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  University of Colorado Boulder  DARPA  AFOSR
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.
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
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

Mason and Clauset, CSCW 2013
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-friends

Mason and Clauset, CSCW 2013
Survey respondents

![Histogram of age distribution with antisocial behavior chart](image)
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 $|a_{ij}|$
  - friendships are sparse in large networks
  - “ground truth” data hard to obtain
statistics to detect friendships

features of interaction time series:

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Formula</th>
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</thead>
<tbody>
<tr>
<td><strong>Temporal features</strong></td>
<td></td>
</tr>
<tr>
<td>1. Autocorrelation</td>
<td>$AC_{x,y}$</td>
</tr>
<tr>
<td>2. Pair volume</td>
<td>$N_{x,y}$</td>
</tr>
<tr>
<td>3. Fraction of interactions</td>
<td>$N_{x,y}/N_{x}$</td>
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<tr>
<td><strong>Entropy features</strong></td>
<td></td>
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<tr>
<td>4. Schedule entropy</td>
<td>$H_{s}(x,y)$</td>
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<tr>
<td>5. Location entropy</td>
<td>$H_{t}(x,y)$</td>
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<tr>
<td>6. Loc.-sched. entropy</td>
<td>$H_{t,s}(x,y)$</td>
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<tr>
<td><strong>Prosocial features</strong></td>
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<tr>
<td>7. Betrayals</td>
<td>$A_{x,y}$</td>
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<tr>
<td>8. Assistance</td>
<td>$V_{x,y}$</td>
</tr>
<tr>
<td>9. Indirect assistance</td>
<td></td>
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</table>

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 $> 0.98$
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?
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

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
impact of friendship on performance

• among survey respondents

• team performance vs. number of friends on team

• team performs better the more friendships it contains

Mason and Clauset, CSCW 2013
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

Merrit, Jacobs, Mason and Clauset, ICWSM 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?
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

Greatest Average Betweenness

Smallest Average Betweenness

Exp 1039 Trial 8
Exp 1043 Trial 6
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

Greatest Maximum Betweenness

Smallest Average Clustering
Exploration / Exploitation

- Players nearly always exploited solution when peak found by neighbor
- Players also exploited when peak not found

![Graph showing exploration vs exploitation](image-url)
Collective problem solvers face a social dilemma.
Invisible networks affect individual behavior

Less efficiency is associated with more copying

Average Proportion of Rounds with Copying Before Peak is Found
How invisible networks affect behavior

Connected neighbors imitate each other

Imitating neighbors lead to more imitation

Clustering

Probability of Similar Neighbors

Number of Similar Neighbors

Probability of Imitating
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 $A[f(x, y) \geq t_c]$
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 ± 0.8

[Graph showing degree distribution with two curves labeled "Tail undersampled" and "Tail oversampled". The graph indicates that the entire inferred network matches the head of the undersampled curve and the tail of the oversampled curve.]
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
  \[ P_{T-1} = fp + (1-f)n \]
  \[ P_{T-2} = 2fp + (1-f)(n+P_{T-1}) \]
  \[ P_{T-3} = 3fp + (1-f)(n+P_{T-2}) \]
  .
  .
  .

  $p$ 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
LF agents
“Vision” = 20 units

Proportion of Games in which Peak was Found
“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%]
Frequency of Finding Maximum

**Human Experiments**

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Networks Affect Convergence Time

• Replicates findings from experimental work
• Suggests model of player behavior is reasonable
Networks Affect Convergence Time

- Replicates findings from experimental work
- Suggests model of player behavior is reasonable
Individual Performance Is Combination of Individual Position and Collective Performance

- 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
    \[ nc(i) = \frac{1}{d^2} \sum_{j \in N(i)} \left( 1 + \sum_{q \in N(i), q \neq j} p_{qj} \right)^2 \]
<table>
<thead>
<tr>
<th>Topology</th>
<th>Radius</th>
<th>Diameter</th>
<th>Closeness</th>
<th>Betweenness</th>
<th>Clustering</th>
<th>Network Constraint</th>
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</table>
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