# Social Networks and Success in Online Games

Winter Mason
Facebook
Stevens Institute of Technology

- Friendships and success in Halo:Reach
- Network structure and success in an experimental game

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- Network structure and success in an experimental game

# joint work

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funded in part by

James S. McDonnell Foundation

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DARPA

AFOSR

AIR FORCE OFFICE OF SCIENTIFIC RESEARCH

# online games

## some basic statistics

•100+ million Americans play online games

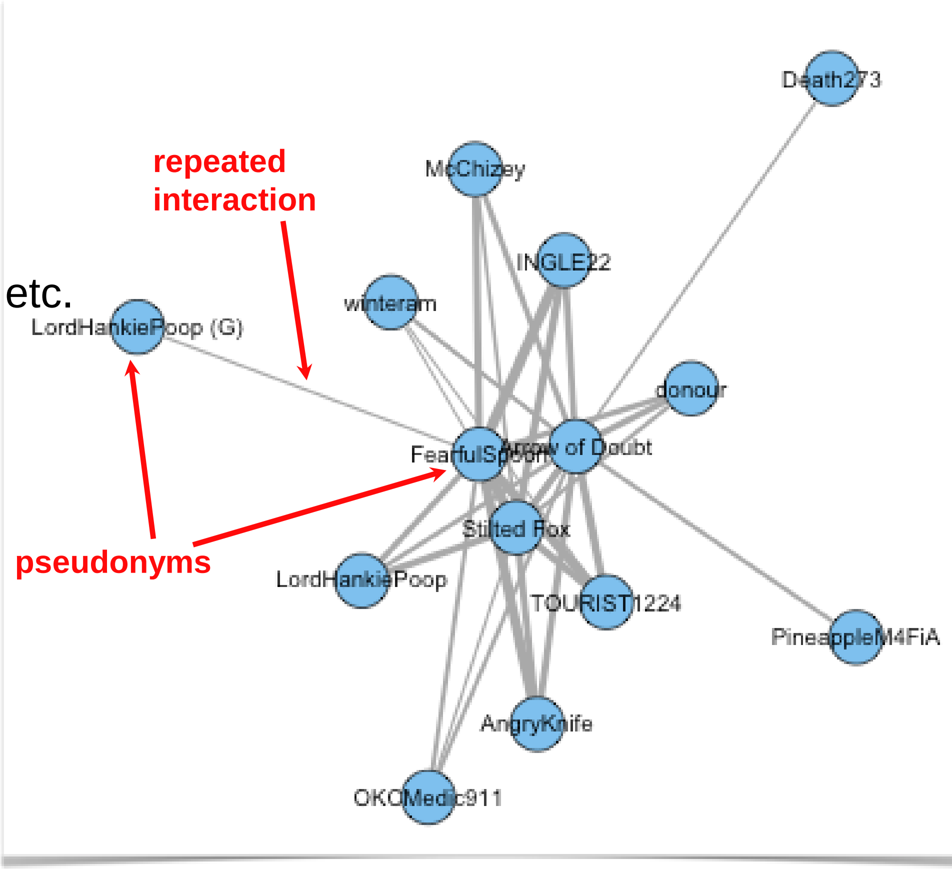
•most prefer to play with friends

•broad age distribution (mean = 41)

•1000s of games, diverse types

# online game social networks

- nodes identified by online pseudonyms
  unique across game / platform & tied to one person (generally)
- edges = online interactions
  interactions = costly
  shared activity, repeated
- nodes attributes
  demographics, online activity, performance, etc.
- edges attributes
  weights, time, character, etc.



# a massive online game

***Halo: Reach (Bungie, 2010)***

•played online via XBox Live platform

•team combat simulation (FPS)

•20TB of game data, spanning

•18 months of time

•17+ million players

•1 billion competitions

- 70% are team competitions
- complex spatial environments
- complex social interactions


XBOX LIVE

## Glossary

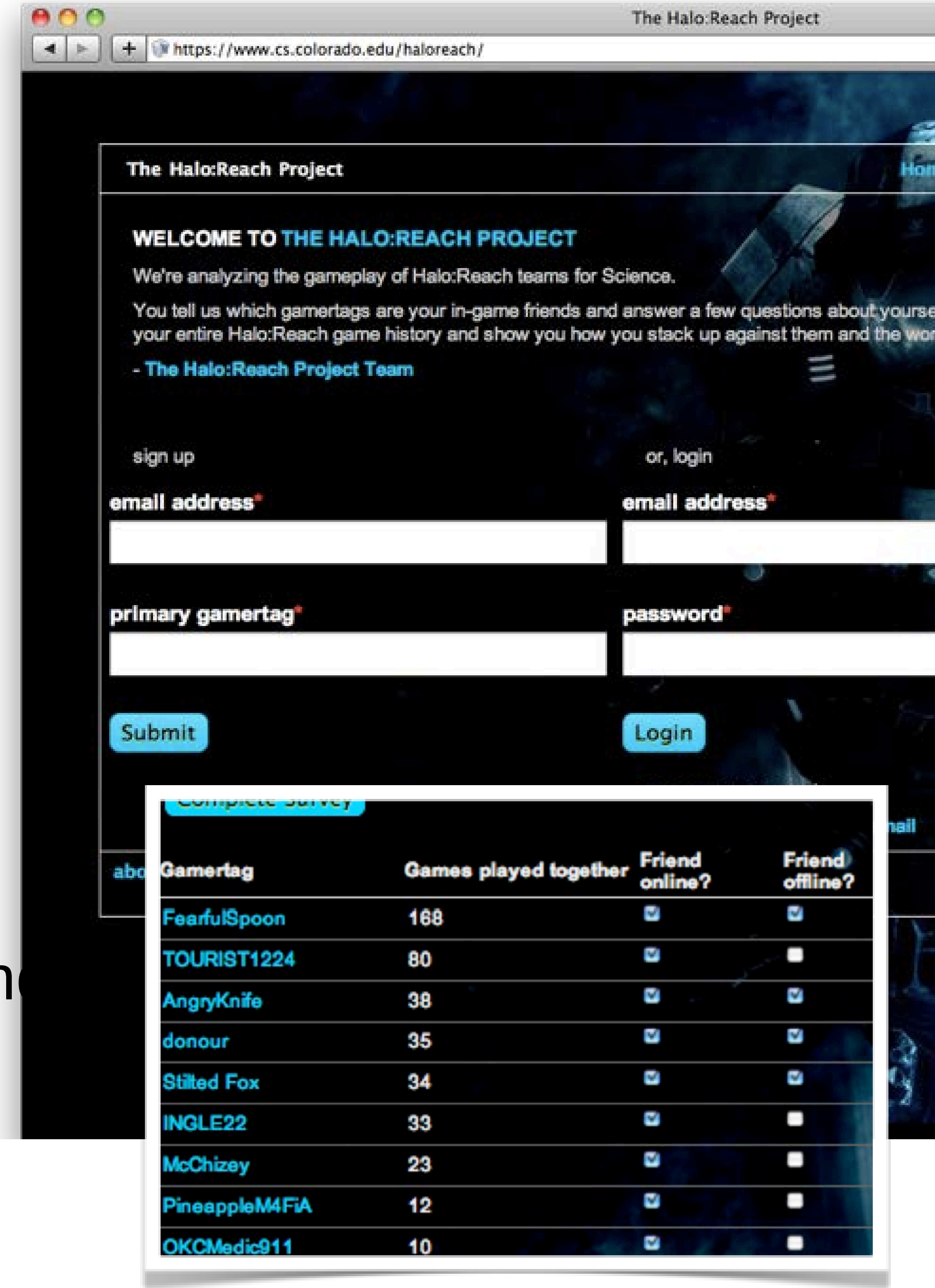
- Kills
- Deaths
- Assists
    - Player 1 greatly injures an opponent, “assisting” Player 2 who kills injured opponent
- Betrayal
    - Killing player on own team
- Suicide
    - Throwing yourself off a cliff

# a small problem

- we observe interactions not friendships
- interactions = matchmaking + friendships
- no demographic information

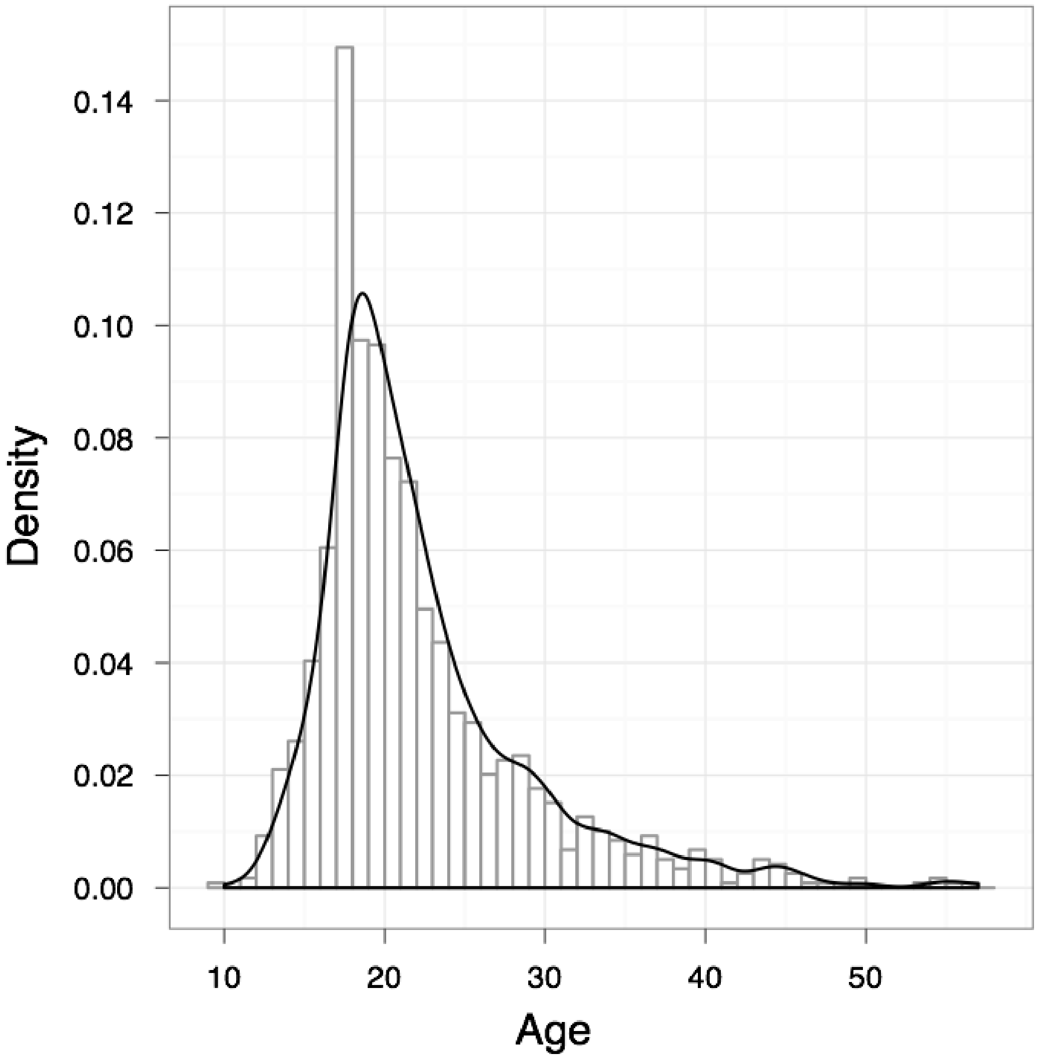
# a small solution

- anonymous web survey
- 847 participants
- demographic questions
  age, sex, location, education
- psychometric questions
  attitudes, play style, etc.
- friendship survey
- 14,405 labeled friends
- 7,159,989 labeled non-frien

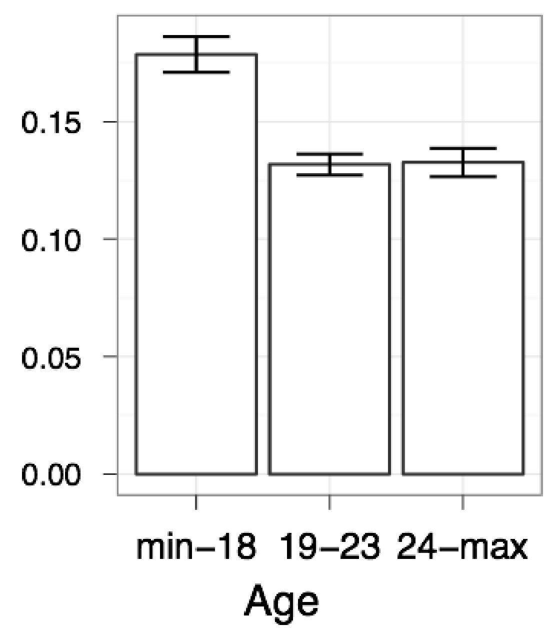



Mason and Clauset, CSCW 2013

# Survey respondents



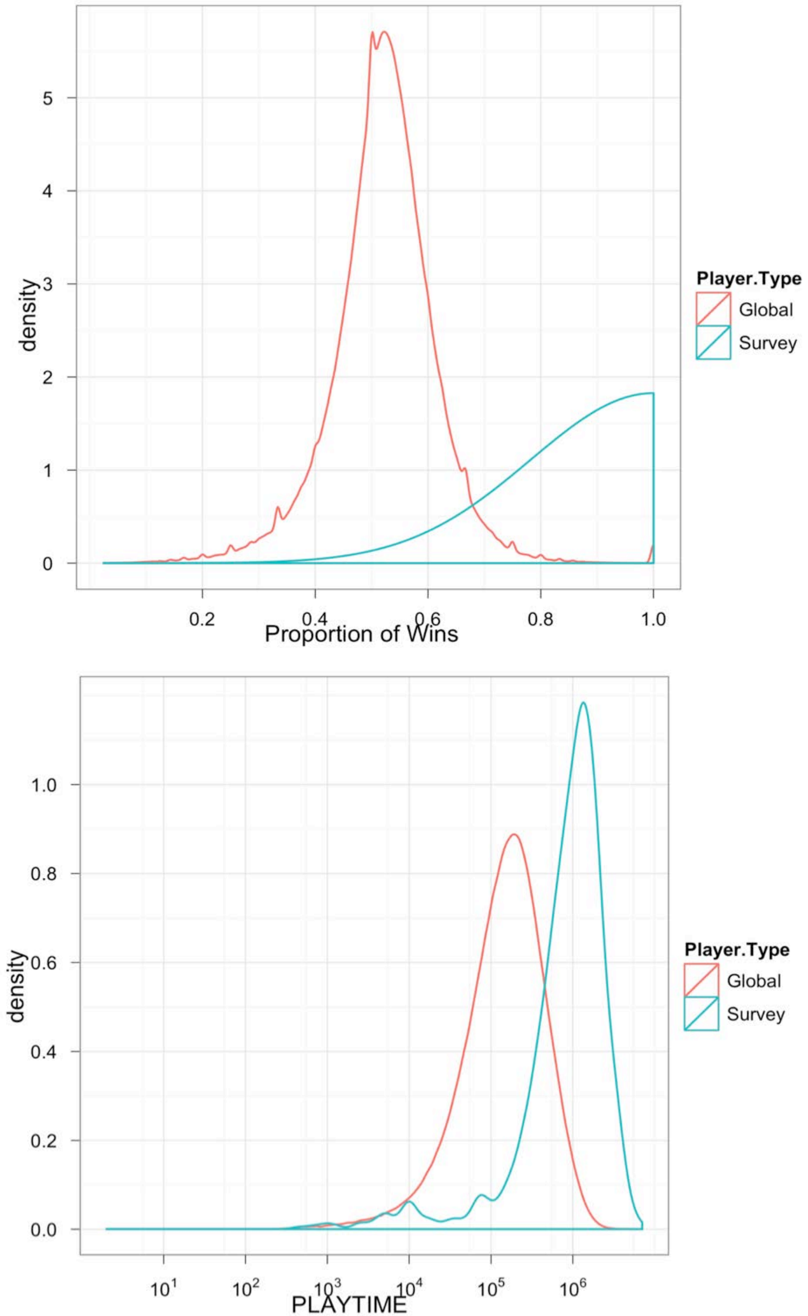

antisocial behavior




Mason and Clauset, CSCW 2013

## Survey respondents are not typical players

- Survey players are much more active, in number of games as well as time spent
- Survey players have more kills, but they also die more
- Survey players are **much better at the game**



## recovering friendships from interactions

we can observe a sequence of pairwise interactions

$$\sigma_{ij} = (i, j, t_1), (i, j, t_2), \ldots$$

- can we robustly distinguish friendships from non-friendships?
- this is a general problem for interaction networks

problems:

- volume of data varies widely by individual = heavy-tailed distribution in $|\sigma_{ij}|$
- friendships are sparse in large networks
- “ground truth” data hard to obtain

# statistics to detect friendships

*features of interaction time series:*

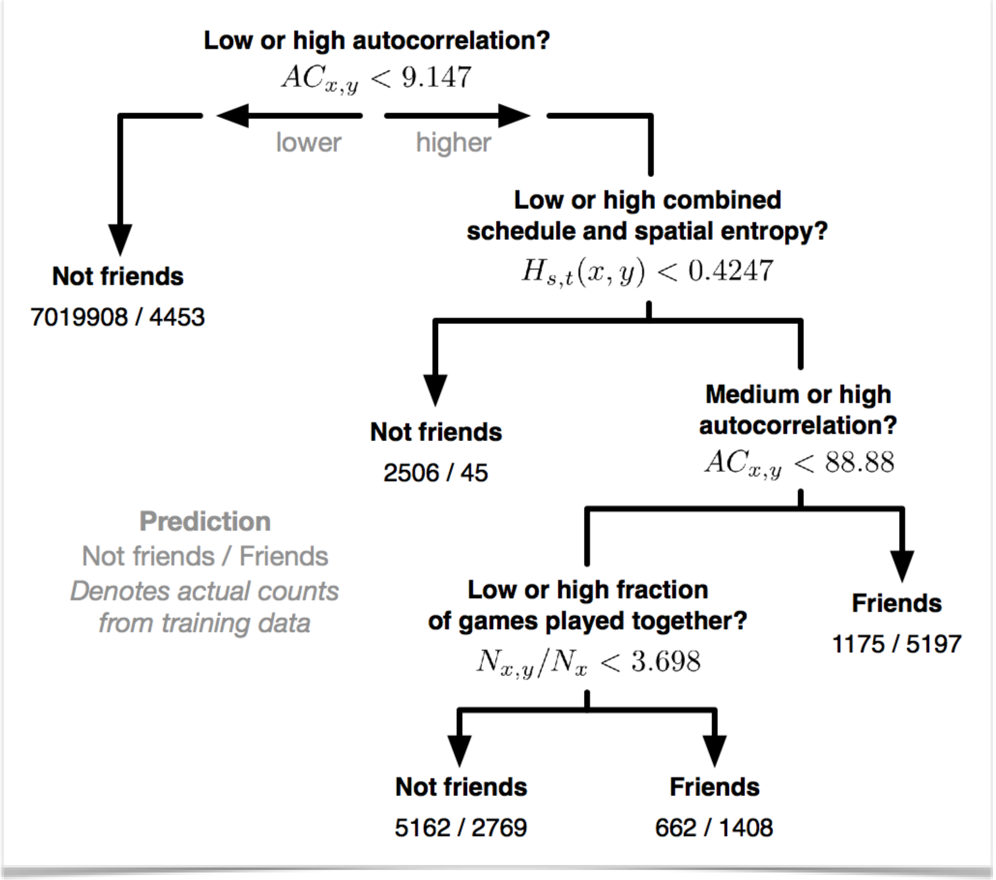
| | | |
|---|---|---|
| 1. autocorrelation | $AC_{x,y}$ | *temporal features* |
| 2. pair volume | $N_{x,y}$ | |
| 3. fraction of interactions | $N_{x,y}/N_x$ | |
| | $H_s(x,y)$ | *entropy features* |
| 4. schedule entropy | $H_t(x,y)$ | |
| 5. location entropy | $H_{t,s}(x,y)$ | |
| 6. loc.-sched. entropy | $B_{x,y}$ | *prosocial features* |
| 7. betrayals | $A_{x,y}$ | |
| 8. assistance | $V_{x,y}$ | |
| 9. indirect assistance | | |

Merrit, Jacobs, Mason and Clauset, ICWSM 2013

# exploring the feature space

*classification tree*

- 50/50 training/test by survey participant
- cross-validation to control tree size
- highly compact trees, high AUCs (often >0.9)
- key feature is $AC_{x,y}$ autocorrelation
- friendships look like periodic + prosocial interactions



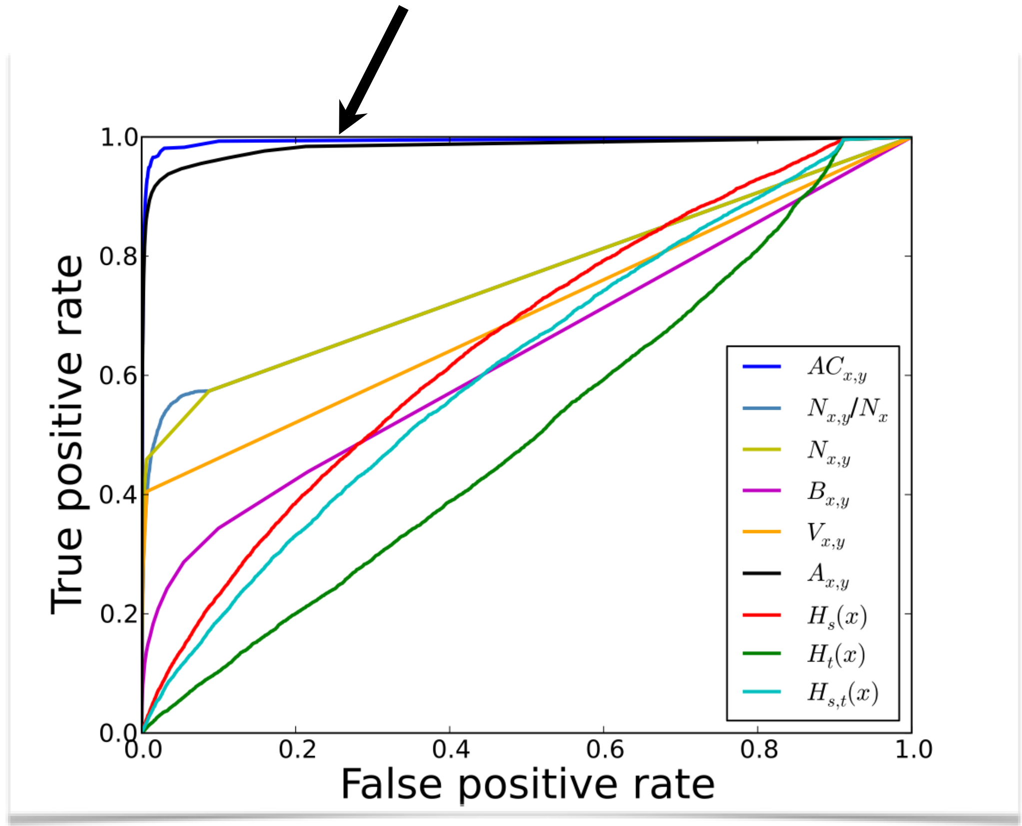

AUC=0.924

Merrit, Jacobs, Mason and Clauset, ICWSM 2013

# lightweight predictors

*logistic regression with individual features*

- single-feature predictors scale up better on real systems (Facebook, etc.)
- ROC curves $AC_{x,y}$
- autocorrelation $A_{x,y}$ and direct assistance both highly accurate: AUC > 0.98

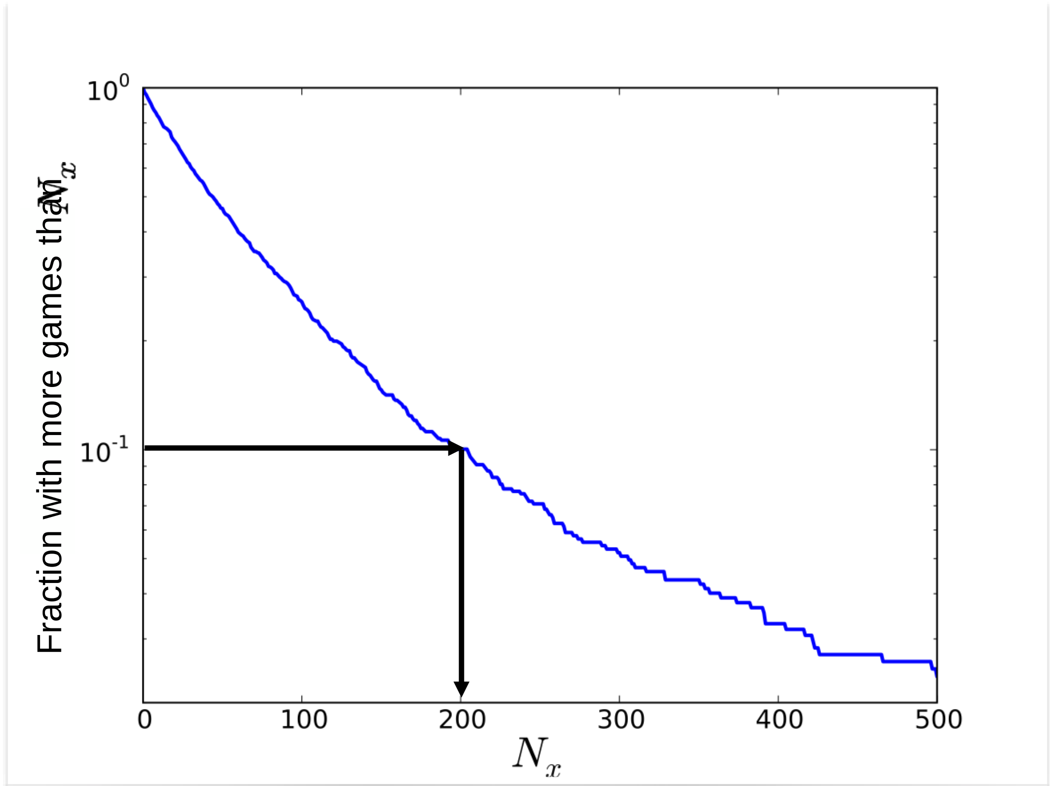



Merrit, Jacobs, Mason and Clauset, ICWSM 2013

# predictions for low-volume individuals

*most people have "shallow" histories*

- 90% have less than 200 games
- most users are "casual"
- true for most online social systems
- do predictions fail on these individuals?




Merrit, Jacobs, Mason and Clauset, ICWSM 2013

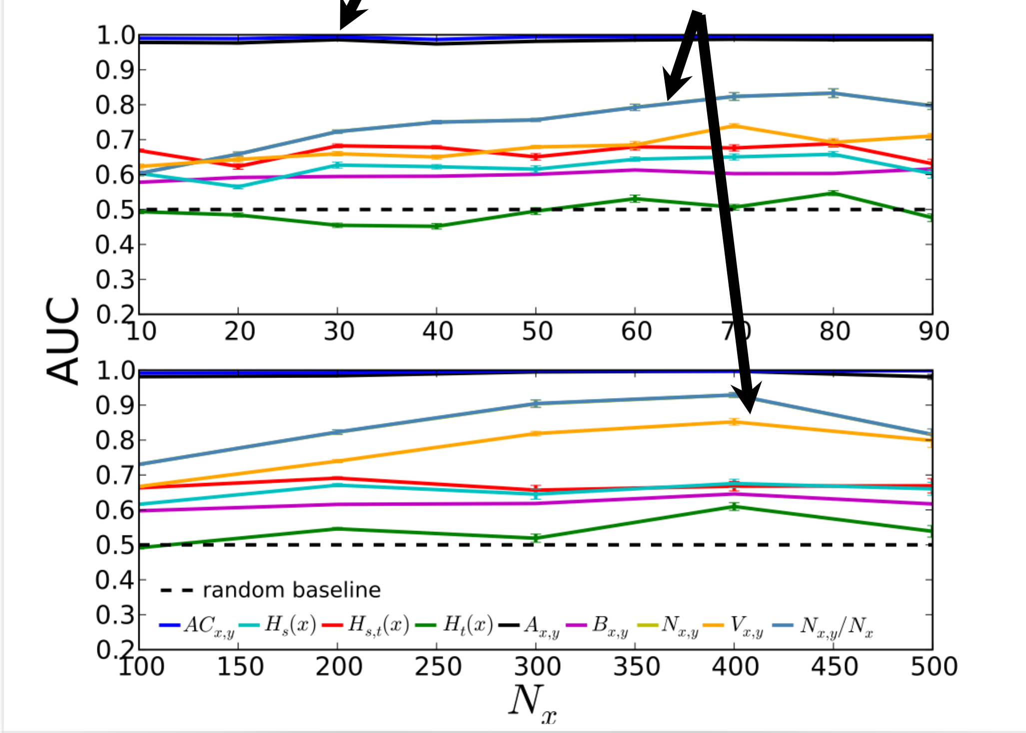
# predictions for low-volume individuals

*most people have "shallow" histories*

- AUC vs. size of history $N_x$
- periodic + prosocial interactions highly robust and efficient
- total interaction count not good, but not efficient

periodic or prosocial

volume of interaction



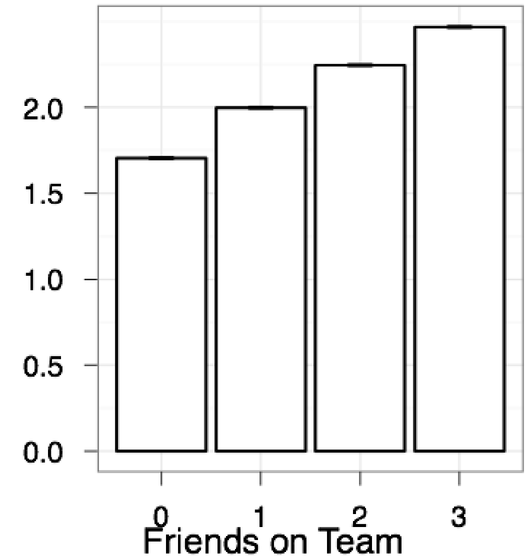

Merrit, Jacobs, Mason and Clauset, ICWSM 2013

does friendship impact individual or team performance?

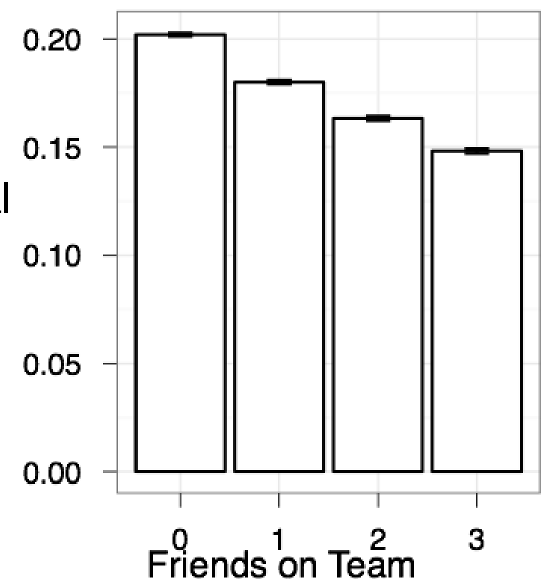
# impact of friendship on performance

- among survey respondents
- individual behavior vs. number of friends on team
- you perform better & nicer when you collaborate with friends

prosocial behavior




antisocial behavior

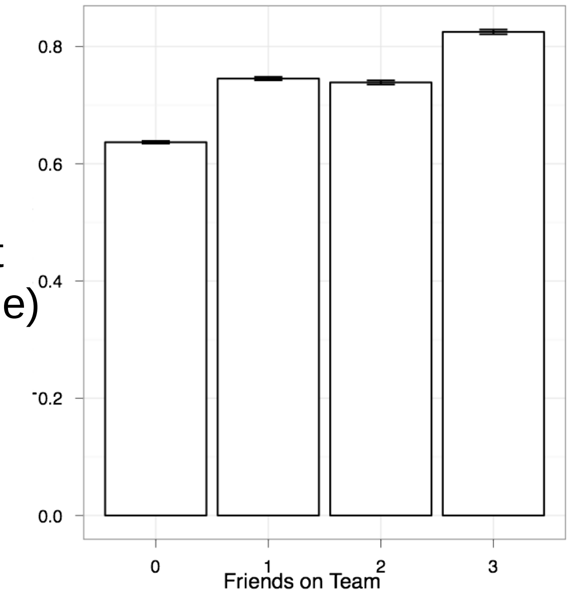



Mason and Clauset, CSCW 2013

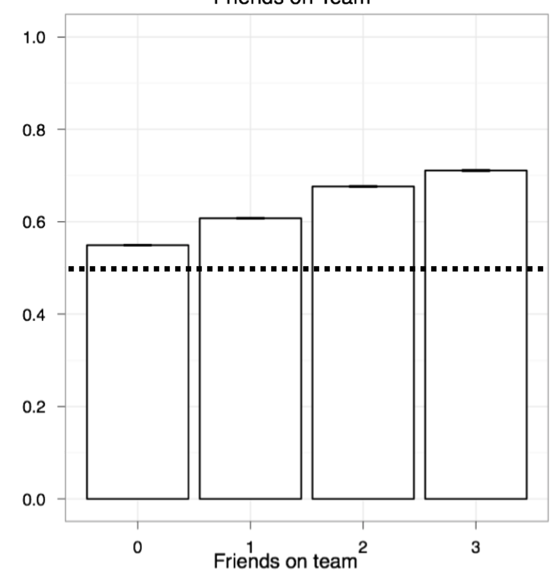
# impact of friendship on performance

- among survey respondents
- team performance vs. number of friends on team
- team performs better the more friendships it contains

performance improvement (over baseline)




proportion wins




Mason and Clauset, CSCW 2013

## summary

recovering friendships from interactions

- friendships *easy* to recover from interactions
- results likely to generalize [see Jones et al. *PLoS ONE* (2013)]
- clarifies "friendship" = periodic + prosocial interactions
- players structure their behavior to enable friend-friend interactions
- raises significant privacy concerns

friendships effect on performance

- the more friends on a team:
  - the better the team performs
  - the better the individual performs



Jones et al. Inferring tie strength from online directed behavior. *PLOS ONE* **8**(1):e52168 (2013).

- Friendships and success in Halo:Reach
- Network structure and success in an experimental game

# Social Learning Strategies

- Background:
  - Many species benefit from social organization because of *social learning*, or “zero-trial learning” (A. Bandura)
  - **Humans’ ability to share information and build on that information is key to our technological advancement.**

# Social learning as a strategy

- The ability to observe and imitate the trials and successes of peers has advantages and disadvantages:
  - Saves the individual from making costly mistakes
  - Allows individuals to “free ride” off others trials
  - Allows the group to try many different approaches in parallel
  - Excessive copying reduces innovation

# What is the optimal strategy?

- The decision to “explore” versus “exploit” is not just a hard problem in biology, but also in psychology, machine learning, artificial intelligence, etc.
- What information should one use to decide whether to explore for new possibilities, observe one’s peers, or exploit the best known method / solution?
- And what consequences do these decision strategies have on the individual & the group?

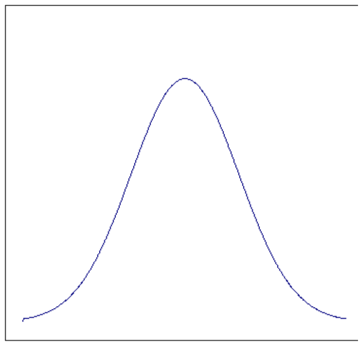
# Collaborative Problem Solving

- Many ways groups work together to solve problems
  - **Cooperatively**, as a team, with specified roles
  - **Collectively**, with (constrained) information sharing
  - **Competitively**, with antagonistic information control
- We focus on collective problem solving
  - Individuals searching for a solution for their own benefit
  - Information sharing is incidental or ultimately self-motivated
- Examples:
  - Scientists searching for a cure to a disease.
  - Inventors competing for the X-prize.
  - *Situations in which innovations are shared and built upon*

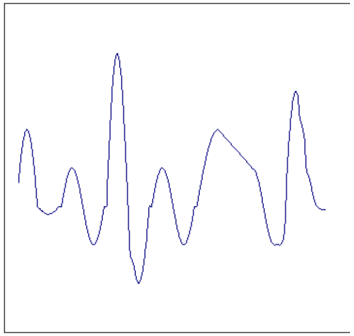
# Characterizing Problems

*(Levinthal, 1997; Lazer, 2005)*

- Simple problems
  - Easy to find, correct solution
  - Can be discovered with local exploration



- Complex problems
  - Many potential solutions
  - Local, suboptimal solutions

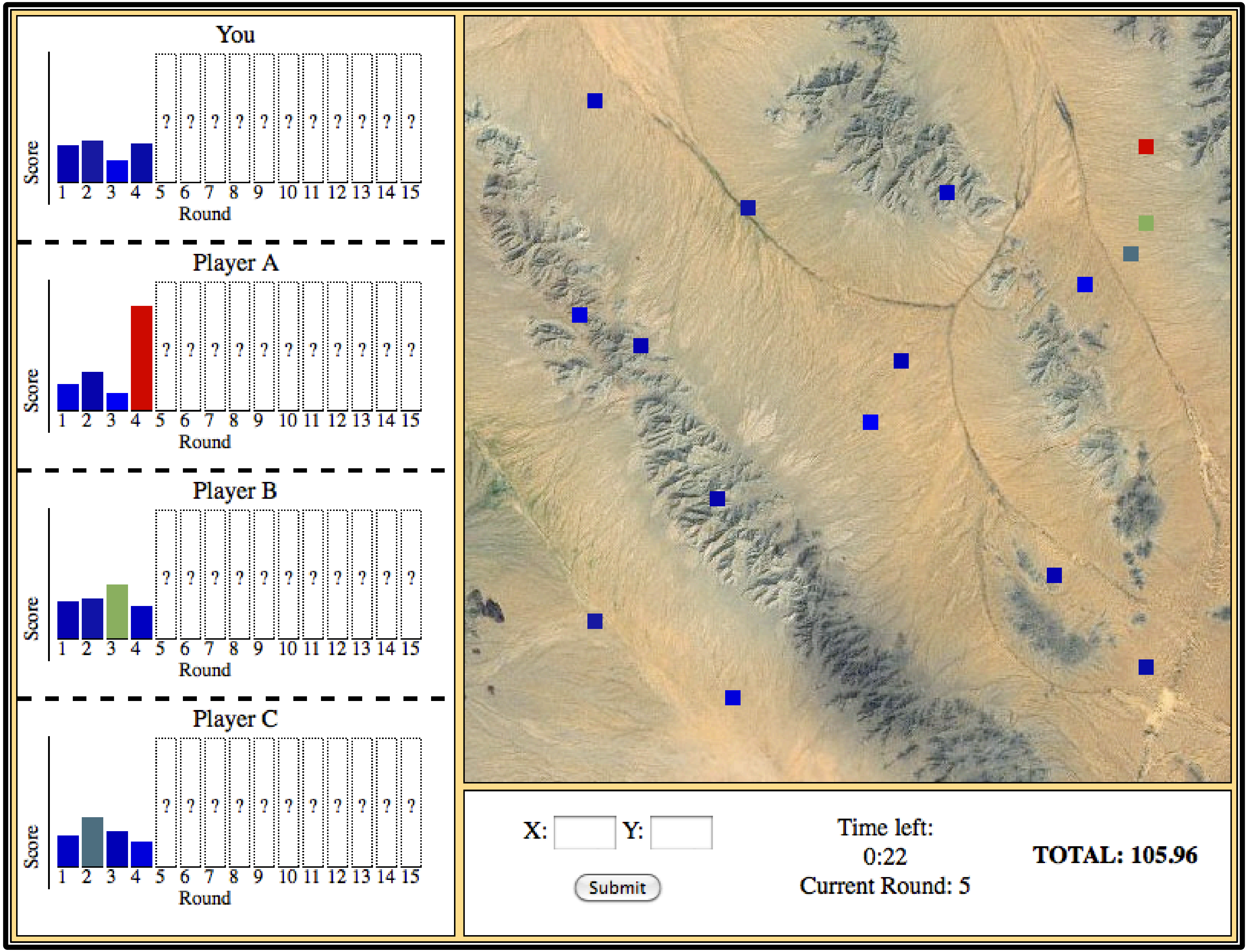


# Key Questions

1. How does the *presence* of a communication network affect complex problem solving?

1. How does the *structure* of the network contribute to collective performance?

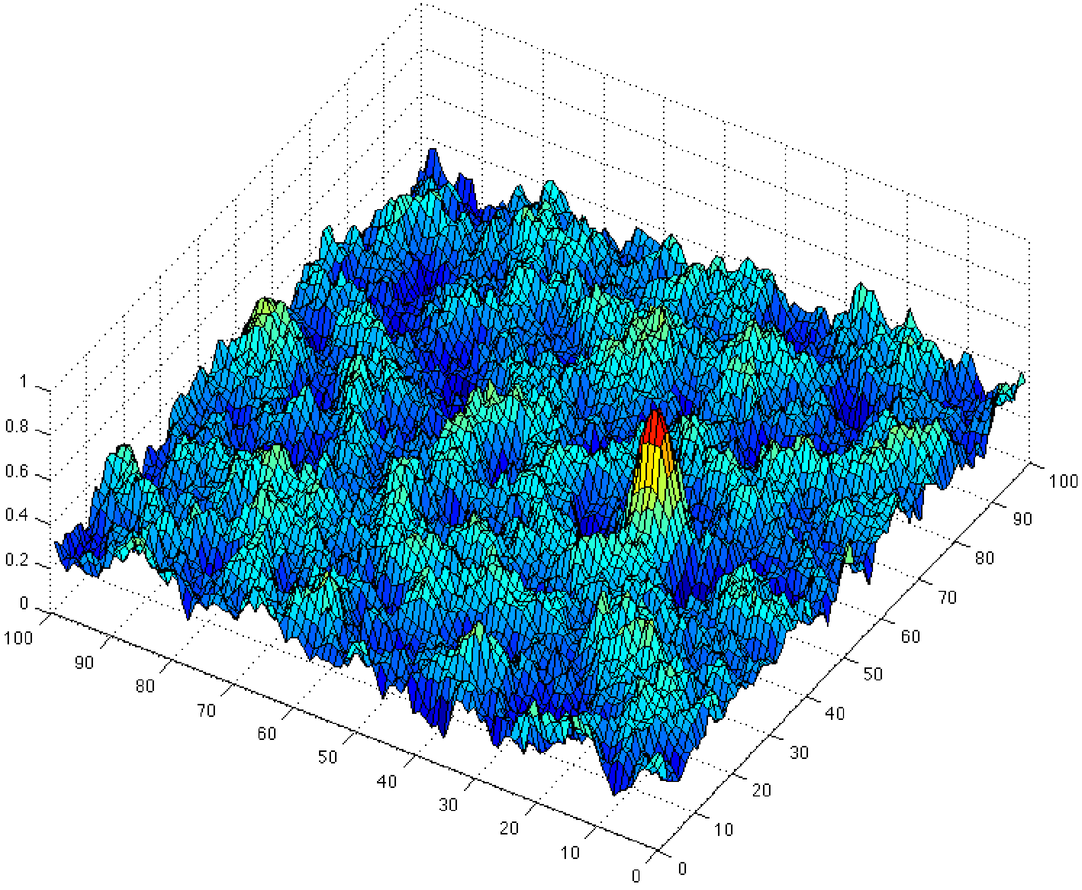
1. How does an individual's position in the network relate to:
   - Individual strategy and performance?
   - Collective performance?

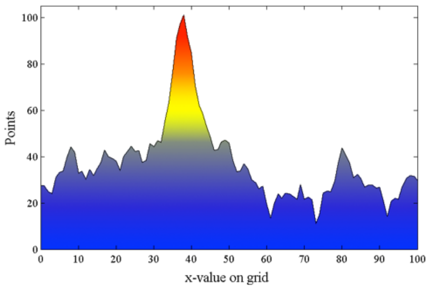

You
Score
Round
Player A
Score
Round
Player B
Score
Round
Player C
Score
Round
X:
Y:
Submit
Time left:
0:22
Current Round: 5
TOTAL: 105.96

# Payoff Functions

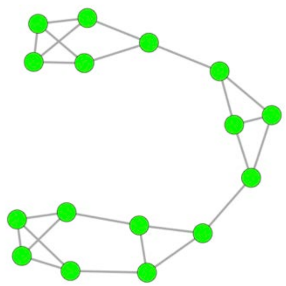
- The “signal” was generated:
  - A unimodal Gaussian function with mean chosen uniformly at random and SD = 3
- The “noise” was added:
  - Background generated with 4-octave Perlin noise

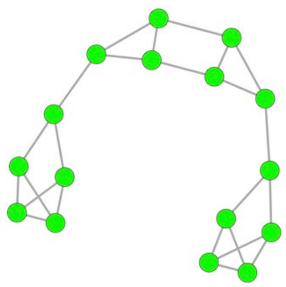
# Payoff Functions

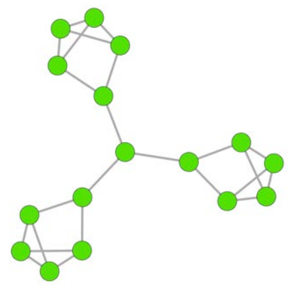


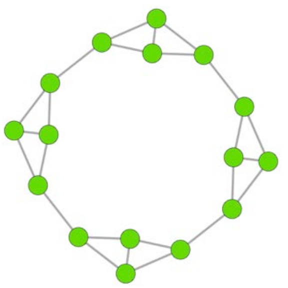



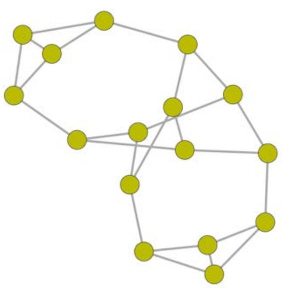
# Communication Networks

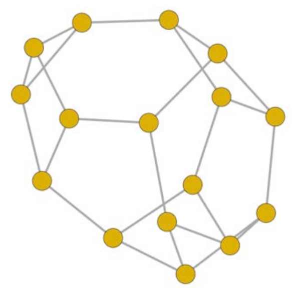

Greatest Average Betweenness

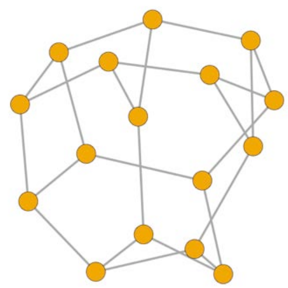

Smallest Maximum Closeness

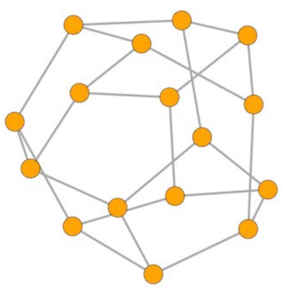

Greatest Maximum Betweenness


Greatest Average Clustering


Greatest Variance in Constraint


Greatest Maximum Closeness


Smallest Average Clustering


Smallest Average Betweenness

# Experiments

- For each session, 16 subjects are recruited from Amazon's Mechanical Turk

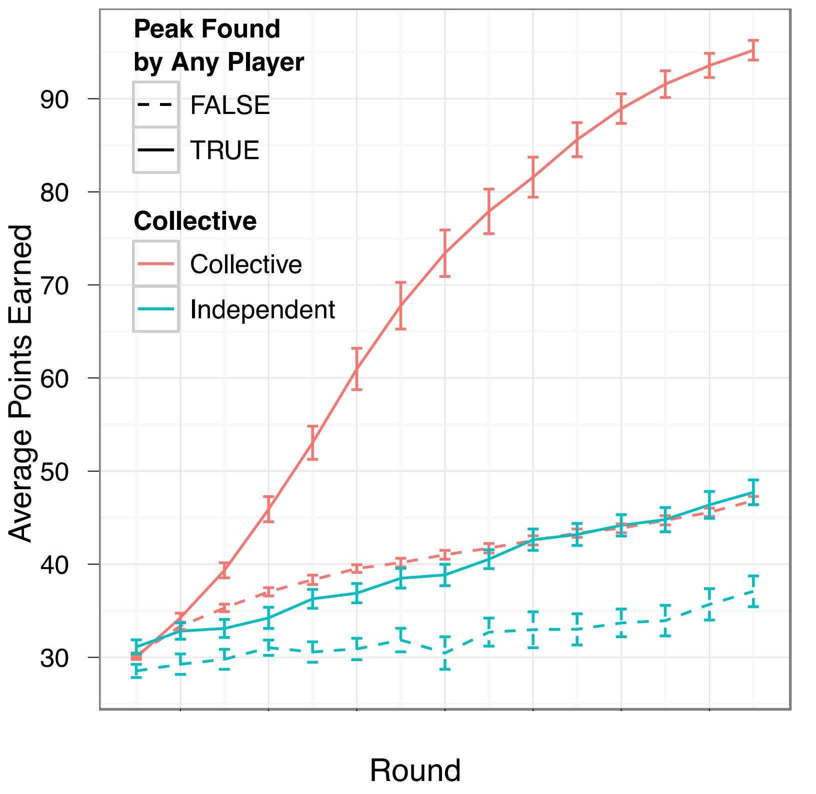
- Each session comprises 8 games
  - One for each network topology

- Each game runs for 15 rounds
  - 100 x100 grid
  - Relative dimensions of peak and landscape adjusted such that peak is found sometimes, but not always

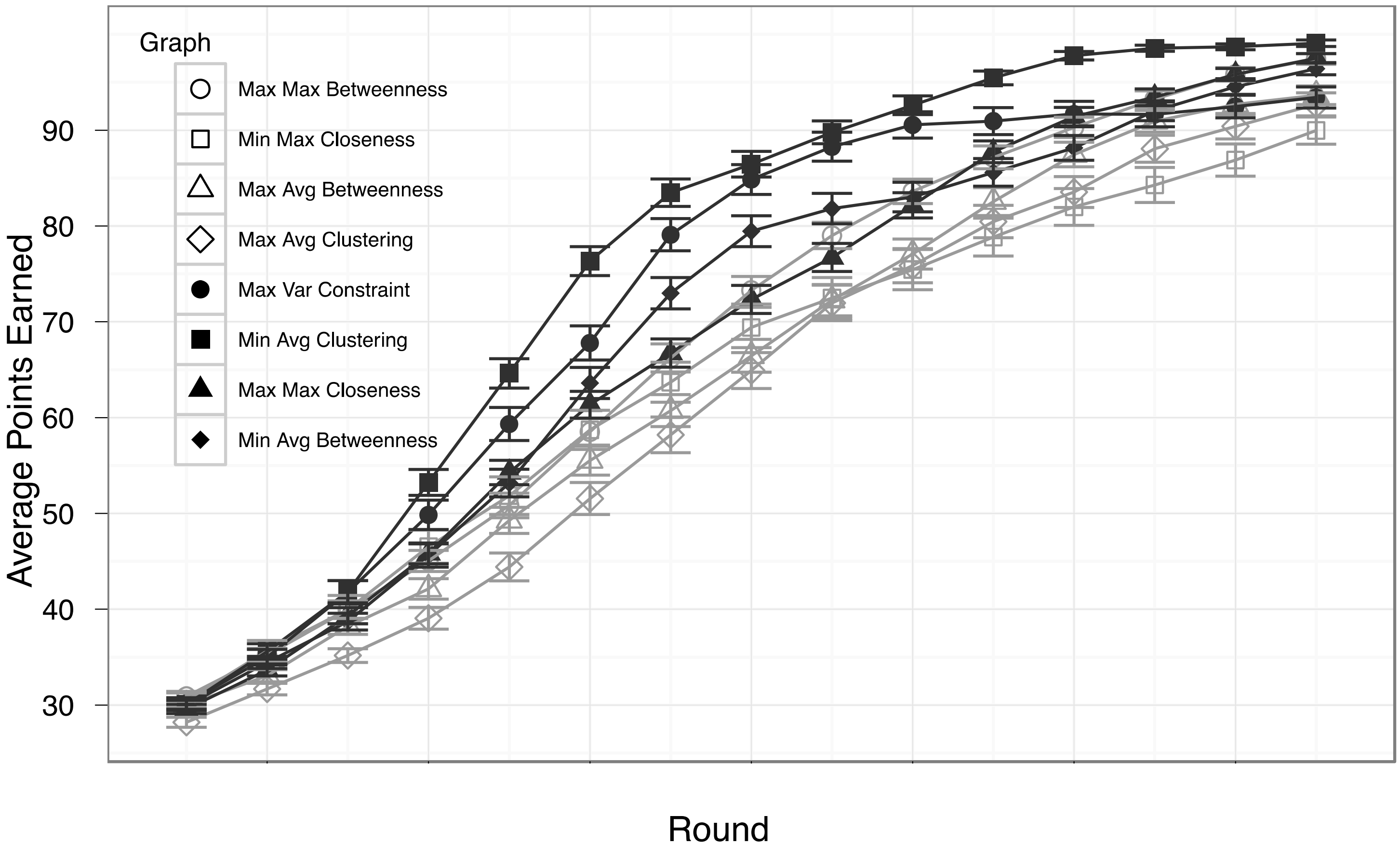
# RESULTS

# It’s a good idea to share ideas

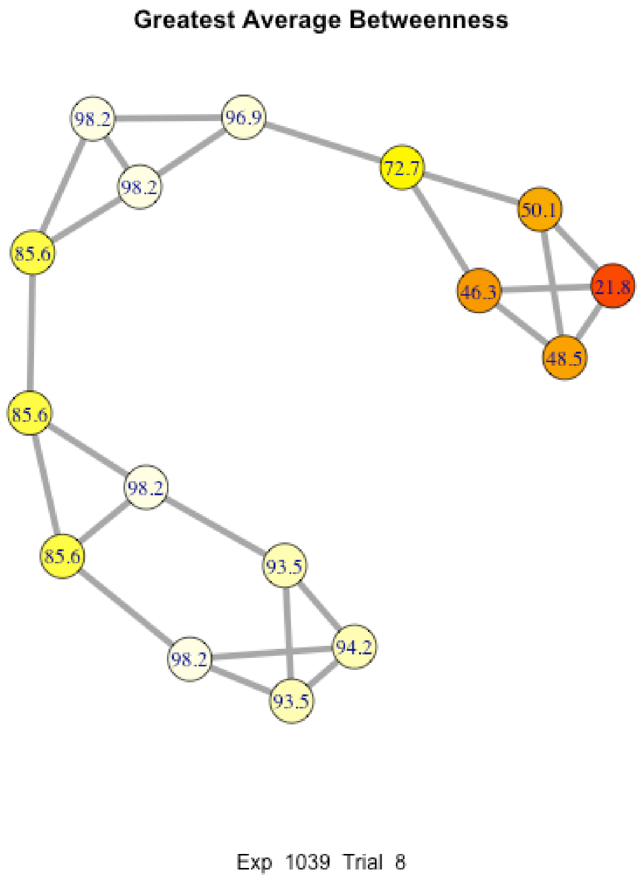
- Collectives do much better when peak is found
- Even when peak is not found, collectives more effectively exploit local optima

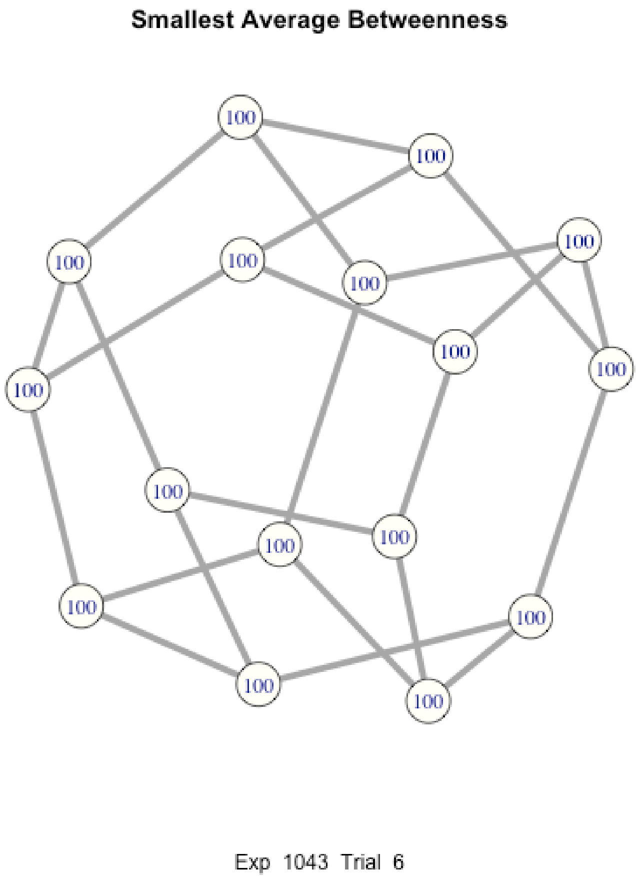


# It's good to share good ideas quickly



# 3. Diffusion of Best Solution

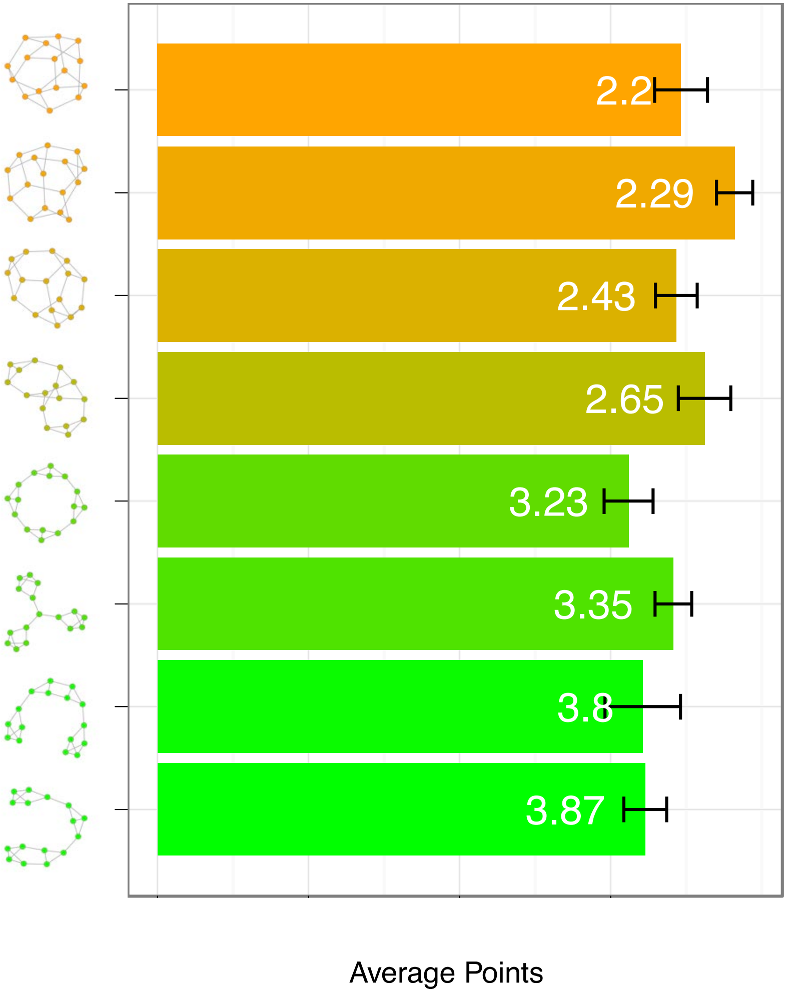


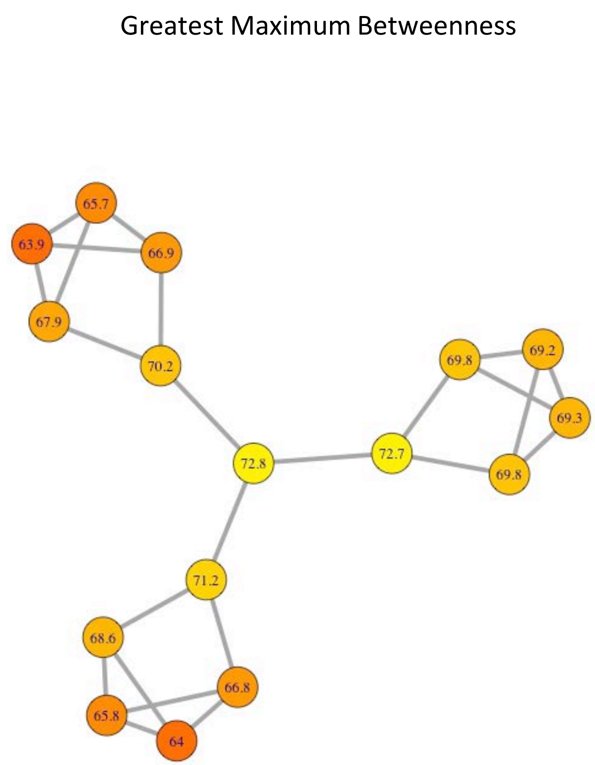
# Path length predicts collective performance

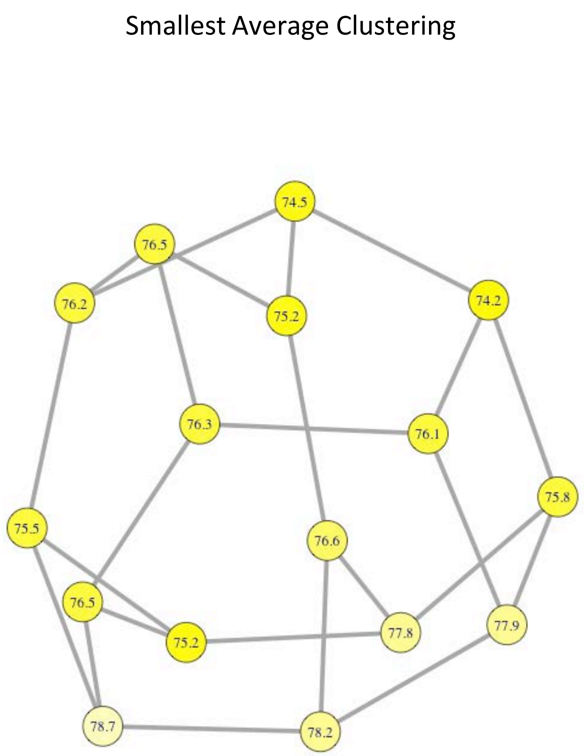
- Roughly breaks into two groups:

1. Short path length, low betweenness, low clustering
2. Higher path length, more centrality, higher clustering



# Individual Performance Is Combination of Individual Position and Collective Performance

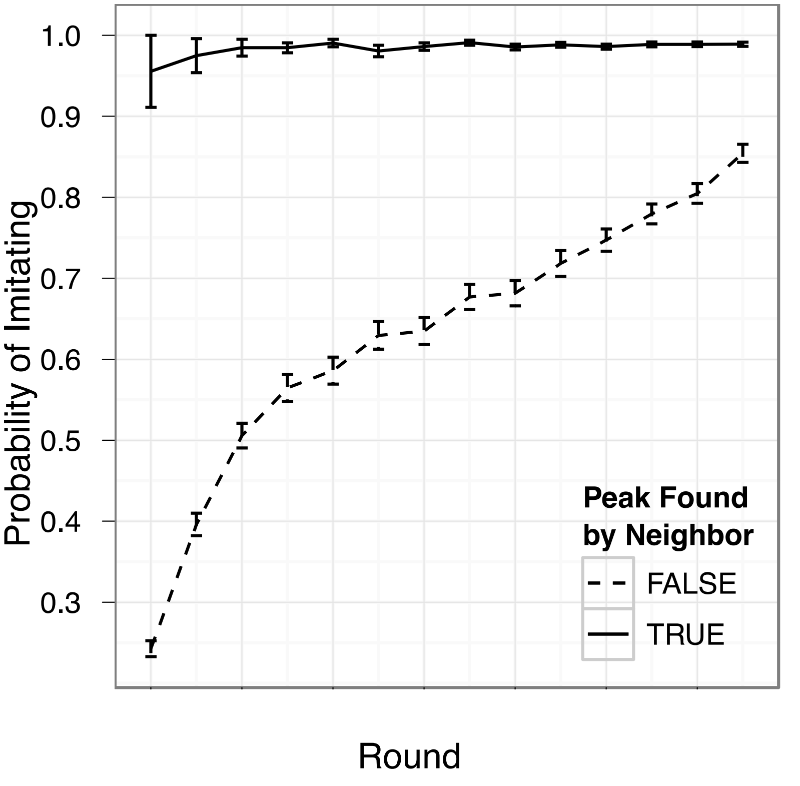


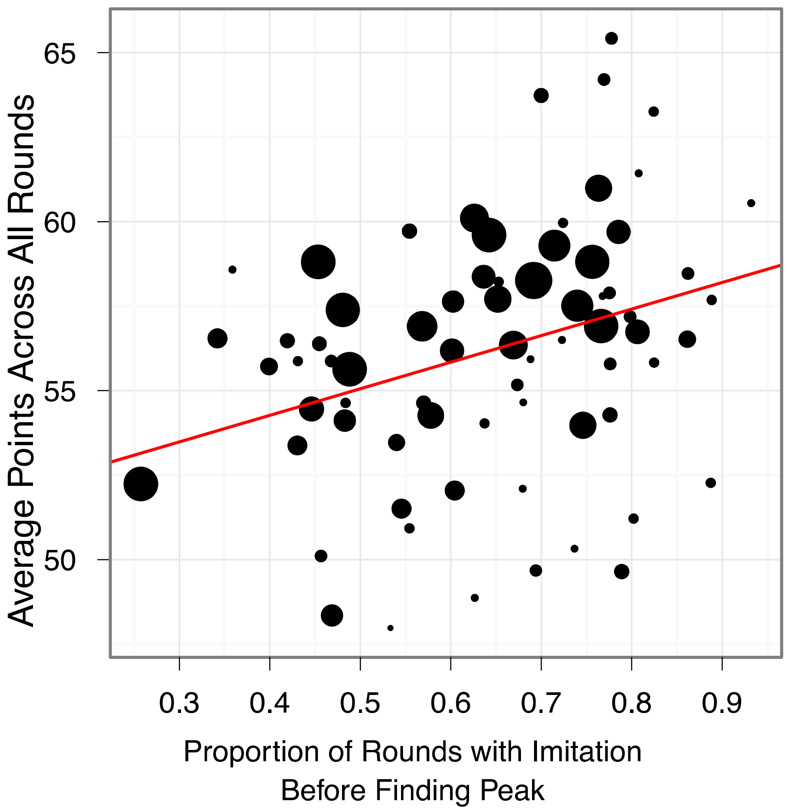
# Exploration / Exploitation

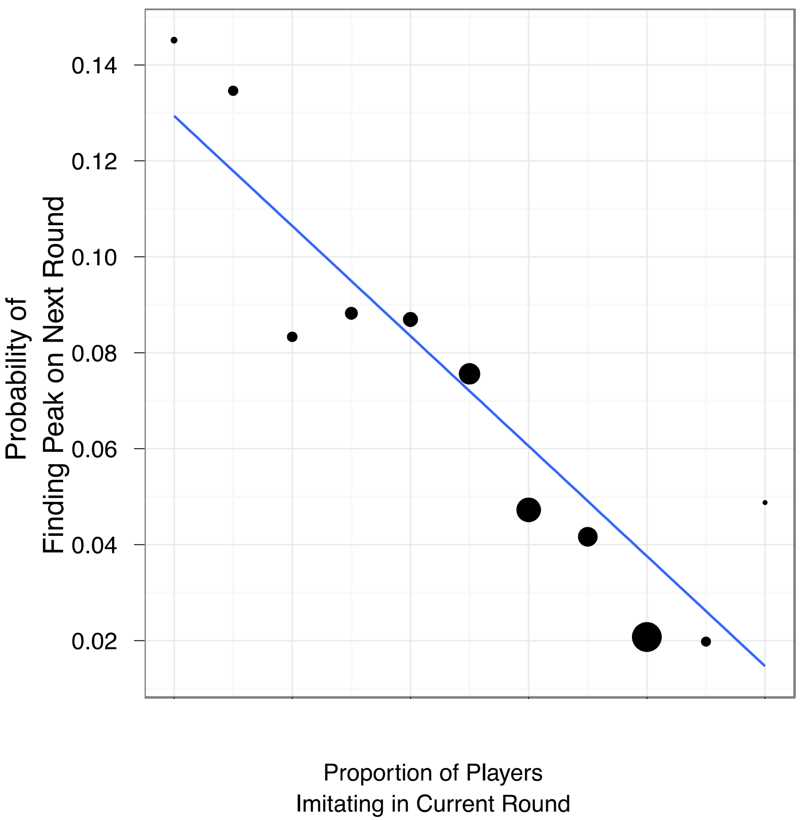
- Players nearly always exploited solution when peak found by neighbor

- Players also exploited when peak not found

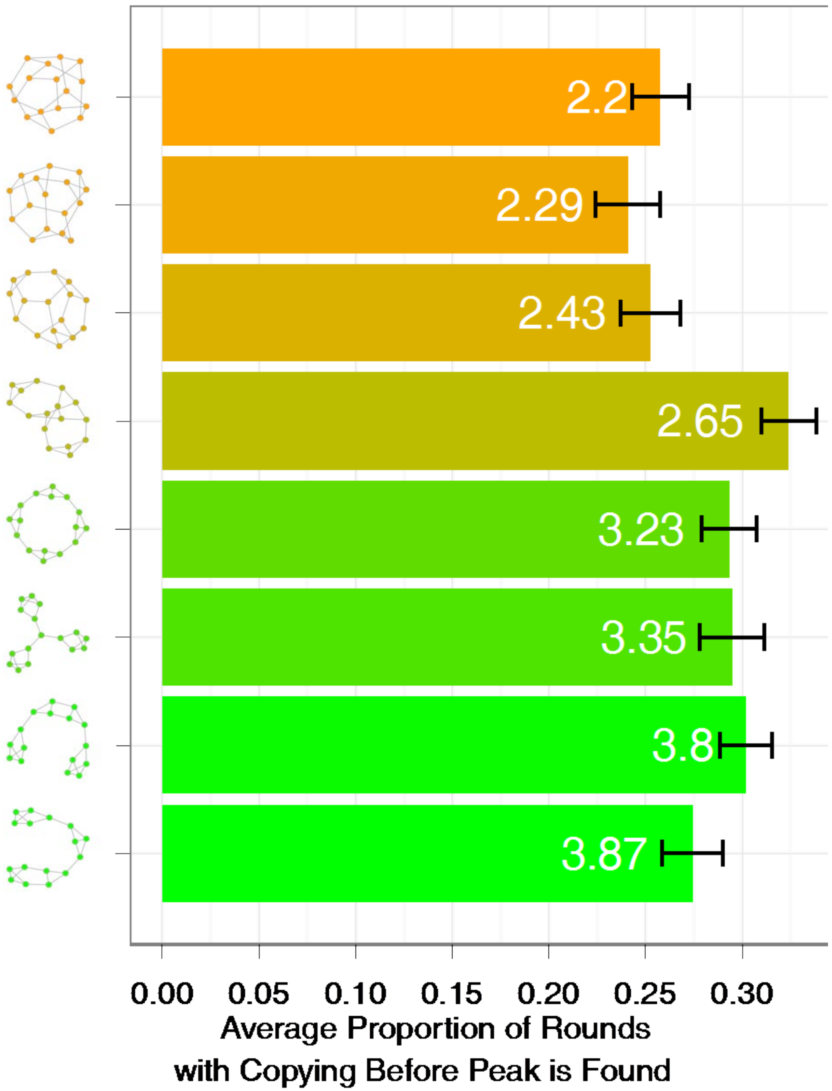


# Collective problem solvers face a social dilemma



# Invisible networks affect individual behavior



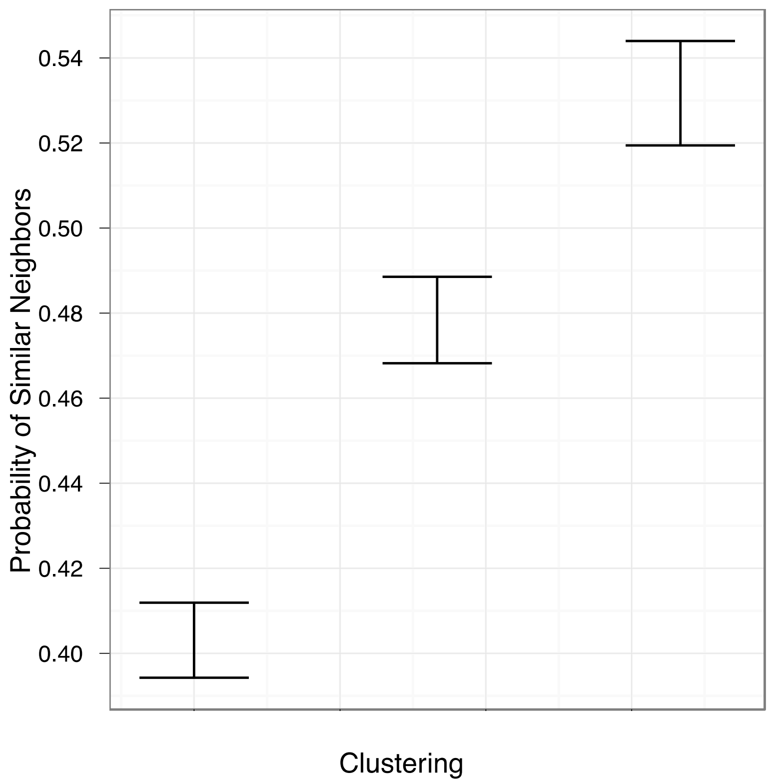

Less efficiency

is associated with

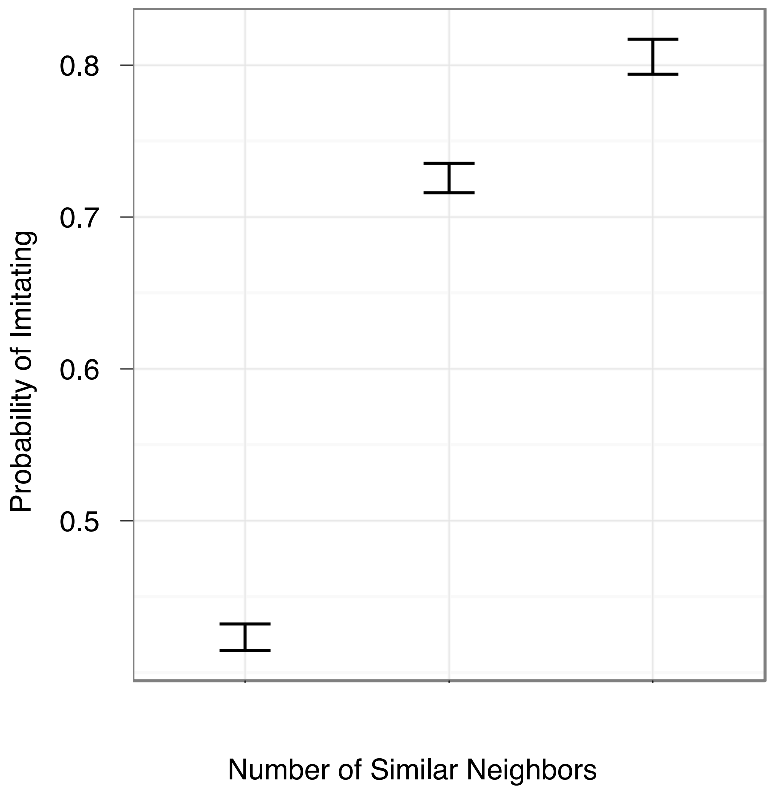
more copying

# How invisible networks affect behavior

## Connected neighbors imitate each other




## Imitating neighbors lead to more imitation



# Summary

1. Having a communication network improves collective success
2. Efficient networks better for collective: less imitation & faster dissemination
3. Performance gap greater in inefficient networks
4. Individuals face a social dilemma: risky exploration vs. free-riding
5. Even though invisible, network structure affects players' strategy of exploration vs. exploitation

Thank you!

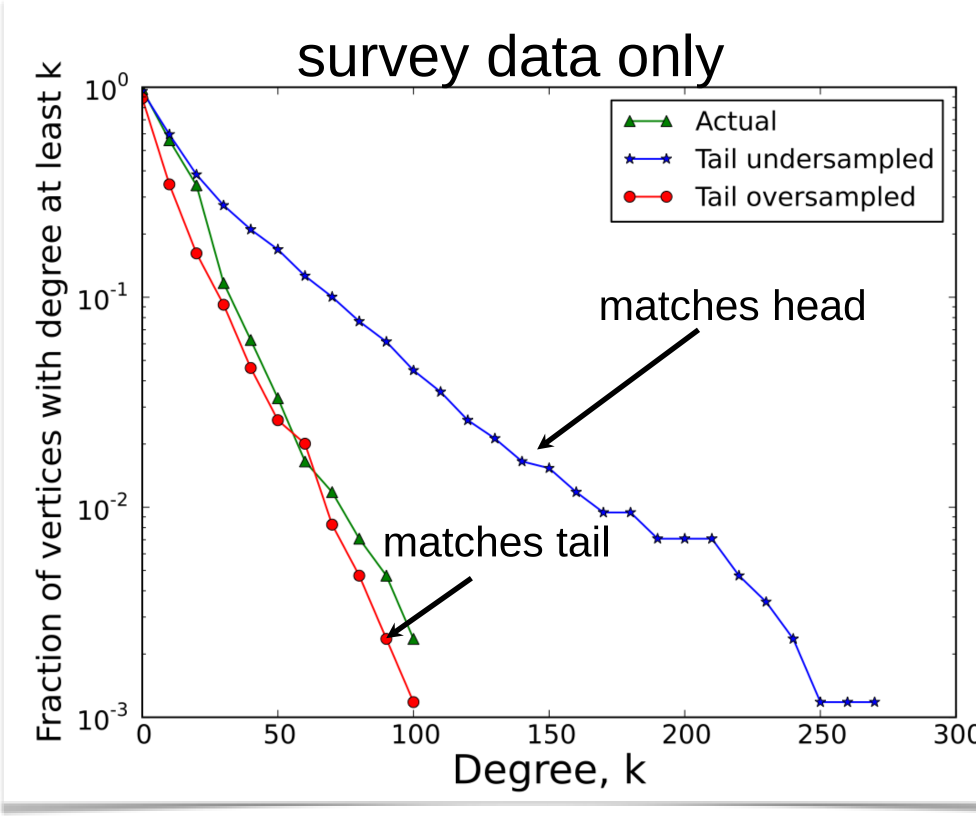
## social network of a massive online game

extracting friendship network from interaction network

- ideally, use generative model
- for now, a threshold: friendship if $AC_{x,y} \geq t_c$

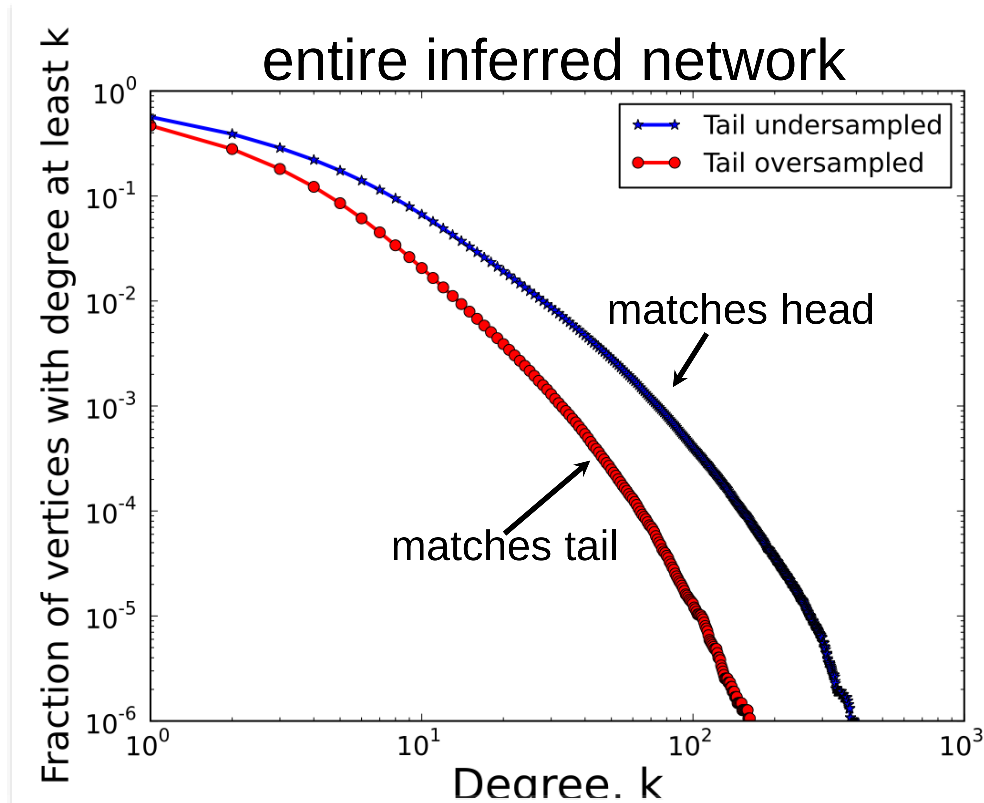
# social network of a massive online game

- choose threshold $t_c$ by matching sampled with recovered degree distribution
- but, survey is a biased sample and, sampling bias is unknown
- do we match head or tail?
- try both



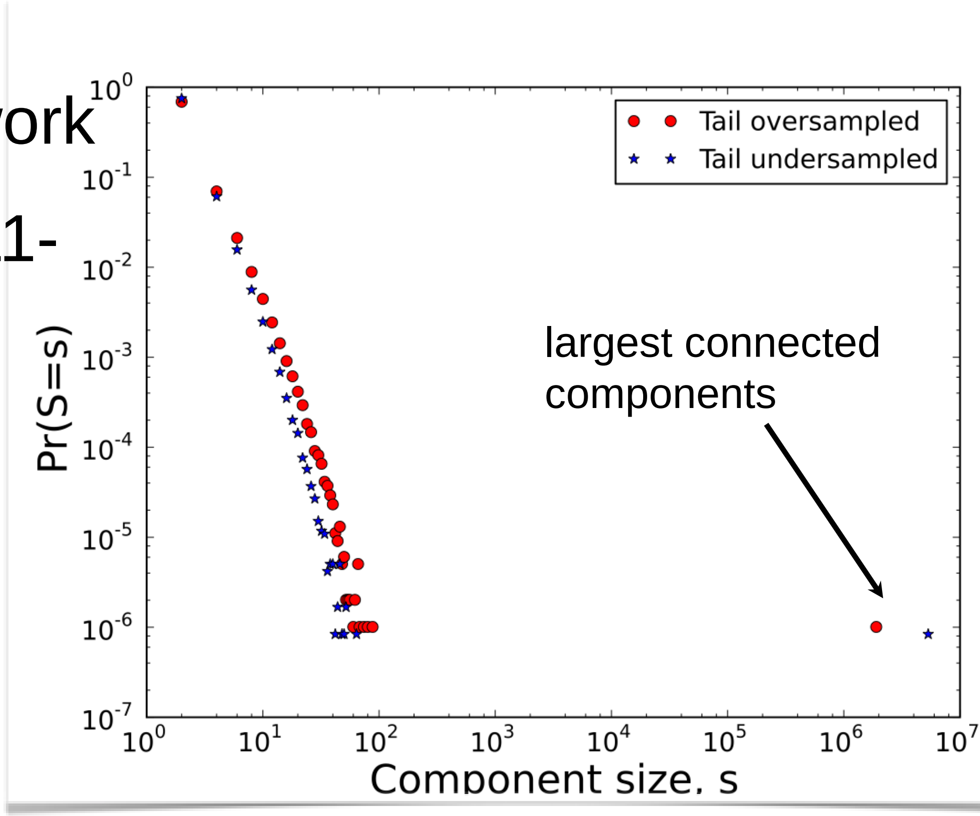
# social network of a massive online game

- choose threshold $t_c$ by matching sampled with recovered degree distribution
- but, survey is a biased sample and, sampling bias is unknown
- do we match head or tail?
  - ➤
- try both
  - ➤
- inferred degree distributions no power laws (shocking!)
- mean degree = 2.4 2.8



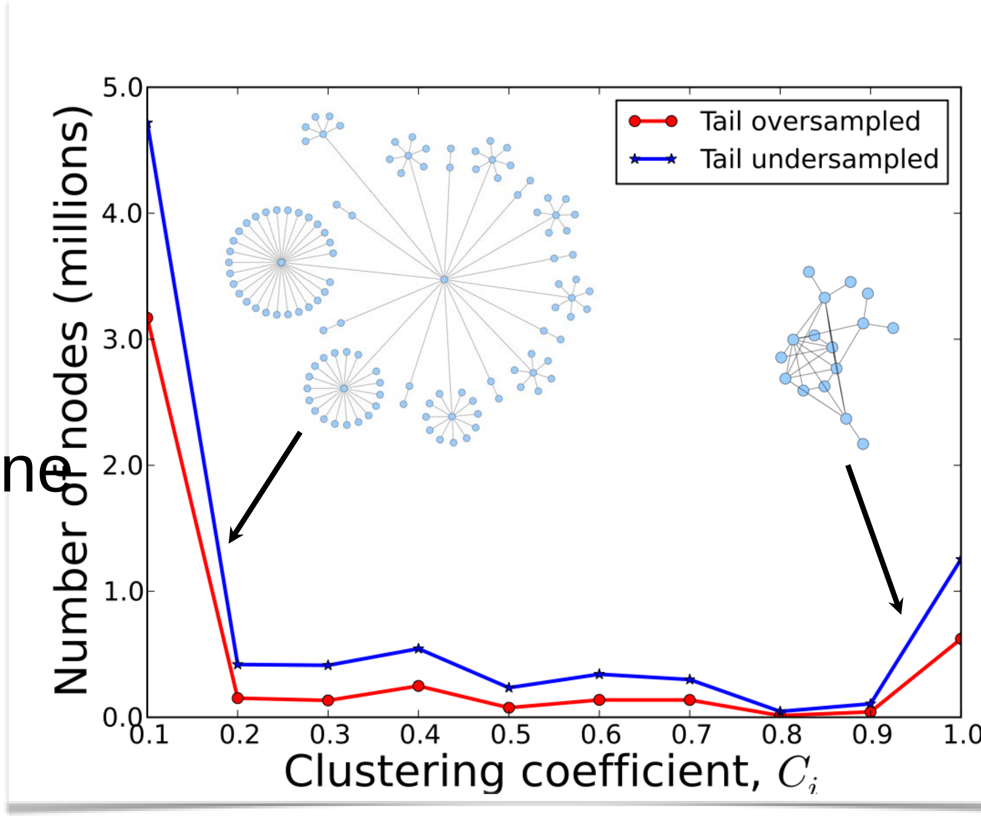
# component sizes

- 17M people in interaction graph
- 4.7-8.4M in friendship network
- largest component is 11-31% of people



# local structure

- vertex-level correlation coefficient
- many near-cliques
  well-defined groups of friends
- many star graphs
  socialites?
- roughly similar to other online social networks

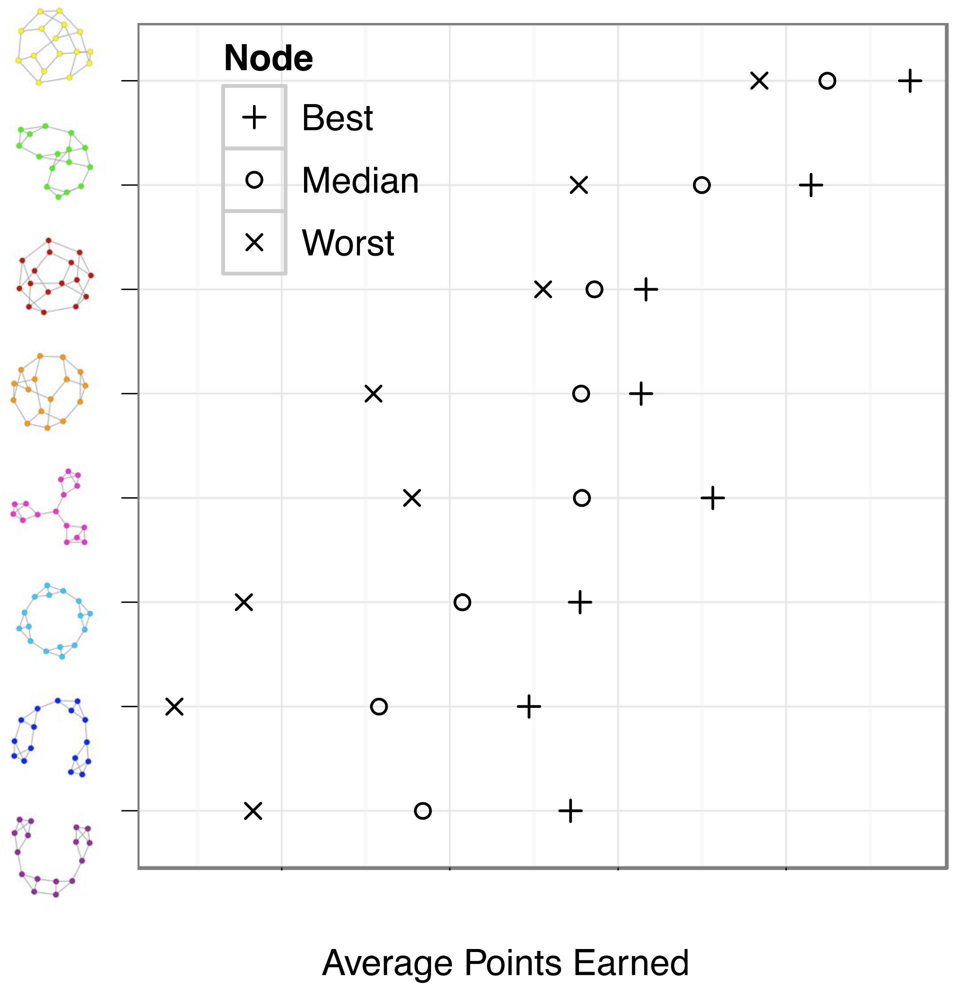


# Individual Performance Is Combination of Individual Position and Collective Performance

Best player in inefficient networks

~

Median player in efficient networks



# Agent-based Models

- How do simple agents compare to human performance?
- Test two simple rule sets:
  - Based on agents in Lazer & Friedman (2007)
  - Based on optimal performance in simplified problem space

# Lazer & Friedman (LF) agents

- If any of your neighbors have found a higher-scoring location, copy them
- Else, explore randomly within some radius R of current location

# Optimal Strategy in Simplified Problem Space

- Characterize the landscape as “solution” and “not solution” with values of each equivalent to average
- Use inductive reasoning to determine optimal strategy in this simplified landscape

# Recursive rule

- On round T-1, the expected payoff is

$P_{T-1} = fp + (1-f)n$

$P_{T-2} = 2fp + (1-f)(n+P_{T-1})$

$P_{T-3} = 3fp + (1-f)(n+P_{T-2})$

.

.

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**p** is the payoff from the solution

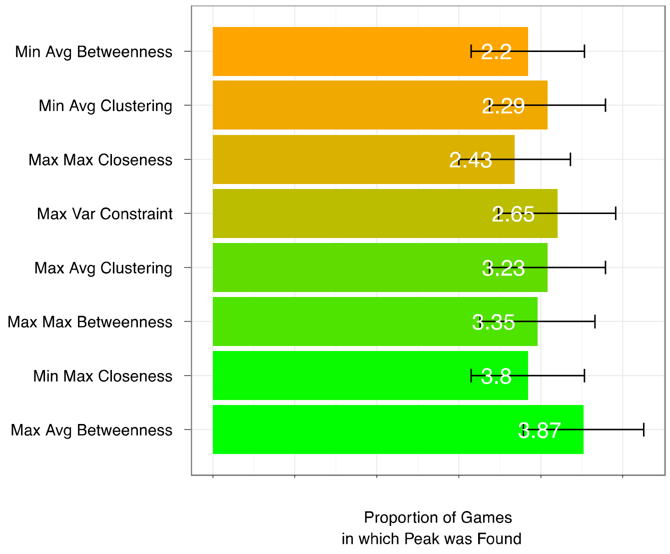
**n** is the payoff from "not solution"

**f** is the probability of finding the peak from random exploration

**T** is the number of rounds

**$P_t$** is the expected payoff to exploration t steps from end

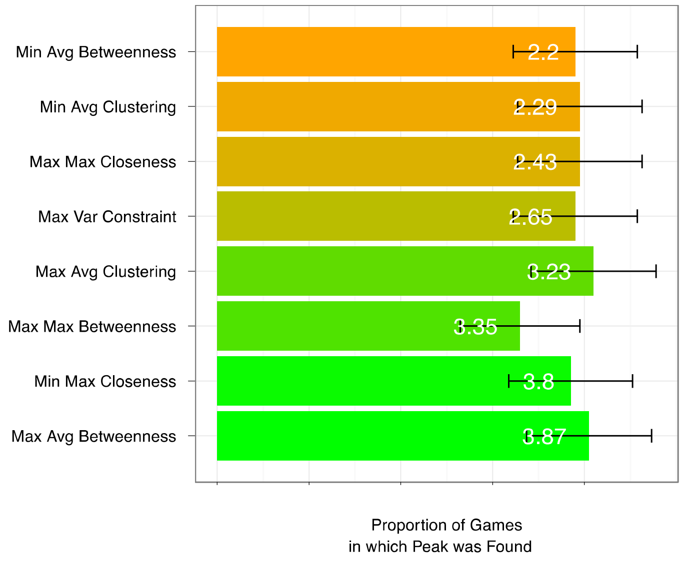
# LF agents
# “Vision” = 3 units



# LF agents
# “Vision” = 12 units

ound

# LF agents
# “Vision” = 20 units



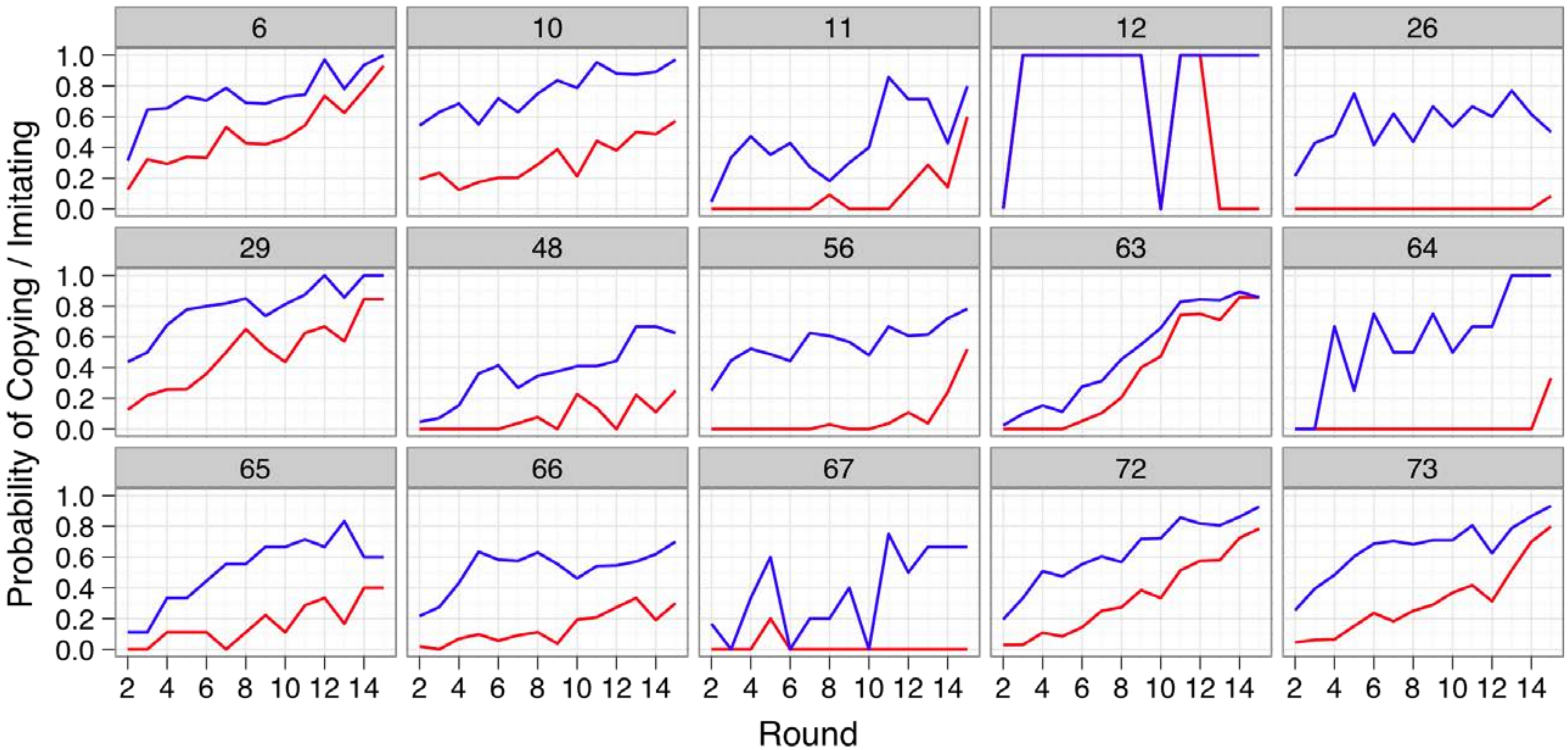
# “Optimal” agents

# Agent Based Model, Based on Real Agents

- Extract individual playing strategies
- Build agent-based simulation where agents play like "real" players
- Explore problem space to discover new hypotheses
  - More complex landscapes
  - Different composition of individual strategies
  - Larger networks
- Return to experiments to test hypotheses

# Exploration vs. Exploitation

Probability of exactly copying / guessing within 5 units from neighbor *given maximum has not yet been found*



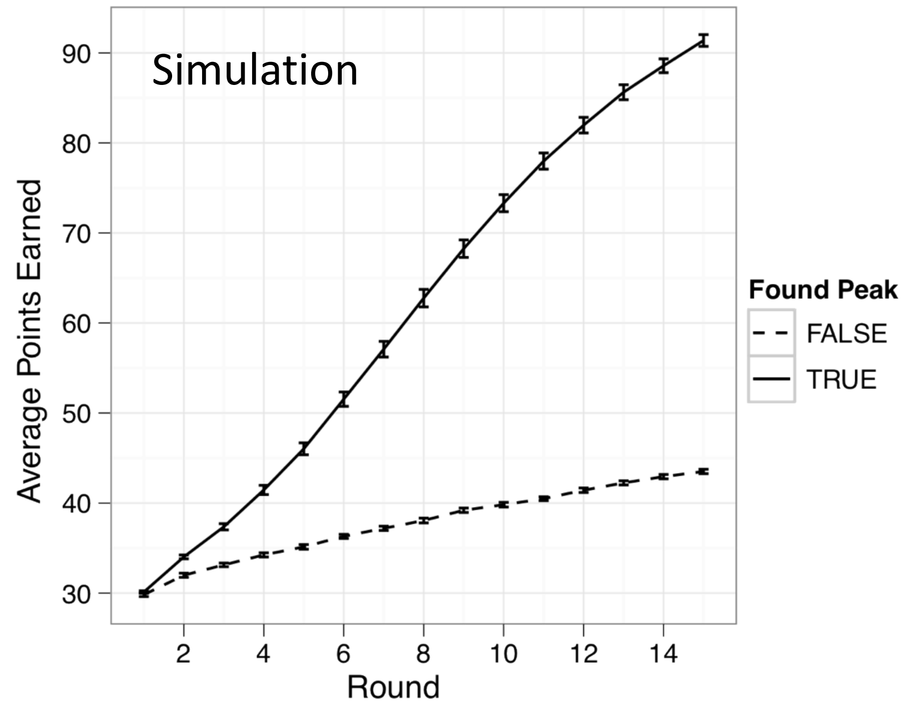
# Simulation Details

- Fit linear model to users' probability of copying by round
- Obtain distribution of slopes & intercepts

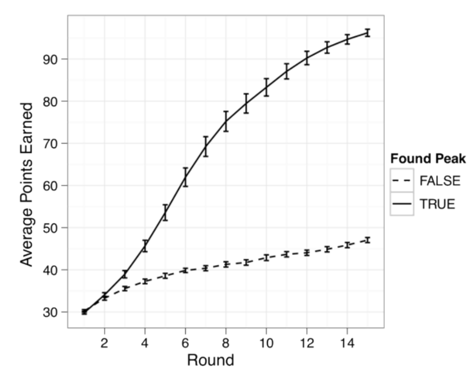
- On each round:
  - If agent or neighbors have score = 100, copy
  - If agent or neighbors have 60 < score < 100, guess within 3 units of score
  - Else, copy highest score with probability based on intercept, slope & round or explore uniformly at random
- 100 simulated sessions (800 simulated games)

# Finding the maximum

- 100 simulated sessions (800 simulated games)
- Maximum is found by at least one agent in 59% of games [63%]
- Maximum is found by all agents in 49% of games [56%]

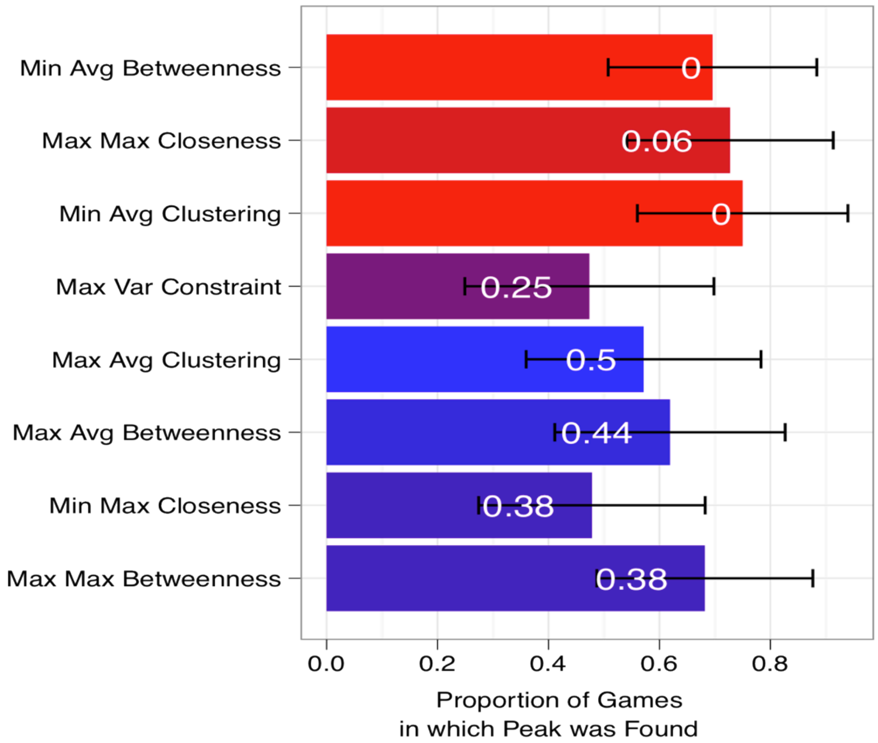



Human Players

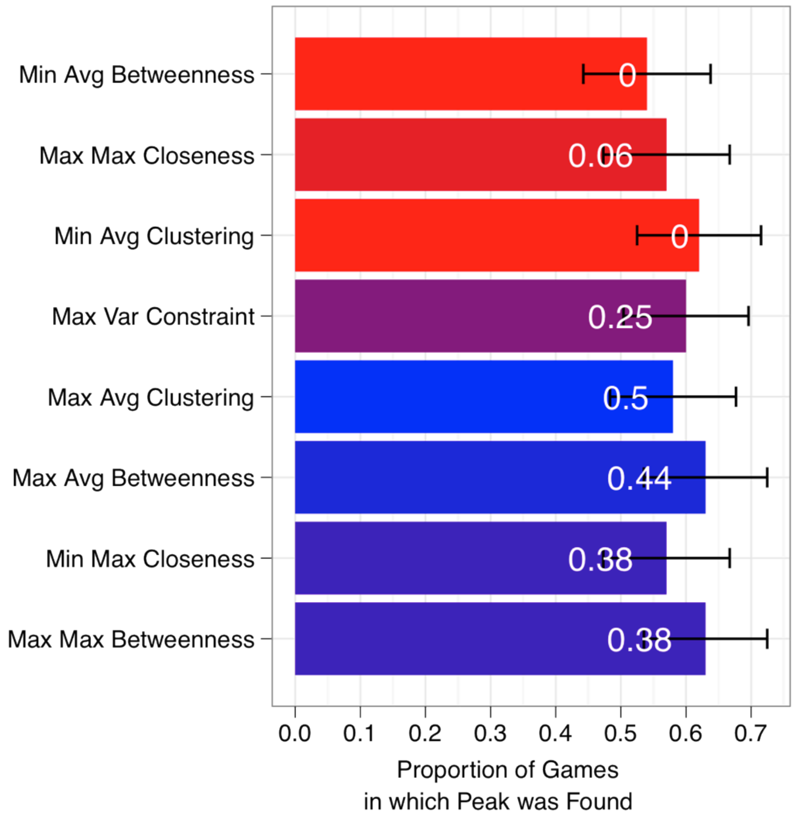


# Frequency of Finding Maximum

Human Experiments

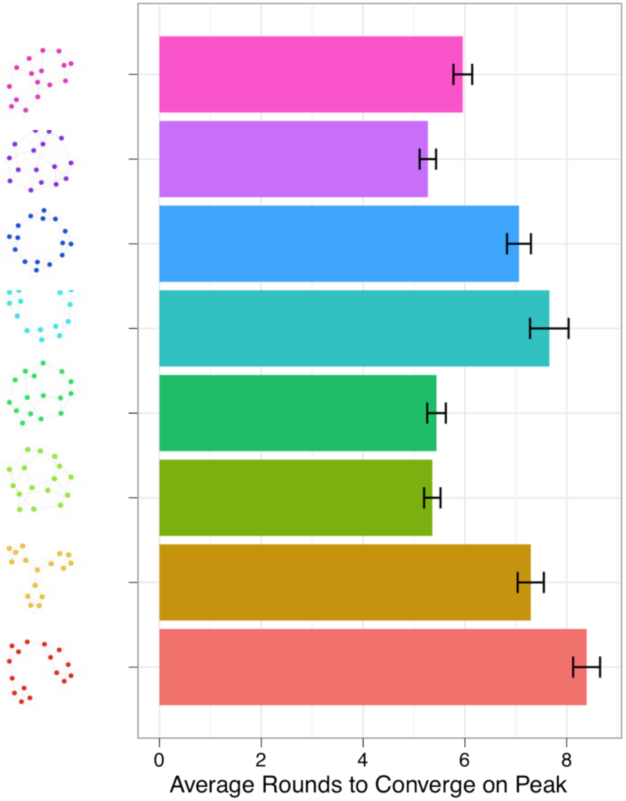



Simulations

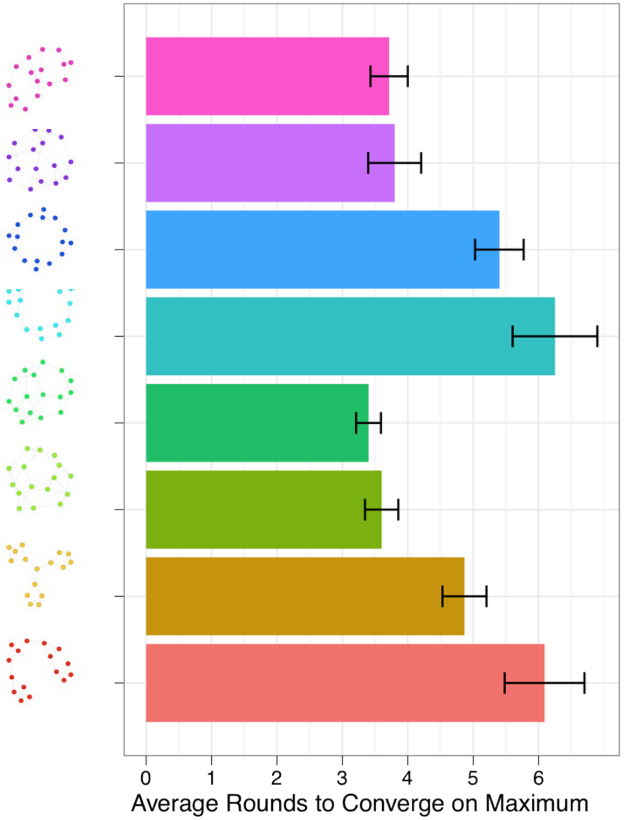


# Networks Affect Convergence Time

Simulation

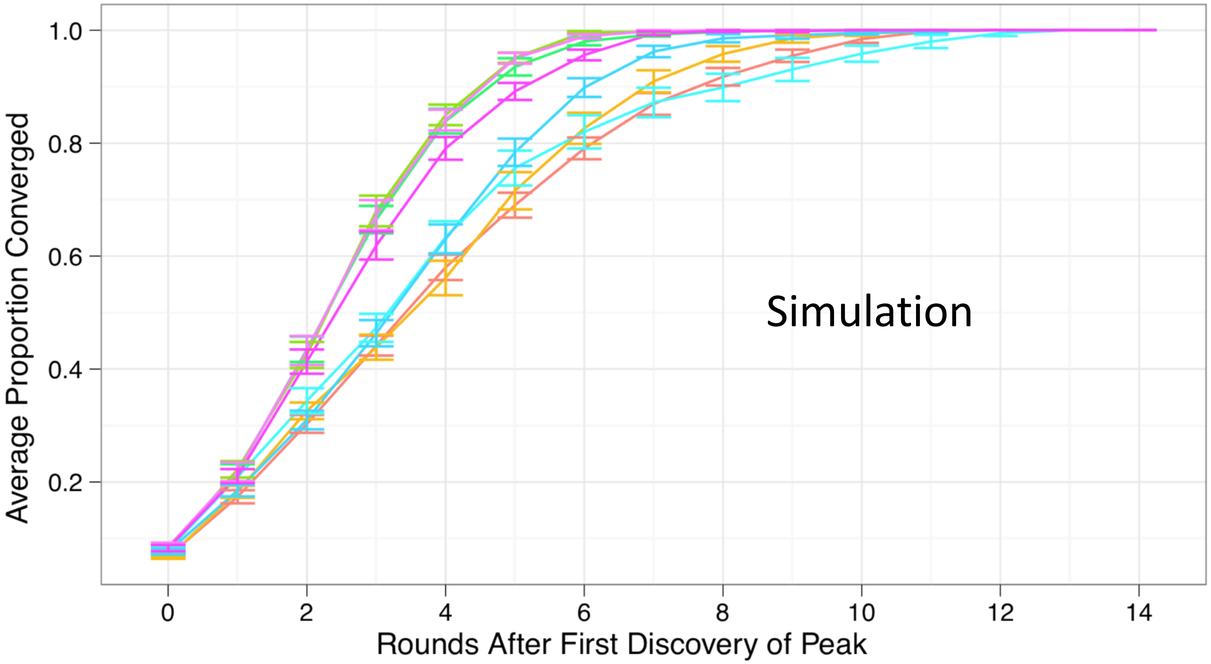



Human Players

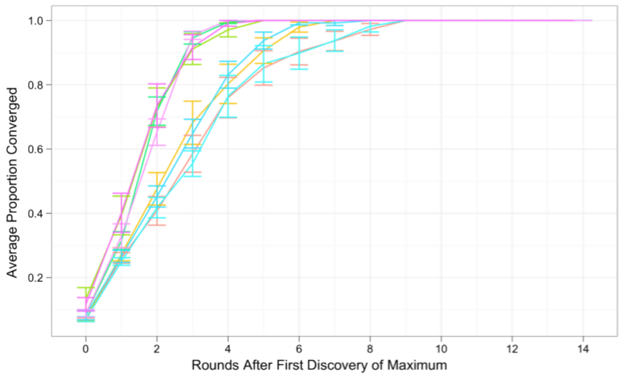



- Replicates findings from experimental work
- Suggests model of player behavior is reasonable

# Networks Affect Convergence Time



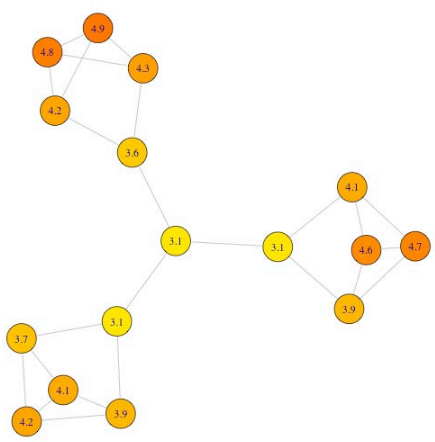

Human Players



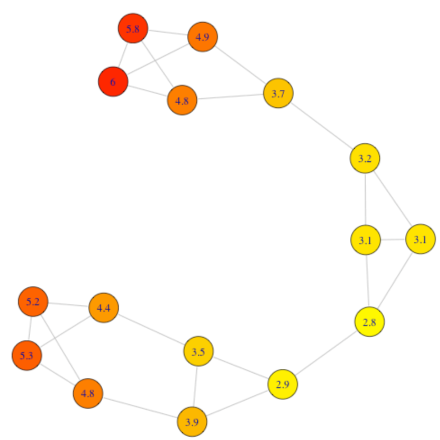

- Replicates findings from experimental work
- Suggests model of player behavior is reasonable

# Individual Performance Is Combination of Individual Position and Collective Performance

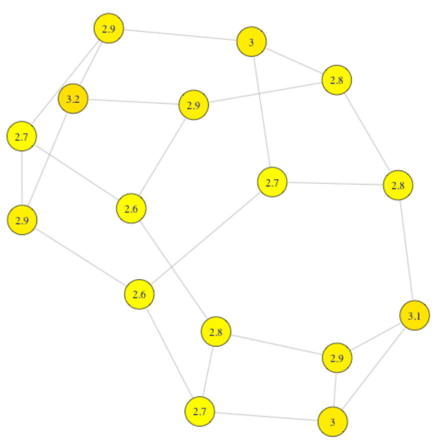
Greatest Maximum Betweenness




Greatest Average Betweenness




Greatest Maximum Closeness




- Individuals in centralized networks perform well, relative to their peers
- All individuals in centralized networks perform poorly relative to individuals in decentralized networks
- Corroborates experimental results

# Next Steps

- Explore problem space to discover new hypotheses
  - More complex payoff functions
  - Larger networks
  - Different composition of individual strategies
- Realistic model, but may be over-fit
  - Point threshold & imitation radius learned from known features of payoff functions
  - Copying / round depends on N rounds
- Return to experiments to test hypotheses

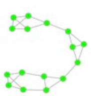
# Constructing Communication Networks

- Goal: 16-node fixed-degree graphs with extreme statistics
- Start with fixed-degree random graphs
  - All players have same amount of information
  - Only position in graph can affect success
- Rewire to increase or decrease some graph feature
  - Maximum, Average, Variance
  - Betweenness, Closeness, Clustering, Network Constraint
  - Ensuring connected graph
- Stop when no rewiring improves feature
- Repeat 100 times, keep maximal graph

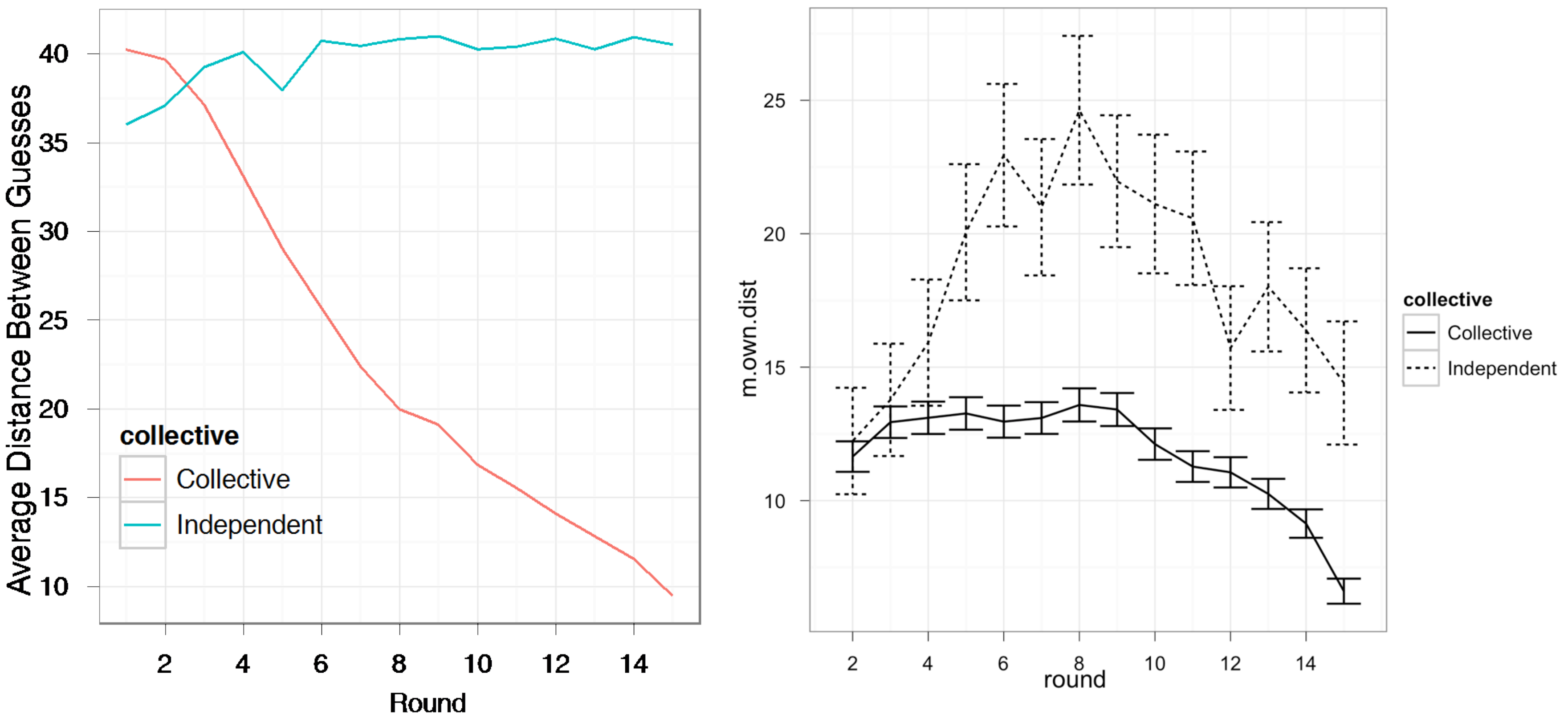
# Features

- Clustering:
  - Number of connected neighbors / Possibly connected neighbors
- Betweenness
  - Number of shortest paths through node
- Closeness
  - Average shortest path to all nodes
- Network Constraint
  - Redundancy with neighbors

$$nc(i) = \frac{1}{d^2} \sum_{j \in N(i)} (1 + \sum_{q \in N(i), q \neq j} p_{qj})^2$$

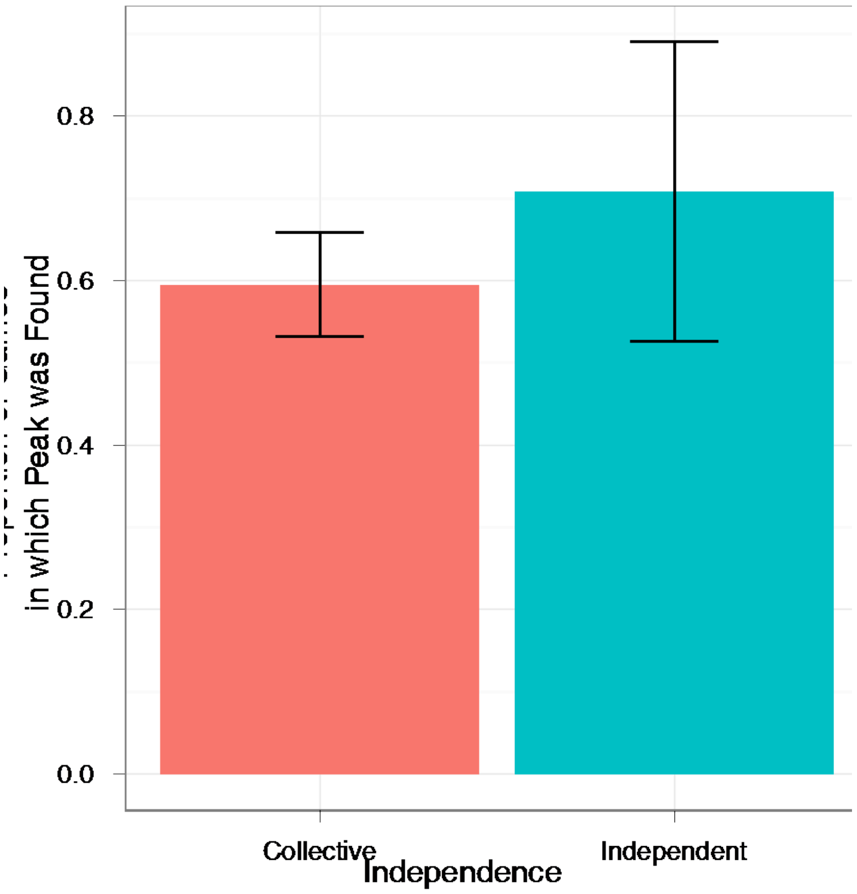
| | Topology | Radius | Diameter | Closeness | Betweenness | Clustering | Network Constraint |
|---|---|---|---|---|---|---|---|
|  | Min Avg Betweenness | 3 | 3 | 0.45 | 0.09 | 0 | 0.33 |
|  | Min Avg Clustering | 3 | 4 | 0.44 | 0.09 | 0 | 0.33 |
|  | Max Max Closeness | 3 | 5 | 0.41 | 0.1 | 0.06 | 0.36 |
|  | Max Var Constraint | 3 | 6 | 0.39 | 0.12 | 0.25 | 0.47 |
|  | Max Avg Clustering | 6 | 6 | 0.31 | 0.16 | 0.5 | 0.6 |
|  | Max Max Betweenness | 3 | 6 | 0.31 | 0.17 | 0.37 | 0.54 |
|  | Min Max Closeness | 5 | 9 | 0.27 | 0.2 | 0.37 | 0.53 |
|  | Max Avg Betweenness | 5 | 9 | 0.27 | 0.2 | 0.44 | 0.57 |

# Exploring vs. exploiting previous best



# No difference in finding peak

- Independent searchers found the peak more often, but not significantly



# No difference in finding peak

- Previous models suggest inefficient networks should find the peak more often

- Slower communication → more exploration