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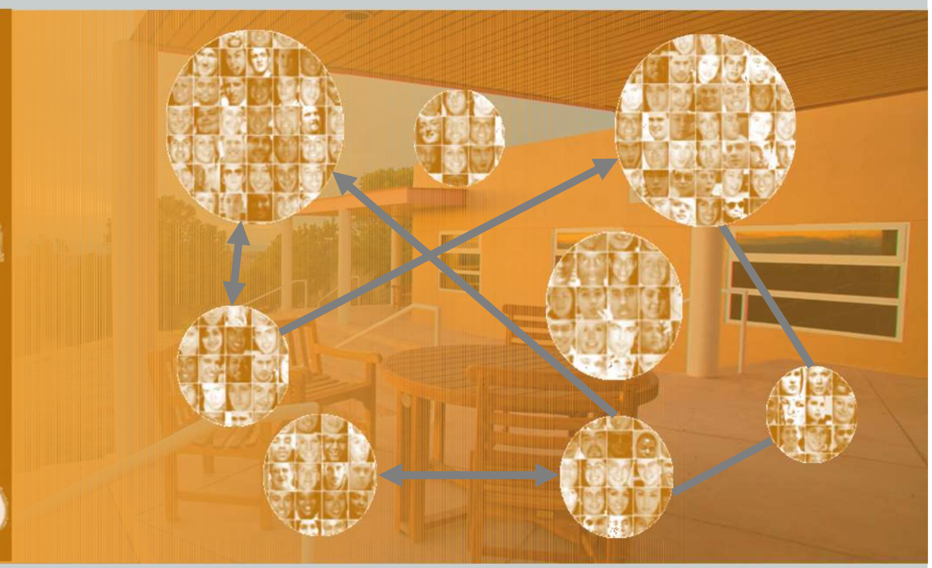
Social learning strategies: Modeling social phenomena

Mirta Galesic



Outline

A blueprint for modeling complex social worlds

- Simplicity: Interaction of social algorithms, task environments, and social networks
- Realism: empirical checks

Social representation: judgments of frequency of people with different characteristics in our social environments.

- Self enhancement and Self depreciation
- False consensus and False uniqueness

Social learning: rules for updating our beliefs based on perceived beliefs of others.

- Exploration and exploitation in collective problem solving
- The wisdom of small crowds
- Spread of beliefs in social circles

Big questions

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"Ms. Jones, there are a number of big questions here to see you. They say they won't leave until they have some answers."

www.NonprofitStrategyRevolution.org

Spread of beliefs

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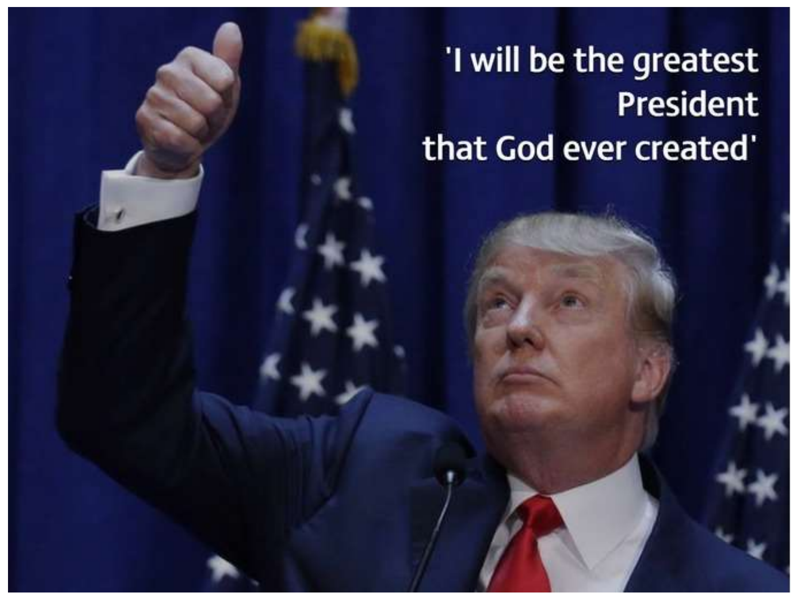

Collective problem solving

http://www.federalreserve.gov/

www.med.upenn.edu/criticalcare/

www.rhuddlantowncouncil.gov.uk/

Cooperation and conflict

Why are humans so uniquely cooperative among primates?

When do armed conflicts occur, and when not?

Messy social world

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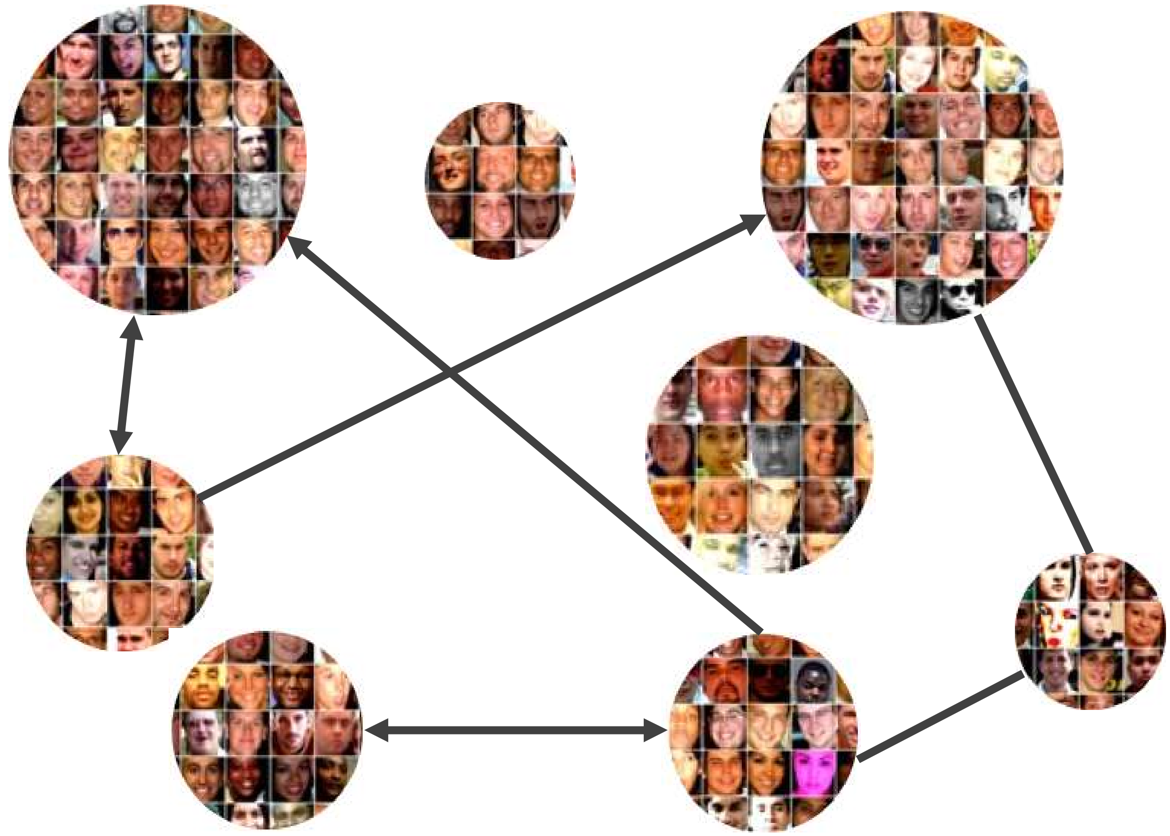
- Strategic interactions of many actors
- Individual differences
- Unstable preferences
- Feedback loops
- Network effects



Complex problems – Complex answers?

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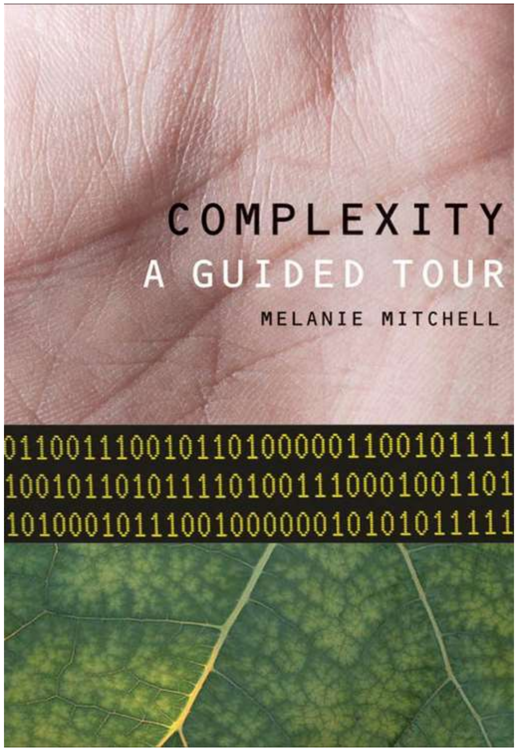
Not necessarily:

- Seemingly complex patterns might emerge from interactions of networked agents using simple algorithms to adapt to their local environment



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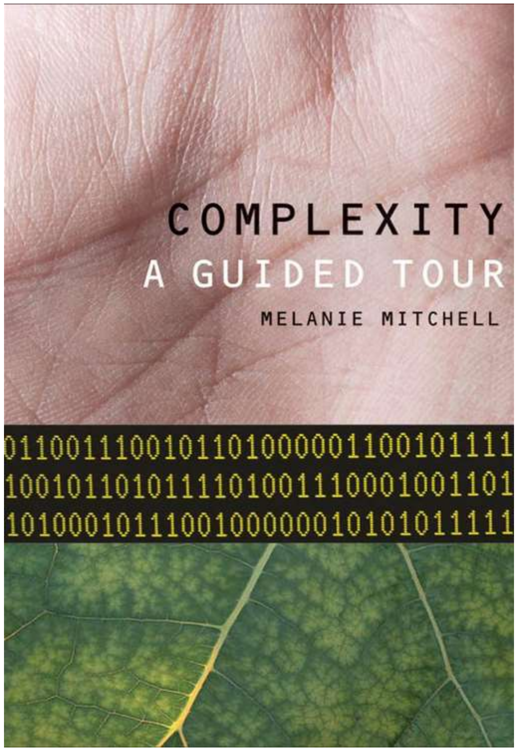

Modeling the messy social world: Complexity approach

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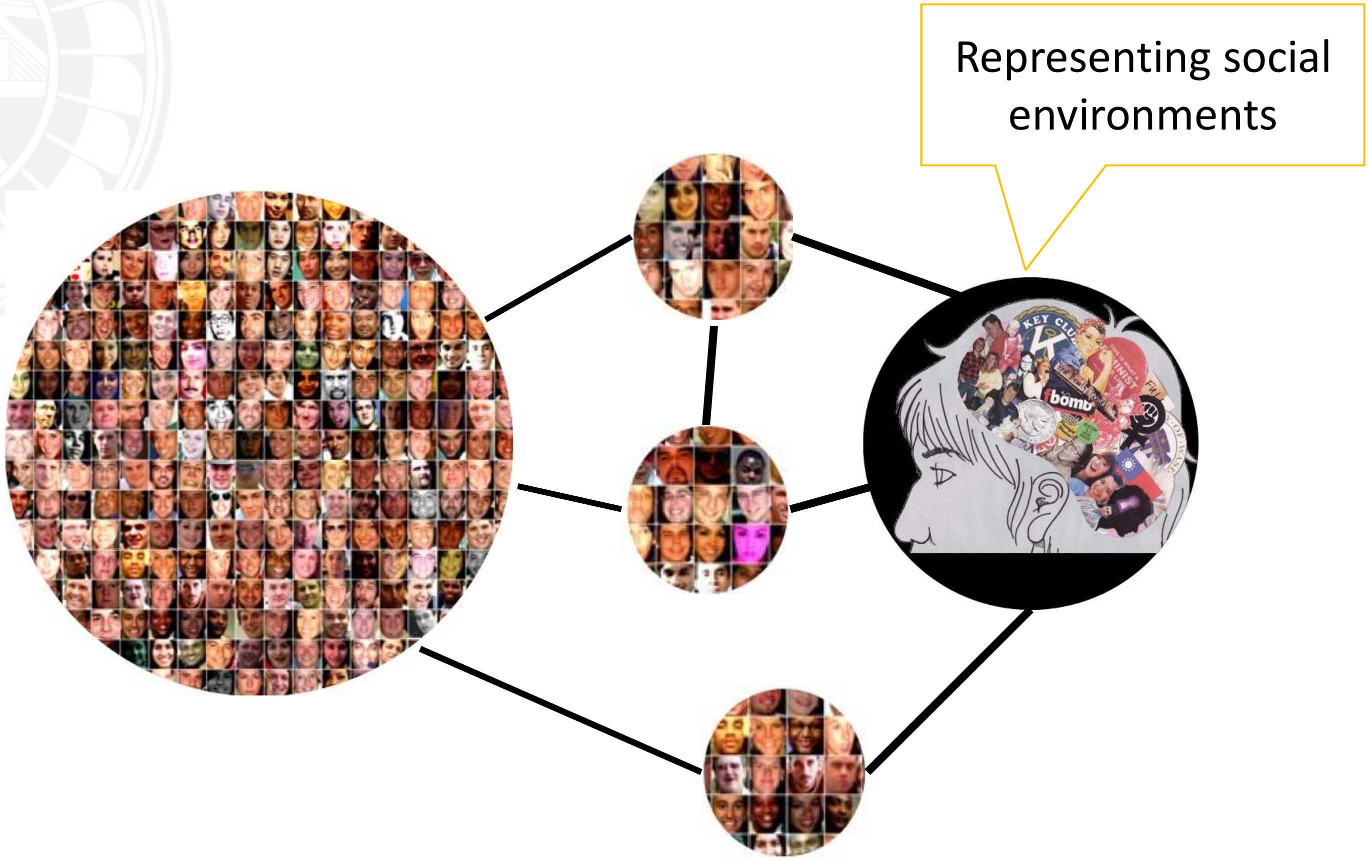
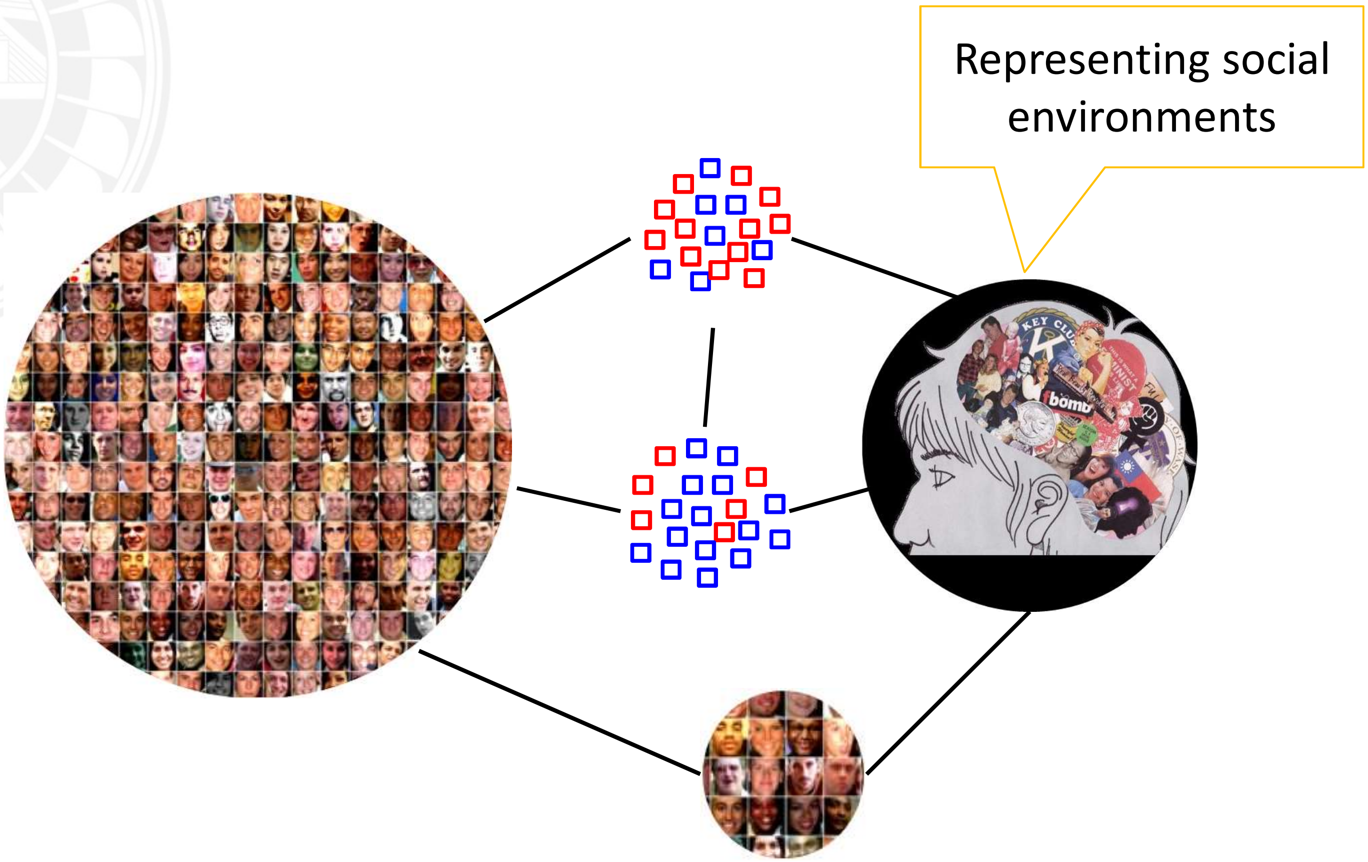
- What social algorithms do people use?
- What is the local task environment?
- What is the underlying social network structure?

→ What patterns of collective behaviors emerge?

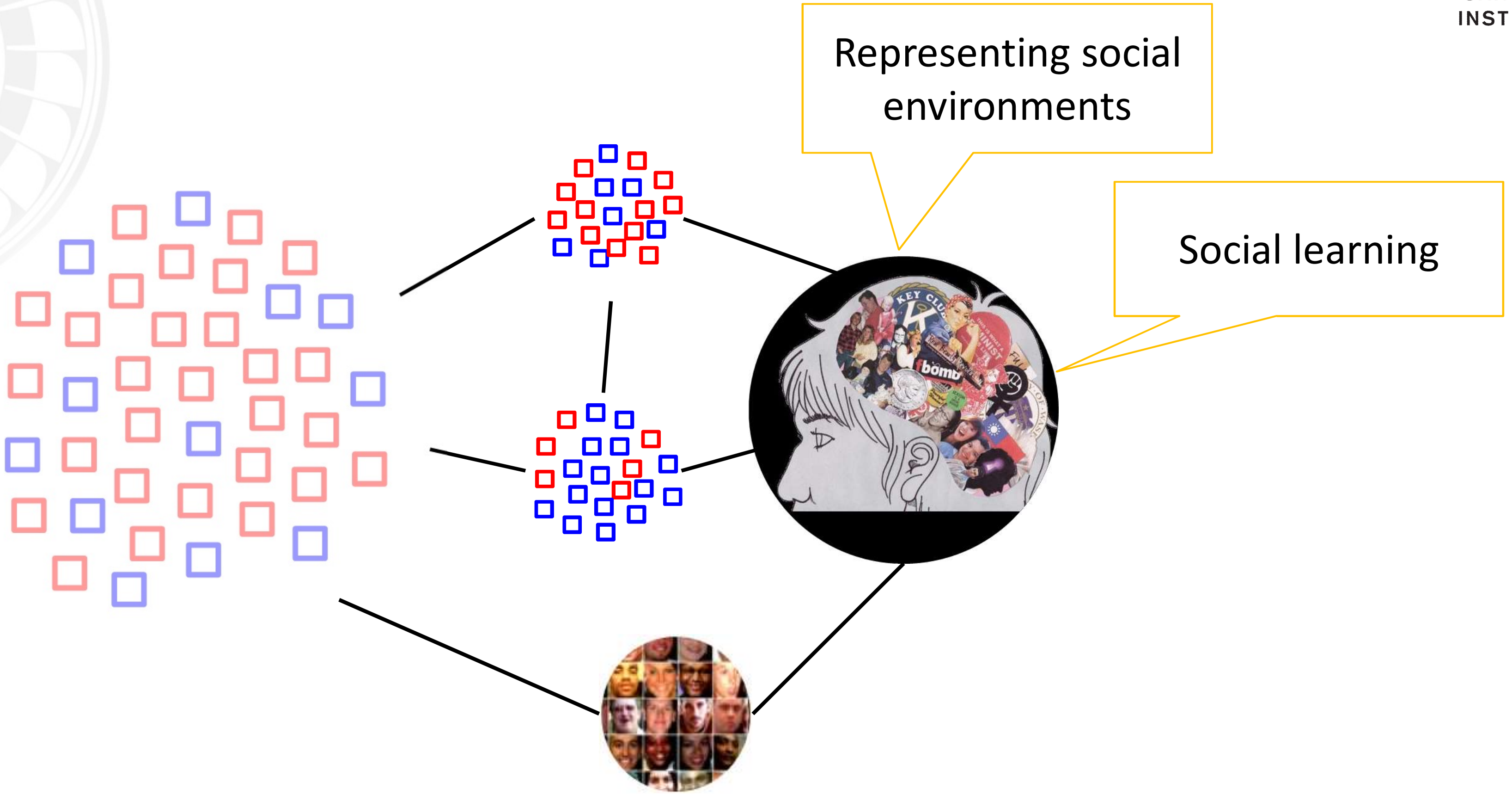
Social algorithms



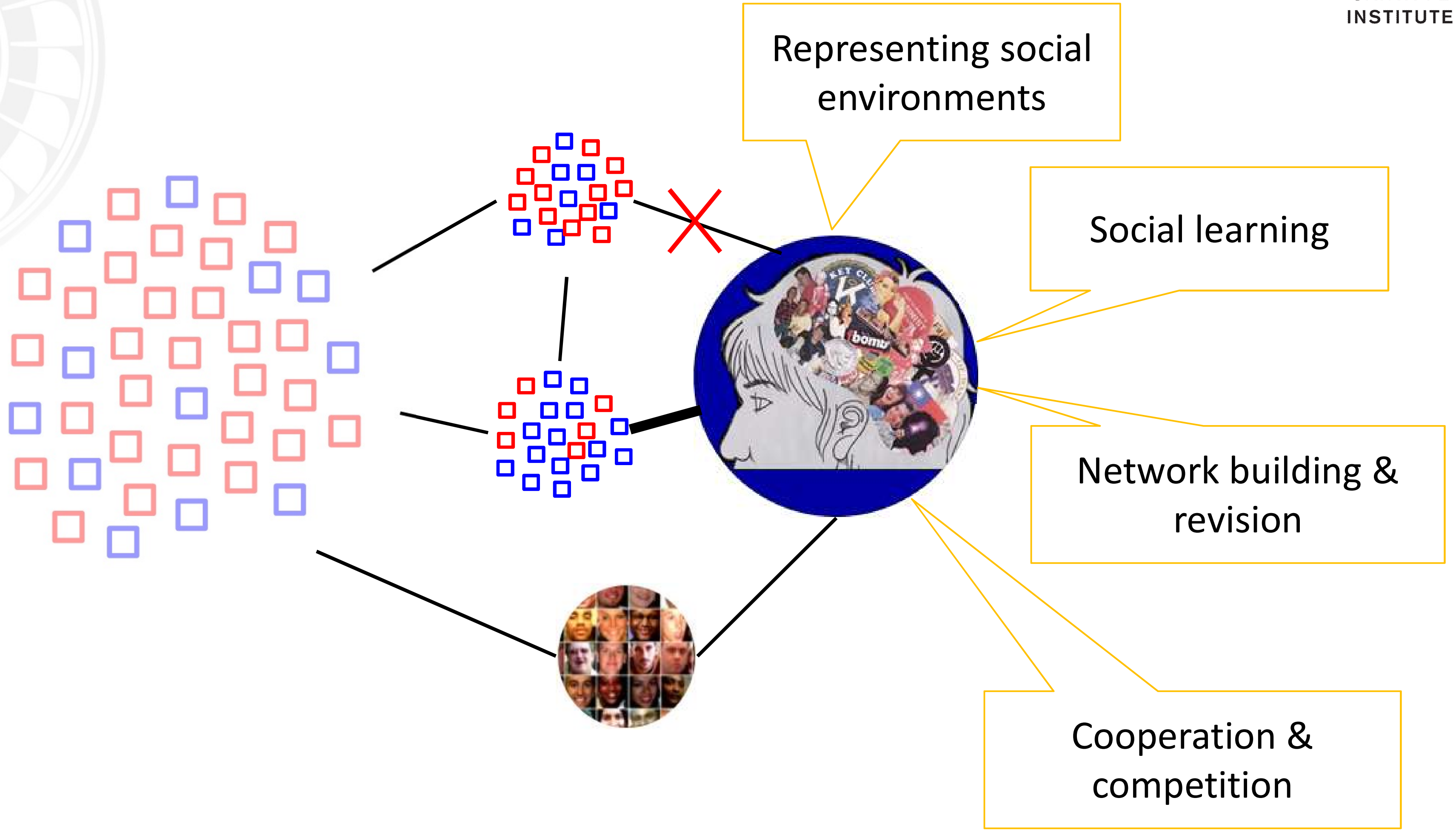
Social algorithms



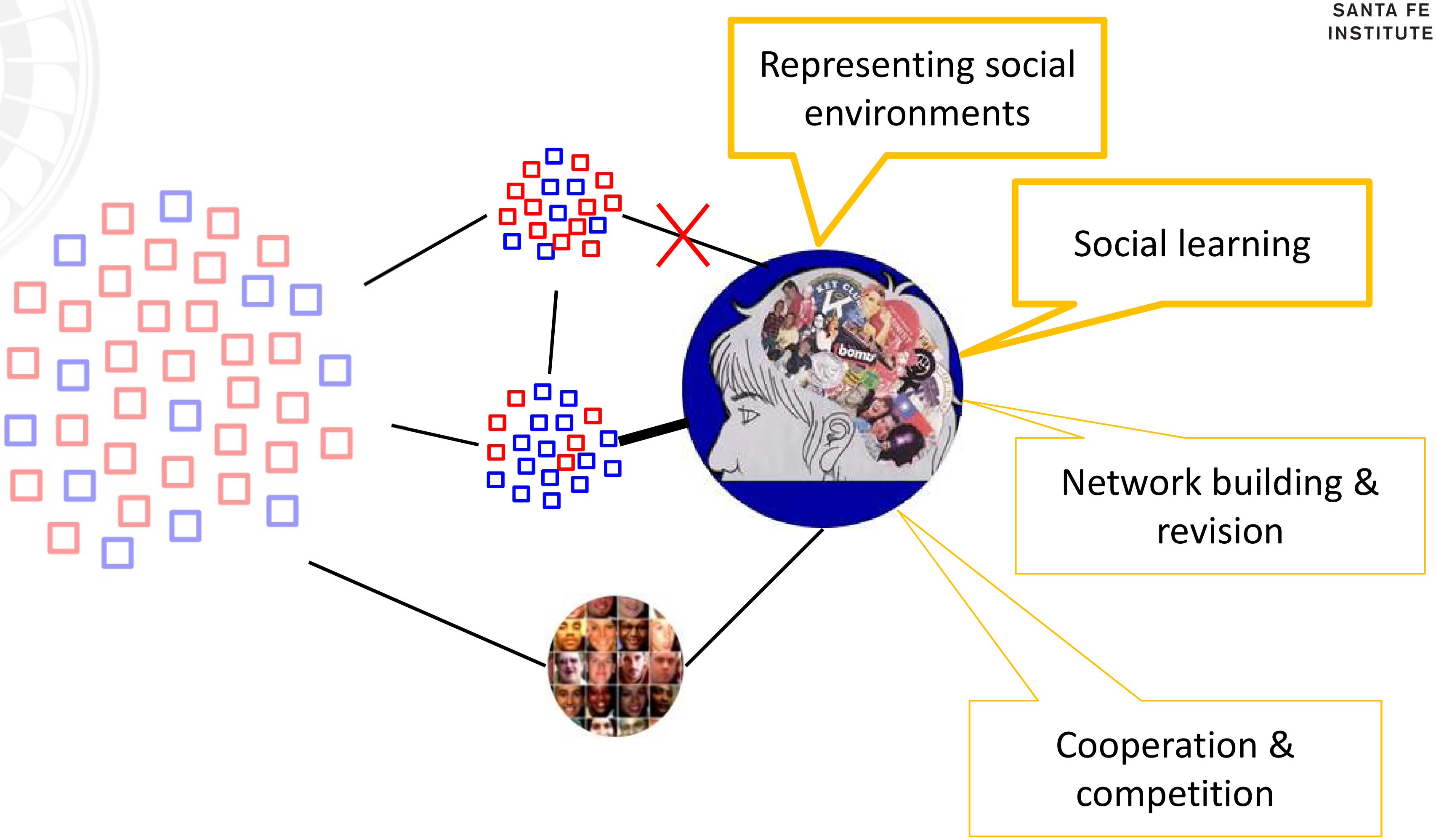
Social algorithms



Social algorithms



Social algorithms



Modeling the messy social world: Complexity approach

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- What social algorithms do people use?
- What is the local task environment?
- What is the underlying social network structure?

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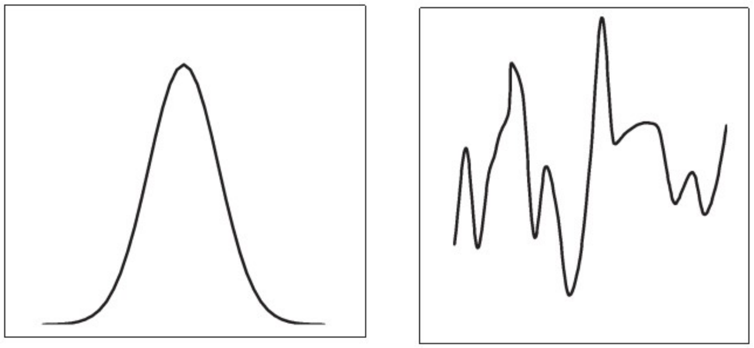
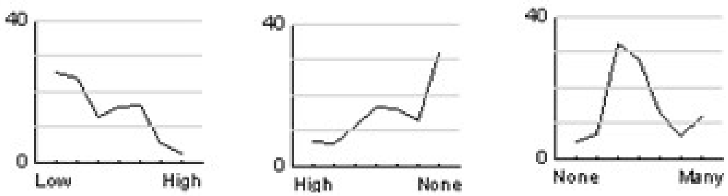
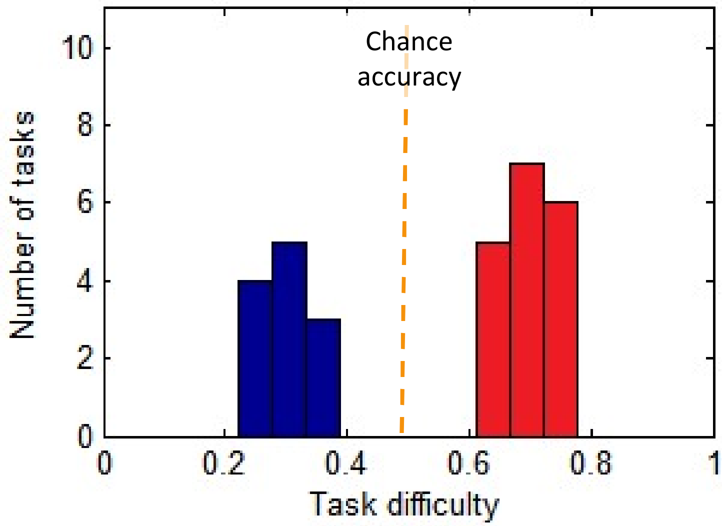
Local task environment







Network structure

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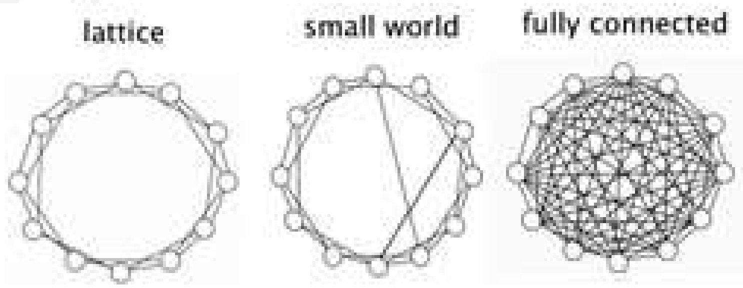
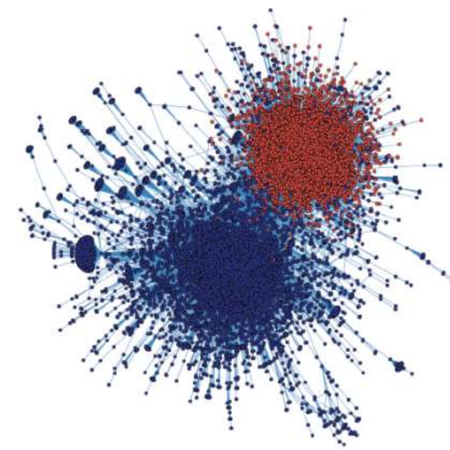
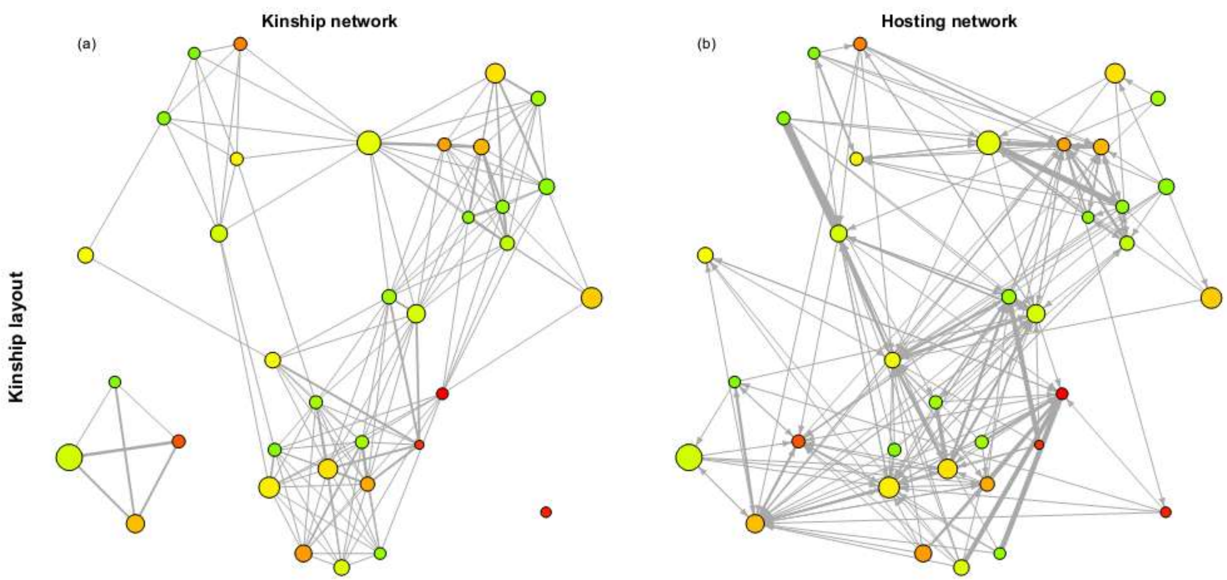




Conover et al (2011)



Hooper, DeDeo, Caldwell-Hooper, Gurven, & Kaplan (2013, Entropy)

A blueprint for modeling social phenomena

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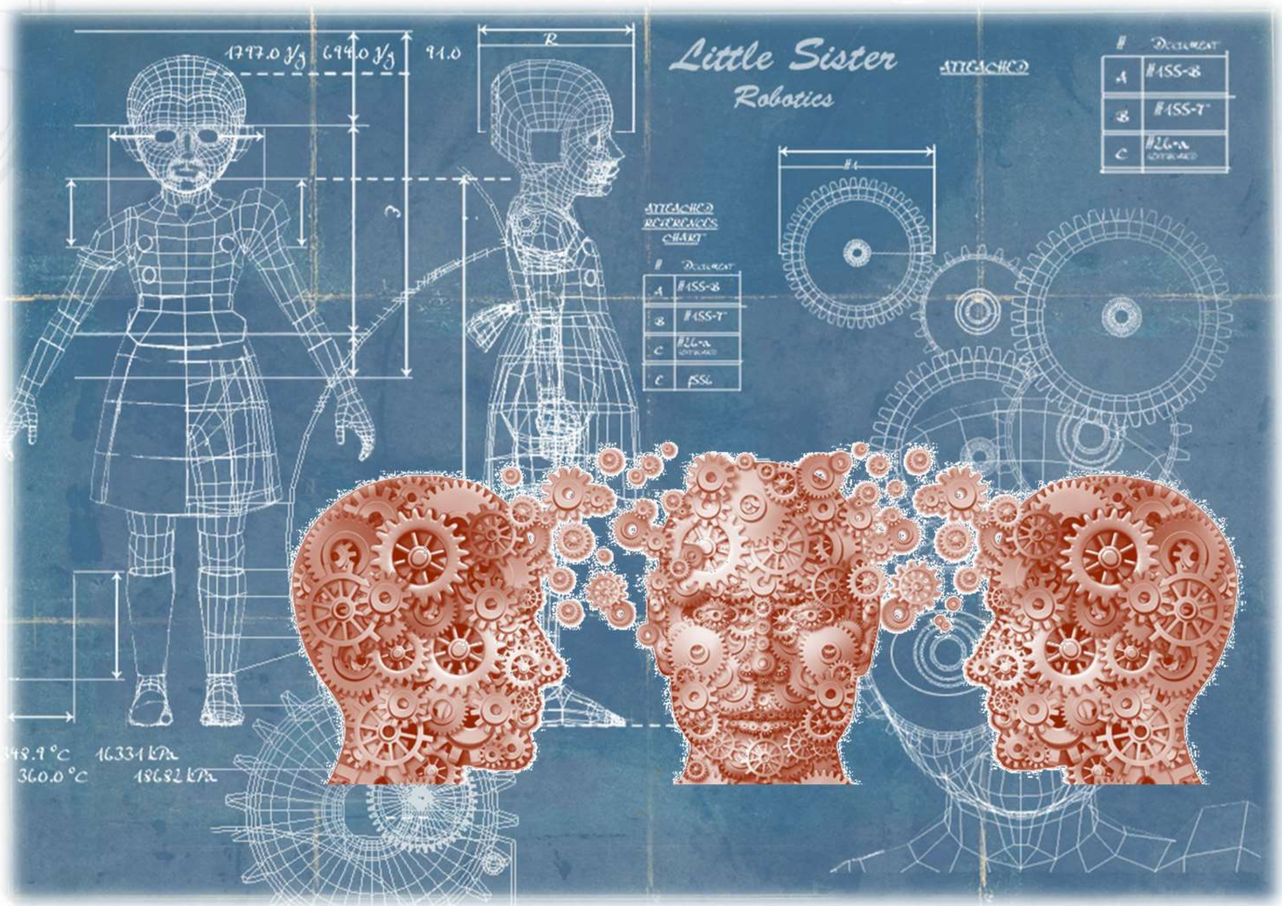

http://bioshock.wikia.com/; https://www.elearningnetwork.org/

A blueprint for modeling social phenomena

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1. Determine cognitively plausible algorithms

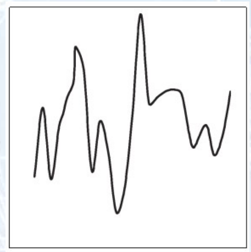
Representing social environments

Social learning

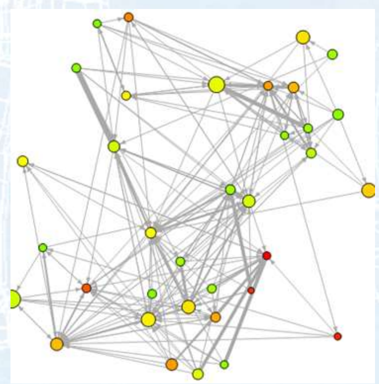
Network building & revision

Cooperation & competition

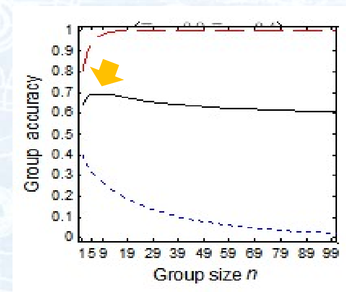
2. Model their performance in realistic task environments



and in realistic social networks



3. Compare model predictions with empirical data



Revise

A blueprint for modeling social phenomena

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1. Determine cognitively plausible algorithms

Representing social environments

Social learning

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Cooperation & competition

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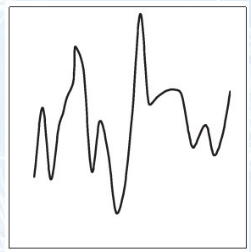

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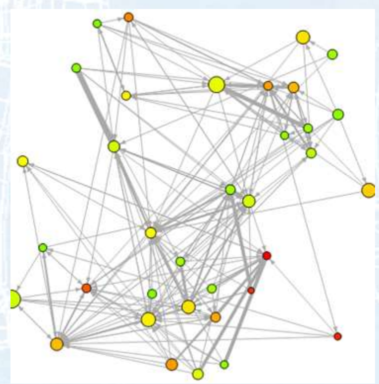

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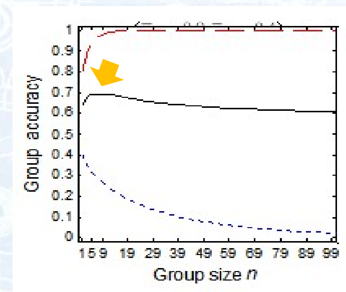

Revise

Representing social environments

with Henrik Olsson & Joerg Rieskamp

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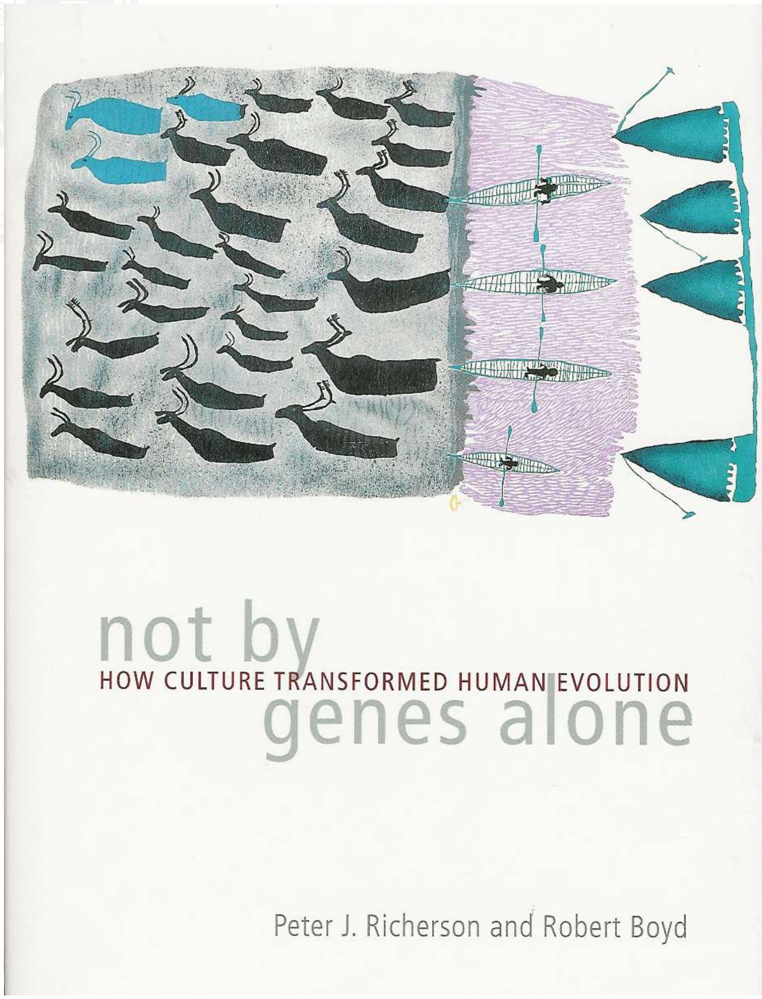
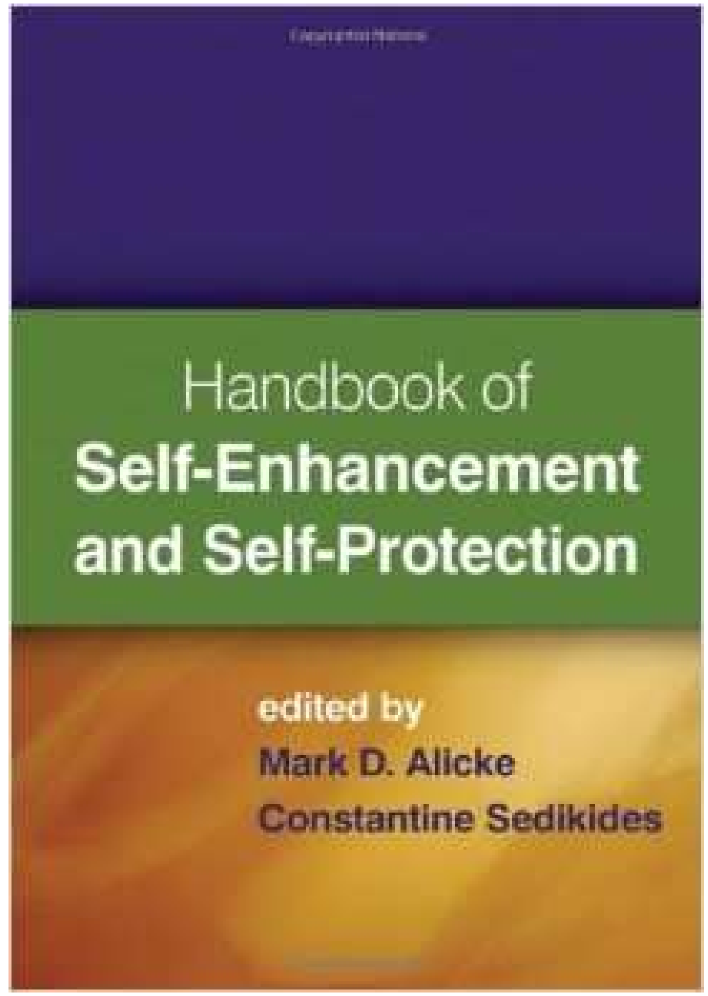
Source: http://www.foxnews.com/tech/2011/08/18/unsocial-networking-is-facebook-blocking-google-links/#ixzz2ZzmAnbIa

Different views of human social cognition





Biases, biases …

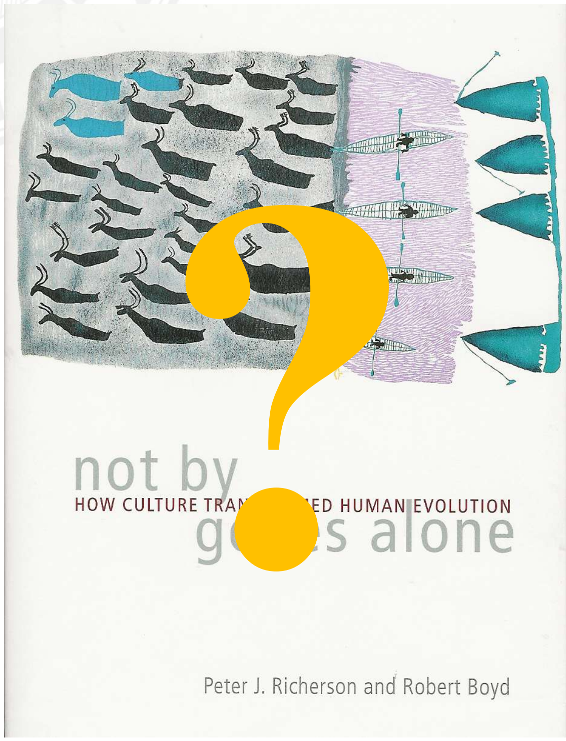


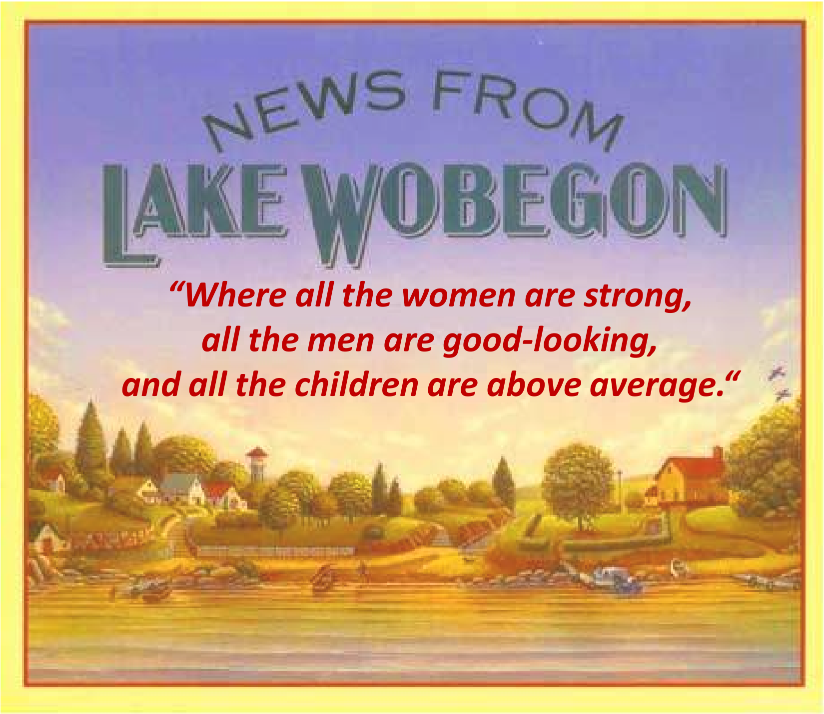
Table 1. *Some errors of judgment identified and labeled by social psychologists*

Overconfidence bias	Correspondence bias
Fundamental attribution error	Halo effect
False consensus effect	False uniqueness effect
Positivity bias	Negativity bias
Confirmation bias	Disconfirmation bias
Justice bias	Male bias
Hot hand fallacy	Gambler's fallacy
Self-protective similarity bias	Hindsight bias
Self-serving bias	"Ultimate" self-serving bias
Optimistic bias	Pessimistic bias
Sinister attribution error	Conjunction fallacy
Ingroup/outgroup bias	Positive outcome bias
Hypothesis-testing bias	Diagnosticity bias
Durability bias	Vulnerability bias
Self-image bias	Labeling bias
Observer bias	External agency illusion
Systematic distortion effect	Intensity bias
Asymmetric insight illusion	Just world bias
Dispositional bias	Romantic bias
Clouded judgment effect	Bias blind spot
Empathy neglect	Empathy gaps

Note: Partial list of major topics of studies published since 1985.

Krueger & Funder, 2004,
Behavioral and Brain Sciences.

Representing social enviornments: Self-enhancement



"Among the most robust and widely replicated phenomena from the literature on social comparative judgments"

(Chambers & Windschitl, 2004; also Alicke & Govorun, 2005; Roese & Olson, 2007).

Self enhancement: Typical finding

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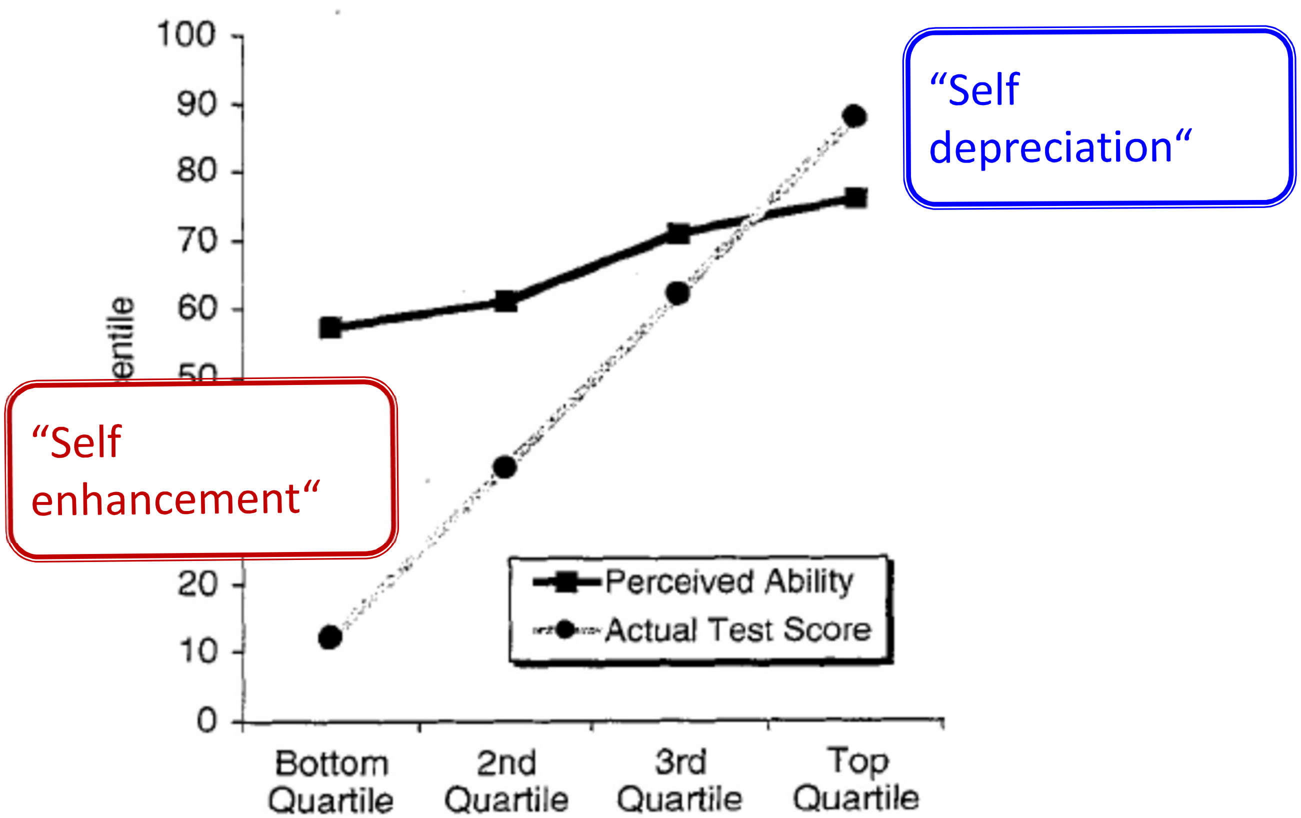
“Compare your ability [in this test] *with an average student.”*



Kruger & Dunning, 1999

“Unskilled and unaware of it“

Some explanations for self-enhancement

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- Motivational bias (Alicke, Klotz, Breitenbecher, Yurak, & Vredenburg, 1995)
- Cognitive incompetence (Kruger & Dunning, 1999)

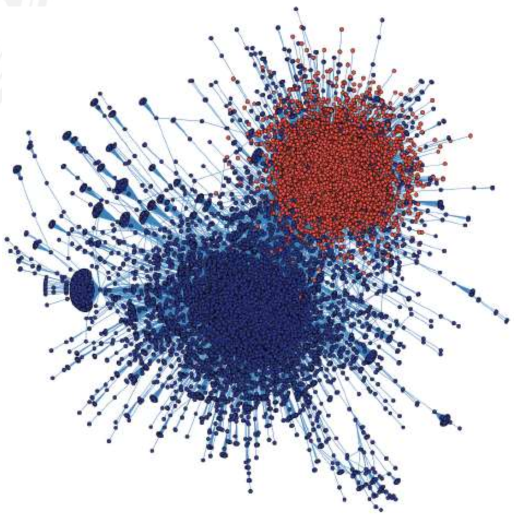
→ Cannot explain self depreciation
  - Other biases needed to invoked to explain it

→ Inappropriate benchmarks
  - *“average student” = “other participants in the study”*

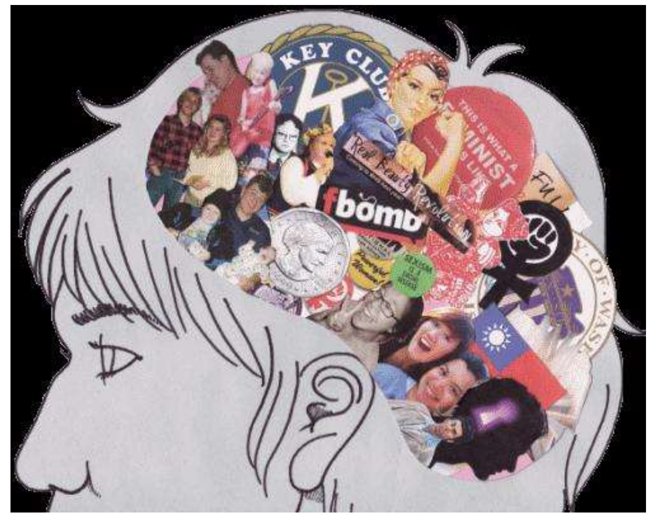
→ Unrealistic normative expectations
  - Assume that people should have good knowledge of distant social environments

Social sampling model

Social networks



Social-cognitive algorithm

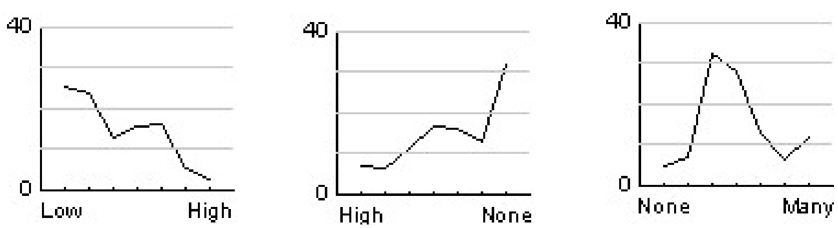


Task properties

J-left: Household wealth

J-right: Frequency of work stress

Symmetrical: Number of friends



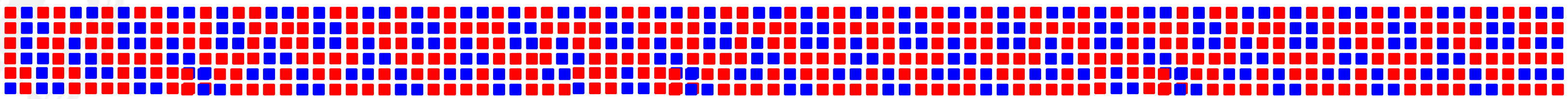
Social sampling model: Algorithm

"What % of group X has a certain characteristic?"

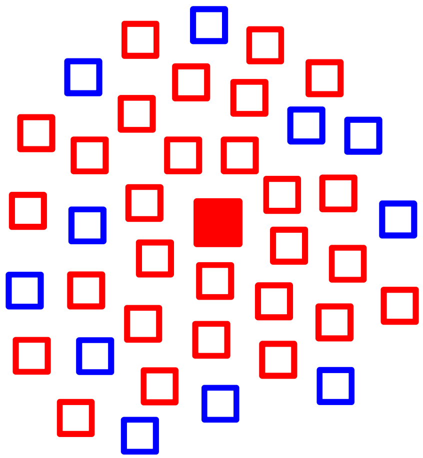
A. Recall own social contacts that are similar to group X
B. Recall those among them who have the characteristic
C. Estimate B/A

Social sampling model: Social networks

Whole society:



Social contacts of a red person:



Example

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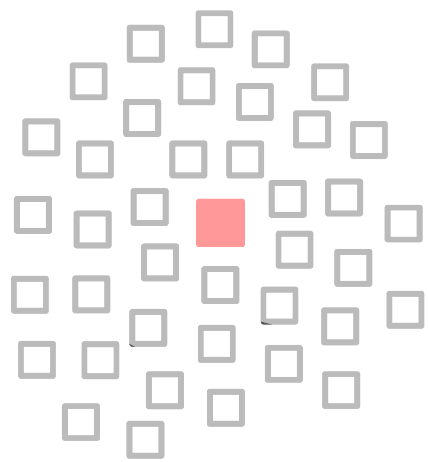
„What % of the general population are red?“

A. Recall ρ social contacts most similar to general population (→ Sample)
B. Recall those who are red (with probability α)



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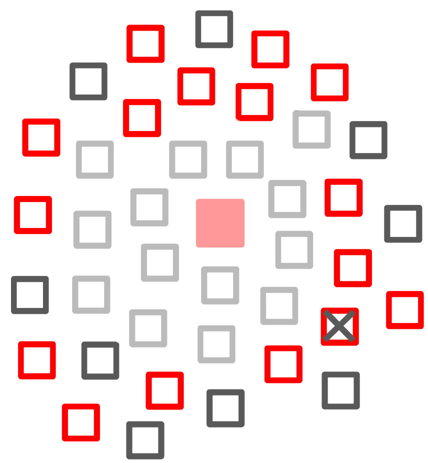

C. Estimate answer: Reds / Sample → 15 / 25 = 60%

Algorithm: formal implementation

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Probability of recall of instance i

Sum over all n instances in one's social circle

Activation due to category membership:
$A_{Ci} = 1$ if $i \in C$,
$A_{Ci} = 0$ otherwise

$$\text{Population estimate } p(C|R) = \frac{\sum_{i=1}^{n} \alpha \times A_{Ci} \times A_{Ri}}{\sum_{i=1}^{n} A_{Ri}}$$

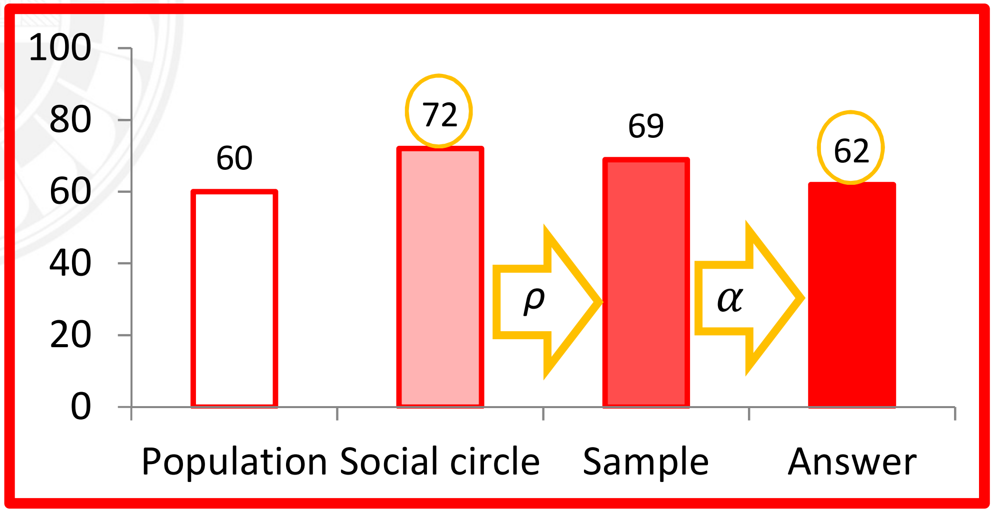
Characteristic C (e.g., red)

Reference class R (e.g., general population)

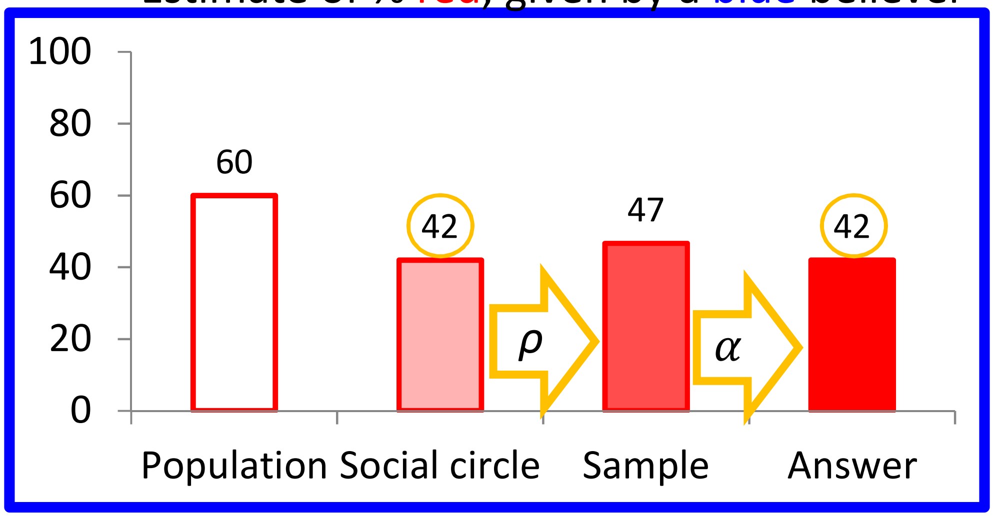
Activation due to belonging to reference class:
$A_{Ri} = 1$ if similarity rank $< \rho$
$A_{Ri} = 0$ otherwise

Tasks with 2 categories

Estimate of % red, given by a red believer



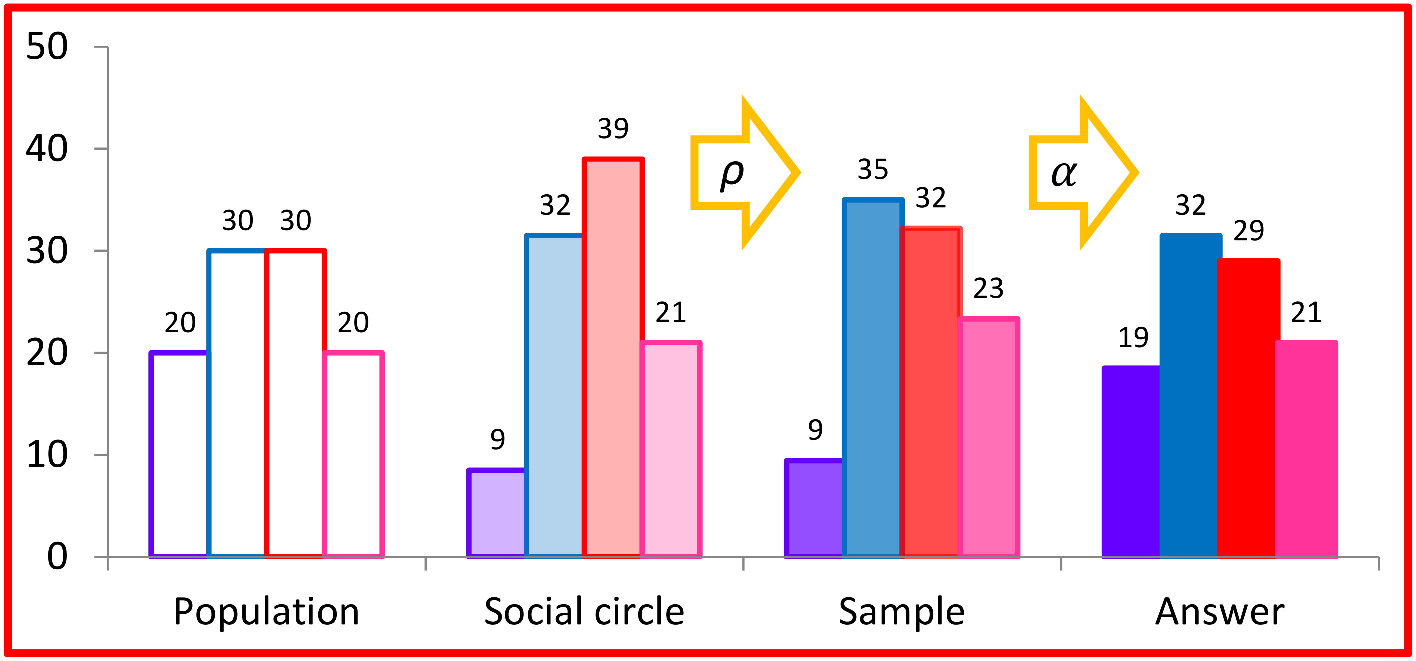
Estimate of % red, given by a blue believer



$\rho = .9,\ \alpha = .9$

Tasks with more than 2 categories

Estimate of % pink, red, violet, and blue, given by a red person



$\rho = .9$, $\alpha = .9$

Testing process assumptions of SSM

Empirical test

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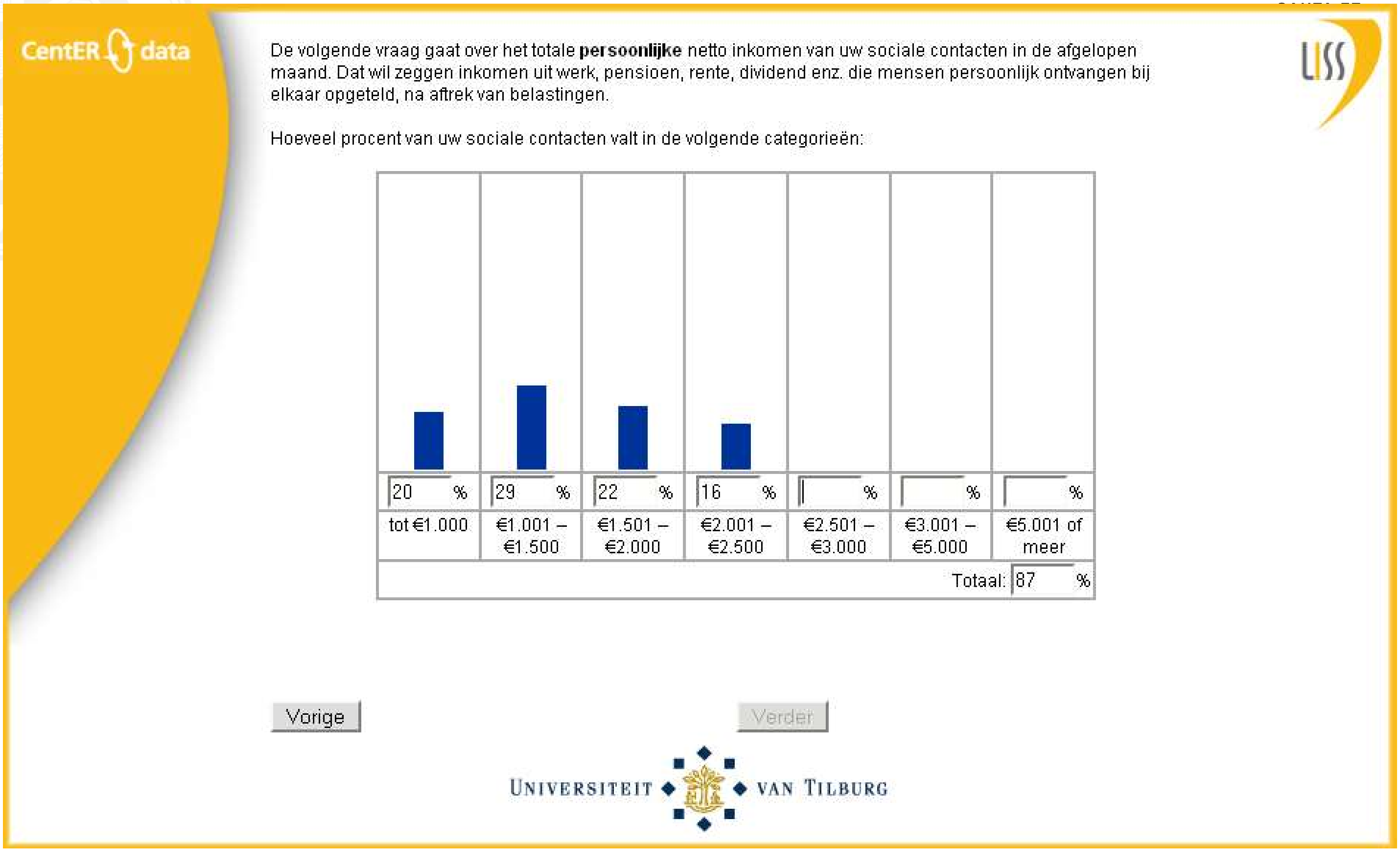
- Probabilistic national sample, n=1400+ Dutch people
- Questionnaire:

1. Own characteristics
   - income, health, partner conflicts, work stress, friends, education
     → actual population distributions (benchmark)
2. Estimates of social circles
   - % of one's *social circle* that belongs into each category

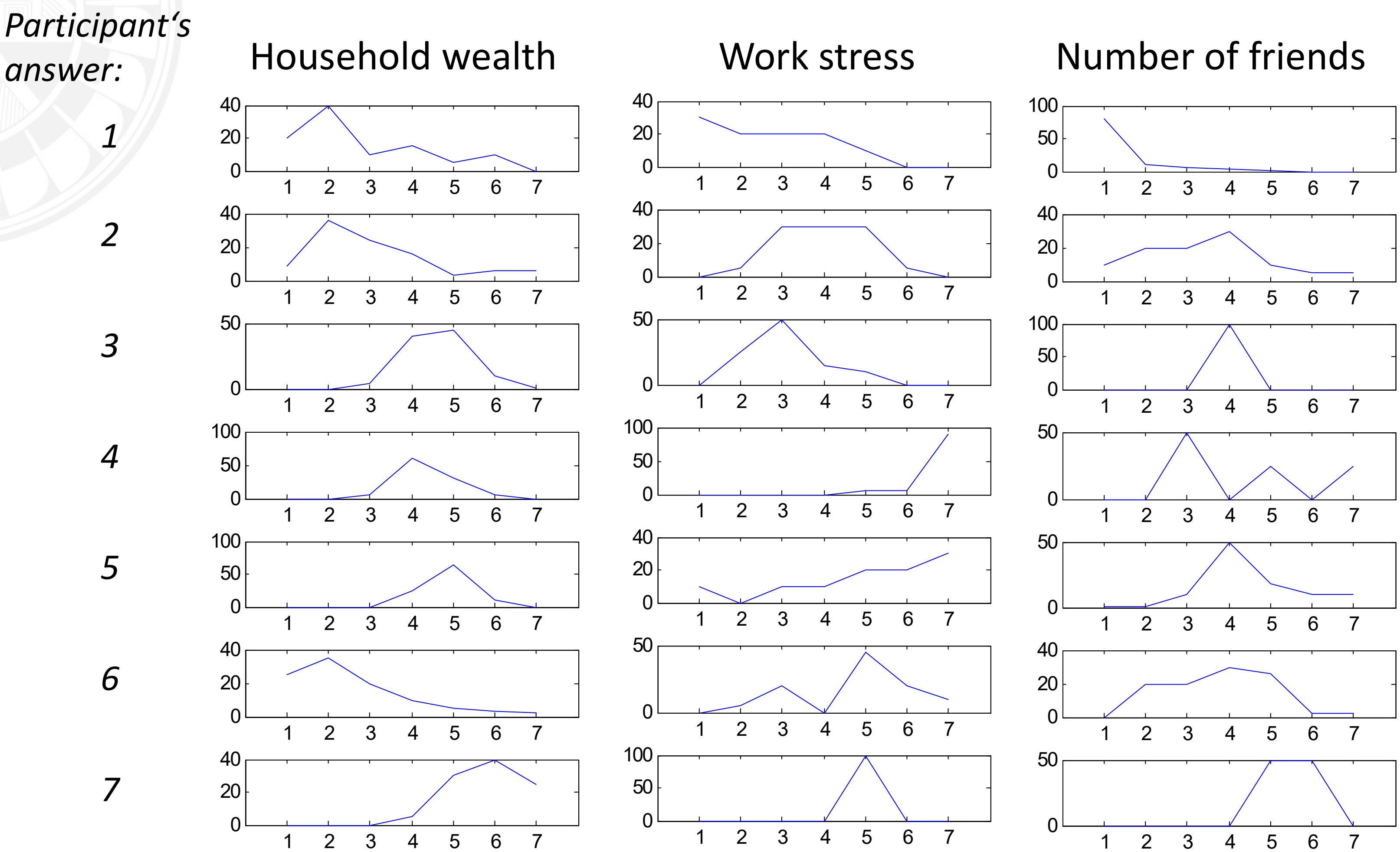
"All adults you were in personal, face-to-face contact with at least twice this year ... your friends, family, colleagues, and other acquaintances."

3. Estimates of general population
   - % of Dutch population in each category

Example question: Personal income

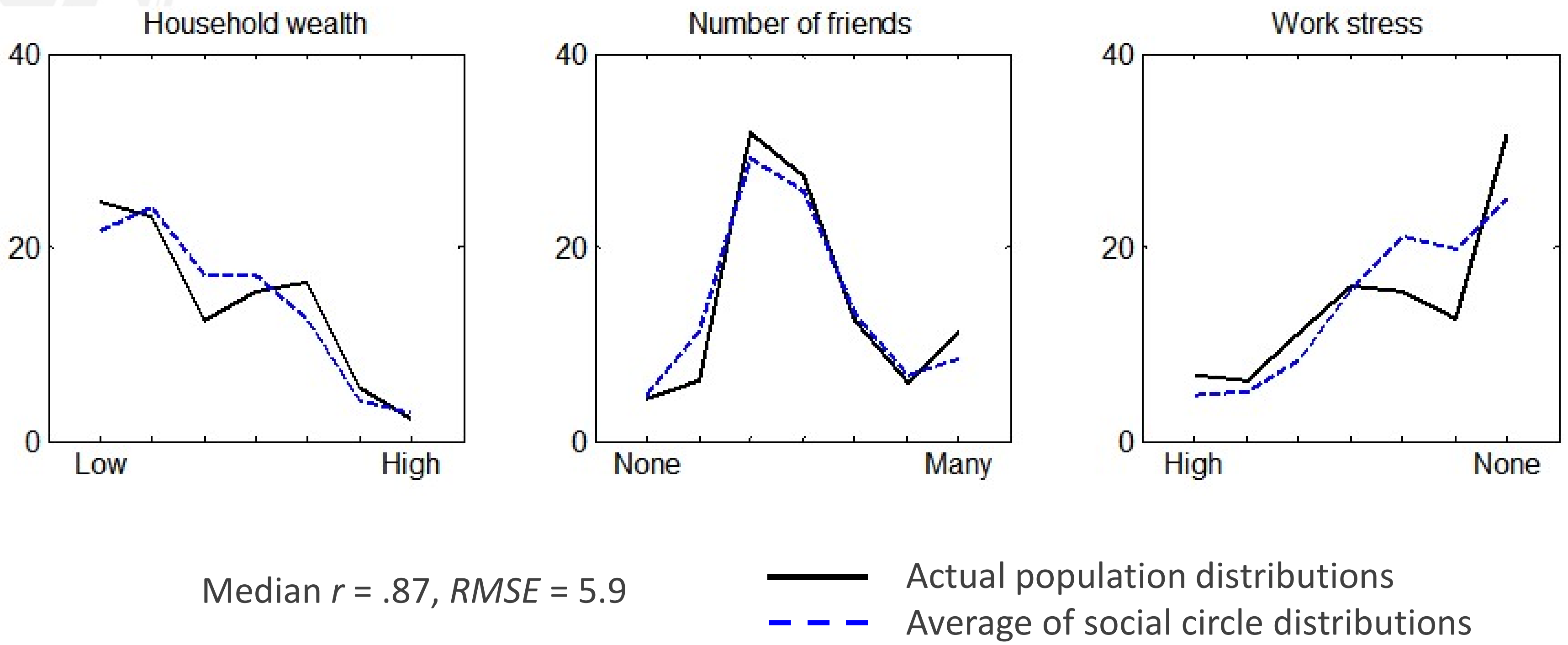


Examples of social circle distributions



Netherlands, n=1416

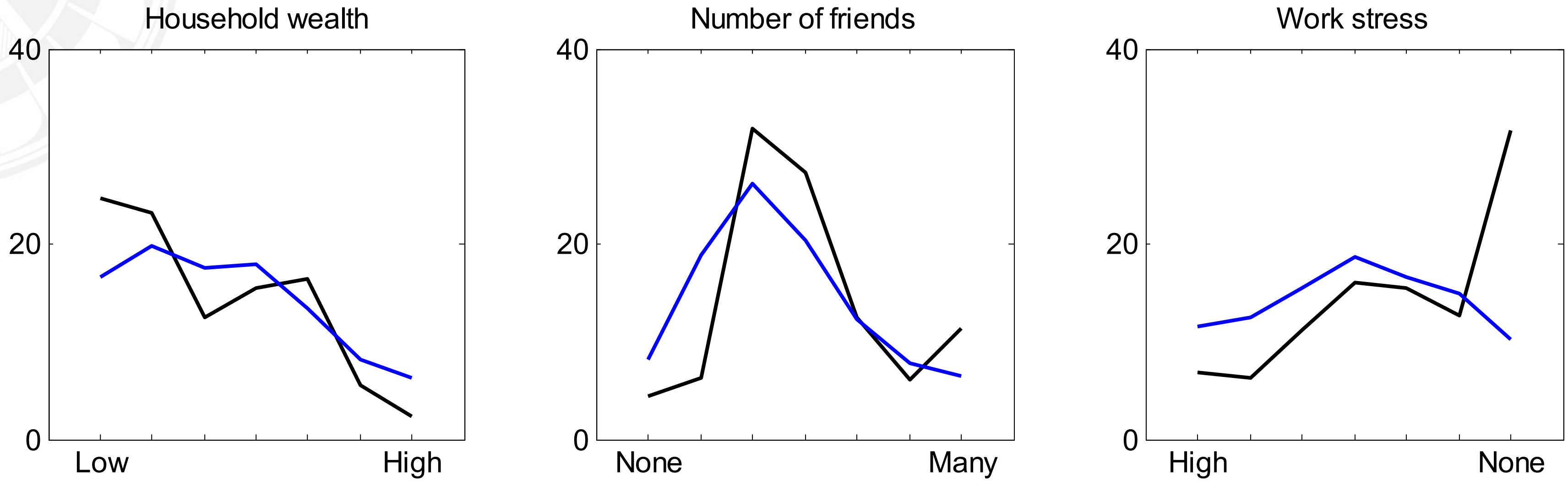
People know their social circles well



Median r = .87, $RMSE$ = 5.9

Netherlands, n=1416

But they know general population less well



Median r = .57, *RMSE* = 8.9

Actual population distributions
Estimated population distributions

Netherlands, n=1416

Population distribution determines apparent biases

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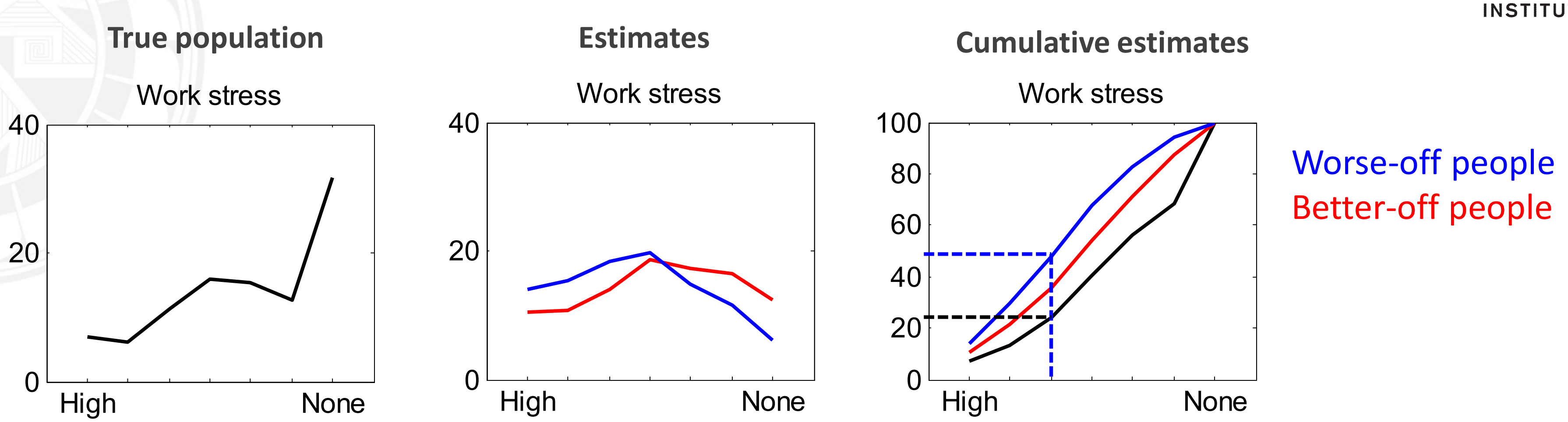


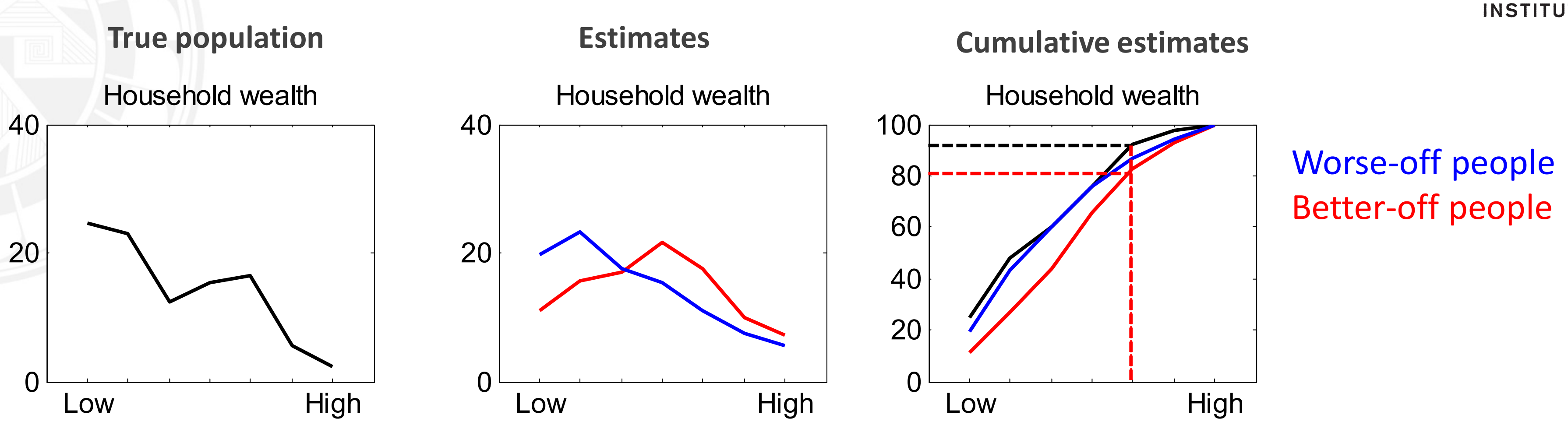
J-right shape

Apparent self-enhancement

- own position appears better than it really is
- more so for worse-off people.

Netherlands, n=1416

Population distribution determines apparent biases



J-left shape

Apparent self-depreciation

- own position appears worse than it really is
- more so for better-off people.

Netherlands, n=1416

Population distribution determines apparent biases

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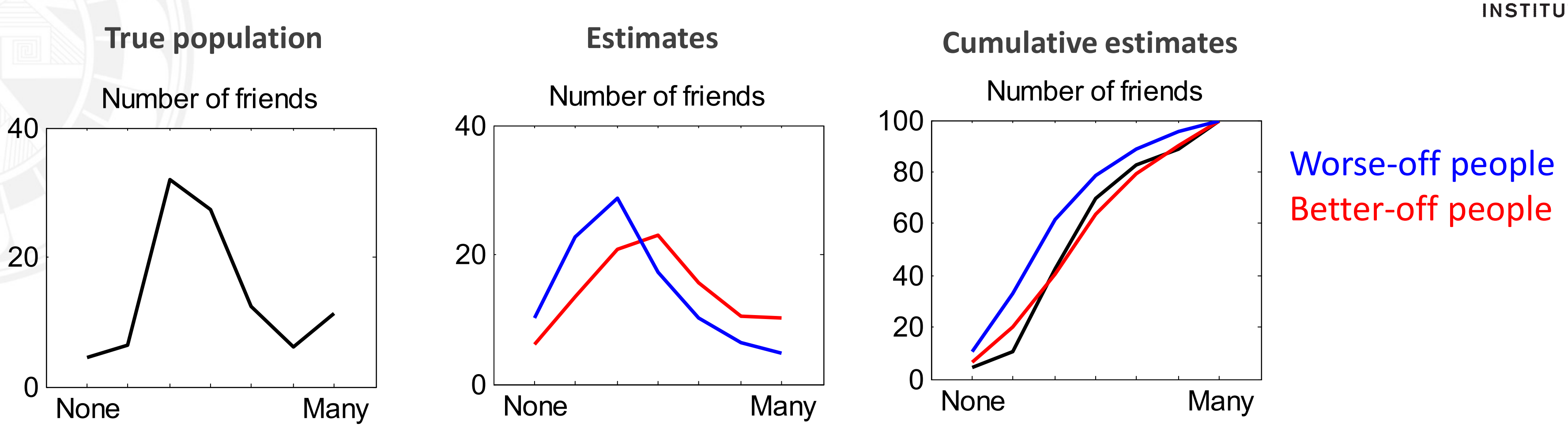


Symmetric shape

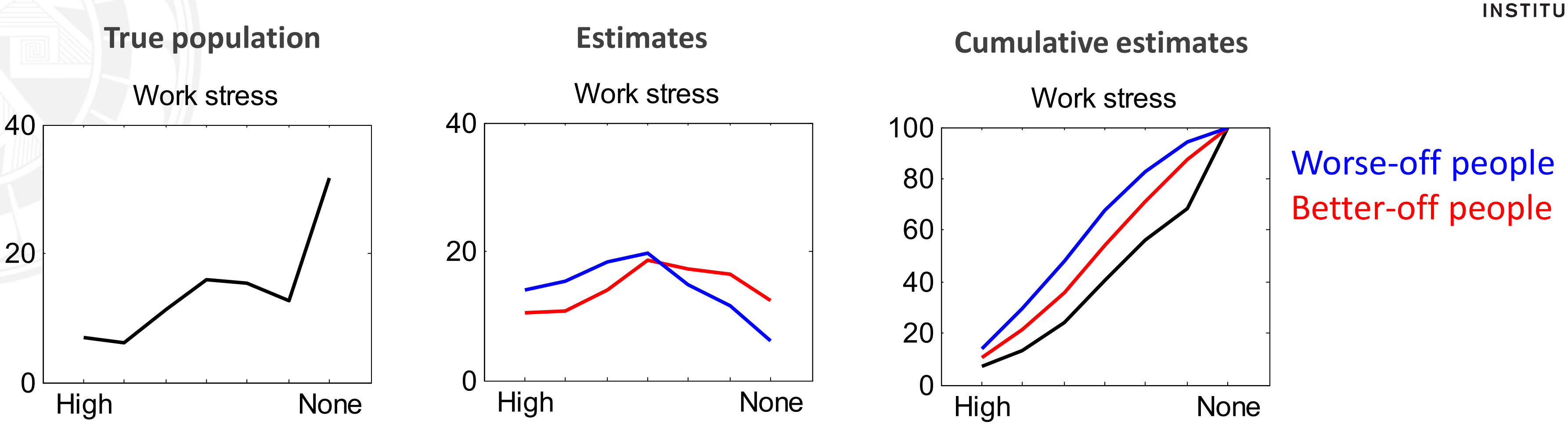
Both apparent biases:

- Self-enhancement for worse-off,

  Self-depreciation for better-off people.

Netherlands, n=1416

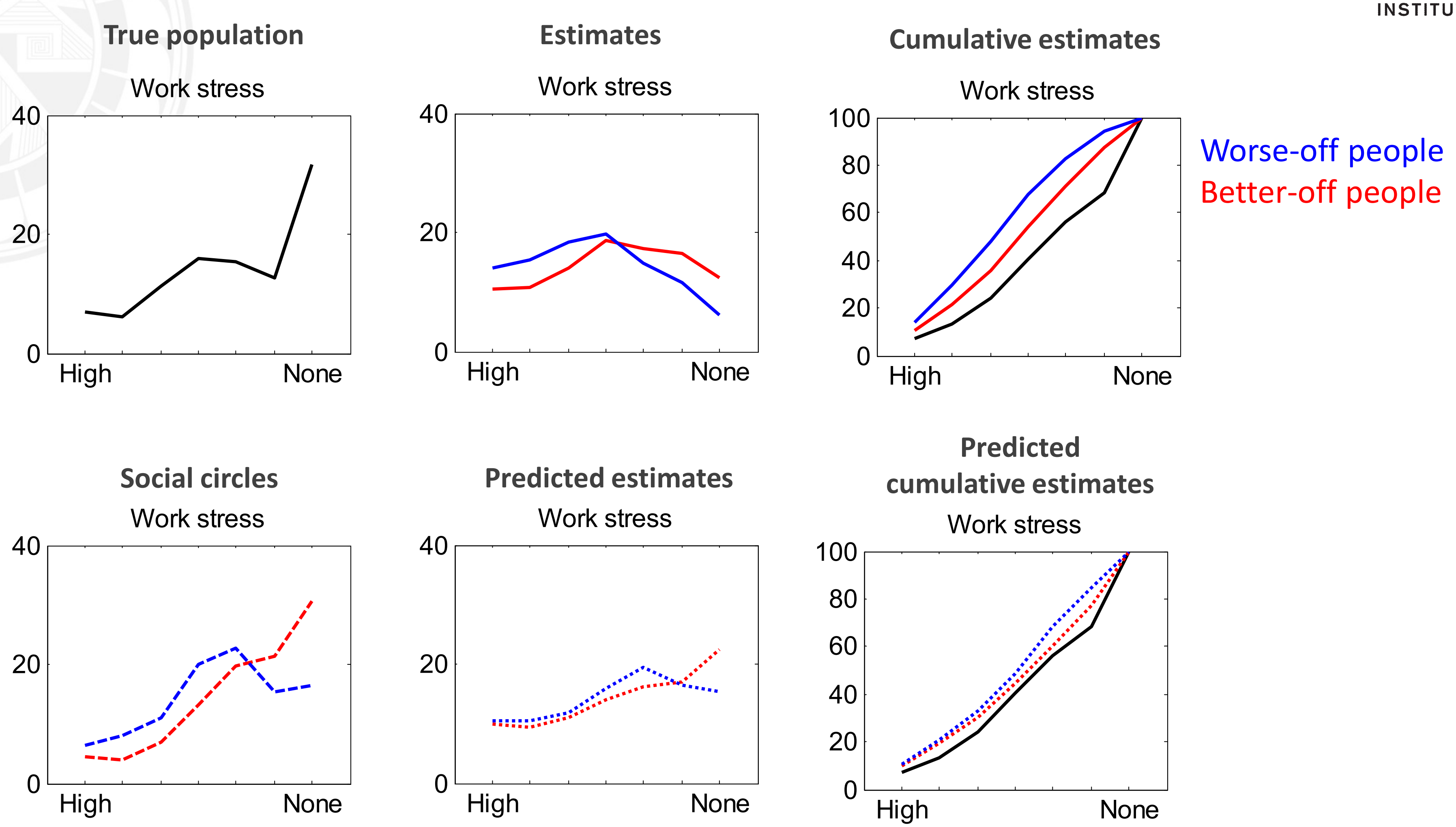
SSM predictions of empirical results



J-right shape → **Apparent self-enhancement**

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results



Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

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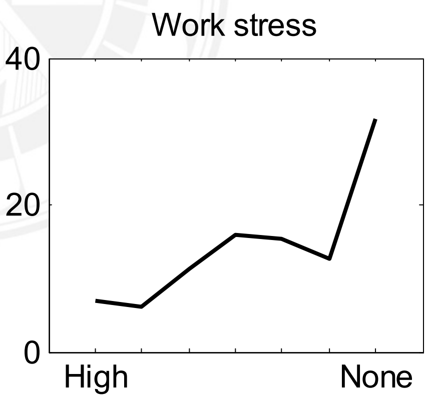
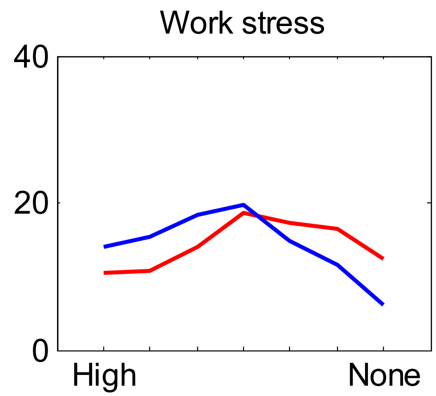
SSM predictions of empirical results

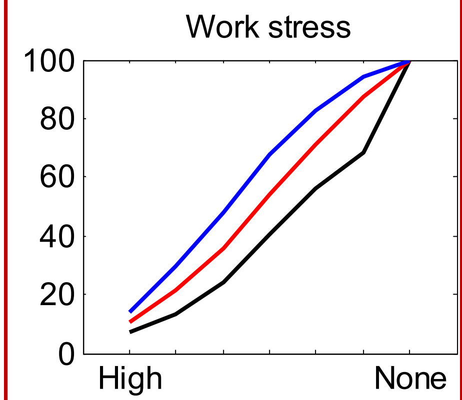
True population



Estimates

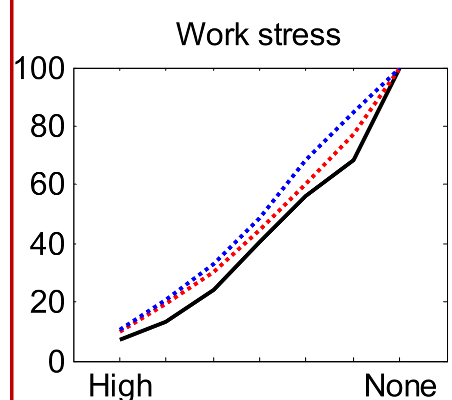


Cumulative estimates



Worse-off people
Better-off people

Predicted cumulative estimates

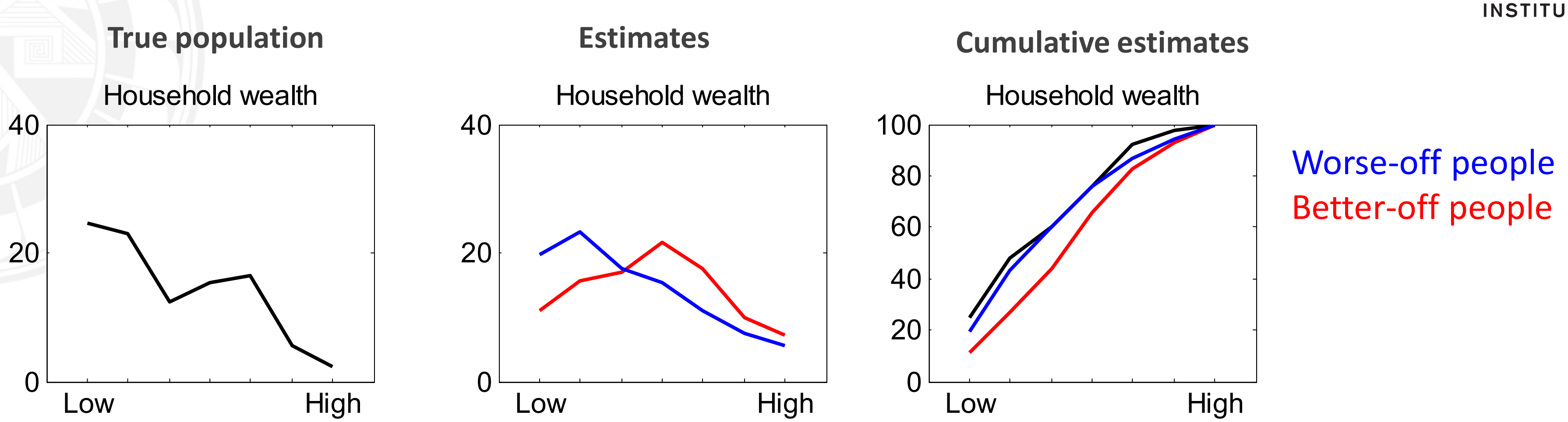


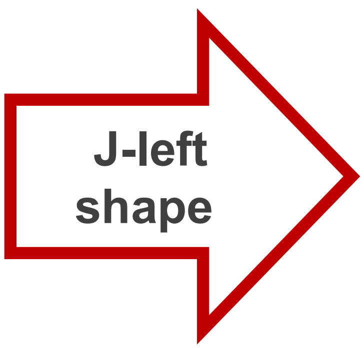
J-right shape

Apparent self-enhancement

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results





Apparent

self-depreciation

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results

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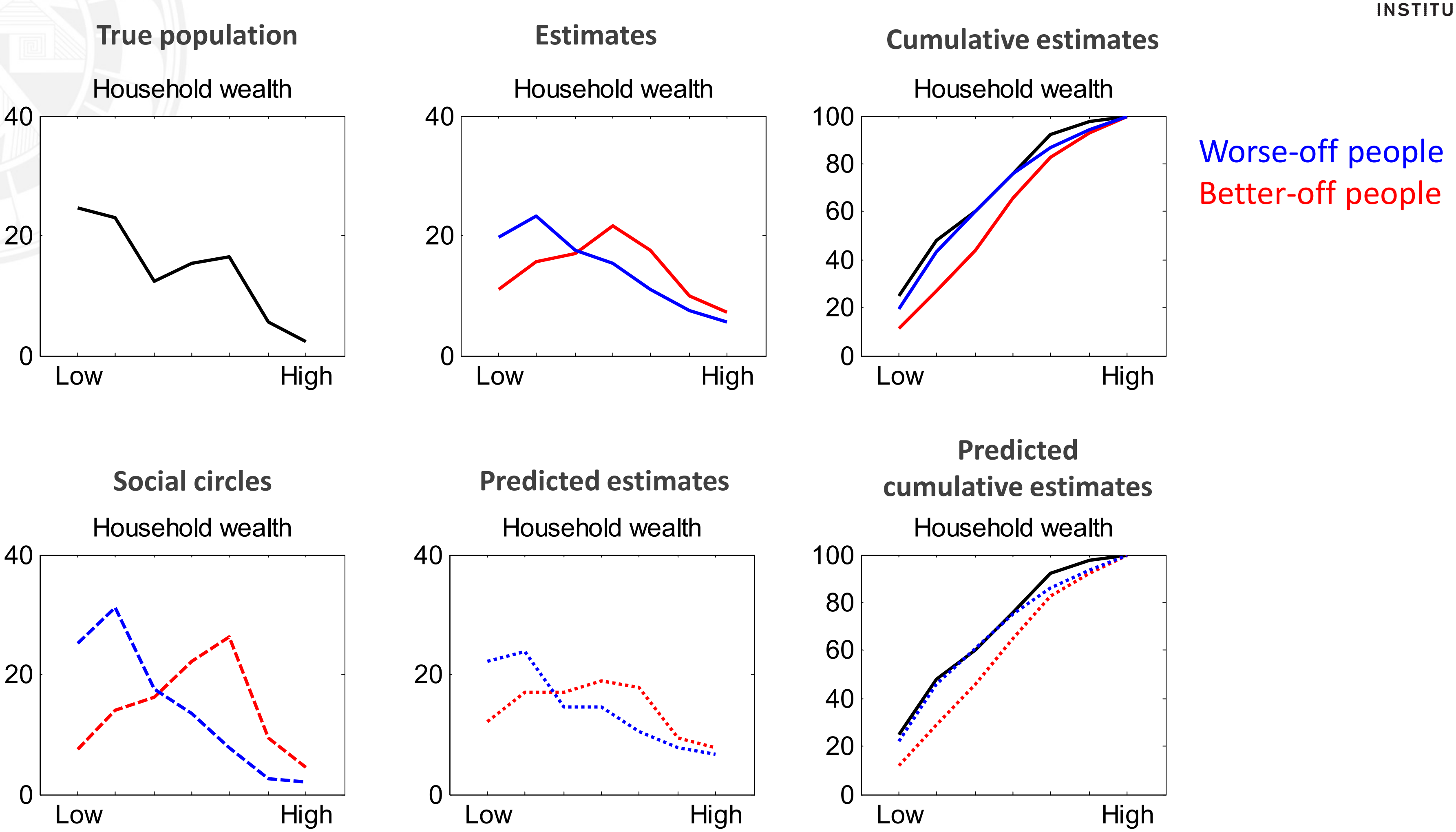

Netherlands, n=1416

$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results

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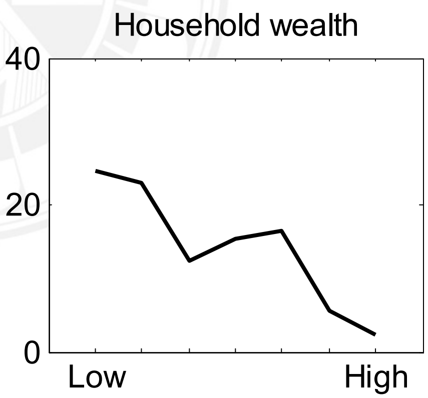
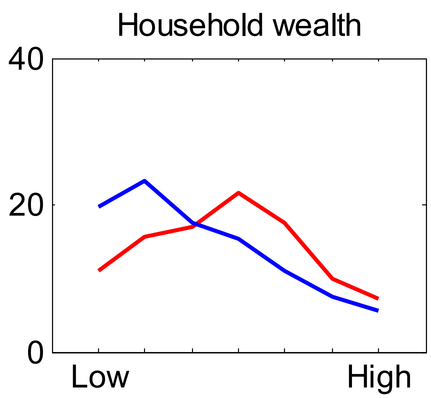
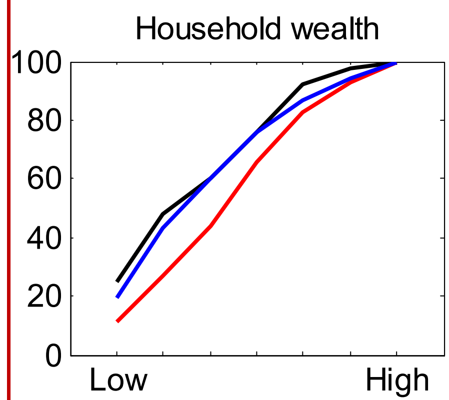
True population



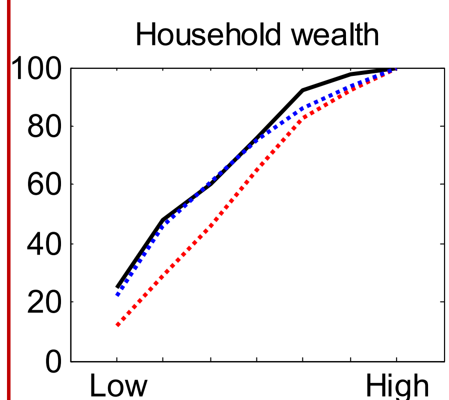
Estimates



Cumulative estimates



Predicted cumulative estimates

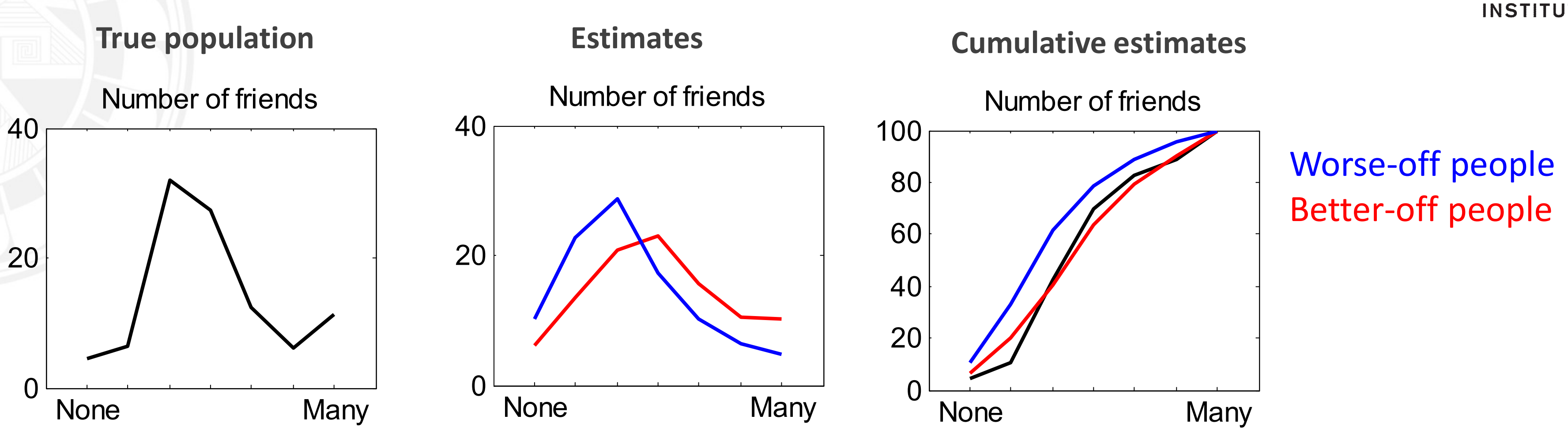


Worse-off people
Better-off people

J-left shape ⇒ **Apparent self-depreciation**

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results



Symmetric shape → **Both apparent biases**

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results

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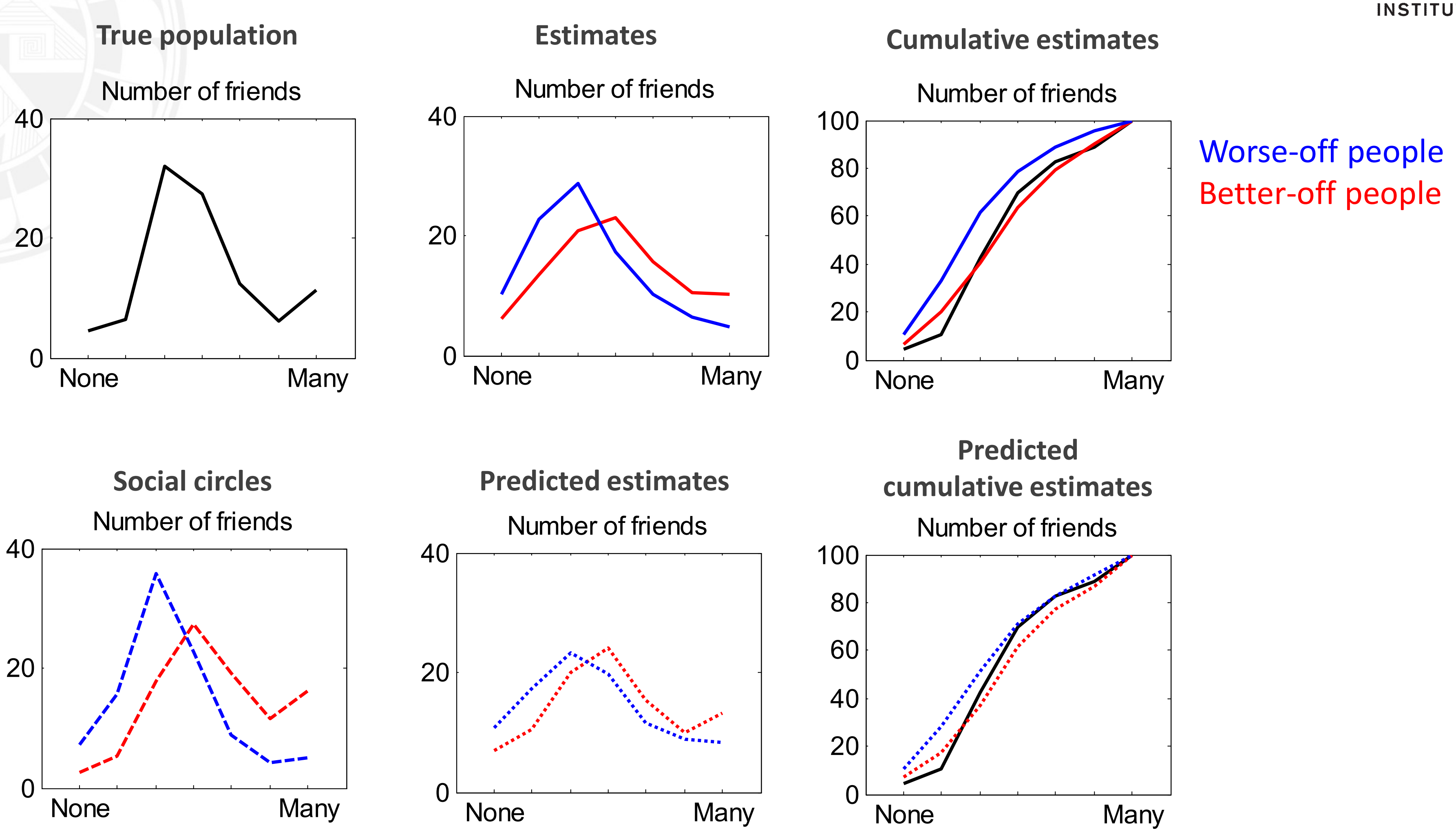
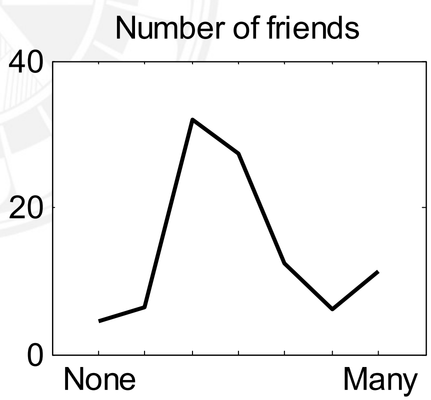


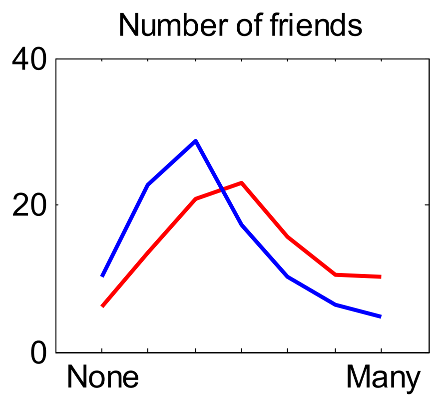
Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

SSM predictions of empirical results

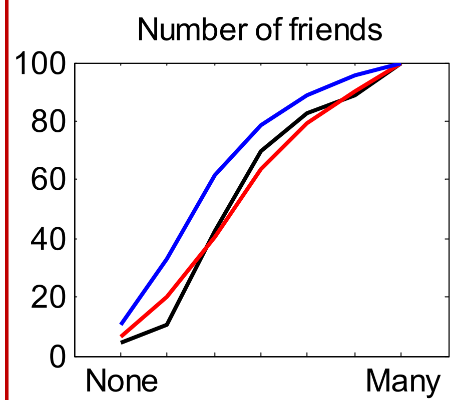
True population



Estimates

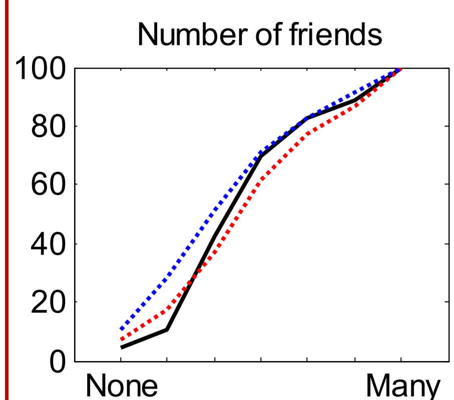


Cumulative estimates



Worse-off people
Better-off people

Predicted cumulative estimates



Symmetric shape

Both apparent biases

Netherlands, n=1416
$\rho = .55$, $\alpha = .47$

Self-enhancement & Self-depreciation - Are they real?

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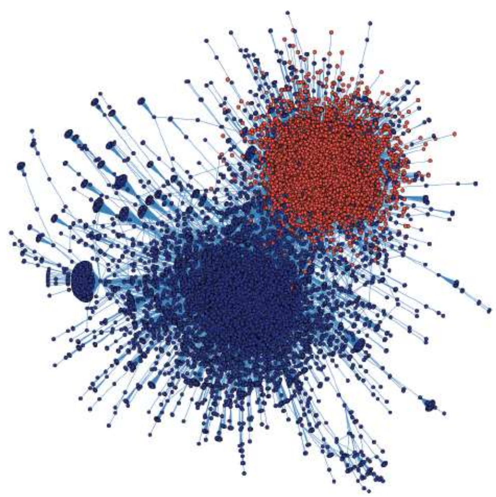
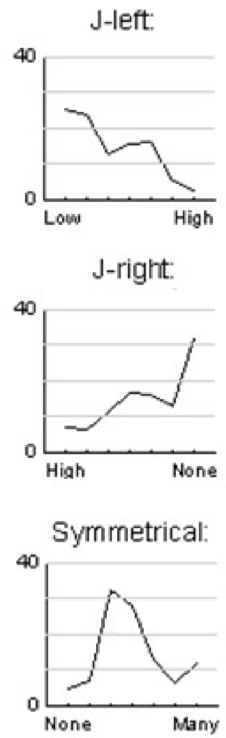
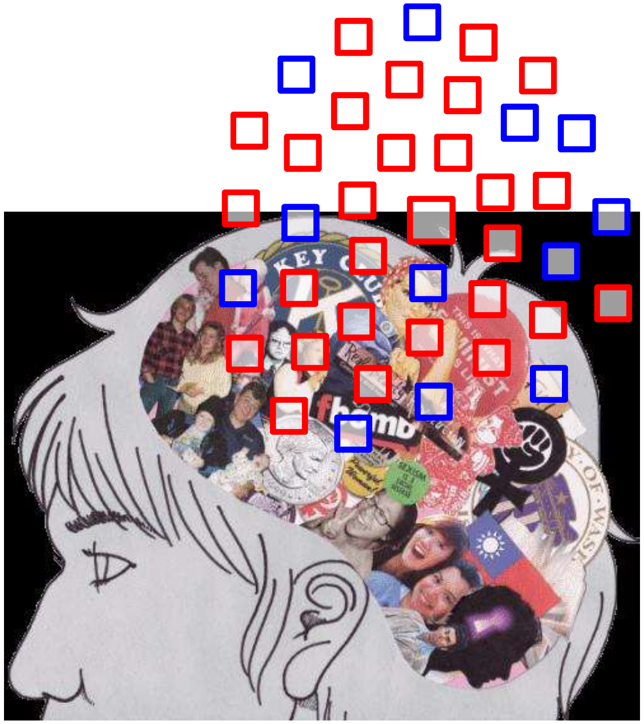
Both apparent biases can be explained as an interplay of a simple social algorithm with social and task environments







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Representing social enviornments: False consensus

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"What % of your peers would carry the sign?"

- Those who would carry: 58%
- Those who would not carry: 30%

Ross, Greene, & House, 1977

Some explanations of False consensus

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- Selective exposure – biased samples
- Salience of own view
- Improving self esteem (Marks & Miller, 1987)
- Bayesian judgment assuming uniform prior and one's own view as the only evidence (Dawes & Mulford, 1996)

→ Cannot explain False uniqueness

Study: US and Germany

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- Answer 10 questions
  - Donating to charity
  - Not having enough money to buy food
  - Being victim of theft
  - Smoking any tobacco products every day
  - Believing in God
  - Belief in God is necessary to be moral
  - Attending place of worship
  - Religion important in daily life
  - Military actions are sometimes necessary
  - Homosexuality should not be accepted by society
- Estimate % of endorsers in social circle
- Estimate % of endorsers in general population

Results: Size of False consensus (uniqueness)

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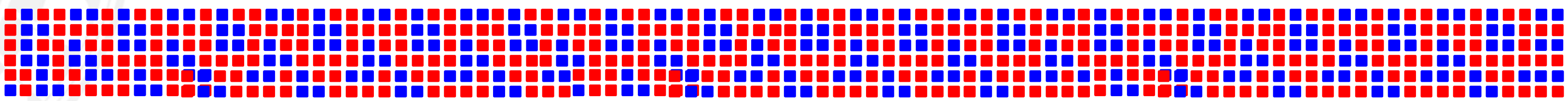
	Size of False consensus
Gay not ok	13
Worship attendance	10
Military force ok	10
Charity donation	9
No money for food	6
Morality needs belief	1
Theft experience	-3
Smoking	-5
Religion importance	-6
Belief in god	-7

US, *n* = 50

Example

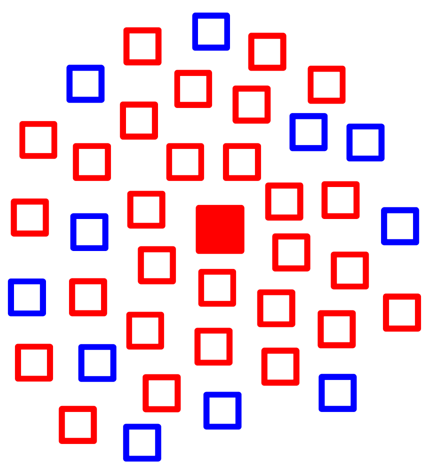
Whole society:



60:40

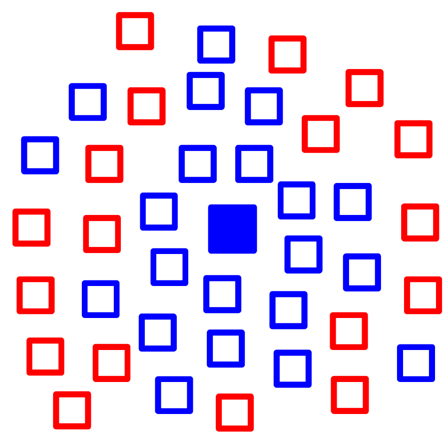
Social contacts – influenced by homophily:

Red person



72:28

Blue person



42:58

Example

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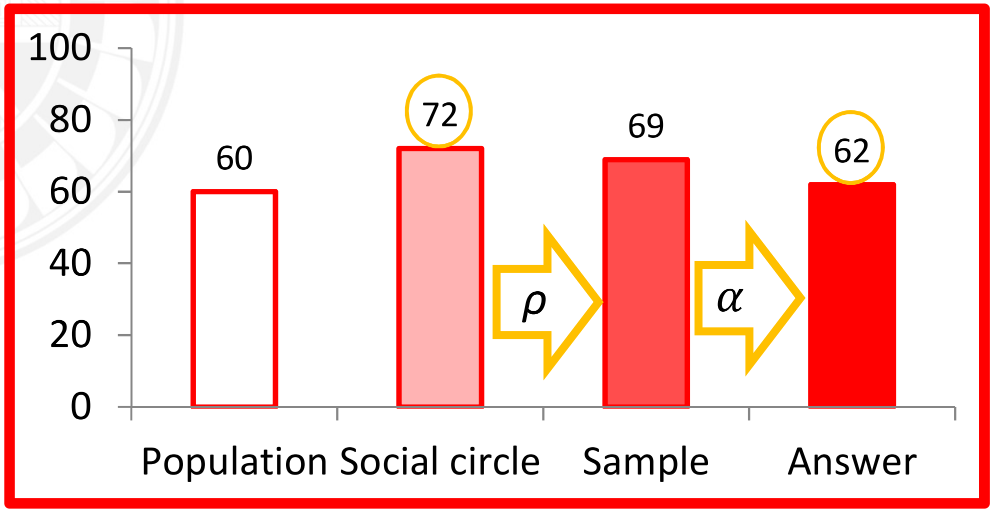
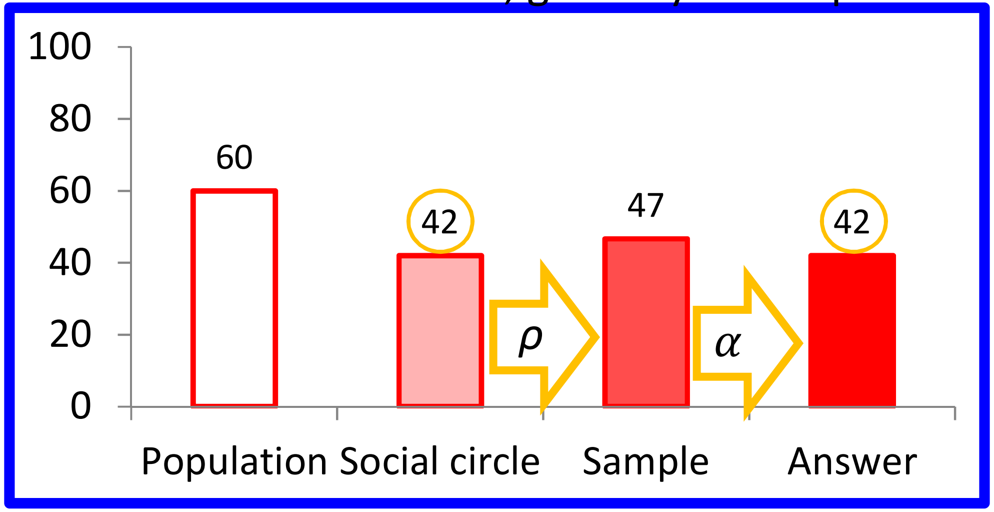
Estimate of % red, given by a red person



Estimate of % red, given by a blue person



$\rho = .9,\ \alpha = .9$

Example

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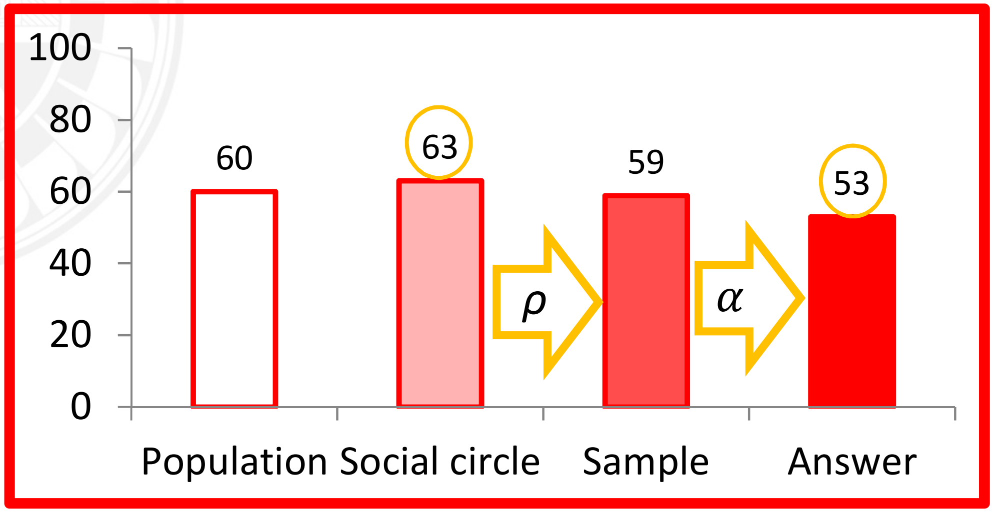
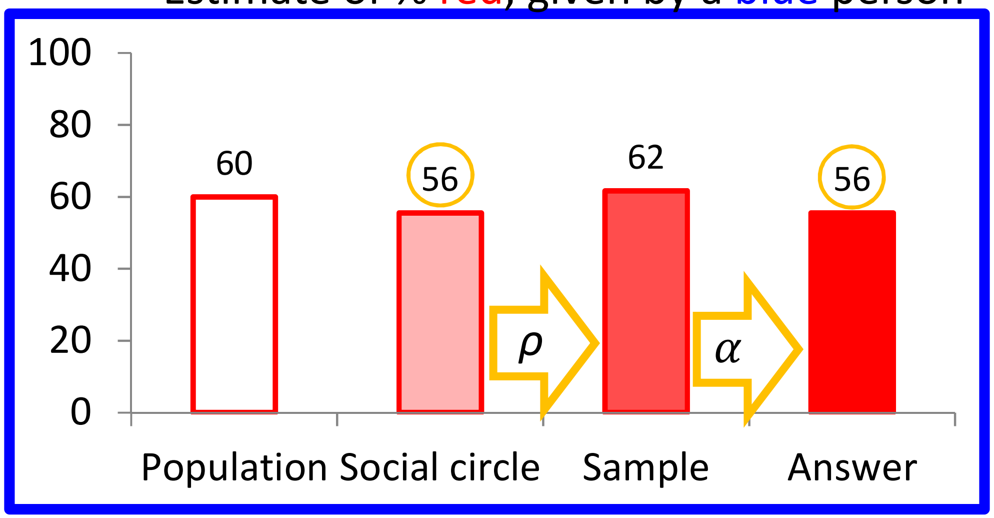
Estimate of % red, given by a red person



"False uniqueness"

Estimate of % red, given by a blue person



$\rho = .9, \alpha = .9$

Predictions of empirical results

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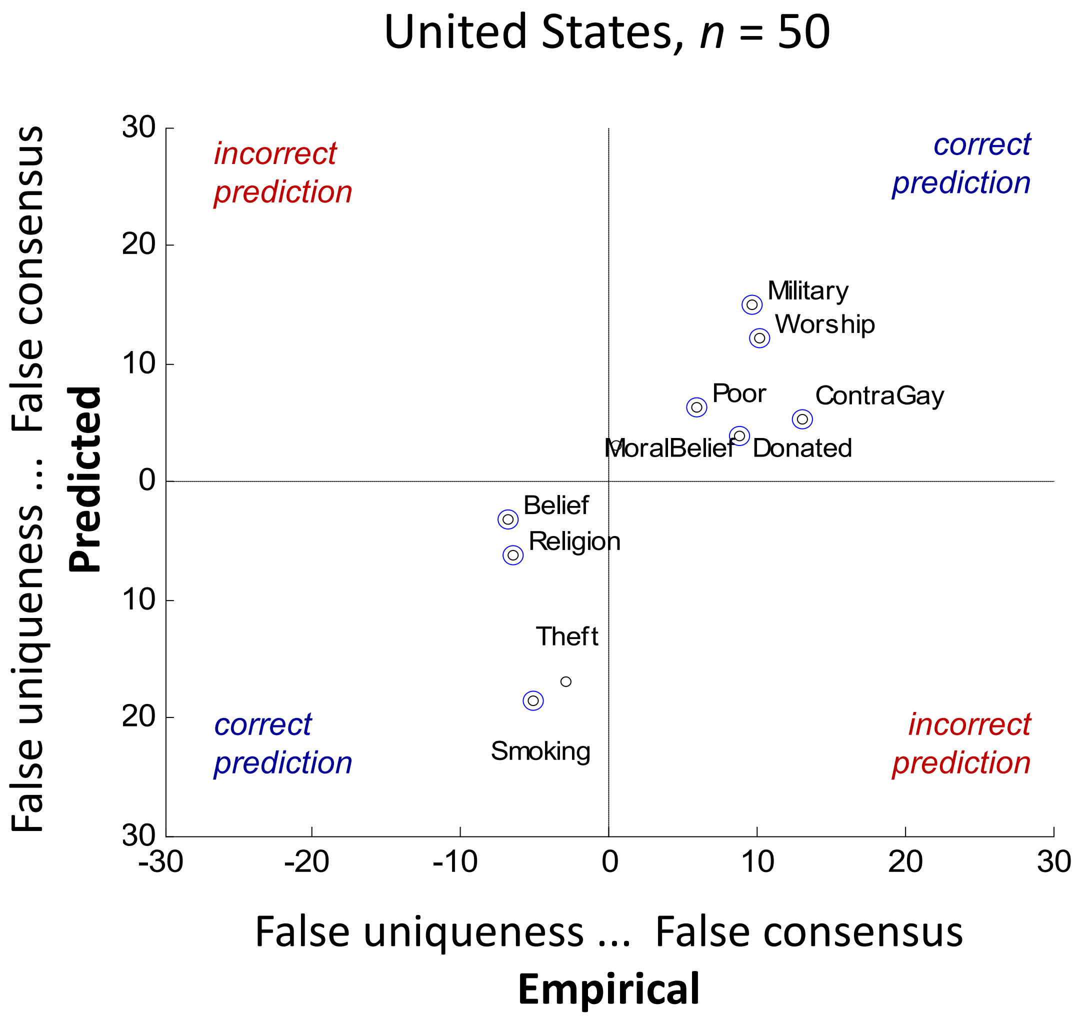
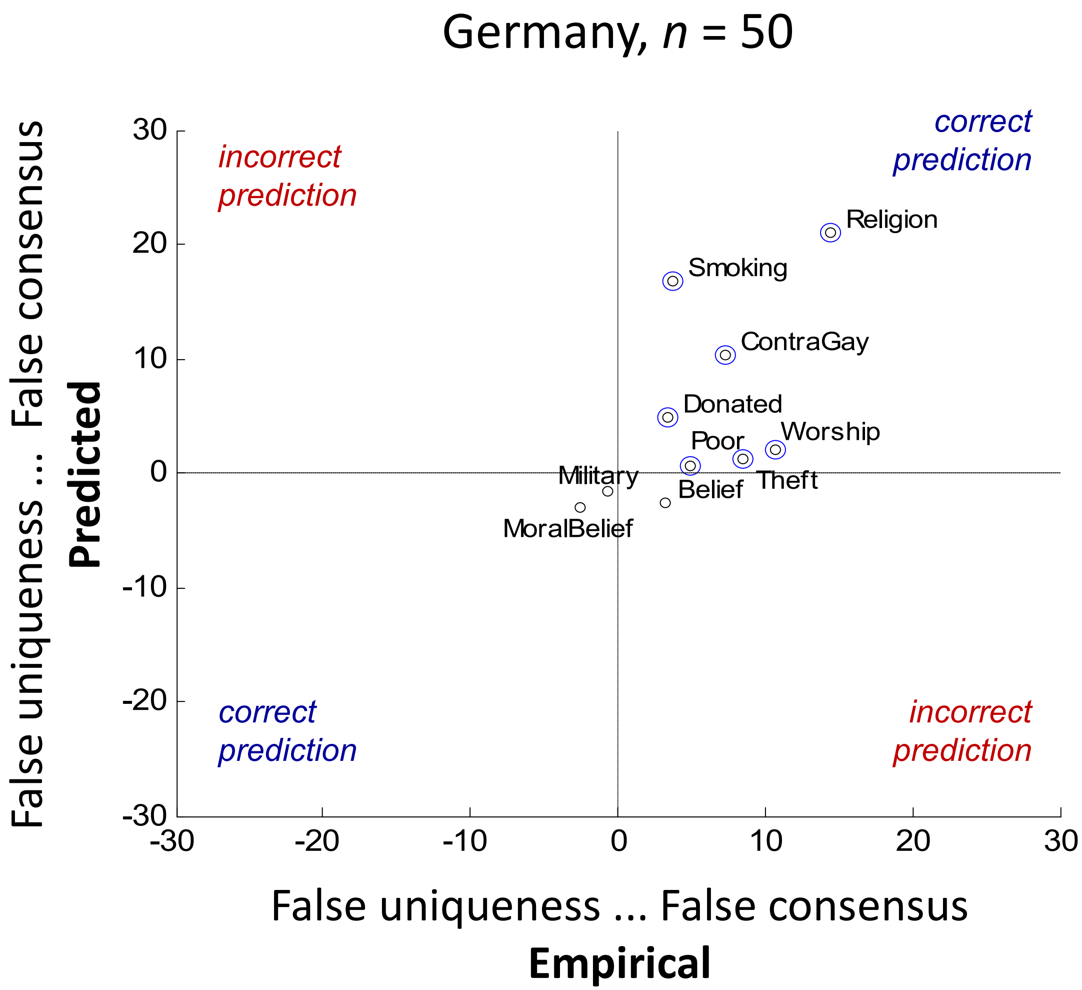


$\rho = .77$, $\alpha = .86$

Predictions of empirical results



$\rho = .81$, $\alpha = .87$

Homophily and „biases“

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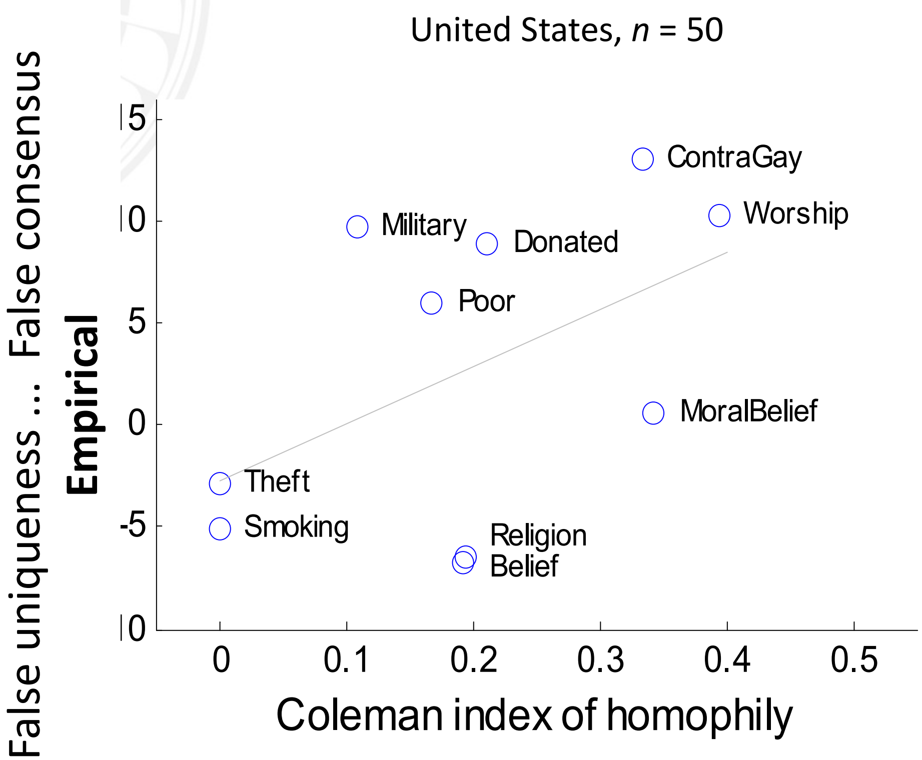
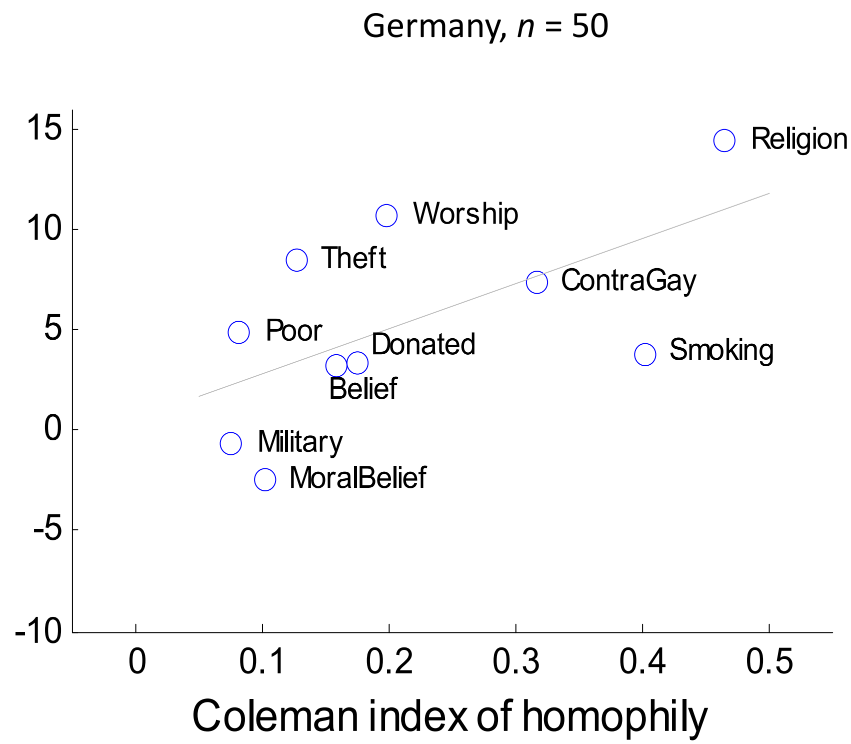




r = .50

r = .61

And more: Effects of response format

When asked…

"Within the past 12 months, have you had money or property stolen from you or another household member?"

Response format 1:

… what percentage of adults living in the United States would answer "Yes"? ☐ %

Question about performers

Response format 2:

… what percentage of adults living in the United States would answer "No"? ☐ %

Question about non-performers

Response format 3:

… what percentage of adults living in the United States would answer…

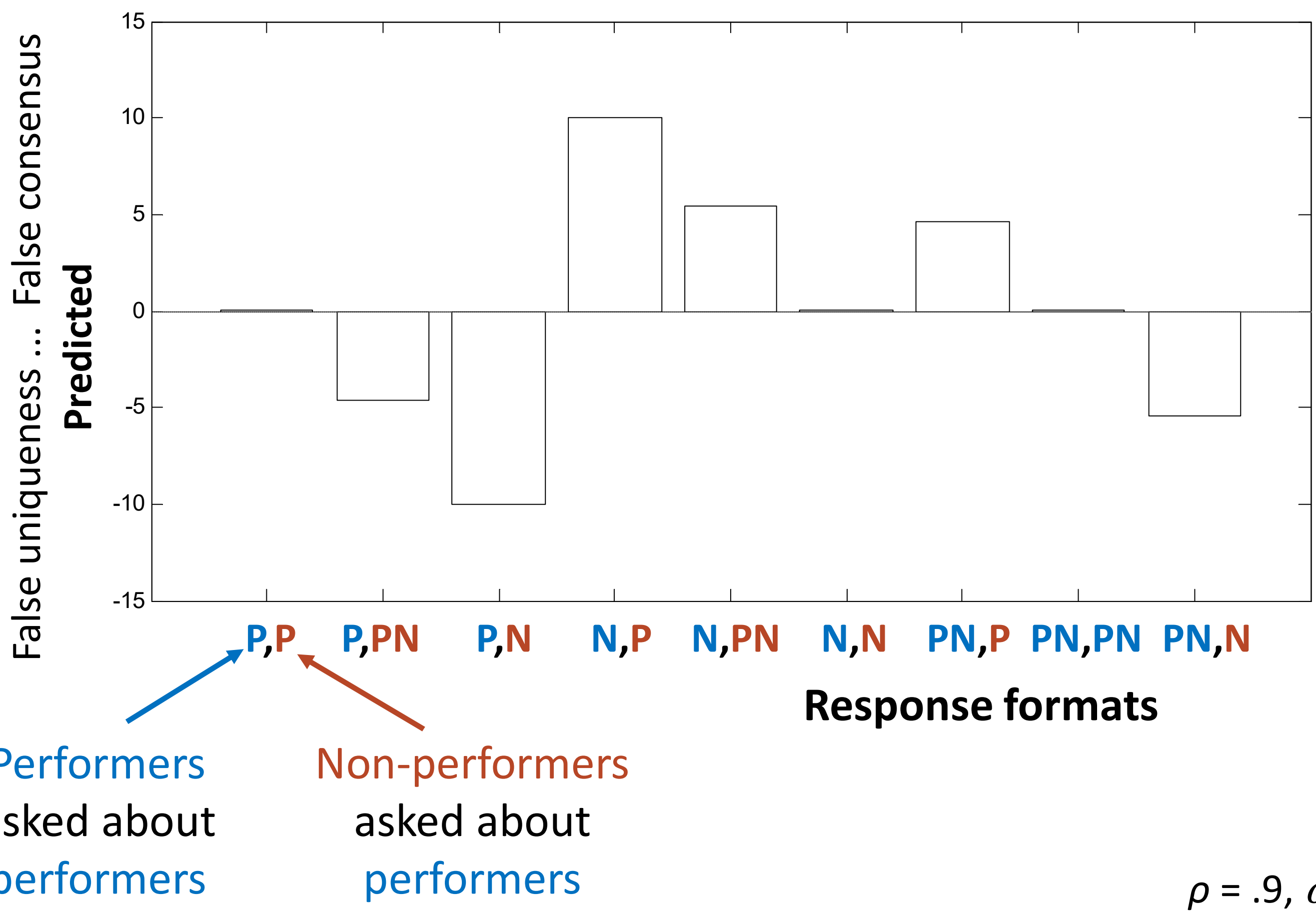
"No"? ☐ % **"Yes"?** ☐ %

Question about both performers and non-performers

→ Imperfect recall of the category one is asked about (parameter α in SSM) could produce both apparent false consensus and false uniqueness effects

Effects of response format

SSM predictions of false consensus for different response formats
(fictitious data – no homophily)



ρ = .9, α = .9

Effects of response format

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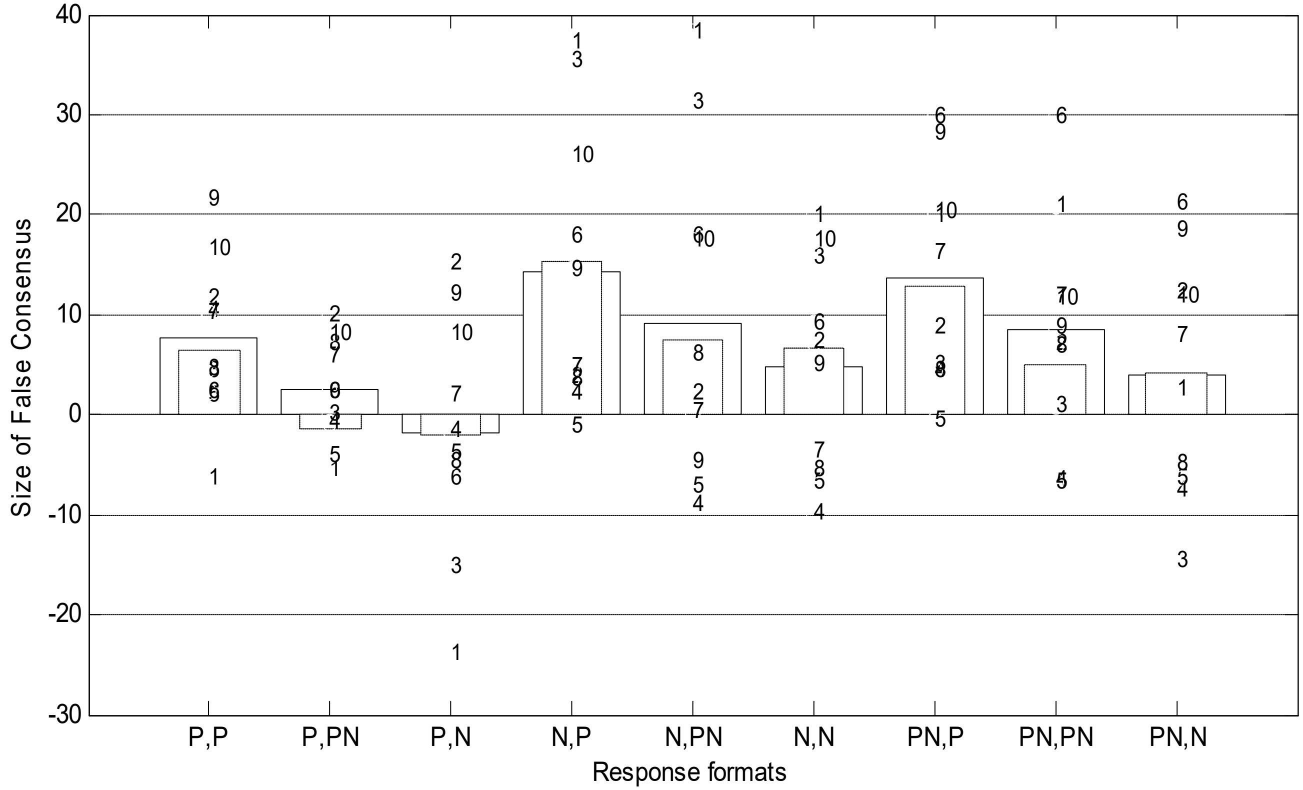
Comparison of SSM predictions (---) with empirically obtained false consensus data (—)



U.S., n = 104

$\rho = .8$, $\alpha = .9$

False consensus & False uniqueness – Are they real?

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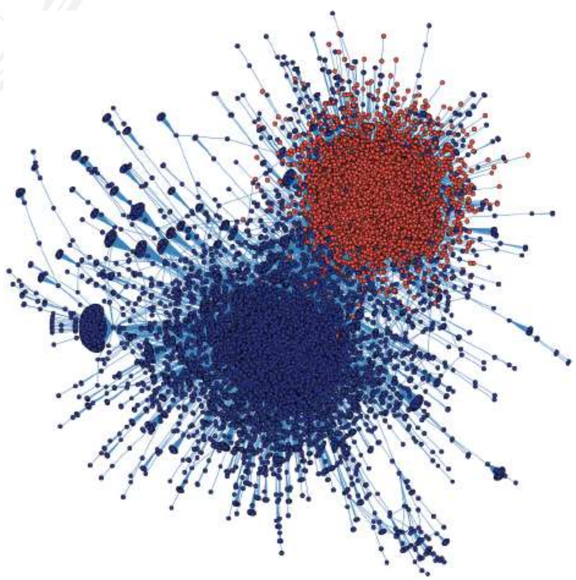
Both apparent biases can be explained as an interplay of a simple social algorithm with social and task environments



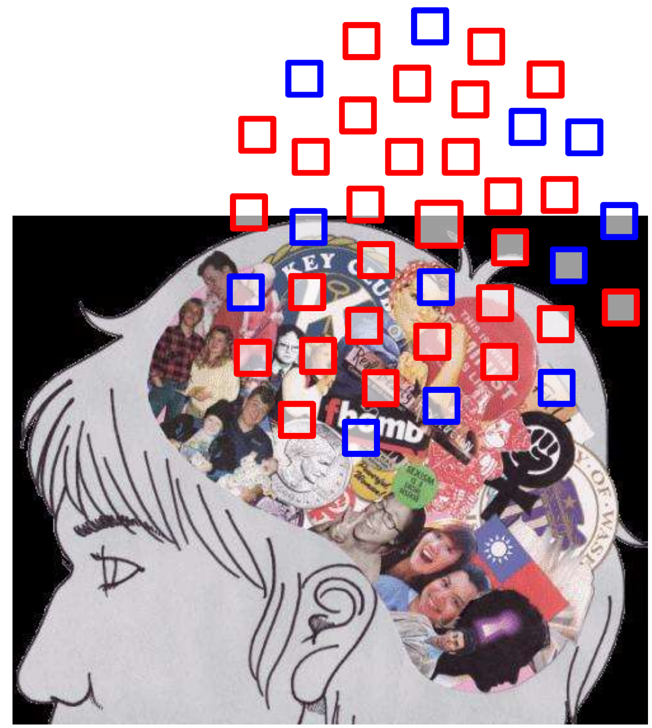
ey or property stolen from you
mber?"

States would answer "Yes"?

%

Response format 2:
… what percentage of adults living in the United States would answer "No"?
%

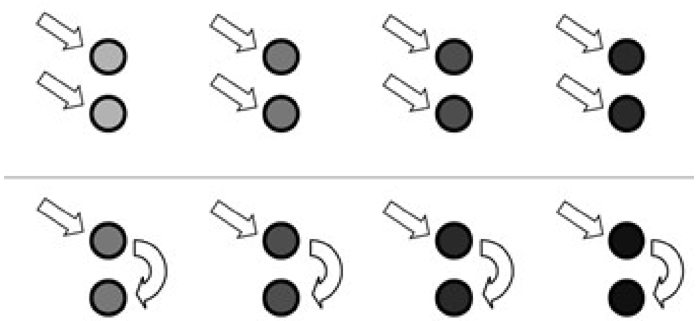
Response format 3:
… what percentage of adults living in the United States would answer…
"No"? % "Yes"? %



Social representation: Practical implications

1. People know their immediate social environments well

→ Peer-to-peer diffusion of useful information can be effective



Diffusion through authorities

Peer-to-peer diffusion

Social representation: Practical implications

2. … But they do not know as much about broader social environments

Example: Perception of wealth inequality

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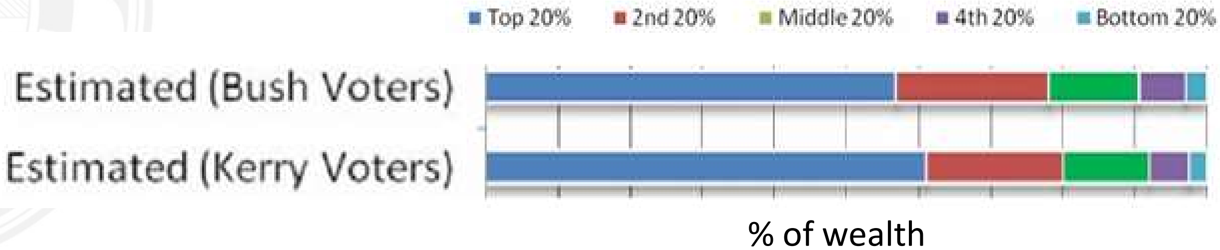
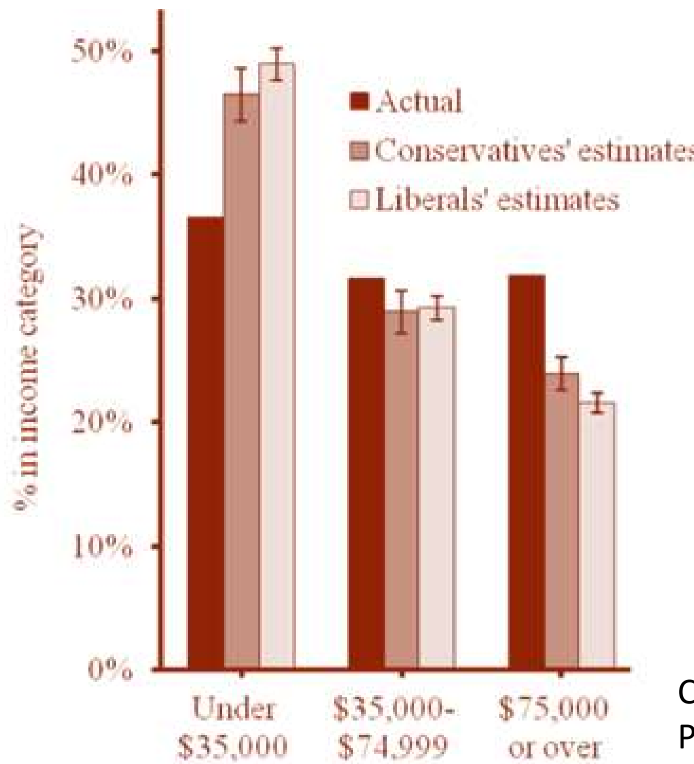


Norton & Ariely (2011). Psychological Science.

Liberals perceive more inequality than conservatives

→ "Ideological bias"



Chambers et al (2014). Psychological Science.

Liberals perceive more inequality than conservatives

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→ Ideological bias?

→ Or differences in social circles?

Median income in social circles of
- liberals = $53,250
- conservatives = $64,000

Galesic et al, 2014

- Differences in social circles explain away most of the ideological bias (Dawtry et al, 2015, Psychological Science)

Social representation: Practical implications

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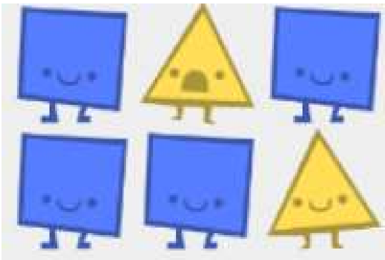
To reduce “biases”, we need to help people experience a broader range of social exemplars

- Encourage diversity in neighborhoods and workplaces
- Provide vivid illustrations of the number of people with different views
- Encourage temporary immersion in different communities



http://ncase.me/polygons/

Social learning

with Daniel Barkoczi

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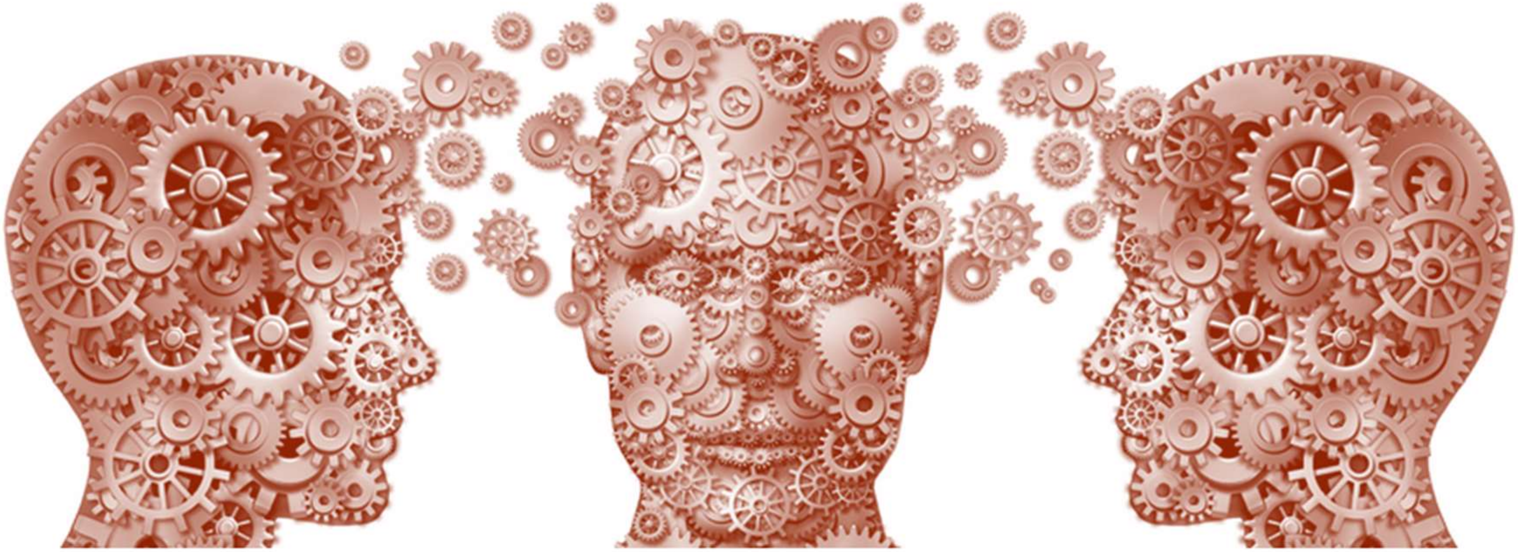
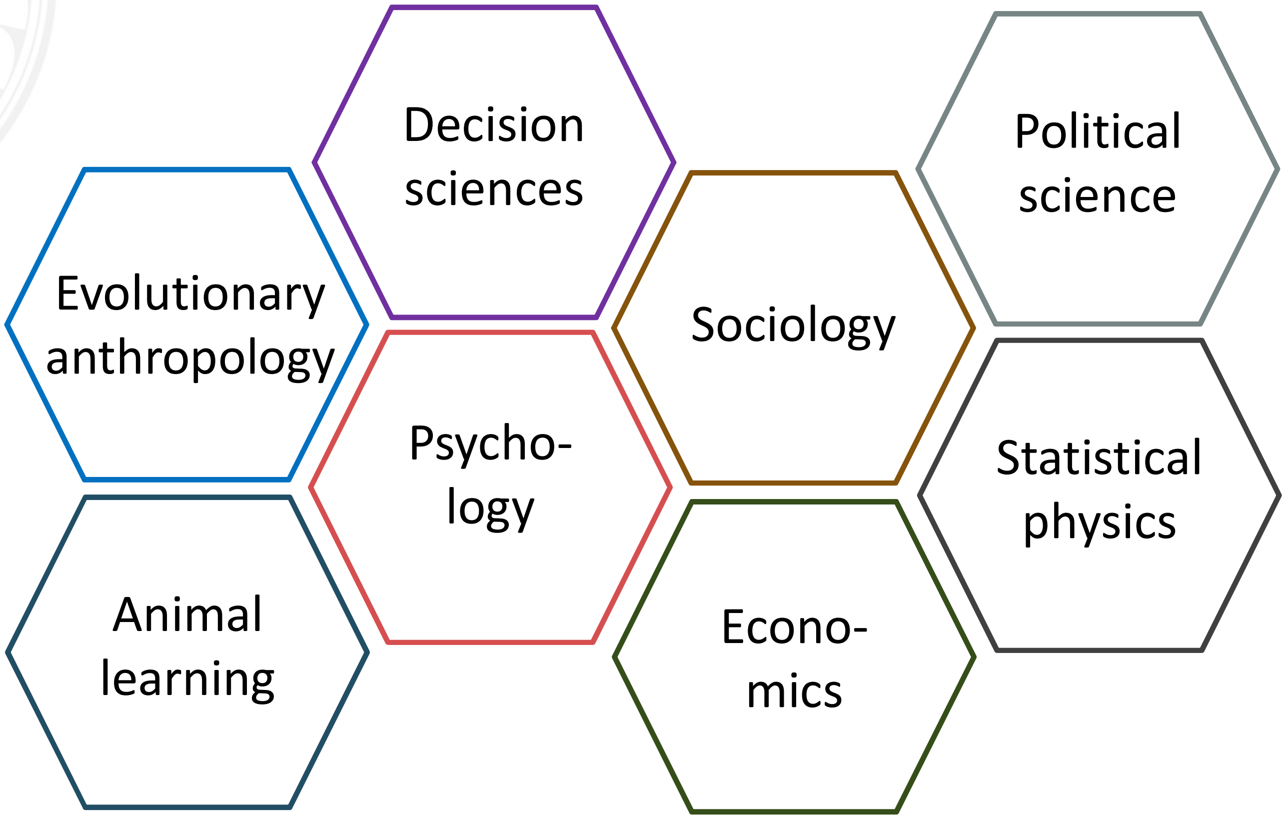
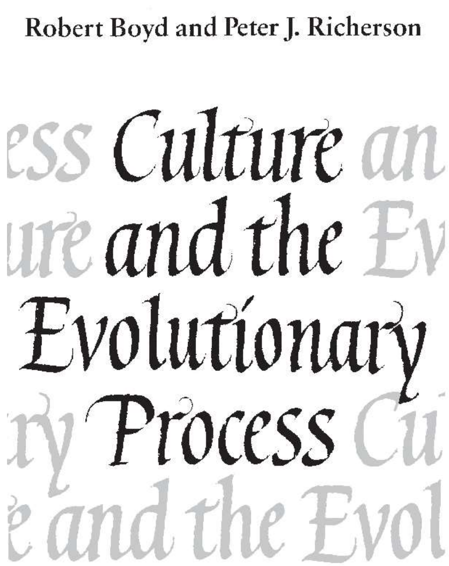


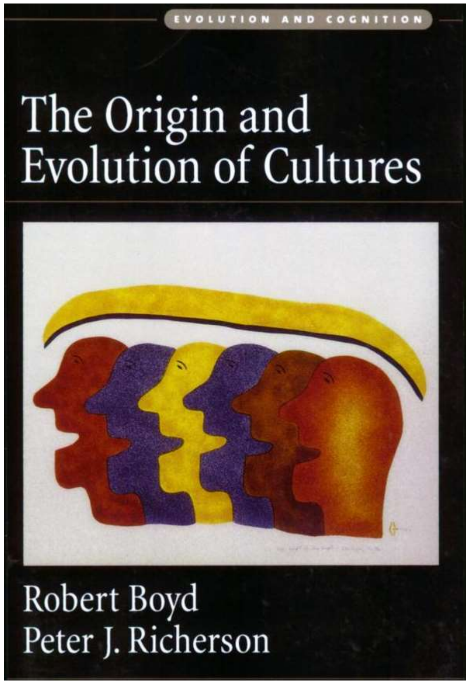
Disciplines studying social learning and collective problem solving



Evolutionary anthropology

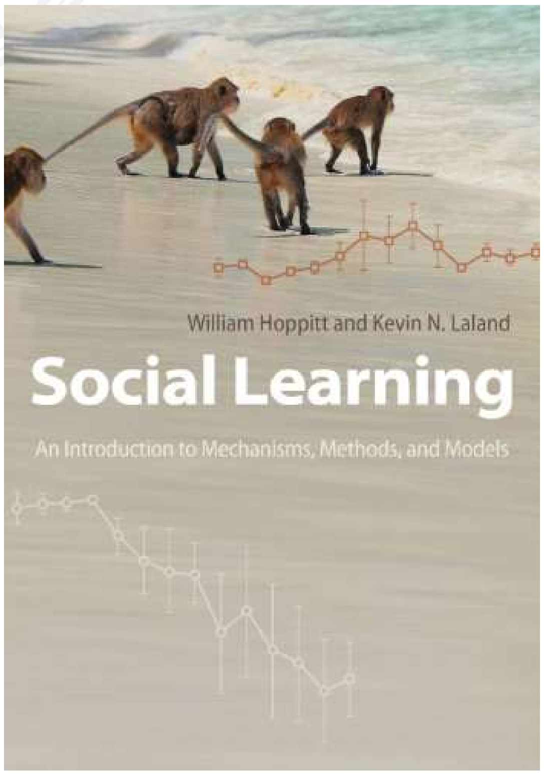
- Population-genetic models of cultural transmission
- Describe evolved social learning biases: conformist bias, payoff bias, unbiased transmission

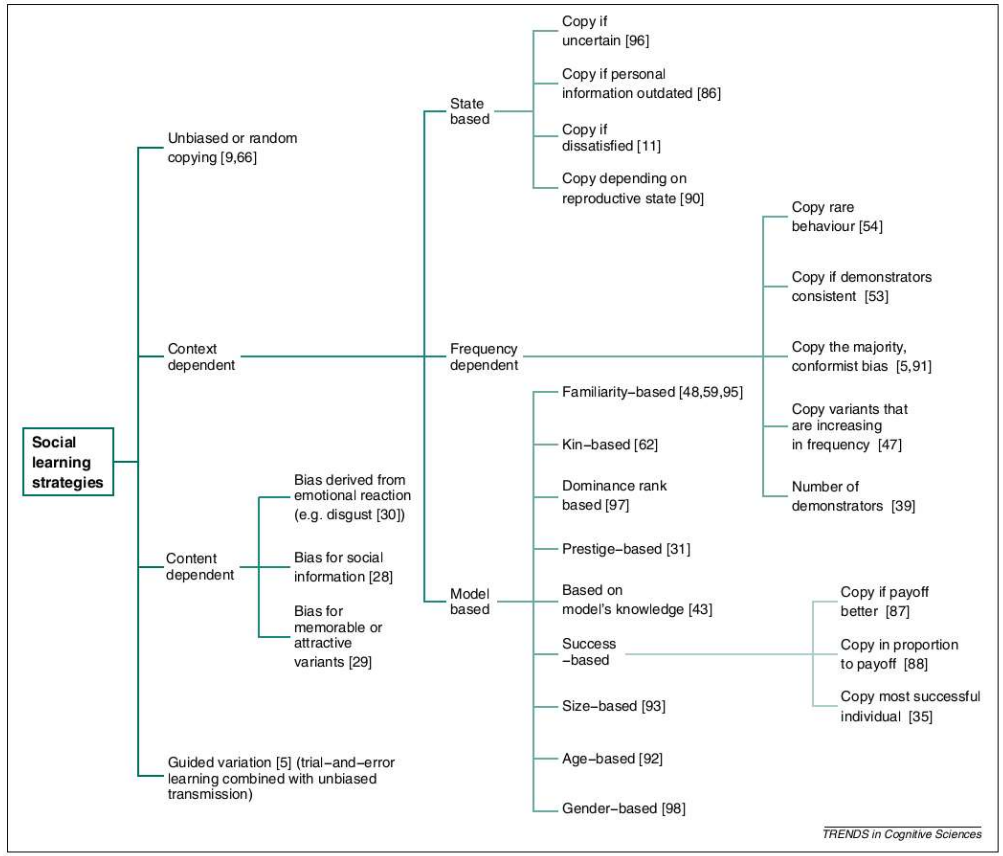




Animal learning

- Social learning strategies observed in animals
- Investigate "when", "who", and "what" is being copied

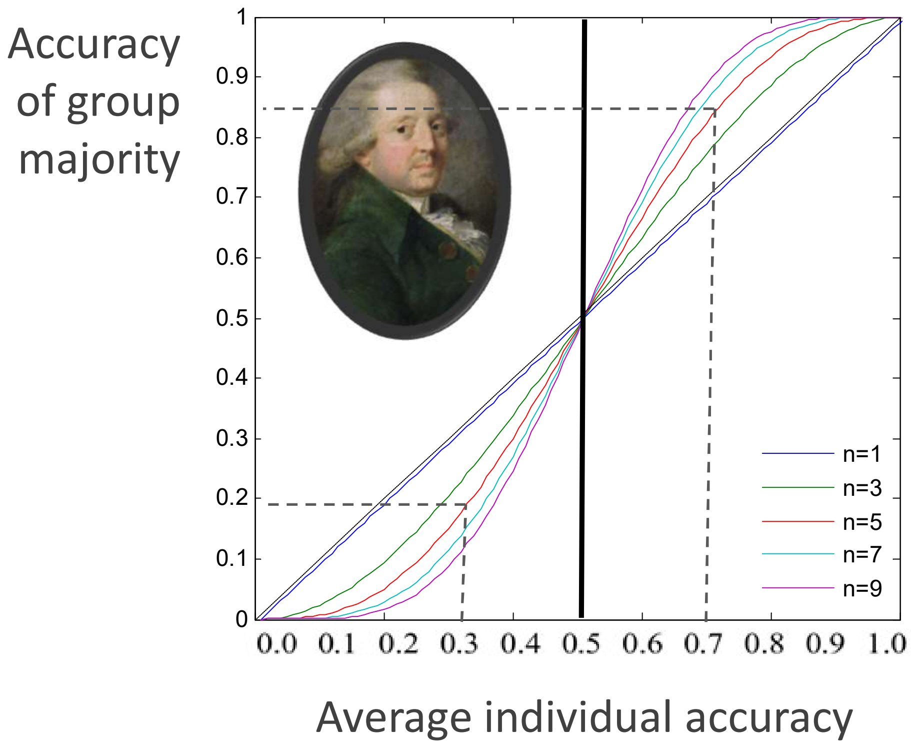




Rendell et al, 2011, *Trends in Cognitive Sciences*

Political science

- Different voting models for aggregation of preferences and information (Dewan & Shepsle, Annu Rev Polit Sci, 2011)
- Example: Condorcet Jury Theorem



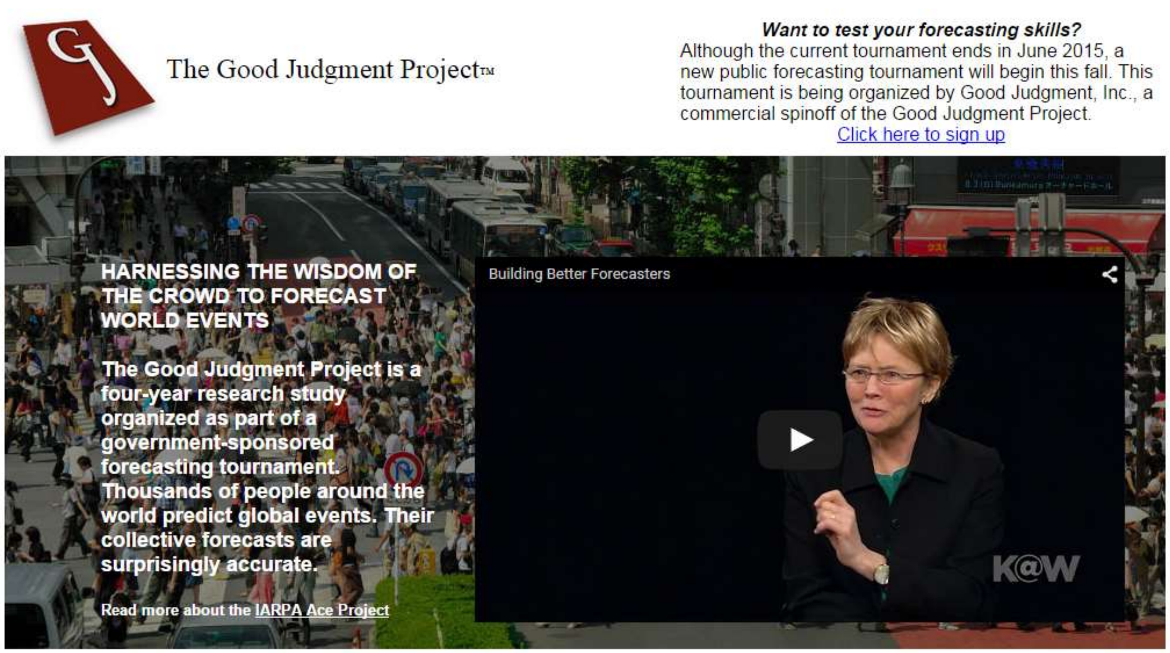
$$M = \sum_{i=m}^{n} \binom{n}{i} p^i (1-p)^{n-i}$$

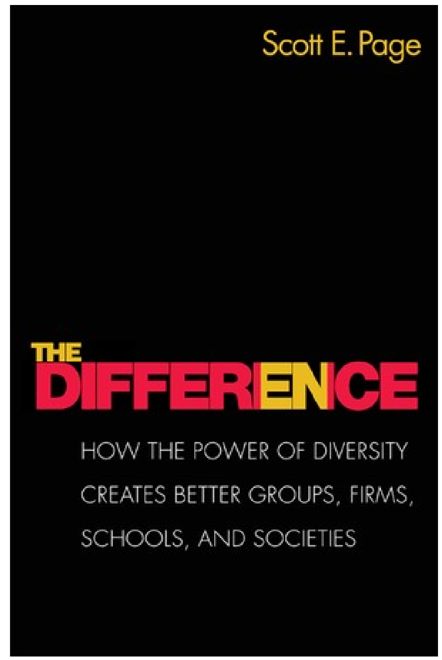
Grofman, Owen, & Feld (1983, Th Dec). 13 Theorems in Search of the Truth.

List & Goodin (2001, J of Pol Phil)

Decision sciences

- Group decision making: when and why groups perform better than individuals?
- How to elicit and aggregate expert forecasts?





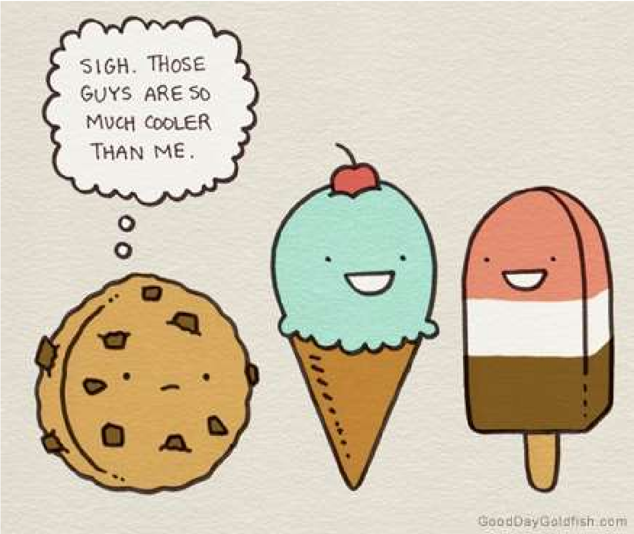
Psychology

- The fundamental role of social learning
  - Bandura (1963): Social learning theory

www.youtube.com/watch?v=Z0iWpSNu3NU

  - Festinger (1954):

    Social comparison



Psychology

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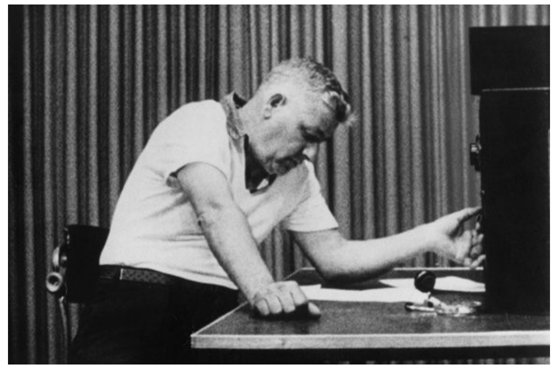
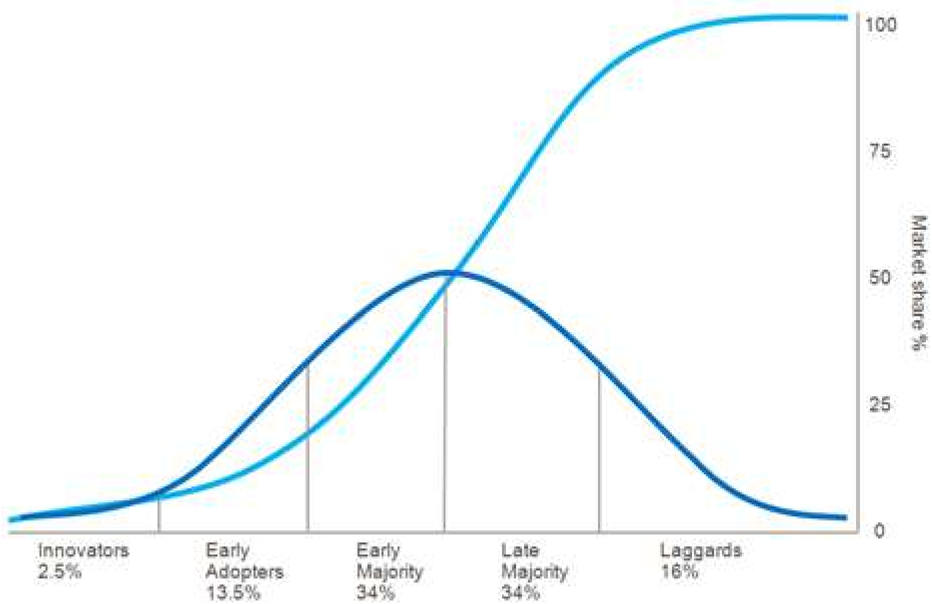
- The dark side of social influence
  - Asch (1955) and Milgram (1963) conformity experiments



- … and the good sides

Sociology

- Mechanisms of social contagion
  - Katz & Lazersfeld (1955): Two-step flow of communication
  - Rogers (1962): Diffusion of innovations
  - Granovetter (1973, 1978): Strength of weak ties, Threshold models
  - Centola (2007, 2010, …): Complex contagion on networks



Rogers (1962)

Economics

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- Opinion formation on networks: How likely is consensus? Who has most influence? How likely is convergence on optimal action?
- Bayesian updating models

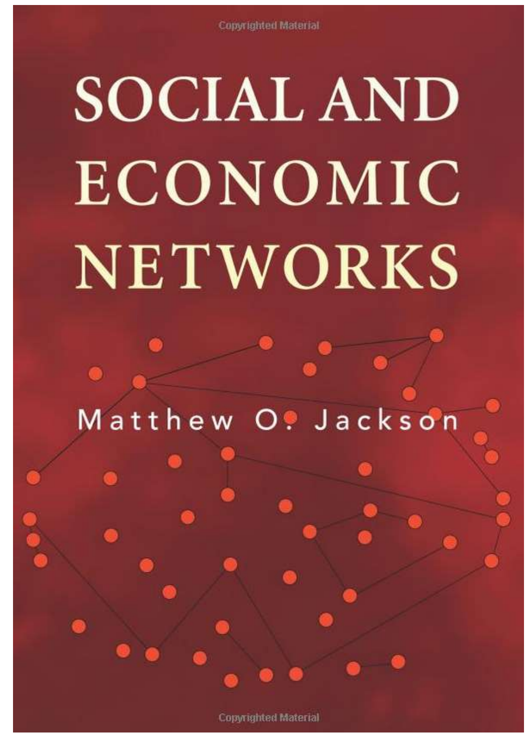
$$P(\theta|s) = \frac{P(s|\theta)P(\theta)}{P(s)}$$

$\boldsymbol{P(\theta)}$ – prior belief
$\boldsymbol{s}$ – social signal

- Non-Bayesian models
  - DeGroot model

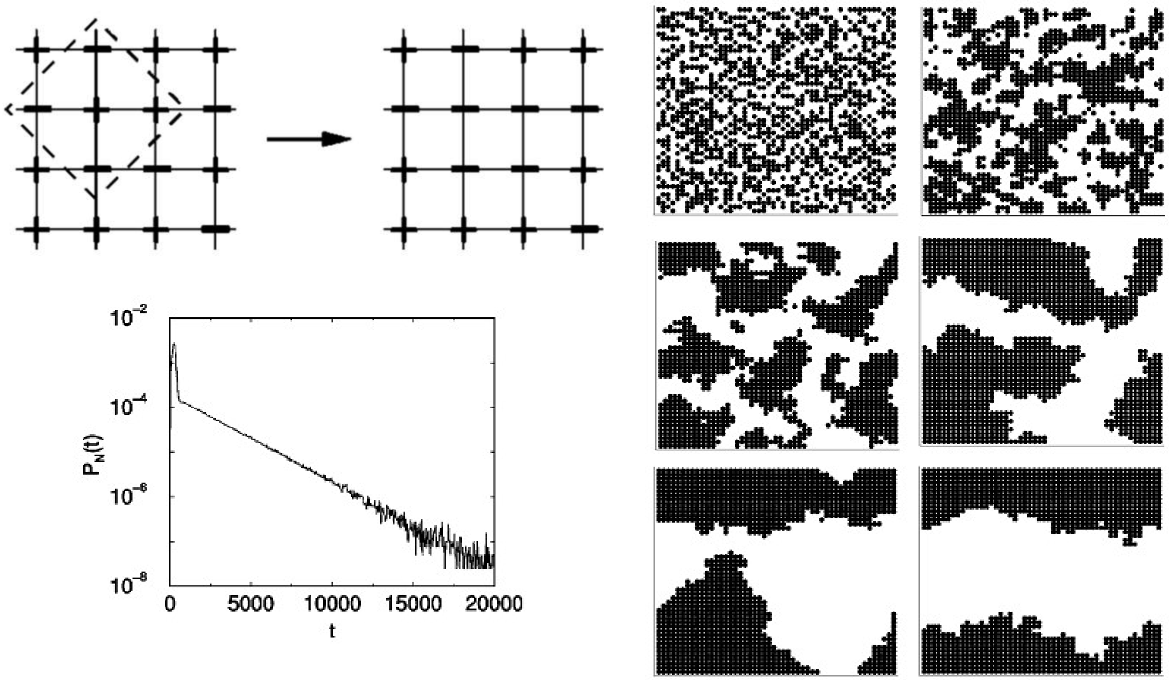
$$x_{i,t+1} = \sum_{j=1}^{n} T_{ij} x_{j,t}$$

x_i– belief of agent i
T_{ij} – trust of i in j's signal



Statistical physics

- How likely is consensus? How long to consensus?
- Ising, Potts models; random walk models - voter, majority rule,… implemented on different topologies



Review: Castellano et al (2009, Rev Mod Phys)

Chen & Redner (2005, Phys Rev). Majority rule dynamics in finite dimensions.

How can we use knowledge from different disciplines to model messy social systems?

A blueprint for modeling social phenomena

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1. Determine cognitively plausible algorithms

Representing social environments

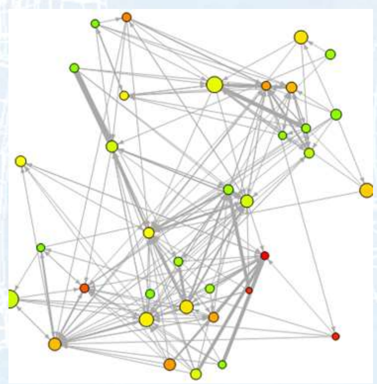
Social learning

Network building & revision

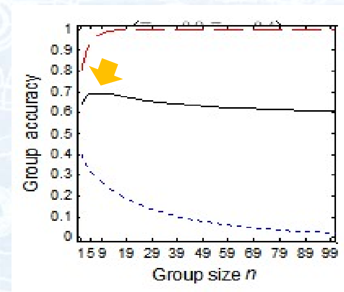
Cooperation & competition

2. Model their performance in realistic task environments

and in realistic social networks



3. Compare model predictions with empirical data



Revise

Importance of an interdisciplinary approach

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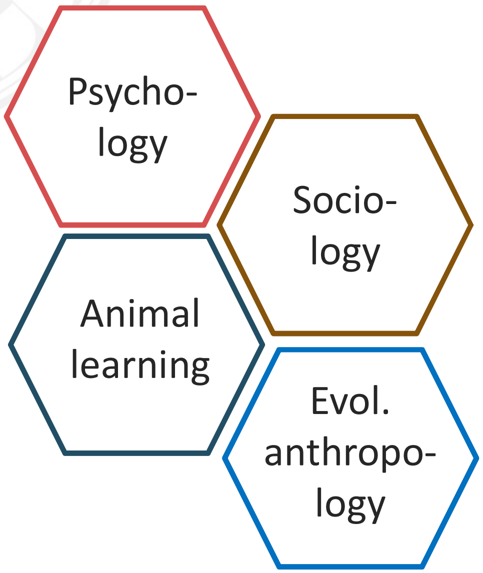
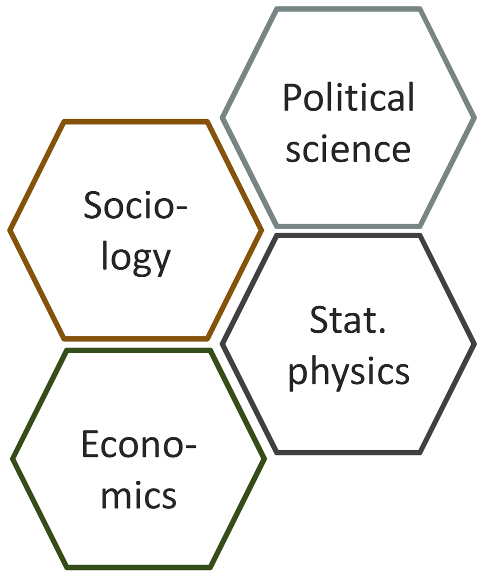
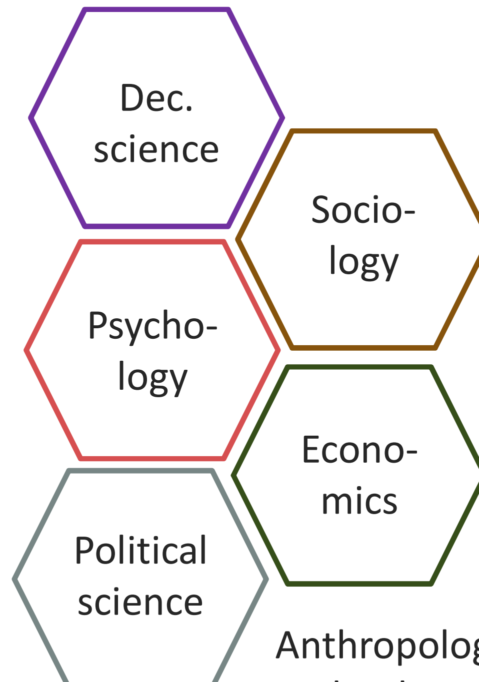
1. Determine cognitively plausible algorithms



2. Model their performance in realistic task environments and social networks



3. Compare model predictions with empirical data



Anthropology,
Archeology,..

Studying collective performance

3 examples:

1. Exploration and exploitation in collective problem solving

2. The wisdom of small crowds

3. Spread of beliefs in social circles

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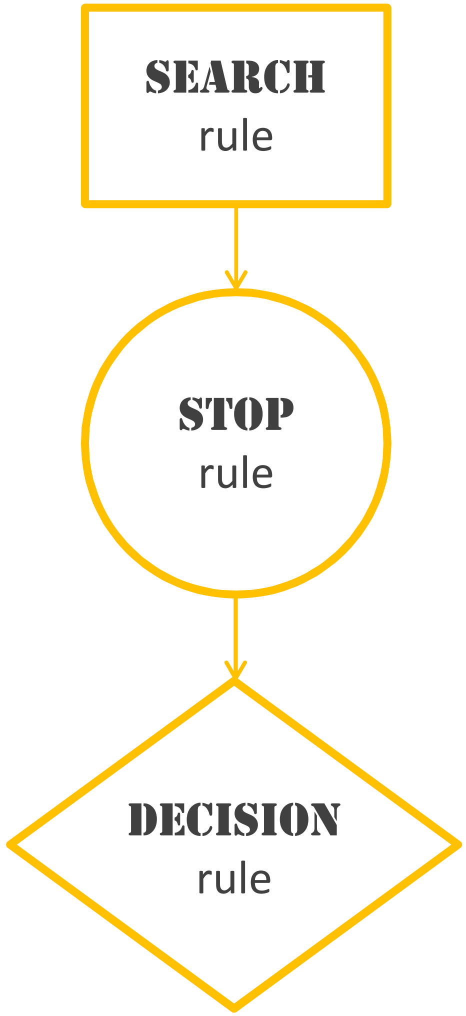
Stencil social algorithm



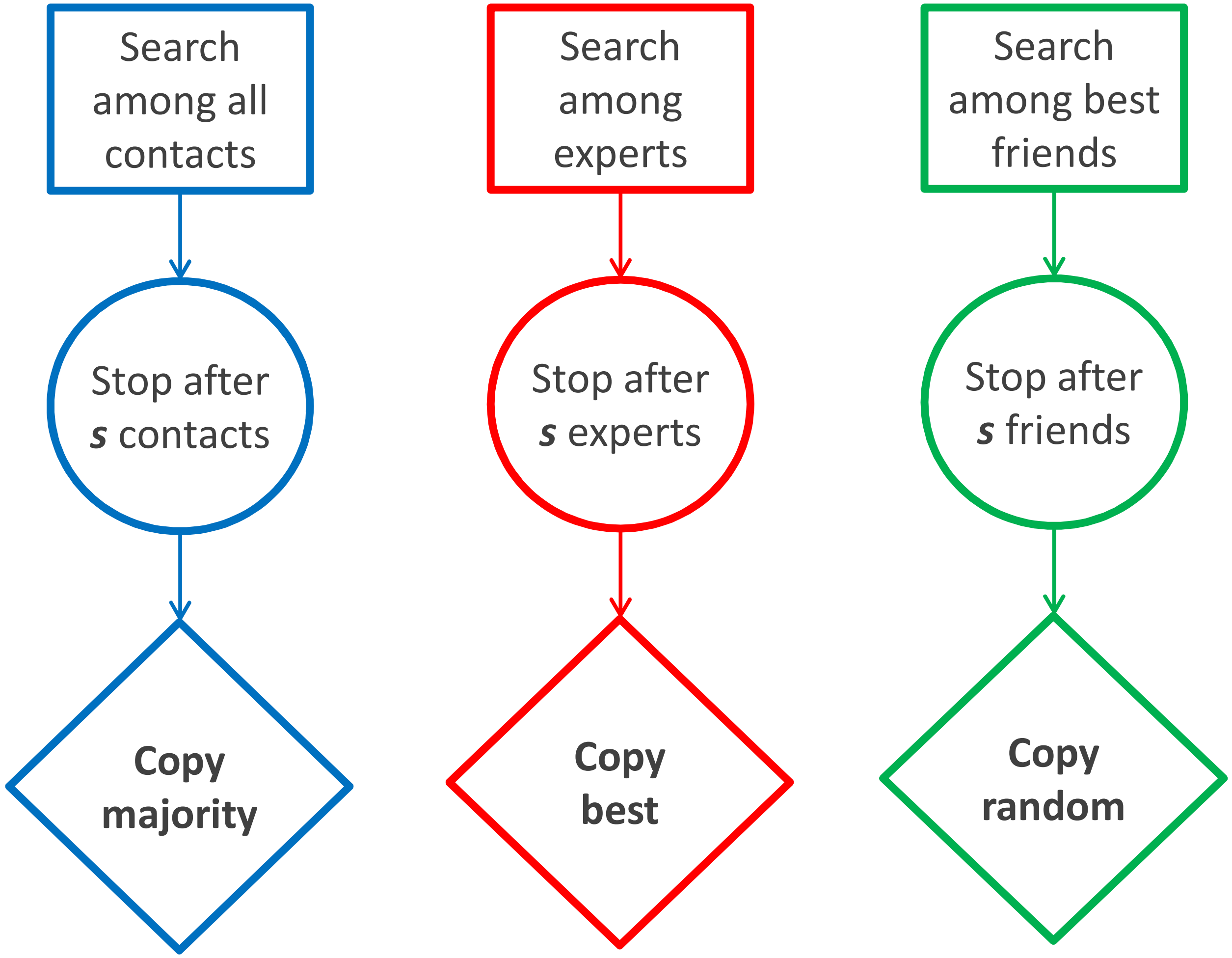
e.g. search among friends, successful people, randomly

e.g. stop after 1, 3, 9 people; after reaching a threshold

e.g. decide by coping majority, successful, average, randomly

Barkoczi, 2015; Gigerenzer, Todd, & ABC Research Group (1999): Simple heuristics that make us smart.

Example social learning algorithms



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1. Exploration and exploitation in collective problem solving

Individual exploration, or

Exploitation of others' solutions

Barkoczi & Galesic, 2016
http://arxiv.org/abs/1606.00753

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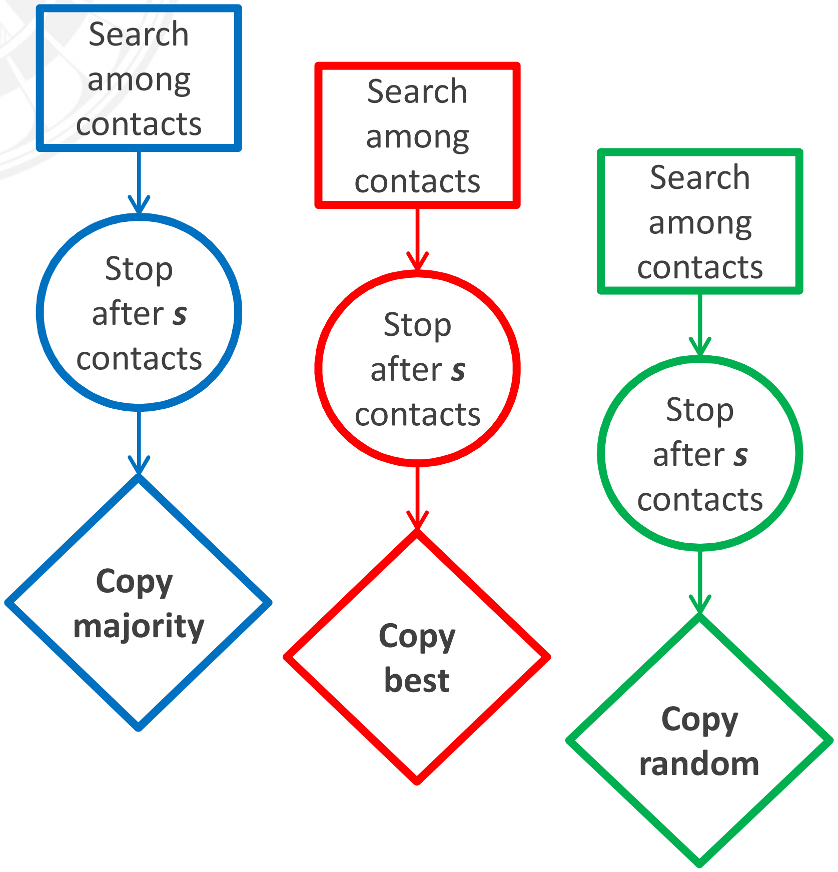
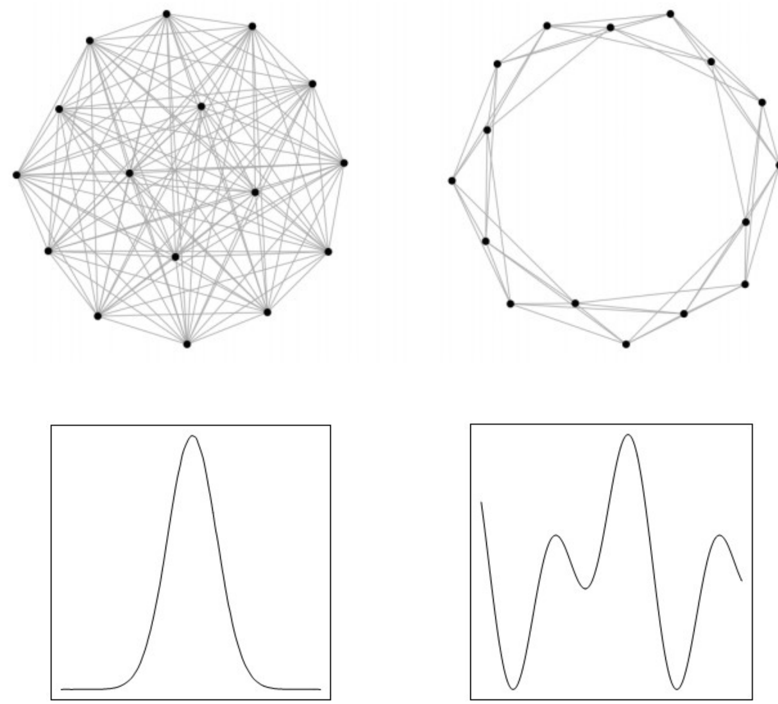
How do social learning algorithms, task, and social structure interact to affect exploration/exploitation and collective performance?





Simulations

Agents go through the following steps:

1. Imitation (exploitation of existing solutions)
- Search: Randomly among contacts
- Stop: Small sample (s=3); Large sample (s=9)
- Decision: Copy Best, Majority, or Random
- → 6 possible social learning rules

2. Compare payoffs
- If social solution is better than own: switch, otherwise go to Step 3.

3. Innovation (exploration for new solutions)
- Search for better solutions locally

Record average payoff in the population on each time step.

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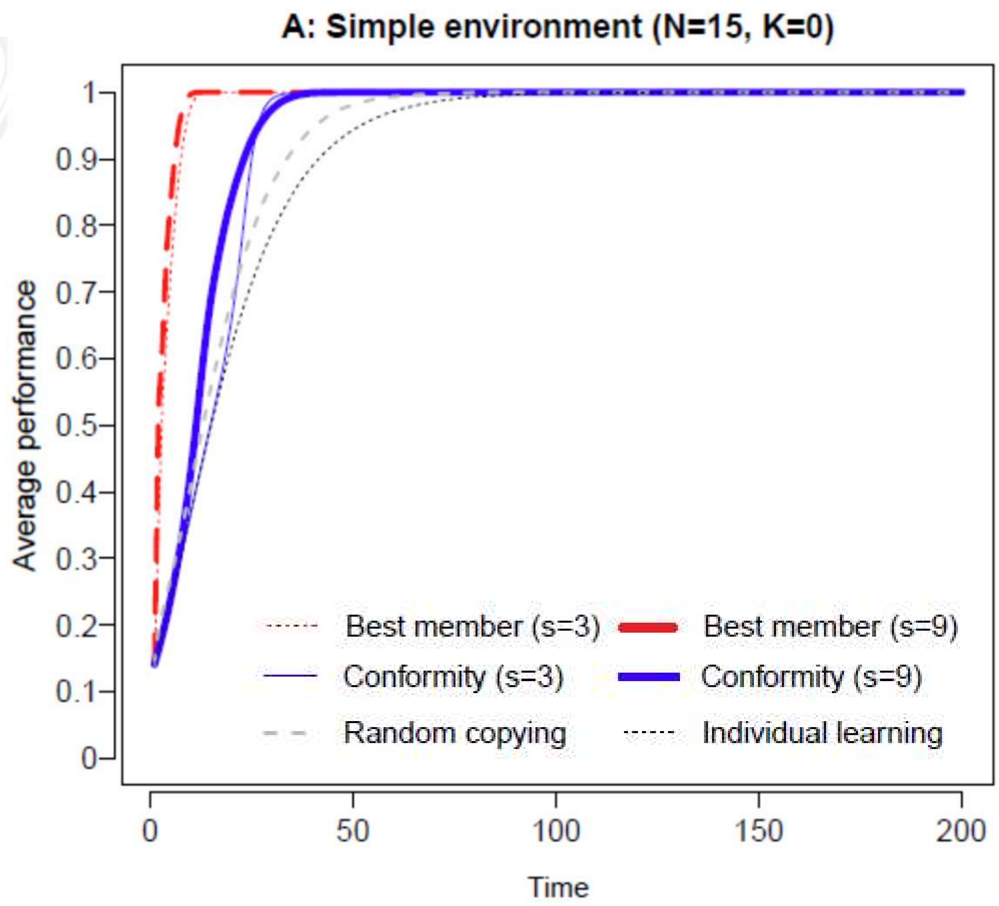
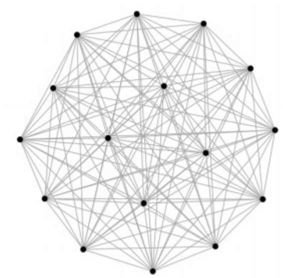
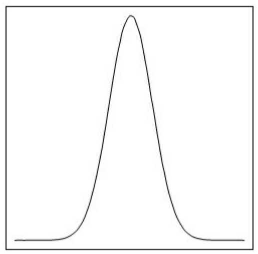
Performance of social learning strategies – full network, simple task







Performance of social learning strategies – full network, complex task

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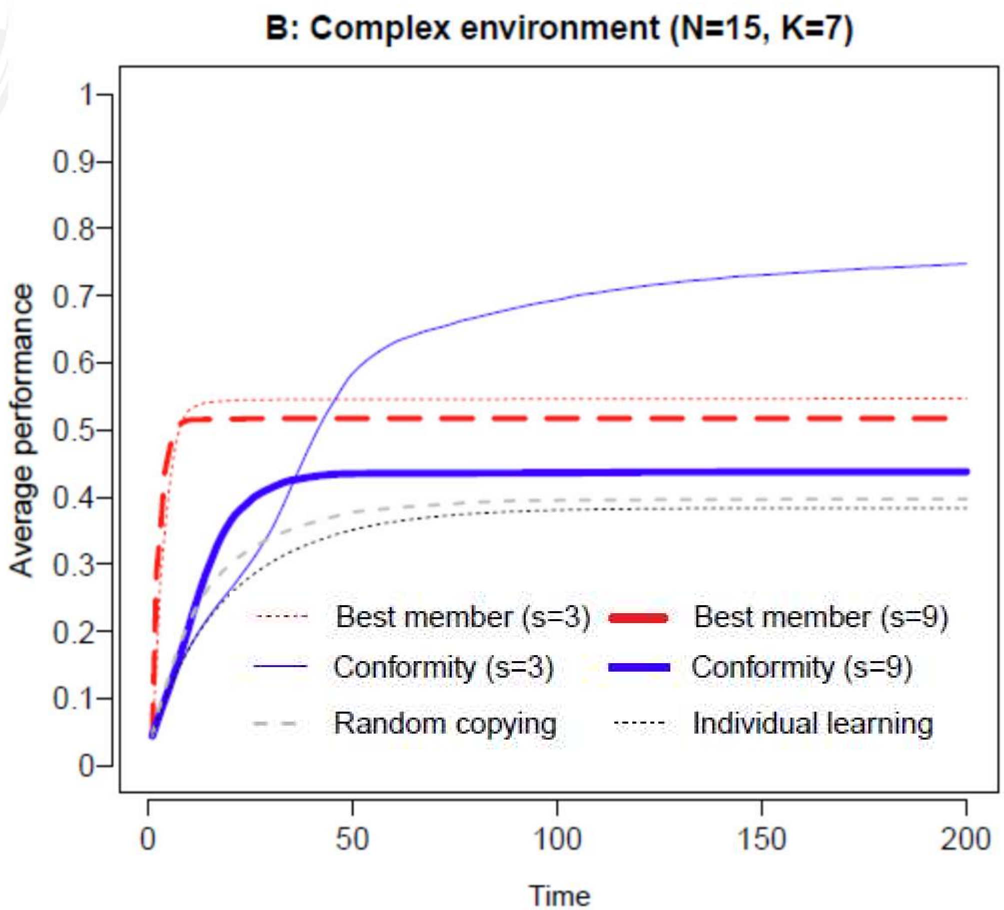

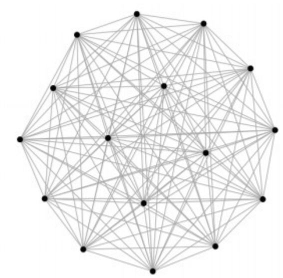

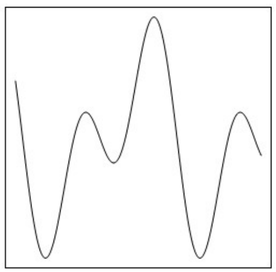

Number of unique solutions

Majority of small samples: more exploration *and* ability to spread good solutions

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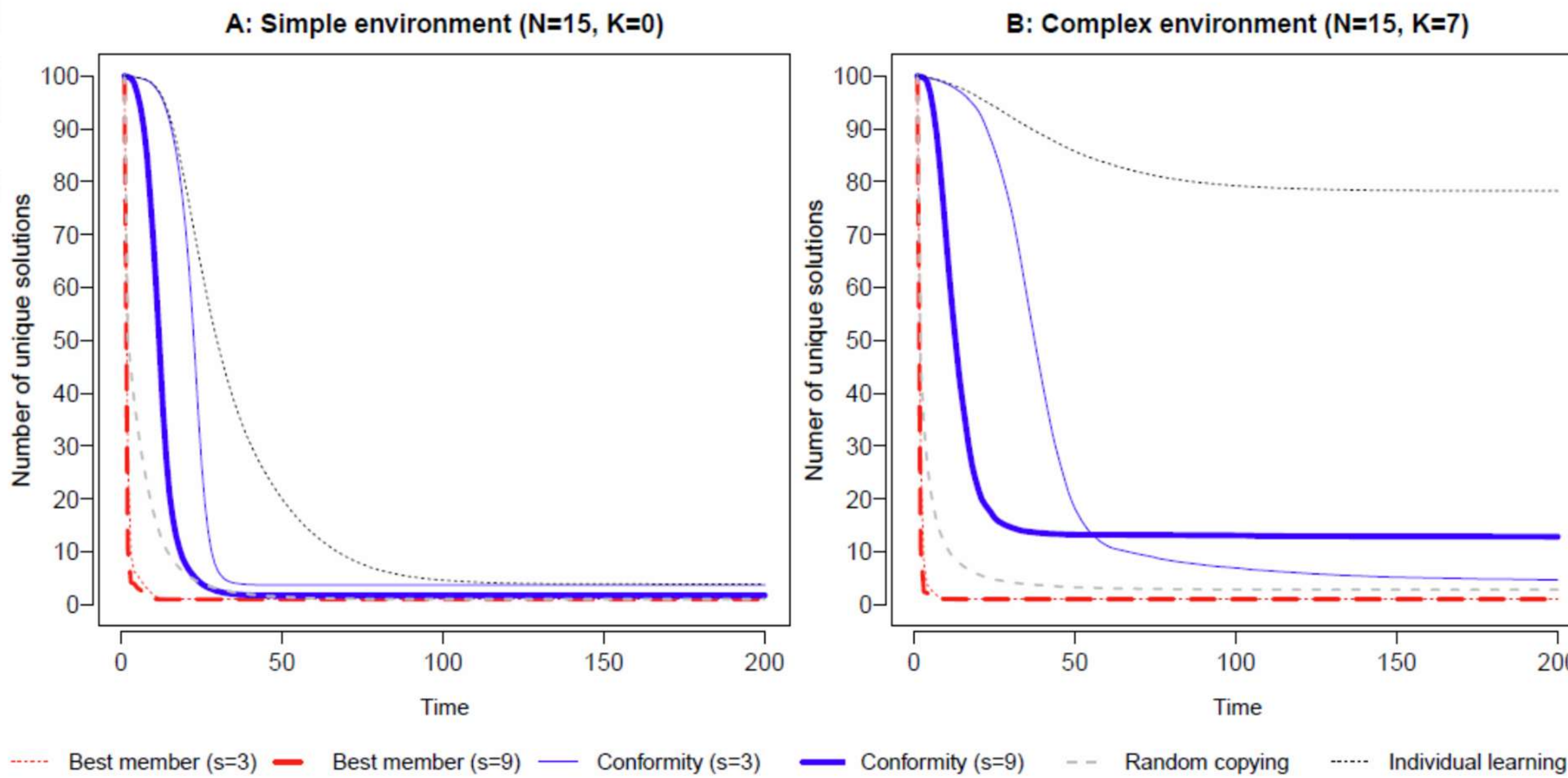
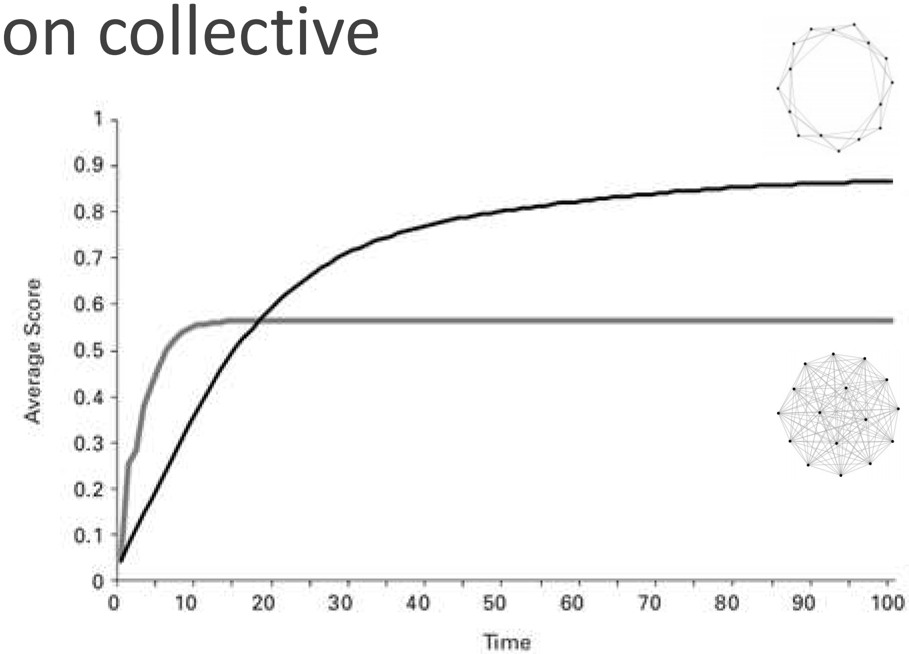


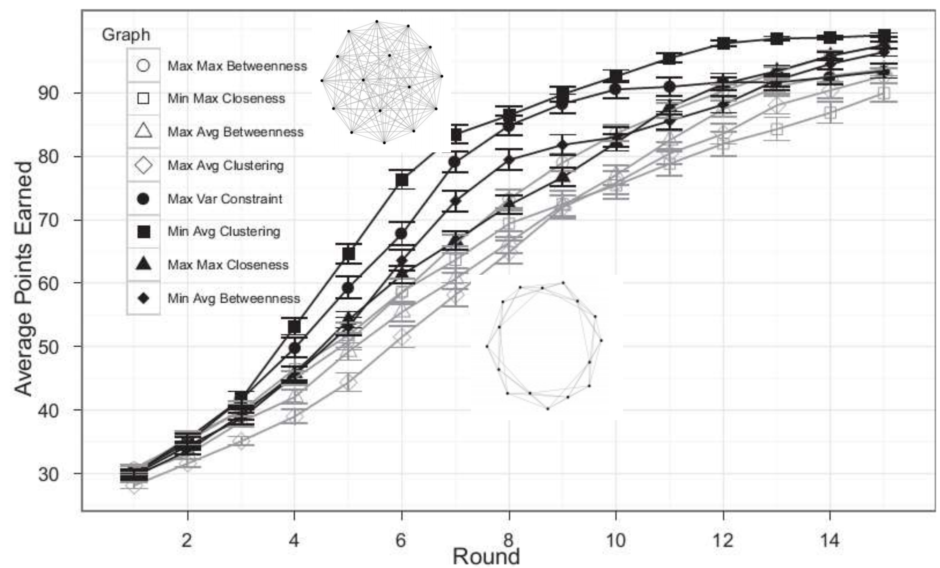
Effect of network structure on collective performance: past work

Apparent disagreement of empirical findings:

- Poorly-connected networks better (Lazer & Friedman, 2007, Derex & Boyd, 2016)



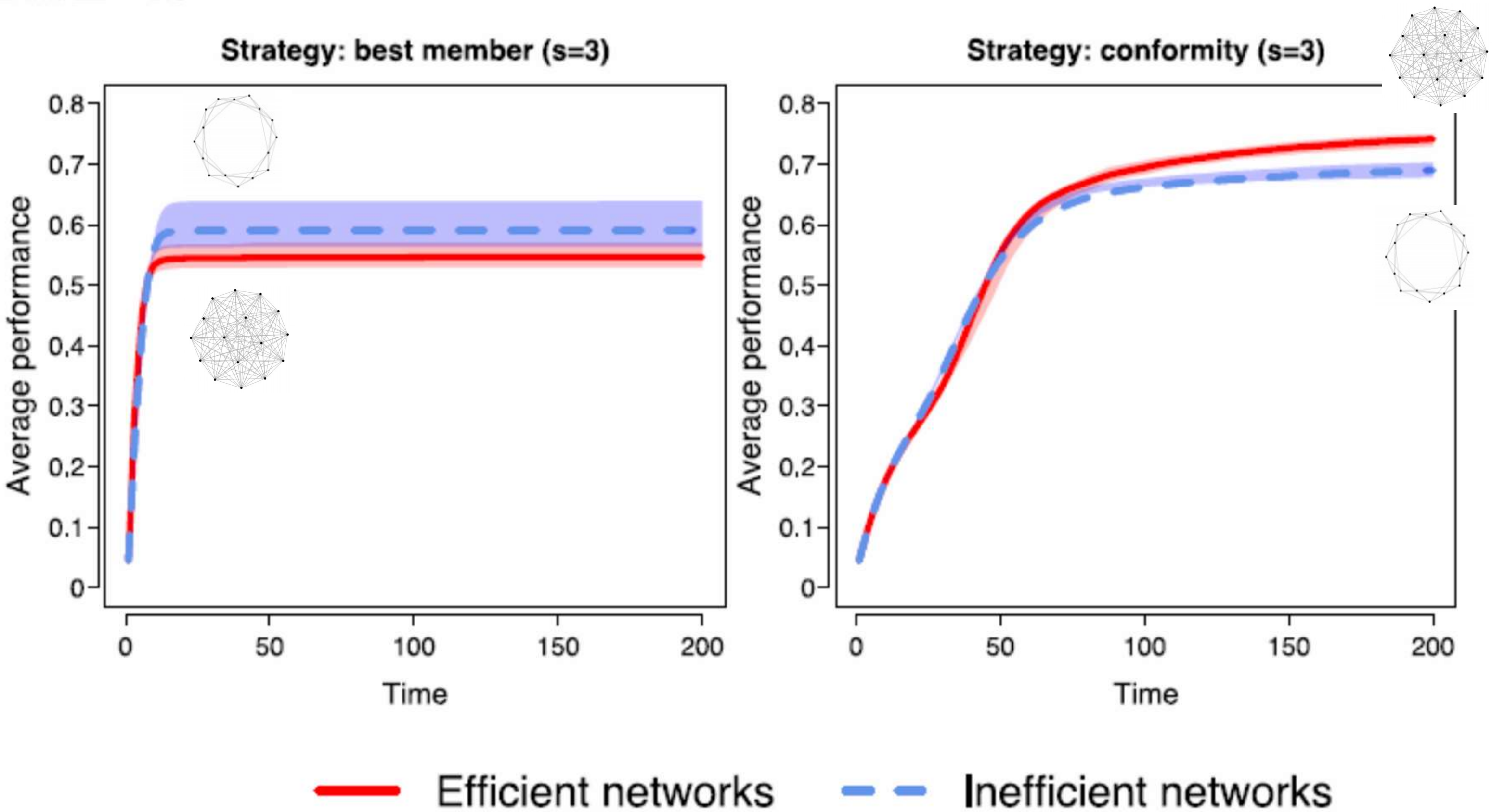
- Well-connected networks better (Mason & Watts, 2012)



If strategy and network structure interact:

→ Both results can be obtained

Interaction of social learning strategies and network structure



Interaction of social learning strategies and network structure

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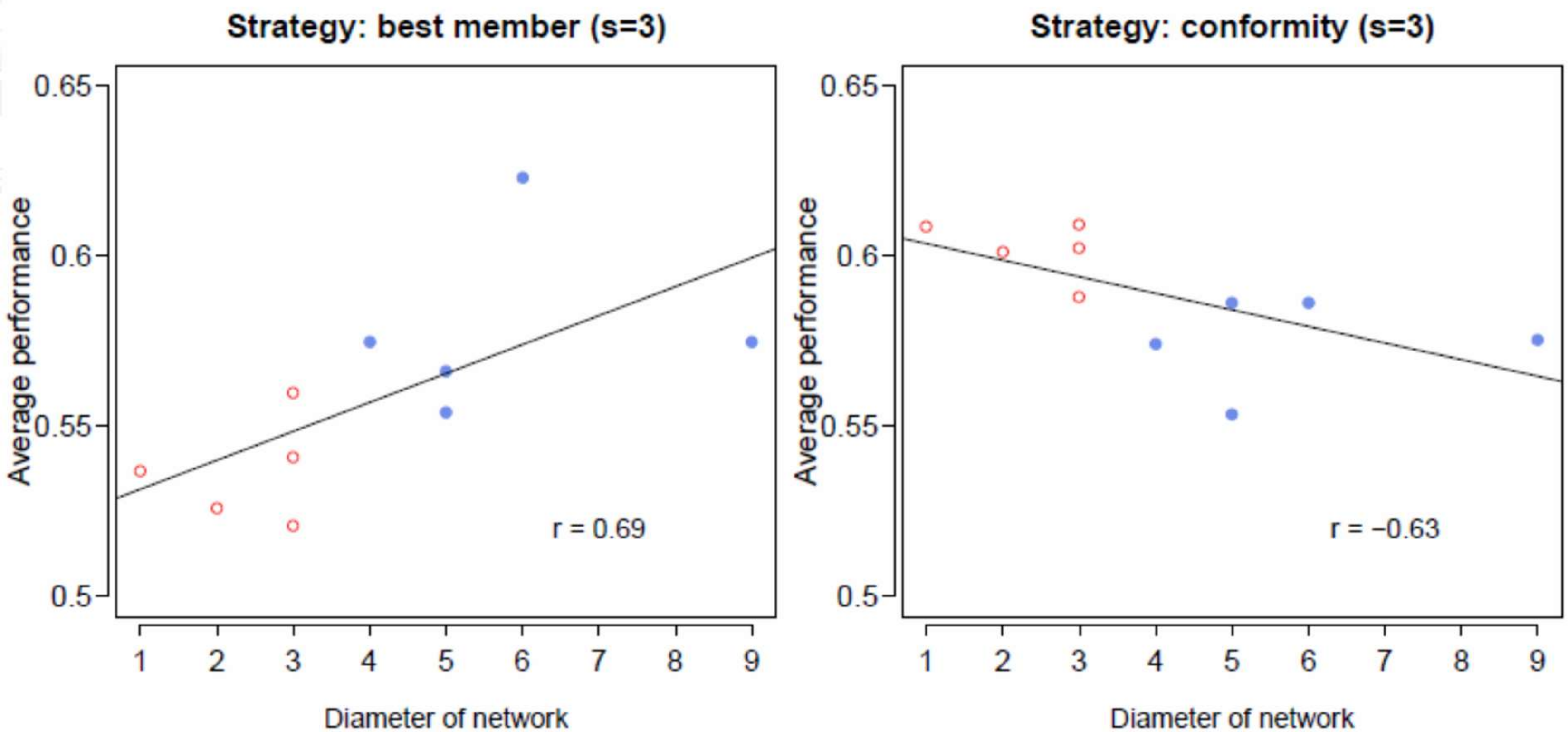

1. Exploration and exploitation in collective problem solving

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When using majority rule, small samples can be better than larger samples

→ more noise promotes exploration early on, while still allowing for exploitation once the signal is strong

Contradictory results in the literature can be explained

→ by considering both social learning strategies and the underlying network structure

2. Wisdom of small crowds for majority vote

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http://www.federalreserve.gov/

www.med.upenn.edu/criticalcare/

www.rhuddlantowncouncil.gov.uk/

Galesic, Barkoczi, & Katsikopoulos, (in press), *Decision*.

Typical committee sizes in real world

Jury sizes in most countries: 6-15 people

Town councils in UK and Australia: 5-30

Parliamentary committees in US, EU, Australia: 20-40

US House and Senate subcommittees: 10-15

Central bank boards: 5-12

Number of close friends: 6 or less

Number of online reviews read: average 5, max 30

Shouldn't groups be larger (wisdom of crowds)?

Typical committee tasks

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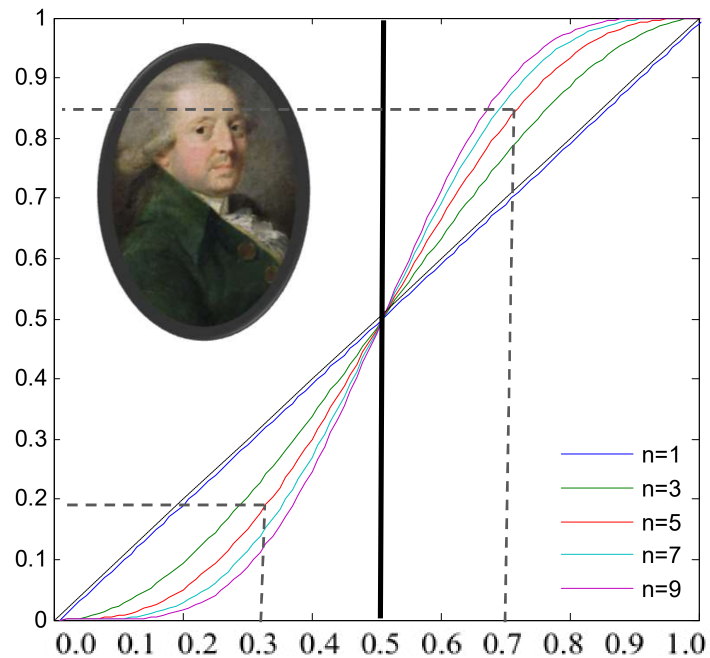
- Group of experts vote by **simple majority** to make predictions about:
  - Will the economy grow or fall in the next period?
  - Which policy to adopt?
  - Who is going to win presidential elections?
  - What is patient’s diagnosis?
  - Should we attack or not?

Accuracy of simple majority rule for a **single** task

- Condorcet Jury Theorem

Accuracy of group majority



Average individual accuracy

$$M = \sum_{i=m}^{n} \binom{n}{i} p^i (1-p)^{n-i}$$

Accuracy of simple majority rule across **many** tasks

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- Committees encounter many tasks over the course of their existence
  - Some are easy
  - Some are surprisingly difficult
  - **We do not know in advance how easy or difficult the next task is going to be**

Accuracy of simple majority rule across many tasks

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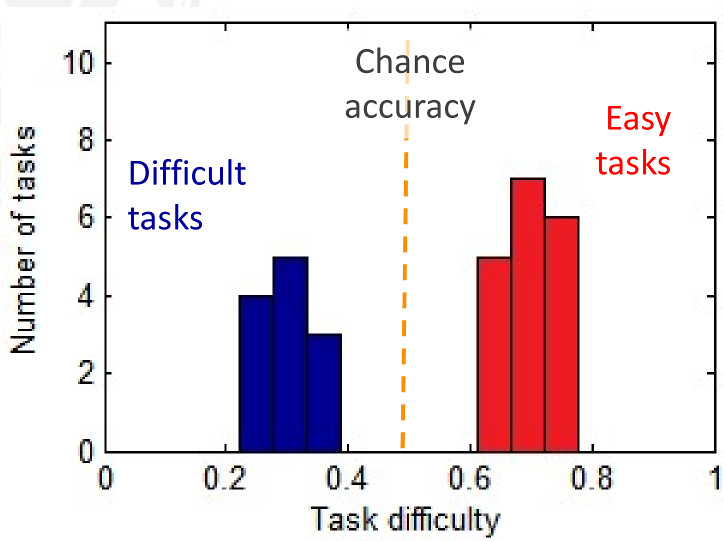
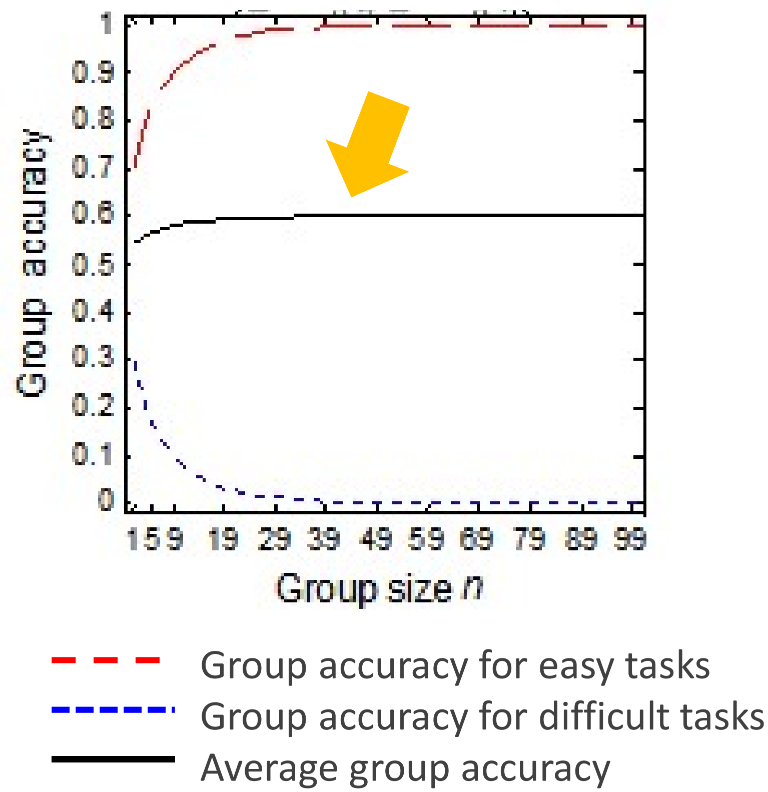
"Neutral" task environment





Proportion of easy tasks: $e = 0.6$

Accuracy of simple majority rule across many tasks

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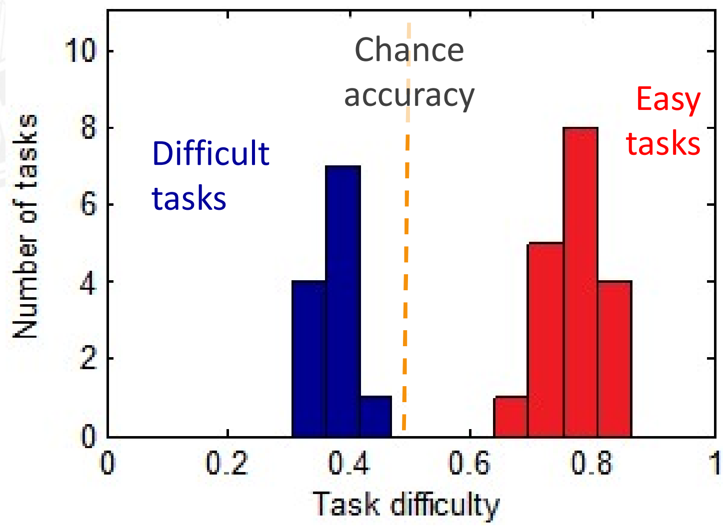
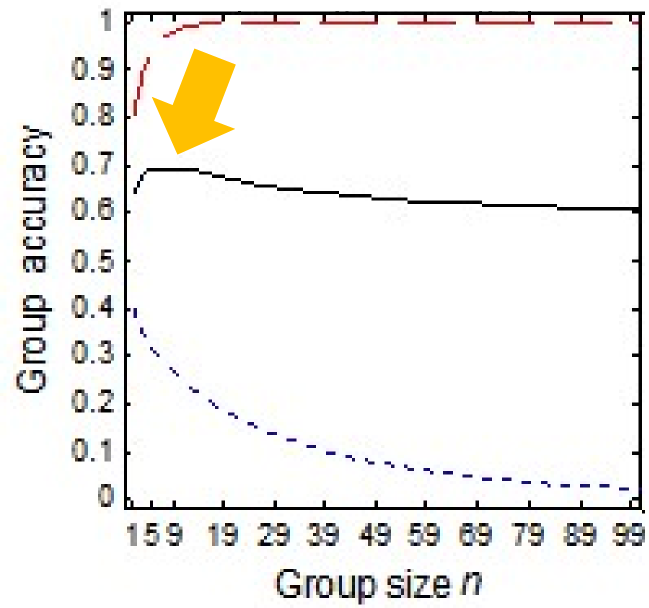
"Friendly" task environment



Proportion of easy tasks: e = 0.6



Group accuracy for easy tasks
Group accuracy for difficult tasks
Average group accuracy

Accuracy of simple majority rule across many tasks

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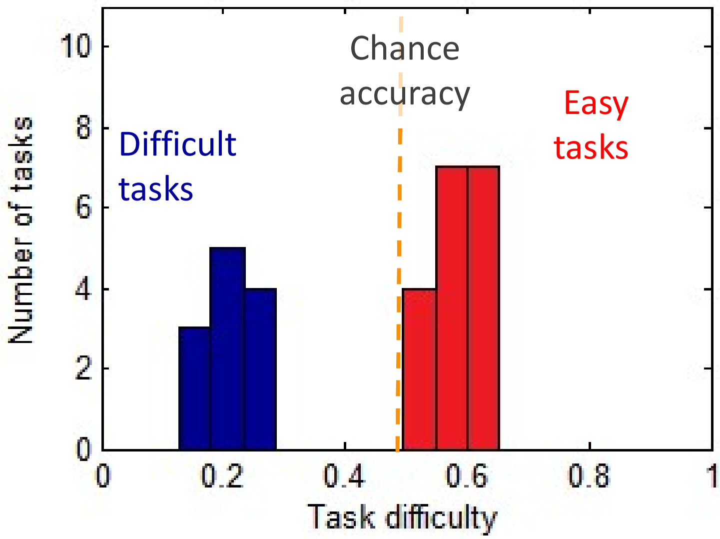
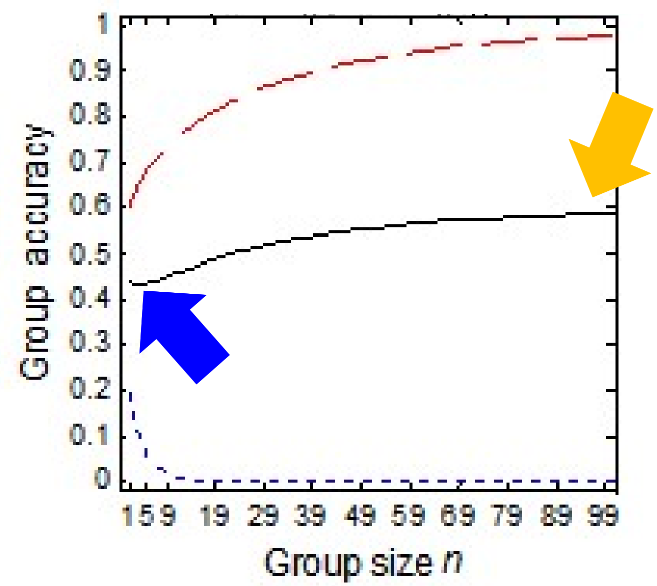
"Unfriendly" task environment





Proportion of easy tasks: e = 0.6

Group accuracy for easy tasks
Group accuracy for difficult tasks
Average group accuracy

More formally

Average group accuracy across many tasks:

$$\overline{P}_n = e\, P_{\mathrm{E},n} + (1-e)P_{\mathrm{D},n}$$

$\bar{P}_n$ → average accuracy of group of size *n* across tasks

e → proportion of easy tasks that group needs to solve

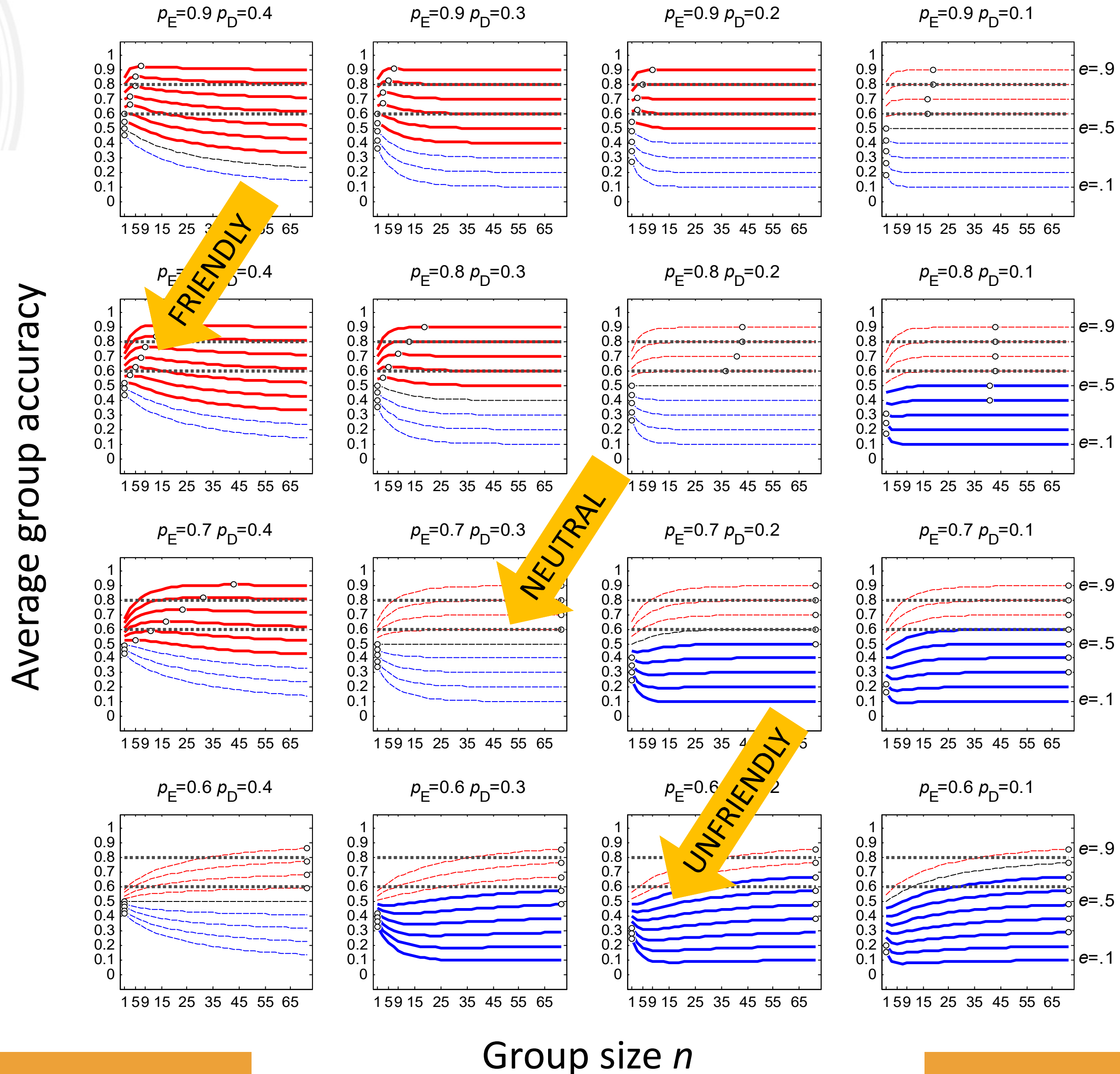
$P_{\mathrm{E},n}$ ($P_{\mathrm{D},n}$) → accuracy of group of size *n* on easy (difficult) tasks

Friendly environment:

$$\overline{p}_{\mathrm{E}} - 0.5 > 0.5 - \overline{p}_{\mathrm{D}} \quad \rightarrow \quad \overline{p}_{\mathrm{E}} + \overline{p}_{\mathrm{D}} > 1$$

$\overline{p}_{\mathrm{E}}$ ($\overline{p}_{\mathrm{E}}$) → individual accuracy on easy (difficult) tasks

Complete set of results



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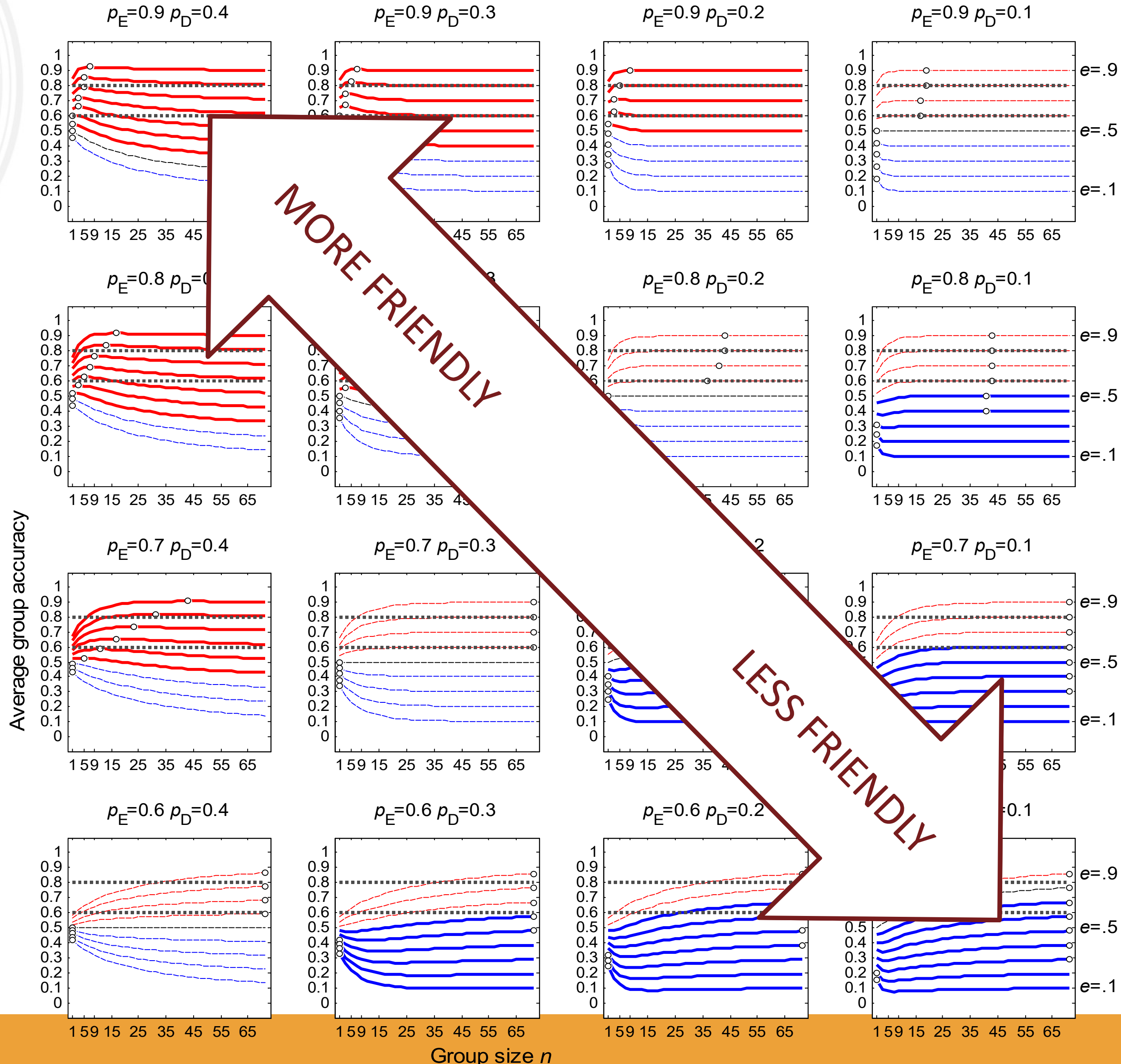
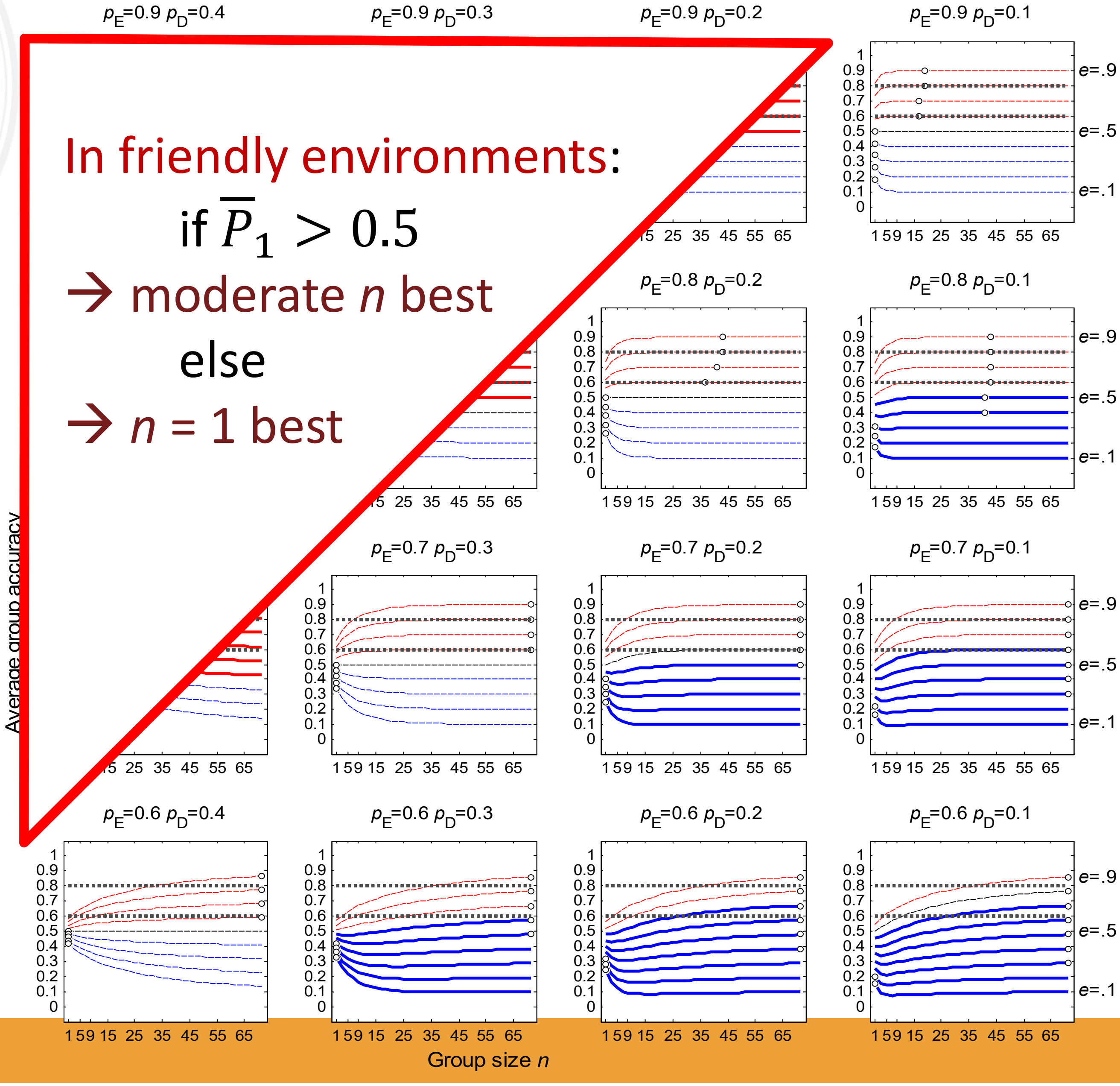
Complete set of results



Complete set of results



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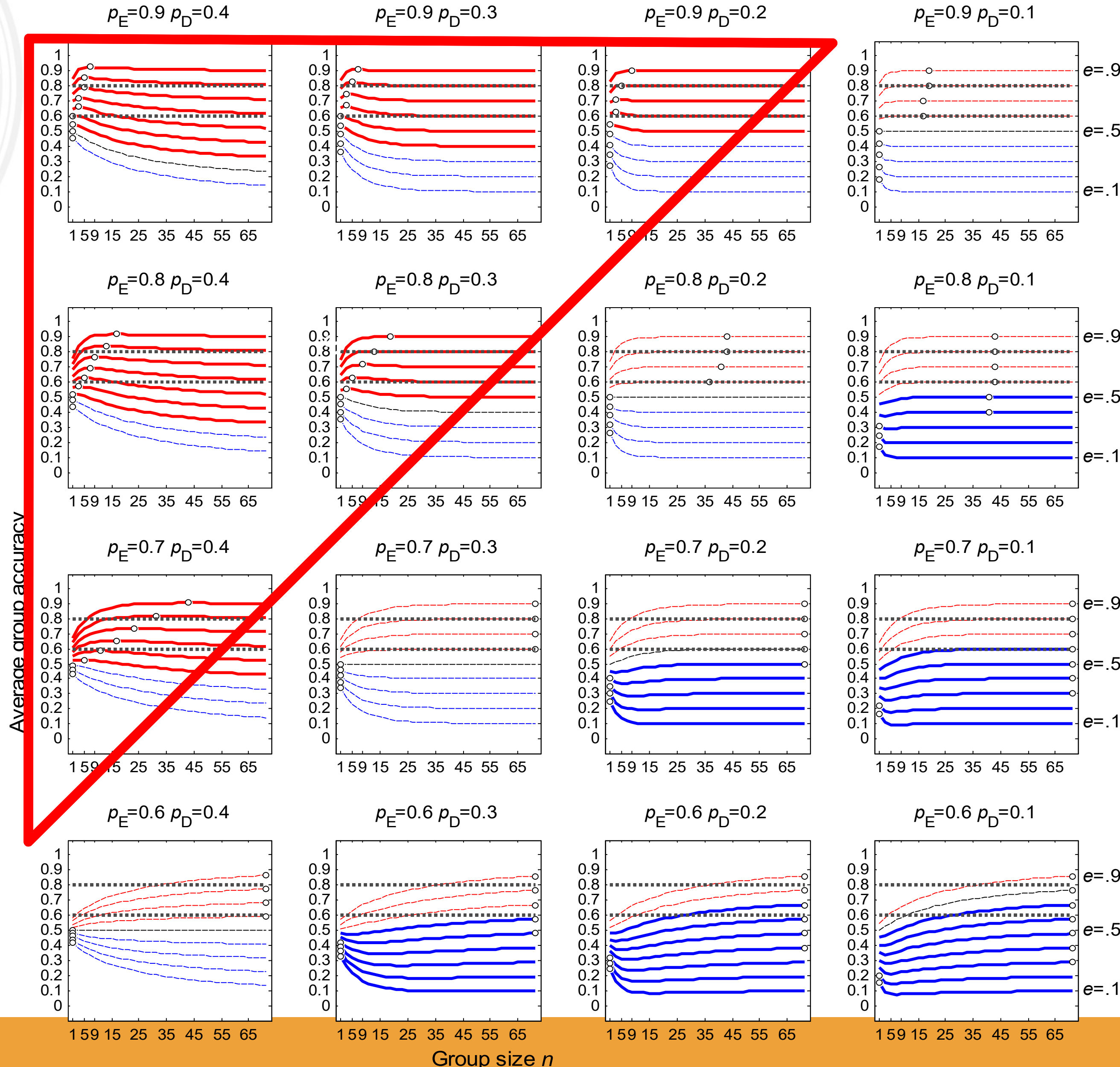
Complete set of results



Complete set of results

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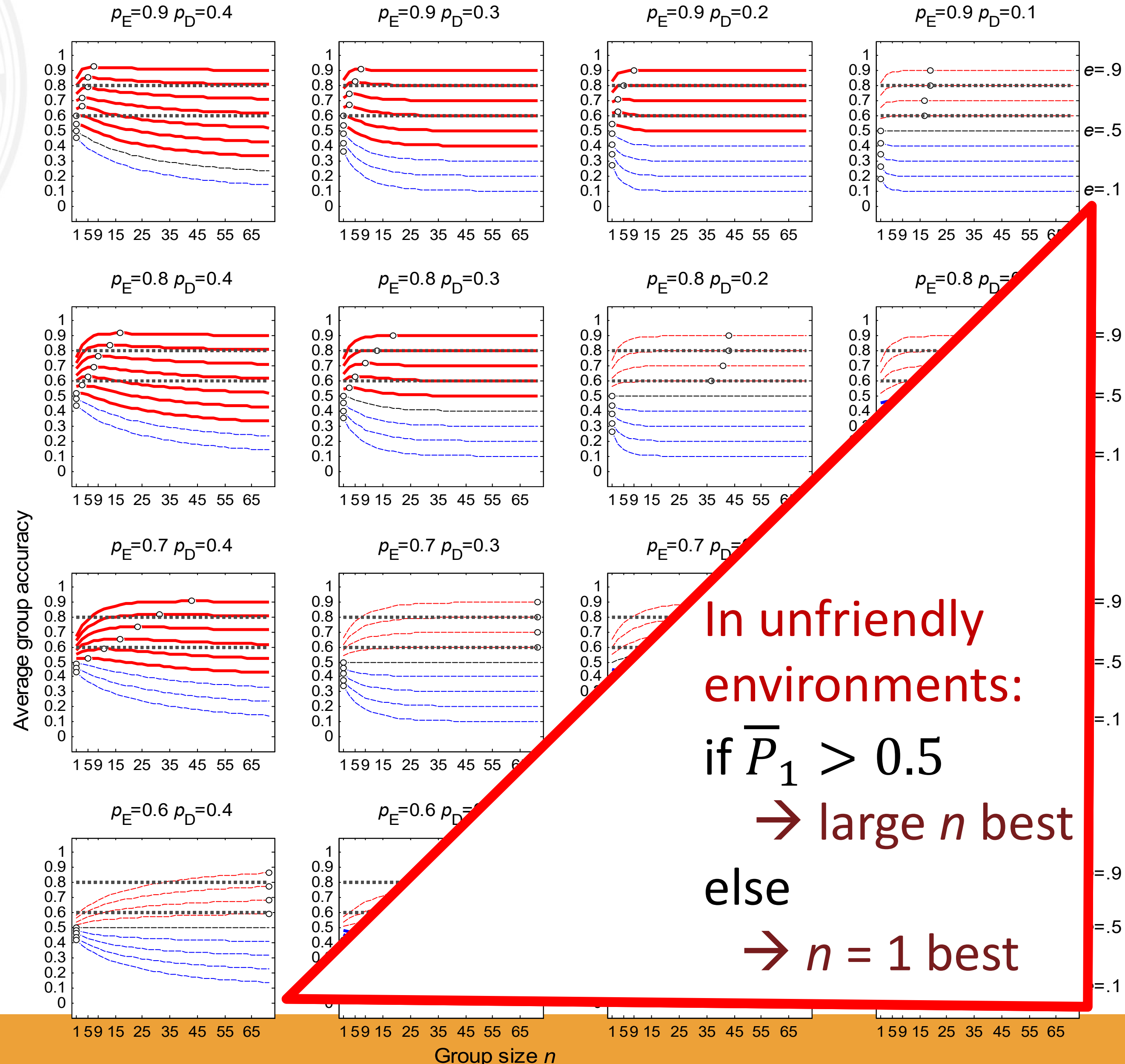


In unfriendly environments:

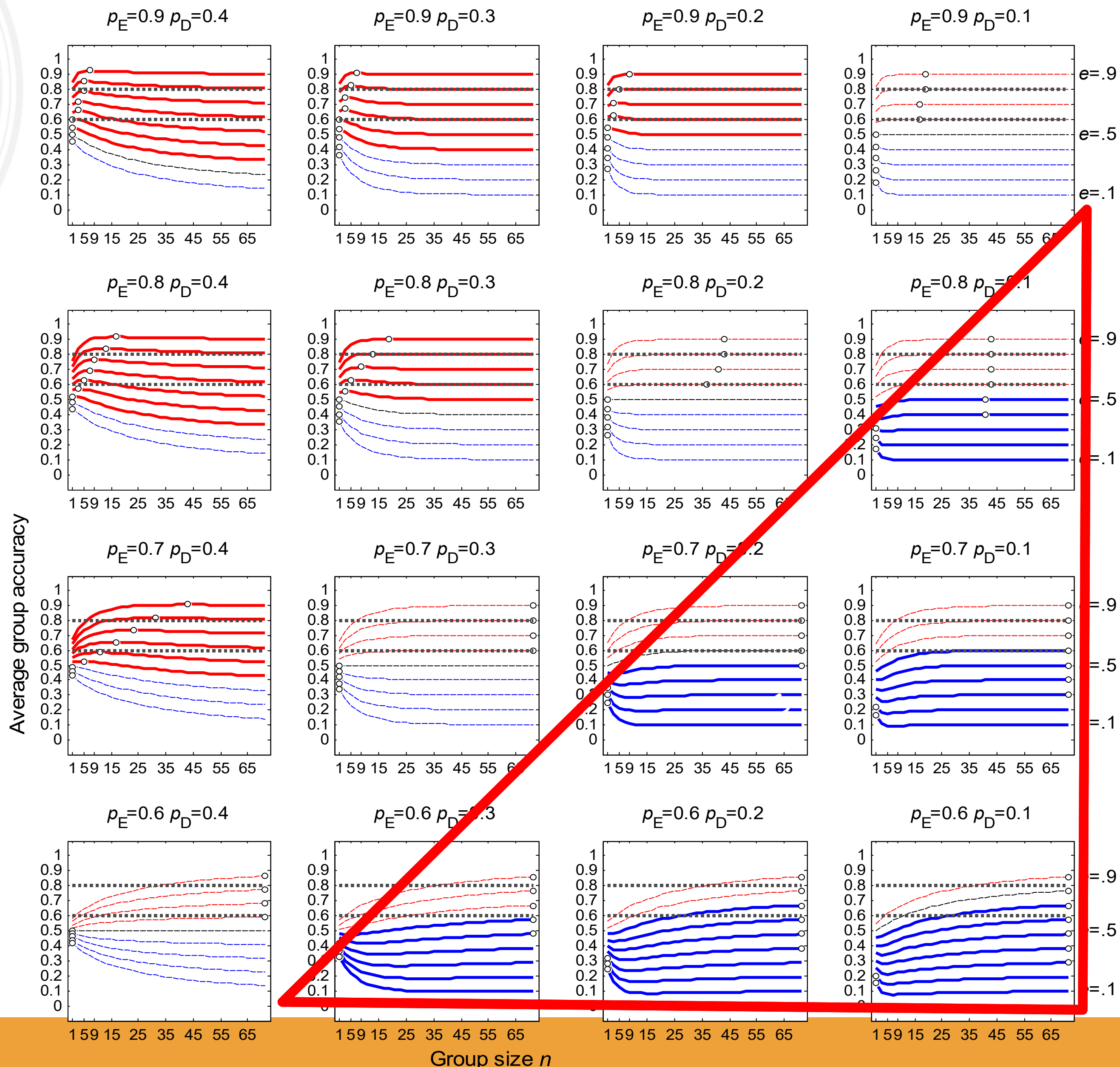
if $\overline{P}_1 > 0.5$

→ large n best

else

→ n = 1 best

Complete set of results



Is the real world friendly or unfriendly?

Real-world task environments: Elections (Graefe, 2014)

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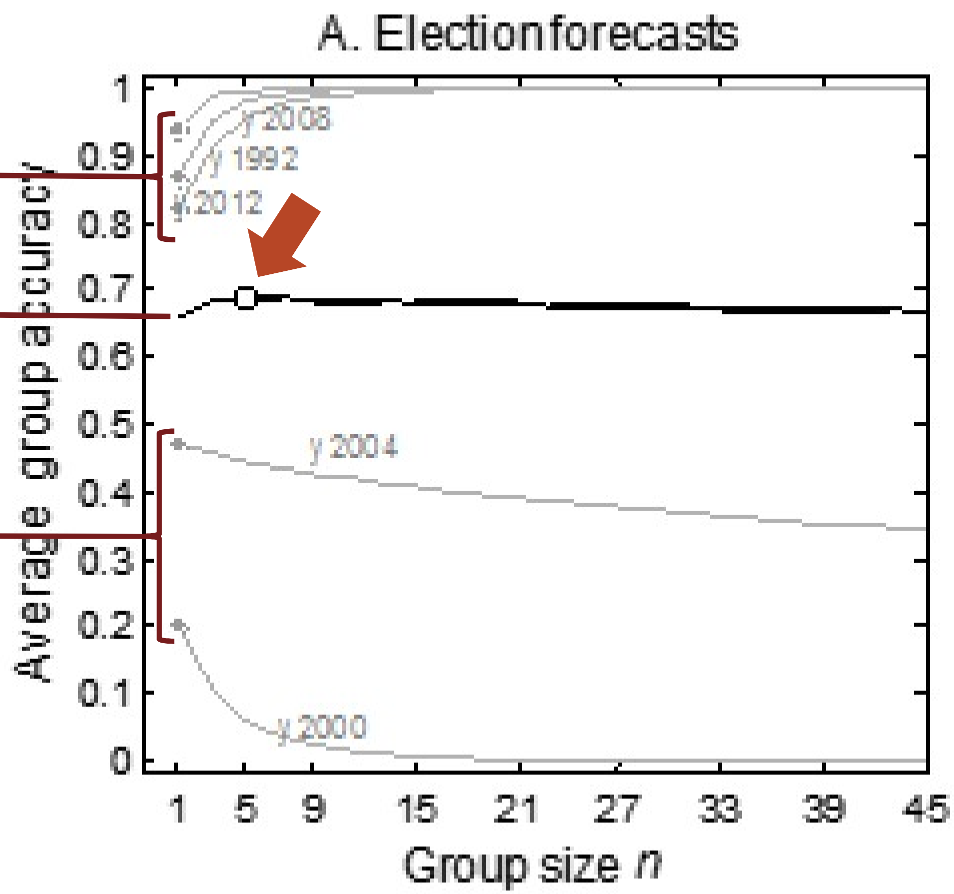
$\overline{p}_{\mathrm{E}} = 0.88$

$\overline{P}_1 = 0.66$

$\overline{p}_D = 0.34$



→ $\overline{p}_{\mathrm{E}} + \overline{p}_{\mathrm{D}} > 1$ and $\overline{P}_1 > 0.5$

(friendly environment, and average expert more accurate than chance across tasks)

Real-world task environments: Medicine (Schiff et al, 2009)

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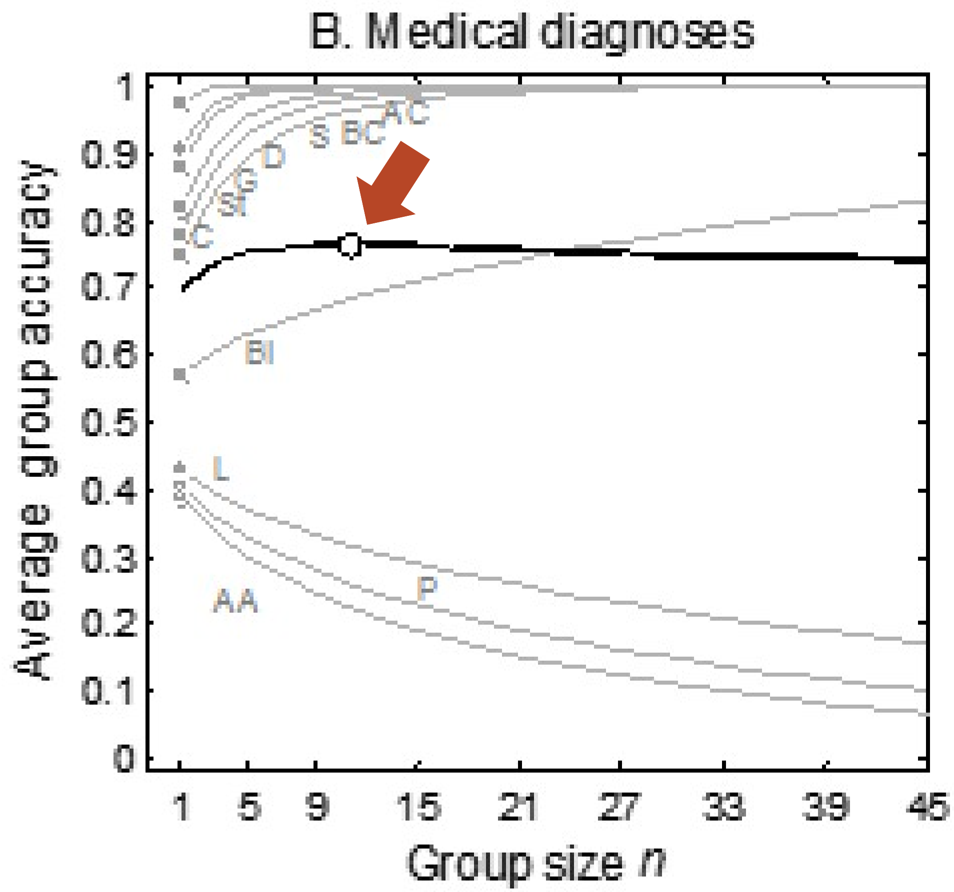
$\overline{p}_{\mathrm{E}} = 0.81$

$\overline{P}_1 = 0.70$

$\overline{p}_D = 0.41$



→ $\overline{p}_{\mathrm{E}} + \overline{p}_{\mathrm{D}} > 1$ and $\overline{P}_1 > 0.5$

(friendly environment, and average expert more accurate than chance across tasks)

Real-world task environments: Economics (Hilsenrath & Peterson, 2013)

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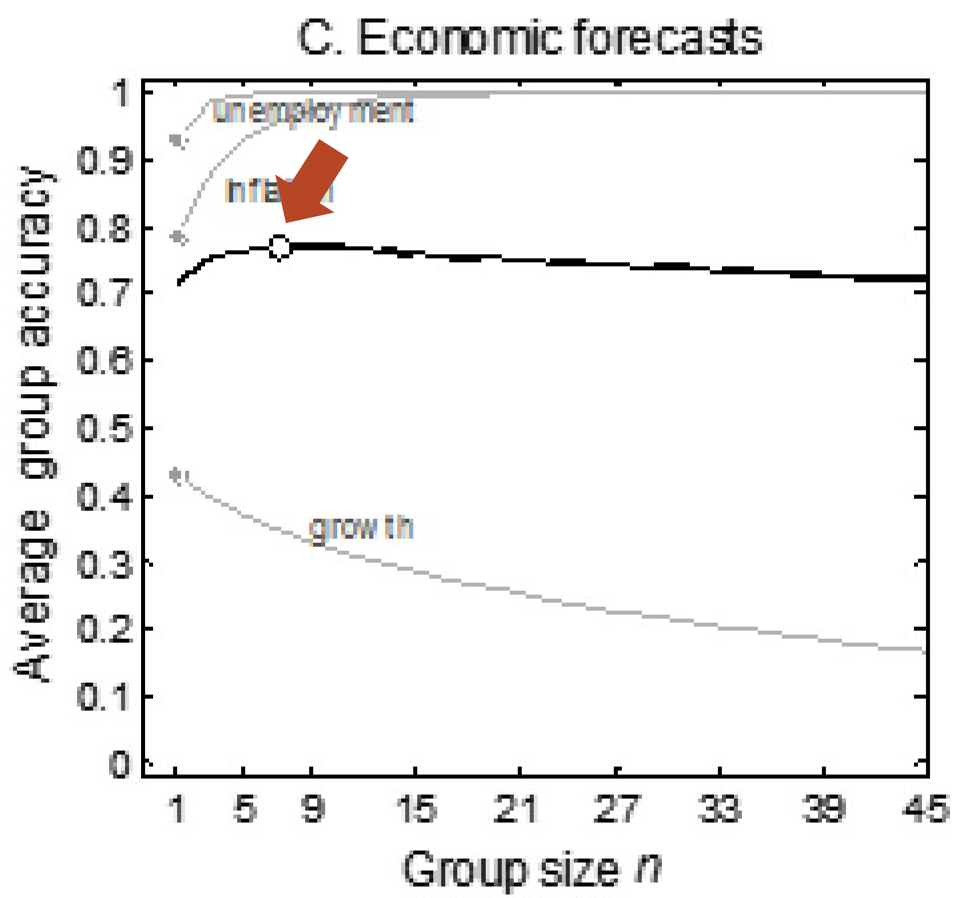
$\overline{p}_{\mathrm{E}} = 0.86$

$\overline{P}_1 = 0.71$

$\overline{p}_D = 0.43$



→ $\overline{p}_{\mathrm{E}} + \overline{p}_{\mathrm{D}} > 1$ and $\overline{P}_1 > 0.5$

(friendly environment, and average expert more accurate than chance across tasks)

Real-world task environments: General knowledge (Juslin, 1997)

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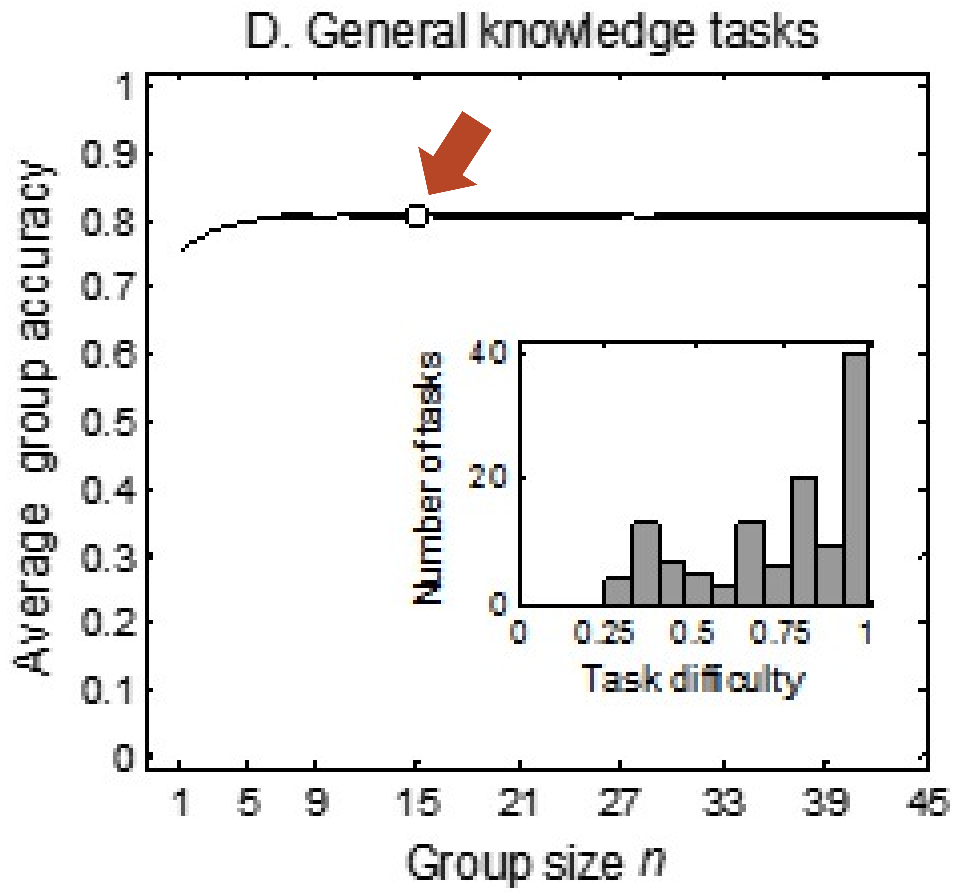
$\overline{p}_{\mathrm{E}} = 0.86$

$\overline{P}_1 = 0.76$

$\overline{p}_D = 0.38$



→ $\overline{p}_{\mathrm{E}} + \overline{p}_{\mathrm{D}} > 1$ and $\overline{P}_1 > 0.5$

(friendly environment, and average expert more accurate than chance across tasks)

2. Wisdom of small crowds for majority vote

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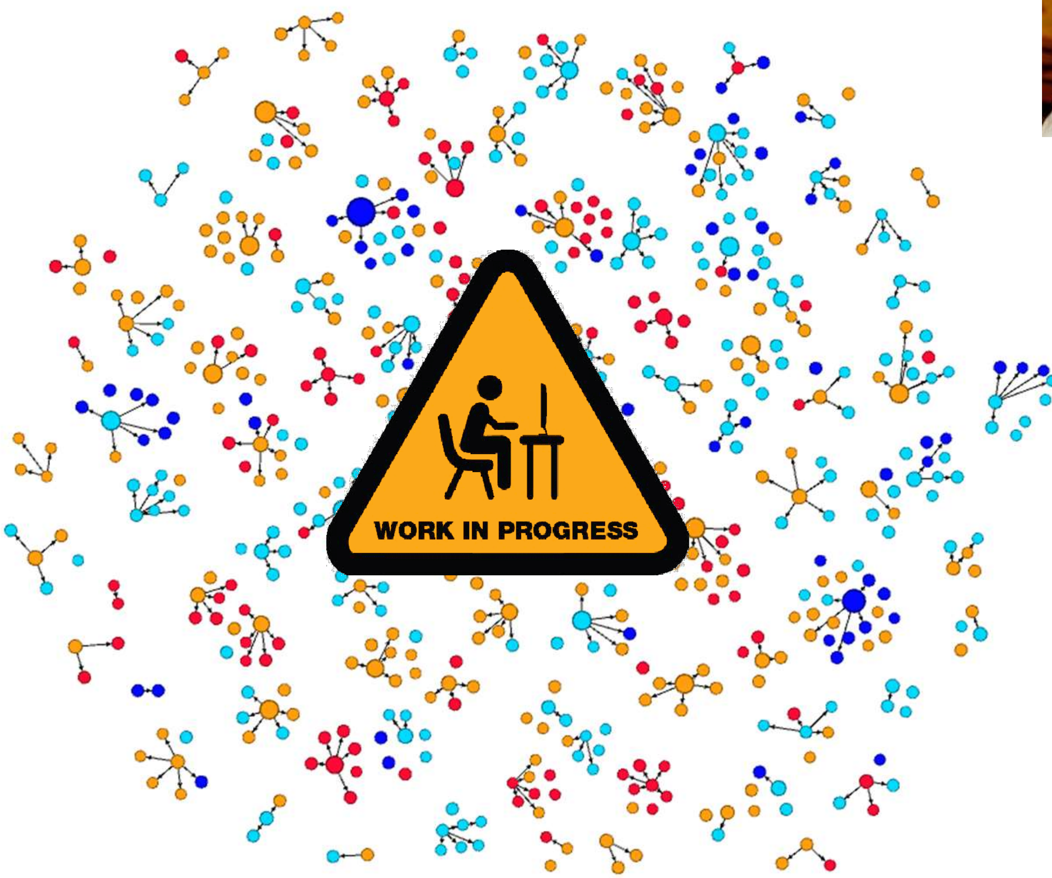
Moderately sized groups outperform large groups and individuals

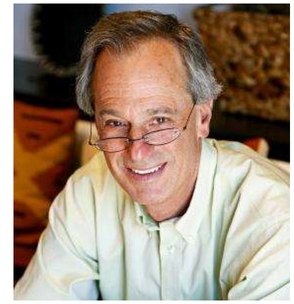
- in realistic circumstances for expert groups: most tasks relatively easy, some surprisingly difficult

Results hold

- for more than two task difficulties
- for more than two options
- when votes are correlated due to leader or a common cue

3. Spread of beliefs in social circles





Dan Stein, NYU

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Study: Different opinions, every 2 weeks, 4 waves

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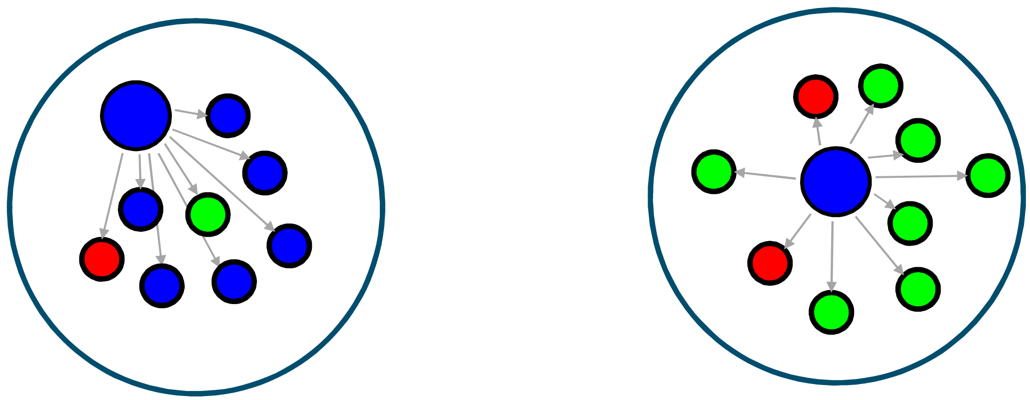
1. Muslims need more scrutiny
2. Islam encourages violence
3. Gun laws need to be less strict
4. Latino immigrants have negative impact
5. Middle East immigrants have negative impact
6. Worry about terrorist attack
7. Global warming is not happening
8. Vaccination of children should be optional
9. GMOs are unsafe to eat
10. PSA test is very effective in preventing prostate cancer eaths
11. Mammography is very effective in preventing breast cancer deaths

Social circles

- "People you discuss these issues with"



~100 participants answered about their and their friends' beliefs across 4 study waves…

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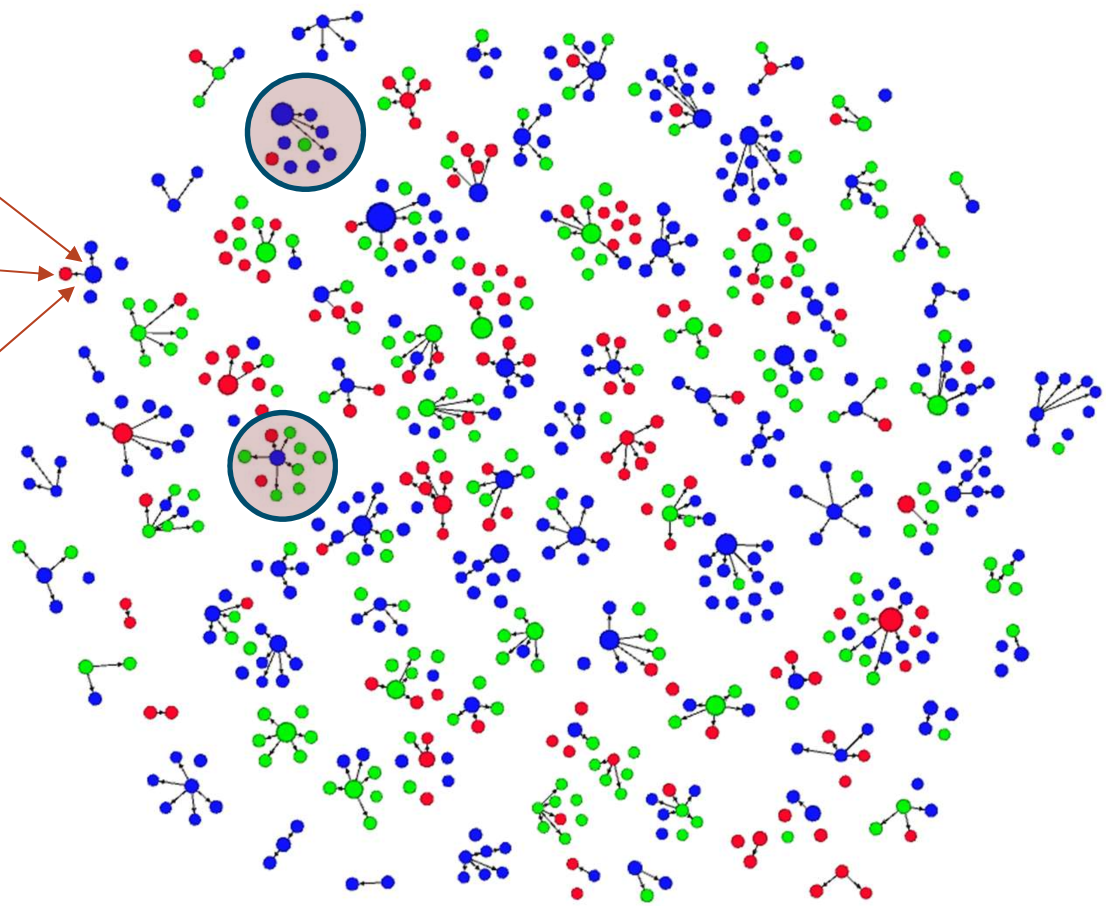
Larger circles: participants

Smaller circles: social contacts

Lines: current links to contacts



Muslims in the US should be subject to … much more scrutiny – bit more – no additional scrutiny … than people in other religious groups

Wave 1 (Jan 17, 2016)

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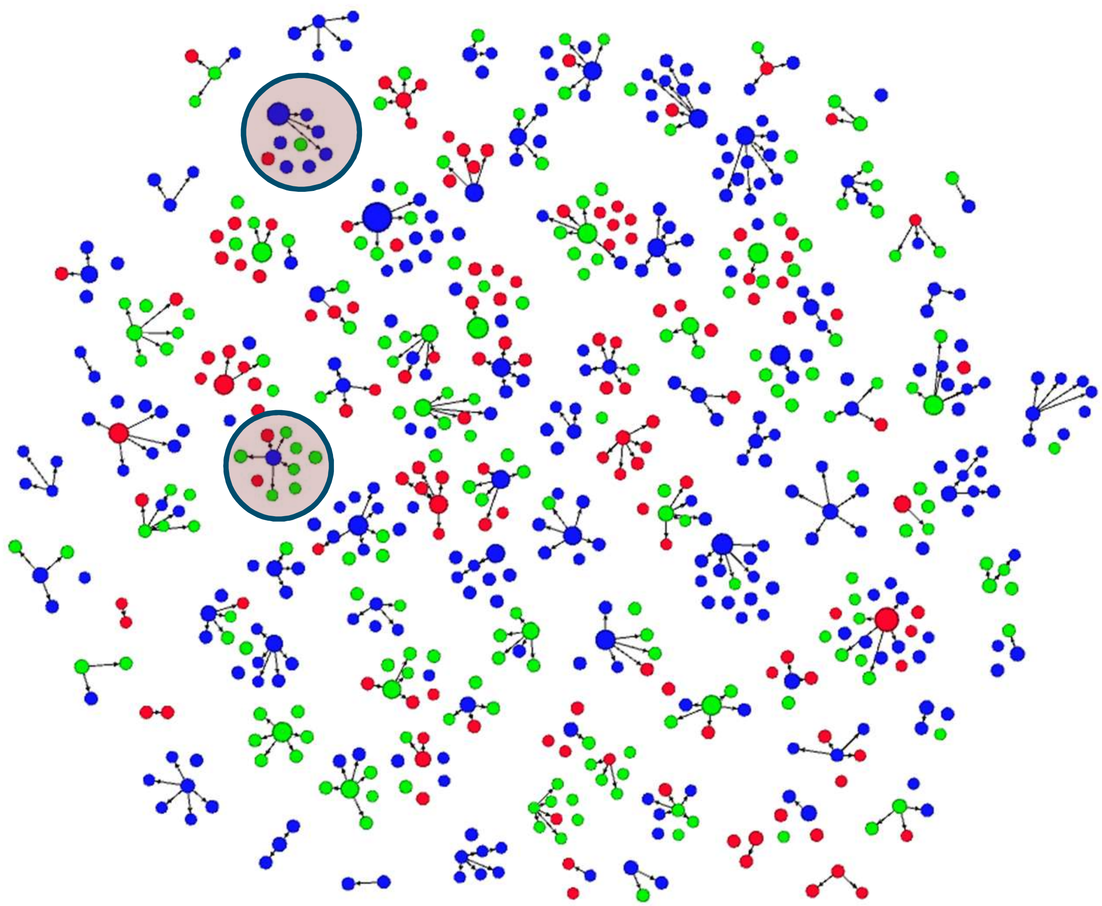
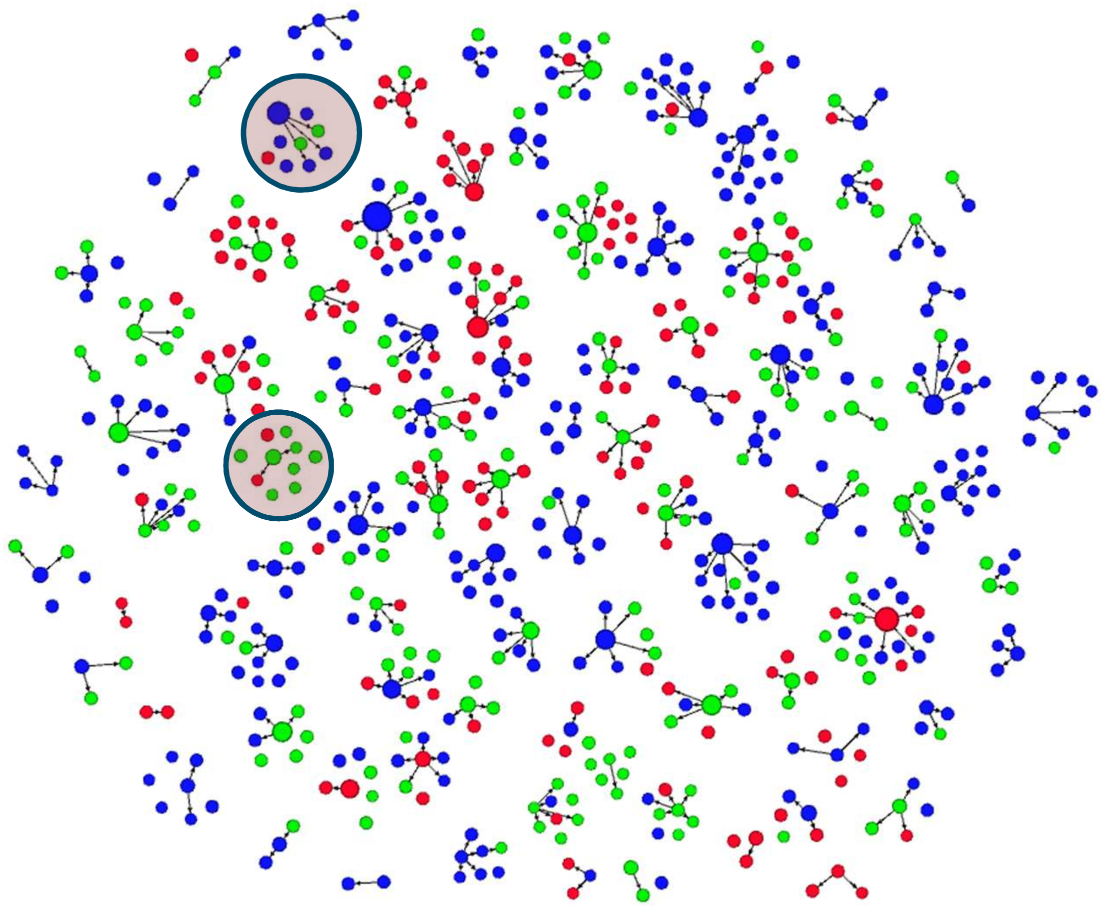


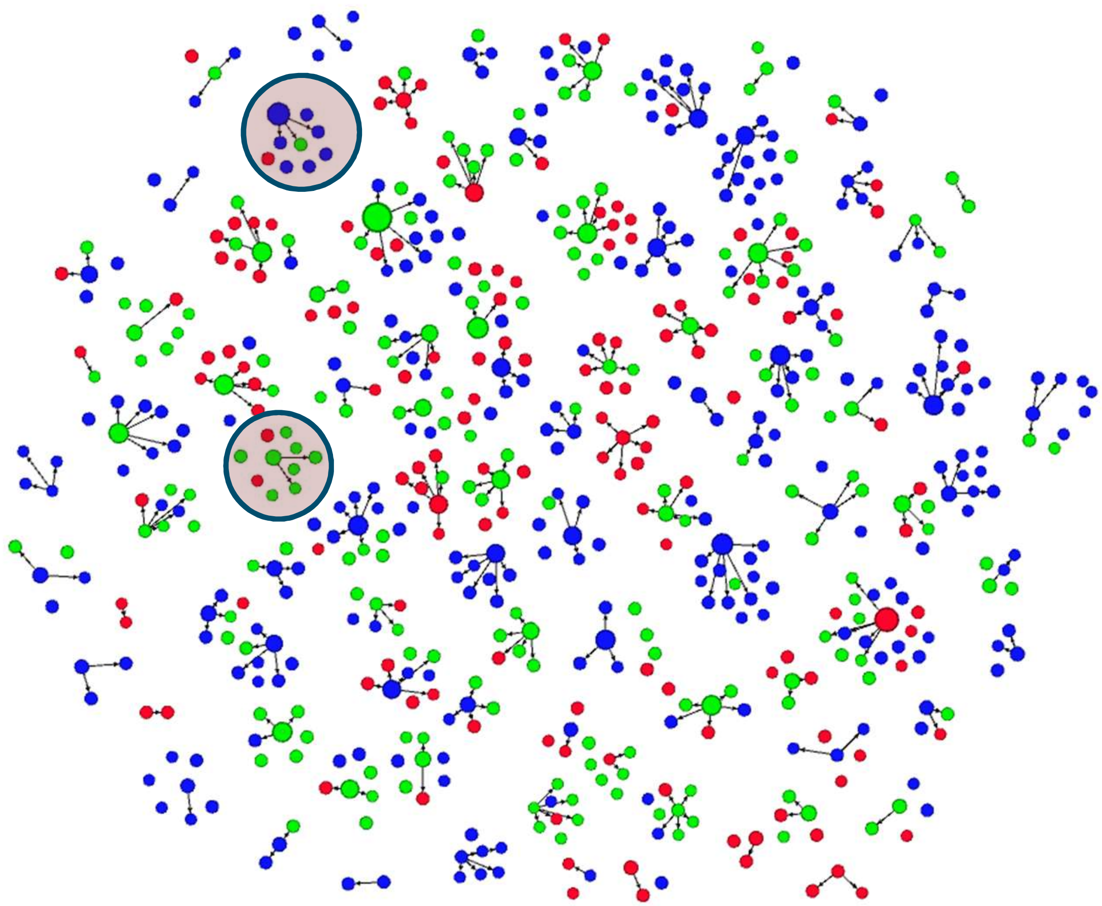
Muslims in the US should be subject to … much more scrutiny – bit more – no additional scrutiny … than people in other religious groups

Wave 2 (Jan 31, 2016)



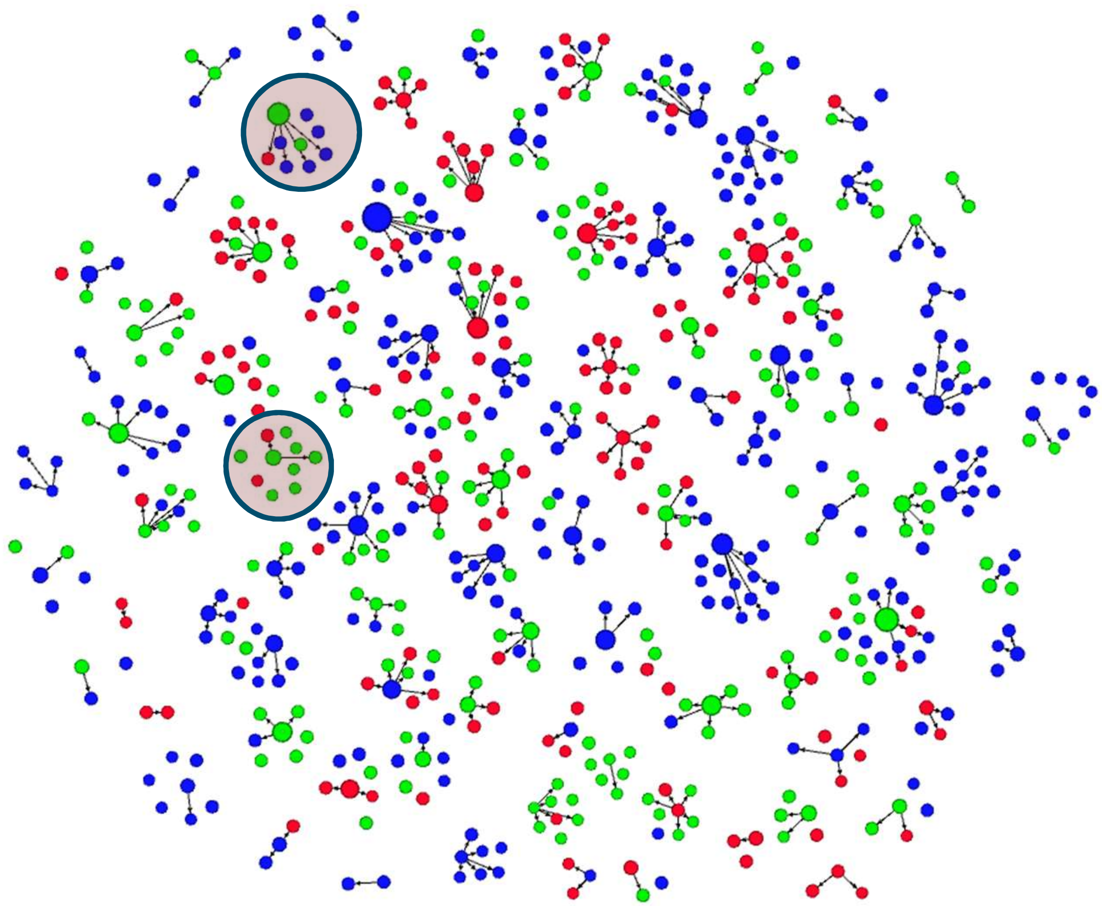
Muslims in the US should be subject to … much more scrutiny – bit more – no additional scrutiny … than people in other religious groups

Wave 3 (Feb 14, 2016)

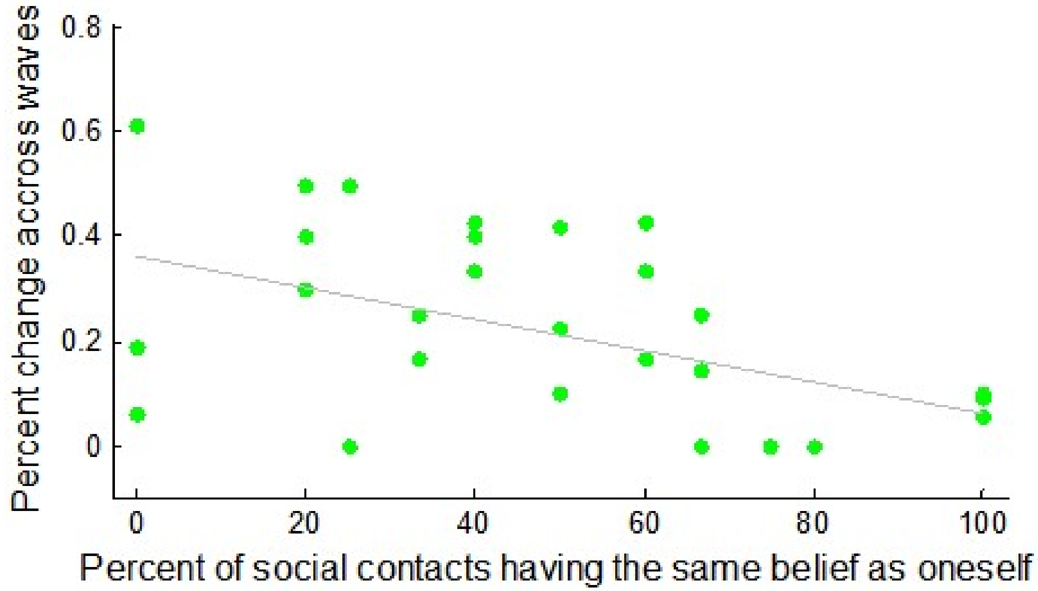


Muslims in the US should be subject to … much more scrutiny – bit more – no additional scrutiny … than people in other religious groups

Wave 4 (Feb 28, 2016)

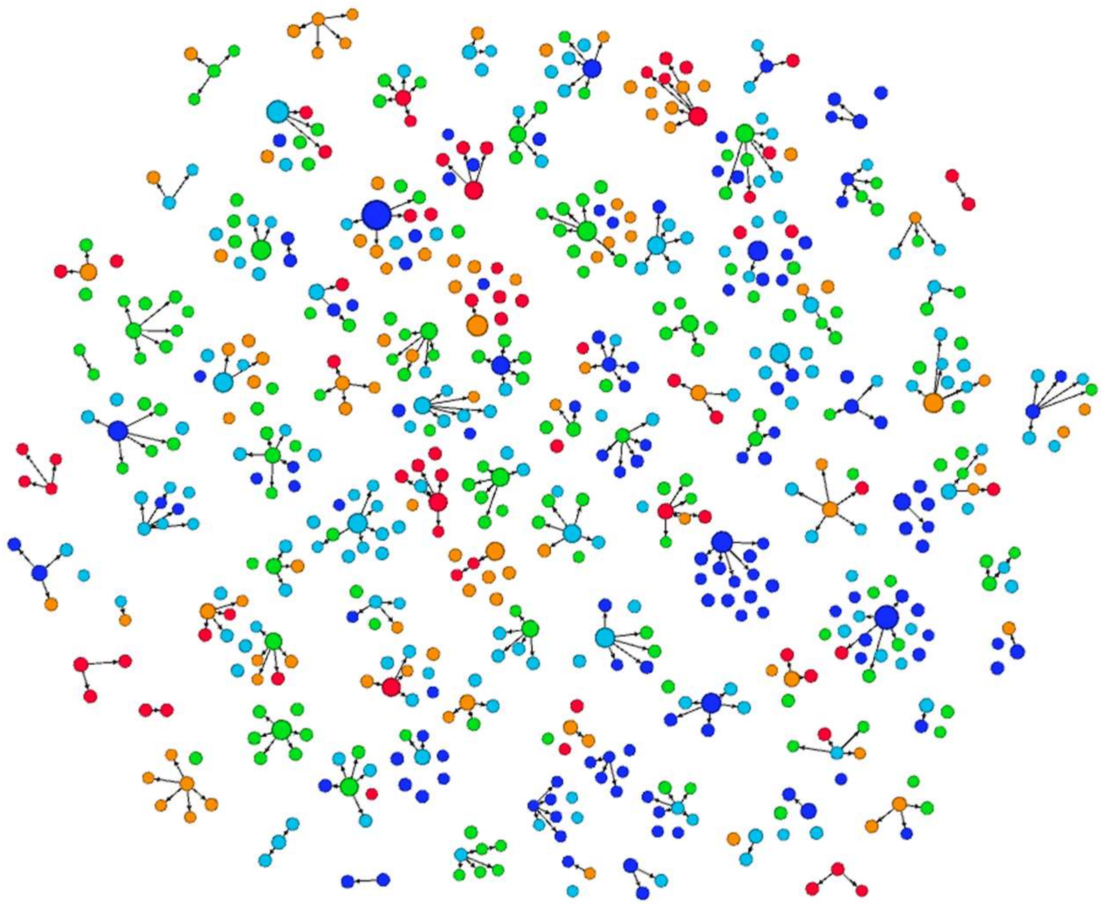


Likelihood of belief change is related to homophily in social circles



Effect of science education

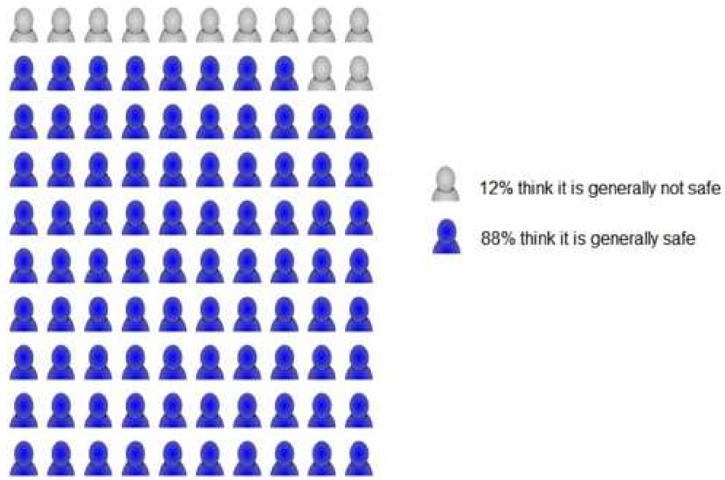
GM crops are: very unsafe – somewhat unsafe – neither nor – somewhat safe – very safe for human health



Scientific facts

Here is some information about GENETICALLY MODIFIED (GM) CROPS. Please review it carefully.

A survey of members of the American Association for the Advancement of Science, the world's largest scientific society, revealed that 88% of scientists think that it is generally safe to eat genetically modified foods. This is shown in the following picture:



Source: Pew Research Center (2014). Public and scientists' views on science and society. http://www.pewinternet.org/2015/01/29/public-and-scientists-views-on-science-and-society/

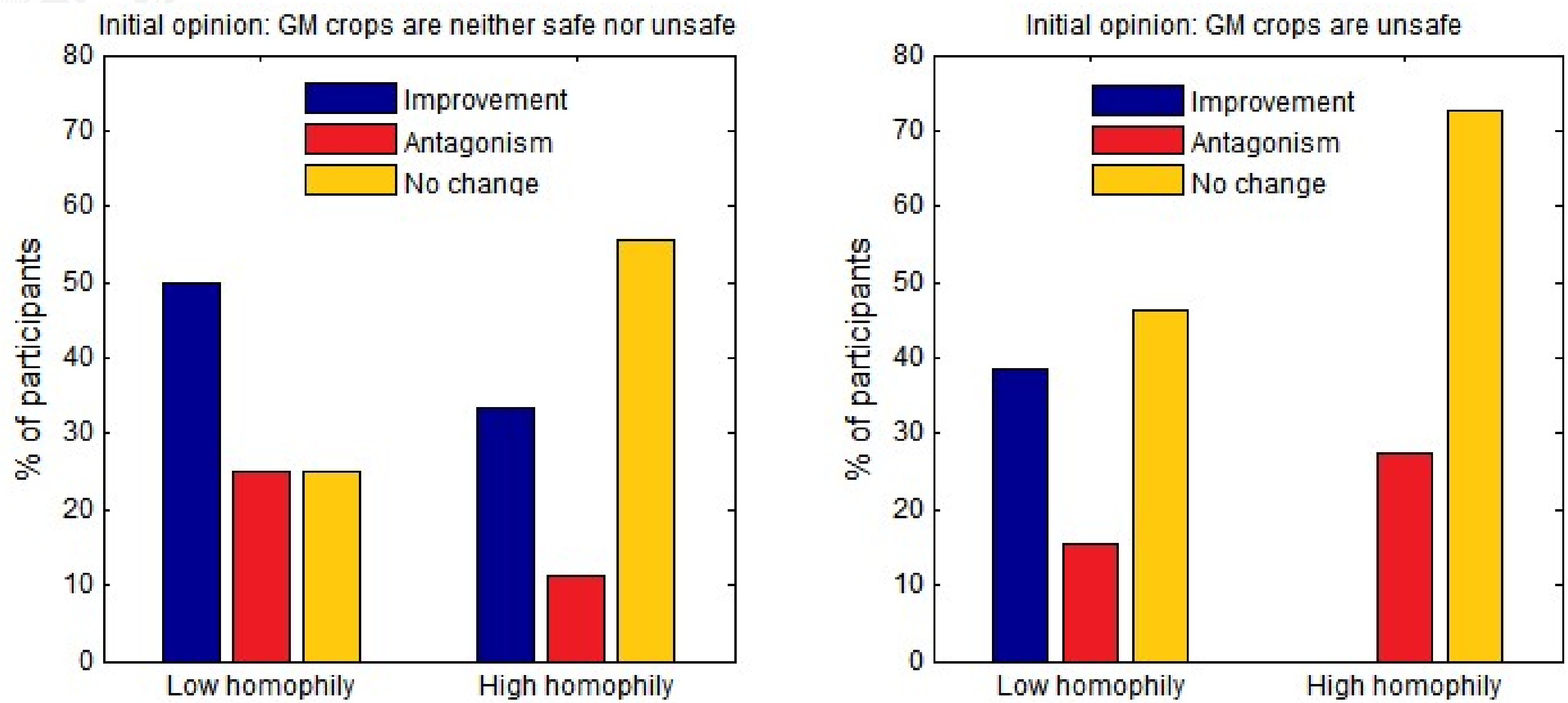
Picture below shows that genetically modified corn (top) repels the kinds of insects that damage unmodified corn (bottom). This reduces the need to spray insecticides that kill insects non-selectively.

Source: http://www.ift.org/~/media/Food%20Technology/Feature%20Images/2014/01/F2GMOs/0114F2_GMOsHero.jpg

Please click Continue when you are ready.

Effect of science education

Likelihood of change by initial opinion and homophily of social circles



Homophily of social circles

Modeling belief change

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Framework:

Models of spread of magnetization from statistical physics

$$\mathcal{H}_i = -\sigma_i s_i - \sigma_i h_i$$

A possible belief

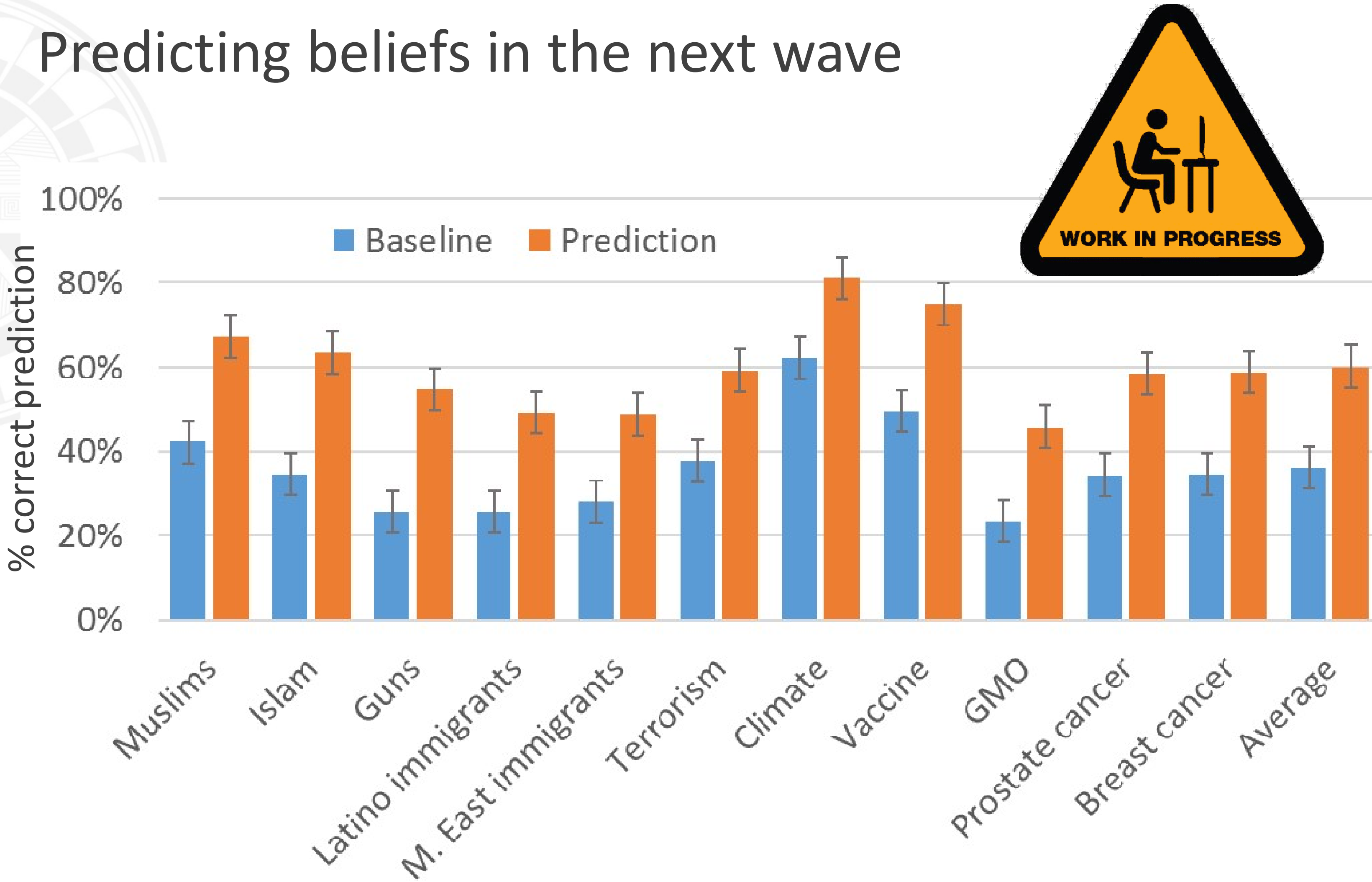
Summary of beliefs in social circle

Broad political orientation

But with realistic rules for summarizing beliefs in social circle:

- Follow majority
- Follow best expert
- Follow random
- …

Predicting beliefs in the next wave



Baseline: Frequency of different beliefs in the sample in the previous study wave
Prediction: Model based on friends' beliefs in the previous study wave and own political orientation

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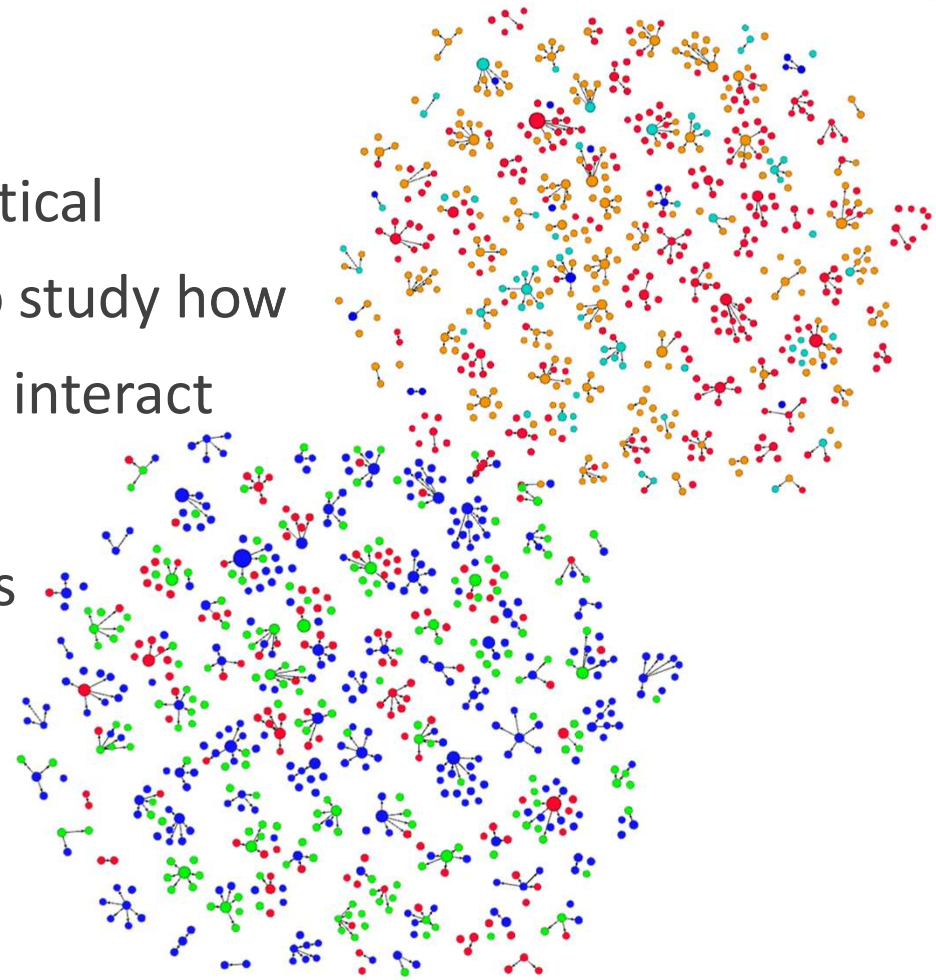
3. Spread of beliefs in social circles

We can use models of magnetization from statistical physics as a framework to study how social learning algorithms interact with task and network structure to spread beliefs



A blueprint for modeling social phenomena

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1. Determine cognitively plausible algorithms

Representing social environments

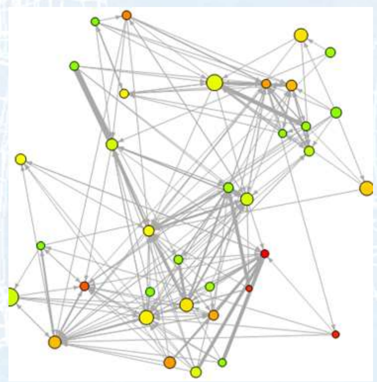
Social learning

Network building & revision

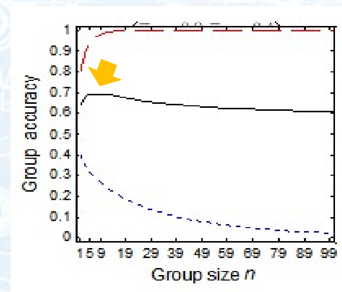
Cooperation & competition

2. Model their performance in realistic task environments

and in realistic social networks

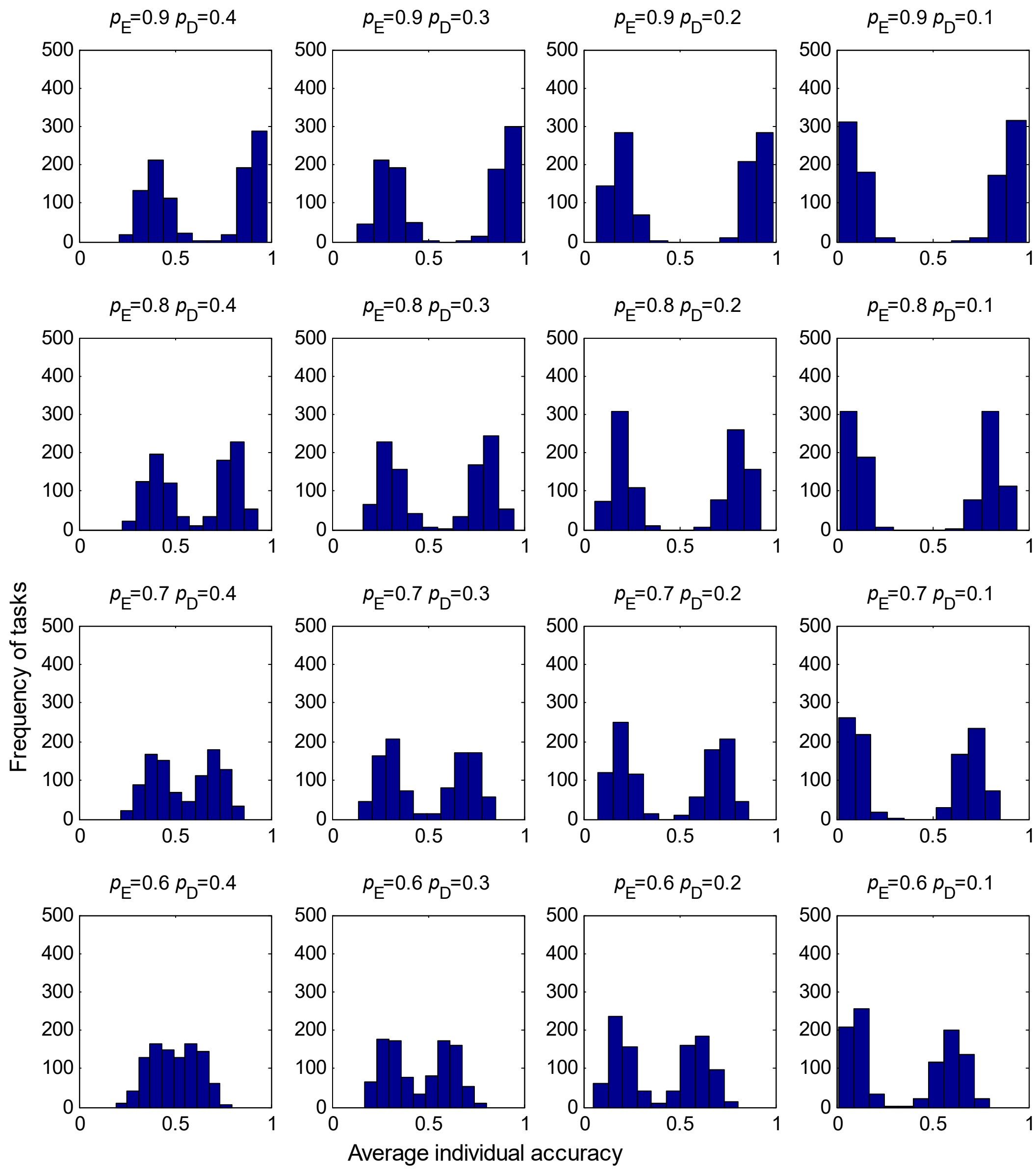


3. Compare model predictions with empirical data



Revise

More than two task difficulties



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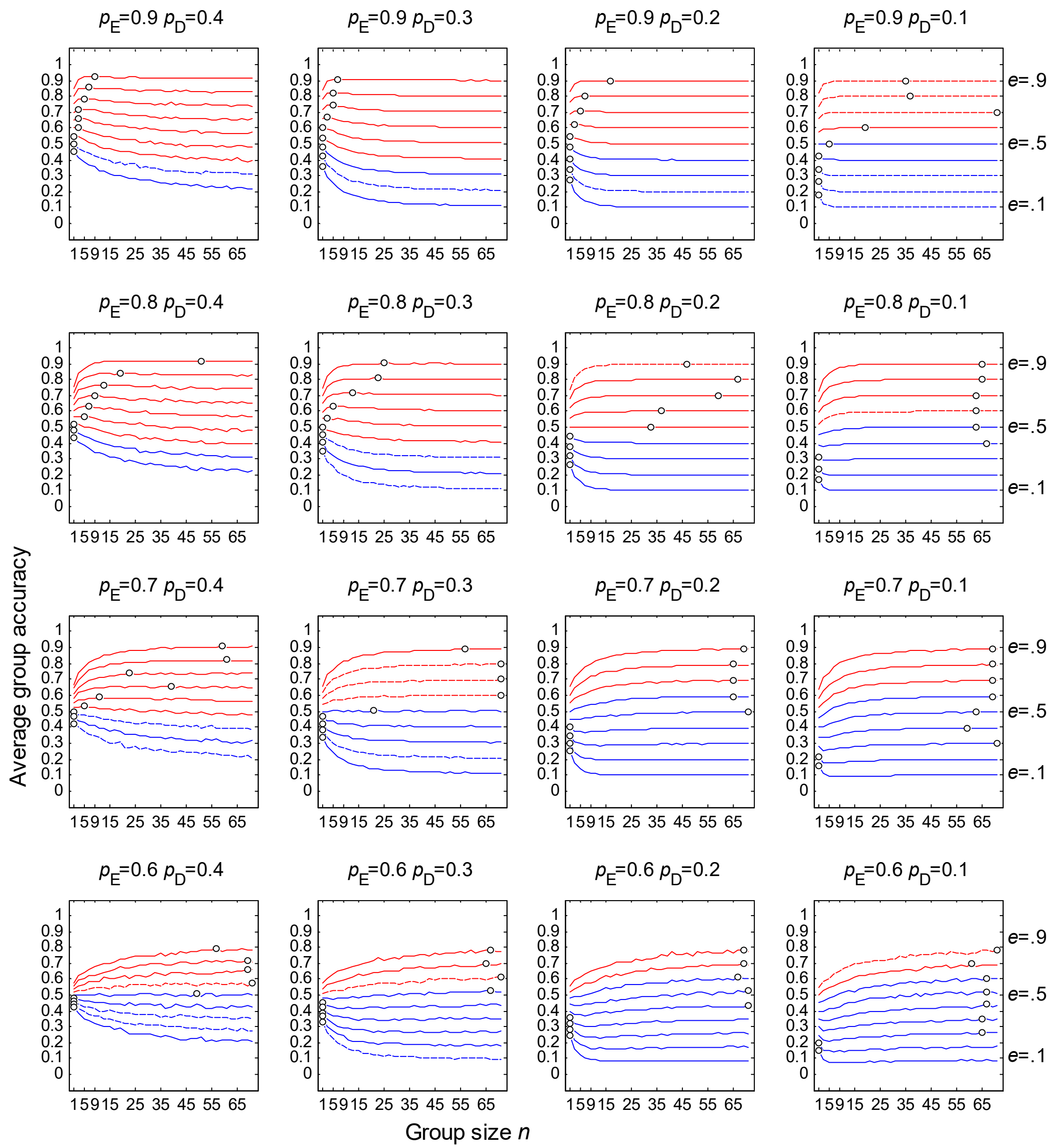
More than two task difficulties



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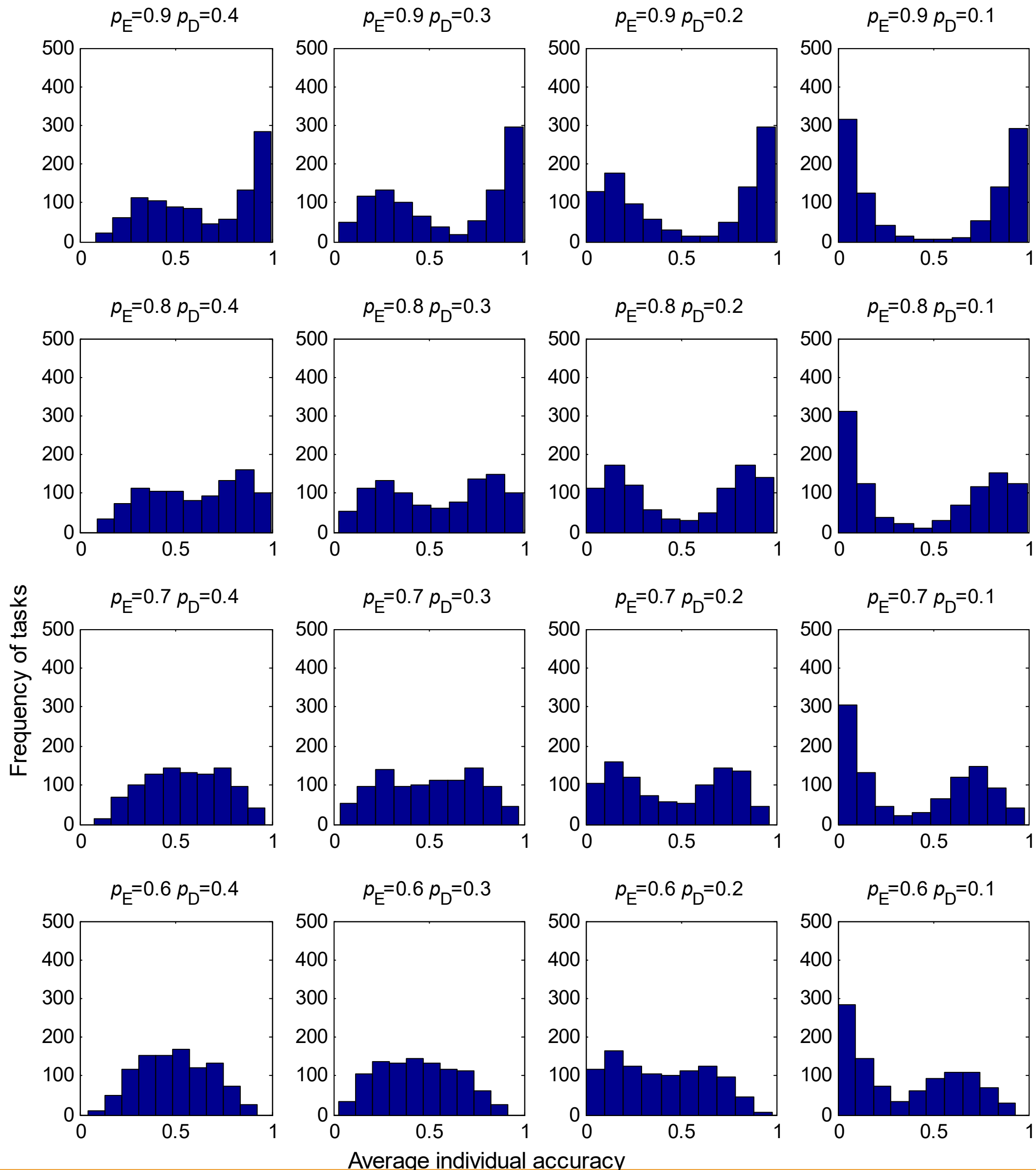
More than two task difficulties



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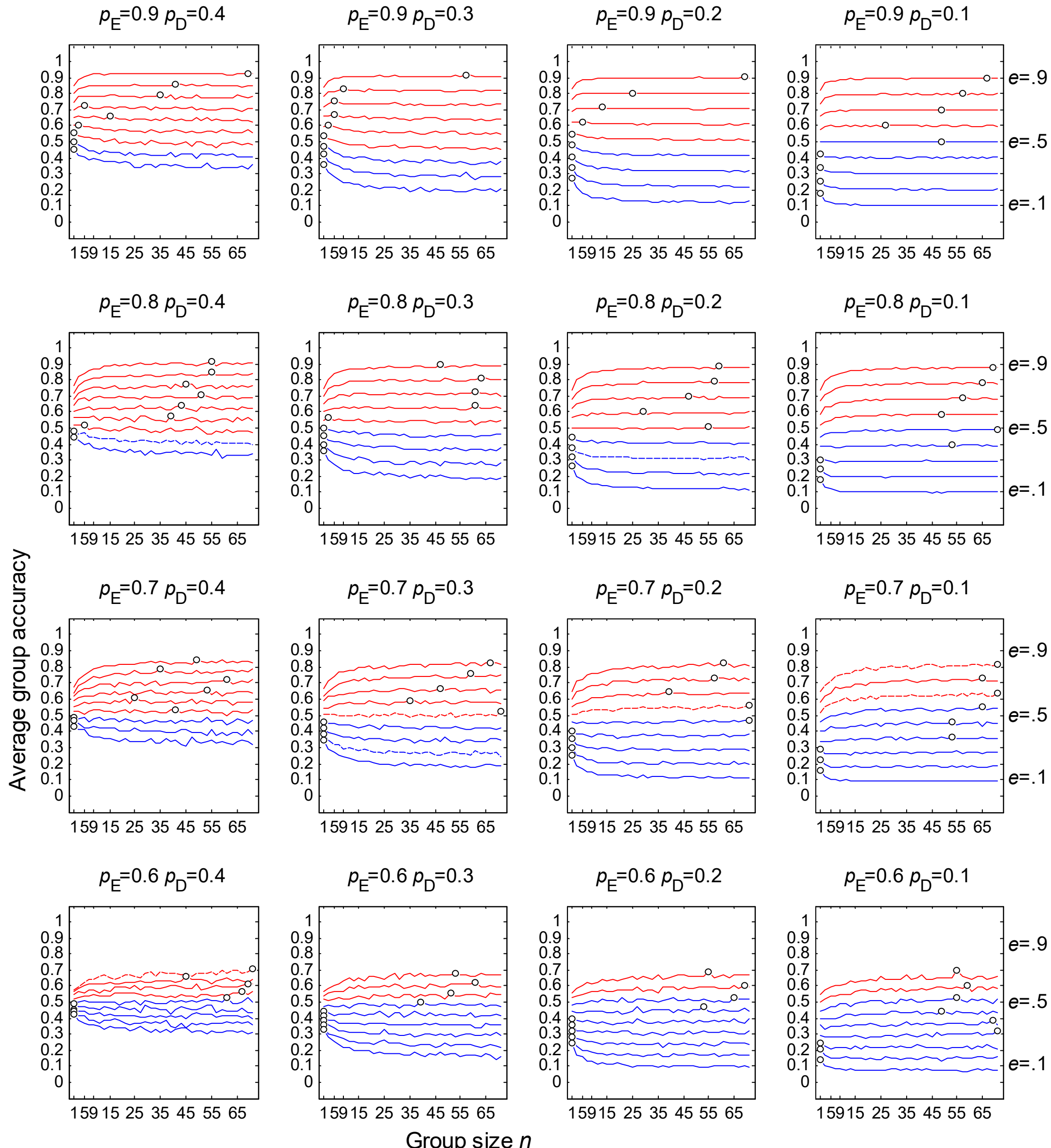
More than two task difficulties



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Correlated votes

$$\overline{P}_n = l(P_n |\, \overline{p}(1-r)+r) + (1-l)(P_n |\, \overline{p}(1-r))$$

$\overline{P}_n$ → average accuracy of group of size *n* across tasks

l → probability that an opinion leader is accurate on any task

$\bar{P}_n$ → average accuracy of group of size *n* across tasks

$\overline{p}$ → average individual accuracy that group members would have without the opinion leader

r → proportion of group members who are following the opinion leader

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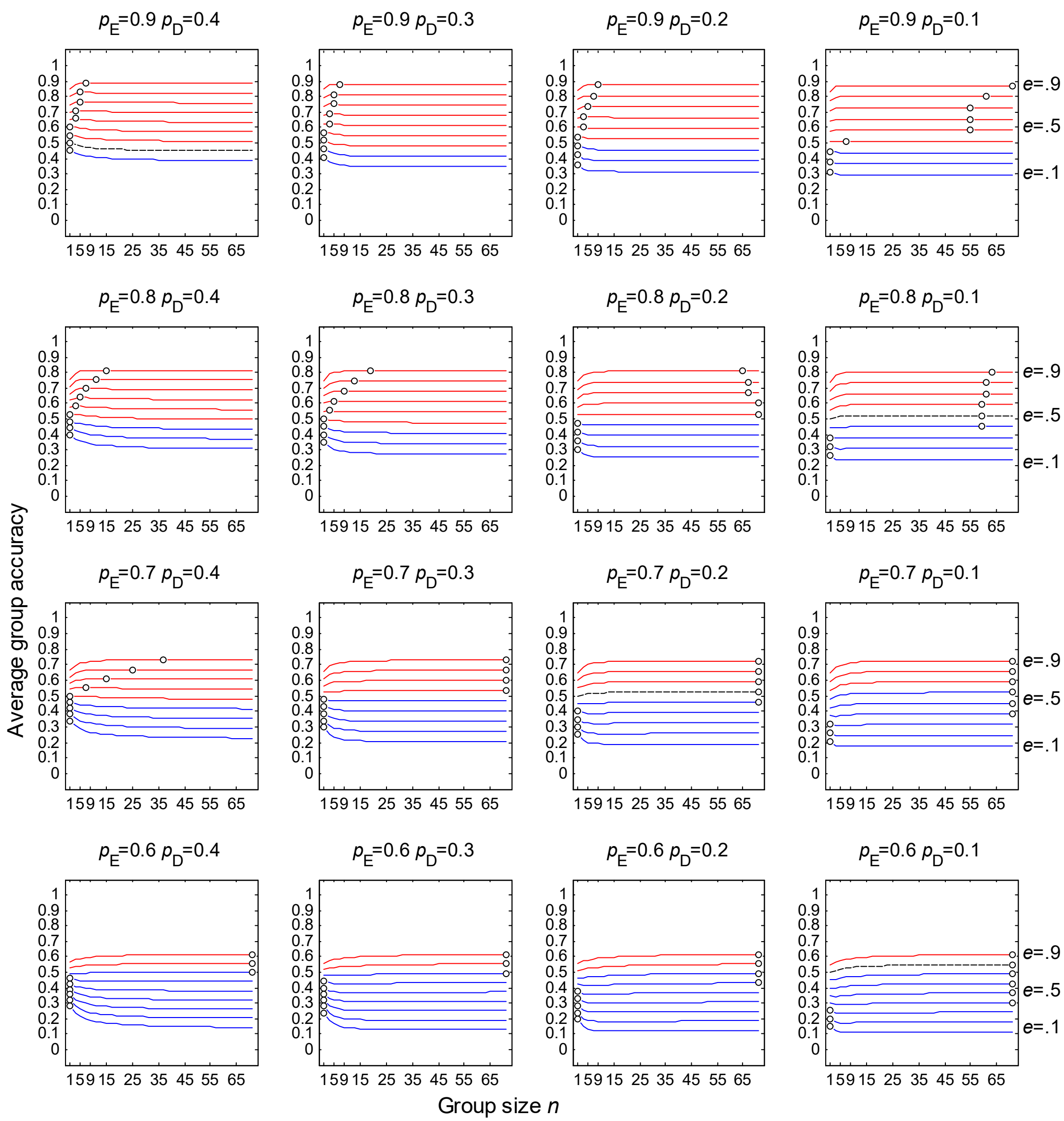
Correlated votes



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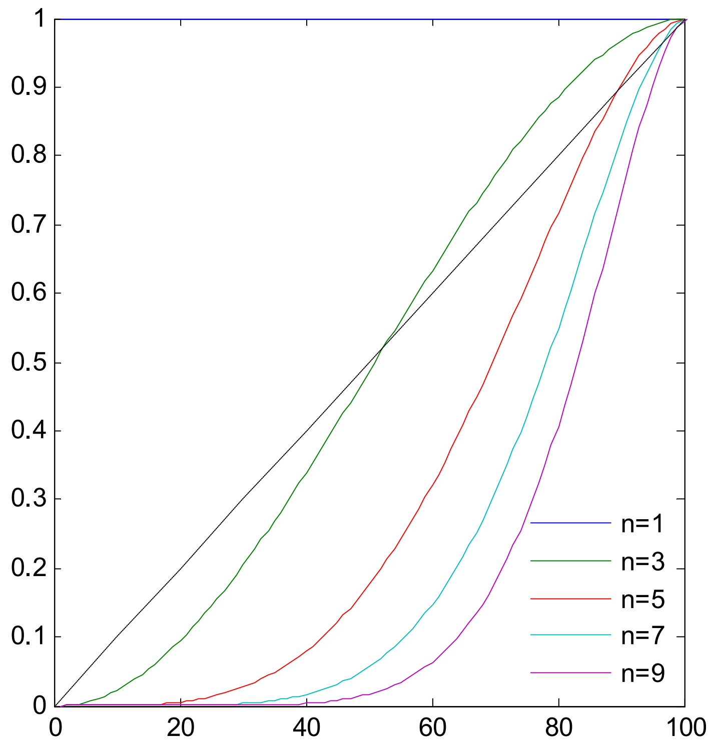
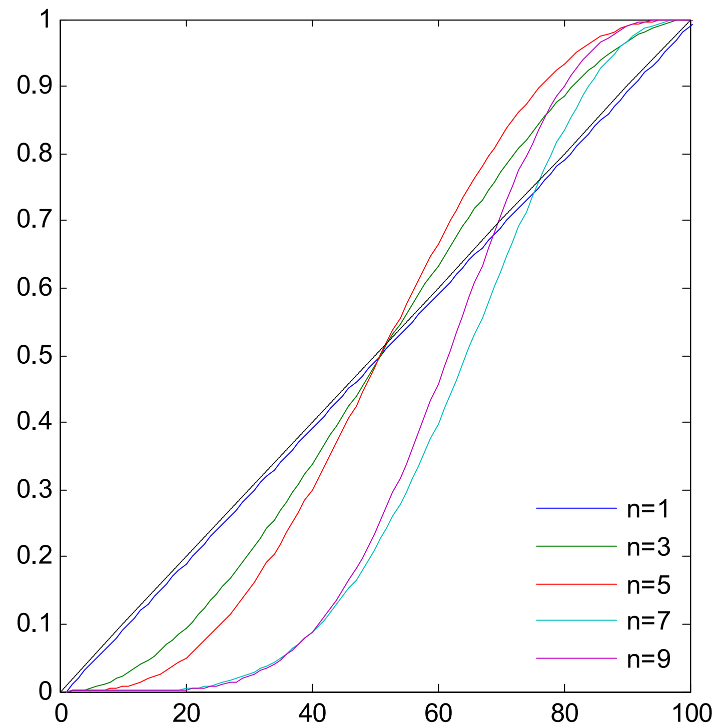
Other rules

Probability that majority in one's **sample** believes X

All but 1

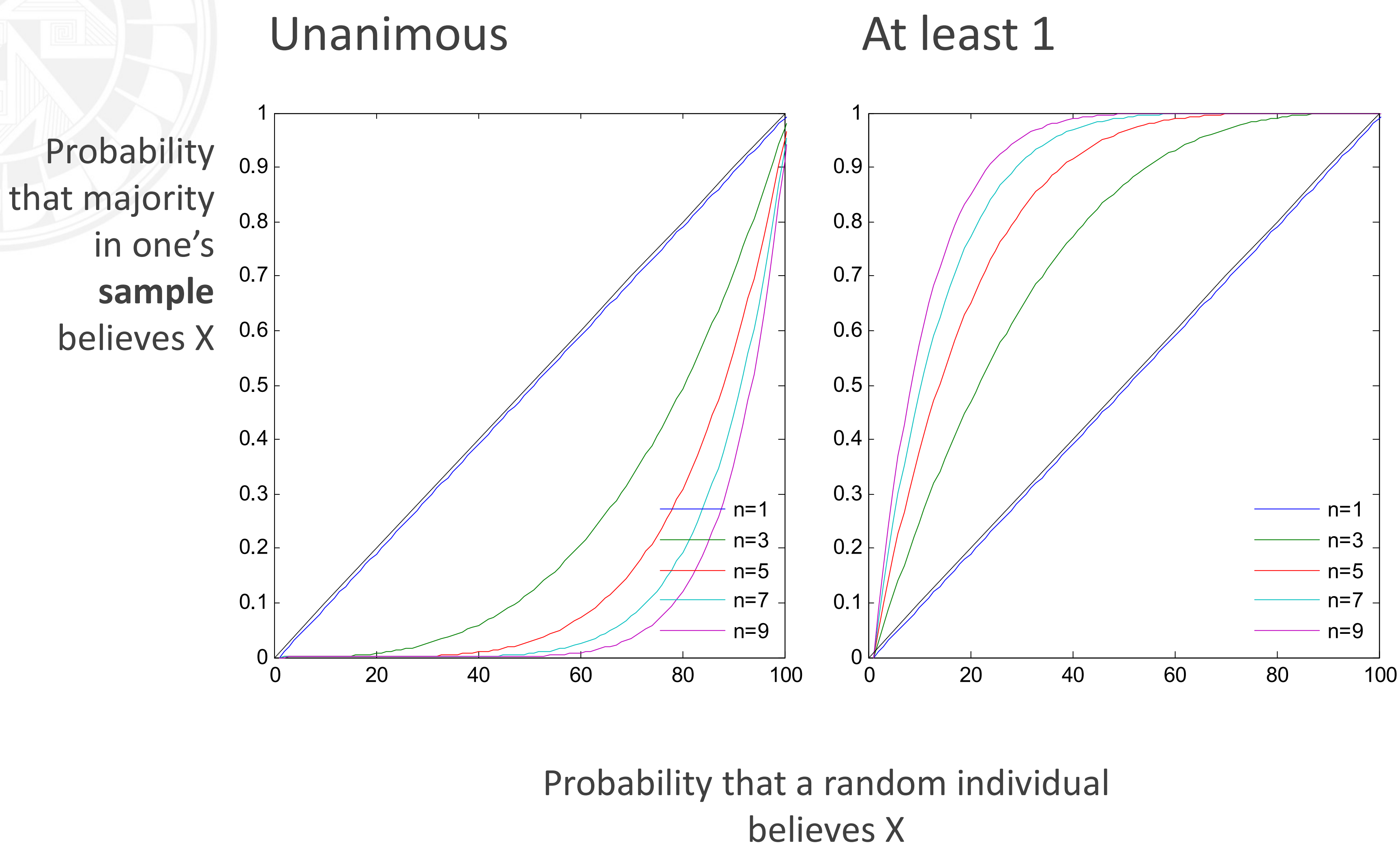


2/3 majority

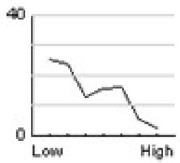


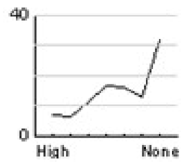
Probability that a random individual believes X

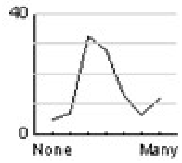
Other rules


Unanimous
At least 1
Probability that majority in one's **sample** believes X
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
20
40
60
80
100
n=1
n=3
n=5
n=7
n=9
Probability that a random individual believes X

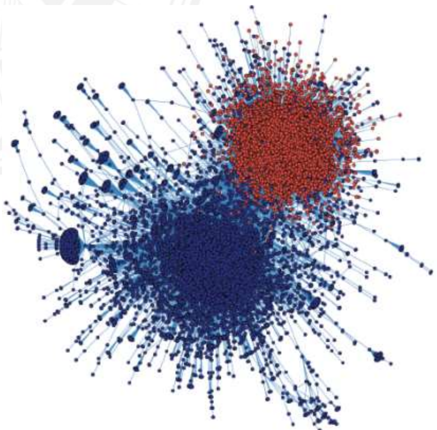
Thank you

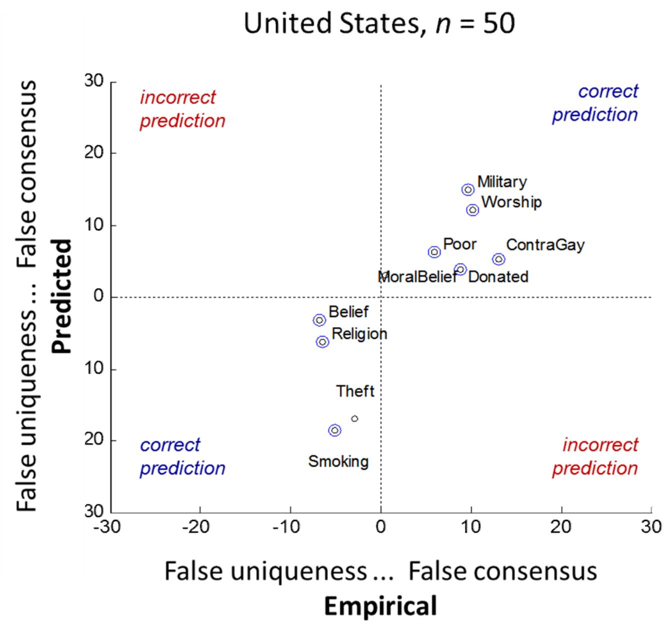


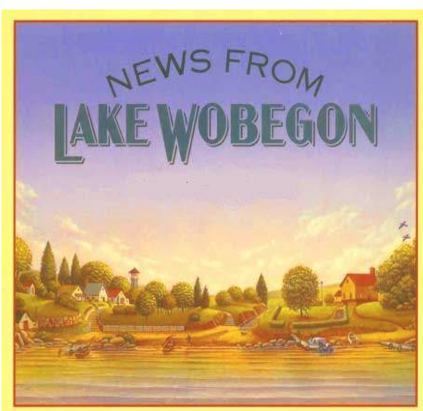


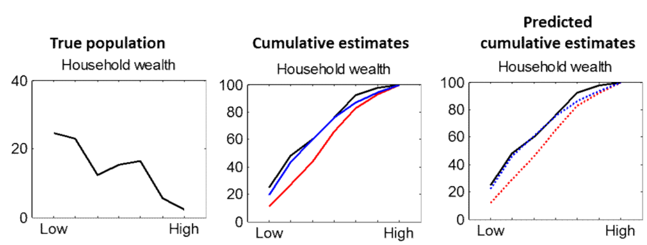


Population estimate $p(C|R) = \dfrac{\sum_{i=1}^{n} \alpha \times A_{Ci} \times A_{Ri}}{\sum_{i=1}^{n} A_{Ri}}$

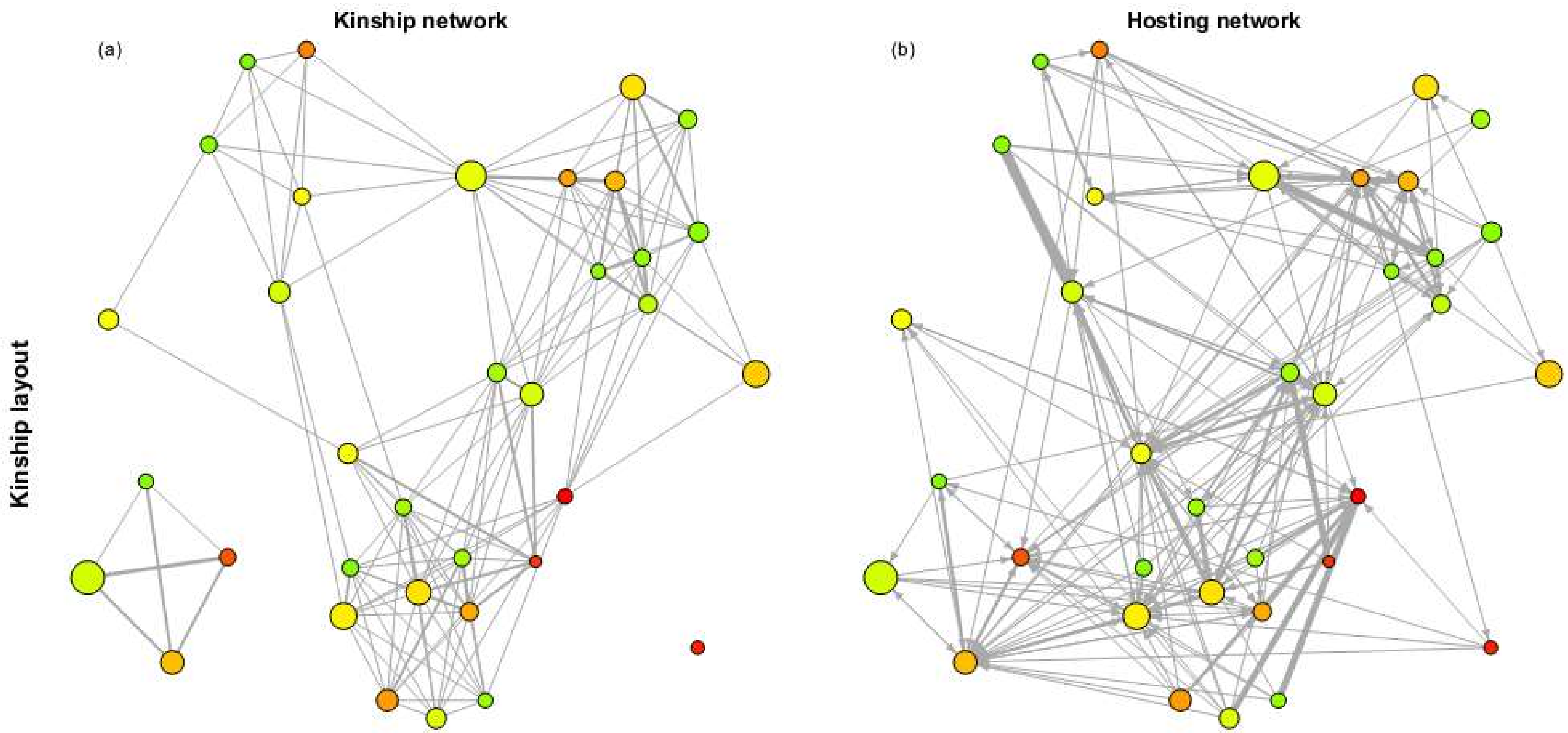








Network structure



From: Hooper, DeDeo, Caldwell-Hooper, Gurven, & Kaplan (2013, Entropy)

… and many other examples in: