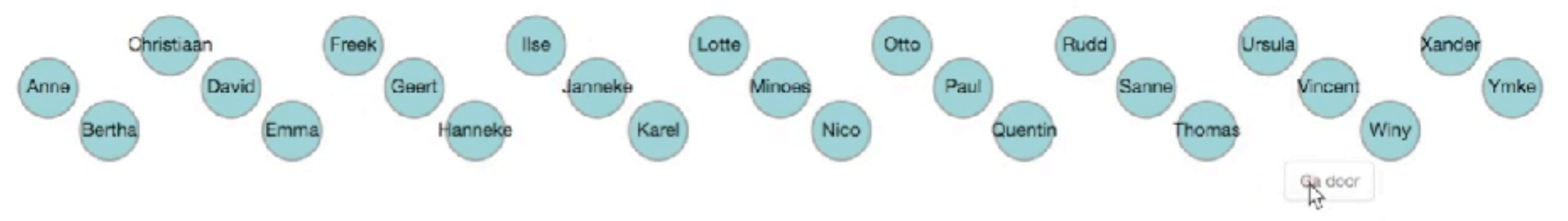
Sex
Age
Education
Relationship type
Closeness
Frequency of contact F2F
Frequency of other contact

Number and age of children
Friend
Wants children
Does not want children
Help with children
Talk about children
Relationship with other alters

Methodology

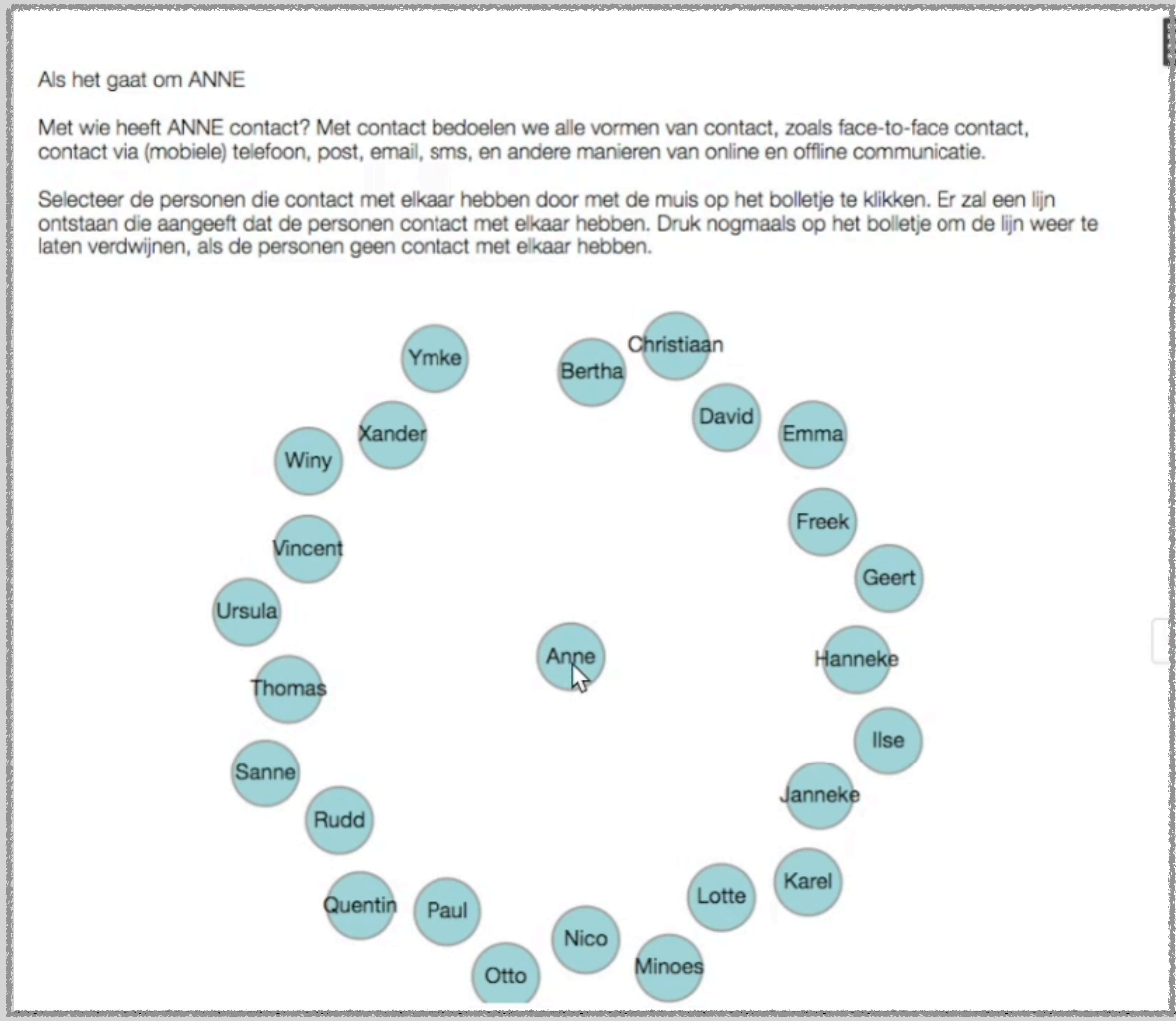
Please list 25 names of individuals 18 years or older with whom you have had contact in the last year. This can be face-to-face contact, but also contact via phone, internet, or email. You know these people and these people also know you from your name or face (think of friends, family, acquaintances, et cetera). You could reach out to these people if you would have to. Please name your partner in case you have one.

Methodology



Which of these 25 individuals could you ask for help

How close are you to these people?



Methodology

Longitudinal Internet Studies for the Social sciences

~750 women
age: 18 - 40

Ego

Age
Education
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Partnership status
Children
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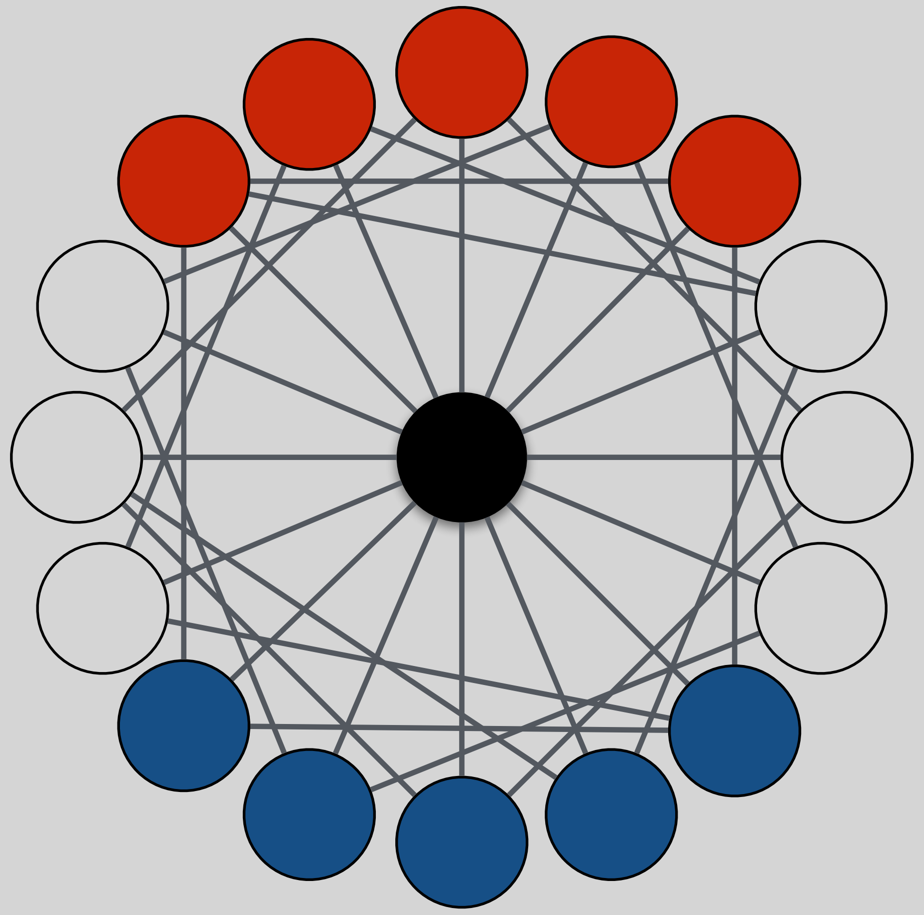
OUTCOMES

Alters (25)

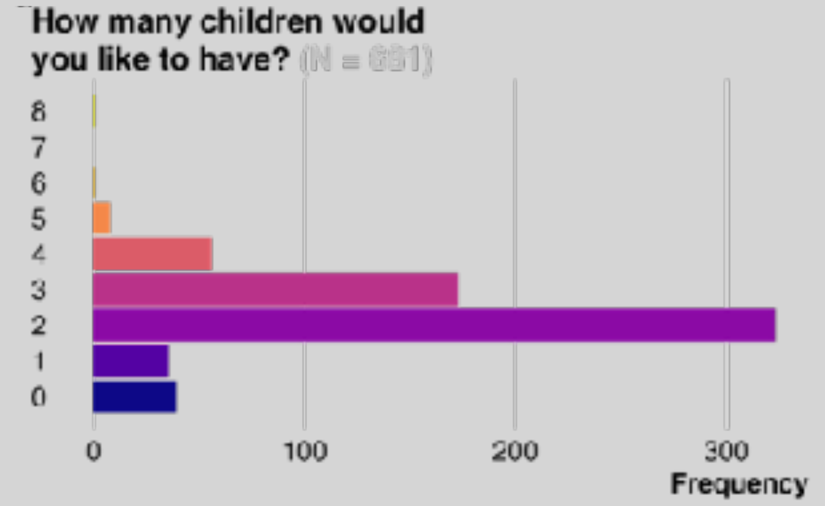


Sex
Age
Education
Relationship type
Closeness
Frequency of contact F2F
Frequency of other contact

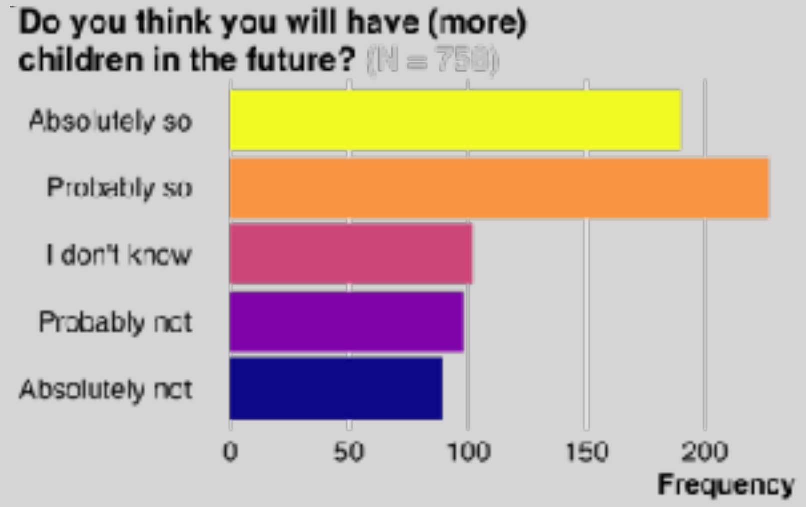
Number and age of children
Friend
Wants children
Does not want children
Help with children
Talk about children
Relationship with other alters

Outcomes

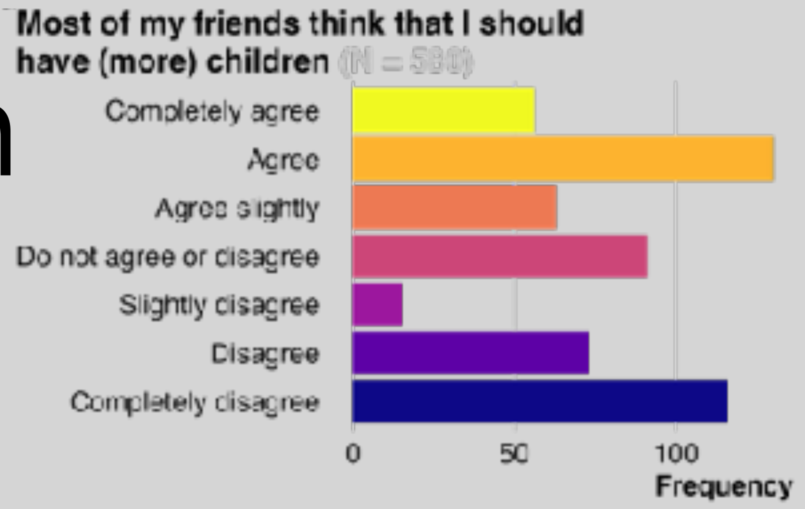
How many children would you like to have?



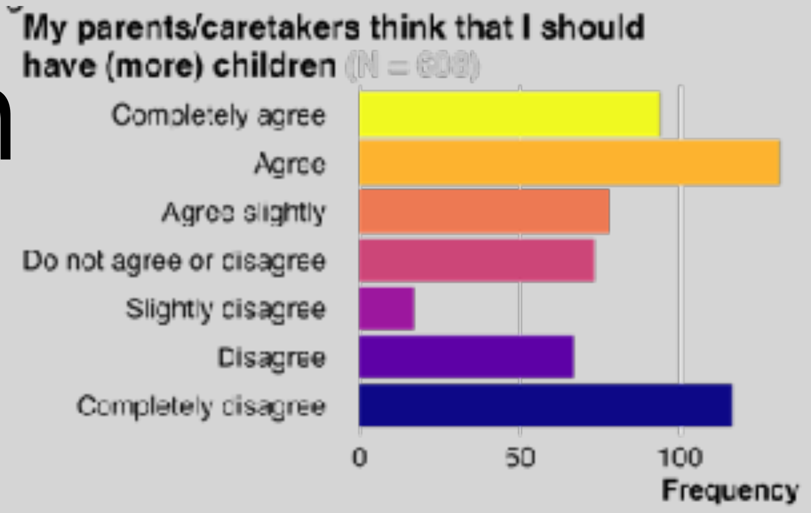
Do you think you will have (more) children in the future?



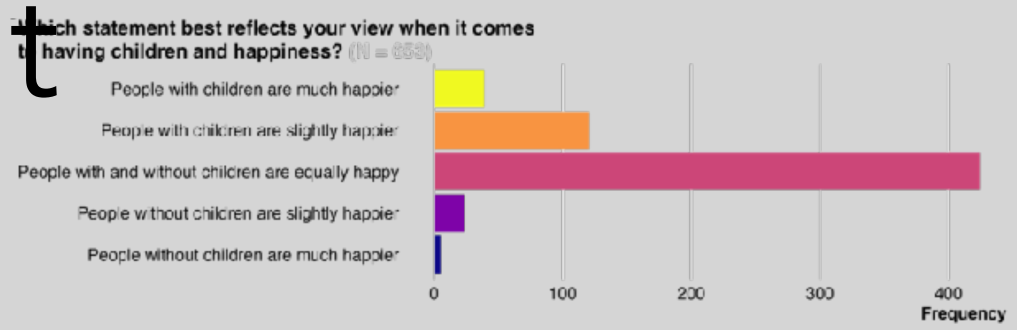
Perceived pressure to have children from friends



Perceived pressure to have children from parents/caretakers



Do you think people with or without children are happier?



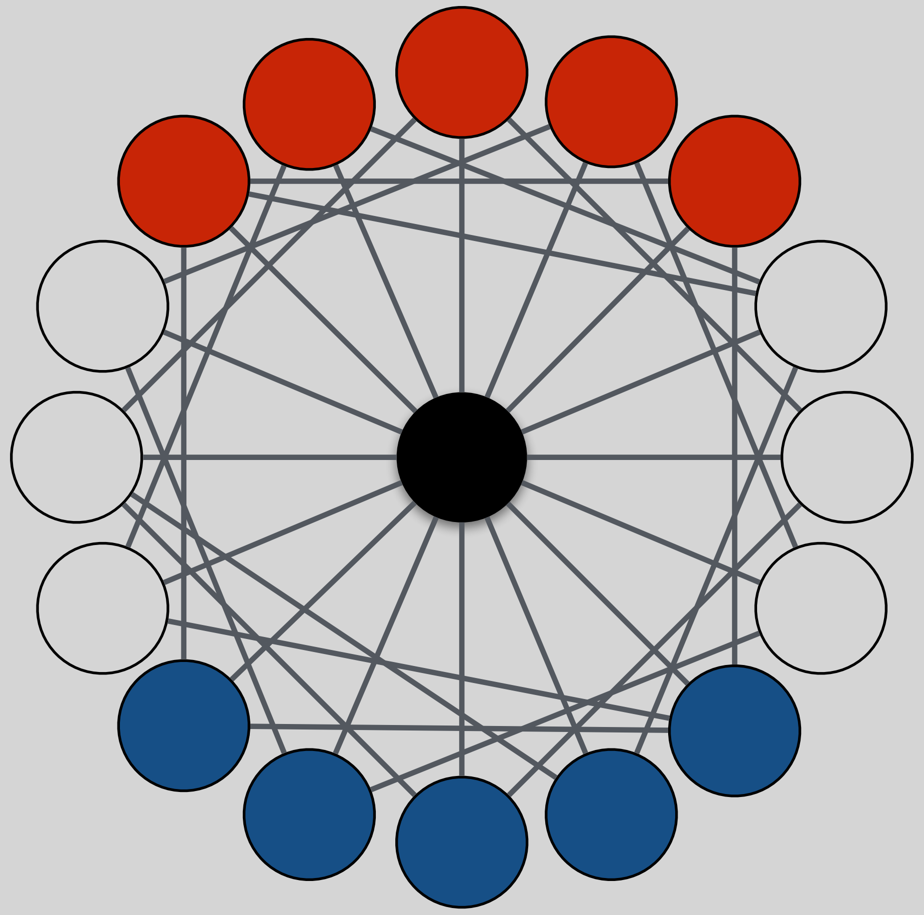
Methodology

Longitudinal Internet Studies for the Social sciences

~750 women
age: 18 - 40

Ego

Alters (25)



EGO VARIABLES

Age
Education
Income
Partnership status
Children
Detailed fertility preferences

NETWORK VARIABLES

Sex	Number and age of children
Age	Friend
Education	Wants children
Relationship type	Does not want children
Closeness	Help with children
Frequency of contact F2F	Talk about children
Frequency of other contact	Relationship with other alters

Personal Networks

tie (strength)

average closeness
average f2f contact
average other contact

average closeness family
average closeness friends
average closeness childfree
…

24 variables

composition

% family
% friends
% childfree
% with children
% who want children
% childfree
% highly educated
% women
% can provide childcare
% can talk to about children

…

13 variables

structure

density
cliques
isolates and duos
communities
modularity
degree centralisation
betweenness centralisation
…

density among family
density among friends
density among childfree
…

20 variables

Personal Networks

tie (strength)

average closeness
average f2f contact
average other conta

average closeness fa
average closeness fr
average closeness ch
…

24 variables

composition

% family
% friends

…

13 variables

structure

density
cliques
and duos
ities
y
ntralisation
ess centralisation

ong family
density among friends
density among childfree
…

20 variables

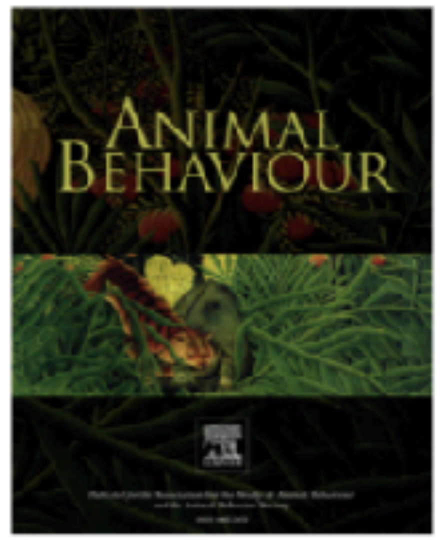
HOW TO CHOOSE WHICH VARIABLES TO FOCUS ON?

Animal Behaviour 168 (2020) 109–120

Contents lists available at ScienceDirect

Animal Behaviour

journal homepage: www.elsevier.com/locate/anbehav



Commentary

Is less more? A commentary on the practice of ‘metric hacking’ in animal social network analysis

Quinn M. R. Webber [a, *], David C. Schneider [a, b, c], Eric Vander Wal [a, c]

[a] Cognitive and Behavioural Ecology Interdisciplinary Program, Memorial University of Newfoundland, St John's, NL, Canada
[b] Department of Ocean Sciences, Ocean Sciences Centre, Memorial University of Newfoundland, St John's, NL, Canada
[c] Department of Biology, Memorial University of Newfoundland, St John's, NL, Canada

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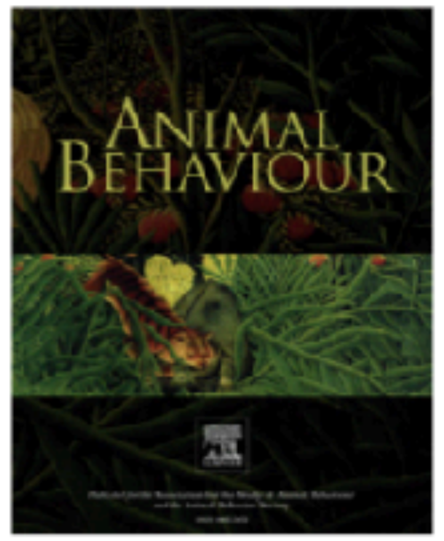

Commentary

Is less more? A commentary on the practice of 'metric hacking' in animal social network analysis

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[a] Cognitive and Behavioural Ecology Interdisciplinary Prog
[b] Department of Ocean Sciences, Ocean Sciences Centre, M
[c] Department of Biology, Memorial University of Newfoun

Check for updates

General Article

Psychological Science
22(11) 1359–1366

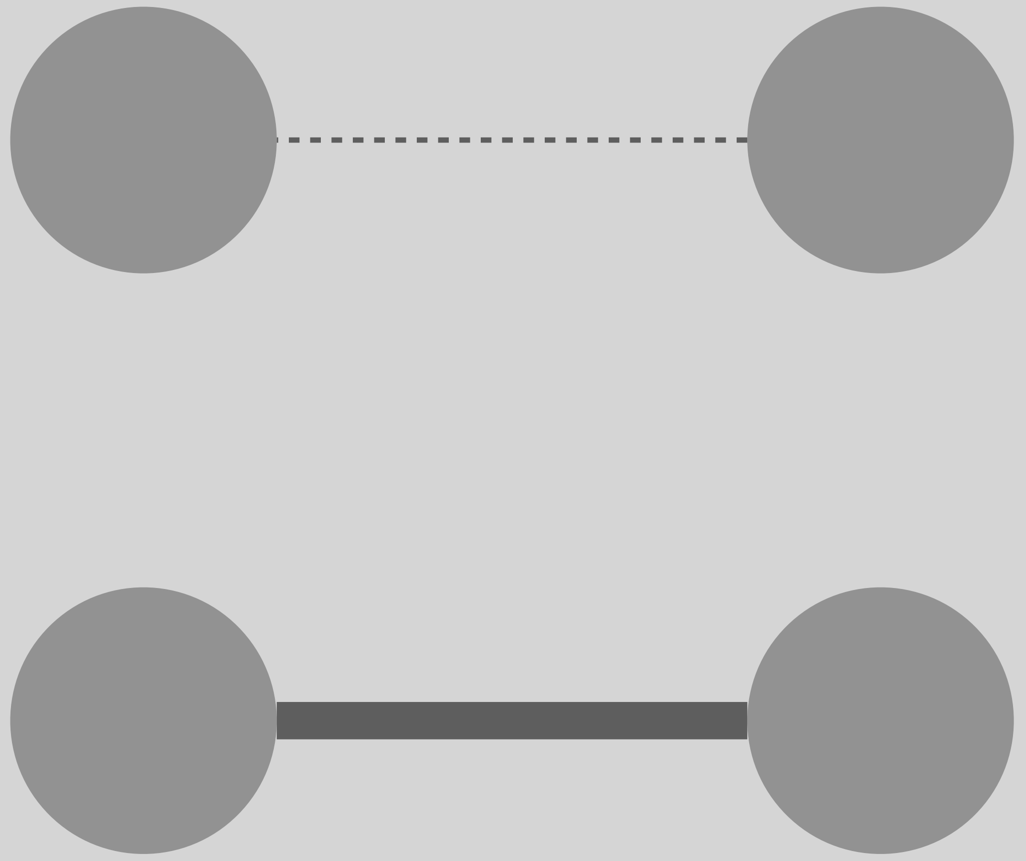
DOI: 10.1177/0956797611417632
http://pss.sagepub.com
SAGE

False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant

Joseph P. Simmons[1], Leif D. Nelson[2], and Uri Simonsohn[1]
[1]The Wharton School, University of Pennsylvania, and [2]Haas School of Business, University of California, Berkeley

Personal Networks

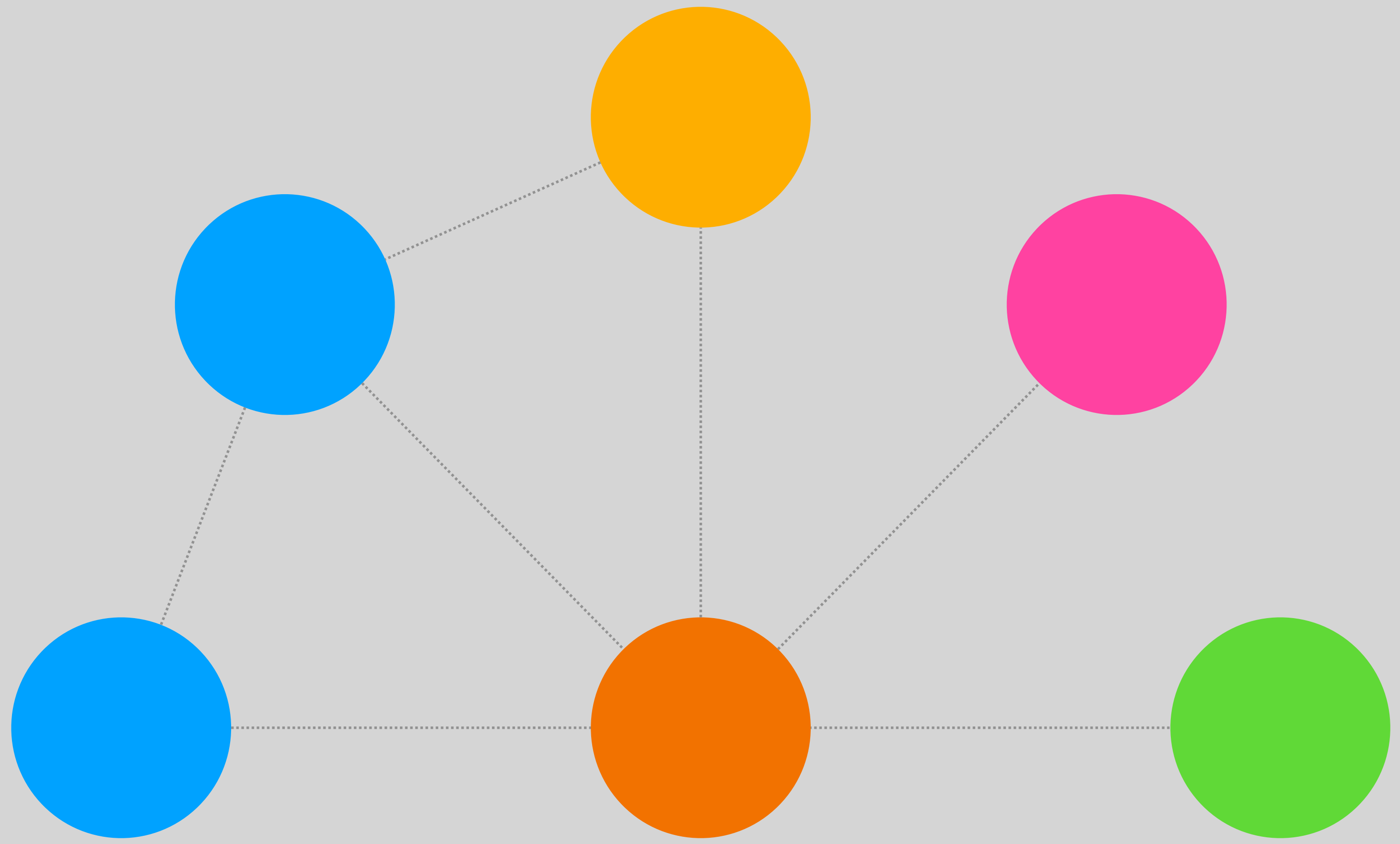
tie (strength)



strong tie, more support/pressure

e.g., quality of relation with parent

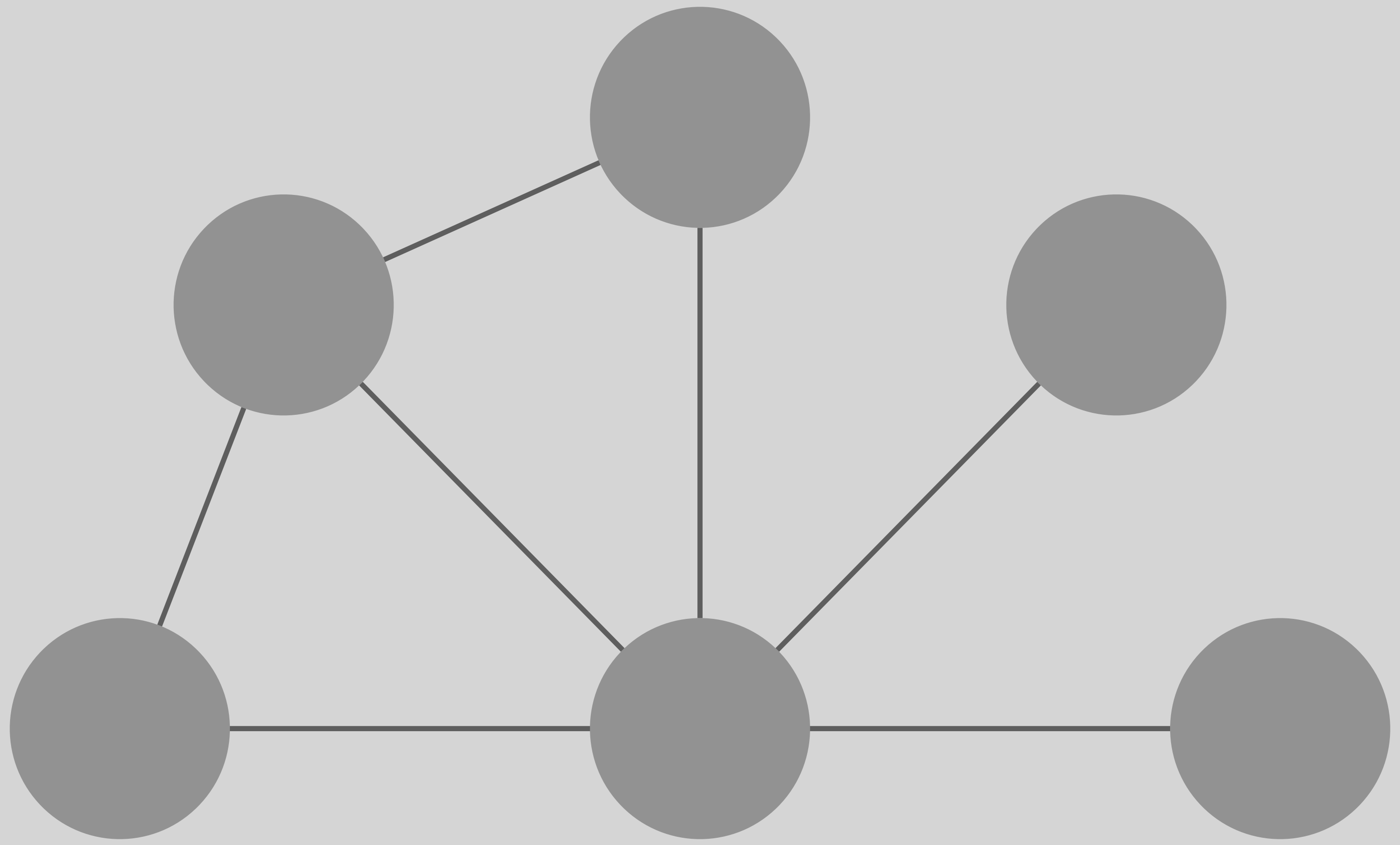
composition



support network, diversity in ideas

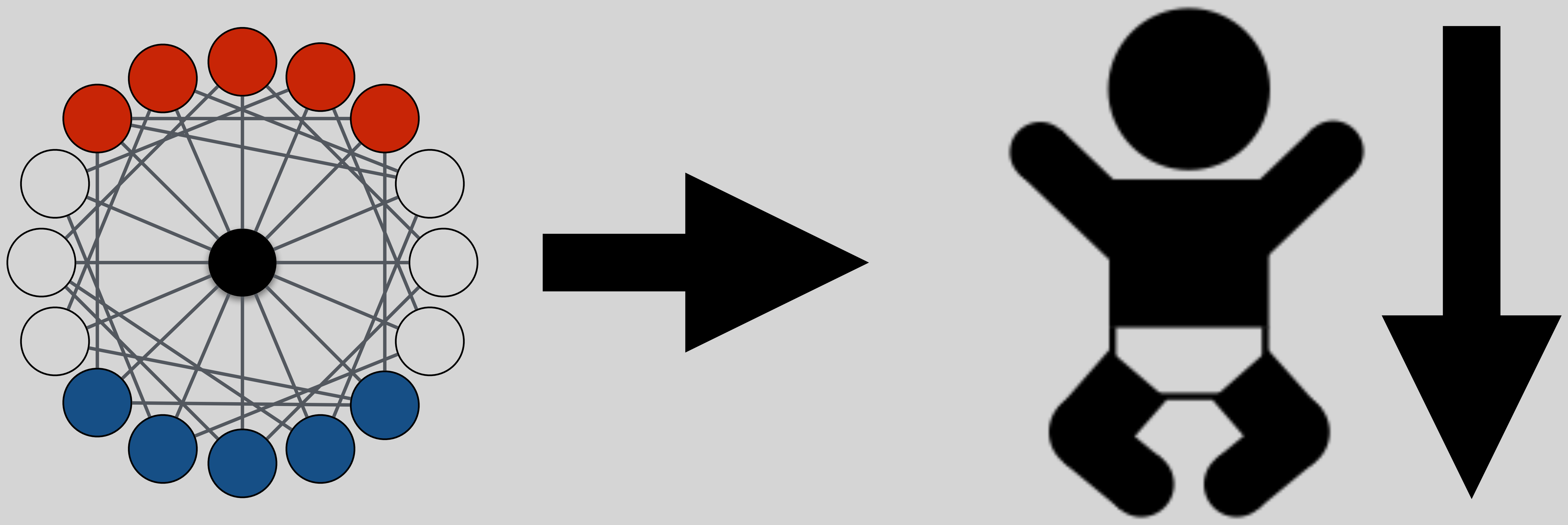
e.g., # kin, # friends, # can help

structure



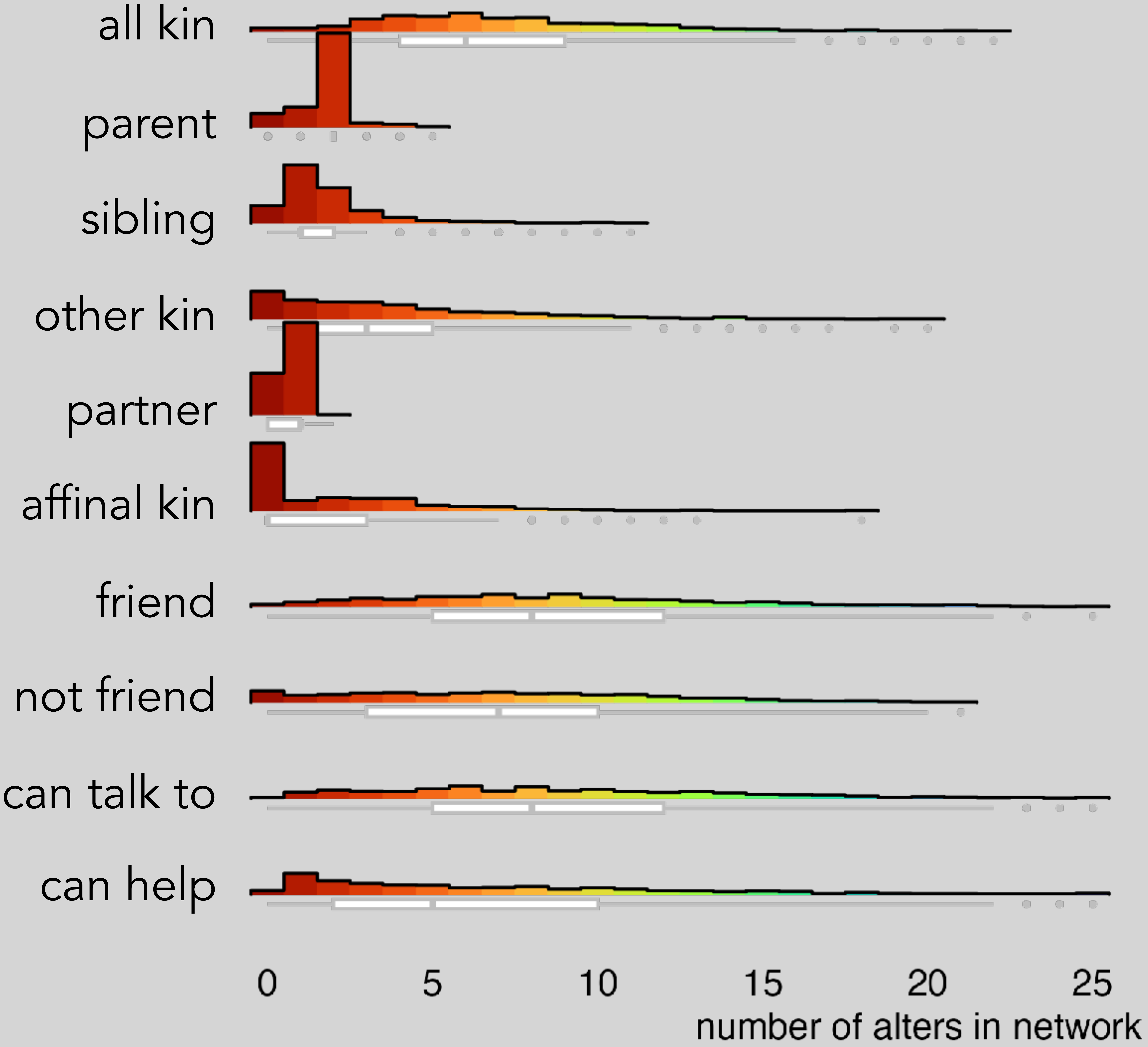
reinforcing norms, flow information

e.g., density, # cliques

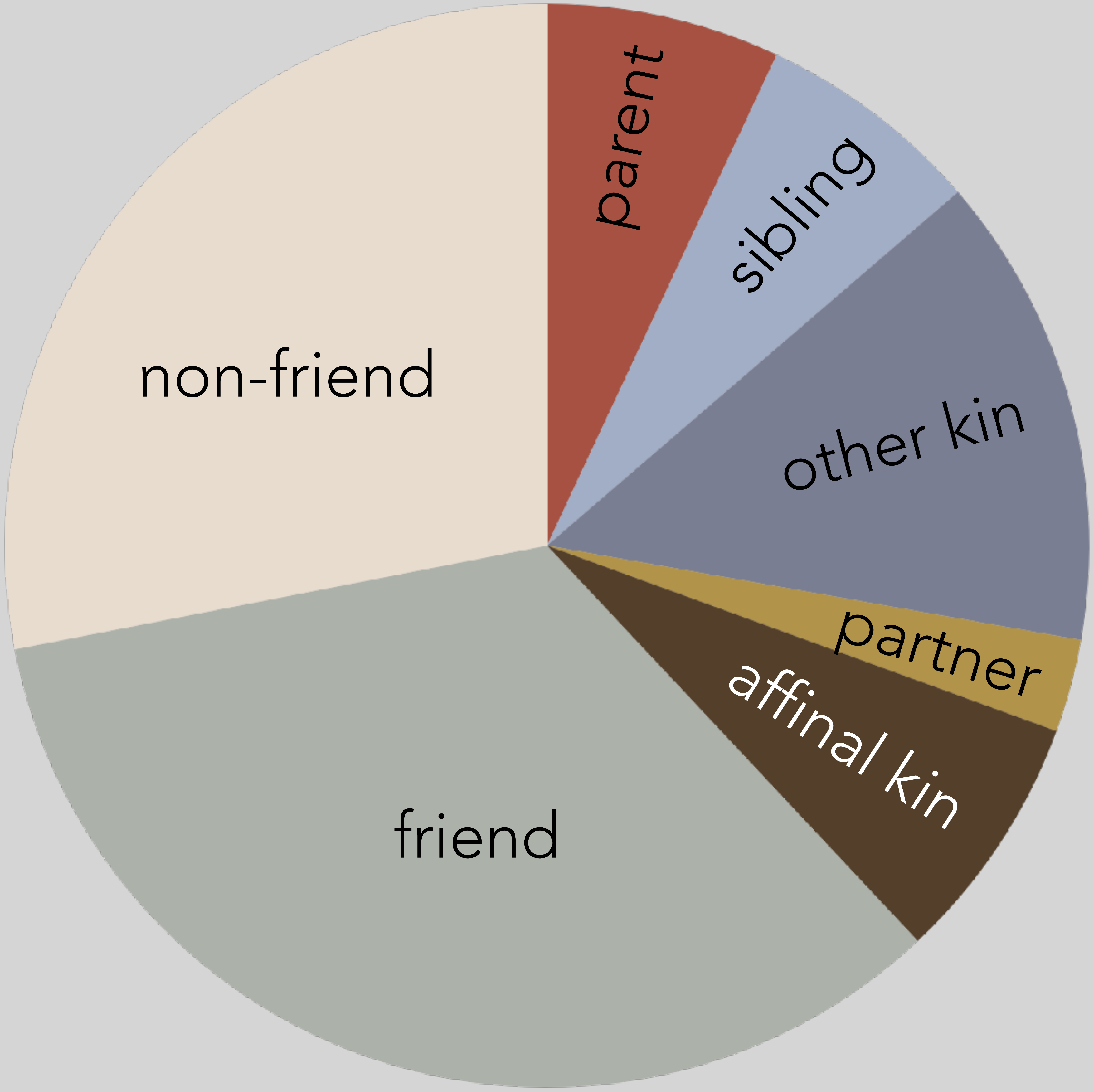


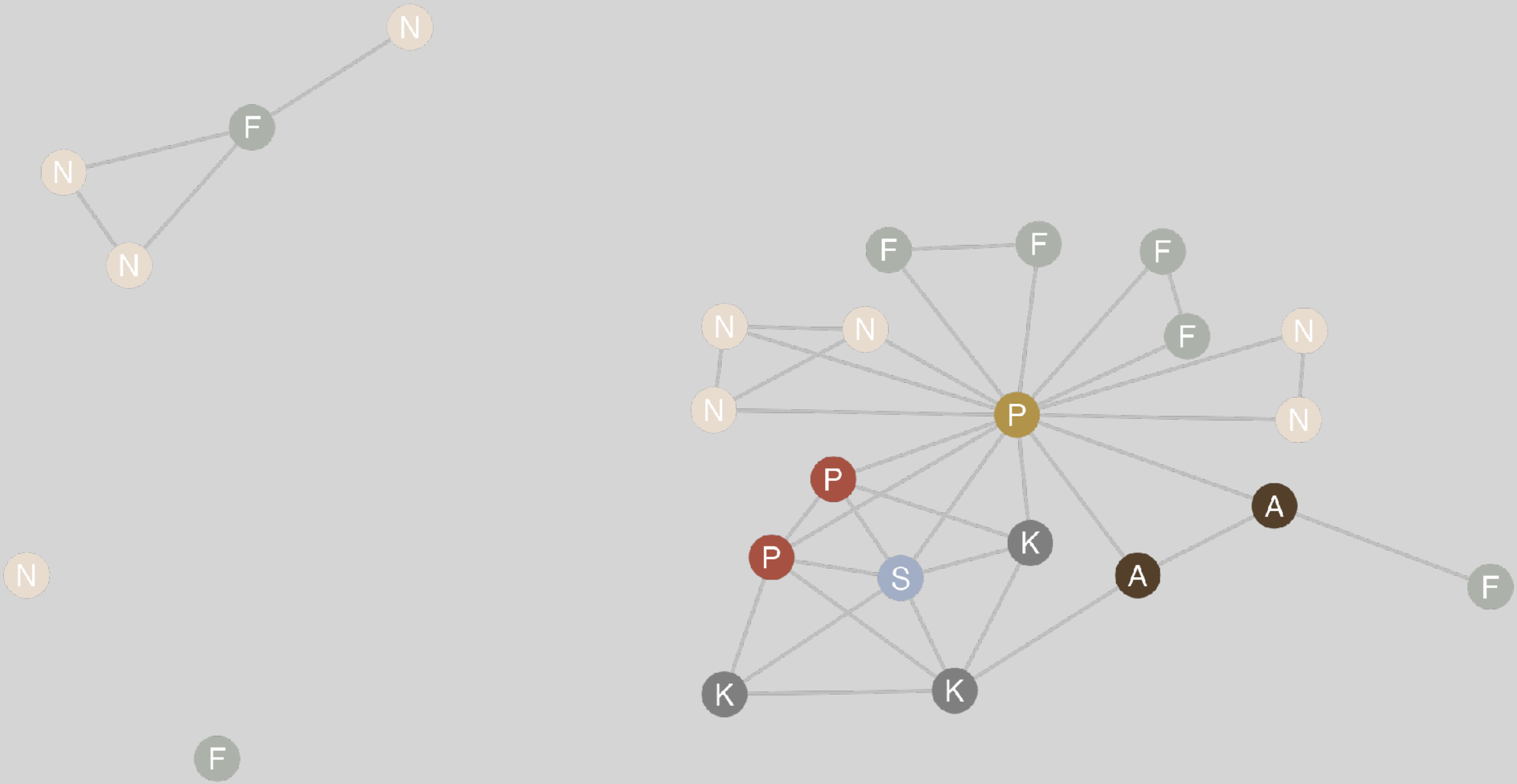
predicting fertility outcomes using personal network data

Composition



kin make up a substantial fraction of the network




N
F
N
N
F
F
F
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F
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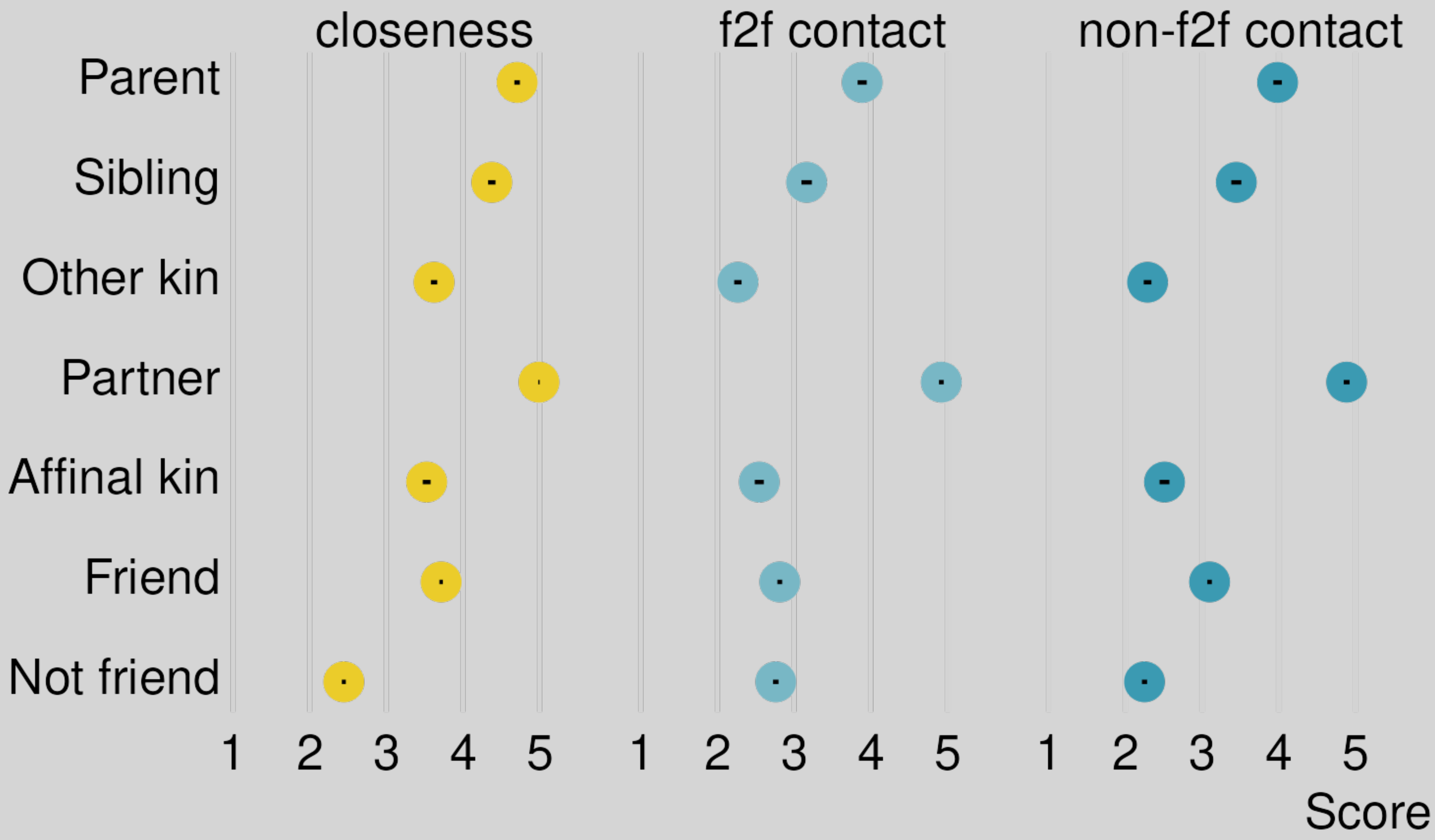
P
A
K
P
N
A
S
F
K
K
F


closeness
f2f contact
non-f2f contact
Parent
Sibling
Other kin
Partner
Affinal kin
Friend
Not friend
1
2
3
4
5
Score

INTERPRETABILITY

LASSO regression

XGBoost

Support Vector Machines

Graph Neural Networks

COMPLEXITY

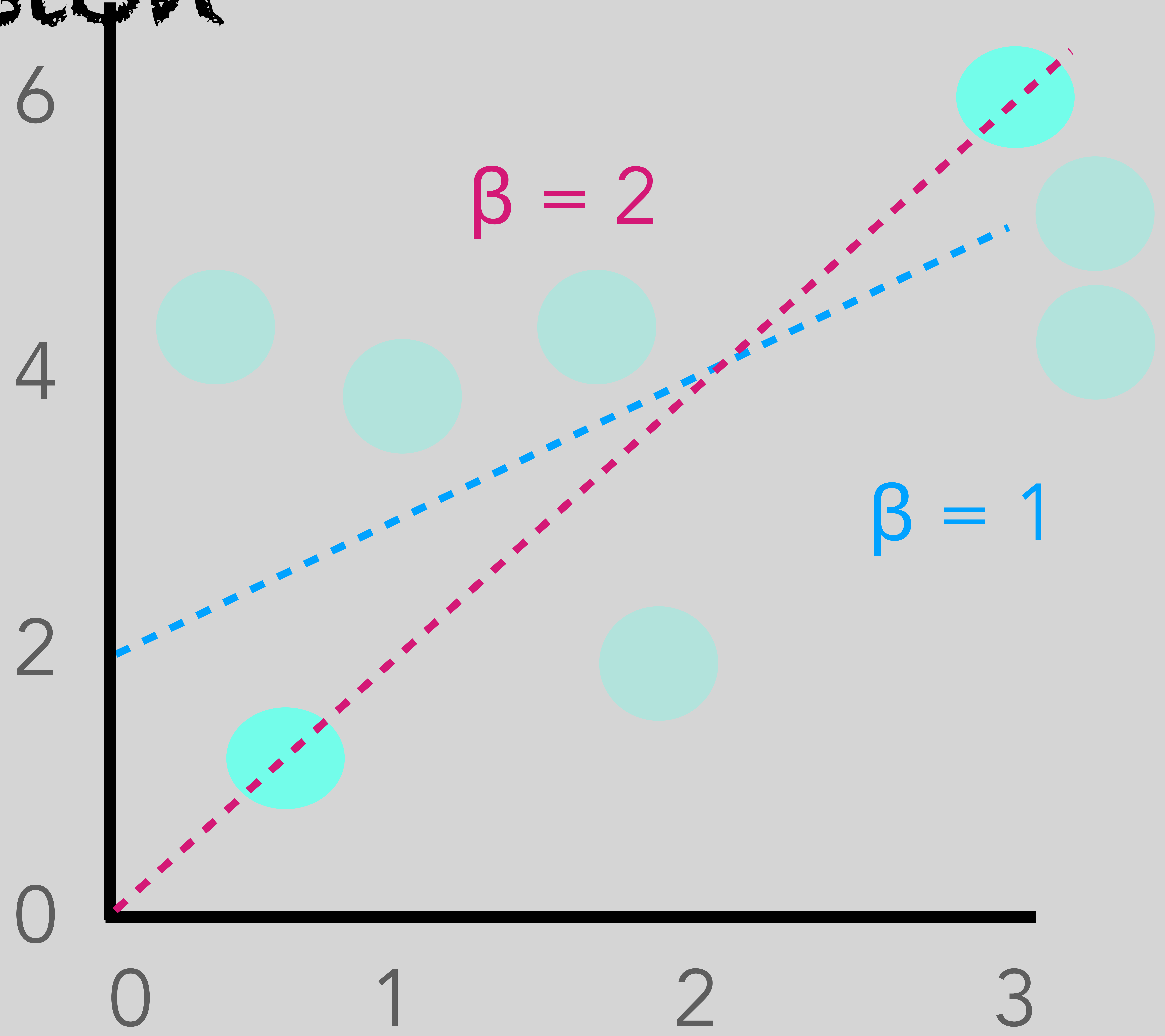
Lasso Regression

$$\underbrace{\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}_{\text{linear regression}} + \underbrace{\lambda \sum_{i=1}^{p}|\beta_j|}_{\text{penalty term}}$$

- can handle many, correlated variables
- leads to sparse, predictive, interpretable models
- reduced variance through increased bias

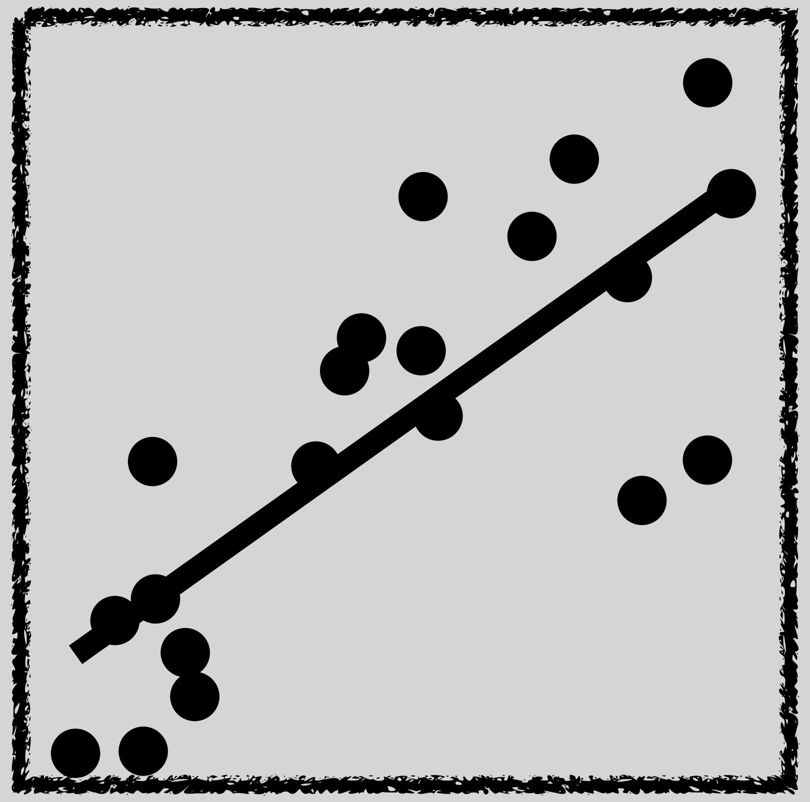
Lasso Regression

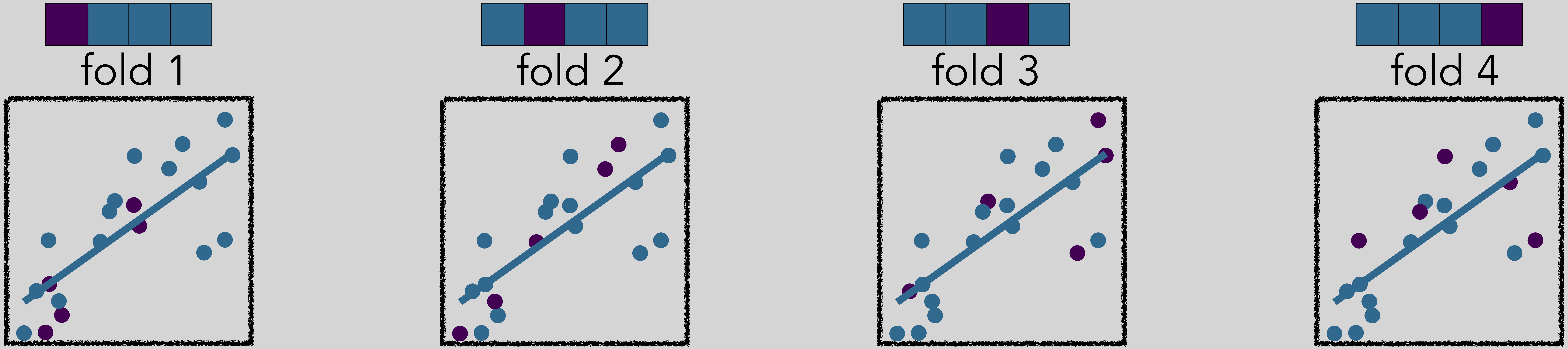
$$\sum_{i=0}^{n}(y_i - \hat{y}_i)^2 + \lambda \sum_{i=1}^{p} |\beta_j|$$



Cross-Validation

λ is determined through cross-validation and **out-of-sample predictive ability**

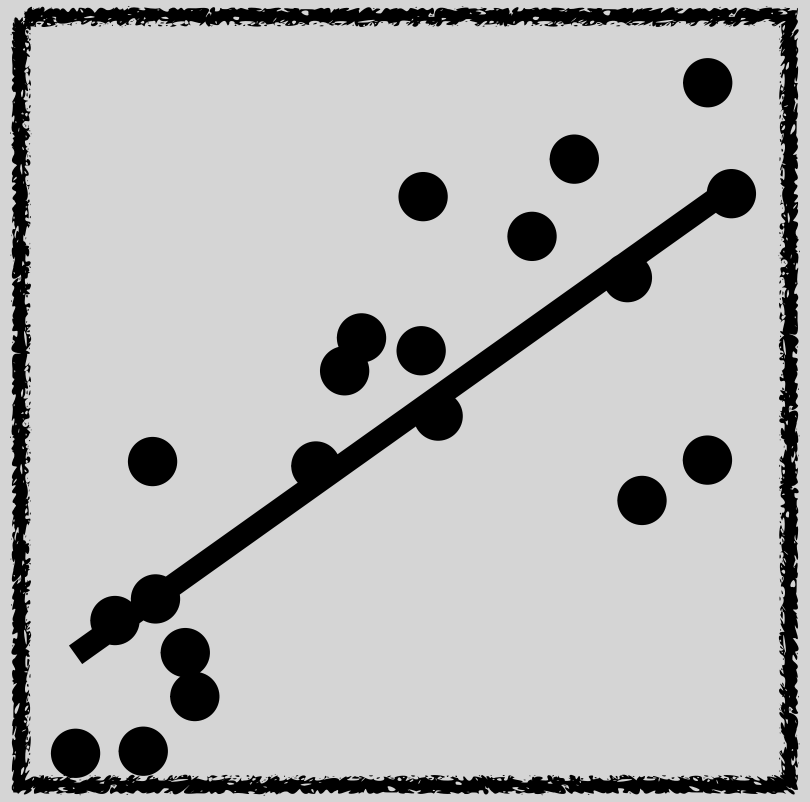




Cross-Validation

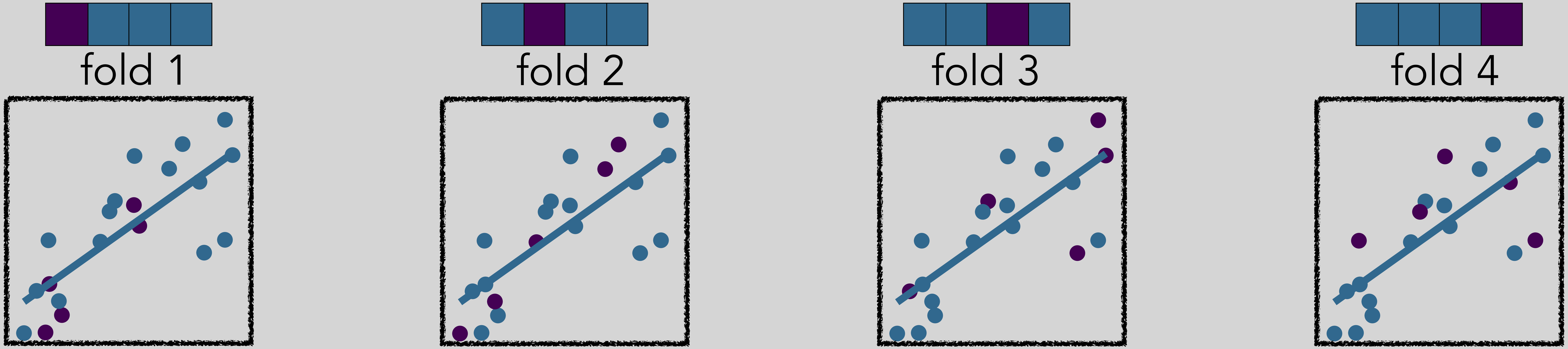
strength of model
quantified by out-of-sample predictive ability

all data



RMSE: 0.41

fold 1 | fold 2 | fold 3 | fold 4

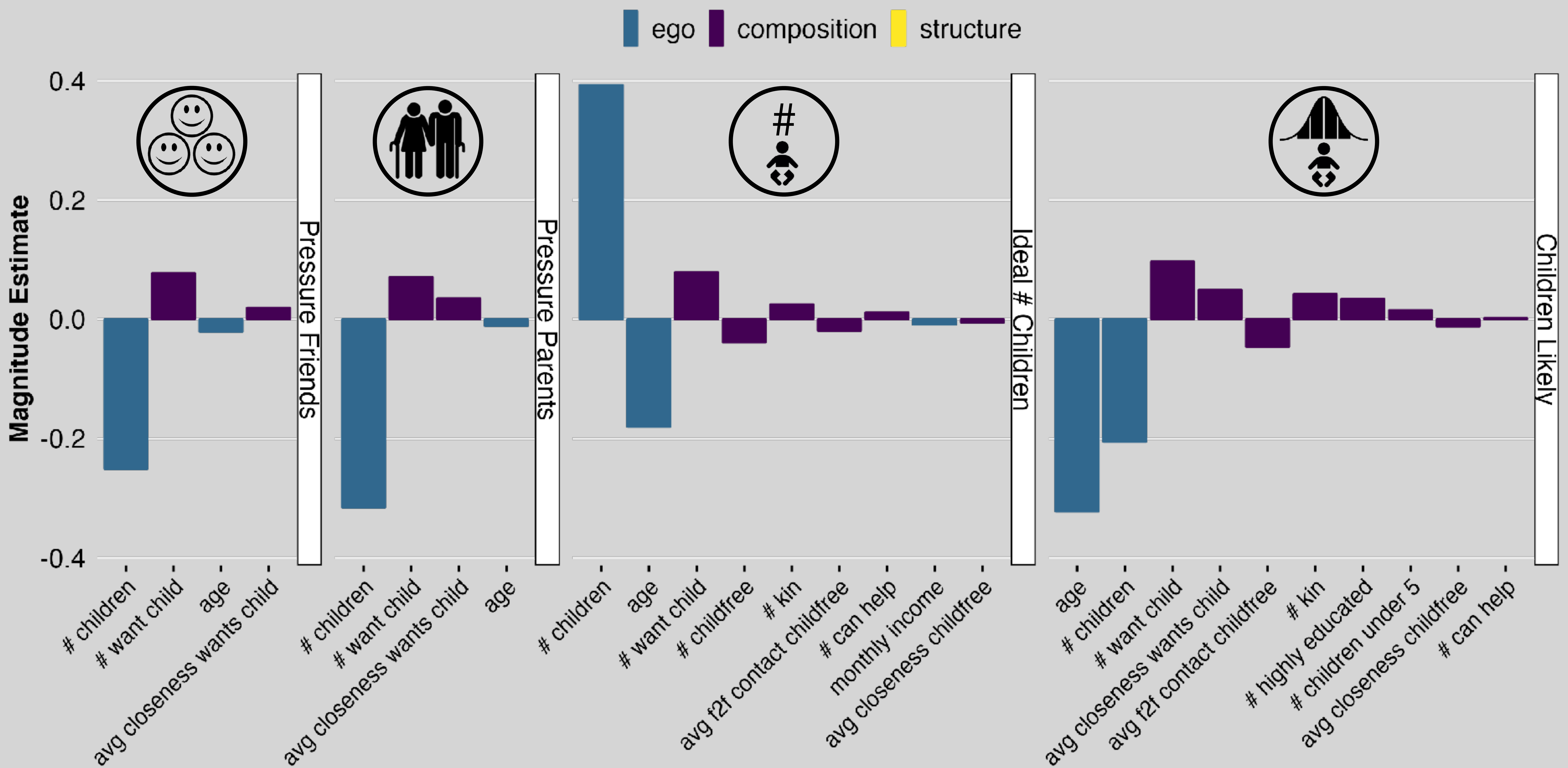


RMSE: 0.38 | RMSE: 0.38 | RMSE: 0.45 | RMSE: 0.62

Happiness
N = 581
Pressure Friends
N = 515
Pressure Parents
N = 546
Ideal # Children
N = 600
Children Likely
N = 664
#
Out-of-Sample R² (Mean ± Standard Error)
0
10
20
30
40
50
full
ego
composition
structure

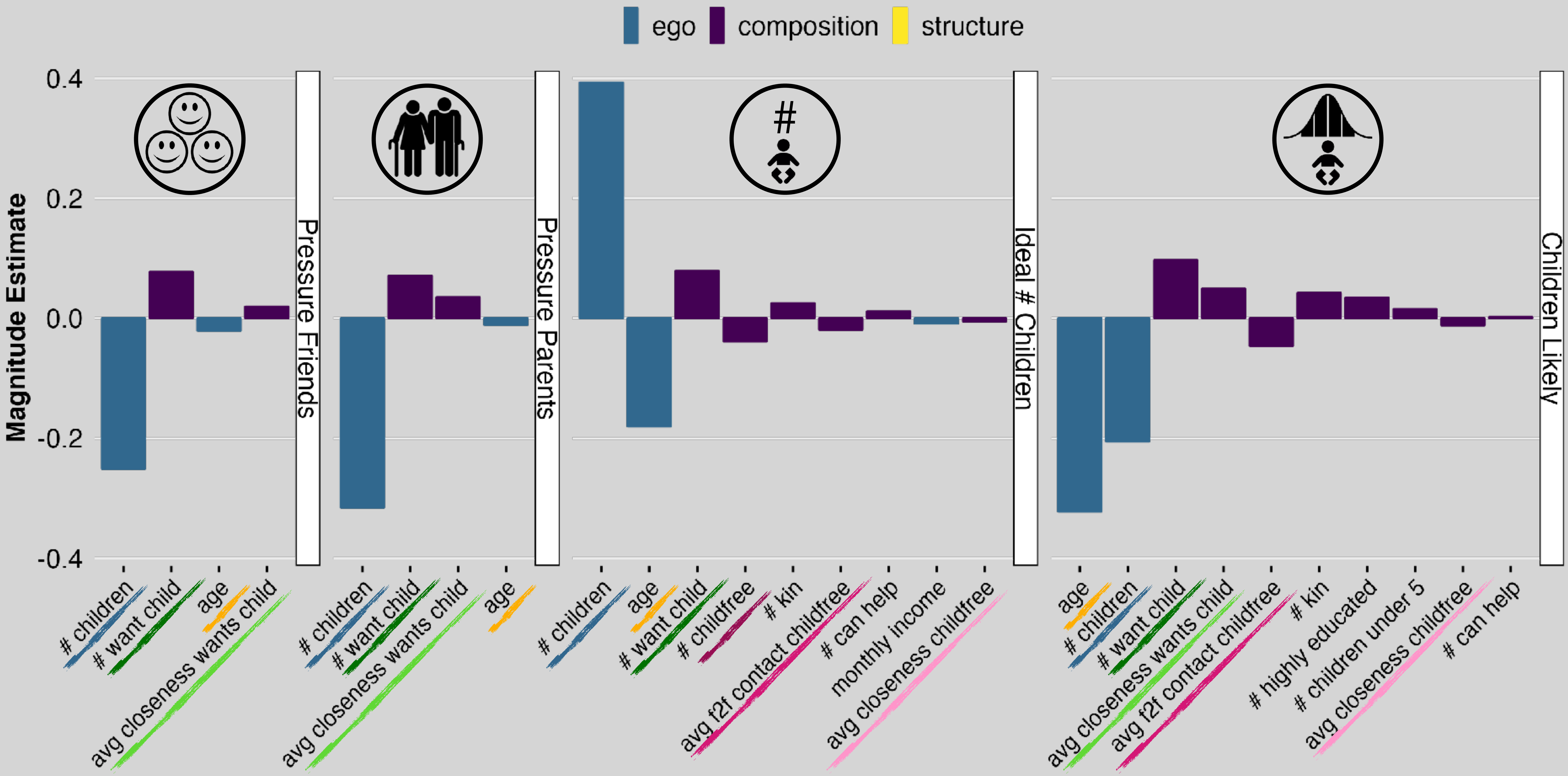
Take-home messages

- ✅ predicting pretty well!
- (❌) massive overfitting (~15 %-points)


ego
composition
structure
Magnitude Estimate
0.4
0.2
0.0
-0.2
-0.4
Pressure Friends
Pressure Parents
Ideal # Children
Children Likely
children
want child
age
avg closeness wants child
children
want child
avg closeness wants child
age
children
age
want child
childfree
kin
avg f2f contact childfree
can help
monthly income
avg closeness childfree
age
children
want child
avg closeness wants child
avg f2f contact childfree
kin
highly educated
children under 5
avg closeness childfree
can help
#

Take-home messages

- ✅ predicting pretty well!
- ❌ massive overfitting (~15 %-points)
- ✅ personal variables important, composition so-so, structure not



ego
composition
structure
Magnitude Estimate
0.4
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-0.4
Pressure Friends
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Ideal # Children
Children Likely
#
children
want child
age
avg closeness wants child
children
want child
avg closeness wants child
age
children
age
want child
childfree
kin
avg f2f contact childfree
can help
monthly income
avg closeness childfree
age
children
want child
avg closeness wants child
avg f2f contact childfree
kin
highly educated
children under 5
avg closeness childfree
can help

Important Variables

- age
- # children
- # alters who **do** want children
- # alters who **do not** want children
- strength of relationship to these people

Take-home messages

- ✓ predicting pretty well!
- ✗ massive overfitting (~15 %-points)
- ✓ personal variables important, composition so-so, structure not
- ✓ people who want children and who do not important

Take-home messages

- ✓ predicting pretty well!
  - difficult to assess how well
- (✗) massive overfitting (~15 %-points)
  - potentially misleading conclusions
- ✓ personal variables important, composition so-so, structure not
  - networks may not be unimportant, few ego variables
- ✓ people who want children and who do not important
  - understudied

social learning

- ✅ # people with childwish, ties to them
- ✅ # childfree people, ties to them

social contagion

- ✅ # children under 5

- ✅ # kin
- ✅ # people that can help

social support

- ✅ people felt pressure
- ✅ # people with childwish

social pressure

INTERPRETABILITY

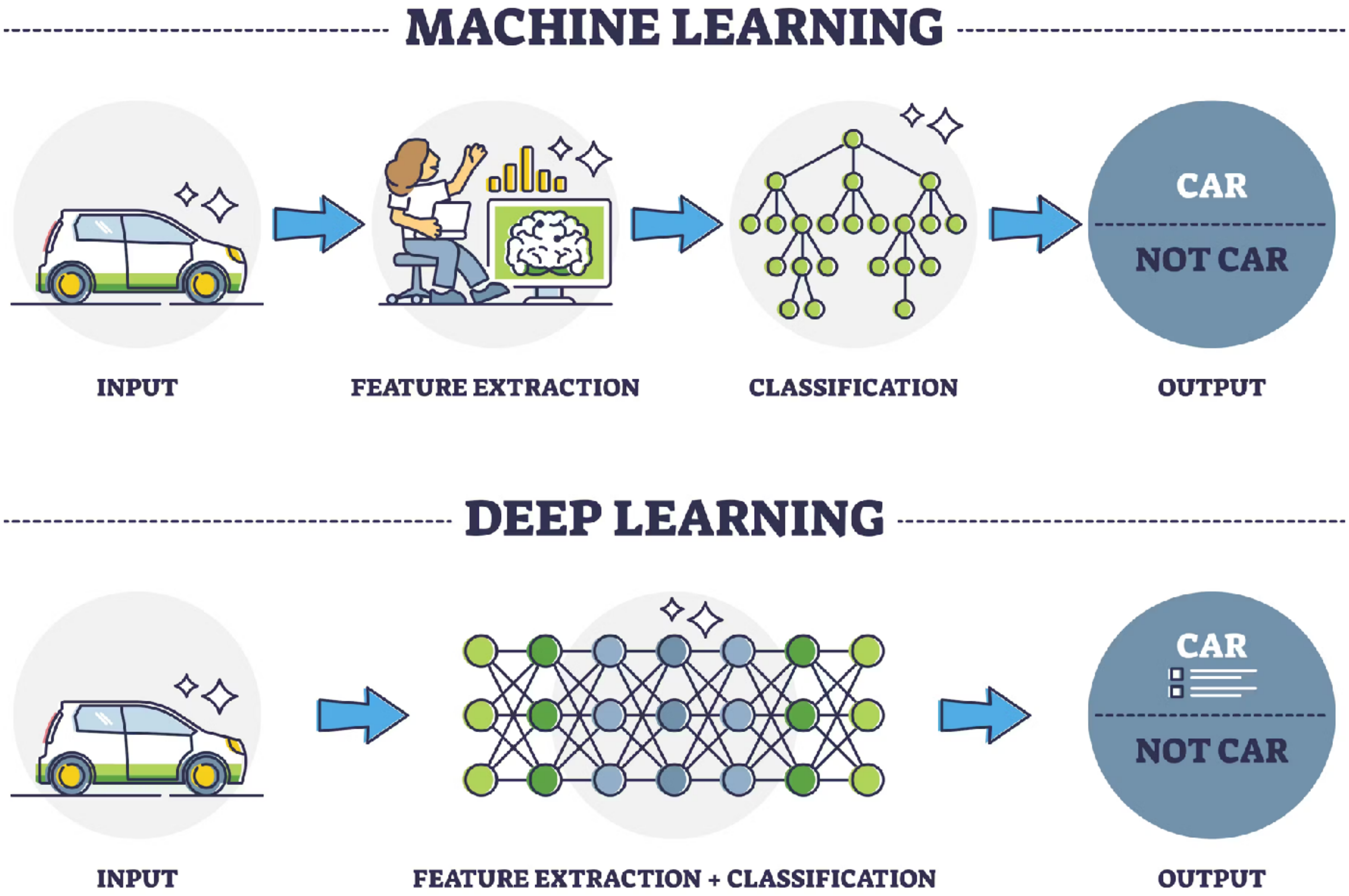
LASSO regression

XGBoost

Support Vector Machines

Graph Neural Networks

COMPLEXITY



LASSO
XGBoost
SVM

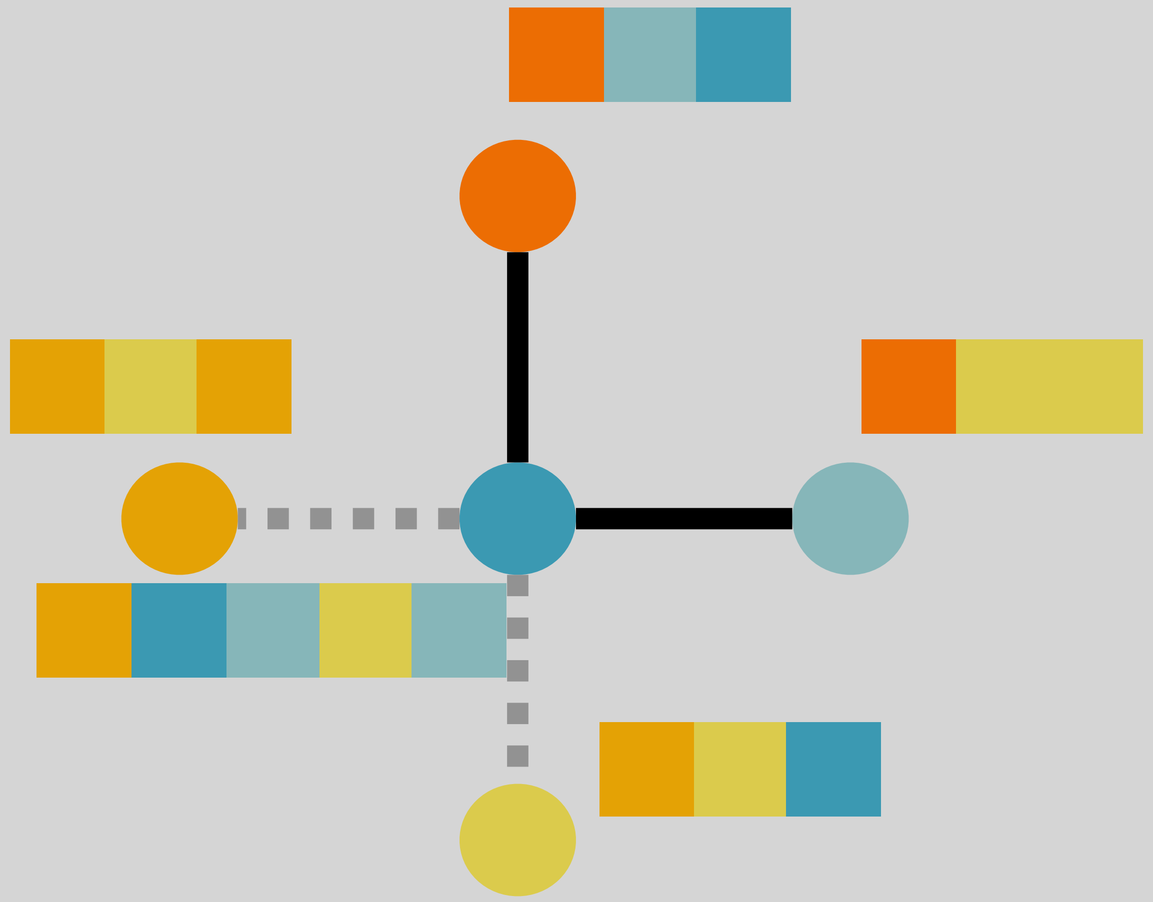
GNN

Graph Neural Networks

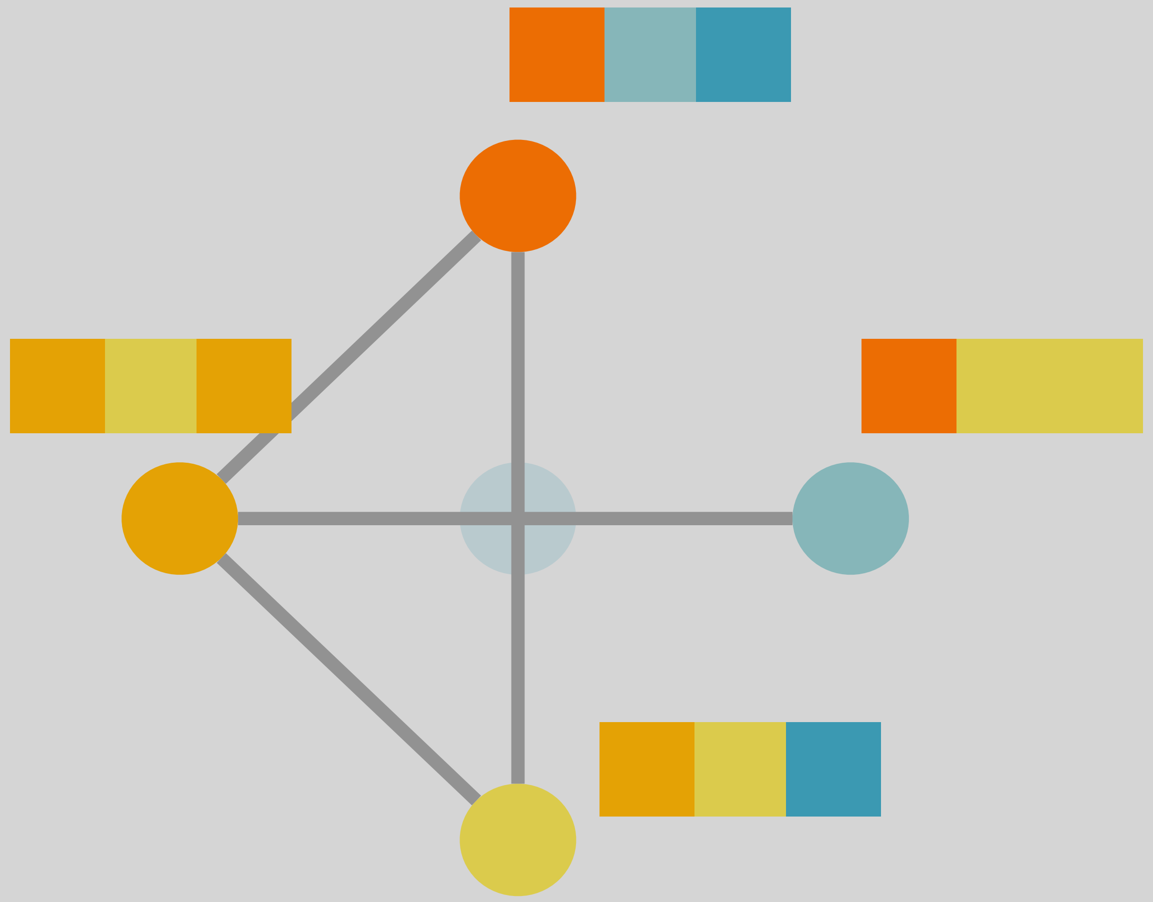
Pau
Vila Soler

Javier
Garcia-Bernardo

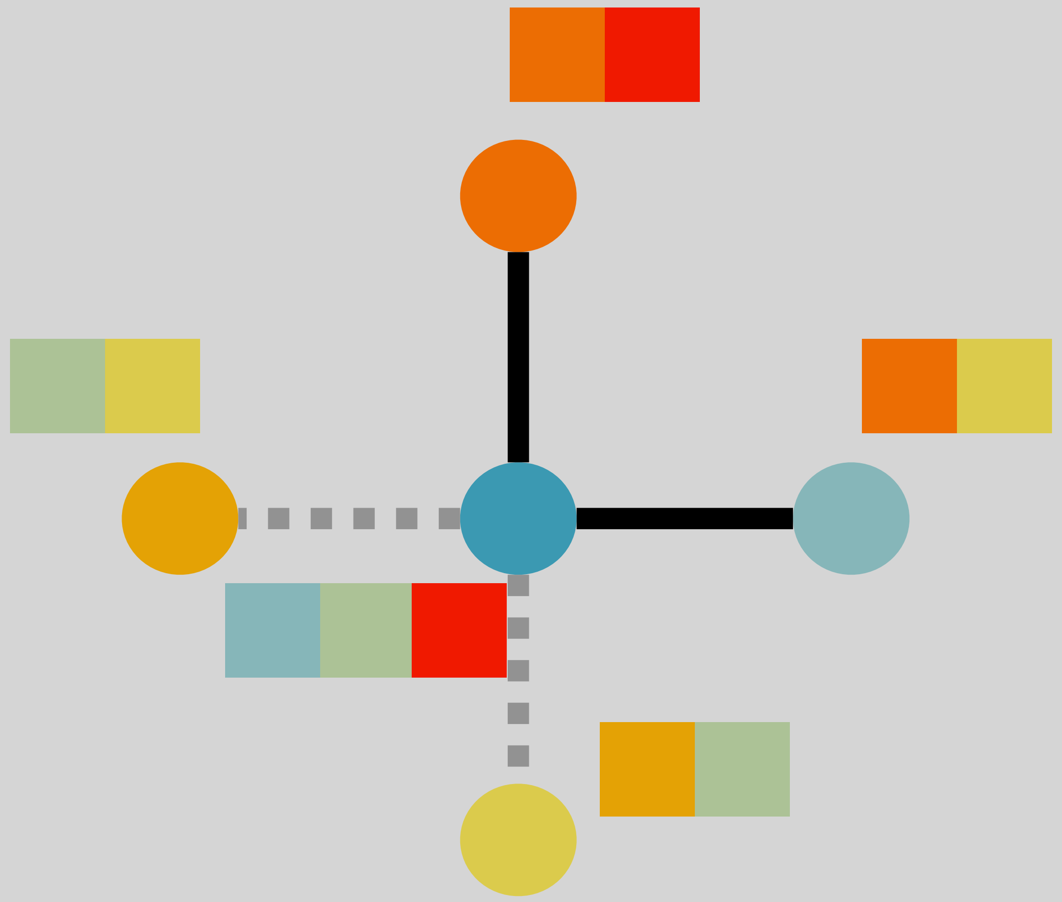
Combining ego-alter information



Combining alter-alter information



Combining alter-ego information

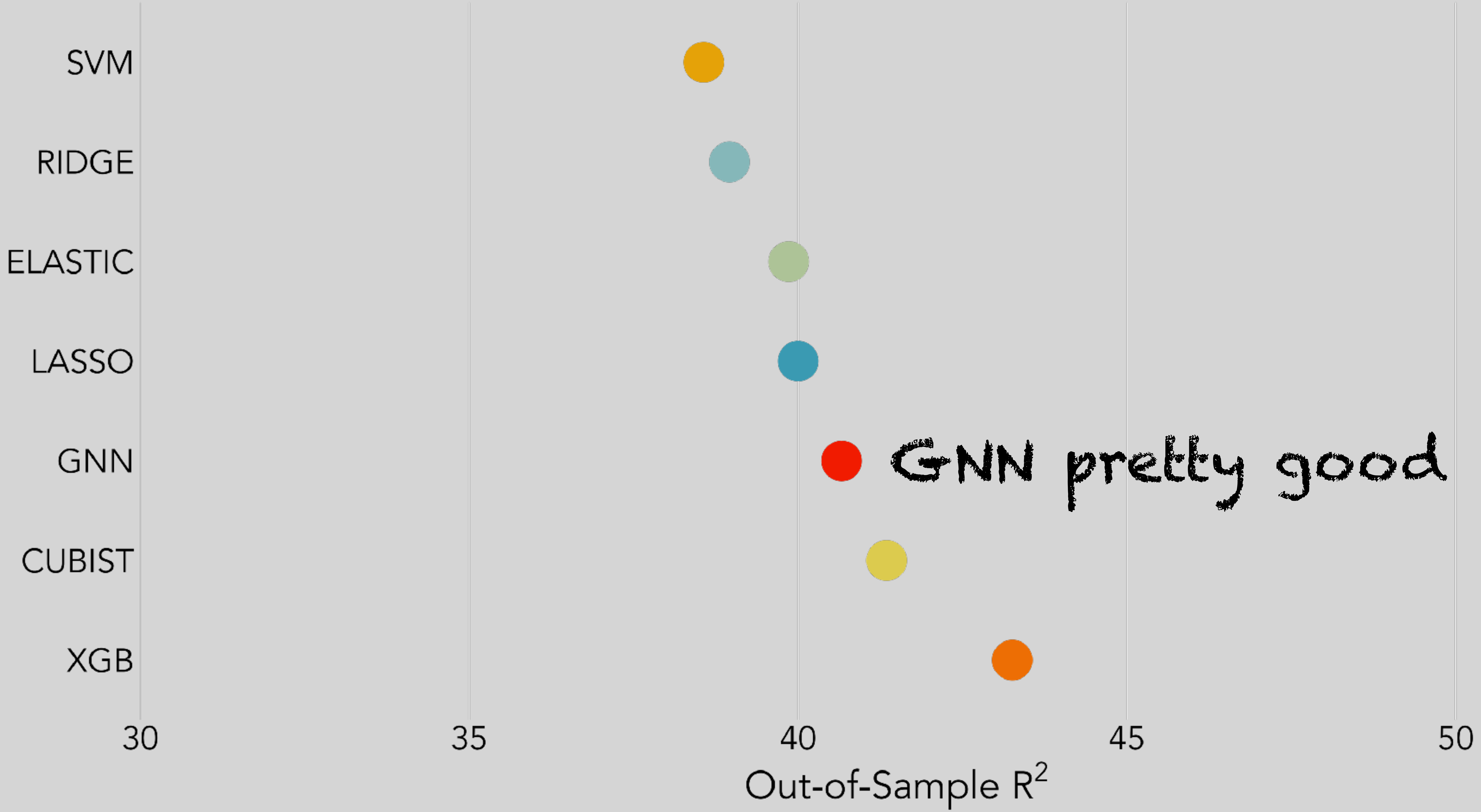


prediction on graph level


children likely?
SVM
RIDGE
ELASTIC
LASSO
GNN
CUBIST
XGB
XGBoost winner
(on average)
30
35
40
45
50
Out-of-Sample R^2

children likely?

children likely?



large variation across iterations

children likely?

Take-home messages

- ✅ some improvement over LASSO regression
  - some evidence for non-linearities
- (❌) improvement over LASSO regression not impressive
  - is lack of interpretability and dozens of hours compute worth it?
- (❌) large variation across iterations
  - sample size clearly a constraint
- ✅ GNN performed well!
  - requires fewer decisions, capitalises on network structure

R package FertNet

FertNet: Process Data from the Social Networks and Fertility Survey

Processes data from The Social Networks and Fertility Survey, downloaded from <https://dataarchive.lissdata.nl>, including correcting respondent errors and transforming network data into network objects to facilitate analyses and visualisation.

Version:	0.1.1
Imports:	haven (≥ 2.5.1)
Suggests:	testthat (≥ 3.0.0), tidygraph (≥ 1.2.2)
Published:	2023-03-16
Author:	Stulp Gert [aut, cre]
Maintainer:	Stulp Gert <g.stulp at rug.nl>
License:	CC BY 4.0
NeedsCompilation:	no
Materials:	README NEWS
CRAN checks:	FertNet results

Documentation:

Reference manual: FertNet.pdf

Downloads:

Package source:	FertNet_0.1.1.tar.gz
Windows binaries:	r-devel: FertNet_0.1.1.zip, r-release: FertNet_0.1.1.zip, r-oldrel: FertNet_0.1.1.zip
macOS binaries:	r-release (arm64): FertNet_0.1.1.tgz, r-oldrel (arm64): FertNet_0.1.1.tgz, r-release (x86_64): FertNet_0.1.1.tgz, r-oldrel (x86_64): FertNet_0.1.1.tgz

Linking:

Please use the canonical form `https://CRAN.R-project.org/package=FertNet` to link to this page.

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DEMOGRAPHIC RESEARCH

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PUBLISHED 8 SEPTEMBER 2023
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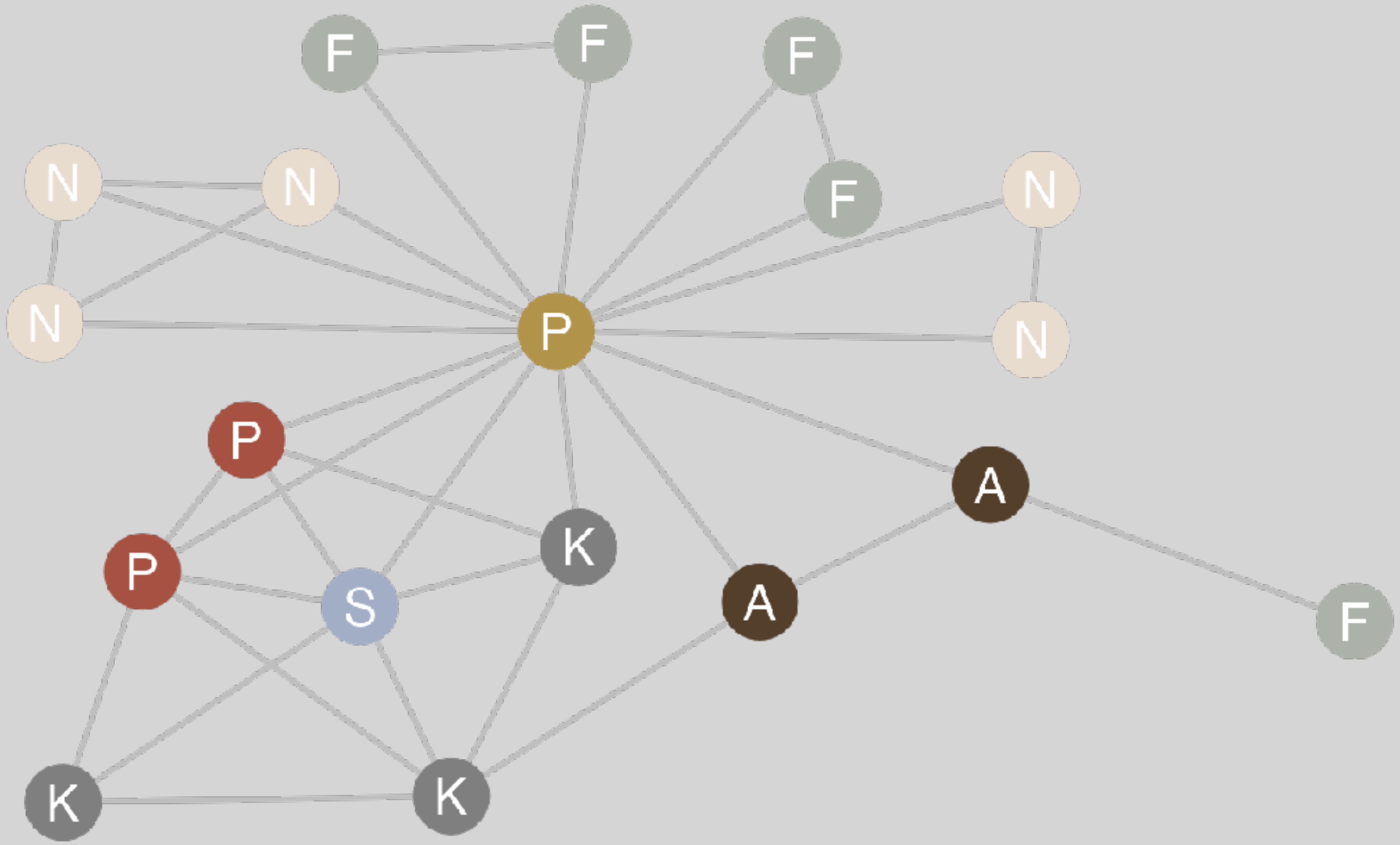
DOI: 10.4054/DemRes.2023.49.19

Data Description

Describing the Dutch Social Networks and Fertility Study and how to process it

Gert Stulp

Predicting fertility outcomes with networks



gert stulp - gertstulp.com