# CS243: Introduction to Algorithmic Game Theory

Crowdsourcing (Dengji ZHAO)

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### **Outline**

- Overview
- Crowdsourcing Markets
- 3 Crowdsourcing Contests
- Peer Prediction

### **Motivations**

Overview

- Imagine you need labels for 10,000 images. How can you tackle this problem?
- Imagine you need a new software architecture for your company's inventory management system. Due to the limited budget, is it possible for you to run an online contest instead of hiring a developer to design the new system.

### Crowdsourcing

Crowdsourcing describes the act of outsourcing a task or multiple tasks to a large, undefined group of workers via ar open call.

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# Examples

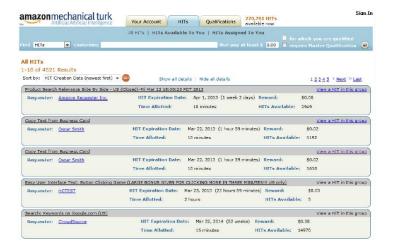
Overview

- Peer Production Systems No employer-employee relationships. e.g., Wikipedia.
- Paid Crowdsourcing Markets Some tasks, like labeling images, require payments to encourage contributions. e.g., Amazon Mechanical Turk.
- Crowdsourcing Contests Workers are invited to compete to submit work in response to a job posting. e.g., DARPA Red Balloon Challenge.

### **Outline**

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- 2 Crowdsourcing Markets
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### Examples: Amazon Mechanical Turk



# The Setting for Crowdsourcing Platforms

Overview

- There is one requester with budget *B*, and *n* workers arrive sequentially (in a random order).
- Each worker  $a_i$  has cost  $c_i \ge 0$  for each task and is willing to perform at most  $t_i \ge 0$  tasks.
- The worker's utility per task if paid price  $p_i$  is  $u_i = p_i c_i$ . (Assume all tasks are of the same kind. e.g., labeling.)
- In every round, a new worker arrives and reports c<sub>i</sub> and t<sub>i</sub>.
  The requester decides how many tasks to allocate and the price per task.

# Pricing Mechanisms for Crowdsourcing Platforms

- Pay  $p = c_i$  per task: Not truthful!
- Pay a fixed price p\* per task: May be too high (wasting budget) or too low (no enough workers)!

#### Target

Maximize the number of tasks that are completed without exceeding the budget and be strategy-proof.

### **Dynamic Pricing**

Overview

#### Idea of Threshold Price

The mechanism calculates a threshold price p based on the reports from past workers, and then uses this price for a while (for next m workers, get allocated when cost is below p and pay p, otherwise get rejected), until the threshold price is updated again.

# Algorithm: Get Threshold

#### An Intuition

What if the requester can know next *m* workers' type profile?

 If next m workers come with ascending costs  $(c_1 \leq c_2 \leq \cdots \leq c_m)$ , then after each worker comes, the requester only to consider whether it is worth to improve the price (to allocate tasks to the new arrival worker).

### Algorithm: Get Threshold

#### Question

What if the requester can know next m workers' type profile? (assuming  $c_1 \le c_2 \le \cdots \le c_m$ .) What's the price p for them?

- Let x<sub>i</sub> be the number of tasks allocated to i
- When worker 1 comes, it is always worth improving price to  $p = c_1$  to allocate  $x_i = t_i$ .
- When worker i comes, it is worth improving price to  $p = c_i$  if we can further allocate at least one more task to i. We shall check whether  $c_i(1 + \sum_{j < i} x_j) \le B$  (we can afford the payments for first i agents when the price is  $c_i$ ).
- Allocate as much work as possible to worker i:  $x_i = \min \left\{ t_i, \lfloor B/p \rfloor \sum_{j < i} x_j \right\}$

### Algorithm: Get Threshold

#### Simulation

But the requester cannot know the type profile of next *m* workers. She can simulate it by assuming they have the same profile with past *m* workers.

**Input:** the past m workers' reports  $\{(c_1, t_1), \ldots, (c_m, t_m)\}.$ 

- Sort reports such that  $c_1 \leq c_2 \leq \cdots \leq c_m$ .
- Set i = 1.
- **3** While  $c_i \leq B/(1 + \sum_{j < i} x_j)$  do:

  - **3** i = i + 1
- Output p for the next m workers.



# Online Mechanism for Task Pricing

#### Question

Overview

- 1. How to decide *m*?
- 2. What's the price for first *m* workers?

#### Solution

m can also be determined dynamically!

# Online Mechanism for Task Pricing

#### The Whole Pricing Mechanism (Singer and Mittal, 2011):

- First set  $p_0 = \epsilon$  for the first worker.
- 2 Then we have the history of the first worker, set m = 1 and we get a price  $p_1$  for the next worker.
- Then we have the history of the first 2 workers, set m = 2 and we get a price  $p_2$  for the next 2 workers.
- Then we have the history of the first 4 workers, set m = 4 and we get a price  $p_3$  for the next 4 workers.
- **5** ... ...
- Then we have the history of the first  $2^k$  workers, set  $m = 2^k$  and we get a price  $p_{k+1}$  for the next  $2^k$  workers.
- For each bucket of workers, set  $B_k = (2^{k-1}/n)B$ .

### Online Mechanism for Task Pricing

#### **Theorem**

Overview

The online pricing mechanism is *budget feasible* and *strategy-proof*.

# What's More: Crowdsourcing Beyond Markets

Sometimes your labour is freely used!



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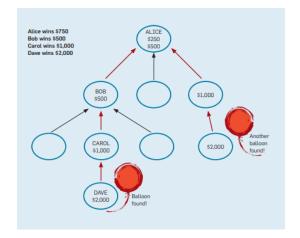
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### Examples: DARPA Red Balloon Challenge

Overview



# Winning Solution in DARPA Red Balloon Challenge



# What's More: Sybil Attack

 If an agent pretends to be multiple agents to get more rewards, it is called Sybil attack.

Crowdsourcing Contests

#### Question

What's the possible Sybil attack in the winning solution in DARPA Red Balloon Challenge?

### **Outline**

- **Peer Prediction**

### **Prediction Markets**

#### **Prediction Market**

A prediction market is a financial market that is designed for information aggregation and prediction.

 Payoffs of the traded item is associated with outcomes of future events.

### **Prediction Markets**

Construct a prediction market to predict an uncertain event:

- Turn an uncertain event of interest into a random variable.
- Create a financial contract, and it's payoff = value of the random variable.
- Open a market in the financial contract and attract traders to wager and speculate (gambling).

### **Prediction Markets**

Overview

Key Aspect: payoff is uncertain!

In theory, price  $\approx$  (expectation of the random variable | all information hold by the market).

### Non-Market Alternative vs. Markets

- Ask Experts
  - Identifying experts can be hard
  - Incentives
  - Combining opinions can be difficult

- Prediction Markets
  - Self-selection
  - Monetary incentive and more
  - Real-time and self-organizing

### Non-Market Alternative vs. Markets

- Machine Learning
  - Need huge historical data
  - Past and future are related
  - Hard to incorporate recent new information

- Prediction Markets
  - No need for data
  - No assumption on past and future
  - Immediately incorporate new information

# Incentives for Experts: Proper Scoring Rules

- Report a probability estimate:  $r = Pr\{r_1, r_2, \dots, r_n\}$ .
- Get payment  $s_i(r)$  if outcome  $\omega_i$  happens.
- Proper: incentive compatible
  - A risk neutral agent should chose  $r_i = \Pr(\omega_i)$  to maximize the expected profit.
- Proper scoring rules
  - Logarithmic:  $s_i(r) = a + b \log(r_i)$
  - Quadratic:  $s_i(r) = a + 2br_i b\sum_i r_i^2$

# Prediction Market: Risk Management

• Why buying insurance?

Overview

- If something is terrible to me, I buy a bunch of
  - \$1 if something happens; \$0 otherwise
- If something really happens, I am compensated.

### Prediction Market: Risk Management

• How insurance market works?

Overview

- I am risk averse  $(u(x) = \log(x))$ , insurance company is risk neutral (u(x) = x). We both believe that *something* might happen with probability 0.01 and value  $x = 20000 10000 \times 1$  (something happens).
- My expected utility:

$$\mathbb{E}[u] = 0.01 \times \log(10000) + 0.99 \times \log(20000) \approx 4.2980$$

My expected utility after buying \$10000 insurance for \$125:

$$\mathbb{E}[u] = 0.01 \log(10000 + 10000 - 125) + 0.99 \log(20000 - 125)$$
  
  $\approx 4.2983 > 4.2980$ 

- Expected utility of insurance company is  $0.01 \times (-9875) + 0.99 \times 125 = 25 > 0$
- Both insurance company and I are happy!

### Prediction Market: Risk Management

Security Market

Overview

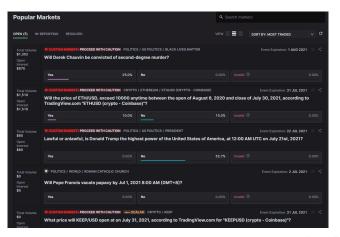
Note, the insurance in the above example is in fact a contract

\$10000 if something happens; \$0 otherwise

 Market mechanism is to allocate risk and allow speculation among participants.

### **Prediction Market: Examples**

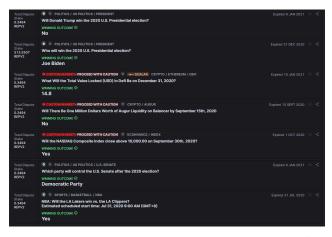
Augur (www.augur.net)



Overview

### Prediction Market: Examples

#### Successful results:



### What's More: Open Questions

Overview

# **5 Open Questions in Prediction Markets** (Wolfers and Zitzewitz, 2006)

- How to attract uninformed trader?
- How to tradeoff interest and contractability?
- How to limit manipulation?
- Are markets well calibrated on small probability?
- How to separate correlation from causation?

- Pricing Mechanisms for Crowdsourcing Markets by Yaron Singer and Manas Mittal (WWW 2013)
- Time-critical Social Mobilization
  by G Pickard, W Pan, et al. (Science 2011)
- Prediction Markets: Economics, Computation, and Mechanism Design
   by Yiling Chen (EC-tutorial 2007)