# Incentivizing Crowdsourced Workers via Truth Detection

**Chao Huang**[1], **Haoran Yu**[2], **Jianwei Huang**[1,3], **and Randall A Berry**[2]

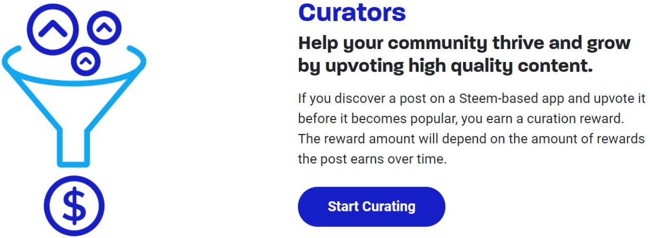
[1]The Chinese University of Hong Kong, Hong Kong

[2]Northwestern University, USA

[3]The Chinese University of Hong Kong, Shenzhen, China

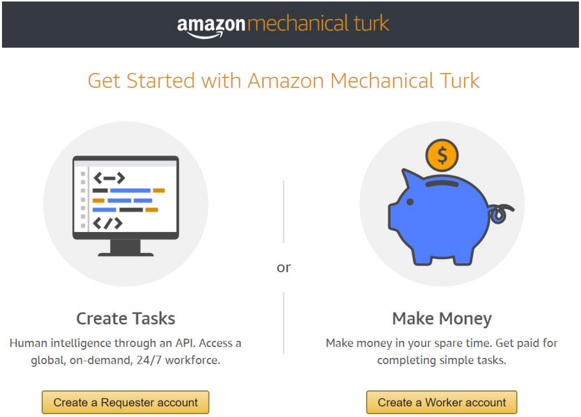
# Crowdsourcing

- Crowdsourcing resorts to crowdsourced workers for solving tasks
  - Crowdsourced workers are semi-skilled, diverse in background, temporally and spatially flexible
  - Boost efficiency and flexibility of task solving
- Examples:
  - Content moderation on platform Steem



# Crowdsourcing

- Crowdsourcing resorts to crowdsourced workers for solving tasks
- Examples:
  - Image labeling on Amazon Mechanical Turk



# Crowdsourcing

- Crowdsourcing resorts to crowdsourced workers for solving tasks
- Examples:
  - Peer grading on MOOCs

# Incentives in Crowdsourcing

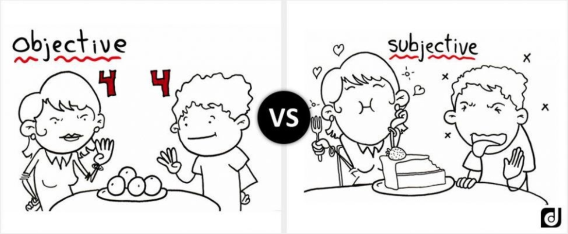
- Crowdsourced workers finish tasks at a cost $\rightarrow$ need rewards as incentive
- A naive way: provide rewards based on workload
  - Workers tend to finish many tasks with low effort (low quality)
- Problem: how to elicit efforts and truthful reports from crowdsourced workers?

# An "Easy" Case: Verifiable Information

- There exists verifiable information, i.e., ground truth will be revealed
  - E.g., prediction markets: predict winner of an election
- The observable ground truth is used as a basis for incentives
  - E.g., [Y. Luo *et al.* 2018]

# A Hard Case: Unverifiable Information

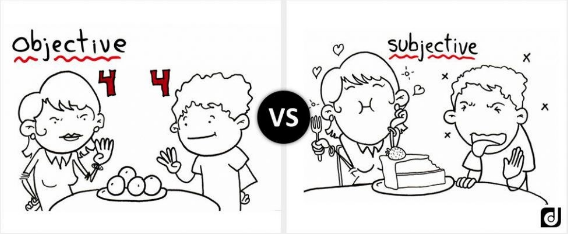
- Workers' solutions cannot be verified ([B. Waggoner *et al.* 2014])
  - No ground truth: subjective tasks
  - Large cost for ground truth: e.g., peer grading, scholarly peer review




**Objective vs. Subjective**

# A Hard Case: Unverifiable Information

- Workers' solutions cannot be verified ([B. Waggoner *et al.* 2014])
  - No ground truth: subjective tasks
  - Large cost for ground truth: e.g., peer grading, scholarly peer review




**Objective vs. Subjective**

- Problem: how to provide incentives without verification?
  - High-quality solution + truthful reporting
  - Tradeoff between quality and cost

# Truth Detection

- Use truth detection to induce truthful reports in public good provision context ([I. Krajbich *et al.* 2009])
- Idea: interaction with truth detector implies truthfulness of one's report
  - E.g., pupil dilation, facial expressions, and verbal cues

# Application: Border Control

- Hungary, Latvia, and Greece use Automatic Deception Detection System (ADDS) to enhance border control
  - Travelers answer personalized questions on gender, ethnicity, and language through a web-cam
  - Quantify the probability of deceit by analyzing micro expressions

# System Model

- **Task**
  - $\mathcal{X} = \{-1, 1\}$: type space of a binary task
  - $x \in \mathcal{X}$: true type, unknown to workers and platform

# System Model

- **Workers**
  - $\mathcal{N}$: worker set, $|\mathcal{N}| = N$

# System Model

- **Workers**
  - $\mathcal{N}$: worker set, $|\mathcal{N}| = N$
  - $x_i^{\text{estimate}} \in \mathcal{X}$: worker $i$'s estimated solution to the task
  - $x_i^{\text{report}} \in \mathcal{X}$: worker $i$'s reported solution to the task

# System Model

- **Workers**
  - $\mathcal{N}$: worker set, $|\mathcal{N}| = N$
  - $x_i^{\text{estimate}} \in \mathcal{X}$: worker $i$'s estimated solution to the task
  - $x_i^{\text{report}} \in \mathcal{X}$: worker $i$'s reported solution to the task
  - $e_i \in \{0, 1\}$: worker $i$'s effort level

$$P(x_i^{\text{estimate}} = x) = \begin{cases} p_i \in (0.5, 1], & \text{if } e_i = 1 \text{ with a cost } c_i \geq 0, \\ 0.5, & \text{if } e_i = 0. \end{cases}$$

  - $r_i \in \{1, -1, \text{rd}\}$: worker $i$'s reporting strategy

$$x_i^{\text{report}} = \begin{cases} x_i^{\text{estimate}}, & \text{if } r_i = 1, \\ -x_i^{\text{estimate}}, & \text{if } r_i = -1, \\ 1 \text{ or } -1 \text{ with equal prob.}, & \text{if } r_i = \text{rd}. \end{cases}$$

  - Strategy space: $s_i \triangleq (e_i, r_i) \in \{(0, \text{rd}), (1, 1), (1, -1)\}$

# System Model

- **Truthful reward** from truth detection
  - $\boldsymbol{t} \triangleq (a, z, y)$: platform's decisions
    - $a$: prob. a worker is chosen
    - $z$: reward
    - $y$: penalty

# System Model

- **Truthful reward** from truth detection
  - $\boldsymbol{t} \triangleq (a, z, y)$: platform's decisions
    - ★ $a$: prob. a worker is chosen
    - ★ $z$: reward
    - ★ $y$: penalty
  - After reporting solutions, a worker will be selected with prob. $a$
  - Chosen workers are asked: "have you exerted effort finishing the task?"

| Reported Value \ Truth Detected Value | 0 | 1 |
| --- | --- | --- |
| 0 | 0 | 0 |
| 1 | $-y$ | $z$ |

  - $q \in [0.5, 1]$: truth detection accuracy
  - If worker $i$ exerts effort and truthfully answers the truth detection question, his expected truthful reward is

$$R_i = qz + (1 - q)(-y).$$

# Incentive Compatibility

- We ensure that workers truthfully answer the truth detection question

**Proposition (Incentive Compatibility)**

For each worker $i$, truthfully answering the truth detection question leads to a higher expected truthful reward than lying if

$$q(y+z) \geq \max\{z, y\}.$$

- IC will be constraint for platform's optimization problem

# Worker Payoff Maximization

- **Workers**
  - Worker $i$'s payoff function is

$$u_i(\boldsymbol{t}, s_i) = \underbrace{aR_i(\boldsymbol{t})}_{\text{truthful reward}} - \underbrace{e_i c_i}_{\text{cost}}.$$

    - ★ $\boldsymbol{t} = (z, y, a)$: platform's decisions
  - Worker $i$'s payoff maximization problem
    - ★ Given $\boldsymbol{t}$, each worker $i$ solves

$$\begin{aligned} \max \quad & u_i(\boldsymbol{t}, s_i) \\ \text{var.} \quad & s_i \in \{(0, \text{rd}), (1, 1), (1, -1)\}. \end{aligned}$$

# Platform Payoff Maximization

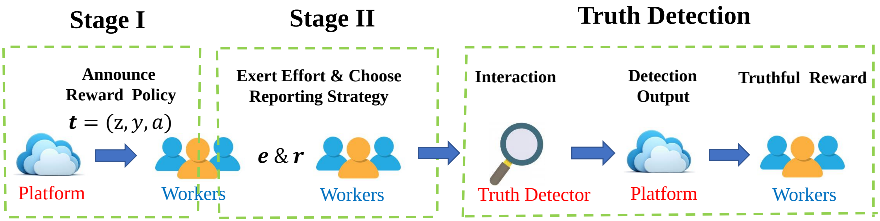
- **Platform**
  - Platform's payoff function is

$$U_p(\mathbf{t}) = \beta \underbrace{P_a(\mathbf{t})}_{\text{aggregated accuracy}} - \underbrace{\mathbb{E}\left[R_{tr}^T\right](\mathbf{t})}_{\text{truthful rewards}} - \underbrace{\mathbb{E}\left[c_{\rm op}^T\right](\mathbf{t})}_{\text{operational cost}}$$

    - ★ $P_a(\mathbf{t})$: accuracy of the aggregated solutions: simple majority rule
    - ★ $\beta > 0$: weight of the accuracy
    - ★ $\mathbb{E}\left[R_{tr}^T\right]$: total expected truthful rewards
    - ★ $\mathbb{E}\left[c_{\rm op}^T\right]$: total expected operational cost, $c_{\rm op}$ per worker
  - The platform's payoff maximization problem is

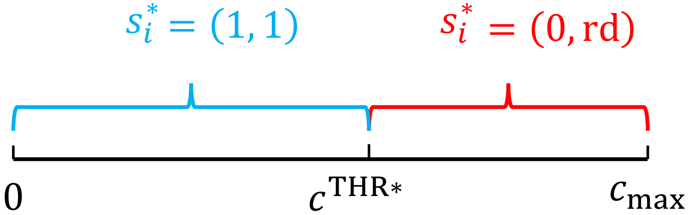
$$\begin{aligned} \max \quad & U_p(\boldsymbol{t}) \\ \text{s.t.} \quad & q(y+z) \geq \max\{z, y\}, \ \text{(IC)} \\ \text{var.} \quad & z \in [0, d], \ y \in [0, d], \ a \in [0, 1]. \end{aligned}$$

# Problem Formulation




- **Platform**
  - Optimizes $\boldsymbol{t} = (z, y, a)$ to maximize its payoff
- **Crowdsourced workers**
  - Each chooses $s_i = (e_i, r_i)$ to maximize his own payoff
  - Heterogeneity
    - ★ cost of effort exertion $c_i$: cdf $F(\cdot)$ on support $[0, c_{\max}]$
    - ★ solution accuracy $p_i$: mean $\bar{p} \in (0.5, 1]$

# Stage II: Worker Strategy




- $c^{\mathrm{THR}*} \triangleq a(qz + qy - y)$

$$s_i^* = \begin{cases} (1,1), & \text{if } c_i \leq c^{\mathrm{THR}*}, \\ (0,\mathrm{rd}), & \text{if } c_i > c^{\mathrm{THR}*}. \end{cases}$$

# Stage I: Platform Payoff Maximization

- In general, the platform's problem is non-convex
- Under certain cost distributions, the problem becomes convex

# Stage I: Platform Payoff Maximization

- In general, the platform's problem is non-convex
- Under certain cost distributions, the problem becomes convex

**Proposition (Uniform Distribution)**

Suppose the workers' costs are drawn from uniform distribution, then the platform's problem is convex.

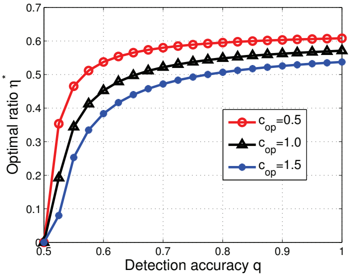
**Proposition (Wrapped Exponential Distribution)**

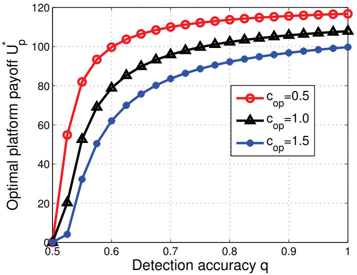
Suppose the workers' costs are drawn from wrapped exponential distribution with cdf $F(c) = \frac{1-e^{-\lambda c}}{1-e^{-\lambda c_{\max}}}$, where $0 < \lambda \leq 2$, then the platform's problem is convex.

- WED : there are mostly low-cost workers within the population

# Optimal Platform Payoff

- $\eta^* \triangleq \int_{c\in[0,c^{\mathrm{THR}*}]} dF(c)$: the ratio of the workers that use $(1,1)$

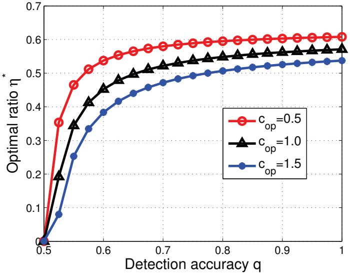


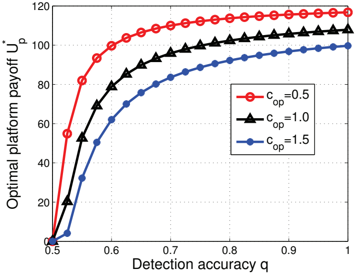




- Accuracy $q \uparrow \rightarrow$ more workers use $(1,1)$
  - Incentivize more workers with no larger total cost

# Optimal Platform Payoff

- $\eta^* \triangleq \int_{c\in[0,c^{\text{THR}*}]} dF(c)$: the ratio of the workers that use $(1,1)$




- Accuracy $q \uparrow \rightarrow$ more workers use $(1,1)$
  - Incentivize more workers with no larger total cost
- Accuracy $q \uparrow \rightarrow$ higher platform payoff
  - Mechanism performs well even if $q$ is not high
    - ★ E.g., for red curve, 60% accuracy ([I. Krajbich *et al.* 2009]) yields 85.4% of the maximum payoff under perfect accuracy (i.e., $q = 1$)
    - ★ By optimizing the reward scheme $\boldsymbol{t} = (z, y, a)$, mechanism with low accuracy can harvest most gain

# Conclusion

We proposed a truth detection mechanism to incentivize crowdsourced workers to complete tasks with high quality and truthfully report solutions

- As the truth detection accuracy improves, the platform should incentivize more workers
- Our mechanism performs well even when the detection accuracy is not very high

# THANK YOU

Network Communications and Economics Lab

http://ncel.ie.cuhk.edu.hk