

Millionaire: A Hint-guided Approach for Crowdsourcing

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Outline

- 1 Background: What are crowdsourcing and existing approaches?
- 2 Motivation: What are our unique novelties and contributions?
- 3 Hint-guided setup: Modelling the physical interface mathematically.
- 4 Hint-guided mechanism: Designing a mechanism from game theory.
- 5 Numerical experiments: Towards the real-world deployment.

Crowdsourcing

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- Pay only when you're satisfied with the results



CROWDSOURCING VALUE CHAIN

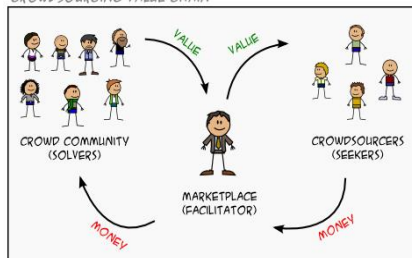


Figure : Amazon Mechanical Turk.

Baseline approach

Which one is the Sydney Harbour Bridge ?



A



B

Figure : Baseline approach.

Modeling baseline approach

- Single-stage setting:

$$\text{select} \begin{cases} \text{"A"} & P_{A,i} \in [\frac{1}{2}, 1), \\ \text{"B"} & P_{A,i} \in (0, \frac{1}{2}]. \end{cases}$$

- Additive mechanism: assume $0 \leq d_- \leq d_+$, $f_a : \{\mathbb{D}_+, \mathbb{D}_-\} \rightarrow \mathbb{R}_+^1$, where $f_a(\mathbb{D}_+) = d_+$, $f_a(\mathbb{D}_-) = d_-$. The additive mechanism f is:

$$f([a_1, \dots, a_G]) = \sum_{i=1}^G f_a(a_i),$$

where the state evaluations of a worker's responses to G questions are denoted by $a_1, \dots, a_G \in \{\mathbb{D}_+, \mathbb{D}_-\}$.

¹The states " $\mathbb{D}_+$ " and " $\mathbb{D}_-$ " denote correct and incorrect answers.

Additive and multiplicative mechanisms

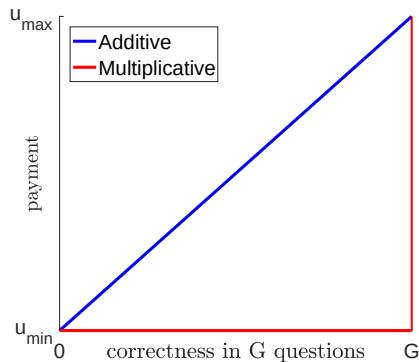


Figure : Comparisons between additive and multiplicative mechanisms.

Motivation



Figure : Who wants to be a millionaire with extra help.

Guess with hints

Which one is the Sydney Harbour Bridge ?



A



? & Hints



B



(a) Main stage.

Which one is the Sydney Harbour Bridge ?



A



? & Hints



B



The Sydney Harbour Bridge is fixed with a pair of concrete pylons at each end of the arch.

(b) Hint stage.

Figure : Hybrid-stage setting in hint-guided approach.

Hybrid-stage setting

- Main stage: “? & Hints” $\rightarrow$ “H” option:

$$\text{select} \begin{cases} \text{“A”} & P_{A,i} \in [\frac{1}{2} + \epsilon, 1), \\ \text{“B”} & P_{A,i} \in (0, \frac{1}{2} - \epsilon], \\ \text{“H”} & P_{A,i} \in (\frac{1}{2} - \epsilon, \frac{1}{2} + \epsilon). \end{cases}$$

- Hint stage: workers' belief given hints $>$ threshold T :

$$\text{select} \begin{cases} \text{“A”} & P_{A|H,i} \in [T, 1), \\ \text{“B”} & P_{B|H,i} \in [T, 1). \end{cases}$$

From setting to mechanism

Each response of G questions gets evaluated to one of four states:

- $\mathbb{D}_+$: main and correct;
- $\mathbb{D}_-$: main and incorrect;
- $\mathbb{H}_+$: hint and correct;
- $\mathbb{H}_-$: hint and incorrect.

We formulate any payment mechanism as a scoring function

$$f : \{\mathbb{D}_+, \mathbb{D}_-, \mathbb{H}_+, \mathbb{H}_-\}^G \rightarrow [\mu_{\min}, \mu_{\max}].$$

Our goal is to design f such that its expected payment for each worker is strictly maximized under the hybrid-stage setting.

Designing goals

Definition (Incentive Compatibility)

f is incentive-compatible if (1) f incentivizes the worker to choose answers by her belief and (2) The expected payment is strictly maximized in both stages.

Definition (Mild No-free-lunch Axiom)

If all answers in G questions are either wrong or based on hints, then the payment should be zero, unless all attempted answers are correct. More formally, $f(a) = 0$, $\forall a \in \{\mathbb{D}_-, \mathbb{H}_+, \mathbb{H}_-\}^G \setminus \{\mathbb{H}_+\}^G$.

Two propositions

Proposition

Let $d_+ = f(\mathbb{D}_+)$, $d_- = f(\mathbb{D}_-)$, $h_+ = f(\mathbb{H}_+)$ and $h_- = f(\mathbb{H}_-)$. When $N = G = 1$, f satisfies Definition 1 if it meets:

- $d_+ > d_-$, $h_+ > h_-$, $d_+ > h_+ \rightarrow$ assist our setting in detecting high-quality workers;
- $\frac{d_+ - d_-}{1 - 2\epsilon} \geq \frac{h_+ - h_-}{2\epsilon} \rightarrow$ directly answer if confident;
- $d_+ - d_- \leq \frac{2T-1}{1/2-\epsilon}(h_+ - h_-) \rightarrow$ leverage hints if unsure.

Proposition

Given $1 \leq G \leq N$, f satisfies both Definitions 1 and 2 if $\epsilon \in [\epsilon_{\min}, 1/2)$ for $\epsilon_{\min} = T - \sqrt{T^2 - 1/4}$.

Hint-guided payment mechanism

Inputs:

Step 1: $f_m: f_m(+\mathbb{D}) = 1; f_m(-\mathbb{D}) = 0; f_m(+\mathbb{H}) = \frac{1/2 - \epsilon_{\min}}{2T-1}; f_m(-\mathbb{H}) = 0.$

Step 2: $a_1, \dots, a_G \in \{+\mathbb{D}, -\mathbb{D}, +\mathbb{H}, -\mathbb{H}\}$ are evaluations to G gold.

Step 3: Set $\mu_{\min}$ and $\mu_{\max}$ properly.

The payment is:

Step 4: $f([a_1, \dots, a_G]) = (\mu_{\max} - \mu_{\min}) \prod_{i=1}^G f_m(a_i) + \mu_{\min}.$

Algorithm 1: Hint-guided Payment Mechanism.

Remark

The multiplicative form not only incentivizes workers to use hints properly, but also prevents spammers.

Uniqueness

Theorem

$\forall T \in (5/8, 1)$ and $1 \leq G \leq N$, f in Algorithm 1 satisfy both Definitions 1 and 2 if and only if $\epsilon = \epsilon_{\min}$.

Definition (Harsh No-free-lunch Axiom)

If all answers in G questions are either wrong or based on hints, then the payment for the worker should be zero. More formally, $f(a) = 0$, $a \in \{\mathbb{D}_-, \mathbb{H}_+, \mathbb{H}_-\}^G$.

Theorem

$\forall T \in (5/8, 1)$ and $\epsilon \in [0, 1/2)$, when $1 \leq G \leq N$, there is no mechanism satisfies both Definitions 1 and 3.

Merits of hint-guided approach

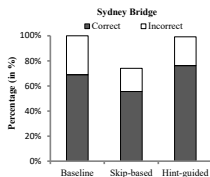
Table : Comparison of related approaches and our hint-guided approach.

Perspective	Metric	Baseline	Skip-based	Self-corrected	Hint-guided
requester	large label quantity	✓	✗	✓	✓
	high label quality	✗	✓	-	✓
worker	worker quality detection	✗	✗	✗	✓
	spammer prevention	✗	✓	✓	✓
platform	low money cost	✗	✓	-	✓
	realization	✓	✓	✗	✓

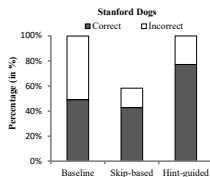
Label quantity and quality

Table : % of the completion of three tasks.

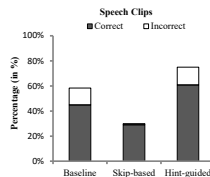
Data set	Baseline	Skip-based	Hint-guided
<i>Sydney Bridge</i>	100.00	74.00	99.11
<i>Stanford Dogs</i>	99.72	58.18	99.91
<i>Speech Clips</i>	58.33	30.00	75.00



(a) Sydney Bridge.



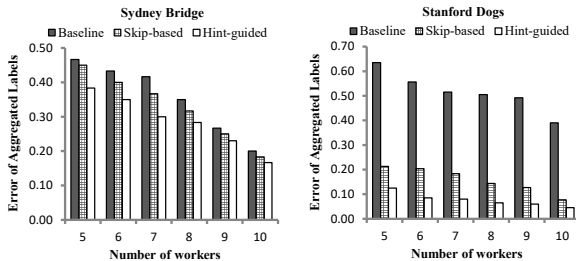
(b) Stanford Dogs.



(c) Speech Clips.

Figure : % of correct answers and incorrect answers.

Prediction of aggregated labels



(a) Sydney Bridge.

(b) Stanford Dogs.

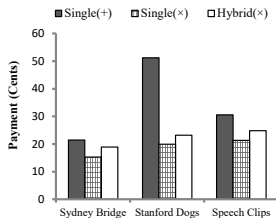
Figure : Error of aggregated labels.

Worker quality detection

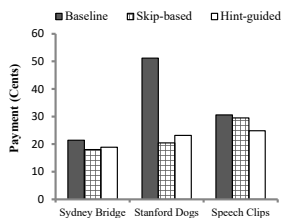
Table : Error rate (in %) for aggregating two crowdsourced labels.

Number of Workers		5	10
<i>Sydney Bridge</i>	origin	38.33	16.67
	rescale	30	11.67
<i>Stanford Dogs</i>	origin	12.5	4.5
	rescale	12	4

Spammer prevention and money cost



(a) Spammer prevention.



(b) Money cost.

Figure : Average payment. (a) explores interaction between settings and “\$”.

Conclusions

- Hint-guided approach = hybrid-stage setting + hint-guided payment mechanism.
- Extending hybrid-stage setting from binary choice to multiple choice.
- Multiple-level hints (coarse to fine) + unsure option.