Lecture 10
Incentive Design: Badges and Attention

Instructor: Chien-Ju (CJ) Ho

Logistics: Deadlines

- Assignment 2: Due this Friday
- Assignment 3: Due ~~Oct 12 (Wed)~~ Oct 17 (Monday)

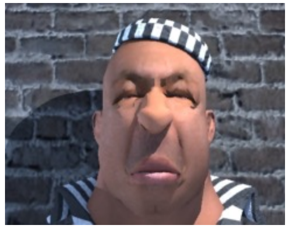
- Project milestone 1: Due Oct 14 (Fri)
  - Initial literature survey (know what other works are out there)
  - A plan on what you want to do for the remaining of the semester
    - Formalize your research question and approaches, e.g.,
      - Theory/simulation project: formalize your models
      - Data-analysis project: figure out where and how to get data and what you plan to do with it
      - Experiment/application project: have a prototype design and an evaluation plan
    - Include a timeline (weekly or biweekly) on what you plan to do
      - Nov 1: Midterm Project Pitch
      - Nov 4: Milestone 2

Recap on Game Theory Basics

Game Theory Basics

- Key elements of game theoretical models
  - Players, strategies, payoffs

- Normal-form game



B

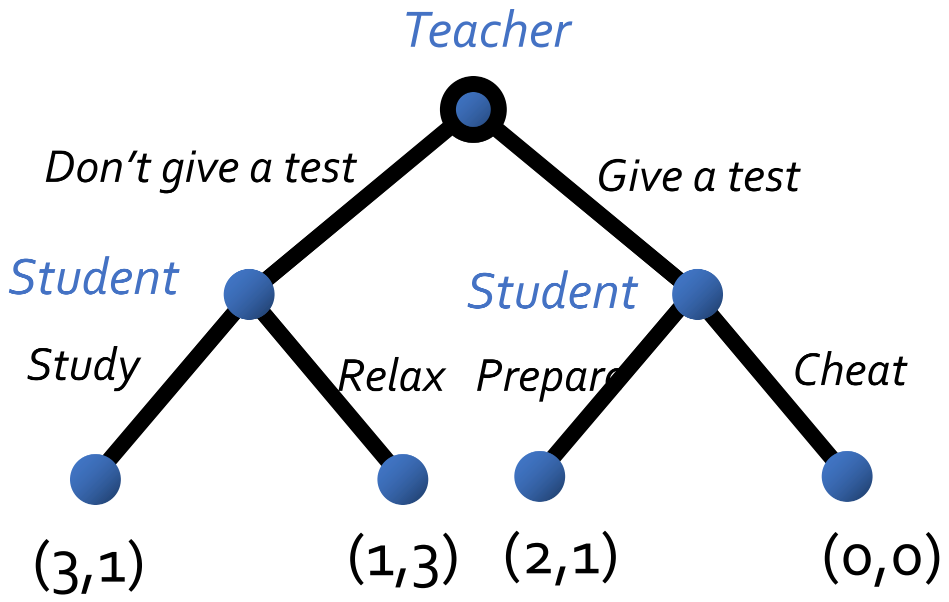
A

	Stay Silent	Confess
Stay Silent	A: 6 months B: 6 months	A: 10 years B: free
Confess	A: free B: 10 years	A: 5 years B: 5 years

Game Theory Basics

- Key elements of game theoretical models
  - Players, strategies, payoffs

- Extensive-form game



Solutions Concepts

- Informally, predictions of what rational agents will do given the game
- Nash equilibrium
  - If everyone else follows Nash equilibrium, it's your best interest to follow

B

A	Movie	Bar
Movie	(2, 1)	(0, 0)
Bar	(0, 0)	(1, 2)

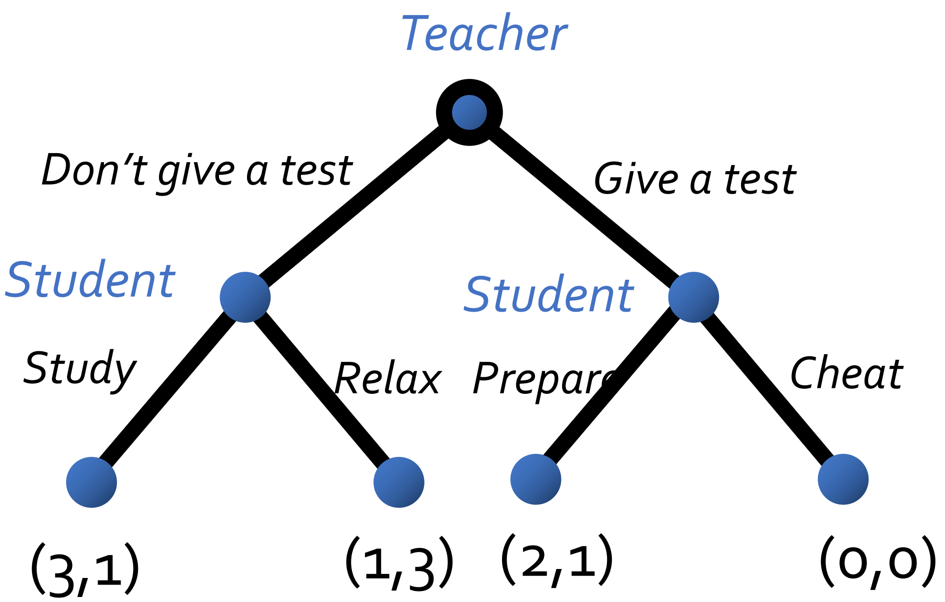
(Movie, Movie) and **(Bar, Bar)** are pure strategy Nash equilibria

Generally speaking, finding a Nash is hard, but verifying whether it's a Nash is easy

Solutions Concepts

- Informally, predictions of what rational agents will do given the game

- Subgame perfect equilibrium
  - Play in each ”subgame” is a Nash equilibrium



- Subgame perfect equilibrium
  - Teacher chooses “Give a test”
  - Student chooses (“Relax”, “Prepare”)

Mechanism Design

- Game theoretical analysis
  - Given the game, analyze what rational agents will do

- Mechanism design (reverse game theory)
  - Give a goal of what you want rational agents to do, design the game rules (e.g., what payoffs agents can receive) such that agents choose the actions you want them to choose.

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

- Sequential decision making instead of one-shot decision

  User history is summarized in a vector $\boldsymbol{a} = (a^1, \ldots, a^{n+1})$
  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 taking 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 $U(\boldsymbol{x}_a)$

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

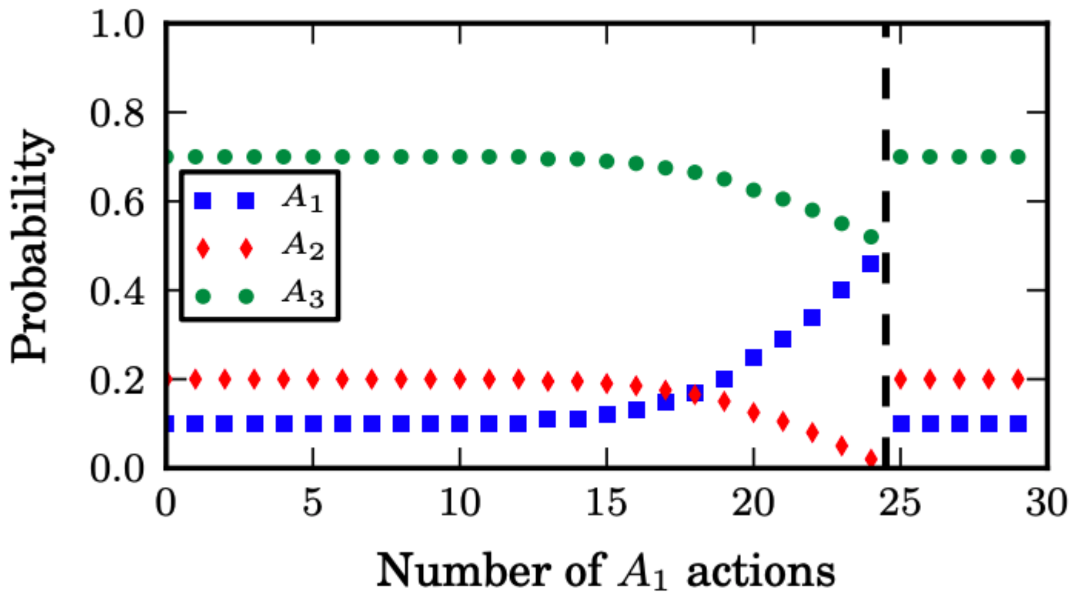
Payoff from current badges

Payoff from "future" badges from actions

Cost of action

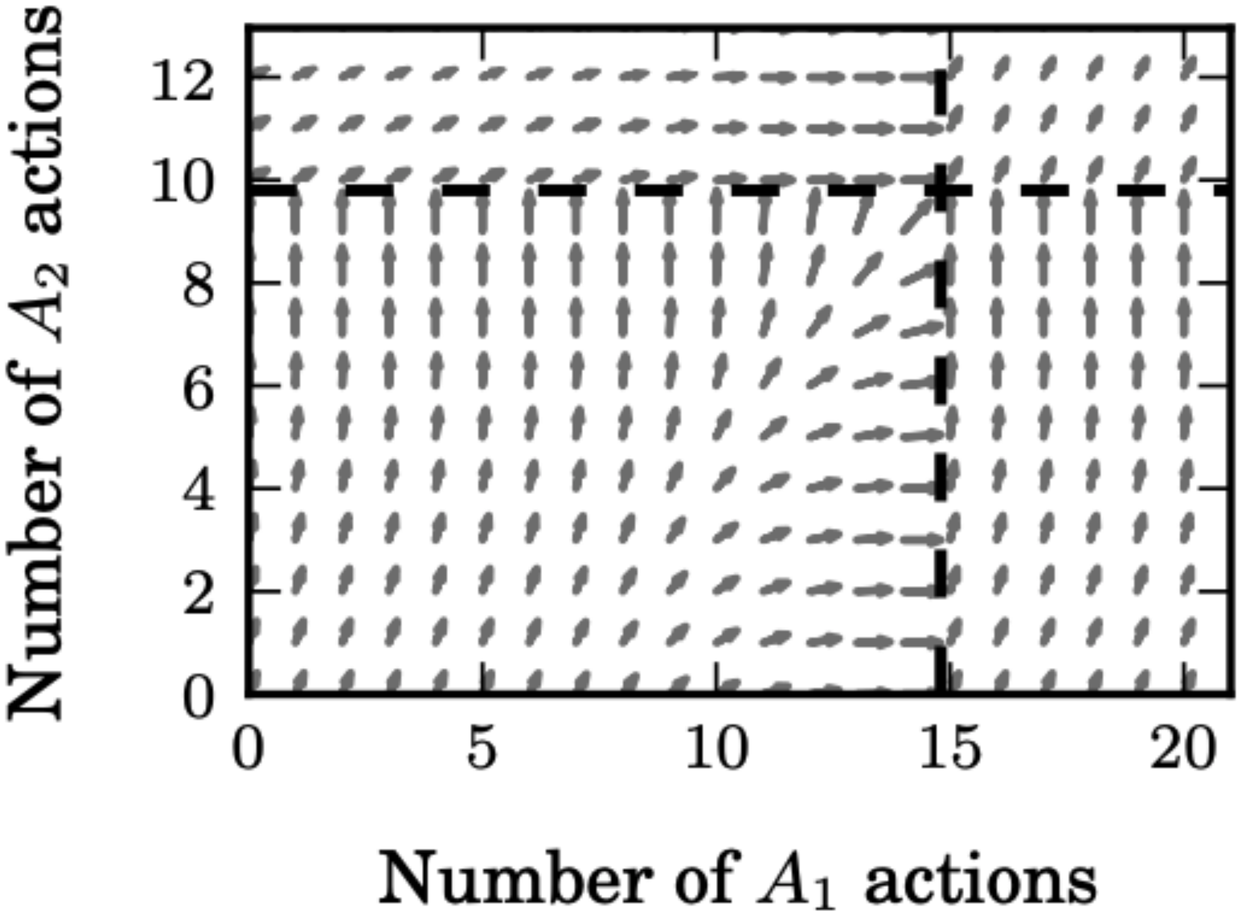
Think about what actions users will take if we believe this model is correct?

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.

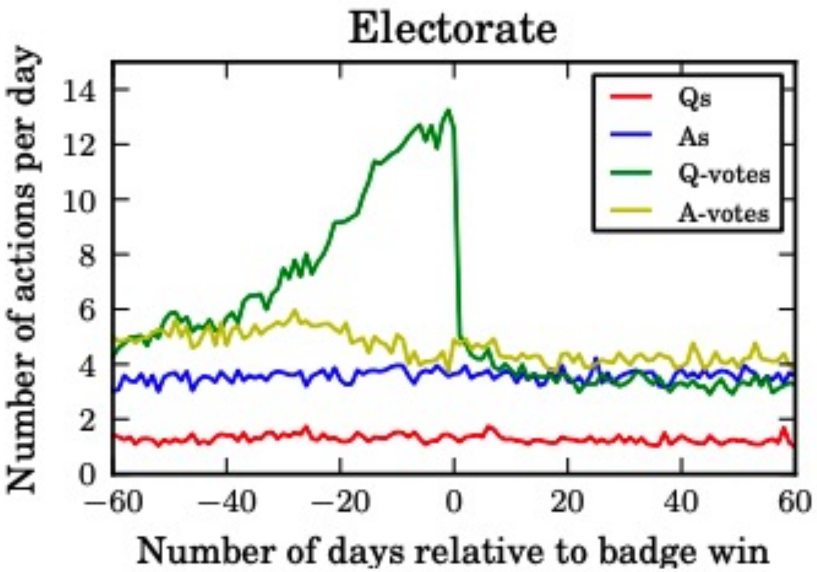
Model Predictions



Empirical Evidence from Stack Overflow

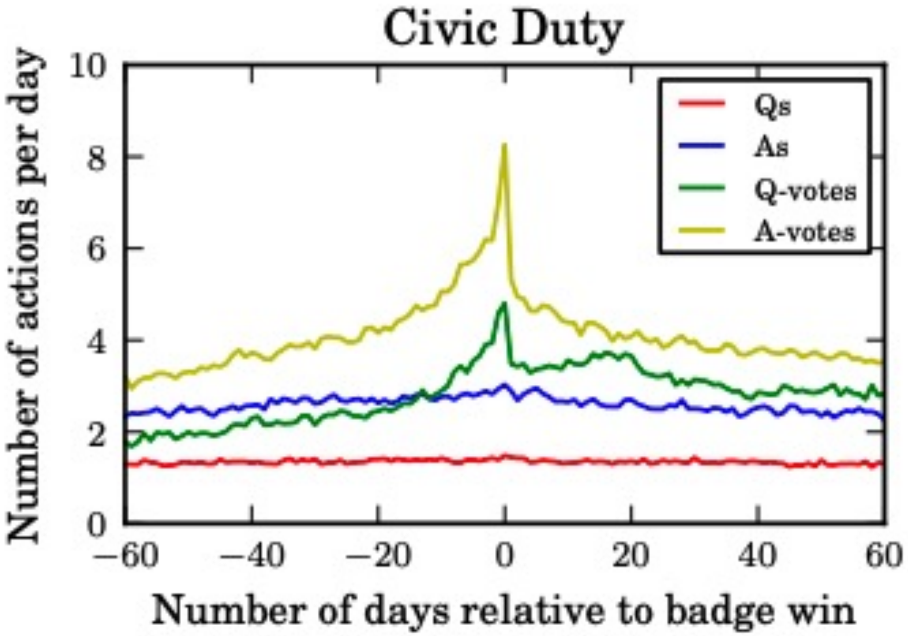
Electorate

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



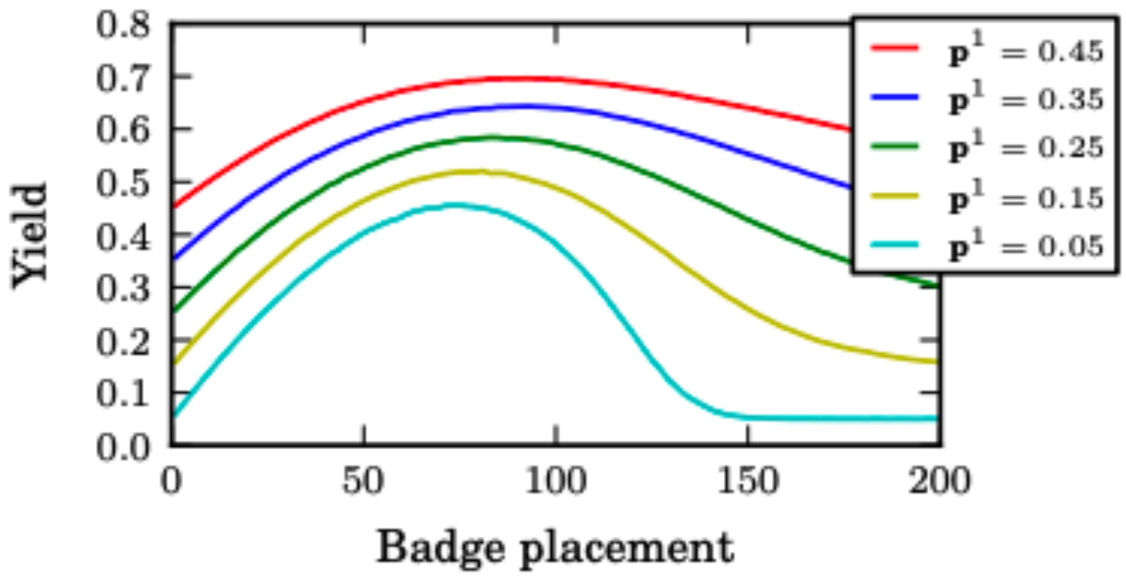
Civic Duty

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.

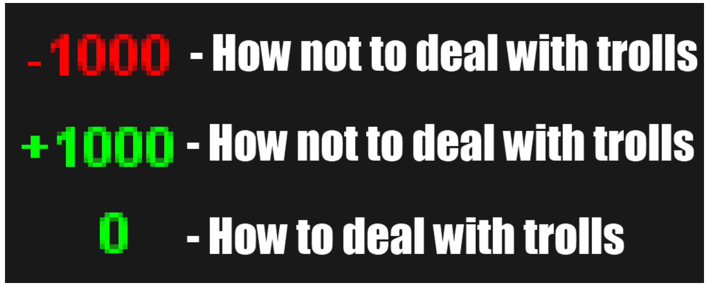
User-Generated Content Platforms

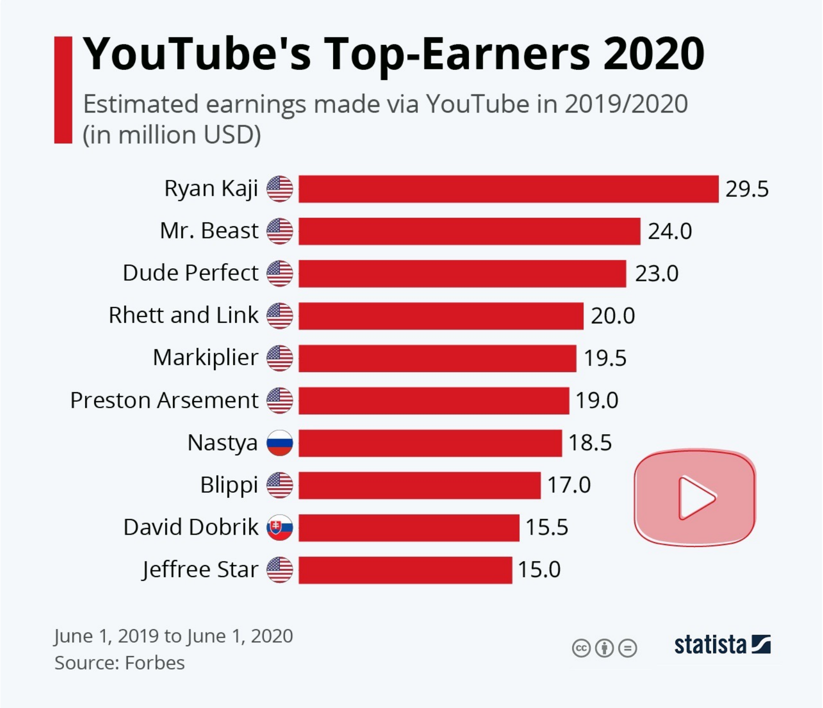
- Content is generated by users instead of the platform

- **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 $q_1, \ldots, q_K$ 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 2^{nd} stage
  - All content in 2^{nd} 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?

Assignment 3

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	Signal 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?

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 $\Omega = \{w_1, w_2, \ldots, w_n\}$ (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

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

- 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.

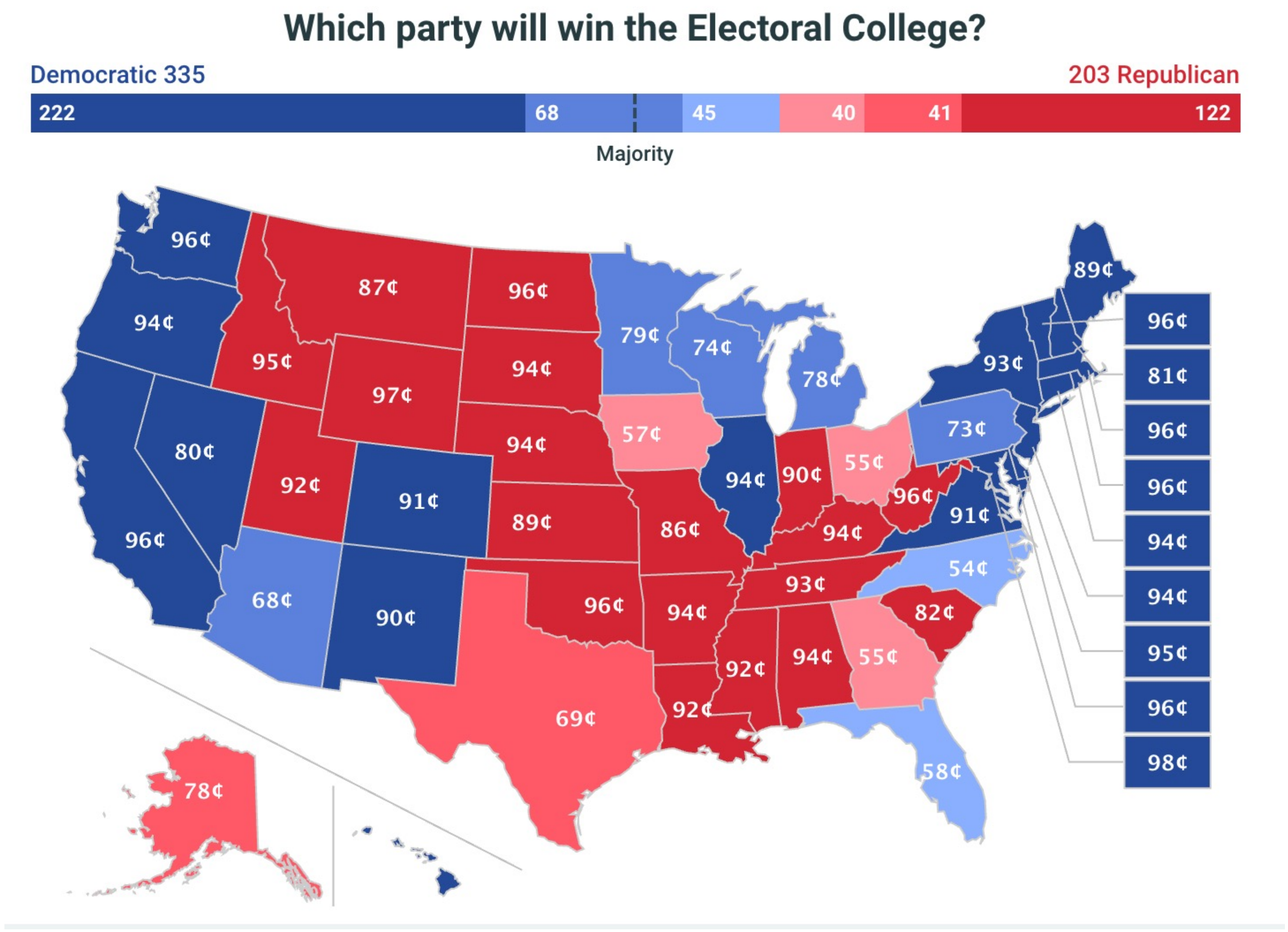
- A scoring rule $S(\vec{r}, w_i)$ is (strictly) proper if and only if

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

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.

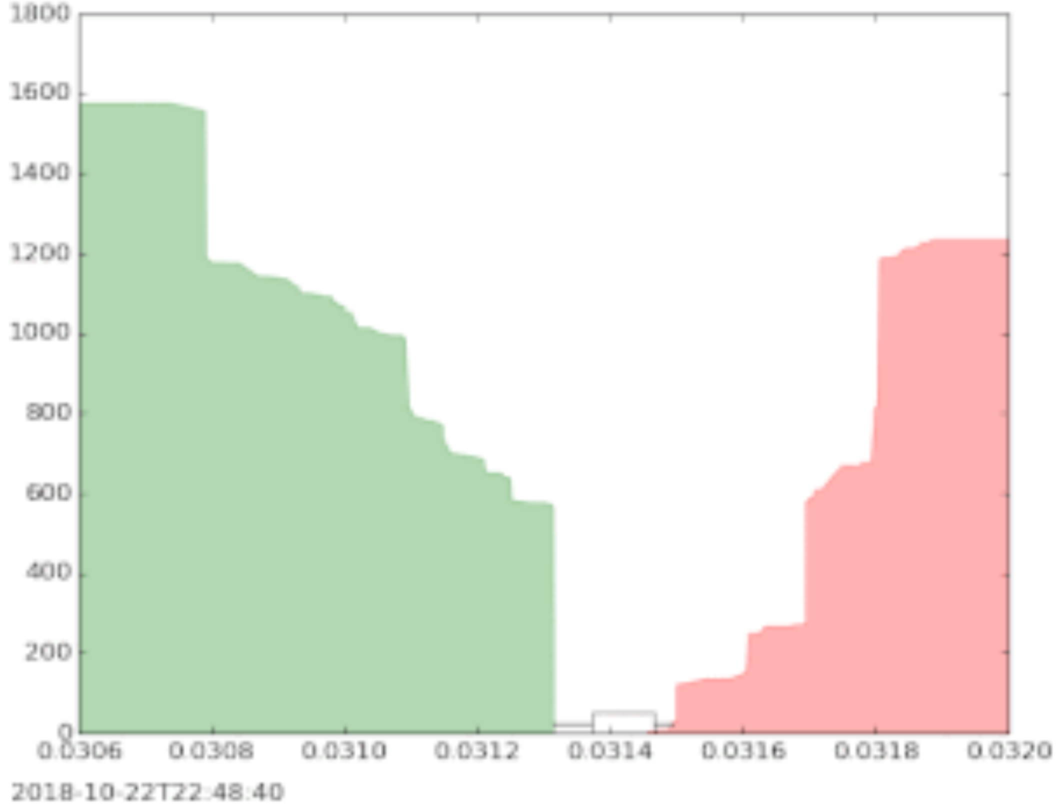
Section 3.1 of Strictly Proper Scoring Rules, Prediction, and Estimation by Gneiting and Raftery.

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…

Oct 7

Application: Prediction Markets

Presenter:
Connor, Calvin, Aditya

Required

The Promise of Prediction Markets, K.J. Arrow et. al., Science. 2008
Results from a Dozen Years of Election Futures Markets Research. Berg et al. 2001.
Please read both. The first one is a two-page non-technical paper.

Optional

Empirical reports:
Using Prediction Markets to Track Information Flows: Evidence from Google. Cowgill, Wolfers, and Zitwewitz. 2008.
Using prediction markets to estimate the reproducibility of scientific research. Dreber et al. PNAS 2015.
Prediction Without Markets. Goel et al. EC 2010.
Prediction Markets. Wolfers and Zitzewitz, The Journal of Economic Perspectives 2004.

Automatic market makers
Logarithmic Market Scoring Rules for Modular Combinatorial Information Aggregation. Hanson. Journal of Prediction Markets 2007.
Combinatorial Information Market Design. Hanson. Information Systems Frontier 2003.
A blogpost by David Pennock that discusses how to implement market scoring rules as a market maker.

- We won't cover too much on prediction markets. In case you are interested, below are a few more papers to follow up:
  - A New Understanding of Prediction Markets Via No-Regret Learning. Chen and Vaughan. EC 2010.
  - An Optimization-Based Framework for Automated Market-Making. Abernethy, Chen, and Vaughan. EC 2011.
  - and more (the papers by these authors)

Very Brief Intro of Peer Prediction

See more discussion in Assignment 3

Eliciting Truthful Reports

- Scoring rule relies on the “truth” to be revealed in the future
- What if there is no ground truth (or the ground truth is hard to obtain)
  - Do you like this movie?
  - Peer grading in MOOCs

- Output agreement:
  - Randomly pick two persons
  - If their reports match, reward them 1, otherwise reward 0
  - Truthful reporting is not an equilibrium (you are encouraged to report the majority’s opinion)

Peer Prediction

- How to fix the issue?
  - Assume knowledge about the report distribution, re-weighting the rewards to make sure truthful reporting is a equilibrium
- Drawbacks:
  - Require knowledge of the prior
  - There are usually multiple equilibrium (including naïve bad ones…)
- Still an ongoing research area
  - Some nice theoretical results, however there is little practical success so far

Eliciting Informative Feedback: The Peer-Prediction Method. Miller et al. 2004

Related Course

- The course on peer grading at Northwestern by Jason Hartine.
  - https://sites.northwestern.edu/hartline/eecs-497-peer-grading/