

Efficient Crowdsourcing of Unknown Experts using Multi-Armed Bandits

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Motivation

Crowdsourcing systems:

combine machine intelligence with **mass of human intelligence**



amazon mechanical turk™
Artificial Artificial Intelligence

Expert crowdsourcing:



New challenges: quality of work matters

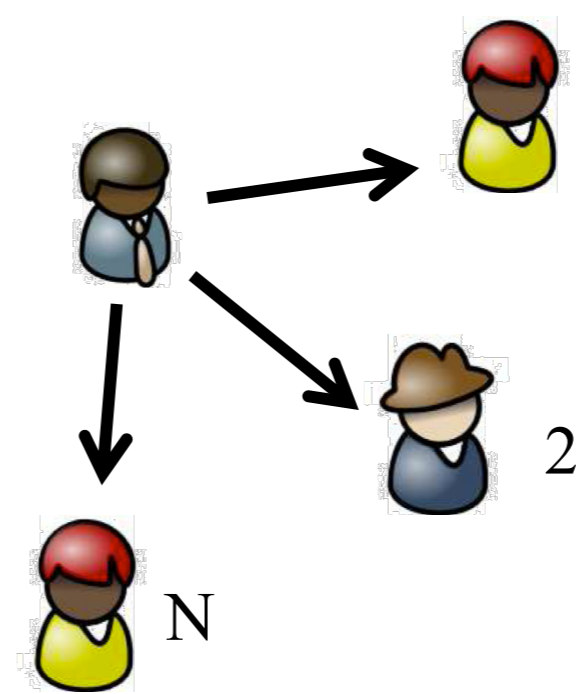


- Hiring a worker is **costly**
- **Limited** by a financial **budget**

Existing systems: oDesk, freeLancer, eLance, geniusRocket, blurGroup

Model Description

Bounded Multi-Armed Bandit model



- N workers, financial budget B
- Each worker i :

- Hiring cost c_i
- Working task limit L_i
- Quality of work: drawn from *unknown* distribution with expected value μ_i

Objective: **maximise** the **total quality** of assigned work, **w.r.t.** budget B

$$A^* = \arg \max_A \sum_i^N \mathbb{E} [N_i^B(A)] \mu_i \cdot P \left(\sum_i N_i^B(A) c_i \leq B \right) = 1.$$

Online learning

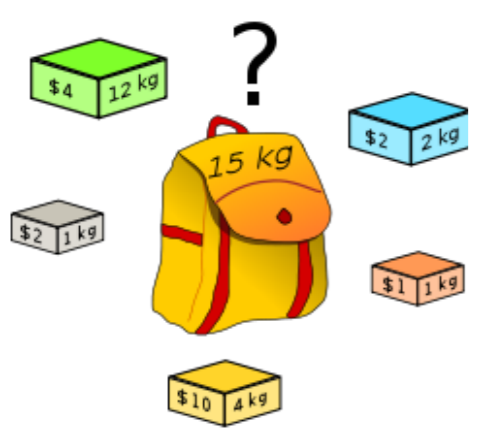
Bounded Epsilon-first: $\epsilon B \leftrightarrow (1 - \epsilon) B$

- Exploration: uniformly assign tasks to workers
 $\hat{\mu}_i$: **estimate** of worker i 's expected quality
- Exploitation: form a bounded knapsack from estimates + solve with density ordered greedy

$$\max \sum_{i=1}^N \hat{\mu}_i x_i^{\text{exploit}} \quad \text{s.t.} \quad \sum_{i=1}^N c_i x_i^{\text{exploit}} \leq (1 - \epsilon) B,$$

$$\forall i: 0 \leq x_i^{\text{exploit}} \leq L_i - x_i^{\text{explore}}$$

Offline version: Bounded knapsack



$$\max \sum_{i=1}^N x_i v_i \quad \text{s.t.} \quad \sum_{i=1}^N x_i w_i \leq C,$$

$$\forall i: 0 \leq x_i \leq L_i \quad x_i \text{ integer}$$

NP-hard problem \rightarrow Approximation algorithms

Density ordered greedy approach

Performance analysis

Theorem 1 Let $0 < \epsilon, \beta < 1$. Suppose that $\epsilon B \geq \sum_{j=1}^N c_j$. With probability $(1 - \beta)^N$, the performance regret of the bounded ϵ -first approach is at most

$$2 + \epsilon B d_{\max} + 2N \left(\sqrt{\frac{B \left(-\ln \frac{\beta}{2} \right) \sum_{j=1}^N c_j}{\epsilon}} \right), \quad (4)$$

where $d_{\max} = \max_{i \neq j} \left| \frac{\mu_i}{c_i} - \frac{\mu_j}{c_j} \right|$ (i.e. the largest distance between different density values).

Theorem 2 Let ϵ_{opt} denote the value that minimises Equation 4. By setting the exploration budget to be $B \epsilon_{\text{opt}}$, the regret of the bounded ϵ -first algorithm is at most

$$2 + 3B^{\frac{2}{3}} \left(N^2 \left(-\ln \frac{\beta}{2} \right) \sum_{j=1}^N c_j d_{\max} \right)^{\frac{1}{3}}.$$

Empirical Evaluation

