Managing the Quality of Crowdsourced Databases

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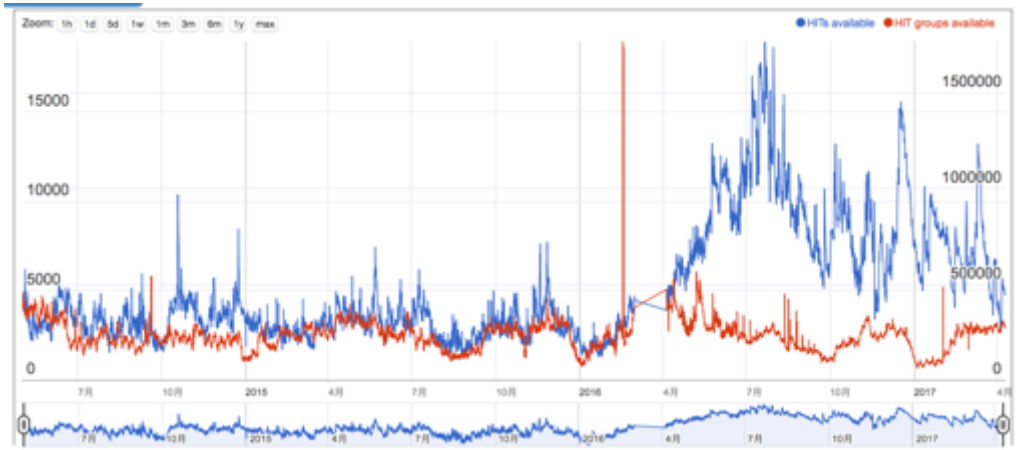
Why Quality Control?

- **Huge Amount** of Crowdsourced Data



amazon mechanical turk
beta
Artificial Artificial Intelligence

Statistics in AMT:
Over 500K workers
Over 1M tasks

- **Inevitable noise & error**

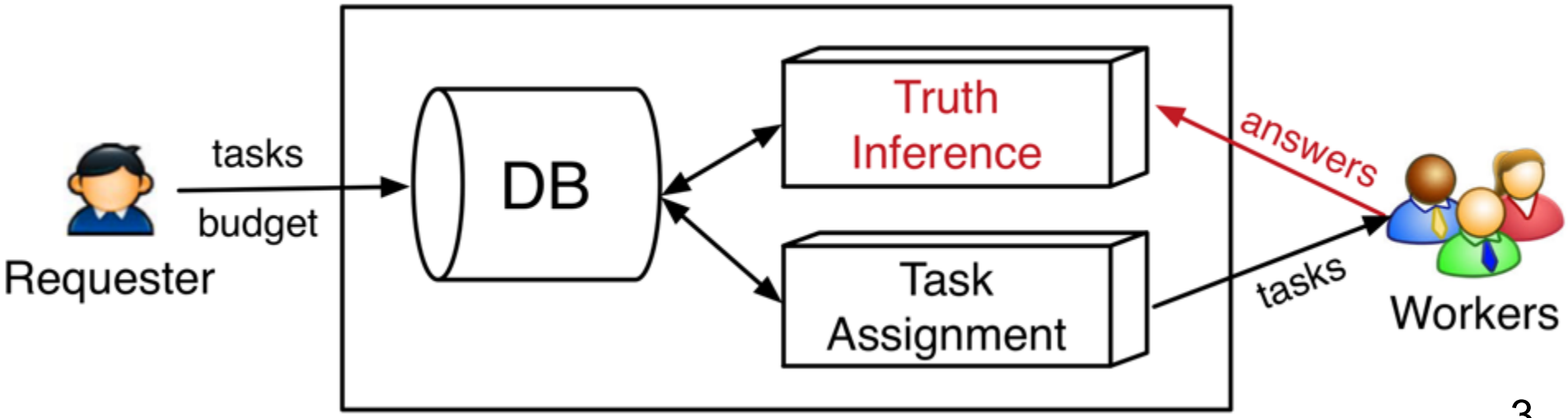
- **Goal: Obtain reliable information in Crowdsourced Data**

Crowdsourcing Workflow

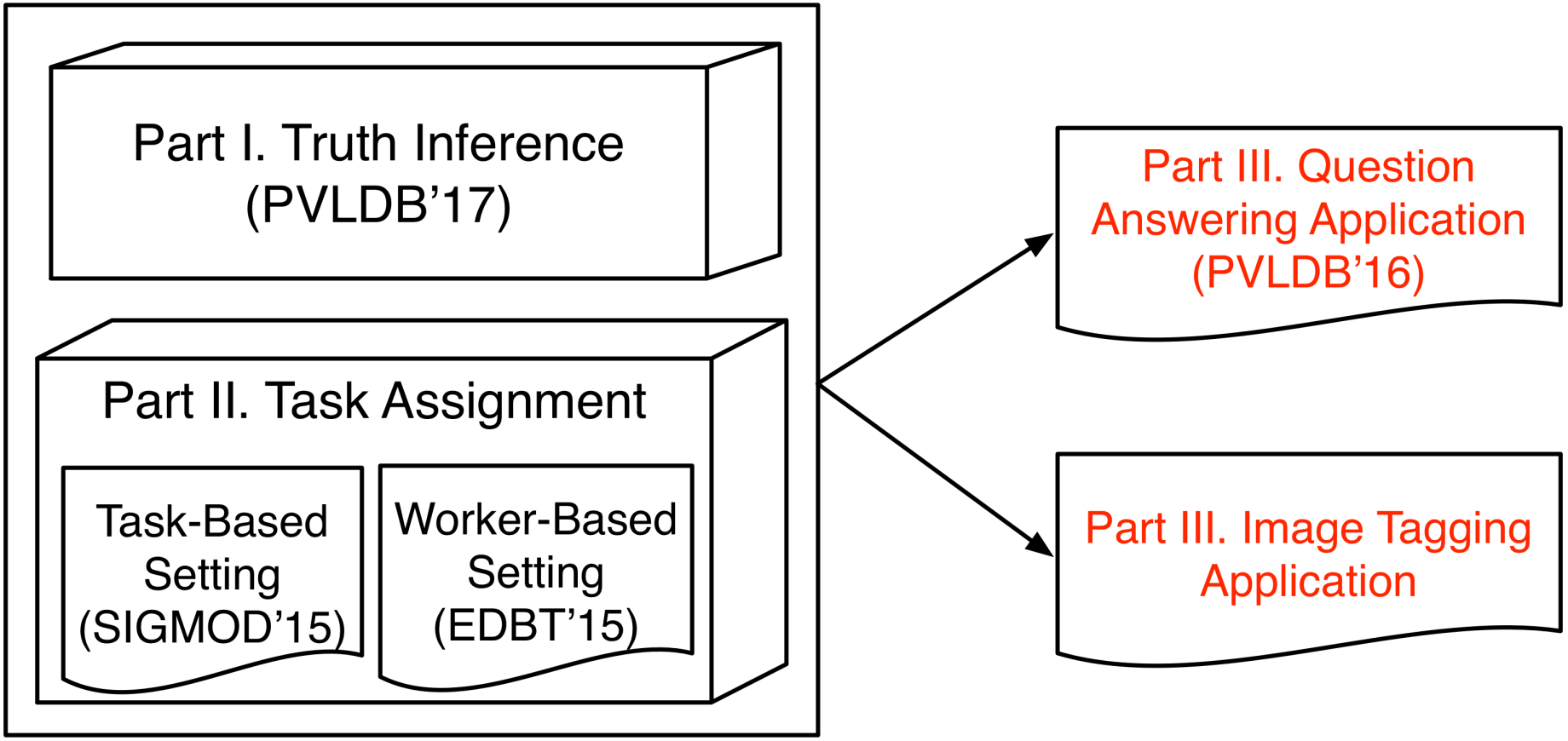
- **Requester** deploys tasks and budget on crowdsourcing platform (e.g., AMT)
- **Workers** interact with platform (**2 phases**)

  Task Assignment: How to assign suitable tasks to appropriate workers?

  Truth Inference: How to aggregate workers' answers and infer the truth of each task?



Overview of the Defense



Outline of the Defense

- **Part I. Truth Inference**
  - **Thorough Analysis and Comparisons (Zheng et al. PVLDB'17)**

- **Part II. Task Assignment**
  - **Task-Based Setting (Zheng et al. SIGMOD'15)**
  - **Worker-Based Setting (Zheng et al. EDBT'15)**

- **Part III. Combinations**
  - **Question-Answering Application (Zheng et al. PVLDB'16)**
  - **Image Tagging Application**

Part I. Truth Inference

- **An Example Task**

Where was ACM SIGMOD 2017 held ?

A. Raleigh 

B. Chicago 

I think
A. Raleigh !

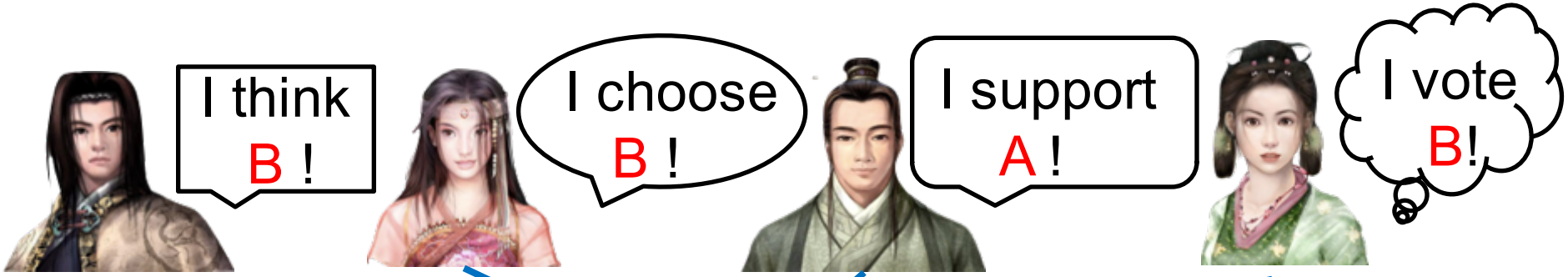
Principle: Redundancy

- **Collect Answers from Multiple Workers**

Where was ACM SIGMOD 2017 held ?

A. Raleigh

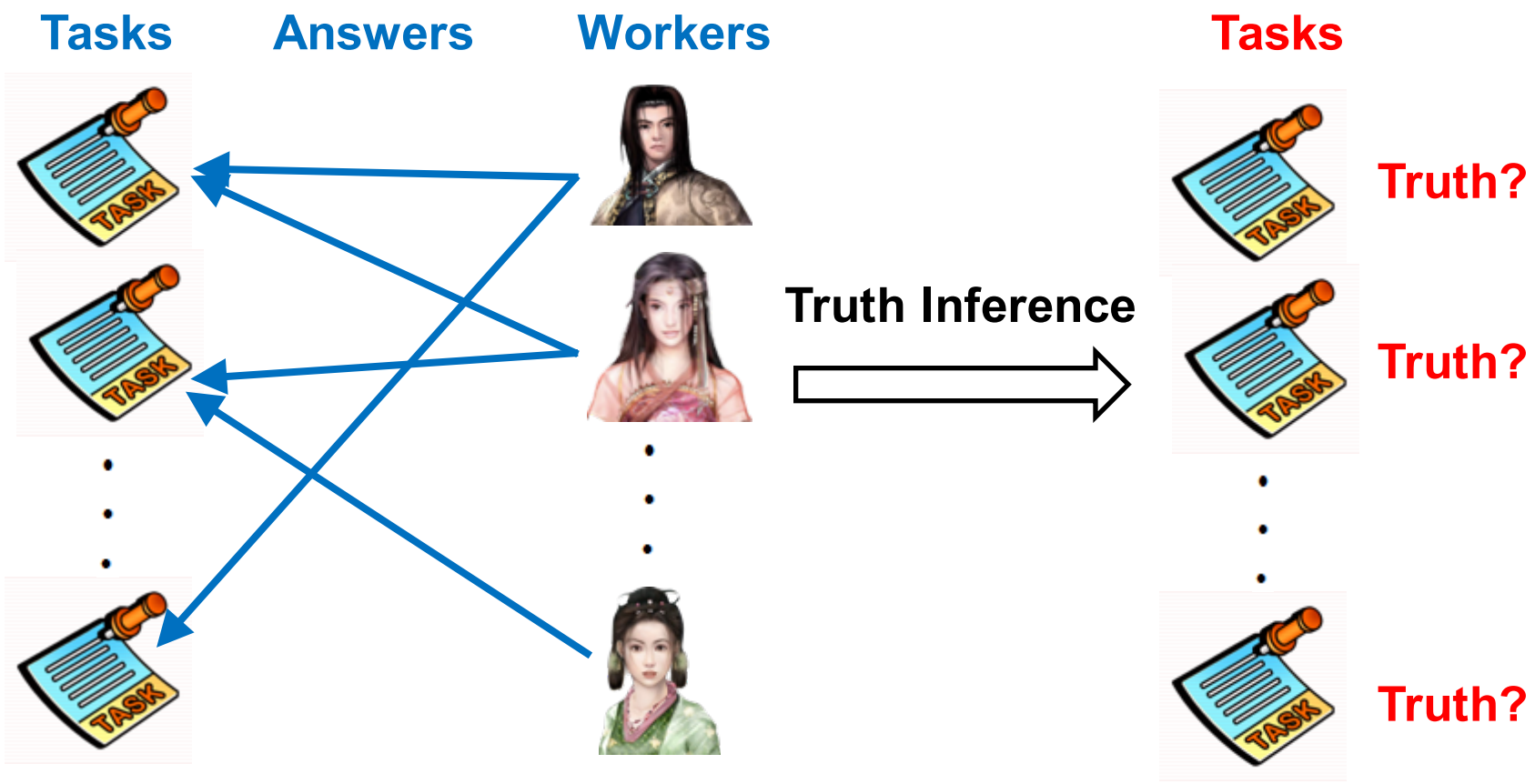
B. Chicago



What is the truth of the task ?

Truth Inference Definition

Given different tasks' answers collected from workers, the target is to infer the truth of each task.



A Simple Solution

- **Majority Voting**

  Take the answer that is voted by the majority (or most) of workers.

- **Limitation**

  Treat each worker equally, neglecting the diverse quality for each worker.

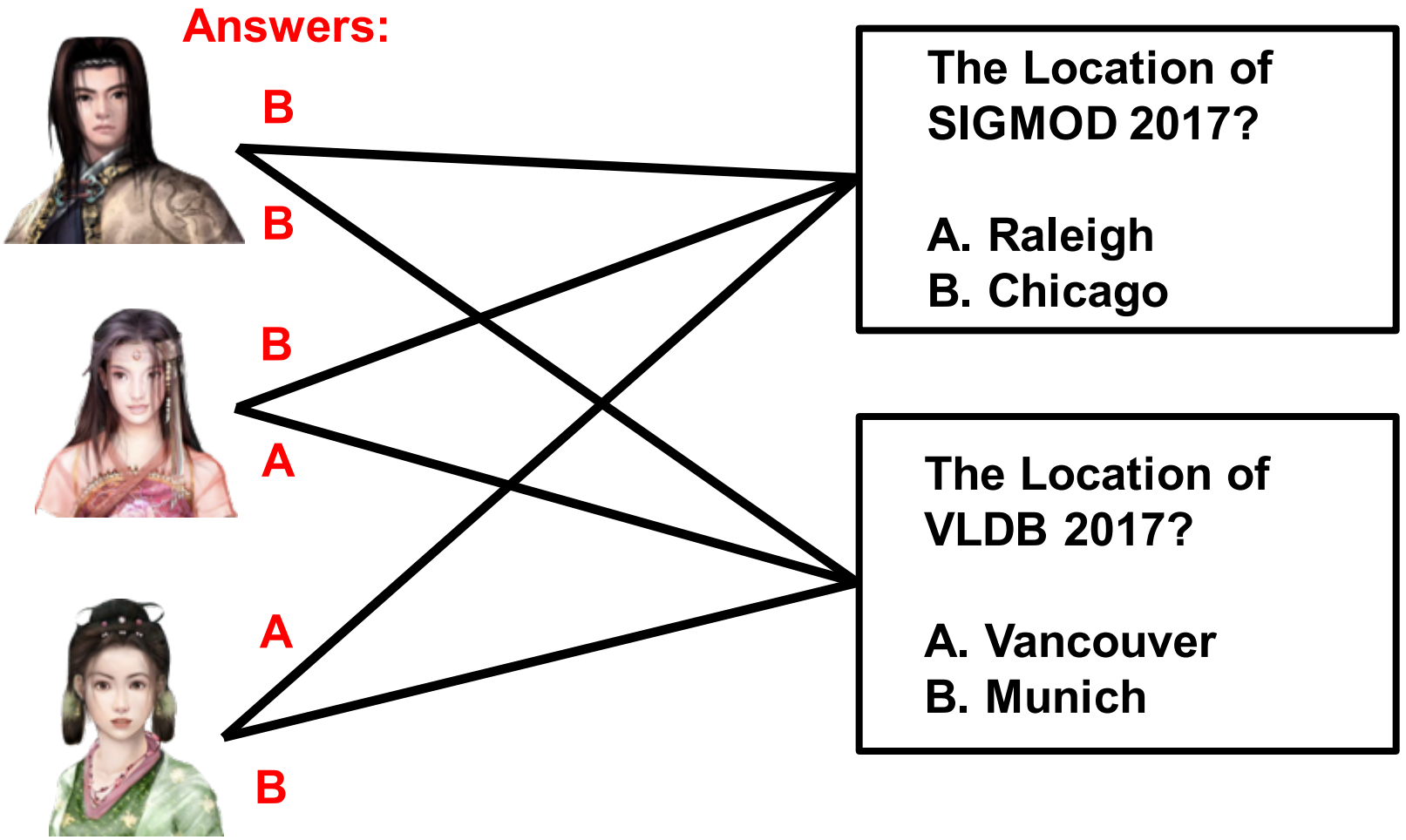
The Key to Truth Inference

- The key is to know **each worker's quality**

Suppose quality of 4 workers are known

How to know worker's quality ?

- Idea: Compute each worker's quality by considering the workers' answers for all tasks



Existing works

- **Classic Method**

D&S [Dawid and Skene. JRSS 1979]

- **Recent Methods**

(1) Machine Learning Community:

GLAD [Whitehill et al. NIPS09], Minimax [Zhou et al. NIPS12], BCC [Kim et al. AISTATS12], LFC [Raykar et al. JLMR10], KOS [Karger et al. NIPS11], VI-BP [Liu et al. NIPS12], VI-MF [Liu et al. NIPS12], LFC_N [Raykar et al. JLMR10]

(2) Database Community:

CATD [Li et al. VLDB14], PM [Li et al. SIGMOD14], iCrowd [Fan et al. SIGMOD15], DOCS [Zheng et al. VLDB17]

(3) Data Mining Community:

ZC [Demartini et al. WWW12], Multi [Welinder et al. NIPS 2010], CBCC [Venanzi et al. WWW14]

Unified Framework in Existing Works (Zheng et al. PVLDB'17)

- **Input:** Workers' answers for all tasks

- **Algorithm Framework:**

Initialize Quality for each worker
While (not converged) {
    Quality for each worker ⇒ Truth for each task ;
    Truth for each task ⇒ Quality for each worker ;
}

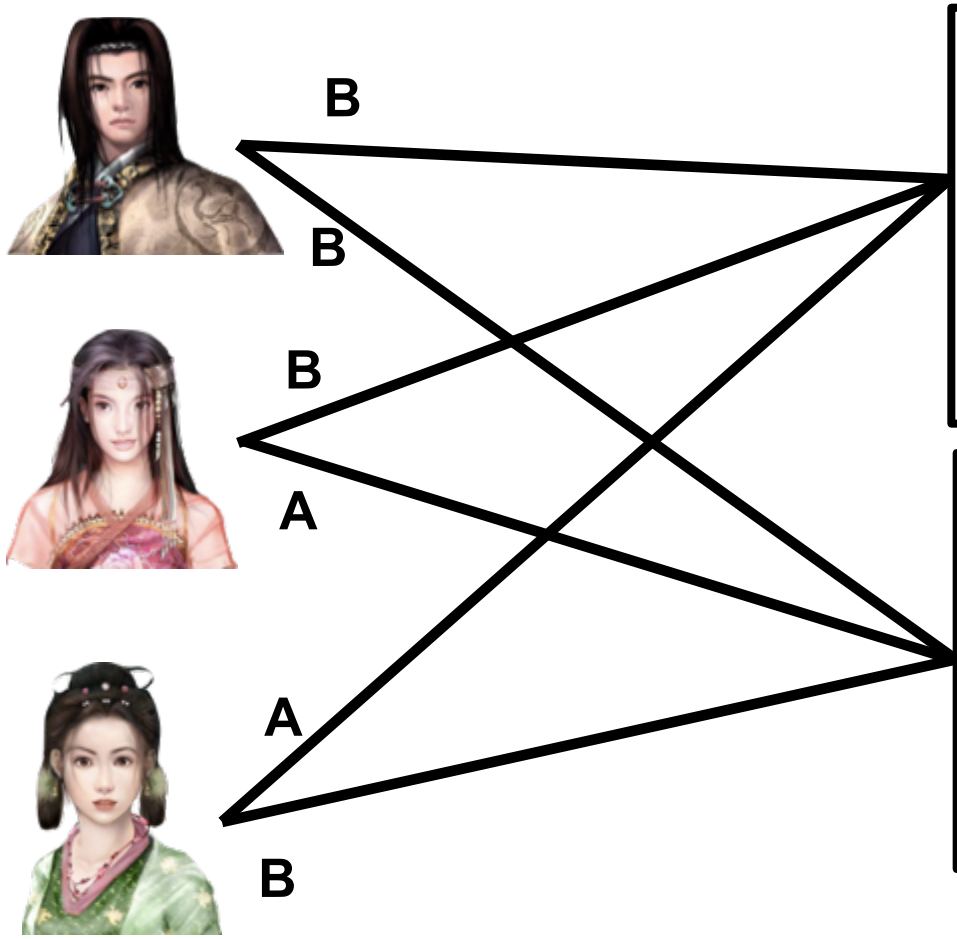
- **Output:** Quality for each worker **and** Truth for each task

Inherent Relationship 1

- 1. Quality for each worker ⟹ Truth for each task

Quality:

(Estimated) Truth:



Location of SIGMOD 2017?

A. Raleigh (1.0 from worker 3)

B. Chicago (1.0 + 1.0 from workers 1 & 2)

Location of VLDB 2017?

A. Vancouver (1.0 from worker 2)

B. Munich (1.0 + 1.0 from workers 1 & 3)

Inherent Relationship 2

- 2. **Truth for each task** ⇒ **Quality for each worker**

(Estimated) Truth:

Location of SIGMOD 2017?

A. Raleigh
B. Chicago

Location of VLDB 2017?

A. Vancouver
B. Munich

Quality:

B
B

1.0

correct: 2/2

B
A

0.5

correct: 1/2

A
B

0.5

correct: 1/2

Differences in Existing works

Tasks

- **Different Task Types**
  - ***What type of tasks they focus on ?***
  - ***E.g., single-label tasks …***

Workers

- **Different Worker Models**
  - ***How they model each worker ?***
  - ***E.g., worker probability (a value) …***

Different Tasks Types

- **Decision-Making Tasks** (yes/no task)

Is Bill Gates currently the CEO of Microsoft ?

O Yes O No

e.g., Demartini et al. WWW12, Whitehill et al. NIPS09, Kim et al. AISTATS12, Venanzi et al. WWW14, Raykar et al. JLMR10

- **Single-Label Tasks** (multiple choices)

Identify the sentiment of the tweet: ……

O Pos O Neu O Neg

e.g., Li et al. VLDB14, Li et al. SIGMOD14, Demartini et al. WWW12, Whitehill et al. NIPS09, Kim et al. AISTATS12

- **Numeric Tasks** (answer with numeric values)

What is the height for Mount Everest ?

[ ] m

e.g., Li et al. VLDB14, Li et al. SIGMOD14

Different Worker Models

- **Worker Probability**: a value $p \in [0,1]$

  The probability that the worker answers tasks correctly
  e.g., a worker answers 8 over 10 tasks correctly, then the worker probability is 0.8.

  e.g., Demartini et al. WWW12, Whitehill et al. NIPS09

- **Confidence Interval**: a range $[p-\varepsilon, p+\varepsilon]$

  ε **is related to the number of tasks answered**
  => the more answers collected, the smaller ε **is.**
  e.g., two workers answer 8 over 10 tasks and 40 over 50 tasks correctly, then the latter worker has a smaller ε.

  e.g., Li et al. VLDB14

Different Worker Models (cont'd)

- **Confusion Matrix**: a matrix

Capture a worker's answer for different choices given a specific truth

	Pos	*Neu*	*Neg*
Pos	0.6	0.2	0.2
Neu	0.3	0.6	0.1
Neg	0.1	0.1	0.8

Given that the truth of a task is "Neu", the probability that the worker answers "Pos" is 0.3.

e.g., Kim et al. AISTATS12, Venanzi et al. WWW14

- **Bias τ & Variance σ : numerical task**

Answer follows Gaussian distribution: $ans \sim N(t+\tau, \sigma)$

e.g., Raykar et al. JLMR10

Summary of Truth Inference Methods

Method	Task Type	Worker Model
Majority Voting	Decision-Making Task, Single-Choice Task	No
Mean / Median	Numeric Task	No
ZC [Demartini et al. WWW12]	Decision-Making Task, Single-Choice Task	Worker Probability
GLAD [Whitehill et al. NIPS09]	Decision-Making Task, Single-Choice Task	Worker Probability
D&S [Dawid and Skene. JRSS 1979]	Decision-Making Task, Single-Choice Task	Confusion Matrix
Minimax [Zhou et al. NIPS12]	Decision-Making Task, Single-Choice Task	Confusion Matrix
BCC [Kim et al. AISTATS12]	Decision-Making Task, Single-Choice Task	Confusion Matrix
CBCC [Venanzi et al. WWW14]	Decision-Making Task, Single-Choice Task	Confusion Matrix
LFC [Raykar et al. JLMR10]	Decision-Making Task, Single-Choice Task	Confusion Matrix

Summary of Truth Inference Methods (cont'd)

Method	Task Type	Worker Model
PM [Li et al. SIGMOD14]	Decision-Making Task, Single-Choice Task, Numeric Task	Worker Probability
Multi [Welinder et al. NIPS 2010]	Decision-Making Task	Worker Bias, Worker Variance
KOS [Karger et al. NIPS11]	Decision-Making Task	Worker Probability
VI-BP [Liu et al. NIPS12]	Decision-Making Task	Confusion Matrix
VI-MF [Liu et al. NIPS12]	Decision-Making Task	Confusion Matrix
LFC_N [Raykar et al. JLMR10]	Numeric Task	Worker Variance
CATD [Li et al. VLDB14]	Decision-Making Task, Single-Choice Task, Numeric Task	Worker Probability, Confidence

Which method is the best ?

- "Majority Voting" if sufficient data is given (each task collects more than 20 answers);
- "D&S [Dawid and Skene JRSS 1979]" if limited data is given (a robust method);
- "Minimax [Zhou et al. NIPS12]" and "Multi [Welinder et al. NIPS 2010]" as advanced techniques.

Summary of Truth Inference (Zheng et al. PVLDB'17)

- **Detailed analysis over 17 existing truth inference methods**
- **Unified truth inference framework**
- **Comparisons over existing works (task model & worker model)**
- **Experimental analysis and open-source codes (http://i.cs.hku.hk/~ydzheng2/crowd_truth_inference/index.html)**

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Part II. Task Assignment

- Requester deploys tasks and budget on crowdsourcing platform (e.g., Amazon Mechanical Turk)
- Workers interact with platform (2 phases)

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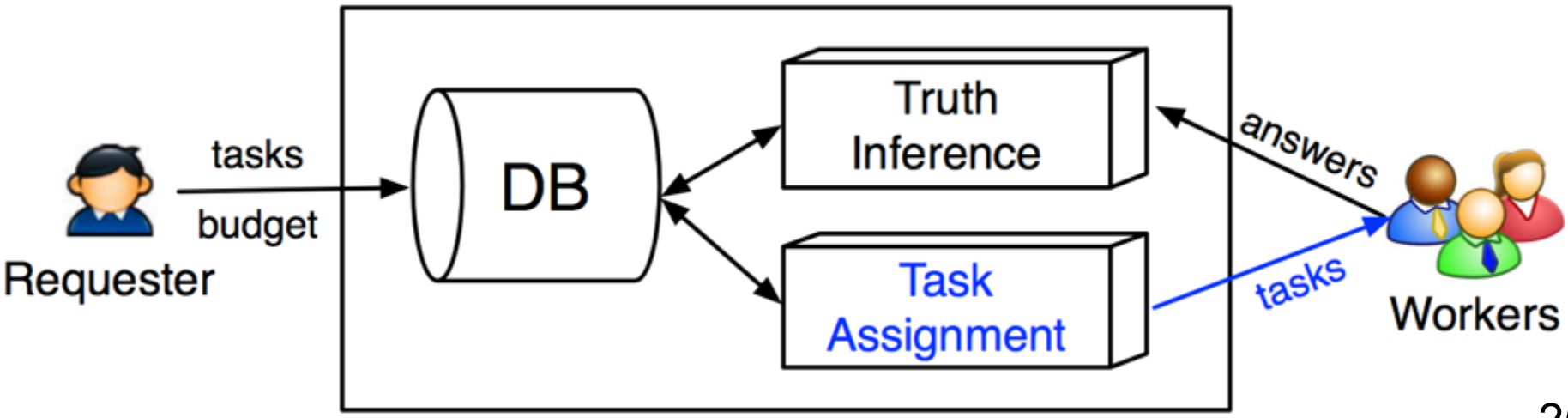
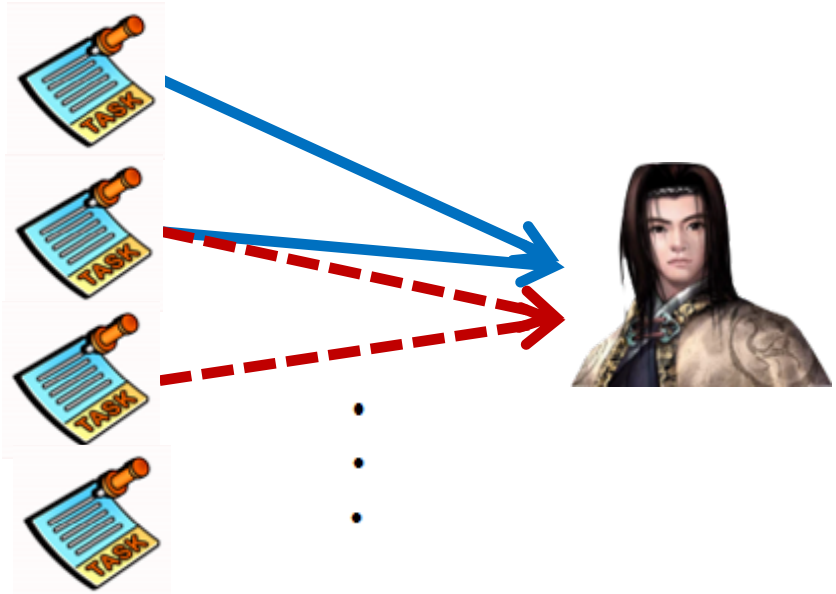
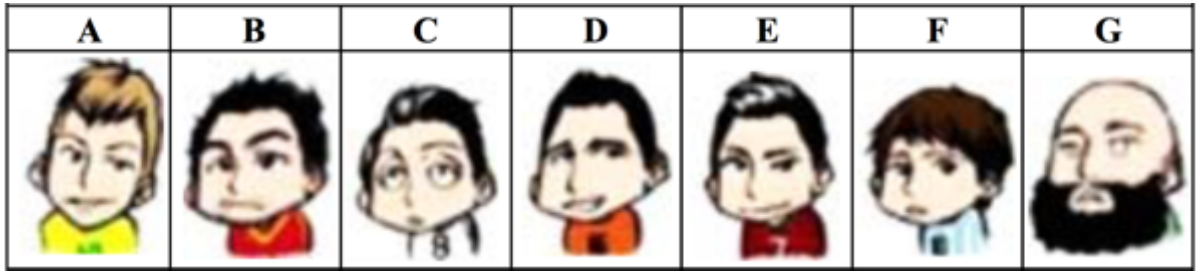


Various Settings in Task Assignment

- (1) **Task-Based Setting**: Given n tasks, select a set of the k tasks and assign to the coming worker.



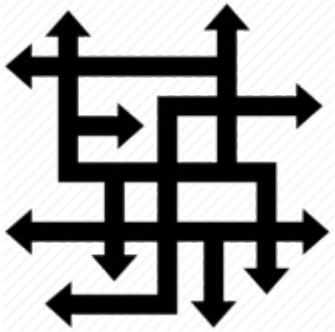
- (2) **Worker-Based Setting**: Given a set of workers, select a subset of workers, such that the task can be completed successfully and economically.



(1) Task-Based Setting

- Simple enumeration considers "n choose k" combinations

  (n = 100, k = 5) ➔ 100M combinations of possible assignments



- Require efficient (online) assignment

  Workers need fast response

- Can we develop efficient heuristics?

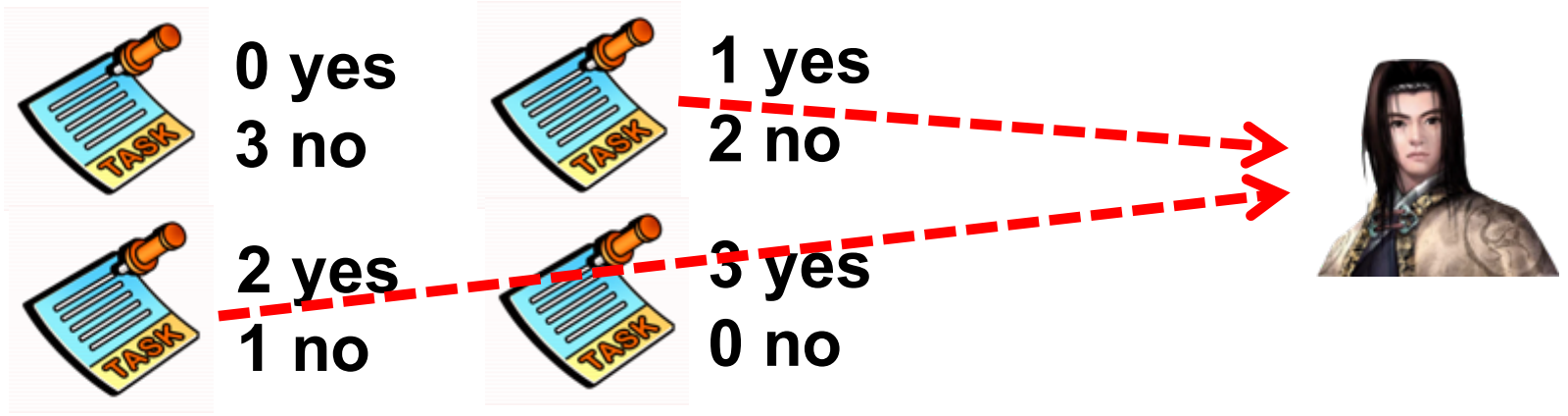
  Assignment time linear in #tasks: O(n)

Existing Works

- Intuition: Consider consistency in the collected answers for each task

  e.g., Liu et al. VLDB12, Roim et al. ICDE12

- Consider Decision-Making Task (yes/no)

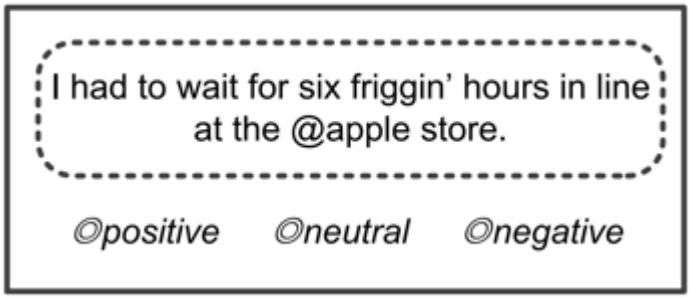
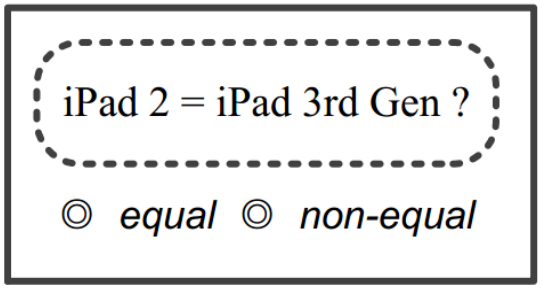


- Limitation: Miss an important factor

  How is the quality defined by an application?

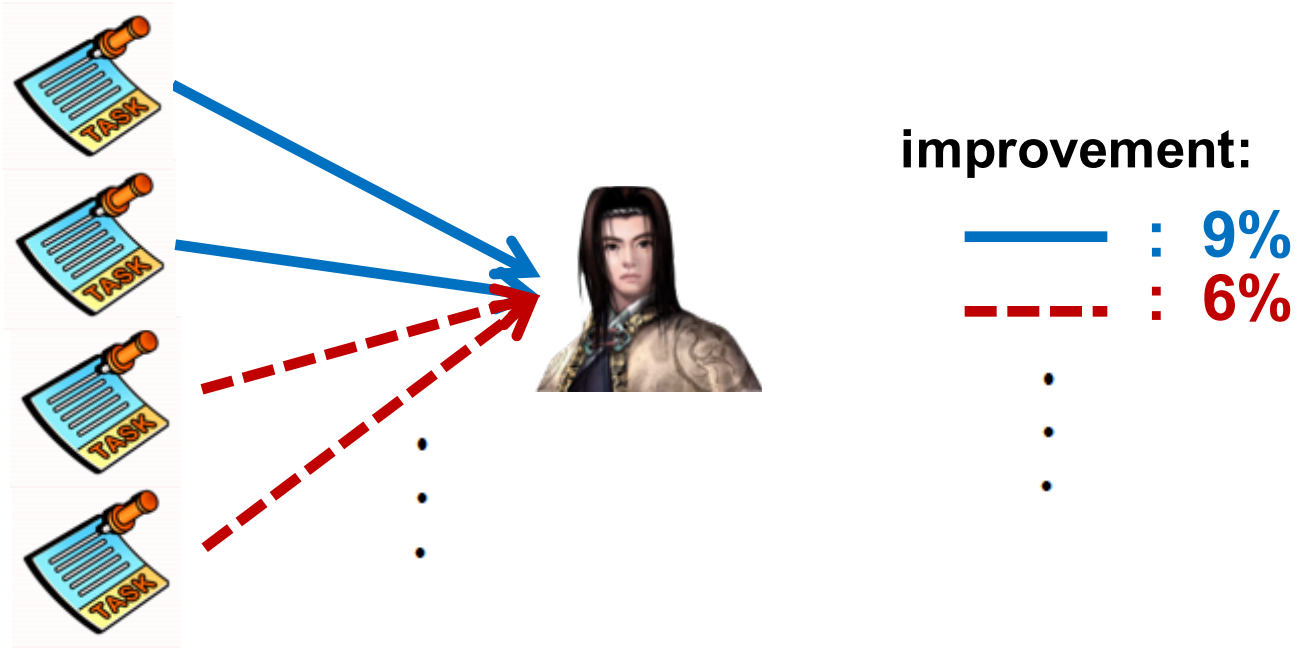
Quality Aware Task Assignment (Zheng et al. SIGMOD'15)

- Different applications may have different qualities (aka "evaluation metric") to optimize

Application	Sentiment Analysis	Entity Resolution
Task		
Evaluation Metric	Accuracy	F-score ("equal" label)

Our Ideas

- Select the best set of tasks with highest quality improvement in the specified evaluation metric.



- Challenges:
  (1) how to estimate the quality improvement for each set of tasks;
  (2) how to efficiently select the optimal set of tasks.

Solutions to Challenge 1: Quality Estimation

- **Solution Framework**

  (1) Leverage the answers collected from workers to create a "distribution matrix";

	Yes	No
Task 1	0.8	0.2
Task 2	0.6	0.4

In the first task, the probability that the first label to be the truth is 80%.

(2) Compute the quality of "distribution matrix", i.e., the highest expected quality w.r.t. an evaluation metric;

Estimated Truth: Task 1: Yes Task 2: Yes

Ground Truth	Probability	Accuracy
Yes, Yes	0.8 * 0.6 = 0.48	100%
Yes, No	0.8 * 0.4 = 0.32	50%
No, Yes	0.2 * 0.6 = 0.12	50%
No, No	0.2 * 0.4 = 0.08	0%

100% * 0.48 + 50% * 0.32 + 50% * 0.12 + 0% * 0.08 = 70%

(3) Estimate the quality improvement of "distribution matrix" for each set of tasks.

Solutions to Challenge 2: Efficient Selection

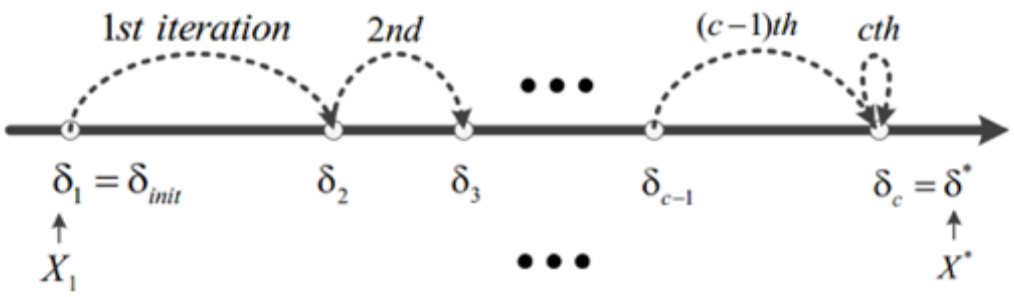
- Focus on 2 evaluation metrics

(1) Accuracy:

Define the benefit of assigning each task;
Choose the task with the highest benefit.

(2) F-score:

Iterative approach (prove that local optimum is global optimum).



The assignment iteratively improves until convergence (global optimal).

Reduce the complexity from $O\left(\binom{n}{k} \cdot n\right)$ to $O(n)$.

Summary of Task-based Assignment (Zheng et al. SIGMOD'15)

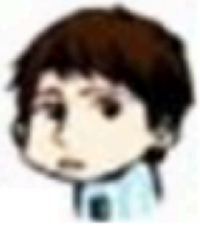
- Consider evaluation metric (Accuracy, F-score) into task assignment
- Use distribution matrix to estimate the quality of improvement
- Devise solutions to select tasks efficiently
- Open-source the task assignment framework (http://i.cs.hku.hk/~ydzheng2/crowd_task_assignment/index.html)

(2) Worker-Based Setting

- **Jury Selection Problem (Cao et al. PVLDB'12)**

Input: (1) A fixed **budget** (e.g., $20);

(2) A set of **workers** (with quality and budget):

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)

- **Goal: Select a subset of workers (called "Jury") such that the Quality of Jury (called "Jury Quality") is maximized and the overall cost <= the budget.**

B	C	D
		
(0.7, $5)	(0.65, $7)	(0.6, $5)

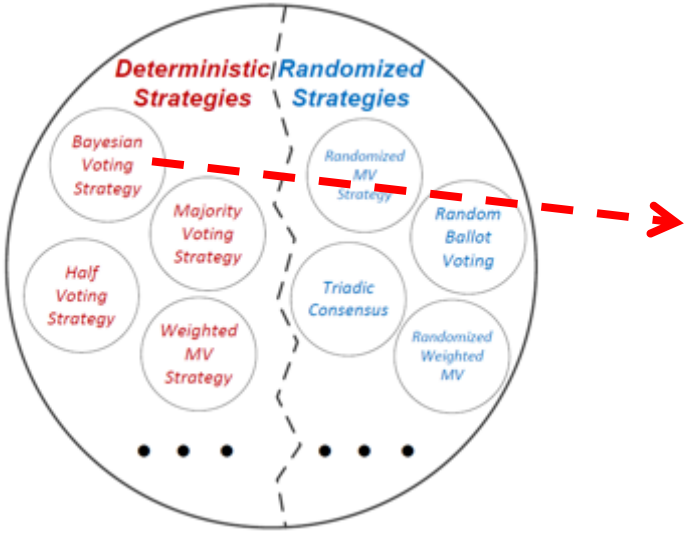
(1) Overall Cost: $5+$7+$5=$18 (<$20);
(2) Jury Quality: JQ({0.7, 0.65, 0.2}).

Jury Quality Computation

- **Jury Quality** in [Cao et al. PVLDB'12]

  JQ({0.7,0.65,0.2}, **Majority Voting**):
  "at least 2 workers answer correctly", i.e.,
  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 Quality** in [Zheng et al. EDBT'15]



"Bayesian Voting"
is Optimal
in Jury Selection Problem!

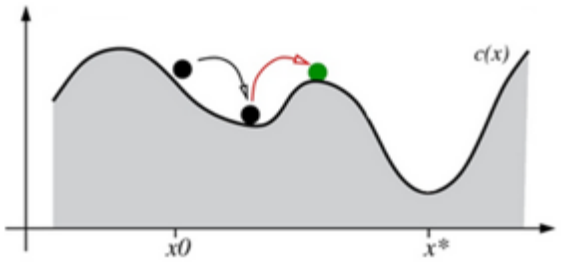
Challenges & Solutions

- **Challenge 1: Computing Optimal Jury Quality (w.r.t. Bayesian Voting) is NP-Hard !**

⇨ **Bucket-Based Approximation Algorithm (Approximation Error within 1% in Polynomial Time)**

- **Challenge 2: Selecting the Best Set of Workers is NP-Hard !**

⇨ **Make use of Simulated Annealing Heuristic which avoids local optimal**



Summary of Worker-based Assignment (Zheng et al. EDBT'15)

- **Define the optimality of "Jury Selection Problem" [Cao et al. PVLDB'12]**
- **Approximate solutions to optimal jury quality estimation (NP-hard)**
- **Heuristic solutions to the optimal jury selection problem (NP-hard)**

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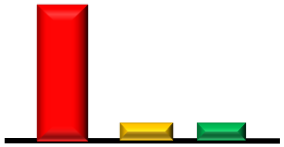
Part III. Question Answering Application (Zheng et al. PVLDB'16)

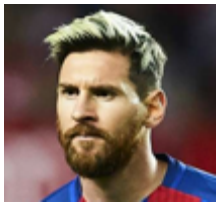
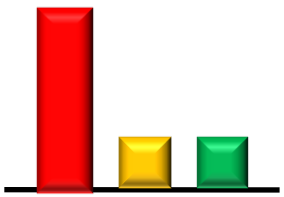
- **Existing methods fail in QA-based tasks**
- **Deeper Analysis in QA-based tasks**

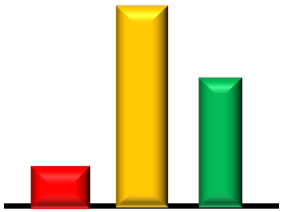
  (1) each task is related to different domains

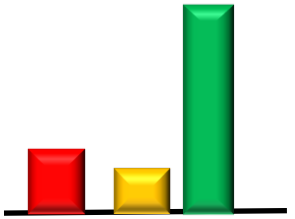
Sports Politics Entertainment

Did Michael Jordan win more NBA championships than Kobe Bryant?	→ Sports	
Is there a name for the song that FC Barcelona is known for?	→ Sports & Entertainment	

(2) each worker has diverse qualities over domains

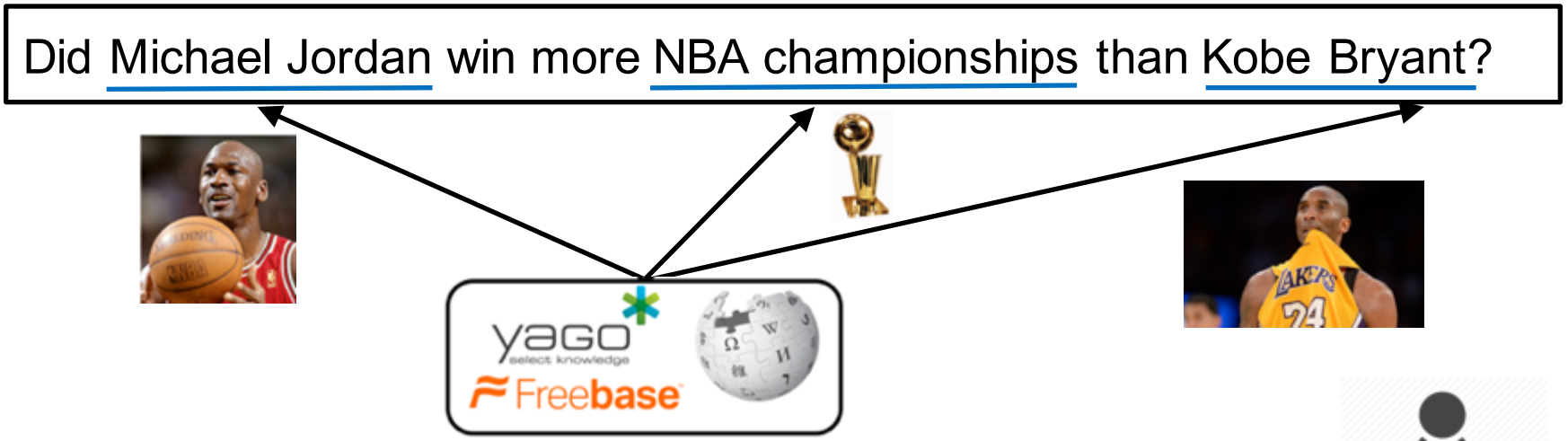







Domain Aware Task Model

- (1) **Entity linking** (map entity to **knowledge bases**)



- (2) **Hierarchical domains in knowledge bases**

- (3) **Obtain the task model (a vector of distribution) for each task**

Sports Politics Entertainment

Did Michael Jordan win more NBA championships than Kobe Bryant?

Domain Aware Worker Model

- **Initialize the model (vector) for a worker**
  Use qualification test (like an "exam") amazonmechanical turk Artificial Artificial Intelligence
  i.e., assign the tasks (with known truth) to the worker when the worker comes at first time

- **Two rules for selecting qualification test**
  (1) each selected task should capture a certain domain

Did Michael Jordan win more NBA championships than Kobe Bryant?	**Good: only related to one domain (sports)**
Is there a name for the song that FC Barcelona is known for?	**Bad: related to multiple domains (both sports & entertainment)**

(2) The domain distribution of selected tasks should approximate the distribution of all tasks

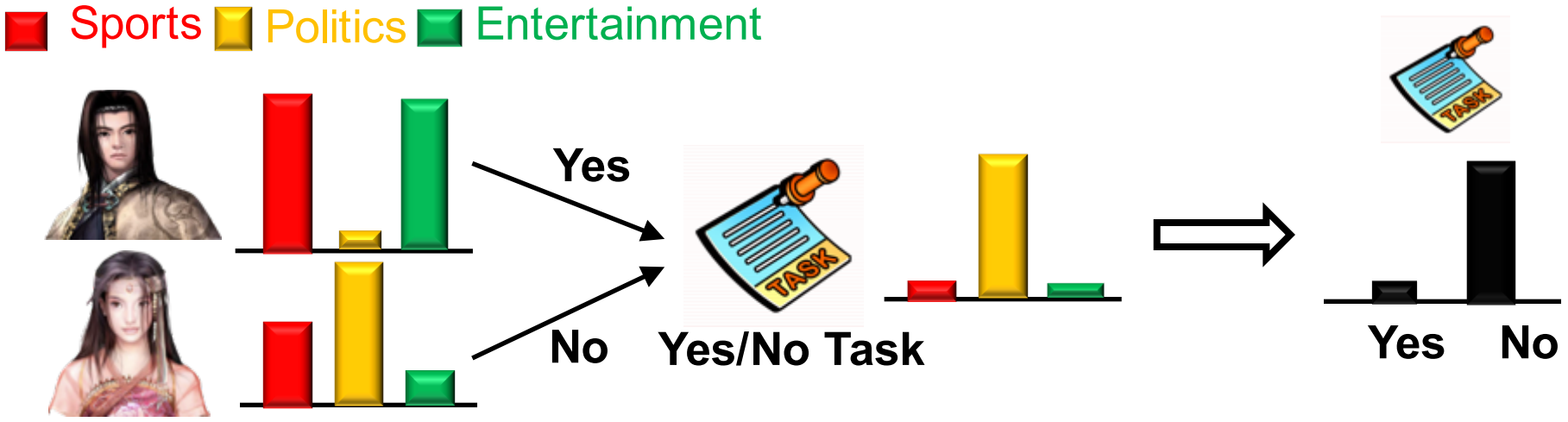
KL-divergence

$$\min_{\{n'_k\}} \sum_{k=1}^{m} \frac{n'_k}{n'} \cdot \ln \frac{n'_k \cdot n}{n' \cdot \sum_{i=1}^{n} r_k^{t_i}}$$

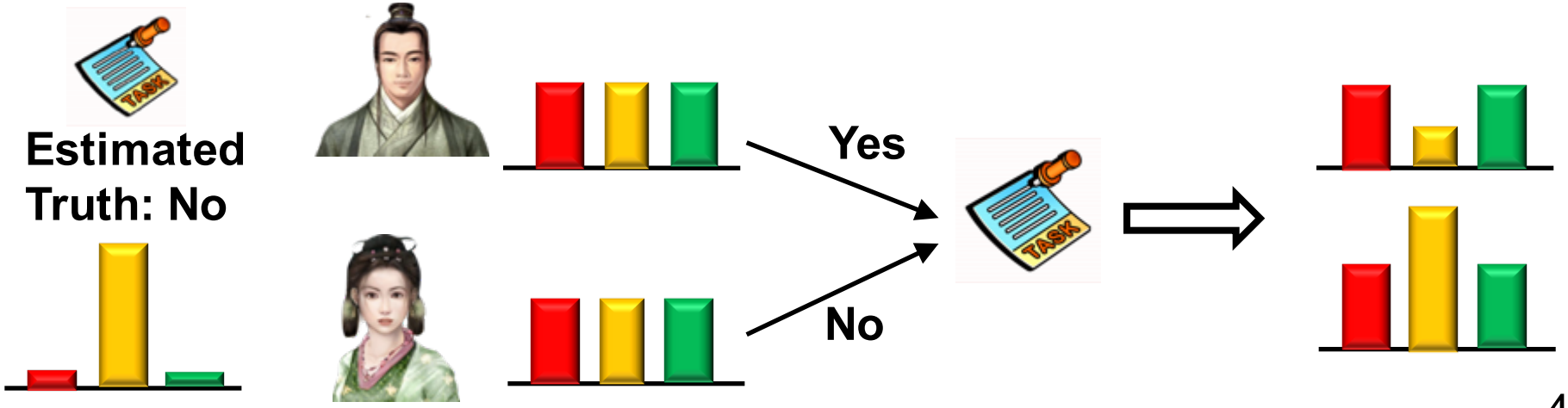
$$\text{s.t.} \sum_{k=1}^{m} n'_k = n' \text{ and } n'_k \in \mathbb{N} \text{ for } 1 \le k \le m.$$

Truth Inference

- **1. Quality for each worker ⇒ Truth for each task**



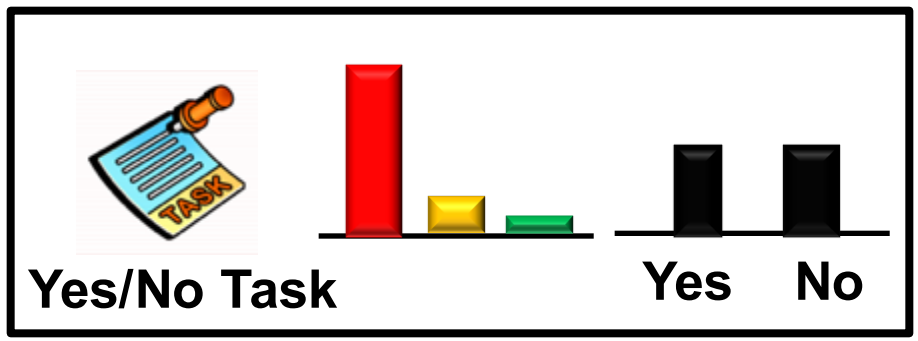
- **2. Truth for each task ⇒ Quality for each worker**

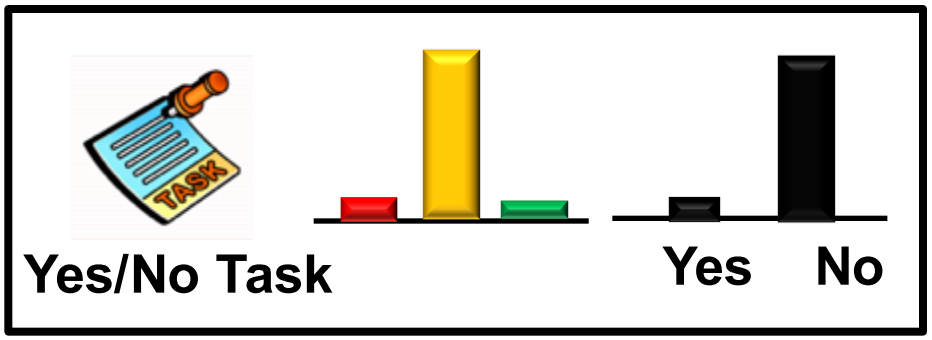


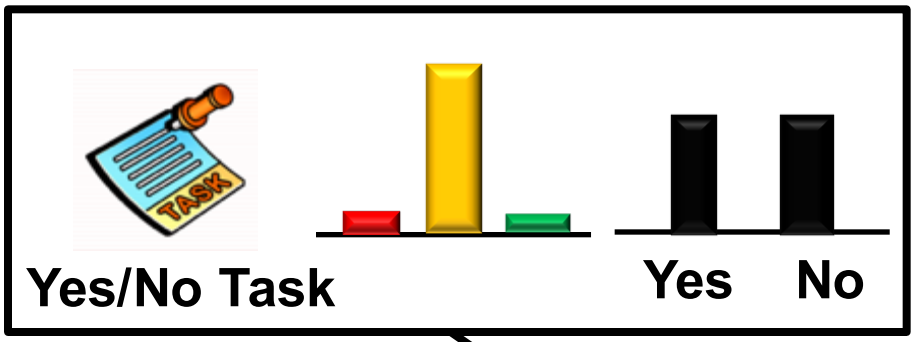
Task Assignment

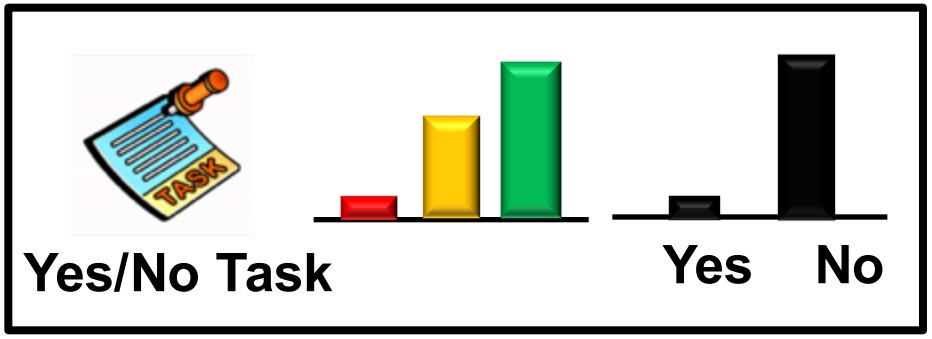
- **Select the most suitable tasks for assignment**

Sports Politics Entertainment









(1) Matching Domains

(2) Answer Uncertainty

Summary of Domain Aware Crowdsourcing (Zheng et al. PVLDB'16)

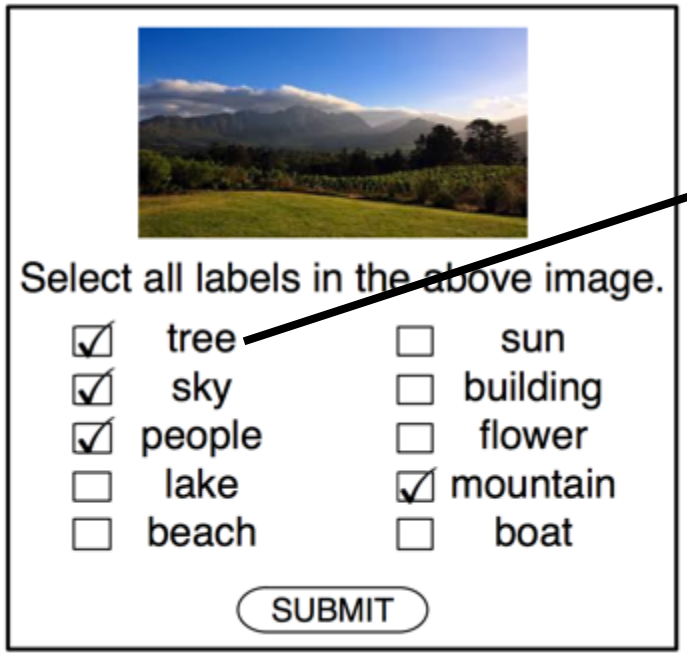
- Consider the domain aware task model and worker model
- Design solutions to accurately estimate the task model and worker model
- Incorporate task model and worker model in truth inference and task assignment

Outline of the Defense

- **Part I. Truth Inference**
  - **Thorough Analysis and Comparisons (Zheng et al. PVLDB'17)**
- **Part II. Task Assignment**
  - **Task-Based Setting (Zheng et al. SIGMOD'15)**
  - **Worker-Based Setting (Zheng et al. EDBT'15)**
- **Part III. Combinations**
  - **Question-Answering Application (Zheng et al. PVLDB'16)**
  - **Image Tagging Application**

Part III. Image Tagging Application

- **Multi-Label Tasks**



Decomposition:

Is "tree" a label in the above image ?
YES **NO**

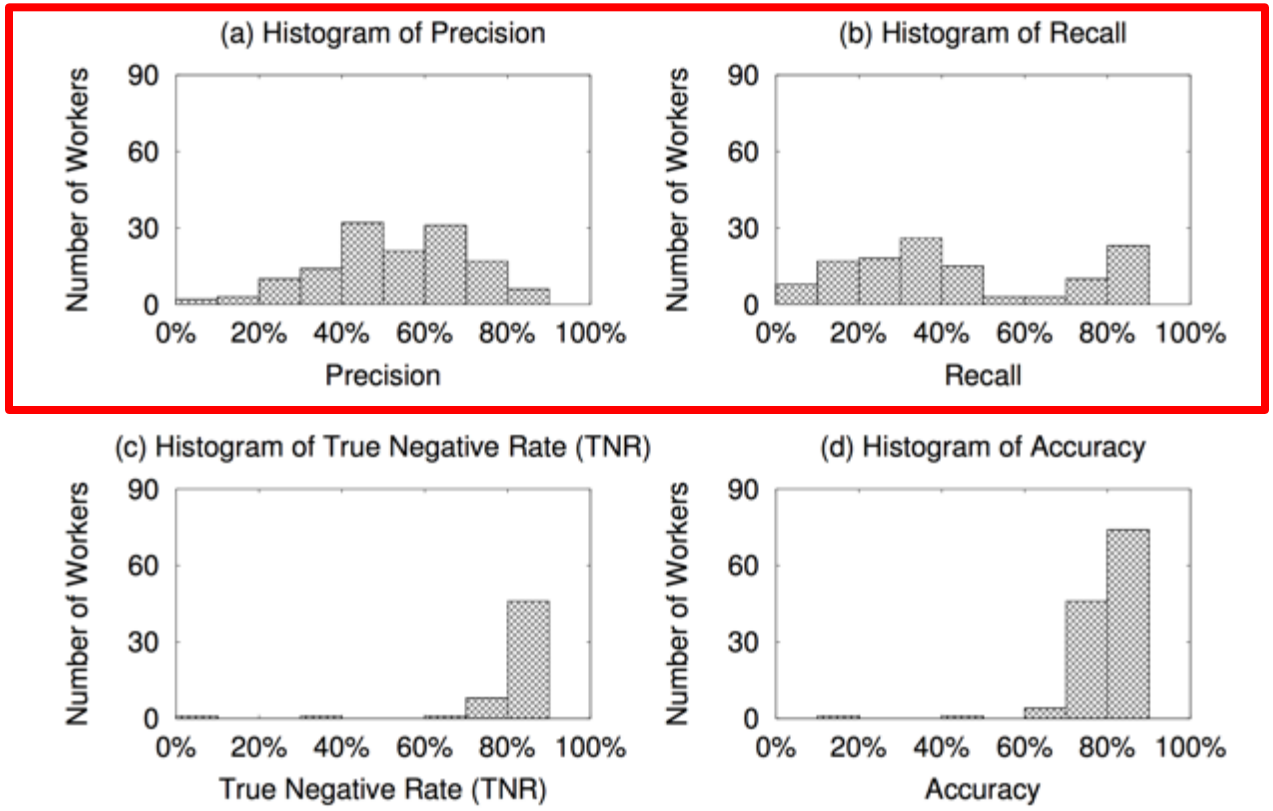
•
•
•

10 tasks

- **Naïve Solution: Multi-Label Tasks will enable six times of improvement in terms of human computation time, without sacrificing much quality. (J. Deng et al. SIGCHI'14)**

Ideas in Our Solutions

- **Worker Quality (Precision, Recall)**



- **Correlation in Labels**

e.g., If "sun" is a correct label, then the probability of "sky" is a correct label is very high.

Summary of Multi-Label Crowdsourcing

- **Design an effective worker model in answering multi-label tasks**
- **Consider label correlations in multi-label tasks**
- **Incorporate worker model and label correlations in truth inference and task assignment**

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Future Work: Scalability

- **Hard to Scale in Crowdsourcing: Tackle the 3Vs of Big Data?**

- **Existing works focus on specific problems, e.g., active learning [Mozafari et al. PVLDB'14], entity matching [Gokhale et al. SIGMOD'14].**

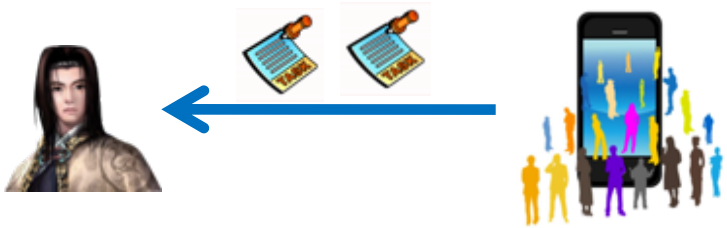
Future Work: Privacy

- (1) Requester wants to protect the privacy of their tasks from workers
  e.g., tasks may contain sensitive attributes, e.g., medical data.

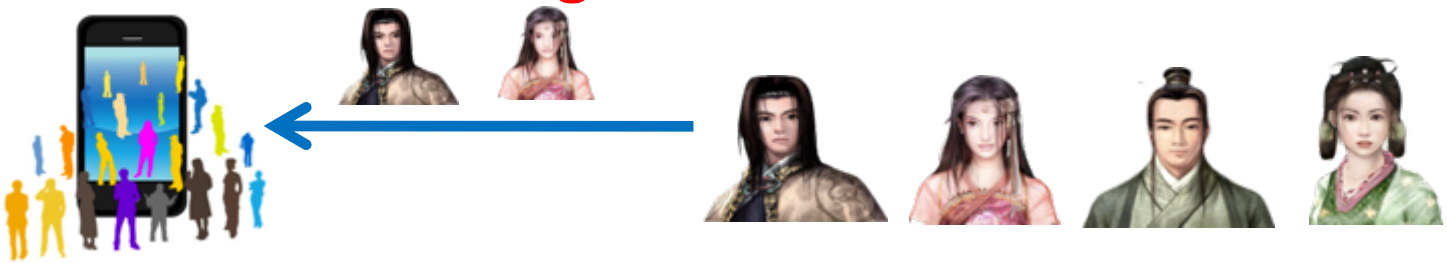
- (2) Workers wants to have privacy-preserving requirement & worker profile
  e.g., personal info of workers can be inferred from the worker's answers, e.g., location, gender, etc.

Future Work: Mobile Crowdsourcing

- Emerging mobile crowdsourcing platforms
  e.g., gMission (HKUST), ChinaCrowd (Tsinghua)
- Challenges
  (1) Other factors (e.g., spatial distance, mobile user interface) affect workers' latency and quality;
- (2) Different mechanisms
  traditional crowdsourcing platforms: workers request tasks from the platform;



for mobile crowdsourcing platform: only workers close to the crowdsourcing task can be selected.

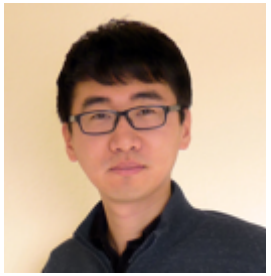


Brief Summary for Me

- Crowdsourcing and Other Projects
- Publish Over 10 Papers in Distinguished Venues

- Tutorial on Crowdsourcing (SIGMOD 2017)
- Research Internships

Thanks for all the collaborators !













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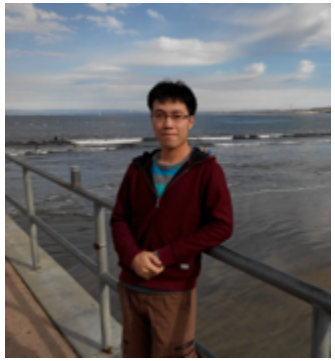
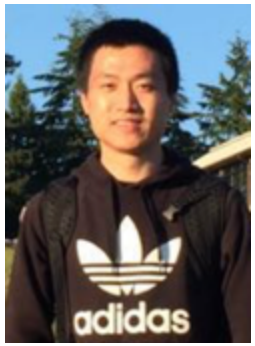
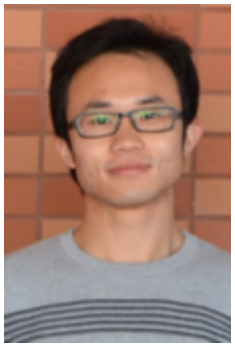
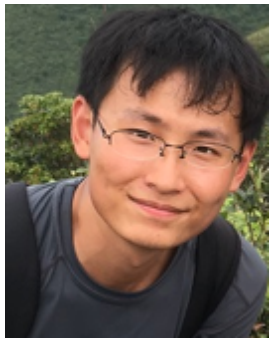
Thanks for the lab mates !

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