THE UNIVERSITY OF HONG KONG
$\begin{array}{lllllllllllll}D & \epsilon & P & A & R & T & M & \epsilon & N & T & O & F \\ C & O & M & P & J & C & R & S & C & E & C & C\end{array}$

## Title: <br> On Optimality of Jury Selection Problem in Crowdsourcing

Yudian, Reynold, Silviu, Luyi
EDBT 2015

## Outline

$\square$ Introduction (Crowdsourcing)
$\square$ Problem Definition (Jury Selection Problem)
$\square$ Our Solution (Optimality)
$\square$ Conclusion

## Why do we need crowd?

## Problems



| Is Bill Gates |
| :---: |
| now the CEO |
| of Microsoft? |
| Yes O No O |

## $\square$ Possible Solutions


M. J. Franklin, D. Kossmann, T. Kraska, S. Ramesh, and R. Xin. Crowddb: answering queries with crowdsourcing. In SIGMOD Conference, pages 61-72, 2011.

## Crowdsourcing Definition

## Definition

## Coordinating a crowd to do micro-tasks that solve problems.

$\square$ Example
problems:
entity resolution
An example micro-task :


## Amazon Mechanical Turk

## Requesters

## Get Results

from Mechanical Turk Workers
Ask workers to complete HITs - Human Intelligence Tasks - and get results using Mechanical Turk. Gegirter Now
As a Mechanical Turk Requester you:

- Have access to a global, on-demand, $24 \times 7$ workforce
: Get thousands of HITs completed in minutes
- Pay only when you're satisfied with the results

Fund your
Fund your
account


Get Searted

## Micro-Tasks

Are they the same?
iPad 2 = iPad Two
OYES ONO
SUBMIT

## Is Bill Gates now the CEO of Microsoft? Yes ○ no ○

## Workers

## Make Money

by working on HITs
HITs - Human Intelligence Tasks - are individual tasks that you work on. Find HITs now.

As a Mechanical Turk Worker you:

- Can work from home
- Choose your own work hours
- Get paid for doing good work

$\square$ Official Amazon Mechanical Blog (August, 2012) more than 500,000 workers from 190 countries


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## Problem Intuition (Worker Selection)-VLDB 12

Given (1) a Task
(2) a fixed Budget B
(3) a set of workers

Worker Selection Problem:
Choose a subset of workers, such that the task can be completed successfully (i.e., with high quality), in the most economical manner ?
$\square$ Next: Task and Worker
C. C. Cao, J. She, Y. Tong, and L. Chen. Whom to ask? jury selection for decision making tasks on micro-blog services. PVLDB, 5(11):1495-1506, 2012

## Task : Decision Making Task

# $\square$ Answers are "yes" and "no" 

$\square$ One (unknown) ground truth

## Decision Making Task <br> Is Bill Gates now the CEO of Microsoft? <br> Yes O <br> No O

$\square$ Simplicity
$\square$ (Extensions) Multiple Choice Tasks

Yudian Zheng, Reynold Cheng, Silviu Maniu and Luyi Mo. On optimality of jury selection in crowdsourcing. In International Conference on Extending Database Technology (EDBT), 2015

## Worker - (quality, cost)

E Each Worker: (quality, cost) Ex: A $(0.77, \$ 9)$

| A | B | C | D | E | F | G |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |
| $(0.77, \$ 9)$ | $(0.7, \$ 5)$ | $(0.65, \$ 7)$ | $(0.6, \$ 5)$ | $(0.6, \$ 2)$ | $(0.25, \$ 3)$ | $(0.2, \$ 6)$ |

$\square$ Jury: a subset of workers (Ex: $\{A, B, D\}$ )
C. C. Cao, J. She, Y. Tong, and L. Chen. Whom to ask? jury selection for decision making tasks on micro-blog services. PVLDB, 5(1) 1):1495-1506, 2012
X. Liu, M. Lu, B. C. Ooi, Y. Shen, S. Wu, and M. Zhang. Cdas: A crowdsourcing data analytics system. PVLDB, 5(10):1040-1051, 2012
P. Venetis and H. Garcia-Molina. Quality control for comparison microtasks. In CrowdKDD, 2012.

## Jury Selection Problem


: Select a Jury (subset of workers) such that the Jury Quality is ! maximized in all Jury whose cost does not exceed the Budget.
$\square$ For each Jury:

(1) Jury Cost: $\$ 5+\$ 7+\$ 6=\$ 18$
(2) Jury Quality: JQ (\{0.7,0.65,0.2\}),
$\operatorname{Pr}$ ( correctly deriving a result
based on workers' answers)

## Jury Quality Computation (MV) - VLDB12

- Jury Quality for Majority Voting Strategy

$\square$ MV : return the answer which receives the highest votes
$\square \operatorname{Cost}(\{\$ 5, \$ 7, \$ 6\})=18 \leqslant 20$
- JQ(\{0.7,0.65,0.2\},MV)
$=0.7 * 0.65 * 0.8+0.7 * 0.35 * 0.2+0.3 * 0.65 * 0.2$ $+0.7 * 0.65 * 0.2=54.3 \%$


## Optimal Jury Set- VLDB 12 (Is it optimal ?)

$\square$ Enumerating all Jury set satisfying budget constraint optimal jury set


$$
\begin{aligned}
& \square \operatorname{Cost}(\{\$ 9, \$ 5, \$ 2\})=16 \leqslant 20 \\
& J Q(\{0.77,0.7,0.6\}, M V)=77.42 \%
\end{aligned}
$$

$\square$ Question: Is it optimal ?
Is it possible to provide a better solution for JSP, by replacing MV with another strategy?

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## Classification of Voting Strategies



Based on whether the result is returned with degree of randomness, we can classify the voting strategies into two categories:
deterministic voting strategy (left part in the graph)
and
randomized voting strategy (right part in the graph).
Example:
$\{0,1,1\}$ 0.7,0.6,0.2
Majority Voting (Deterministic):
return 1
Randomized Majority Voting
(Randomized):
return 0 with probability $1 / 3$
return 1 with probability $2 / 3$

## Existence of Optimal Voting Strategy

Given a Jury set J and a strategy S, the corresponding Jury Quality JQ(J,S) can be computed. An important question is:

Does there exists an optimal strategy $S^{*}$, such that given a Jury set J, the JQ for this strategy is not lower than the JQ for any strategy (including all deterministic and randomized strategies) ?
$J Q\left(J, S^{*}\right) \geqslant J Q(J, S)$ for any $S$
We formally prove that the Bayesian Voting Strategy (BV) is the optimal strategy, i.e., $S^{*}=B V$.

## *Proof of Optimality

To answer this question, let us reconsider Definition $\overline{3}$. Let $h(V)=\mathbb{E}\left[\mathbb{1}_{\{S(V)=0\}}\right]$. We have (i) $h(V) \in[0,1]$; and (ii) $\mathbb{E}\left[\mathbb{1}_{\{S(V)=1\}}\right]=1-h(V)$. Also, let $P_{0}(V)=\operatorname{Pr}(\mathbf{V}=V, \mathbf{t}=0)$, and $P_{1}(V)=\operatorname{Pr}(\mathbf{V}=V, \mathbf{t}=1)$. Hence, $J Q(J, S, \alpha)$ can be rewritten as

$$
\begin{aligned}
& \sum_{V \in \Omega}\left[P_{0}(V) \cdot h(V)+P_{1}(V) \cdot(1-h(V))\right] \\
= & \sum_{V \in \Omega}\left[h(V) \cdot\left(P_{0}(V)-P_{1}(V)\right)+P_{1}(V)\right]
\end{aligned}
$$

This gives us a hint to maximize $J Q(J, S, \alpha)$ and find the optimal voting strategy $S^{*}$. Let $h^{*}(V)=\mathbb{E}\left[\mathbb{1}_{\left\{S^{*}(V)=0\right\}}\right]$. It is observed that $P_{1}(V)$ is constant for a given $V$ and $h(V) \in[0,1]$ for all $S$ 's (no matter it is a deterministic one or a randomized one). Thus, to optimize $J Q(J, S, \alpha)$, it is required that

1. if $P_{0}(V)-P_{1}(V)<0, h^{*}(V)=0$, and so, $S^{*}(V)=1$;
2. if $P_{0}(V)-P_{1}(V) \geq 0, h^{*}(V)=1$, and so, $S^{*}(V)=0$.

## Bayesian Voting Strategy

## Example:

$$
\{0,1,1\} \quad 0.7,0.6,0.2
$$

Majority Voting Strategy:
give 1 vote for the supported answer
0: 1 (by worker 1)
1: 1 (by worker 2$)+1($ by worker 3) $=2$
Bayesian Voting Strategy (Deterministic Strategy): give $\log [p /(1-p)]$ vote for the supported answer
$0: \log (0.7 / 0.3)=0.8473$
1: $\log (0.6 / 0.4)+\log (0.2 / 0.8)=-0.981$


JQ(\{0.77,0.7,0.6\},MV)
= 77.42\%

JSP solution: $\{A, B, E\}$

$J Q(\{0.77,0.6,0.25,0.2\}, B V)$
= 86.95\%
JSP solution: $\{A, E, F, G\}$

## JSP for BV : Complexity (1)(2)

1. Given Jury J, JQ computation for BV, or JQ(J,BV)

Recall that the JQ computation requires enumerating exponential number (w.r.t $|\mathrm{J}|$ ) of states, i.e.,

$$
|\{0,1\}|^{*}|\{0,1\}|^{|J|=2^{|J|+1}}
$$

2. The number of Jury set satisfying Budget

Constraint is

Exponential w.r.t. N , in the worst case $2^{\mathrm{N}}$

## Complexity 1 of JSP

1. Given Jury J, JQ computation for BV , or JQ(J,BV) Recall that the JQ computation requires enumerating exponential number (w.r.t |J| ) of states, i.e.,

$$
|\{0,1\}|^{*}|\{0,1\}|^{|J|=2^{|J|+1}}
$$

$\square$ NP-hardness of JQ computation
$\square$ Polynomial Approximation Algorithm (with Pruning Technique)
$\square$ Bounded by 1\% Error

## *Q1: Computing JQ for BV is NP-hard

Partition Problem (NP-Complete Problem)
Input: $W=\left\{w_{1}, w_{2}, \cdots, w_{n}\right\}, w_{i}$ is integer $(1 \leqslant i \leqslant n)$ Output: yes/no

Decide whether $W$ can be partitioned into two disjoint multi-sets $W_{1}$ and $W_{2}$, such that the sum of elements in $W_{1}$ is equal to the sum of elements in $W_{2}$.

## Reduction

Input: $\mathcal{W}=\left\{w_{1}, w_{2}, \cdots, w_{n}\right\}, w_{i}$ is integer $(1 \leqslant i \leqslant n)$
Construct $\mathrm{J}=\left\{\mathrm{j}_{1}, \mathrm{j}_{2}, \cdots, \mathrm{j}_{\mathrm{n}}\right\}$ and $\mathrm{J}^{\prime}=\left\{\mathrm{j}_{1}, \mathrm{j}_{2}, \cdots, \mathrm{j}_{\mathrm{n}+1}\right\}$ based on W , then
(1) if $J Q\left(J^{\prime}, B V\right)>J Q(J, B V)$, then
the output for partition problem of W is "yes";
(2) if $J Q\left(J^{\prime}, B V\right) \leq J Q(J, B V)$, then
the output for partition problem of W is "no";

In order to prove the NPhardness of computing JQ for BV, we can reduce the partition problem, a wellknown NP-Complete Problem (also a decision problem) to the problem of computing JQ for BV.

Since computing JQ for BV is not in NP (it is not a decision problem), then it is a NP-hard problem.

## *Q1:Bucket-Based Approx. Alg. (Pruning)

Settings:

$$
\sigma\left(q_{1}\right)=\sigma\left(q_{2}\right)=1.2 \quad \sigma\left(q_{i}\right)=\log \frac{q_{i}}{1-q_{i}}
$$

Approximations

$$
\log \frac{0.99}{1-0.99}<4.6
$$

Aggregated bucket number

Compute JQ(J,BV):


Real Computed JQ(J,BV):
$q_{1} q_{2}+\left[q_{1}\left(1-q_{2}\right)+\left(1-q_{1}\right) q_{2}\right] / 2$

$A=\log \frac{q_{1}}{1-q_{1}} \quad B=\log \frac{q_{2}}{1-q_{2}}$

## numBuckets

## *Q1:Approximation Error Bound

Notations:
Let $\widehat{J Q}(J, B V)$ denote the estimated $J Q$ of the approximation algorithm, and $J Q(J, B V)$ denote the real $J Q$.

We can prove:

$$
\begin{equation*}
\widehat{J Q}(J, B V) \leq J Q(J, B V) \quad \text { and } \tag{1}
\end{equation*}
$$

$$
\begin{equation*}
J Q(J, B V)-\widehat{J Q}(J, B V)<e^{\frac{5}{4 \cdot d}}-1 \tag{2}
\end{equation*}
$$

The time complexity of approximation algorithm is $\mathcal{O}\left(d n^{3}\right)$ and if $d \geq 200$, the approximation error is bounded within $1 \%$.
[Real: $\overline{8} \overline{0} \%-----7$
The polynomial algorithm will give within $1 \%$ approximation error bound.

## Complexity 2 of JSP

2. The number of Jury set satisfying Budget Constraint is

Exponential w.r.t. N , in the worst case $2^{\mathrm{N}}$
$\square$ NP-hardness of JSP
$\square$ Simulated Annealing Heuristic for general JSP

## *Q2- NP-hardness

## Combinatorial Optimization Problem

- Similar to Knapsack Problem, with the difference in the Objective Function
*NP-hard, intuitively as computing the JQ
(Objective Function) is NP-hard
*Even though regarding it as an oracle, deriving the optimal solution is also NP-hard
=> N-th order knapsack problem


## *Q2- Simulated Annealing Heuristic

Simulated Annealing Heuristic

- Heuristic solving combinatorial optimization problem
- avoid local minimum, probability of accepting a worse place minimize the cost



## *Simulated :Different Voting Strategies


(a) Varying $\mu$

(b) Varying $n(\mu=0.3)$

(c) Varying $n(\mu=0.7)$

Randomly generate 10 workers with quality $\mathcal{N}\left(\mu, 0.1^{2}\right)$
MV: Majority Voting
BV: Bayesian Voting
RB: Random Ballot Voting (Randomly returns 0 or 1)
RMV: Randomized Majority Voting

## *Simulated : Proposed Approx. Algorithm

## Observe the effect of our proposed approximation algorithms


(a) Varying $\mu$ and $\sigma^{2}$

(b) Varying numBuckets

(c) Approximation Error

(d) Varying $n$
(a) effect with the change of mean and variance
(b) vary the bucket number
(c) approximation error bound
(d) pruning techniques

## Real: End-to-End System Comparison

## Collect Data from AMT:

600 questions, each question answered by 20 workers

## Known Ground Truth -> workers' qualities


(b) Varying $B$

(c) Varying $N$

(d) Varying $\widehat{\sigma}$
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## System (Optimal Jury Selection System)



## Thank you!

Contact Info: Yudian Zheng DataBase Group Computer Science Department The University of Hong Kong

