Lecture 9
Incentive Design: Badges and Attention

Instructor: Chien-Ju (CJ) Ho

Logistics: Assignment 2 and Project Proposal

- Assignment 2
  - Due: Feb 28 (Wed)
  - 3 long-ish math questions that extend the lecture today

- Project Proposal
  - <u>Tentative</u> due: Mar 1 (Friday)
  - Requirement
    - 1~2 paragraph description of the project
    - Identify at least one research paper on the topic

Logistics: Presentation

- The schedule is posted on Piazza

Date	Topic	Presenters
Feb 12	Incentive Design: Financial Incentives	CJ
Feb 14	Incentive Design: Badges and Attention	CJ
Feb 26	Workflow Design for Crowdsourcing	CJ
Feb 28	Learning in the Presence of Disagreements	Kai Ang, Sangwook Suh
Mar 4	LLM as a Proxy for Humans	Yifan Yuan, Ilan Barr, Nancy Patel
Mar 6	Adapting Crowdsourcing Techniques for LLM	Oscar Ortiz, Zhiyuan He
Mar 18	Fairness in AI	CJ
Mar 20	Human Perceptions of Fairness	Oen McKinley, Kyle Stein
Mar 25	Ethical Decision Making and Participatory Design	Garrett Kearney, Jake Valentine, Leib Malina
Mar 27	Human Trust in AI-Assisted Decision Making	Vincent Siu, Arpit Jain
Apr 1	Designing AI for AI-Assisted Decision Making	Joshua Tang, Sunny Yuan, Meichuan Yin
Apr 3	Explainable Machine Learning	Kaitlin Day, Micah Benson, Victoria Black
Apr 10	Human-Centered Explainable Machine Learning	Tory Farmer, Stuart Aldrich
Apr 15	Designing Collaborative AI in Human-AI Teams	CJ

Badge as Incentives

Steering User Behavior with Badges. Anderson et al. WWW 2013.

Modeling Badges

- Focus on threshold badges

Civic Duty	Vote 300 or more times
Editor	First edit
Strunk & White	Edit 80 posts
Copy Editor	Edit 500 posts (excluding own or deleted posts and tag edits)

- Representation of threshold badges:
  - Earn a badge for “taking an action K times”

Modeling Badges as Incentives

- Key elements in modeling incentives
  - Players, Action space, Payoff
- One naïve model for threshold badges
  - Players: Only single user since there is no user interaction in threshold badges
  - Action space: # actions the user decides to take
  - Payoff: Utility(HasBadge(# actions)) - Cost(# actions)
- Model prediction: Users take actions that maximizes payoff
- This model helps answer some questions but not others
  - What can this model tell us?

All models are wrong

but some are useful

George E.P. Box

Modeling Badges (Action)

- Interactions between different types of actions.

  Introduce action types $(A_1, \dots, A_n, A_{n+1})$, where A_{n+1} is the "life action"

- Sequential decision making instead of one-shot decision

  User history is summarized in a vector $\boldsymbol{a} = (a^1, \dots, a^{n+1})$

  a^i: # times actions of type i has been taken

  The user can only take one (mixed) action at a time
  User policy $\boldsymbol{x}_{\boldsymbol{a}}$: given history $\boldsymbol{a}$, the prob. distribution over action types

Modeling Badges (Payoff)

- Cost of actions

  User have a preferred (mixed) action $\boldsymbol{p}$

  Cost for take action $\boldsymbol{x}$: $g(\boldsymbol{x}, \boldsymbol{p})$ distance to the preferred action

- Utility for obtaining badges

  Value of the badge b: V_b (assume this is given)

  Indicator function of whether the badge is obtained

$$I_b(\boldsymbol{a}) = \begin{cases} 1, \text{if the history } \boldsymbol{a} \text{ qualify for badge} \\ 0, \text{ otherwise} \end{cases}$$

Modeling Badges (Payoff)

- Discounted future payoff

  The payoff in the next round is discounted by $\theta = 1 - \delta < 1$

  Users aim to choose policy $\boldsymbol{x}_a$ that maximizes $U(\boldsymbol{x}_a)$

$$U(\mathbf{x_a}) = \sum_{b \in B} I_b(\mathbf{a}) V_b + \theta \sum_{i=1}^{n+1} \mathbf{x}_\mathbf{a}^i \cdot U(\mathbf{x}_{\mathbf{a}+\mathbf{e}_i}) - g(\mathbf{x_a}, \mathbf{p})$$

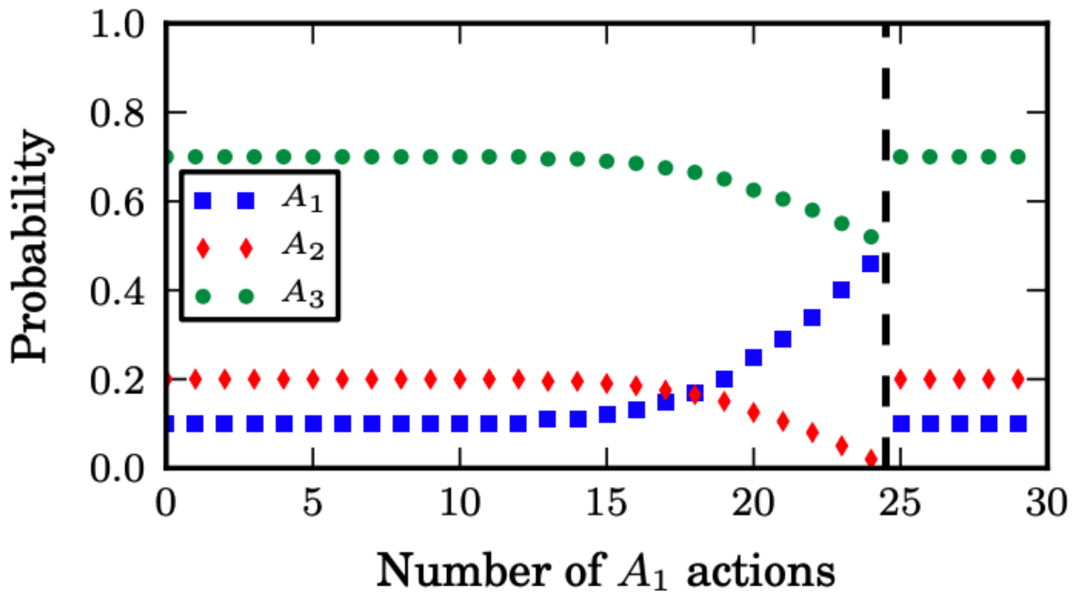
Payoff from current badges

Cost of action

Payoff from “future” badges from actions

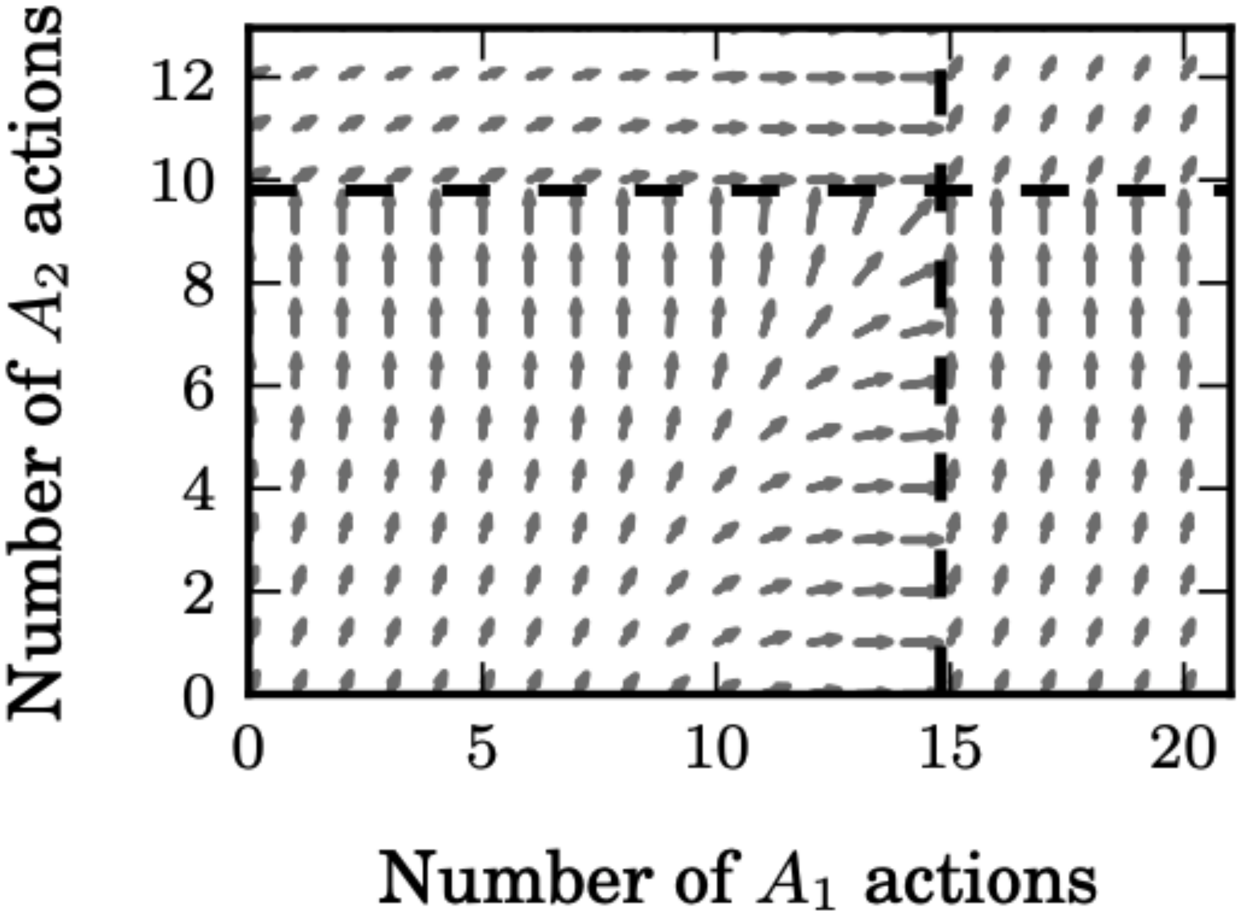
Think about what actions users will take if we believe this model is correct?

Model Predictions



- More sensitive to badges when closer to obtaining it.
- Increase the action of one type decrease the others.
- The incentive of a badge disappears after obtaining it.

Model Predictions



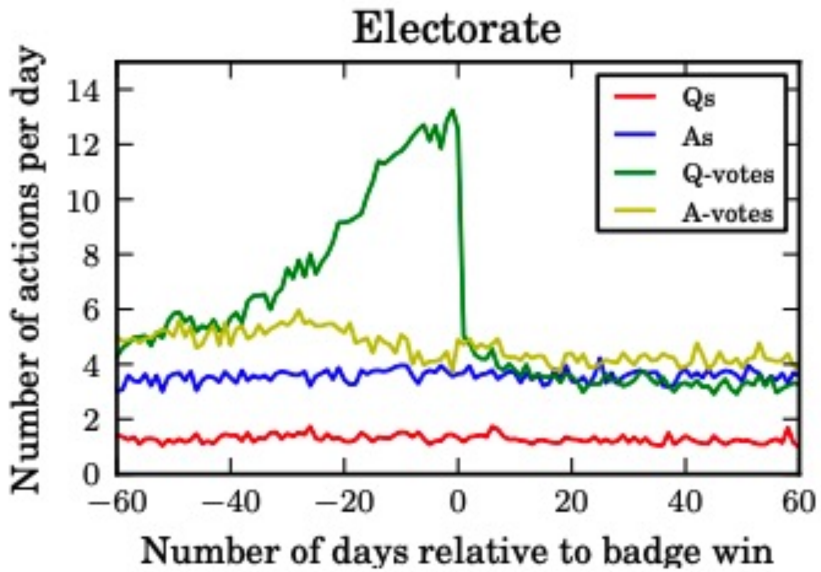
Empirical Evidence from Stack Overflow

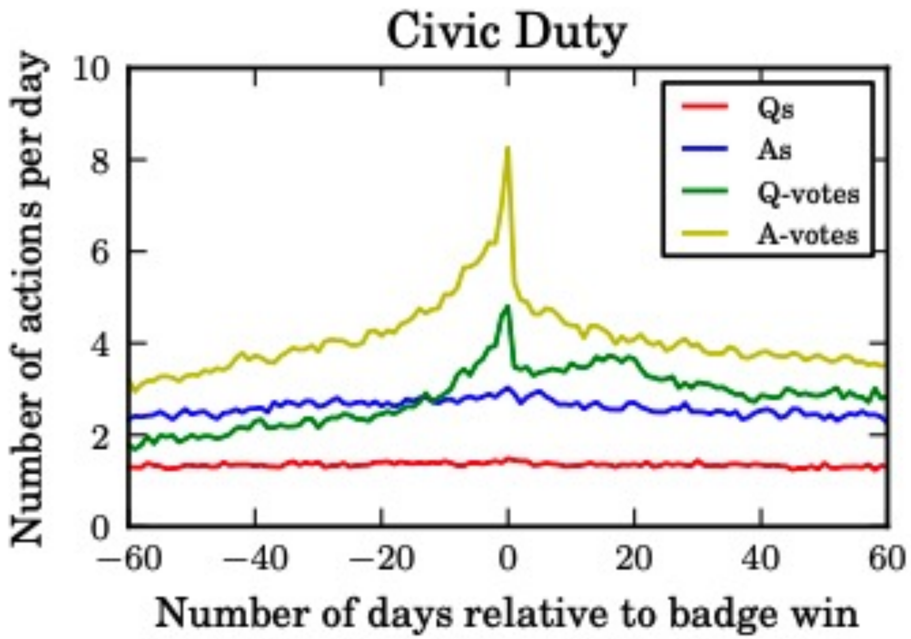
Electorate

Vote on 600 questions and 25% or more of total votes are on questions

Civic Duty

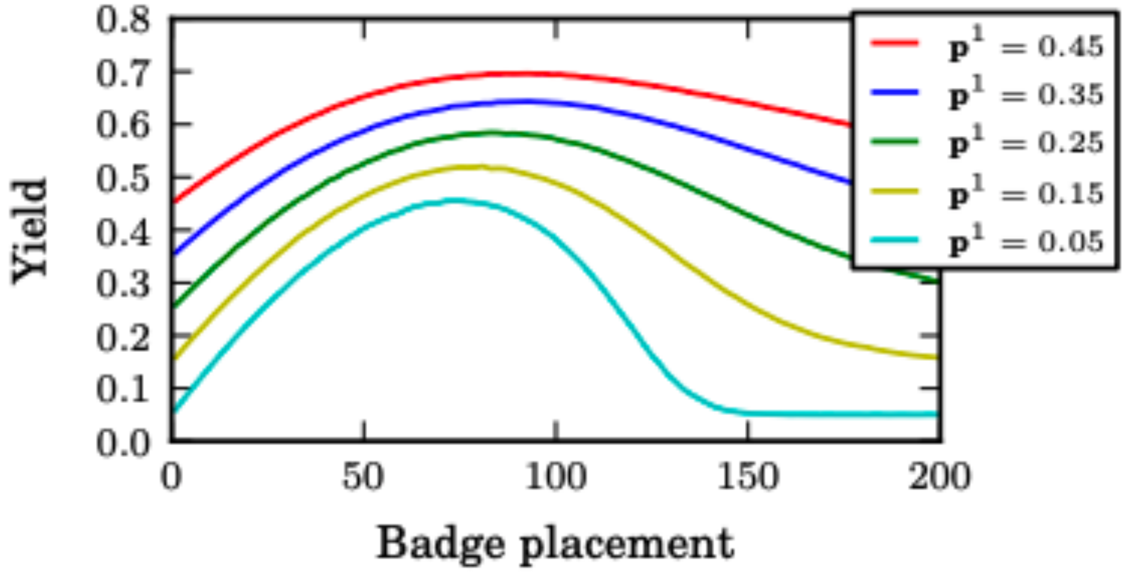
Vote 300 or more times





Badge Design

- How to optimally design the badges?
- Single threshold badge: what is the optimal threshold



The paper discusses more design questions, but be careful on what the model/evidence really captures.

Other Badges

- Requires a "sustained" performance

Curious	Ask a well-received question on 5 separate days, and maintain a positive question record
Inquisitive	Ask a well-received question on 30 separate days, and maintain a positive question record
Socratic	Ask a well-received question on 100 separate days, and maintain a positive question record

- Associates with quality

Favorite Question	Question favorited by 25 users
Stellar Question	Question favorited by 100 users

- And more …(e.g., requires competition)

Final Notes

- Connections to gamification, social status, and reputation systems.
- For all these modeling work, try to always remind yourself what the settings/assumptions are, and consider when/whether they might be useful.

Discussion

- Have you ever been incentivized by badges? Share your experience with other students.
- Discuss on whether those badges can be designed better? Try to more formally describe the aspects of design and define what you mean by better.
  - Think of this as a practice to ”model” the world that you care about.
- What additional features/perspectives do you think are the most interesting/important next questions to ask for badge design?

Attention as Incentives

Incentivizing High-Quality User-Generated Content. Ghosh and McAfee. WWW 2011.

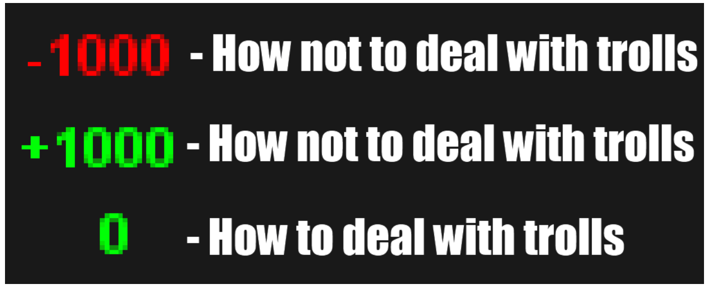
User-Generated Content Platforms

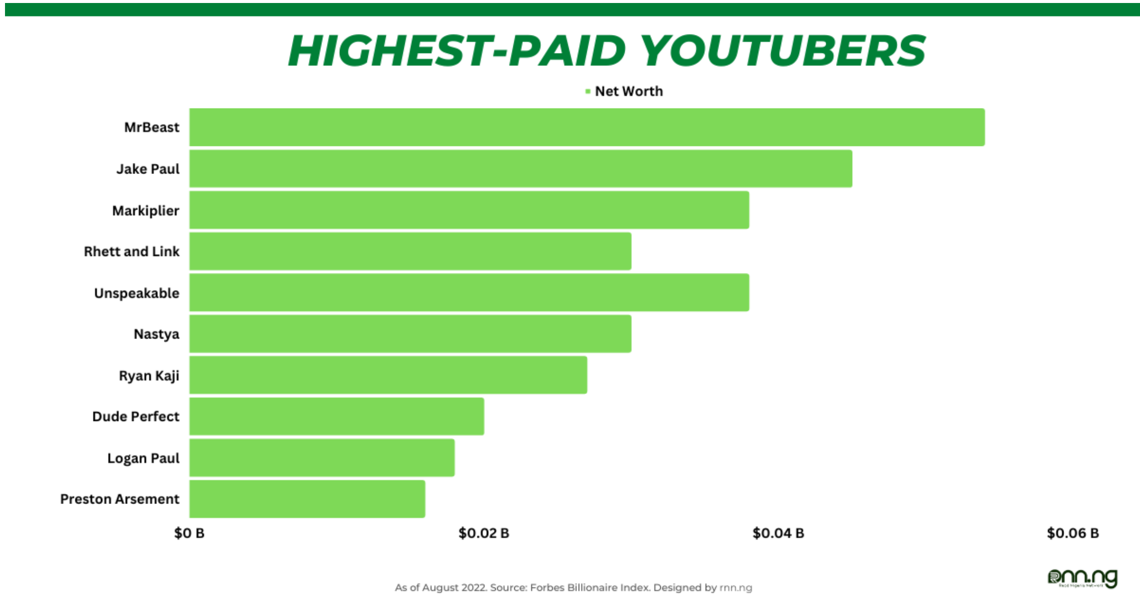
- Content is generated by users instead the platform

- **Why** do people post content on YouTube, Instagram, Quora?

Attention is One of the Major Incentives

- Psychological motivation





- Probably more importantly,
  Attention => Money (e.g., through advertisements)

- Platforms have huge power on influencing which content will receive more attention

Assuming attention is the main motivation for contributors, how should the platform design their content displaying algorithm?

Modeling Attention as Incentive

- Players: Platform, Users
- Actions:
  - Extensive-form game: the platform takes action first, then users take actions
  - Platform: Content displaying mechanism
  - Users: quality of the contributed content
    - Simplification: Quality $q \in [0,1]$: a ratio of q viewers will like the content
    - Higher cost to generate better-quality content
- Payoff:
  - Platform: some function of the quality of all content on the platform
  - Users: Utility(# views(quality)) – Cost(quality)
- Solving the equilibrium (everyone is taking the best-response action)

More Settings/Assumptions

- The platform aims to allocate M views to K contributors (assuming viewers just read/watch whatever the platform recommends)

- Extensive-form game
  1. The platform announces her allocation mechanism
  2. K contributors simultaneously decide on the quality of their contributions

Each contributor aims at maximizing Utility(# views(quality)) – Cost(quality)

Mechanisms

What are the outcomes of the mechanism?

Assumption: Each contributor aims at maximizing Utility(# views(quality)) – Cost(quality)

- Random: randomly allocating M views to K content

Flood of bad content

- Proportional mechanism:
  - Let $q_1, \dots, q_K$ be the quality of the K content
    - (assume q means the ratio of viewers who like the content)
  - Content i receives $M \frac{q_i}{\sum_{j=1\ to\ k} q_j}$ views

Requires good estimate of q

Quality converge to a suboptimal value

- Can we do better?

Mechanisms

What are the outcomes of the mechanism?

Assumption: Each contributor aims at maximizing Utility(# views(quality)) – Cost(quality)

- Elimination mechanism:
  - Each content is evaluated by a random select of A viewers
  - Only when all A viewers like the content, it goes to the 2nd stage
  - All content in 2nd stage equally shares the remaining views

By tuning A, content quality might achieve optimal

Simultaneously estimate content quality.

Additional follow-up work

- Mixture of learning and incentives: [Ghosh and Hummel. ITCS 2013]
  - Showing a content to viewers:
    - Create incentives for contributors
    - Platform can learn content quality from viewer feedback
  - How to simultaneously address joint issues of learning and incentives
- Incorporating human biases in learning [Tang and Ho. AAMAS 2019]

Herding Effect

Discussion

- We have discussed the incentive design problem for financial incentives and non-financial incentives such as badges and attention.

- What are the other types of incentives you think we can utilize to promote human-in-the-loop computation?
  - Reputation, access to information, recommendation accuracy, etc

- How do you model and analyze the incentives?
  - Players, actions, payoff? What’s the equilibrium?
    How to perform the design?

Social Networks and Incentives

The Small-World Experiment [Stanley Milgram, 1967]

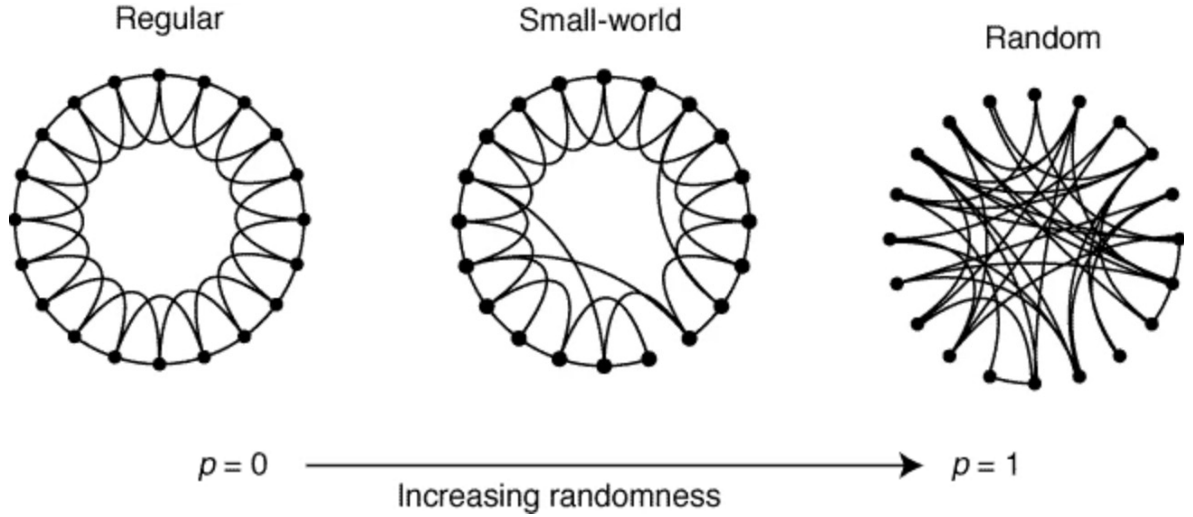
[The figure is from Wikipedia]

- How many hops does it take to deliver a mail from a person in Nebraska/Kansas to a person in Massachusetts?
- A person can only pass the mail to someone she/he knows in a first-name basis.
- Average: Around 5.5~6 hops
    - Six degrees of separation

There are criticisms on the methodology, but the results are still very impressive

Small-World Networks [Watts and Strogatz, Nature 1998]

- Two characteristics
  - People form “cliques” (my friends are usually my friends’ friends)
  - There are some random links



- “One of the models” that explain the small world phenomenon

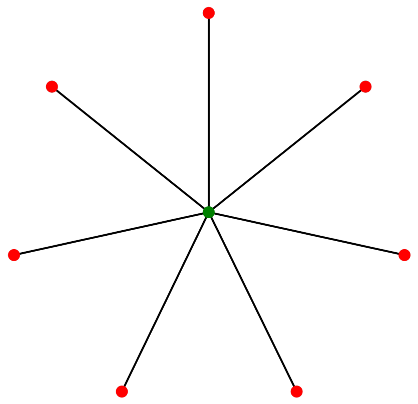
Another Social Network Model

- Preferential Attachments (Barabási–Albert Model)
  - People join the network on by one
  - Attach (form edges) to existing members
  - Attach probability proportional to edges

- Explains the rich-gets-richer effect

Friendship Paradox [Scott L. Feld. 1991]

- On average, do your friends have more friends than you have?
  - Yes, if we take the average over everyone in the network.



Average # friends: $\frac{7*1+7}{8} = 1.75$

Average # friends a person's friends have: $\frac{7*7+1}{8} = 6.25$

- Local observations could be distorted by the network structure
  - One's friends are happier, wealthier, more popular…

Utilizing the Power of Networks

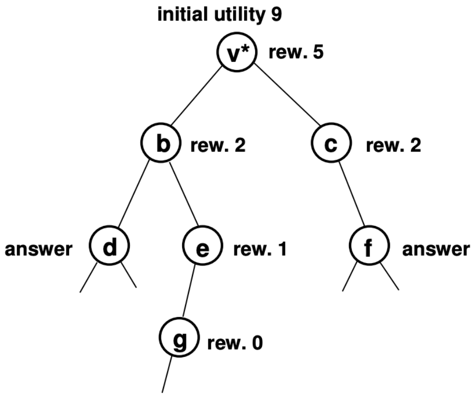
- Given we can reach most people in a small number of hops, can we utilize the people in networks to help with tasks.

- Not that trivial
  - A replication of the small world experiment using emails has faced a high-level of drop-out rate since people are not motivated in attending.

- Need proper incentives:
  - See more in the seminal paper of query incentive networks

Query Incentive Networks [Kleinberg and Raghavan, 2005]

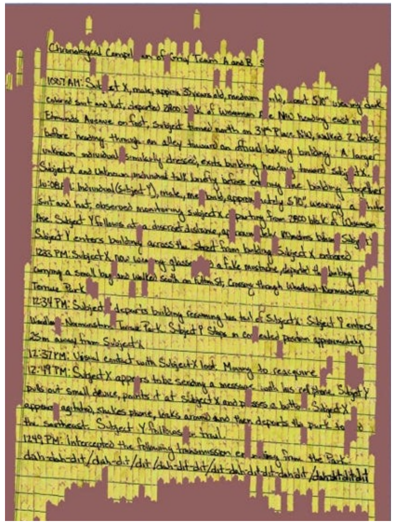
- Formalize the theoretical discussion on incentives in networks

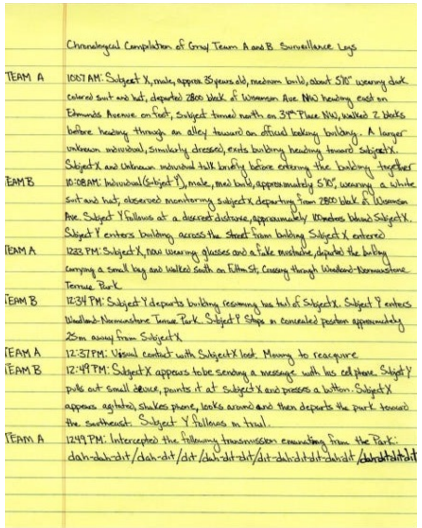


- Successful example: DARPA network challenge

Generalize the Results from DARPA Network Challenge

- DARPA shredder challenge, 2011
  - Goal: Piece together the information in shredded paper





Chronological Compilation of Gray Team A and B Surveillance Logs

TEAM A 10:07 AM: Subject X, male, approx 35 years old, medium build, about 5'10" wearing dark colored suit and hat, departed 2800 block of Wisconsin Ave NW heading east on Edmunds Avenue on foot, Subject turned north on 34th Place NW, walked 2 blocks before heading through an alley toward an official looking building. A larger unknown individual, similarly dressed, exits building heading toward Subject X. Subject X and Unknown individual talk briefly before entering the building together

TEAM B 10:08 AM: Individual (Subject Y), male, med build, approximately 5'10", wearing a white suit and hat, observed monitoring subject X departing from 2800 block of Wisconsin Ave. Subject Y follows at a discreet distance, approximately 100 meters behind Subject X. Subject Y enters building across the street from building Subject X entered

TEAM A 12:33 PM: Subject X, now wearing glasses and a fake mustache, departed the building carrying a small bag and walked south on Fulton St, Crossing through Woodland-Normanstone Terrace Park

TEAM B 12:34 PM: Subject Y departs building resuming his tail of Subject X. Subject Y enters Woodland-Normanstone Terrace Park. Subject Y Stops in concealed position approximately 25m away from Subject X

TEAM A 12:37 PM: Visual contact with Subject X lost. Moving to reacquire

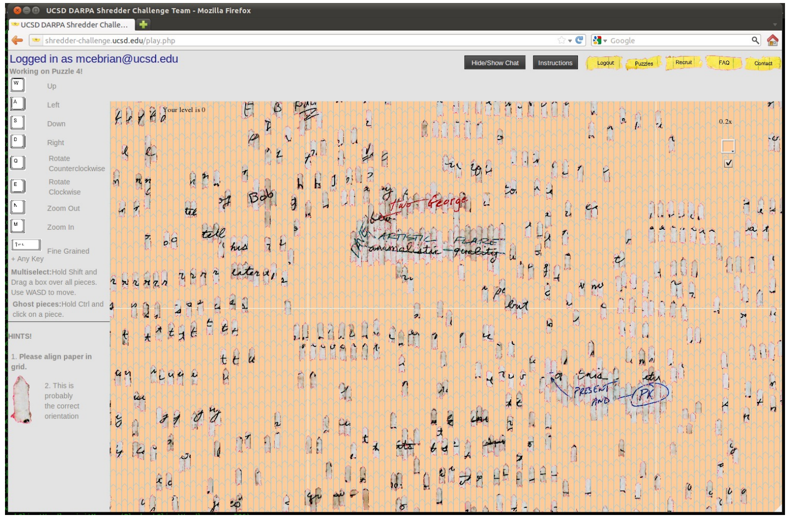
TEAM B 12:49 PM: Subject X appears to be sending a message with his cell phone. Subject Y pulls out small device, points it at Subject X and presses a button. Subject X appears agitated, shakes phone, looks around and then departs the park toward the southeast. Subject Y follows in trail.

TEAM A 12:49 PM: Intercepted the following transmission emanating from the Park: dah-dah-dit/dah-dit/dit/dah-dit-dit/dit-dah-dit-dit-dah-dit/dah-dit-dit-dit

  - First team to complete 5 puzzles win $50,000
  - Duration: October 27, 2011 to December 4, 2011

Generalize the Results from DARPA Network Challenge

- UCSD team tried the same method as MIT team did in network challenge



"However, the crowd was hopeless against a determined attacker. Before the first attack, our progress on the fourth puzzle had combined 39,299 moves by 342 users over more than 38 hours. Destroying all this progress required just 416 moves by one attacker in about an hour."

"creation took 100 times as many moves and about 40 times longer than destruction." [How Crowdsourcing Turned On Me]. Iyad Rahwan.

- Solved 3 (out of 5) puzzles in 5 days
- No progress after that
  - Too many sabotage attempts to ruin their results
  - Designing mechanisms **robust** to adversarial attacks is important but non-trivial

Utilizing the Power of Networks

- Influence maximization [Who should we start to ask questions?]
  - You can send products to K people to try on
  - Assume people who try the product will tell their neighbors with some probability
  - Who should you choose to send the products maximize the expected number of people knowing your product?

Generally a NP-hard question.

There exists efficient approximation algorithms, if you know the network structure.

What if you don't know the network structure?

- Learning and sampling

Utilizing the Power of Networks

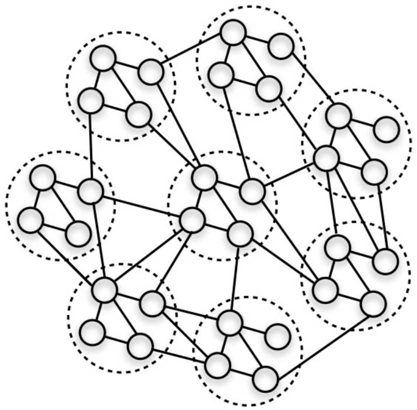
- AI for social good:
  Taking interventions to prevent HIV for homelessness youth [Wilder et al. 2021]

- Procedure
  - Recruit “peer leaders” in drop-in centers
  - Train the leaders and have them help disseminate the information
  - Adapt techniques from influence maximization to maximize the information spread

- Help reduce 31% chance of risk behavior

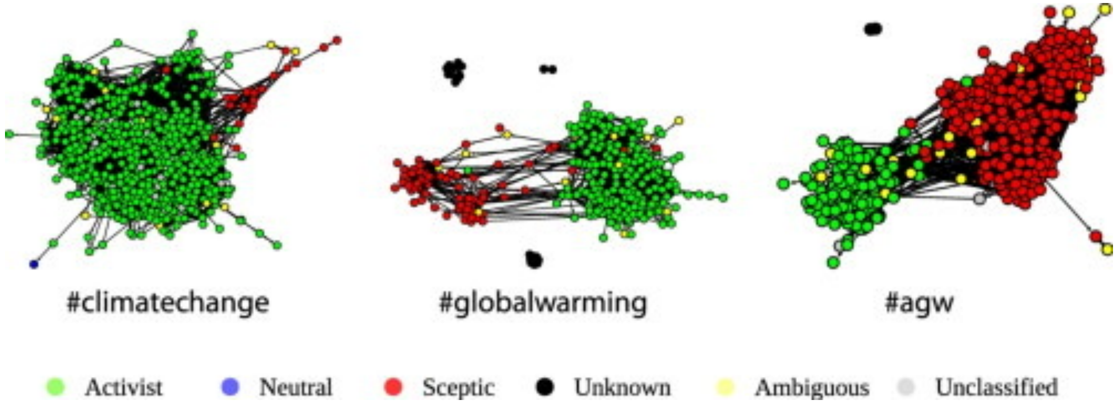
Other Challenges/Opportunities of Networks

- Network could create biases in data collection [Saveski et al. 2017]

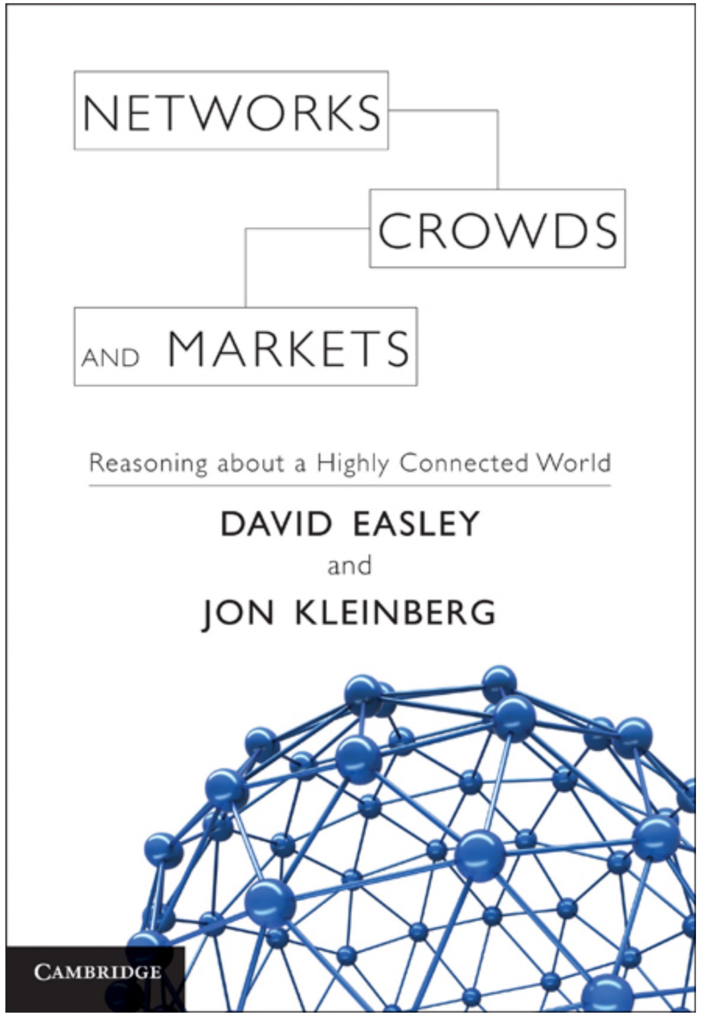


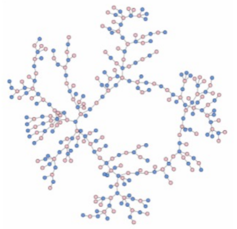
Neighbors might have similar opinions
Break the common "independence" assumption

- Opinion formation: Human opinions might be influenced by networks

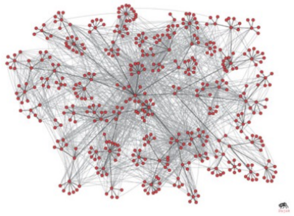


[Williams et al. 2015]



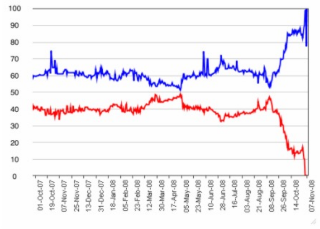


High School Dating
(Bearman, Moody, and Stovel, 2004)
(Image by Mark Newman)



Corporate E-Mail Communication
(Adamic and Adar, 2005)

Trails of Flickr Users
in Manhattan
(Crandall et al. 2009)



Prediction Market for the
2008 U.S. Presidential Election
(Iowa Electonic Markets, 2008)

Networks, Crowds, and Markets:

Reasoning About a Highly Connected World

By David Easley and Jon Kleinberg

https://www.cs.cornell.edu/home/kleinber/networks-book/

Proper Scoring Rules

Incentivizing Truthful Reports About Probabilities

- Example scenarios:
  - Ask a weather forecaster: will it rain tomorrow?
  - Ask a political researcher: will Trump win 2020 election?
  - Ask a Microsoft employer: will the new version of Office be shipped on time?

- Want to obtain forecasts about future events
- How do we make sure we obtain **truthful** reports?

Incentivizing Truthful Reports

- Setting
  - Consider a rational agent with linear utility for cash
  - Suppose there are n mutually exclusive and exhaustive states of the world $\Omega = \{w_1, w_2, \dots, w_n\}$ (e.g., Sun, Rain, Snow)
  - p_i is the subjective belief of the agent that state w_i will occur
- Question
  - How do we motivate this agent to tell us her beliefs about the likelihood of each state?

Scoring Rules

- A scoring rule rewards an agent $S(\vec{r}, w)$ when her reported distribution is $\vec{r}$ and the realized outcome is w

Scoring Rules

- Let's consider a linear scoring rule

$$S(\vec{r}, w_i) = r_i$$

- If a risk-neutral agent believes the probability for Rain and Sun are

$$\vec{p} = (0.7, 0.3)$$

What report should the agent provide?

Scoring Rules

- A scoring rule rewards an agent $S(\vec{r}, w)$ when her reported distribution is $\vec{r}$ and the realized outcome is w

- A scoring rule is called ***proper*** if the agent maximizes her utility by providing truthful report

$$\vec{p} = \text{argmax}_{\vec{r}} \sum_{i=1}^{n} p_i S(\vec{r}, w_i)$$

- A scoring rule is ***strictly proper*** if honestly reporting is the **unique** maximizer.

Examples of Strictly Proper Scoring Rules

- Quadratic scoring rule (Brier score):

$$S(\vec{r}, w_i) = r_i - \frac{1}{2}\sum_j r_j^2$$

We can verify this by taking the gradient of the expected payoff

- Affine transformation of the proper scoring rule is still proper.

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VERIFICATION OF FORECASTS EXPRESSED IN TERMS OF PROBABILITY

GLENN W. BRIER

U. S. Weather Bureau, Washington, D. C.

[Manuscript received February 10, 1950]

Examples of Strictly Proper Scoring Rules

- Logarithmic scoring rule:

$$S(\vec{r}, w_i) = \log r_i$$

  We can verify this by taking a gradient of the expected payoff

- In logarithmic scoring rule, the score for outcome w_i only depends on the report r_i and not r_j for $j \neq i$

More examples?

- How do we construct a strictly proper scoring rule?
- How many strictly proper scoring rules are there?

Characterization of Proper Scoring Rules

- Connections between convex functions and proper scoring rules.

- A scoring rule $S(\vec{r}, w_i)$ is (strictly) proper if and only if

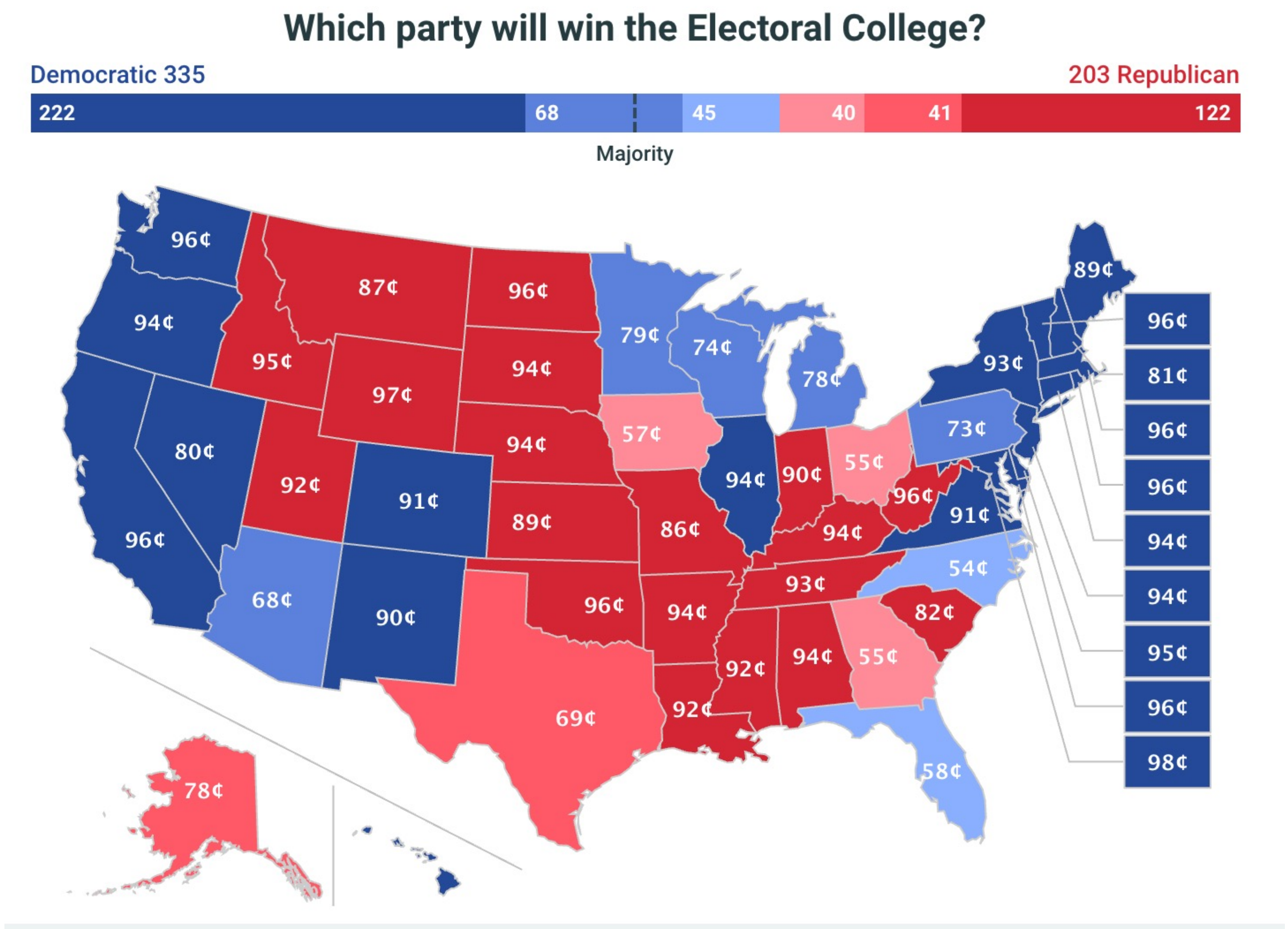
$$S(\vec{r}, w_i) = G(\vec{r}) - \sum_{j \neq i} G'_j(\vec{r}) p_j + G'_i(\vec{r})$$

where $G(\vec{r})$ is a (strictly) convex function, $G'(\vec{r})$ is a subgradient of G at $\vec{r}$, and $G'_i(\vec{r})$ is its i-th component.

Section 3.1 of Strictly Proper Scoring Rules, Prediction, and Estimation by Gneiting and Raftery.

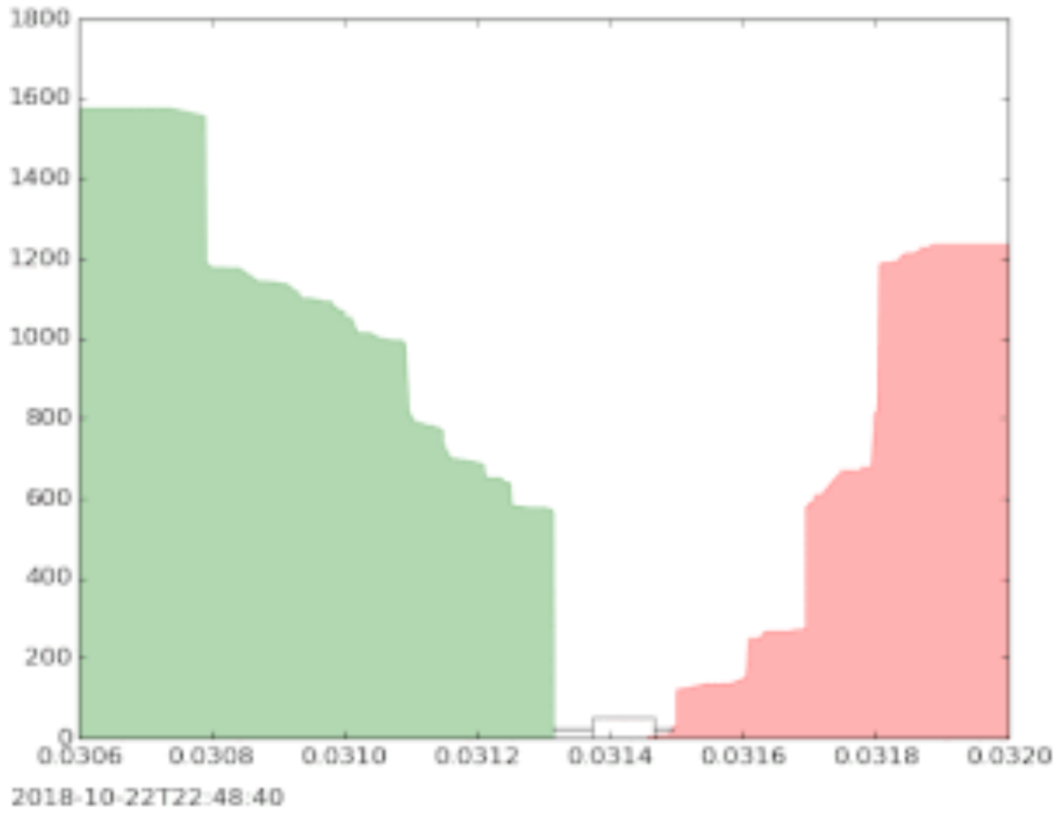
Prediction Market

Connection to Prediction Market



Designing Automatic Market Makers

- Traditional market mechanisms might not work when the market is thin



Designing Automatic Market Makers

Goal of the market maker

Incentivize ***multiple*** agents to share their beliefs, and find a way to ***aggregate*** these beliefs into a unified prediction

1. Could use one scoring rule per agent, but not clear how to aggregate
2. Market itself is an aggregation mechanism (use final price as the prediction). However, standard stock-market-style trading might encounter issues for less popular predictions (market is too *thin*).

Market Scoring Rules

- See Hanson's papers in the optional readings of the Prediction Market lecture
- Intuitions: a "sequentially shared scoring rule"
  - An automatic market maker
  - Market maintains a vector of predictions $\vec{r}^{(t)}$
  - If a trader changes the vector from $\vec{r}^{(t)}$ to $\vec{r}^{(t+1)}$ and the outcome is w_i, the trader obtains reward

$$S\left(\vec{r}^{(t+1)}, w_i\right) - S\left(\vec{r}^{(t)}, w_i\right)$$

- Under some conditions:
  - Agents truthfully report their beliefs
  - The prediction will converge

Market Scoring Rules

- The connection to convex optimization opens up an interesting line of research in the design of efficient market maker…

Assignment 2

Cooperation and Repeated Prisoner's Dilemma

- Prisoner's dilemma predicts that people are not going to cooperate in the game setup, but in practice, people sometimes do.

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	(2,2)	(0,3)
	Defect	(3,0)	(1,1)

- Will look at this using repeated versions of prisoner's dilemma
  - Sequential decision making
  - Discount utility u_t obtained at time t by δ^{t-1}, with $\delta \in (0,1)$

$$U = \sum_{t=1}^{T} \delta^{t-1} u_t$$

Peer Grading and Peer Prediction

- Can we design ”incentives” for peer grading?
  - Ground truth (goodness of assignment) is hard to obtain
  - Students (graders) have noisy signals that reveal the assignment quality
  - Want to incentivize graders to truthfully reveal the signals

	Signal	
	G	B
Good	80%	20%
Bad	40%	60%

Common prior:
80% of the assignments are “good”

- Randomly pick two students to grade the same assignment
  - Simply rewarding “the same report” is probably not a good idea
    - Every grader can just give high score for every assignment
  - How should we do it?

Information Design with Bayesian Persuasion

- A company wants to hire interns from our class and asks me for recommendation letters

- Assumption
  - 30% of students are "good" -> meet their requirement
  - They don't know who are good but I know

- How do I write letters to maximize the number of students getting hired?