Incentive Design: Badges and Attention

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Logistics: Assignments

- The deadline of assignment 2 extended to Oct 9 (next Wednesday).
- Assignment 3 is scheduled to be announced later this week and due around October 18.

Logistics: Projects

- Project Milestone 1: Due on October 11
  - Literature review
  - A concrete plan (with a timeline).
  - You should know exactly what you need to do for this project.
  - One-page report is fine, and no more than two pages.

- Project Milestone 2: Due on Nov 1
  - Making progress with the goal of identifying whether the project is feasible
  - Last chance to convert to a extensive literature survey (what counts as extensive)

- Project Presentations: Dec 2/4
  - It’s right after Thanksgiving, so you might want to get things ready early.

Logistics: Presentations

- You can present in ways you feel comfortable with. In case you have no clues on what to do, below is one potential format (Not required to follow this format).
  - Short overview of the topic
  - Summarize the required reading (25 min)
  - Discussion (10 min)
  - Summarize another paper (25 min)
  - Discussion (10 min)
  - (Optional) Any materials you like to share.
- Rehearsals and practices usually help.
- Additional note: Try to come up with research questions to include in reviews.

Today's Lecture

- Continuing on the Sep 25 lecture
  - Scoring rule
  - Brief notes on peer predictions

- Discussion on non-financial incentives
  - Badges (Steering User Behavior with Badges. Anderson et al. WWW 2013.)
  - Attention (Incentivizing High-Quality User-Generated Content. Ghosh and McAfee. WWW 2011.)

Proper Scoring Rules

Incentivizing Truthful Reports

- 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 his 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, Sun, and Snow are

$$\vec{p} = (0.7, 0.2, 0.1)$$

What report should the agent provide?

Scoring Rules

- A scoring rule rewards an agent $S(\vec{r}, w)$ when his 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.

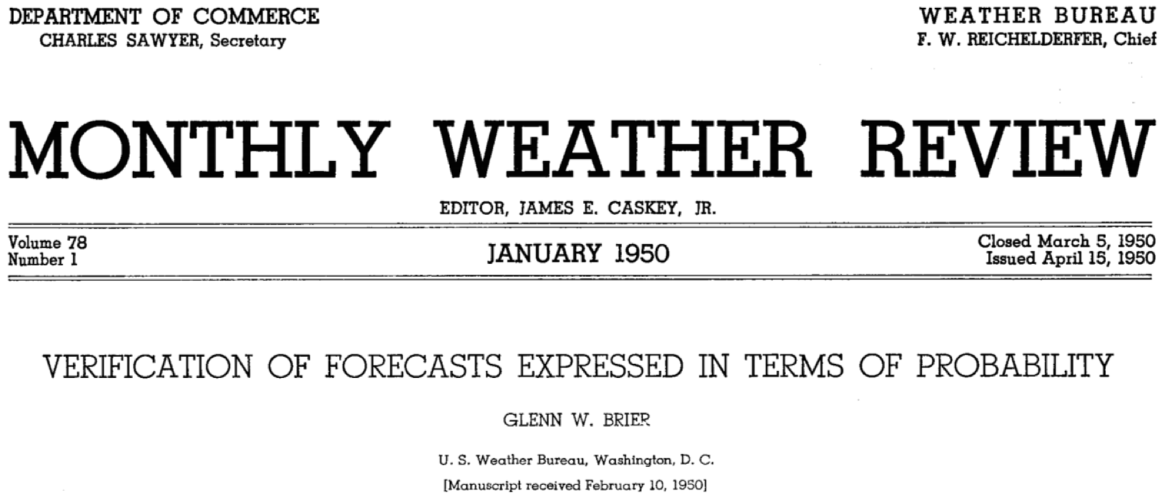
Examples of Strictly Proper Scoring Rules

- 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.



DEPARTMENT OF COMMERCE
CHARLES SAWYER, Secretary

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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

Who will win the 2020 Democratic presidential nomination?

Contract	Latest Yes Price		Best Offer			Best Offer
Elizabeth Warren	45¢	NC	46¢	Buy Yes	Buy No	55¢
Joe Biden	26¢	2¢↓	27¢	Buy Yes	Buy No	74¢
Bernie Sanders	10¢	1¢↓	11¢	Buy Yes	Buy No	90¢
Andrew Yang	9¢	1¢↓	9¢	Buy Yes	Buy No	92¢
Pete Buttigieg	6¢	1¢↑	7¢	Buy Yes	Buy No	94¢
Kamala Harris	4¢	1¢↓	5¢	Buy Yes	Buy No	96¢
Hillary Clinton	4¢	2¢↓	5¢	Buy Yes	Buy No	96¢
Cory Booker	2¢	1¢↑	2¢	Buy Yes	Buy No	99¢

24 More Contracts

Connection to Prediction Markets

Goal:

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

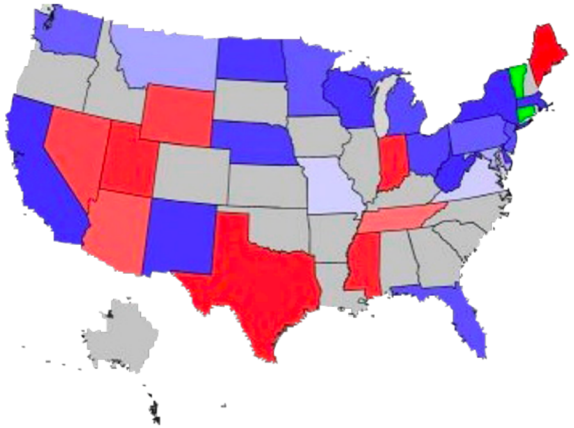
$$S\left(\vec{r}^{(t+1)}, w_i\right) - S\left(\vec{r}^{(t)}, w_i\right)$$

- 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…
- There are potentially many possible securities, and they could be related.

$n!$



2^n

Oct 7	Application: Prediction Markets Presenter: Ali, Davis, and Kristen	**Required** Results from a Dozen Years of Election Futures Markets Research. Berg et al. 2001. You should first read the first page of the following two-page (not too technical) article for a brief explanation of prediction markets. The Promise of Prediction Markets, K.J. Arrow et. al., Science. 2008 **Optional** Empirical reports: Using Prediction Markets to Track Information Flows: Evidence from Googl Cowgill, Wolfers, and Zitwewitz. 2008. 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 discuss how to implement market scorin 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 authored on these authors)

Very Brief Intro of Peer Prediction

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

- Does output agreement work?
  - 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/

Badge as Incentives

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

Warm-up Discussion

- Have you ever been incentivized by badges?
  Share your experience with neighbors.

- 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.

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

- 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(Earned-Badge(# actions)) - Cost(# actions)
- Model prediction: Users take actions that maximizes payoff
- The 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 $\boldsymbol{x_a}$: 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 $\boldsymbol{x}$: $g(\boldsymbol{x}, \boldsymbol{p})$

- 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 take action $\boldsymbol{x_a}$ that maximizes $U(\boldsymbol{x_a})$

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

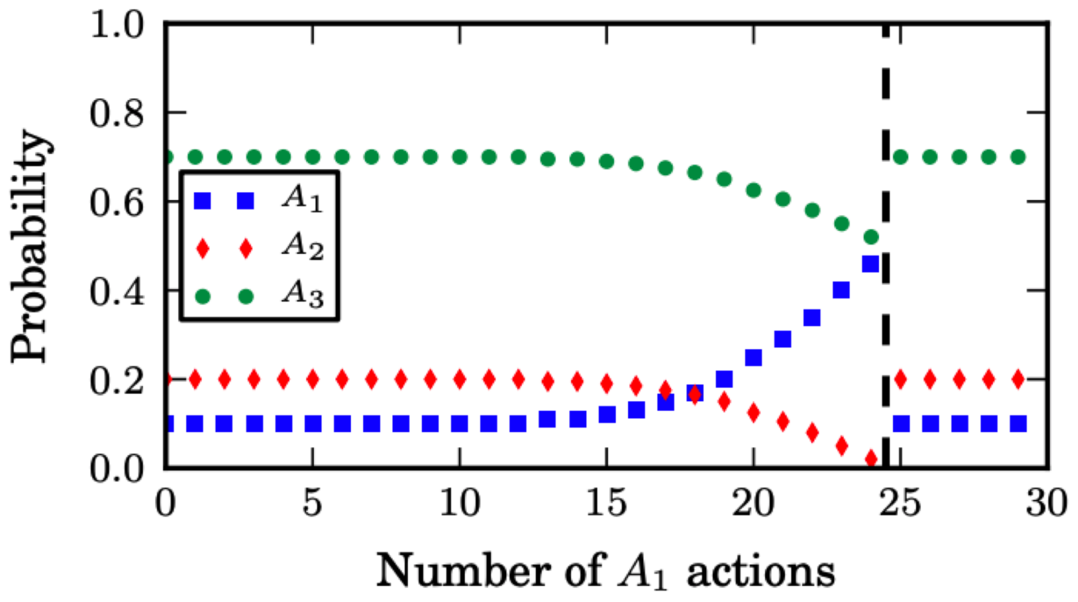
Payoff from current badges

Cost of action

Payoff from "future" badges from actions

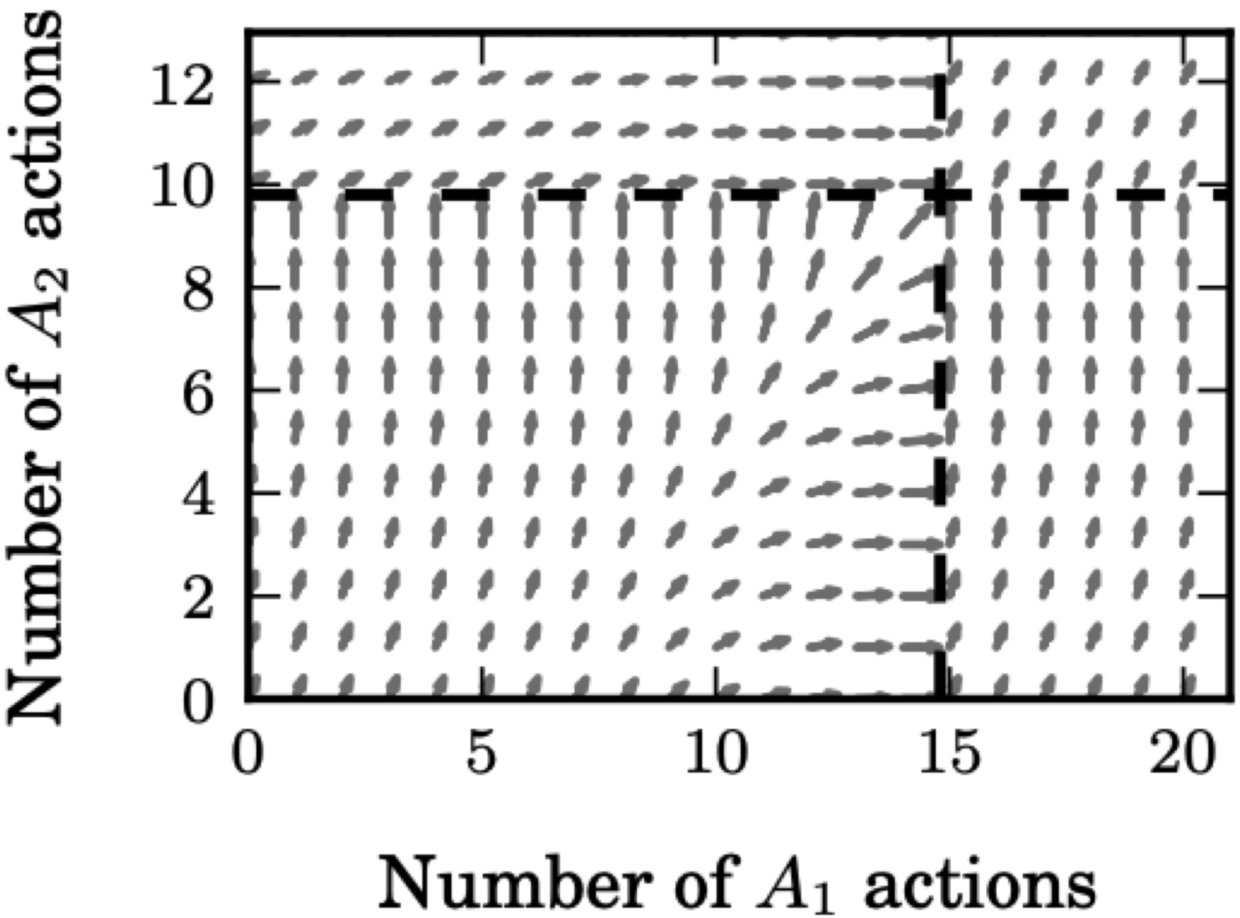
Think about what actions users will take if we believe this model is correct?

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.

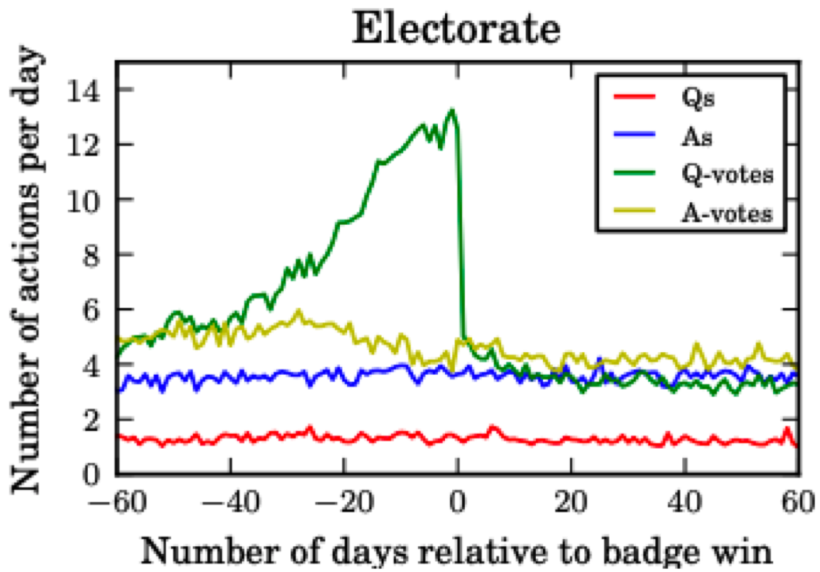
Model Predictions



Empirical Evidence from Stack Overflow

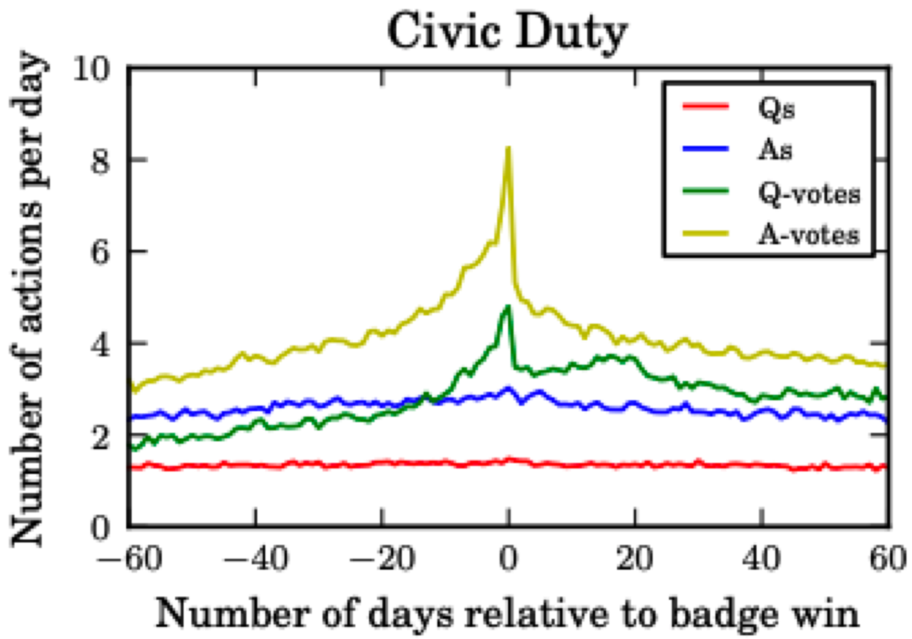
Electorate

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



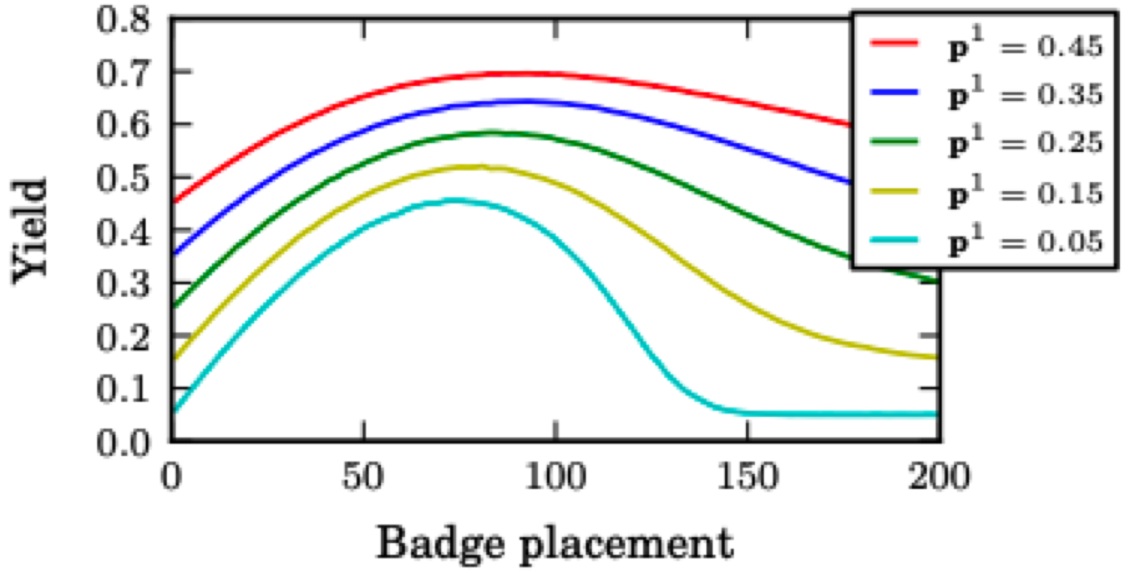
Civic Duty

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:
  - Your general thoughts about the paper.
  - What additional features / perspectives do you think would be the most interesting/important next questions to ask for badge design?

Attention as Incentives

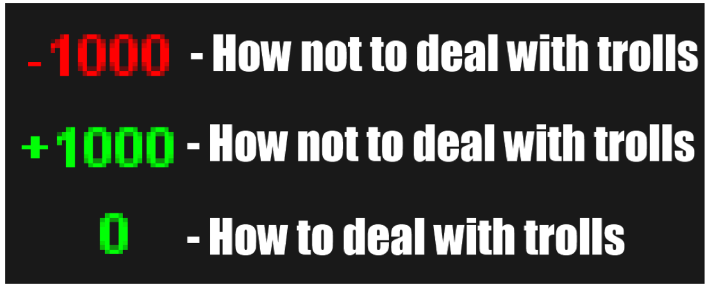
Incentivizing High-Quality User-Generated Content. Ghosh and McAfee. WWW 2011.

User-Generated Content Platforms

- 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:
  - Sequential game: platform takes action first, then users take actions
  - Platform: Content displaying mechanism
  - Users: quality of the contributed content
- Payoff:
  - Platform: depending on the qualities of content on the platform
  - Users: Utility(# views(quality)) – Cost(quality)

<u>Common assumptions:</u>
Utility is concave/submodular
Cost is convex/supermodular

- Solving the equilibrium (everyone is taking best-response actions)

More Settings/Assumptions

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

- Decision flow
  1. The platform announces her allocation mechanism
  2. K contributors decide on the quality of their contributions

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

Three Mechanisms

Q: What are the implications/results of the mechanisms?

- Random: randomly allocating M views to K 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

- 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

Three Mechanisms

Flood of bad content

- Random: randomly allocating M views to K content

Requires good estimate of q
Quality converge to a suboptimal value

- 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

By tuning A, quality might achieve optimal if M->infinity

- 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

Additional follow-up work

- Mixture of learning and incentives:
  - 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

Herding Effect