Incentives in Human Computation

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HCOMP 2013 TUTORIAL

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Introduction

- Human computation: It's everywhere, changing everything
 - Content production: Wikipedia, reviews, ...
 - Microtasks: Paid (Amazon Mechanical Turk) and Unpaid (Citizen Science, GWAPs)
 - Problem solving: Crowdsourcing contests, Q&A forums, ...

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- User behavior depends on *incentives*
 - Users have own costs; benefits to participation
 - Evidence (anecdotal, formal) of self-interested users

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Incentives are central!

Incentives in Human Computation

- The why and how of contribution:
 - Why do users contribute: what motivates, or constitutes a reward?
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- 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

A user's basic decision problem:

$$\pi = \mathbf{v}(\mathbf{a}) - \mathbf{c}(\mathbf{a})$$

- a: Action choice
- v: Value
- *c*: Cost

$$\pi_i = \mathbf{v}_i(\mathbf{a}_i, \mathbf{o}(\mathbf{a}_i, \mathbf{a}_{-i})) - \mathbf{c}_i(\mathbf{a}_i)$$

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 Value from a_i: Intrinsic rewards
 - Value from $o(a_i, \mathbf{a}_{-i})$: Extrinsic rewards

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- c_i: i's cost to action a_i

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- How do users derive value from reward?
- So what: *Designing* effective incentives for high participation and contribution
 - Diverse spectrum of motivators across systems
 - Different rewards; constraints on rewards; observability of output
- Design: Aligning incentives of users and system
 (i) Social psychology, HCI (ii) Game theory & economics

$$\pi_i = v_i(a_i, o(a_i, \mathbf{a}_{-i})) - c_i(a_i)$$

Incentives in Human Computation

• An illustration: Incentives and the ESP Game

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 - What they say: Qualitative studies
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- Incentives for overall contribution

Caveats: What we won't

Incentives in Human Computation

What this tutorial is not:

- 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
- 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

Incentives in Human Computation

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!

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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?

An informal overview of the game-theoretic approach

- 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

ESP game rules and player preferences

• 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
Improving the design: Eliciting rare-words labels

• 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

Improving the design: Eliciting rare-words labels

- 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

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PART II

WHY?

Incentives in Human Computation



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MOTIVATIONS FOR CONTRIBUTION

Incentives in Human Computation

Why do people participate and contribute?

• Motivations: Vary across, and within systems

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 - Self-selection: User population and offered rewards

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- 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), ...

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-pyschological 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

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- Interviews with 22 Wikipedians (Forte & Bruckman, GROUP'05)
 - Motivated to "collaboratively identify and publish true facts"
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 - Respondents rated motivations for volunteer contribution
 - Top motivations: Fun, ideology
 - Social, career not highly ranked

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 - Contribution level not significantly correlated with ideology motivation :)

Why unpaid contributions?: Tagging

- 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

Why unpaid contributions? Online Q&A forums

- 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: Atttention 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
 - $\bullet\,$ 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

Why unpaid contributions?: Citizen Science

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

Understanding user motivation: Caveats

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 - Common issue with survey methodologies: Framing effects, divergence between user response and behavior

Understanding user motivation: Caveats

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- 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

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 (≥ 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

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

Extrinsic Motivation: More evidence from crowdsourcing markets

The Labor Economics of Paid Crowdsourcing, Horton & Chilton, EC'10

- 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, 2×3 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

Outline: What we'll do

• An illustration: Incentives and the ESP Game

- Understanding why and how:
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PART III

INCENTIVE DESIGN

Incentives in Human Computation



- 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

Designing incentives: Revisiting the decision problem

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Incentive design:

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

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

- 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

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

- Publicize lists of needed contributions; make list easily visible
 Common pratice: 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)

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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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• Revisiting $\pi = v(a) - c_i(a)$: Increase v for a = participation

Enhancing intrinsic motivation

- 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

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• Revisiting $\pi = v(a) - c_i(a)$: Increase v for a = participation

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

- 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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• Revisiting
$$\pi = E[v(a_i, a_{-i})] - c(a_i)$$
: Increase v

- 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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• Revisiting
$$\pi = E[v(a_i, a_{-i})] - c(a_i)$$
: Increase $E[v]$

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

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

Incentivizing effort in contests

- 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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 - Contestants have cost to effort and value offered prize
 - How to split total available reward budget to induce 'optimal outcomes'?
- 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))

- 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

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 ${\approx}4400$ 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
 - ${\scriptstyle \bullet}\,$ 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)
 - \mathcal{M}_r : Order content by number of votes
 - \mathcal{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?

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 - What $a_i \leq A_i$ lead to 'best' outcomes?
- Full reward to all but lowest possible rank is optimal
 - $a_i = A_i, i = 1, ..., n 1;$ $a_n = \min(A_n, c(0))$
 - 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)

Incentives in UGC: Virtual points rewards

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-contigent reward: Low effort with rater *cooperation*
Incentives in competitive evaluation (Alon et al, TARK'11)

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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)

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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

Incentives in Human Computation

Moving beyond single tasks: Incentivizing overall contribution

• So far: Models, incentives for *single* action/contribution/task

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- Rewarding contributors for *overall* identity:
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- 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 activites
- 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

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- 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_ρ*: Reward fixed number of winners (*M^p_ρ*), not fraction of competitors
 - Absolute versus relative standards badges 'equivalent' if population parameters known
 - With uncertainty, or unknown parameters, \mathcal{M}^{p}_{ρ} more 'robust': Guarantees non-zero participation

- 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
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 - 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

Incentives in Human Computation

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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

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 - Design: Provide, allocate rewards that incentivize sustained contribution
- 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]
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- Game theory and *interface* design
 - Interfaces determine *meaning* and *space* of available inputs to mechanisms
 - Ratings, information visibility, ...

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 - Models, mechanism design
- User valuations of social-pyschological rewards
 - 'Shape' of reward functions: Marginal benefits (attention, ...)
 - Value from set of rewards
 - How do rewards retain value over time?