Incentives in Human Computation

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Human computation: It’s everywhere, changing everything
- Microtasks: Paid (Amazon Mechanical Turk) and Unpaid (Citizen Science, GWAPs)
- Problem solving: Crowdsourcing contests, Q&A forums, . . .
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Success of system depends critically on users behaving as intended

User behavior depends on *incentives*
- Users have own costs; benefits to participation
- Evidence (anecdotal, formal) of self-interested users
Human computation: It’s everywhere, changing everything
- Content production: Wikipedia, reviews, ...
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Success of system depends critically on users behaving as intended

User behavior depends on incentives
- Users have own costs; benefits to participation
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Incentives are central!
Understanding incentives in human computation

The why and how of contribution:
Why do users contribute: what motivates, or constitutes a reward?
How do users derive value from reward?

So what:
Designing effective incentives for high participation and contribution

Design:
Aligning incentives of users and system

Diverse spectrum of motivators across systems
Different rewards; constraints on rewards; observability of output
The why and how of contribution:

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- Design: **Aligning incentives** of users and system
- Diverse spectrum of motivators across systems
- Different rewards; constraints on rewards; observability of output
A user’s basic decision problem:

$$\pi = v(a) - c(a)$$

- $a$: Action choice
- $v$: Value
- $c$: Cost
A more complete (and less) basic decision problem:

\[ \pi_i = v_i(a_i, o(a_i, a_{-i})) - c_i(a_i) \]
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- \( a_i \): User \( i \)’s action choice;
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- \( o \): *Outcome* dependent on all actions
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- $a_i$: User $i$’s action choice; $a_{-i}$: Other users’ action choices
- $o$: Outcome dependent on all actions
- $v_i(a_i, o)$: How $i$ derives value from action $a_i$, outcome $o$
  - Value from $a_i$: Intrinsic rewards
  - Value from $o(a_i, a_{-i})$: Extrinsic rewards
A more complete (and less) basic decision problem:

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- \(c_i\): \(i\)’s cost to action \(a_i\)
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So what: Designing effective incentives for high participation and contribution
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- Different rewards; constraints on rewards; observability of output

Design: Aligning incentives of users and system
(i) Social psychology, HCI (ii) Game theory & economics

\[ \pi_i = v_i(a_i, o(a_i, a_{-i})) - c_i(a_i) \]
Outline: What we’ll do

- An illustration: Incentives and the ESP Game
- Understanding why and how:
  - What they say: Qualitative studies
  - What their data says: Empirical evidence
  - What they do: Experimental studies

Incentive design:
- Increasing expected benefit: Guidelines from social psychology
- Allocating reward to align incentives: Economics, game theory

Incentives for overall contribution
An illustration: Incentives and the ESP Game
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Incentives for overall contribution
Caveats: What we won’t

Comprehensive: Huge and growing literature, (biased) sample

Does not cover all problem domains, nor all literature in covered domains

An introduction to techniques

Specifically: Not a game theory or mechanism design tutorial

Your decision problem:

$$\pi = v_i(o(a_i, a_{-i}) - c_i(a_i))$$

$$c_i$$: Opportunity cost of time

(It's a beautiful day outside in Palm Springs...)
Caveats: What we won’t

What this tutorial is not:

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- A silver bullet for crowdsourcing incentive design
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- \(c\): Opportunity cost of time
  (It’s a beautiful day outside in Palm Springs...)
PART I

AN ILLUSTRATION: THE ESP GAME
Games with a Purpose (GWAPs)

GWAPs: Players produce input to task as side effect of game play
von Ahn and Dabbish, CACM’08

- Verbosity: Generating word descriptions
  - Matches two players: Both ‘win’ if player 1 correctly guesses word described by player 2

- TagATune: Generating descriptions for sound clips
  - Two players create description for assigned sound clips
  - ‘Win’ if correctly determine whether they have same clip

- ESP Game: Labeling images
  - Both partners generate single-word descriptions for given image
  - Points if agree on descriptive word: Label for image!

...
GWAPs *align incentives* of system with incentives of players
(Assume players incentivized by points, winning)

- ‘Inversion-problem’ games: Win if guesser correctly guesses input
  - Verbosity: Incentives to create good word description
- ‘Input-agreement’ games: Win if correctly decide if inputs are same
  - TagATune: Incentives to generate accurate sound clip descriptions
- ‘Output-agreement’ games: Win if produce matching outputs
  - ESP game: Incentives to generate accurate labels
GWAP design: Principles from social psychology

- Effort designed to be enjoyable
  - ESP Game: Players asked to type what ‘partner is thinking’, rather than ‘keyword’

- Challenge, (clear) goals elicit higher effort
  - Timed response
  - Score keeping
  - Player skill levels
  - High-score lists
  - Randomness
Incentive analysis in the ESP game

- Basic incentives evidently well-designed: Over 200,000 players, 50 million tags in first $\approx 4$ years
  - Fun is valid reward; game generates adequate reward to compensate participation effort
  - Players do not know partner’s identity (random pairings): Cannot coordinate; easiest way to agree on output is to base it on input

- But what about quality of generated labels?
  - Labels do not always give useful information: High percentage of colors, synonyms, generic words (Weber et al, MSR Technical Report’08)
Game-theoretic model: (i) Explaining label quality (ii) Designing for better quality (Jain and Parkes, GEB’13)

- Each player independently chooses low or high effort
  - Low effort: Player samples labels from ‘frequent’ (common) words (colors; generic common nouns)
  - High effort: Sample labels from entire universe of words
  - Assume players know relative frequencies of sampled words

- Player can choose in what order to output sampled words

- Rules of ESP game constitute mechanism: How are outcomes affected?
System design induces mechanism: Rules specifying reward allocation

Agents make choices over actions:
- Rules: Determine outcomes for all possible sets of agents’ actions
- Agent’s payoff depends on outcome

Equilibrium: Vector of action choices by agents such that no agent can improve payoff by choosing different action
- Analysis: What actions will agents choose to maximize their payoffs, given (rules induced by) system design?
- Design: Choose rules so agents pick ‘desirable’ actions
The rules of the ESP game

- Two randomly paired players matched for a set of 15 images

- For each image:
  - Both players enter sequence of single-word descriptions
  - Move on to next image when common descriptive word ('label') is found
  - Neither player can see other’s choices until common label entered

- 2.5 minute time limit: Continue labeling images until deadline

- Players awarded points for each successful labeling
2.5 minute time limit induces ‘match-early’ preferences:

- Points awarded per labeled image
- Players see more images if quickly agree on descriptive word per image
- Players prefer to agree earlier in sequence of descriptive words attempted
  (more likely to earn more points with more viewed images)

What player behavior, and therefore labels, arise in equilibrium for ‘match-early’ preferences induced by the ESP game design?
Theorem (Jain-Parkes’13, Informal.)

With match-early preferences, choosing low effort and returning labels in decreasing order of frequency (i.e., from most common to least common) is a Bayes-Nash equilibrium in the ESP game.

- Such undesirable equilibria with coordination on common words are only equilibria
- Explains exactly how design choices (specific rules of the ESP game) can lead to observed outcomes of common or generic labels for images
Suppose game is designed to induce ‘rare-words’ preferences
   - Player’s utility depends only on frequency of matched label
   - Points awarded for quality of matches: Quality based on frequency of agreed-upon label

**Theorem ([Jain-Parkes’13, Informal.])**

*Suppose players have rare-words preferences, and have chosen effort levels. Returning words in decreasing order of frequency (common words first) is a strictly dominated strategy, while increasing order of frequency (least common words first) is an ex-post Nash equilibrium.*

Strictly dominated strategy: Another strategy always leads to larger payoffs regardless of other players’ choice
Players ‘try’ rarer words first in equilibrium: More useful labels than under match-early preferences

This change in reward design alone not adequate to induce effort

High effort sampling need not be equilibrium strategy even under rare-words preferences

Theorem (Jain-Parkes’13, Informal)

High effort sampling followed by coordination on rare words becomes an equilibrium in the ESP game if

- Distribution of words in dictionary is Zipfian (as in English)
- Rewards designed so that utilities obey certain (multiplicative or additive) structure
An illustration: Incentives and the ESP Game
Outline: What we’ll do

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- Understanding why and how:
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- Incentive design:
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- Incentives for overall contribution
PART II

WHY?
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WHY?

MOTIVATIONS FOR CONTRIBUTION
Why do people participate and contribute?

Motivations: Vary across, and *within* systems
Why do people participate and contribute?

- Motivations: Vary across, and within systems
  - Self-selection: User population and offered rewards

Two broad classes of human computation systems:

- Systems with financial incentives: Amazon Mechanical Turk, crowdsourcing contests, . . .
- Payment-free systems: Citizen Science projects, user-generated content (Wikipedia, Amazon reviews, Q&A forums), . . .
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Motivators in unpaid online collective effort

Why participate and contribute in payment-free systems?
Motivators in unpaid online collective effort

- Why participate and contribute in payment-free systems?
- **Social-psychological rewards**
  - Social psychology theory: Intrinsic motivation, generalized reciprocity, reputation, status, ...
- Qualitative studies, empirical investigations of motivation
  - A sample of surveys: Wikipedia, del.icio.us, Amazon, Citizen Science, ...
  - Inferences from empirical studies: Attention, virtual points, ...
No explicit credit to writers in Wikipedia: Why contribute?

Two samples from a vast literature
No explicit credit to writers in Wikipedia: Why contribute?
  Two samples from a vast literature

Interviews with 22 Wikipedians (Forte & Bruckman, GROUP’05)
  Motivated to "collaboratively identify and publish true facts"
  Wikipedia has indirect, non-explicit attribution of authorship
  Writers seek ‘credibility’ (versus credit)
Why unpaid contributions?: Wikipedia

- No explicit credit to writers in Wikipedia: Why contribute?
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- Survey of 151 Wikipedians (Nov, CACM’07)
  - Respondents rated motivations for volunteer contribution
  - Top motivations: Fun, ideology
  - Social, career not highly ranked
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  - Social, career not highly ranked
  - Contribution level not significantly correlated with ideology motivation :)

Incentives in Human Computation
Survey, data from 237 Flickr users (Nov et al, CHI’08)

Explain tagging activity using three elements:
- Intended target audience for tags (Self, Friends & Family, Public)
- ‘Social presence’ indicators (groups, contacts)
- Participation: Number of images uploaded (Control)

Main findings:
- ‘Self’, ‘Public’ motivation level positively correlated with tagging
- ‘Friends & family’: Does not significantly affect activity
- Number of contacts, groups also positively correlated
Large number of online Q&A forums: Y! Answers, Naver, StackOverflow, Quora…

Most sites are unpaid (Exception: Google Answers): Why provide answers?

Qualitative study of Naver (Nam, Ackerman, Adamic’09)
  - Interview of 26 users
  - Frequent motivations for top answerers: Altruism, learning, competency
  - Virtual points system also motivator: Direct motivation from point accumulation; higher visibility, reputation from high point totals
Why unpaid contributions? YouTube, Digg

- Hypothesis: Attention is a reward in peer production (Wu, Wilkinson, Huberman, CSE’09)

- Empirical study of contributors on YouTube, Digg

- Main finding: ‘Submitters who stop receiving attention tend to stop contributing’
  - Low attention leads to stopping
  - Positive feedback loop of attention for prolific contributors
  - Power law distribution of contributions
Why unpaid contributions?: Amazon reviews

How Aunt Ammy Gets Her Free Lunch (Pinch and Kessler’11)

- Survey of Top-1000 reviewers on Amazon.com: 166 participants ranking 7 motivations
  - Self expression, enjoyment ranked amongst top 3 motivators by 80%
  - Writing skills, enhancing understanding ranked in top 3 by 60%
  - Responsibility to community ranked in top 3 by 46%, enhancing status by 34%
  - Utilitarian ranked in bottom 3 by 65%

- Free-form responses for ‘additional motivations’:
  - Altruism (very common, with 25 responses)
  - Developing sense of community
  - Using reviews as “memory device”
  - Reactive: Expressing disagreement with existing reviews
Motivations in Online Citizen Science (Reed et al’13); Handbook of Human Computation

- **Zooniverse**: Virtual Citizen Science platform with 860,000 users
  - Few users make majority of contributions in both primary science tasks and talk forums

- **Motivations for contribution: GalaxyZoo**
  - Qualitative study: Contribution to science, learning and teaching, interaction, aesthetics, fun, helping, interest
  - Content analysis of online talk forum finds similar motivators

- **Larger qualitative study of motivation (199 Zooniverse users)**
  - Social engagement: Interaction with Zooniverse community
  - Enjoyment
  - Positive feelings from helping or volunteering
Several common themes from case studies:

- **Intrinsic motivations**: Fun, interest, altruism, social interactions
- **Extrinsic motivations**: Status, reputation, visibility/attention

Surveys and empirical studies, important but not adequate:

- Common issue with survey methodologies: Framing effects, divergence between user response and behavior
- System-dependent variation, specificities
- Response to rewards are in context of system design
- Chicken-egg problem: Spectrum of possible rewards restricted to those built into system
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How do people vary participation, effort choices in response to incentives?

- Participation: Deciding to perform (at least) a task

- Dimensions of effort (conditional on participation):
  - Quantity: How many tasks ($\geq 1$) to perform
  - Quality: Accuracy on task

- Experiments on MTurk: Response to motivators/rewards
  - Extrinsic (financial) motivation
  - Intrinsic motivation
  - How do extrinsic and intrinsic motivations interact?
Overview of findings

- Financial motivations do matter, *even* at AMT scales
- Effect of task price only partially fits standard economic model
  - Participation, quantity are (largely) sensitive to price
  - Quality (largely) unaffected by price
  - Target earning behavior
- Intrinsic motivation matters, interacts with extrinsic motivation
- Geographic variation in behavior patterns
Extrinsic Motivation: Crowdsourcing labor markets

Financial Incentives and the Performance of Crowds, Mason & Watts, HCOMP’09

- Experiment on Amazon MTurk: Image ordering task
  - Sorting 2, 3, or 4 images from traffic camera in time order
  - Vary payment per task
  - Quantity: Number of tasks worker chooses to do
  - Quality: Accuracy of ordering

- Increasing financial incentives increases quantity, but not quality of work

- ‘Anchoring’ effect: Higher-paid workers perceive value of work to be greater
  - Workers across all payment levels report ‘value’ of work higher than payment
Price as a Predictor of Answer Quality in an Online Q&A Site; Jeon, Kim & Chen, CHI’10

- **Field experiment** on Google Answers: Effect of price on quality in user-generated content
  - Google Answers: Payment-based online Q&A (ex-)site
  - Users post questions, prices for answers
  - Questions answered by Google-approved contractors

- Price effect is two-fold
  - Higher price significantly increases likelihood of answer
  - For questions with an answer, price has no effect on answer quality
  - Answer price is incentive for quantity, but not quality
Rational model of crowdsourcing labor supply
- Workers: Cost to time, choose how many tasks to perform
- Number of tasks should decrease with (i) per-task pay rate (ii) difficulty of task (time to complete)

Test predictions in AMT experiment: Vary difficulty, pay
- Clear price sensitivity: Decrease output for lower prices
- Insensitivity to difficulty: Per-task costs?

Target earners: Preferences for ‘focal point’ earnings
- Preference for earnings amounts evenly divisible by 5cents
- $v(R)$: Step function rather than linear valuations to pay
Breaking Monotony with Meaning, Chandler and Kapelner’10

- How does task “meaningfulness” affect worker effort?
  - Effort: (i) Participation (ii) Quantity (iii) Quality

- Three conditions: Identical tasks, pay; different framings
  - ‘Meaningful’: Labeling tumor cells to assist cancer researchers
  - Control: No information on purpose of task
  - ‘Shredded’: No information; also told labels will be discarded

- Results:
  - Meaningful: Increase in participation, quantity; insignificant change in quality
  - Shredded: No change in quantity; decrease in quality
  - Meaning may affect how workers trade quantity for quality
Comparative studies: Intrinsic and financial motivations

Intrinsic and Extrinsic Motivation on Task Performance in Crowdsourcing Markets, Rogstadius et al, ICWSM’11

- AMT experiment: Image analysis task, $2 \times 3$ design
  - Intrinsic motivation: Not-profit and for-profit
  - Extrinsic motivation: 3 per-task payment levels

- Participation:
  - Higher pay yields higher uptake rates, number of tasks completed, irrespective of intrinsic motivation

- Quality:
  - Varying payment does not significantly affect accuracy
  - Intrinsic motivator has significant, consistent effect on quality
  - Effect is particularly strong at lower payment levels
  - Intrinsic value might need to be kept larger than extrinsic value for accuracy benefits
Comparative studies: Social and financial incentives

Designing Incentives for Inexpert Human Raters, Shaw et al, CSCW’11

- Non-expert content analysis task: Compare fourteen incentive schemes on worker performance

- Framing of questions: ‘Social’ and ‘financial’ incentives
  - Social: Tournament scoring, Cheap Talk (Surveillance, Normative), Solidarity, Humanization, Trust, Priming
  - Financial: Reward/Punish Accuracy, Reward/Punish Agreement, Promise of future work, Bayesian truth serum

- Easy questions: Performance outdoes random guessing; negligible effect of treatment

- Difficult questions: Widely varying performance
Experimental results (Shaw et al ’11)

- Only 2 of 14 treatments significantly improve worker performance: (i) Punishment Agreement (ii) Bayesian Truth Serum
  - Purely social incentives do not alter performance significantly
  - Punishment more consequential than reward agreement: Loss aversion effects?

- Hypothesis: Cause subjects to reason carefully about other subjects’ responses

- Higher engagement drives cognition, improved performance
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- An illustration: Incentives and the ESP Game

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Incentives for overall contribution
PART III

INCENTIVE DESIGN
Understanding incentive design: Revisiting the decision problem

Increasing expected benefit: Social psychology and HCI design

Allocating reward to align incentives: Economics and game theory
  - Contest design
  - User-generated content
  - Social search
  - Incentives in peer evaluation
A user’s decision problem:

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Incentive design:

- Increase \( v \), decrease \( c \) for desired action \( a \)
  (Design guidelines from social psychology)
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Incentive design:

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- Design rewards \( o(a_i, a_{-i}) \) so user’s payoff is maximized by system-preferred \( a_i \)
  (Economics and game theory)
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- **Change the game:**
  - Space of available actions \( a_i \)
A user’s decision problem:

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Incentive design:

- Increase \( v \), decrease \( c \) for desired action \( a \)  
  (Design guidelines from social psychology)

- Design rewards \( o(a_i, a_{-i}) \) so user’s payoff is maximized by system-preferred \( a_i \)  
  (Economics and game theory)

- \textit{Change the game}:
  - Space of available actions \( a_i \)
  - \textit{What} is rewarded (Popovic: Rewarding growth mindsets)
  - \textit{What rewards} are offered (von Ahn: Games with a Purpose)
Incentive design

- Understanding incentive design: Revisiting the decision problem

- Increasing expected benefit: Guidelines from social psychology and HCI design

- Allocating reward to align incentives: Economics and game theory
  - Contest design
  - User-generated content
  - Social search
  - Incentives in peer evaluation
Design guidelines: Eliciting contributions

*Building successful online communities: Evidence-based social design*, Kraut and Resnick, 2012

- Publicize lists of needed contributions; make list easily visible
  - Common practice: Gnome open source project, Wikipedia, ... 
- Easy-to-use tools for searching, tracking needed contributions
- Directed requests: Matching tasks to people by ability, interest
  - Automated (Y! Answers Suggestions) or human-driven (Quora)
Building successful online communities: Evidence-based social design, Kraut and Resnick, 2012

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- Revisiting $\pi = v_i(a) - c_i(a)$: Decrease $c$; choose $i$ with low $c_i$
Structuring Requests to Enhance Motivation

- Personal directed requests for contribution more effective than ‘request-all’

- Originator of requests affect likelihood of compliance
  - High-status/authority community members more effective requesters than anonymous/low-status requesters
  - ‘Friends’, socially desirable members

- Social proof: Evidence of others’ complying increases probability of compliance
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- ‘Friends’, socially desirable members

Social proof: Evidence of others’ complying increases probability of compliance

Revisiting $\pi = v(a) - c_i(a)$: Increase $v$ for $a = \text{participation}$
Intrinsic motivation: Process of performing activity provides utility

Social interaction: Increase opportunities for social contact

Design for ‘flow’: ‘Immersive’ experiences (game design)

Feedback on contributions increases motivation
  - Feedback on relative performance comparisons: Mixed effects
Enhancing intrinsic motivation

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Enhancing extrinsic motivation

- Extrinsic motivation: Outcome from activity provides utility

- Rewards (status, site privileges, money) increase contribution
  - Also create reasons to ‘game the system’
  - (i) Reward for quality (ii) Non-transparent reward schemes

- Tradeoffs between extrinsic and intrinsic motivation
  - Rewards increase contribution, but can decrease intrinsic motivation
  - Effect larger for monetary rewards than prizes/gifts, status rewards
  - Size of monetary reward matters: Small rewards can worsen contribution overall
Contributions to public goods projects

- Collective effort tasks: Outcome, value depends on others’ action choices

- Collective effort model (Karau & Williams’93)
  - Higher contribution when value group outcomes more
  - Uniqueness of contribution: Higher effort when ‘essential to group outcome’

- Cap group size, emphasize uniqueness of contribution
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Two key reasons not to contribute in volunteer project
(The Economies of Online Cooperation, Kollock’08):
- Free-ride on other contributors’ efforts
- Others may not contribute enough to make one’s efforts fruitful
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  - Linux was considered ‘inherently interesting’
  - One person was able to write the core of the program
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Incentive design

- Understanding incentive design: Revisiting the decision problem
- Increasing expected benefit: Social psychology and HCI design
- Allocating reward to align incentives: Economics and game theory
Incentives in human computation: Reward allocation

What aspects of a system govern nature of reward allocation problem?

- Nature of reward:
  - Monetary versus social-psychological rewards (status, reputation, ...)
  - Constraints on rewards, reward regimes, objective functions vary across reward types

- Observability of (value of) agents’ output
  - Can only reward what you can see
  - Spectrum of observability: Perfect rank-ordering (contests), imperfect (noisy votes in UGC), unobservable (judgement elicitation)
Allocating reward to align incentives: Economics and game theory

- Contest design: Crowdsourcing contests (Topcoder, Innocentive, TaskCN, . . .)
- User-generated content: Online Q&A forums, reviews, . . .
- Social search: DARPA challenge, . . .
- Incentives in peer evaluation
Basic contest design problem:
- Contestants have cost to effort and value offered prize
- How to split total available reward budget to induce ‘optimal outcomes’?
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What constitutes optimal? Designer’s objective:
- Maximize expected value of total contributions, best contribution, expected value from top $k$ minus prize, ... 

Large and growing literature on contest design, analysis
- Optimal design of single contest (Glazer-Hassin’88, ...) 
- Crowdsourcing contests: Multiple contests, large contest limits (DiPalantino-Vojnovic’09, Archak-Sundararajan’09, ...)
What parameters can affect structure of optimal contest?

- **Entry**: Number of competitors influences effort choices
  - Too many participants: Decreases winning probability; erodes incentives for effort
  - Individual effort (*typically*) decreases with contest size
  - Overall outcome may be better or worse: Optimal entry
  - *Open, free, entry may not be optimal* (Taylor, AER’95)

- Homogeneity versus heterogeneity of abilities
  - Homogeneity: Self-selection, ability correlation with enjoyment
  - Effort-governed versus ability *and* effort-governed output
  - Optimal contest designs can differ greatly
    (Glazer-Hassin, Economic Inquiry’88 cf Moldovanu-Sela, AER’01)
Contest design: Overview

- Shape of effort cost function: Convexity vs concavity
  - Winner-take-all optimal with linear/concave costs, but not for convex costs (Moldovanu-Sela, AER’01)
  - Single versus sub-contests (Moldovanu-Sela, JET’06)

- Objective of designer: Maximum versus total output
  - Single contest versus two-divisional final (Moldovanu-Sela, JET’06)

- Risk preferences: Risk-neutral versus risk-averse contestants
  - Single versus multiple prizes (Archak-Sundararajan’09)
  - Size of reward (scale of contest) may determine risk preference (Large prize contests (Innocentive) versus little ones (TaskCN))
Contest design with status rewards

- Results so far on contest design:
  - Reward is monetary (or equivalent): Participants derive value only from winning prize
  - Social-psychological rewards from winning a contest: Prestige, status, . . .
    - Suppose agents care about status: Relative position in contest
    - How to ‘design’ contest to maximize contestant effort?
    - Design choice is partition: Number, size of status classes
Incentivizing effort with status utility

Contests with status rewards (Moldovanu-Sela-Shi, Journal of Political Economy’07)

- **Model with status-based utility:**
  - Contestants partitioned into *status categories* by output
  - Reward derived based on number of contestants in classes above and below own
  - Agents choose effort, incur ability-dependent cost
  - Objective: Maximize total output across all agents

- **Optimal partition structure:**
  - Top category has single element: One ‘best’ contribution
  - Remainder of partition depends on ability distribution

- **Coarse partitions work:** Optimal two-category partition achieves $\geq 1/2$ of optimal effort
Crowdsourcing information-seeking via social networks

- Provide incentives for (i) participation (ii) *propagating* query

- A real instance: The DARPA red balloon challenge (2009)
  - 10 red balloons, distributed across US
  - First team to correctly locate all balloons wins $40,000
  - Challenge won by MIT team in < 9 hours, recruiting ≈4400 participants

- ‘Recursive’ incentive scheme [Pickard et al, Science’11]
  - Exponential reward structure, decreasing from ‘finder’ to root
  - Respects total budget constraint
  - Incentivizes further propagation, does not create incentives to bypass ‘inviters’
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  - *Does* provide incentives for false-name attacks: Sybil attacks
Incentive properties of social search mechanisms

- **Fixed-payment contracts** (Kleinberg-Raghavan, FOCS’05)
  - Each node offers fixed reward to child if reporting answer
  - Cost to retrieve answer with constant probability is *linear* in depth if branching factor $b > 2$, exponential otherwise

- **Split contracts** (Cebrian et al, STOC’12)
  - Answer-holder receives entire reward, shares reward on path to root
  - Achieves low cost even with branching factor $b < 2$
  - Scheme *not sybil-proof* (unlike fixed-payment contracts)

- **Direct referral mechanisms** (Chen et al, EC’13)
  - Distribute most reward to agent with answer and its direct referral (parent)
  - Incurs low cost for any $b > 1$ *and* discourages sybils
Incentive design: User-generated content

- User-generated content (UGC) on the Web:
  - Reviews (Amazon, Yelp, TripAdvisor, ...)
  - Knowledge-sharing forums (Quora, StackOverflow, Y!A, ...)
  - Comments (Slashdot, News, ...)
  - Social media (Blogs, YouTube, Flickr, ...)
  - Metadata: Tags, bookmarks (del.icio.us, ...)

- (Typically) no monetary rewards for production

- Technology-reliant incentives for contribution:
  - Functionality in exchange for content (bookmarking, photo storage, ...)
  - *Exclusion* mechanisms: Block or limit access to content based on contribution level (Glassdoor, P2P, ...)

User-generated content: *Attention rewards* (Wu et al’09)

- Rank-order $M_r$ or proportional ($M_p$) mechanisms? (Ghosh-Hummel, EC’11)
  - $M_r$: Order content by number of votes
  - $M_p$: Randomize display order so attention proportional to votes
  - Contributors benefit from attention, incur cost to quality
    (Analysis agnostic to why users like attention)
  - Diverging attention regimes: Rank-order *dominates* proportional mechanism in equilibrium quality

- *Learning contribution qualities* (Ghosh-Hummel, ITCS’13)
  - Low regret explore-exploit mechanisms that incentivize contribution
Incentives in UGC: Attention rewards

Should all contributions be displayed? (Ghosh-McAfee, WWW’12)

- Crowdsourced content (Q&A forums): Suppress low-ranked contributions (eliminate, display less prominently...)
  - $A_i$: Maximum possible attention (‘eyeballs’) at position $i$
  - $a_i < A_i$: Payoff to poor quality falls, but less reward overall
  - What $a_i \leq A_i$ lead to ‘best’ outcomes?

Full reward to all but lowest possible rank is optimal

$a_i = A_i$, $i = 1, \ldots, n - 1$; $a_n = \min(A_n, c(0))$

Optimal reward for lowest possible rank depends on cost of producing lowest quality

Reward structure optimal for any increasing function of qualities: Best, average, ... (accounting for participation choices)
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Virtual points rewards: Online Q&A forums (Nov et al’08)

- Many sites use best-contribution mechanisms (Y! Answers, MSN, ...)
  - Winner gets $p_B$, everyone else gets $p_C$
  - Objective may not always be to maximize ‘best answer’ quality

Can $(p_B; p_C)$ structure ‘implement optimal outcomes’? (Ghosh-Hummel, WWW’12)

- Yes: When contribution’s value largely determined by expertise
- When value depends on expertise and effort: Only (possibly) with noisy rankings!
• System cannot directly observe quality of output in many human computation systems

• Relies on ratings from users

• What if raters are strategic? Different kinds of strategic issues:
  • Fixed available reward: Misreporting due to rater competition
  • Scalable evaluation-contingent reward: Low effort with rater cooperation
Incentives in competitive evaluation (Alon et al, TARK’11)

- Online sites: Voters also contributors of content
- Compete with other contributors for high rankings
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- Online sites: Voters also contributors of content
- Compete with other contributors for high rankings
- Approval voting: Every voter is also a candidate
- Want to select $k$-best subset amongst candidates
  - Strategyproof, approximately optimal mechanisms: Lower bound for deterministic mechanisms, construct 4-optimal randomized mechanism
  - Optimality-simplicity tradeoffs
Eliciting effort in crowdsourced rating applications
(Dasgupta-Ghosh, WWW’13)

- Crowdsourced judgement applications: Image labeling/identification, content rating, peer grading, ...
Incentives in evaluation: Eliciting effort under peer evaluation

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  - Unobservable ground truth
  - *Effort*-dependent accuracy
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  - Subtract statistic term penalizing *blind* agreement: Designed so agents receive zero payoff without effort
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(See also Witkowski et al, HCOMP’13)
Outline: What we’ll do

• An illustration: Incentives and the ESP Game

• Understanding why and how:
  • What they say: Qualitative studies
  • What their data says: Empirical evidence
  • What they do: Experimental studies

• Incentive design:
  • Increasing expected benefit: Guidelines from social psychology
  • Allocating reward to align incentives: Economics, game theory

• Incentives for overall contribution
PART IV

INCENTIVES FOR OVERALL CONTRIBUTION
Moving beyond single tasks: Incentivizing overall contribution

- So far: Models, incentives for single action/contribution/task
Moving beyond single tasks: Incentivizing overall contribution

- So far: Models, incentives for *single* action/contribution/task
- Rewarding contributors for *overall* identity:
  - Site-level accomplishments based on cumulative contribution: Badges, leaderboards, reputations...
Moving beyond single tasks: Incentivizing overall contribution

- So far: Models, incentives for single action/contribution/task
- Rewarding contributors for overall identity:
  - Site-level accomplishments based on cumulative contribution: Badges, leaderboards, reputations...
- Rewards valued by users: Increased engagement
  - Reputation: Value online and offline (StackOverflow, ...)
  - Badges: Formal inference from data [Anderson et al, WWW’13]
  - Anecdotal: Online discussion boards for Amazon Top-Reviewer list, Y! Answers Top-Contributor badge
What social-psychological rewards can badges provide?
(Antin & Churchill, CHI’11)

- **Goal setting**: Challenge users to achieve contribution goals
  - “Conceptual consumption”: Individuals “consume” experience of striving for goals
- **Instruction**: Inform users what are valued activities
- **Reputation**: Identify trustworthy/expert users on site
- **Status and affirmation**: Advertise (and remind of) accomplishments
- **Group identification**: Communicate set of shared activities
Badges and incentive design

- Gamification rewards valued by agents; contribution to earn reward is costly
- Badges induce *mechanisms*: *Design* affects participation, effort contributors
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Badges induce *mechanisms*: Design affects participation, effort contributors

Different badge *designs* online:
- ‘Absolute’ badges: StackOverflow, Foursquare, . . .
- ‘Competitive’ badges: Top-contributor badges (Y!Answers, Quora, Tripadvisor, . . .), top reviewer list on Amazon, . . .
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  - ‘Competitive’ badges: Top-contributor badges (Y!Answers, Quora, Tripadvisor, …), top reviewer list on Amazon, …
- What *incentives* do different badge designs create?
  - ‘Absolute’ or ‘competitive’ badges?
  - ‘Competitive’ badges: Fixed *number* or *fraction* of participants?
Equilibrium analysis of incentives created by badges; information visibility (Easley & Ghosh, ACM EC’13)

- Design recommendations from equilibrium analysis
  - Relative standards badges $M_\rho$: Reward fixed number of winners ($M_\rho^p$), not fraction of competitors
  - Absolute versus relative standards badges ‘equivalent’ if population parameters known
  - With uncertainty, or unknown parameters, $M_\rho^p$ more ‘robust’: Guarantees non-zero participation
Information and equilibrium effort

- Social-psychological reward: Perceived value from badge may depend on **scarcity**
  - Suppose value of badge depends on mass of other winners
  - \( v(m) \): Value from winning when mass of winners is \( m \)

- Site design choice: Display information about number of winners or not
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- How does information about winners affect equilibrium effort?
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- Different designs online: StackOverflow, Y! Answers, ...

How does information about winners affect equilibrium effort?
- Effort depends on *convexity of value* as function of winners
- **Theorem (Easley & Ghosh’13):** Uncertainty decreases effort if $v(m)$ is concave, and increases it if $v(m)$ is convex
Badges as mechanisms: Open questions

- Understanding user preferences:
  - How, and how much, do users value absolute and relative achievements?
  - Measuring $v(m)$: How does scarcity affect value?
  - *Endogeneity of contributor pool*: Offered rewards select site population

- Incentives created by *mixed* badge designs:
  - Awarding badges for both absolute and relative standards
  - What efforts are induced from different ability-users?

- Rank-based rewards: Top-contributor *rankings*
PART V

OPEN QUESTIONS
Open directions: Overall contribution

- **Sustained** participation in payment-free systems:
  - Which motivators ‘last’? Marginal returns from different reward types
  - Does motivation for contribution evolve over time?
  - Design: Provide, allocate rewards that incentivize sustained contribution
Open directions: Overall contribution

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- Incentivizing overall effort:
  - Leaderboard design: Unequal rewards to winners
  - Frequency of contribution *(Ghosh-Kleinberg, ACM EC’13)*
  - Reputation as reward for overall contribution
    - Qualitative differences between payment-free systems and labor markets
  - Incentivizing effort across multiple tasks: Unpaid systems *(Anderson et al, WWW’13)*; labor markets
Content production: More nuanced models of quality, output
- Diversity; vertical and horizontal differentiation [MacKie Mason’09]
- Modeling value from set of contributions
- Incentives for production with strategic ratings
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Game theory and interface design
- Interfaces determine meaning and space of available inputs to mechanisms
- Ratings, information visibility, …
(Even more) open directions

(Game Theory and Incentives in Human Computation (in Handbook of Human Computation), Ghosh'13)

- Different participant roles (contribution, moderation, . . .)
  - Interaction between role-specific incentives
  - Endogenous ability-based selection into roles
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Mixed incentives: How do users cumulatively value, tradeoff differing incentives? (Mao et al, HCOMP'13)

Models, mechanism design

User valuations of social-psychological rewards

'Shape' of reward functions: Marginal benefits (attention, ...)

Value from set of rewards

How do rewards retain value over time?
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