Human-Powered Database Operations: Part 1

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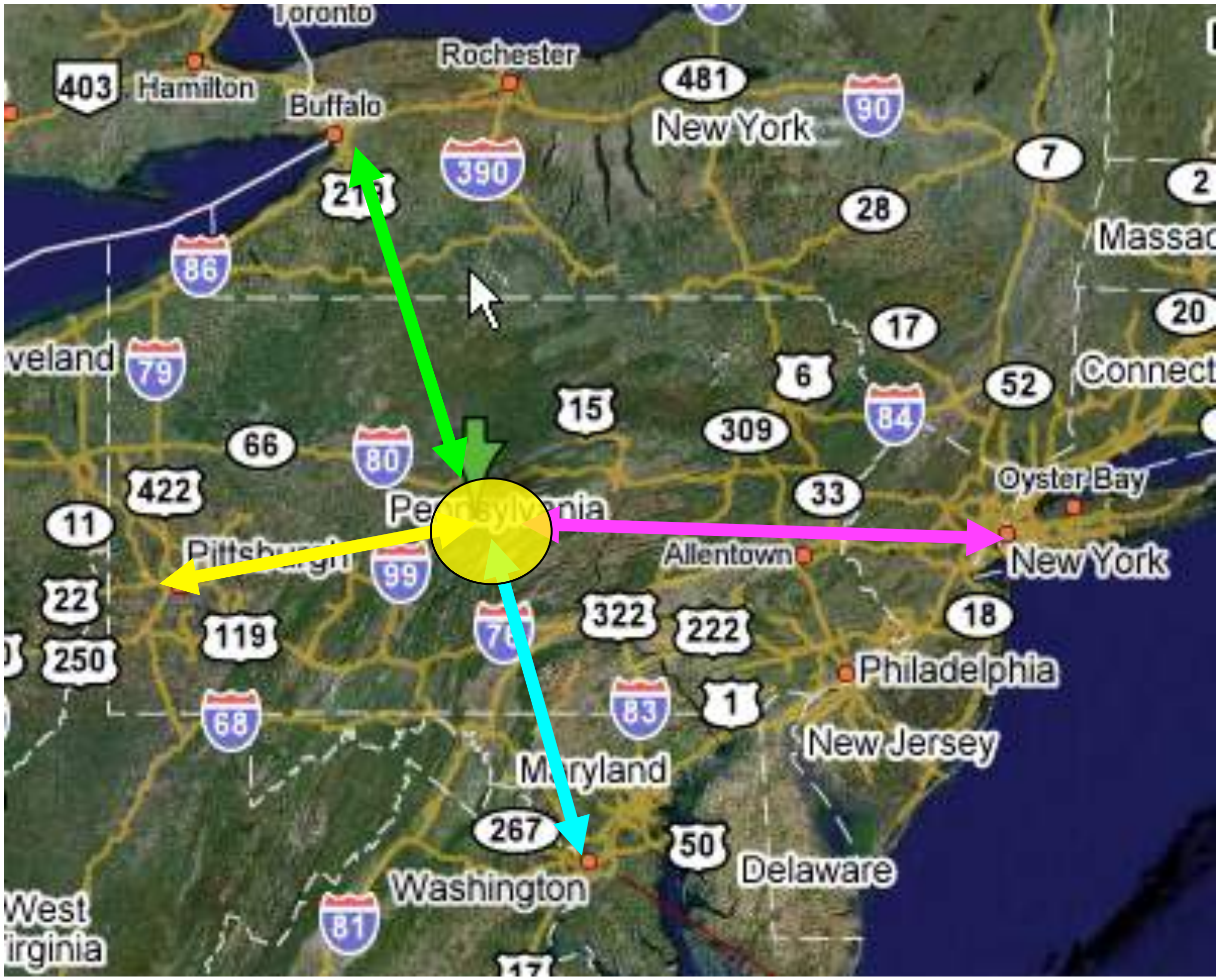
Slide available @ **http://goo.gl/4pNUhB**

SBBD 2014 Tutorial

Where Am I From?

Penn State University



- State College, PA
  - Out of nowhere, but close to everywhere
- West: 2.5 hours to **Pittsburgh**
- East: 4 hours to **New York**
- South: 3 hours to **Washington DC**
- North: 3 hours to **Niagara Fall**

Penn State *i*-School

- College of Information Sciences and Technology (IST)
  - http://ist.psu.edu/
- 40+ tenure-track faculty on diverse areas
  - CompSci & EE
  - MIS & LIS
  - Design
  - Law
  - Psychology
  - Medical Infomatics

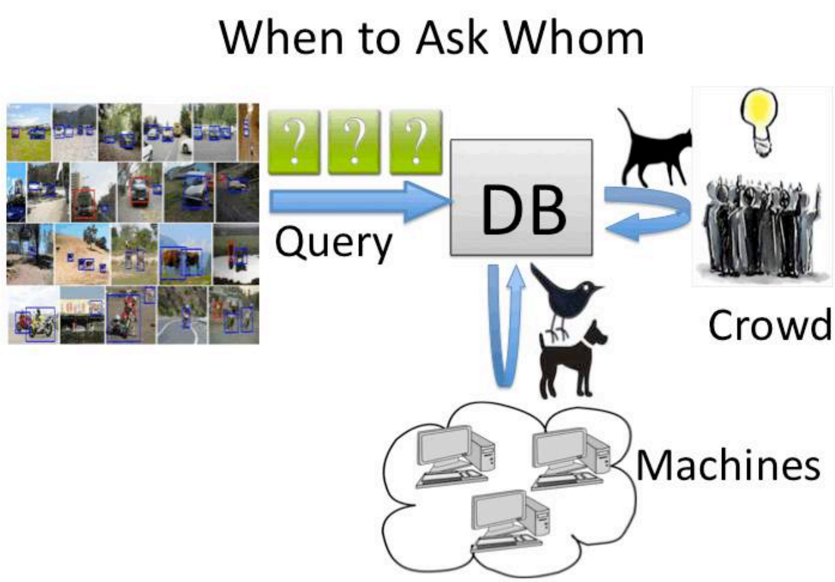
Other Tutorials on Crowdsourcing

Year	Sub-field	Venue	Title
2013	Crowdsourcing	SDM	Crowdsourcing & Human Computation
2013	Crowdsourcing	HCOMP	Incentives in Human Computation
2012	HCI	AAAI	Crowdsourcing using MTurk for HCI Research
2012	Crowdsourcing	SBP	Crowdsourcing, Human Computation, and Collective Intelligence
2012	IR	SIGIR	Human Computation and Crowdsourcing
2012	DB	SIGMOD	Designing a Scalable Crowdsourcing Platform
2011	Crowdsourcing	AAAI	Human Computation: Core Research Questions and State of the Art
2011	IR	CLEF	Crowdsourcing for IR Experimentation and Evaluation
2011	ML	ICML	Collective Intelligence and Machine Learning
2011	Social Science	EC	Conducting Behavioral Research using AMT
2011	Multimedia	MM	Frontiers in Multimedia Search
2011	DB	VLDB	Crowdsourcing Application and Platforms
2011	Crowdsourcing	WWW	Managing Crowdsourced Human Computation
2010	Vision	CVPR	Mechanical Turk for Computer Vision
2008	IR	CIKM	Crowdsourcing for Relevance Evaluation

The Focus of This Tutorial

- Part 1 on basics of crowdsourcing

- Part 2 on DB operations that exploit crowdsourcing



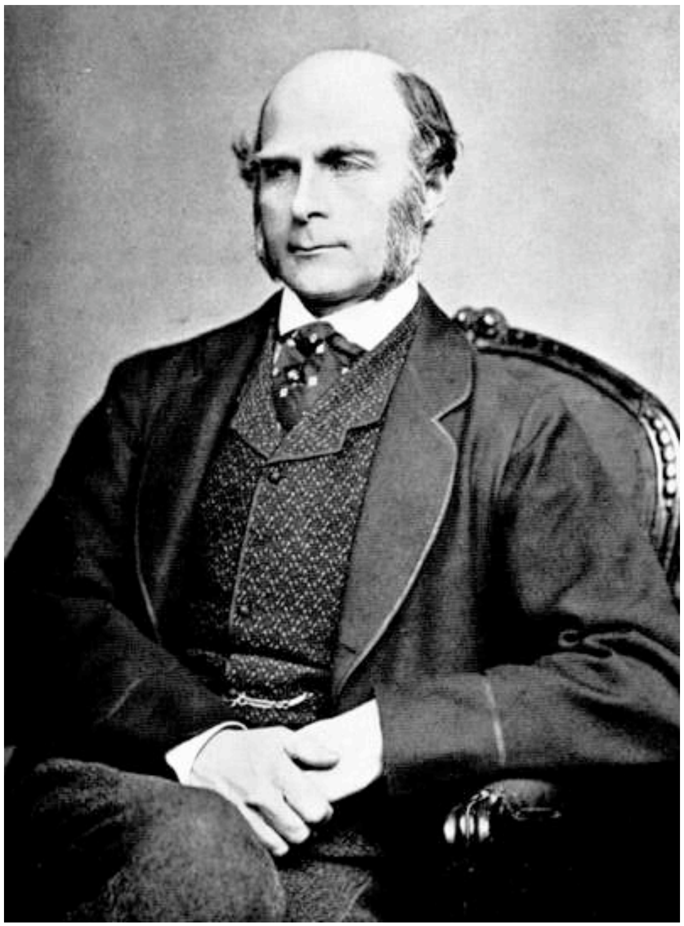
http://istc-bigdata.org/index.php/crowdsourcing-big-data/

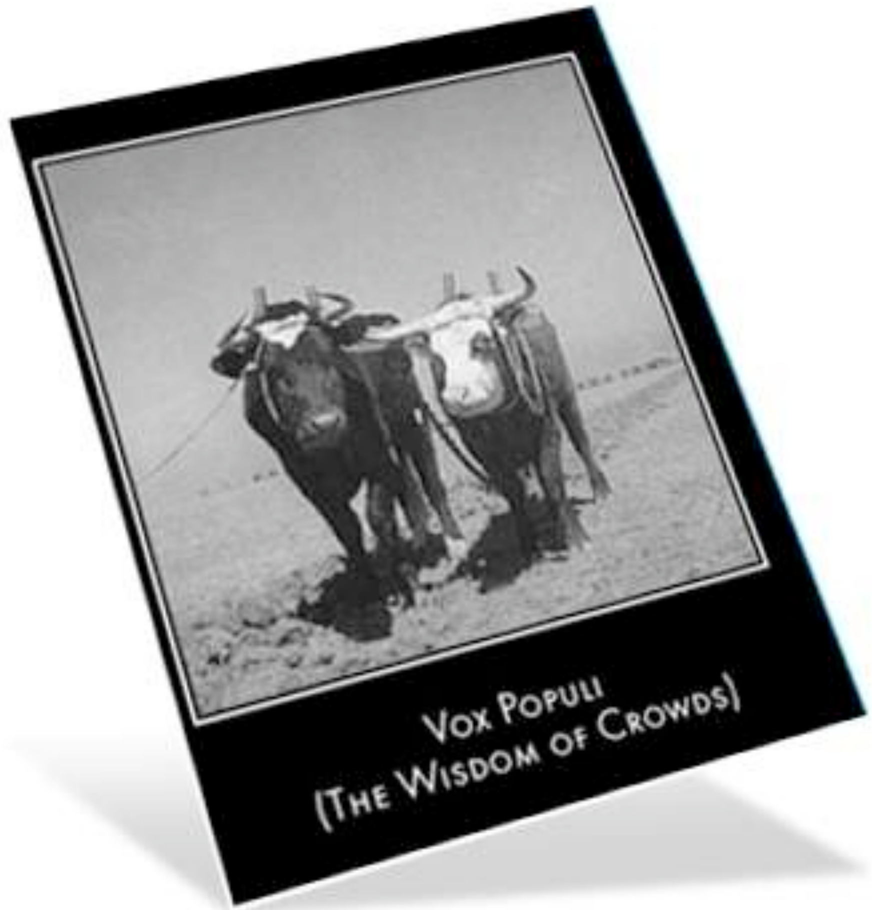
Part 1: Crowdsourcing Basics

- **Examples**
- Definitions
- Marketplaces
- Computational Crowdsourcing
  - Preliminaries
  - Transcription
  - Sorting
- Demo

Eg, Francis Galton, 1906

Weight-judging competition:
1,197 (mean of 787 crowds) vs. 1,198 pounds (actual measurement)





Eg, StolenSidekick, 2006

- A woman lost a cellphone in a taxi
- A 16-year-old girl ended up having the phone
  - Refused to return the phone
- Evan Guttman, the woman's friend, sets up a blog site about the incident
  - http://stolensidekick.blogspot.com/
  - http://www.evanwashere.com/StolenSidekick/
  - Attracted a growing amount of attention → the story appeared in Digg main page → NY Times and CNN coverage → Crowds pressure on police …
- NYPD arrested the girl and re-possessed the phone

http://www.nytimes.com/2006/06/21/nyregion/21sidekick.html?_r=0

Eg, Finding "Jim Gray", 2007

COMMUNICATIONS OF THE ACM

HOME | CURRENT ISSUE | NEWS | BLOGS | OPINION | RESEARCH

Home / Magazine Archive / July 2011 (Vol. 54, No. 7) / Searching for Jim Gray: A Technical Overview / Full Text

CONTRIBUTED ARTICLES

Searching for Jim Gray: A Technical Overview

By Joseph M. Hellerstein, David L. Tennenhouse

Communications of the ACM, Vol. 54 No. 7, Pages 77-87
10.1145/1965724.1965744

Comments

VIEW AS: SHARE:

- Loosely coupled teams q
  software polytechtures w
  interfaces, decoupling da
  from analysis to enable u
  at a distance.
- The U.S. Coast Guard dev
  to aid search and rescue a
  interesting potential rese
  computer scientists.
- New open-source tools a
  could help with group co
  crowdsourced image acq
  volume image processing,
  ocean drift modeling, and analysis
  of open-water satellite imagery.

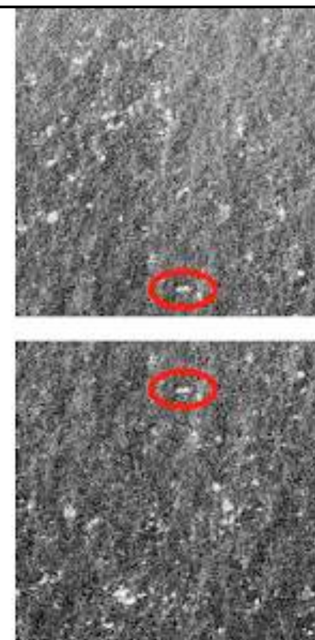


Image A @ time t_1

Image B @ time t_2

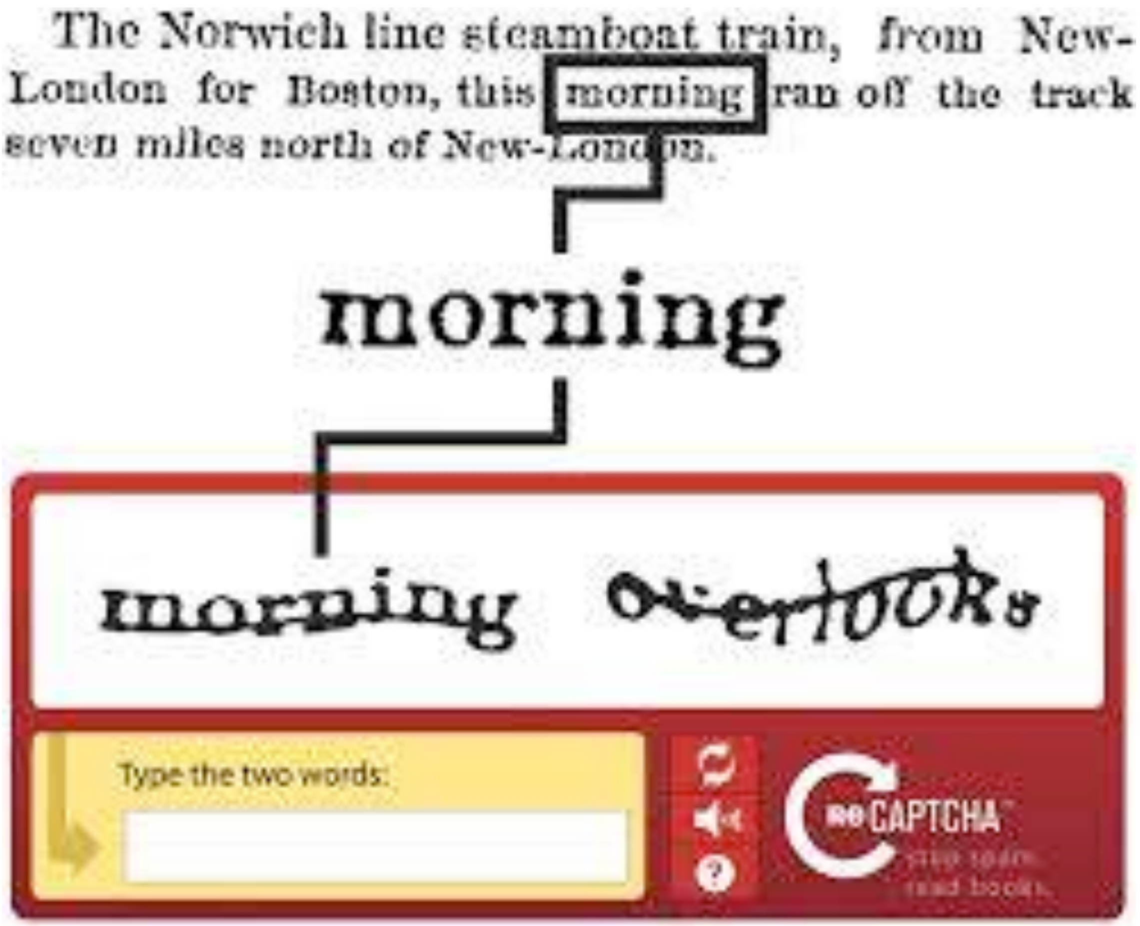
Eg, Threadless.com

- Sells t-shirts, designed/voted by crowds
- Artists whose designs are chosen get paid

Eg, KICKSTARTER

- Crowdfunding, started in 2009
- Project creators choose a deadline and a minimum funding goal
  - Creators only from US, UK, and Canada
- Donors pledge money to support projects, in exchange of non-monetary values
  - Eg, t-shirt, thank-u-note, dinner with creators
  - Donors can be from anywhere
- Eg, Pebble, smartwatch
  - 68K people pledged 10M

Eg, reCAPCHA



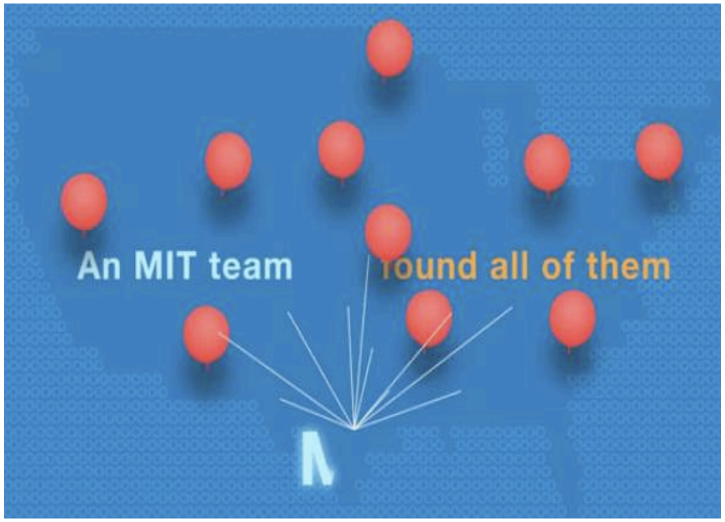
As of 2012

Captcha: 200M every day

ReCaptcha: 750M to date

Eg, DARPA Challenge, 2009

- To locate 10 red balloons in arbitrary locations of US
- Winner gets $40K
- MIT team won the race with the strategy:
  - 2K per balloon to the first person, A, to send the correct coordinates
  - 1K to the person, B, who invited A
  - 0.5K to the person, C, who invited B, …



Eg, Berkeley Mobile Millennium

mobile millennium

University of California, Berkeley

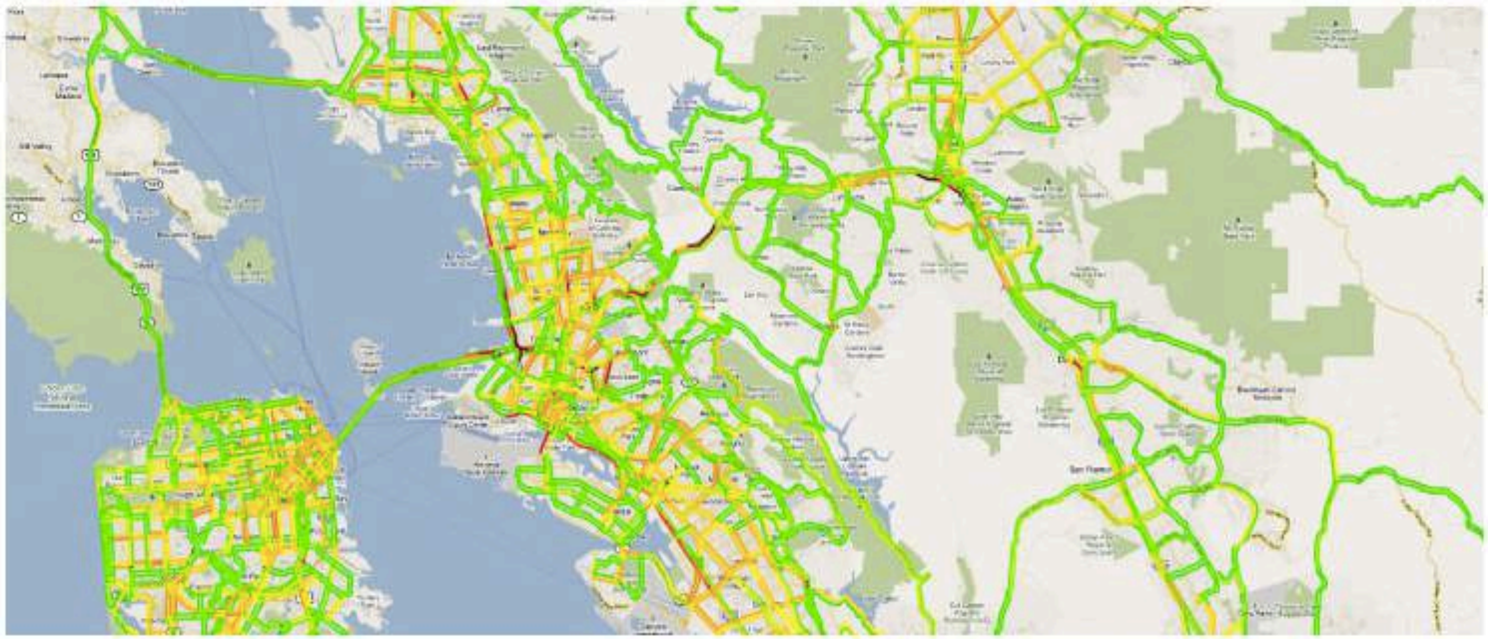
HOME PROJECT IN THE NEWS GALLERY ABOUT

Events

Mobile Millennium presented at the 2011 Transportation Research Board annual conference workshop on pervasive data, Washington DC, see more

Data Fusion

Snapshot of Mobile Millennium Traffic in San Francisco and the Bay Area



Project Overview

Mobile Millennium is a research project that includes a pilot traffic-monitoring system that uses the GPS in cellular phones to gather traffic information, process it, and distribute it back to the phones in real time.

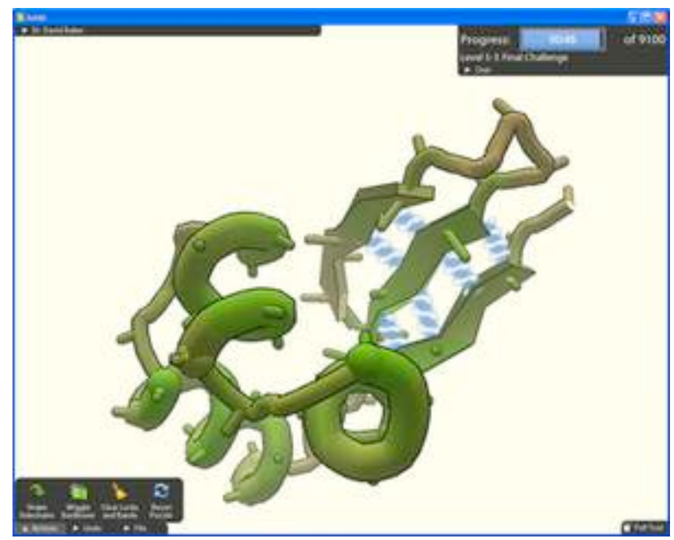
Eg, Who Wants to be a Millionaire?

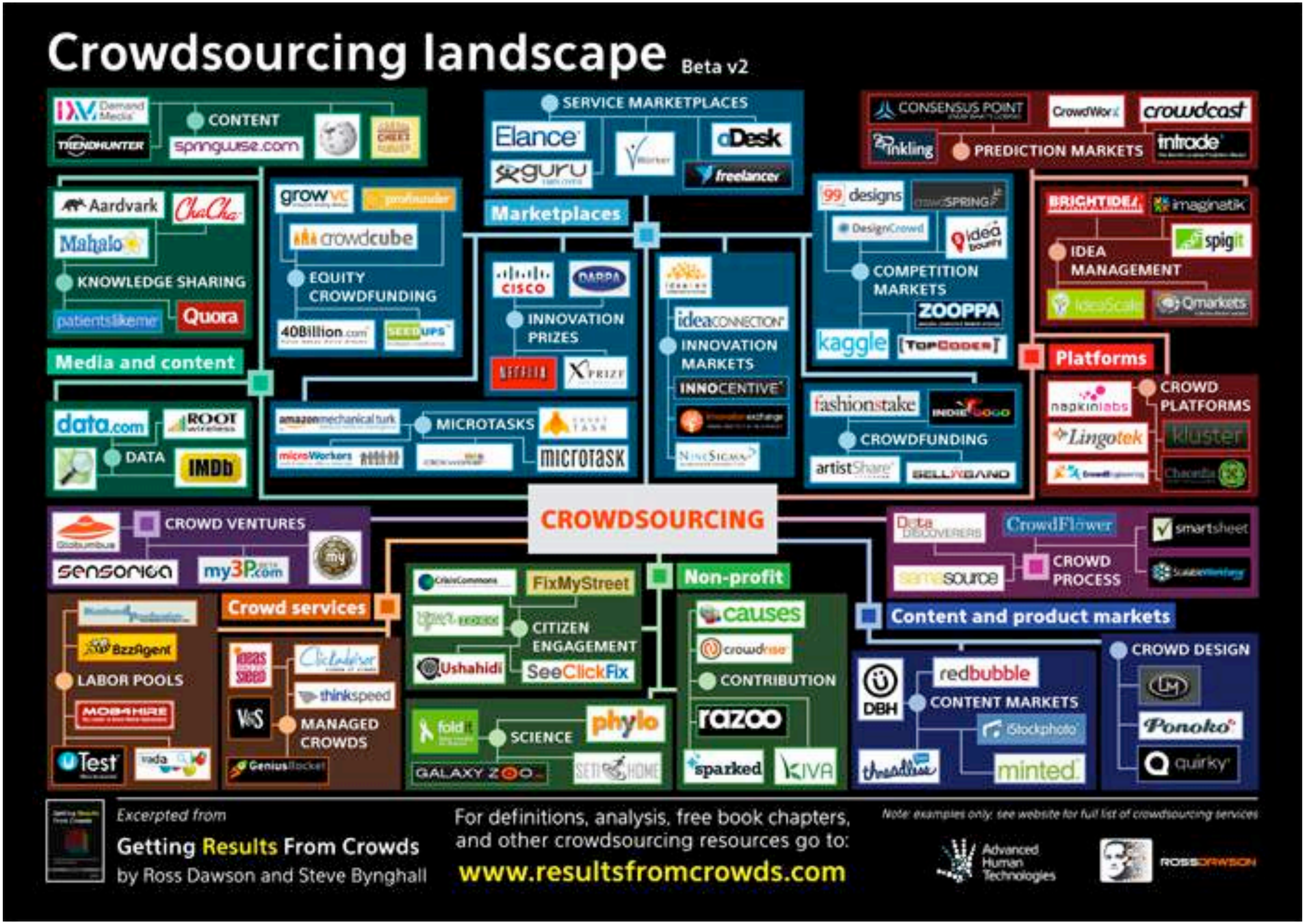
Asking the audience usually works ➔ Audience members have *diverse* knowledge that can be coordinated to provide a correct answer in sum

Eg, Who Wants to be a Millionaire?

Eg, Game-With-A-Purpose: GWAP

- Term coined by Luis von Ahn @ CMU
- Eg,
  - ESP Game → Google Image Labeler: image recognition
  - Foldit: protein folding
  - Duolingo: language translation





http://www.resultsfromcrowds.com/features/crowdsourcing-landscape/

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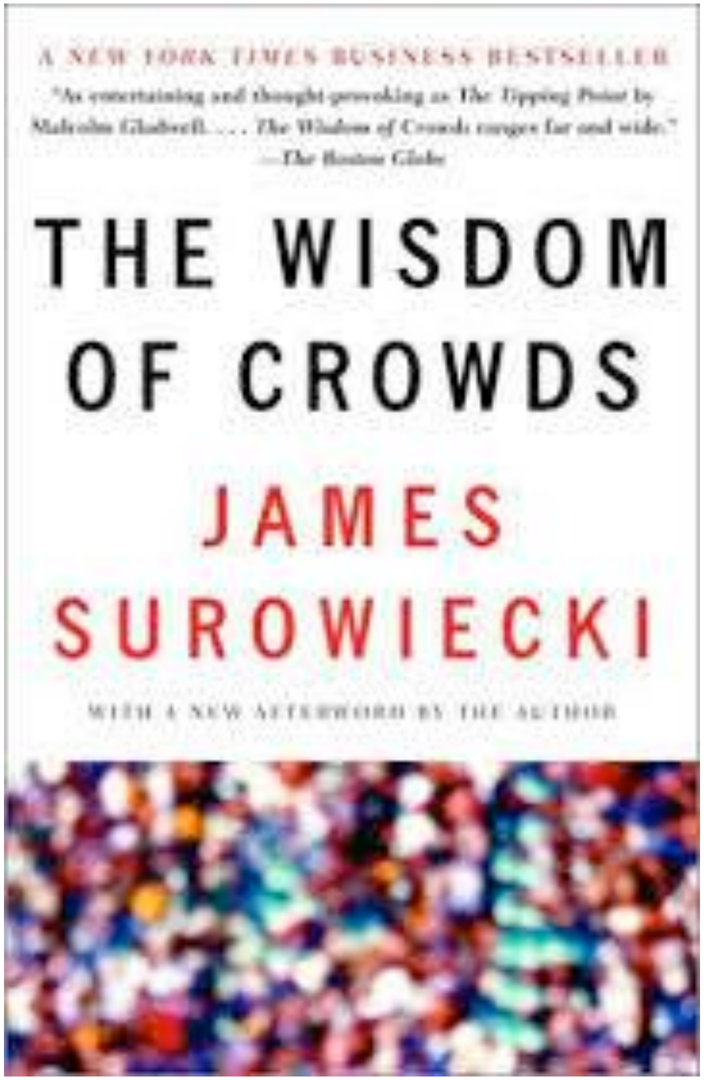
James Surowiecki, 2004



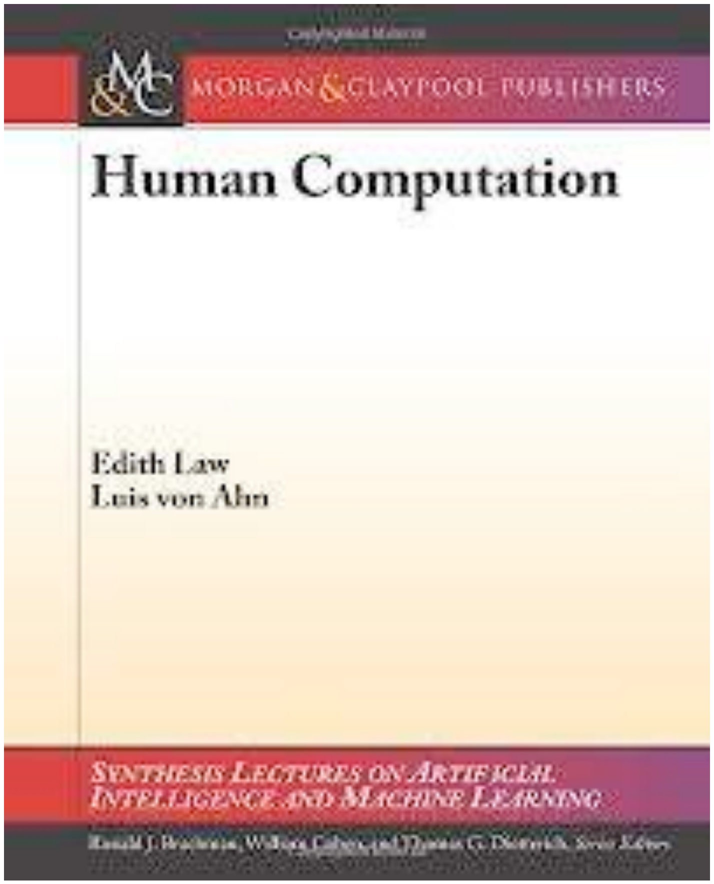
"**Collective intelligence** can be brought to bear on a wide variety of problems, and complexity is no bar… conditions that are necessary for the crowd to be wise: *diversity*, *independence*, and … *decentralization*"

Jeff Howe, WIRED, 2006

"**Crowdsourcing** represents the act of a company or institution taking a function once performed by employees and *outsourcing* it to an undefined (and generally large) network of people in the form of an open call. … The crucial prerequisite is the use of the *open call* format and the *large* network of potential laborers…"

http://www.wired.com/wired/archive/14.06/crowds.html

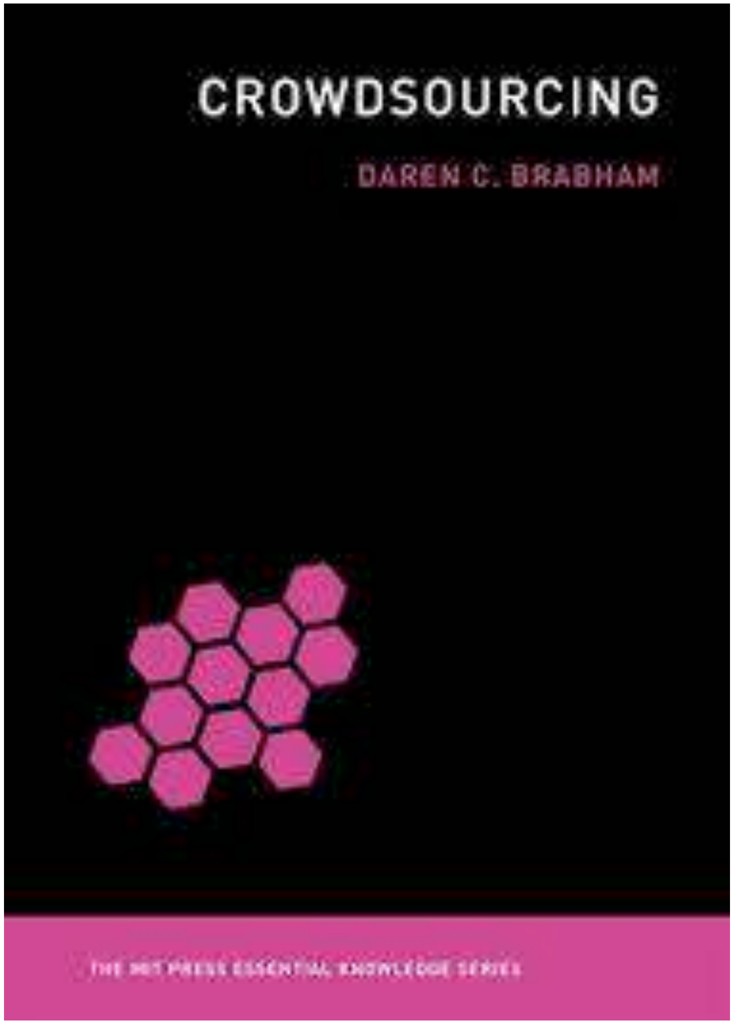
“Human Computation”, 2011



“**Human computation** is simply computation that is carried out by humans… **Crowdsourcing** can be considered a method or a tool that human computation systems can use…”

By Edith Law & Luis von Ahn

Daren Brabhan, 2013



"**Crowdsourcing** as an *online*, *distributed* problem-solving and production model that leverages the collective intelligence of online communities to serve specific *organizational* goals… *top-down* and *bottom-up* …"

What is Crowdsourcing?

- Many definitions

- A few characteristics
  - **Outsourced** to **human** workers
  - **Online** and **distributed**
  - Open call & right **incentive**
  - **Diversity** and **independence**
  - Top-down & bottom-up

What is Computational Crowdsourcing?

- Focus on computational aspect of crowdsourcing
  - Algorithmic aspect
  - Non-linear optimization problem

- Mainly use micro-tasks

- When to use Computational Crowdsourcing?
  1. Machine cannot do the task well
  2. Large crowds can probably do it well
  3. Task can be split to many micro-tasks

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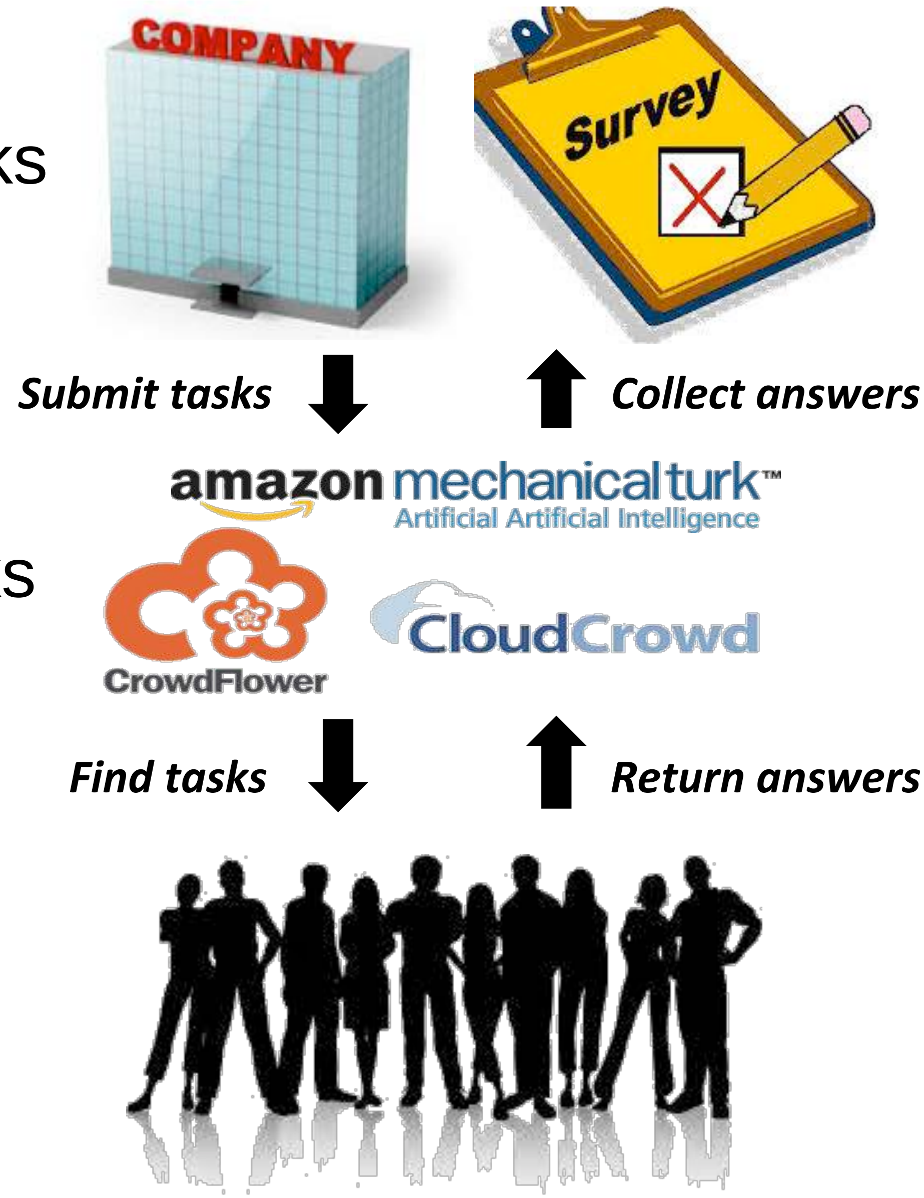
Three Parties

- Requesters
  - People submit some tasks
  - Pay rewards to workers
- Marketplaces
  - Provide crowds with tasks
- Crowds
  - Workers perform tasks



Notable Marketplaces

- Mechanical Turk
- CrowdFlower
- CloudCrowd
- Clickworker
- SamaSource

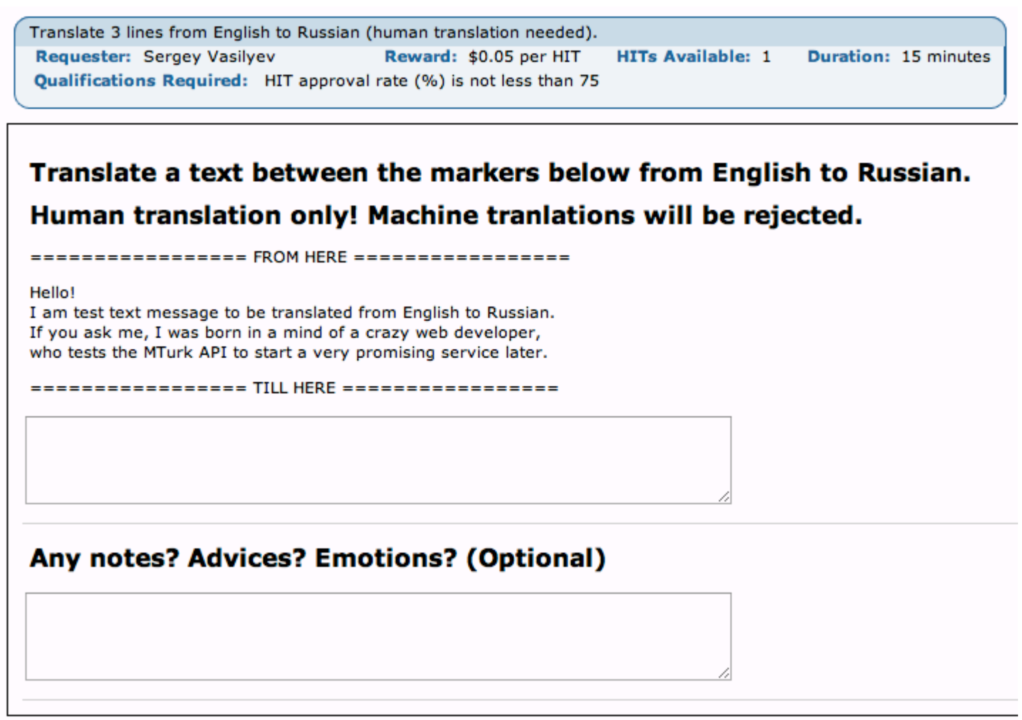
AMT: mturk.com

AMT: Workers vs. Requesters

- Workers
  - Register w. credit account (only US workers can register as of 2013)
  - Bid to do tasks for earning money
- Requesters
  - First deposit money to account
  - Post tasks
    - Task can specify a qualification for workers
  - Gather results
  - Pay to workers if results are satisfactory

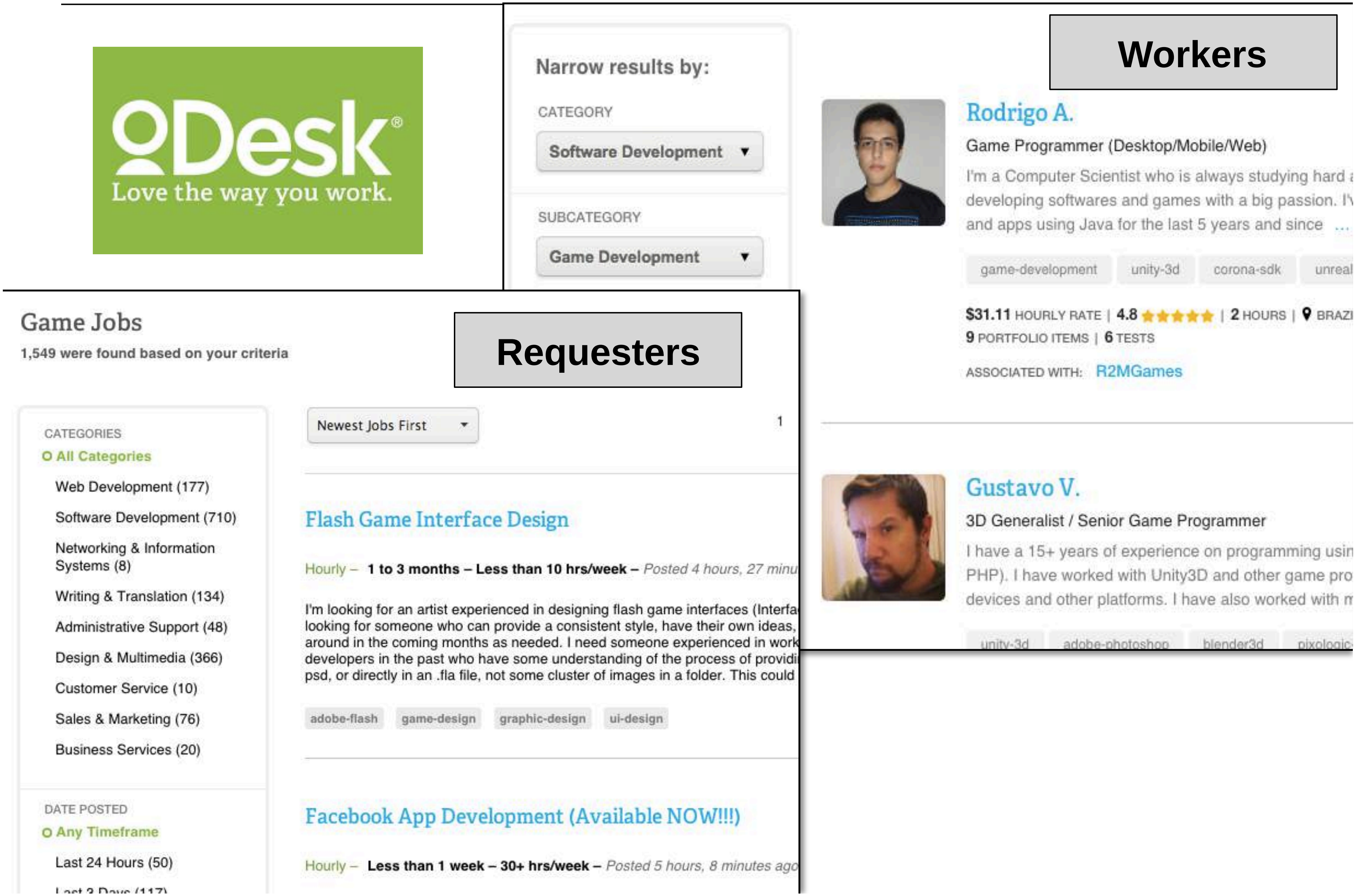
AMT: HIT

- Tasks
  - Called **HIT** (Human Intelligence Task)
  - Micro-task
- Eg
  - Data cleaning
  - Tagging / labeling
  - Sentiment analysis
  - Categorization
  - Surveying
  - Photo moderation
  - Transcription

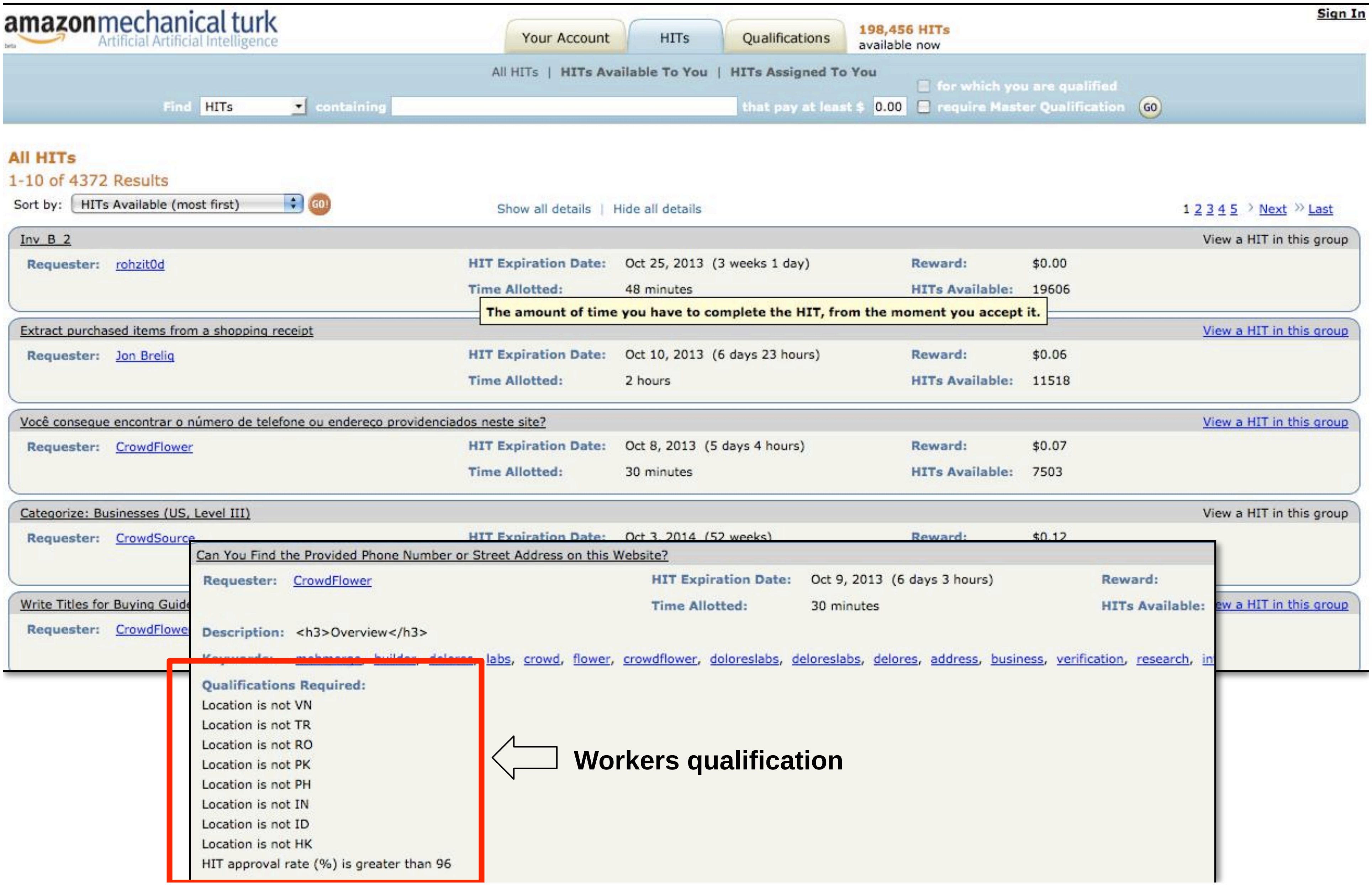


Translation task

Micro- vs. Macro-task: Eg, oDesk



AMT: HIT List


amazonmechanical turk
Artificial Artificial Intelligence
Your Account
HITs
Qualifications
198,456 HITs available now
Sign In
All HITs | HITs Available To You | HITs Assigned To You
Find HITs containing that pay at least $ 0.00 for which you are qualified require Master Qualification GO
All HITs
1-10 of 4372 Results
Sort by: HITs Available (most first) GO!
Show all details | Hide all details
1 2 3 4 5 Next Last
Inv_B_2 View a HIT in this group
Requester: rohzit0d HIT Expiration Date: Oct 25, 2013 (3 weeks 1 day) Reward: $0.00
Time Allotted: 48 minutes HITs Available: 19606
The amount of time you have to complete the HIT, from the moment you accept it.
Extract purchased items from a shopping receipt View a HIT in this group
Requester: Jon Brelig HIT Expiration Date: Oct 10, 2013 (6 days 23 hours) Reward: $0.06
Time Allotted: 2 hours HITs Available: 11518
Você consegue encontrar o número de telefone ou endereço providenciados neste site? View a HIT in this group
Requester: CrowdFlower HIT Expiration Date: Oct 8, 2013 (5 days 4 hours) Reward: $0.07
Time Allotted: 30 minutes HITs Available: 7503
Categorize: Businesses (US, Level III) View a HIT in this group
Requester: CrowdSource
Write Titles for Buying Guide
Requester: CrowdFlower
Can You Find the Provided Phone Number or Street Address on this Website?
Requester: CrowdFlower HIT Expiration Date: Oct 9, 2013 (6 days 3 hours) Reward:
Time Allotted: 30 minutes HITs Available:
Description: <h3>Overview</h3>
labs, crowd, flower, crowdflower, doloreslabs, deloreslabs, delores, address, business, verification, research
Qualifications Required:
Location is not VN
Location is not TR
Location is not RO
Location is not PK
Location is not PH
Location is not IN
Location is not ID
Location is not HK
HIT approval rate (%) is greater than 96
Workers qualification

AMT: HIT Example

Can You Find the Provided Phone Number or Street Address on this Website?

Instructions ▴

Overview

In this task, you'll be provided a web page for a business, including its name, address, and phone number. Your goal is to answer a few questions about the business on the web page.

IMPORTANT: Sometimes the business will have multiple locations, and you will have to search the website for the specific business that we provide in order to verify the website.

Step by step instructions:

- Click the link to go to the provided site.
- First, please tell us whether or not the **name** of the business on the provided website is a **close** or **identical** match to the name of the business shown at the top of the page.
- Next, please tell us whether the provided business has
- Please be sure to click the appropriate option if the site

Wrinkles Day Spa

Phone:	+61893455333
Street:	Shop 5a Stirling Central Shopping Centre, 478 Wanneroo Rd
City:	Westminster
State:	WA
Postalcode (Zip):	6061
Country Code:	AU

Click here to visit the website.

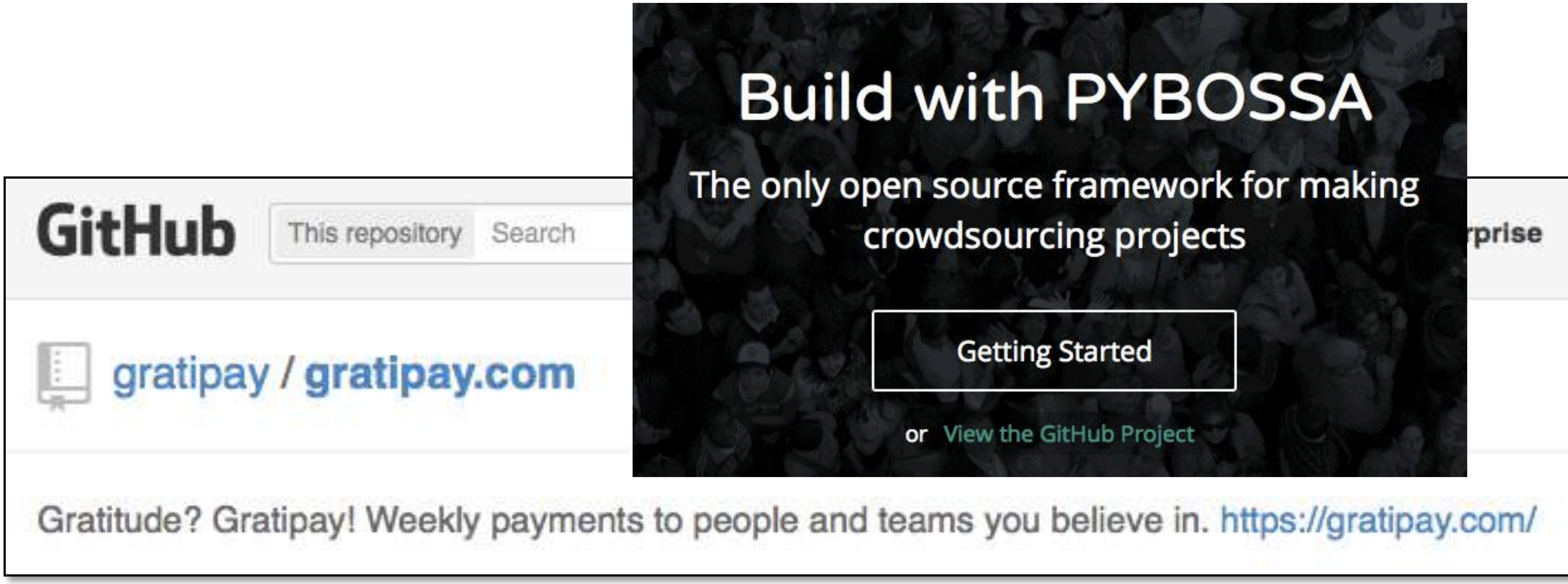
Is the name of the business on the web page similar or identical to 'Wrinkles Day Spa'?

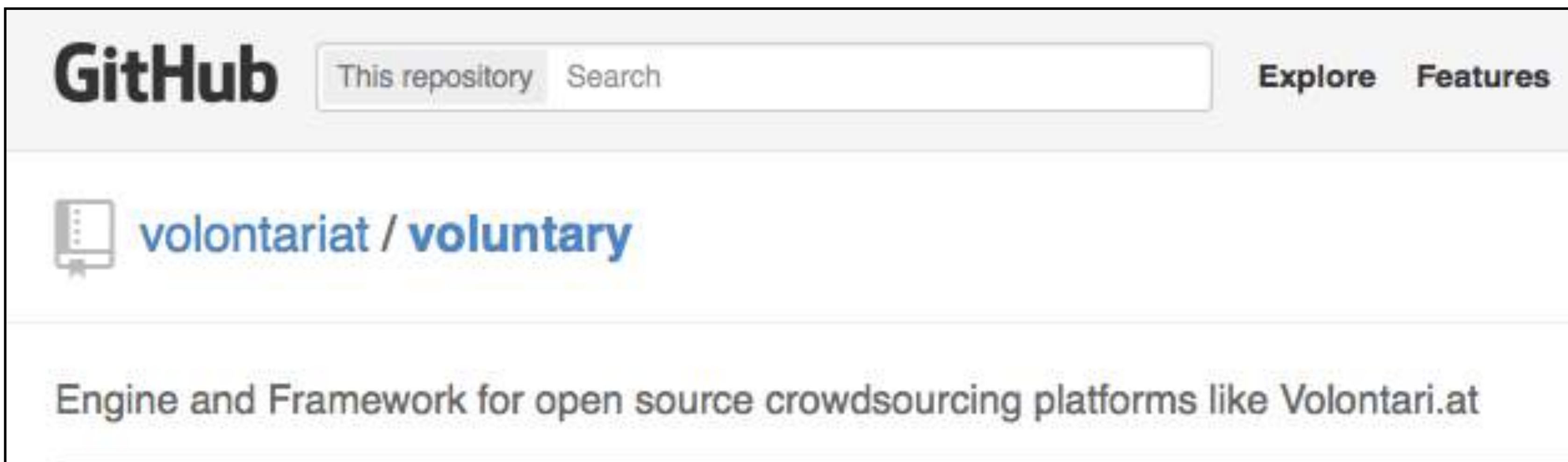
- ○ Yes: the name of the business is *similar* to *Wrinkles Day Spa*
- ○ Yes: the name of the business is *nearly identical* to *Wrinkles Day Spa*
- ○ No: the name is very different from *Wrinkles Day Spa*

ℹ For the first option, the street **number** does not need to match, just the street, **Shop 5a Stirling Central Shopping Centre, 4**

AMT: HIT Example

Open-Source Marketplace S/W





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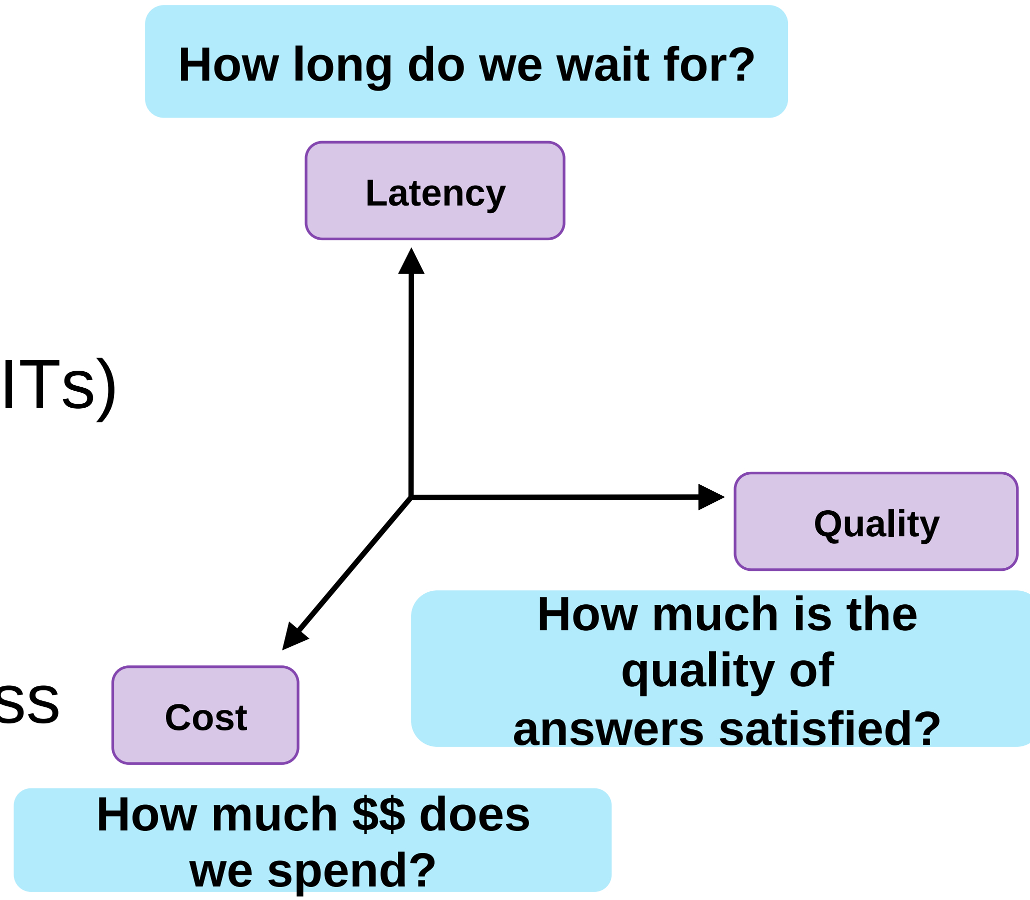
Three Computational Factors

- Latency (or execution time)
  - Worker pool size
  - Job attractiveness
- Monetary cost
  - Cost per question
  - # of questions (ie, HITs)
  - # of workers
- Quality of answers
  - Worker maliciousness
  - Worker skills
  - Task difficulty



#1: Latency

- Some crowdsourcing tasks finish faster than others
  - Eg, easier, or more rewarding tasks are popular
- Dependency among tasks

#2: Cost

- Cost per question
- # of HITs

Remaining cost to pay:
$0.03 X 2075 = $62.25

Image Keyword Verification — View a HIT in this group

Requester:	Corbis Holdings, Inc	**HIT Expiration Date:**	Oct 13, 2014 (6 days 19 hours)	**Reward:**	$0.03
		Time Allotted:	15 minutes	**HITs Available:**	2075

Enter information about a forum discussion thread in which a vehicle is being built, rebuilt, or restored — View a HIT in this group

Requester:	Jonathan R	**HIT Expiration Date:**	Oct 14, 2014 (7 days 20 hours)	**Reward:**	$0.20
		Time Allotted:	30 minutes	**HITs Available:**	2000

Transcribe up to 25 Seconds of Media to Text - Low Priority — View a HIT in this group

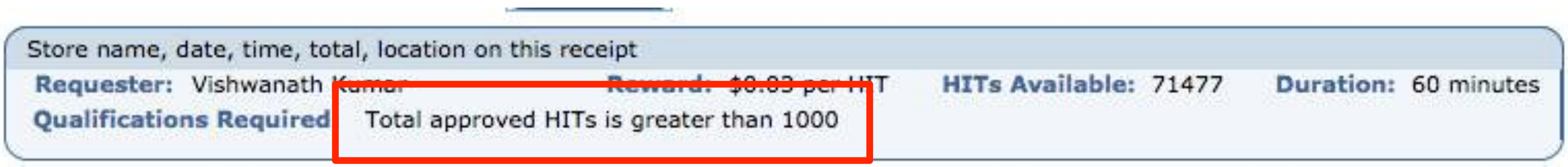
Requester:	Crowdsurf Support	**HIT Expiration Date:**	Oct 20, 2014 (2 weeks)	**Reward:**	$0.08
		Time Allotted:	15 minutes	**HITs Available:**	1836

PADs_US_consumables_20140824-Thu Sep 11 16:15:50 PDT 2014 — View a HIT in this group

Requester:	Amazon Requester Inc.	**HIT Expiration Date:**	Oct 11, 2014 (5 days)	**Reward:**	$0.00
		Time Allotted:	1 hour 46 minutes	**HITs Available:**	1605

#3: Quality of Answers

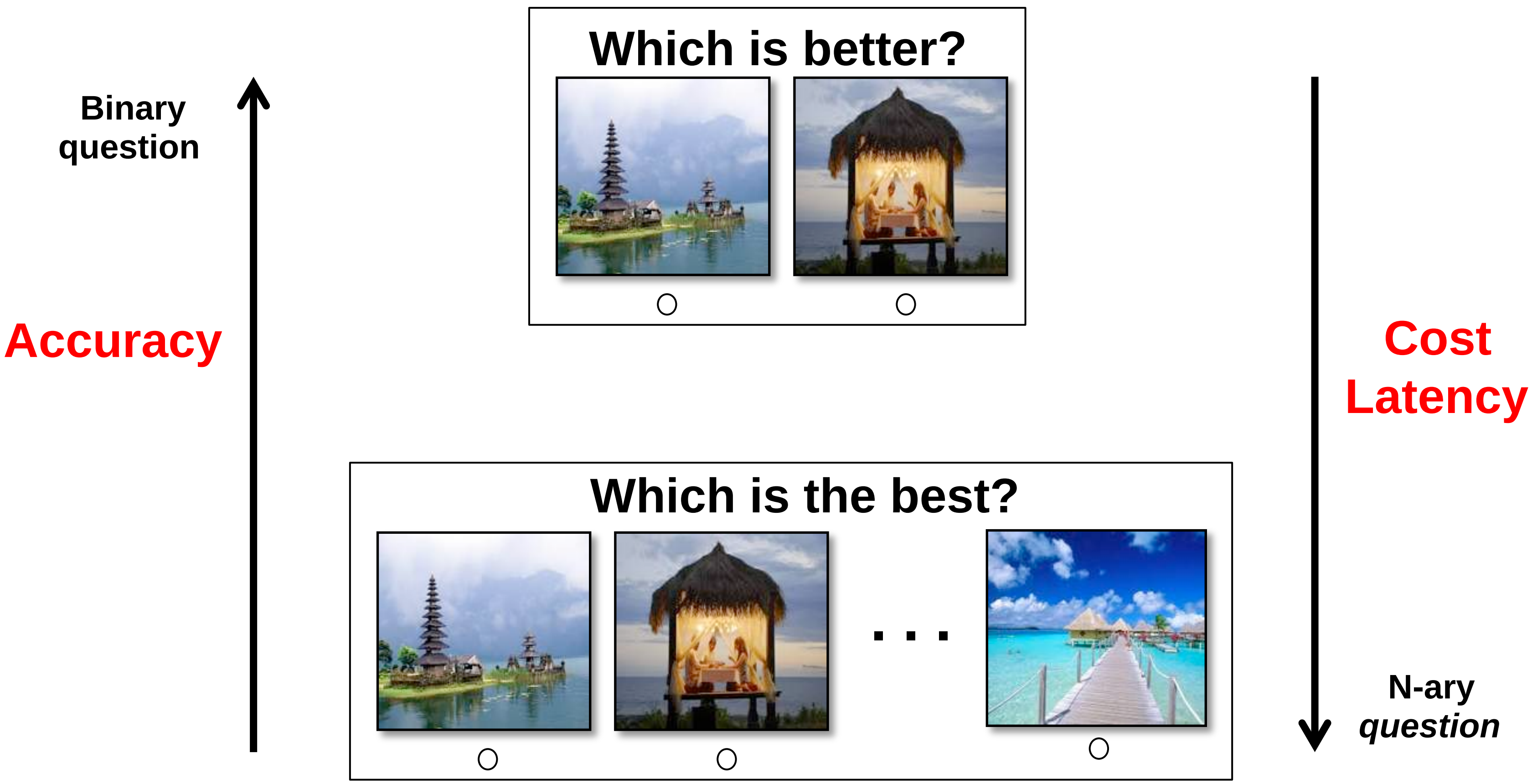
- Avoid spam workers
- Use workers with reputation



- Ask the same question to multiple workers to get consensus (eg, majority voting)
- Assign more number of (better-skilled) workers to more difficult questions

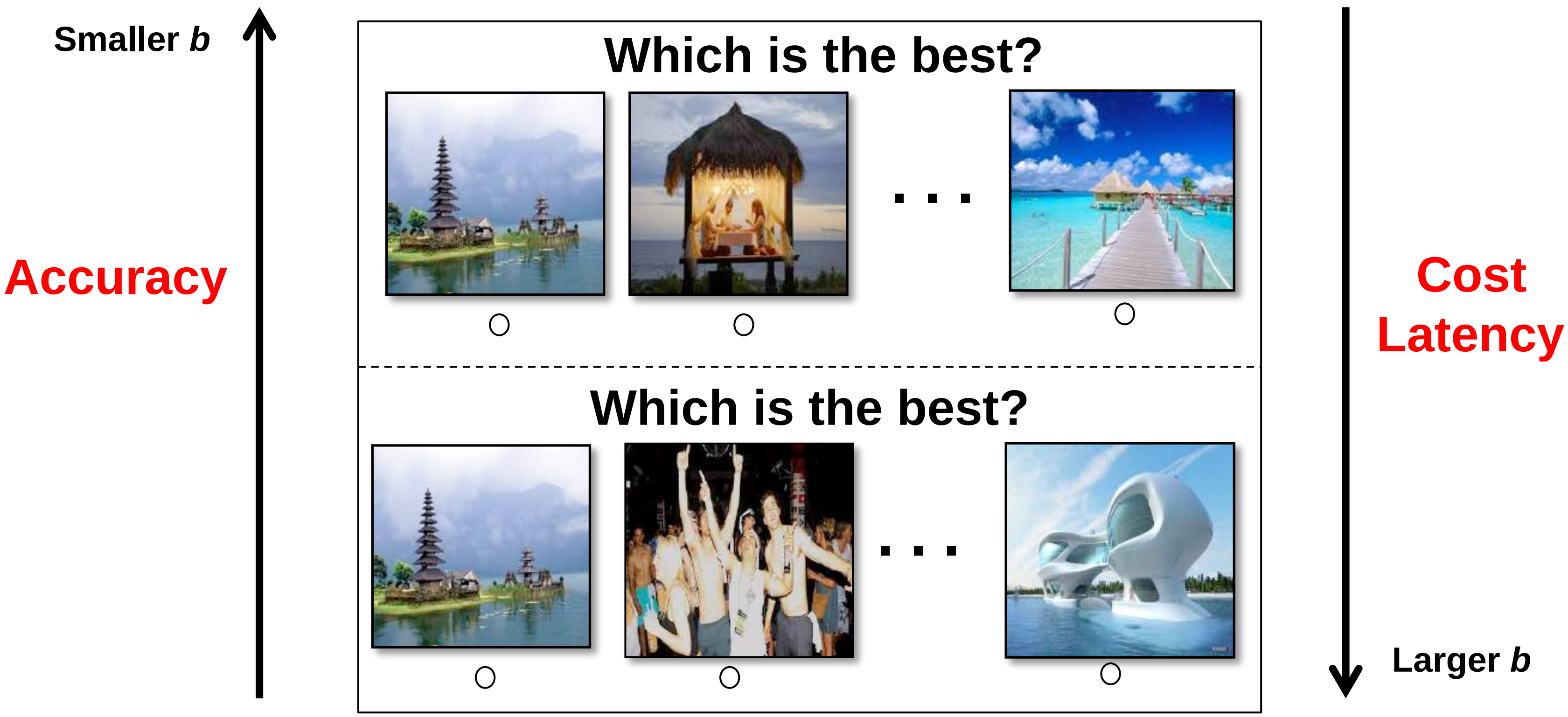
Size of Comparison

- Diverse forms of questions in a HIT
- Different sizes of comparisons in a question



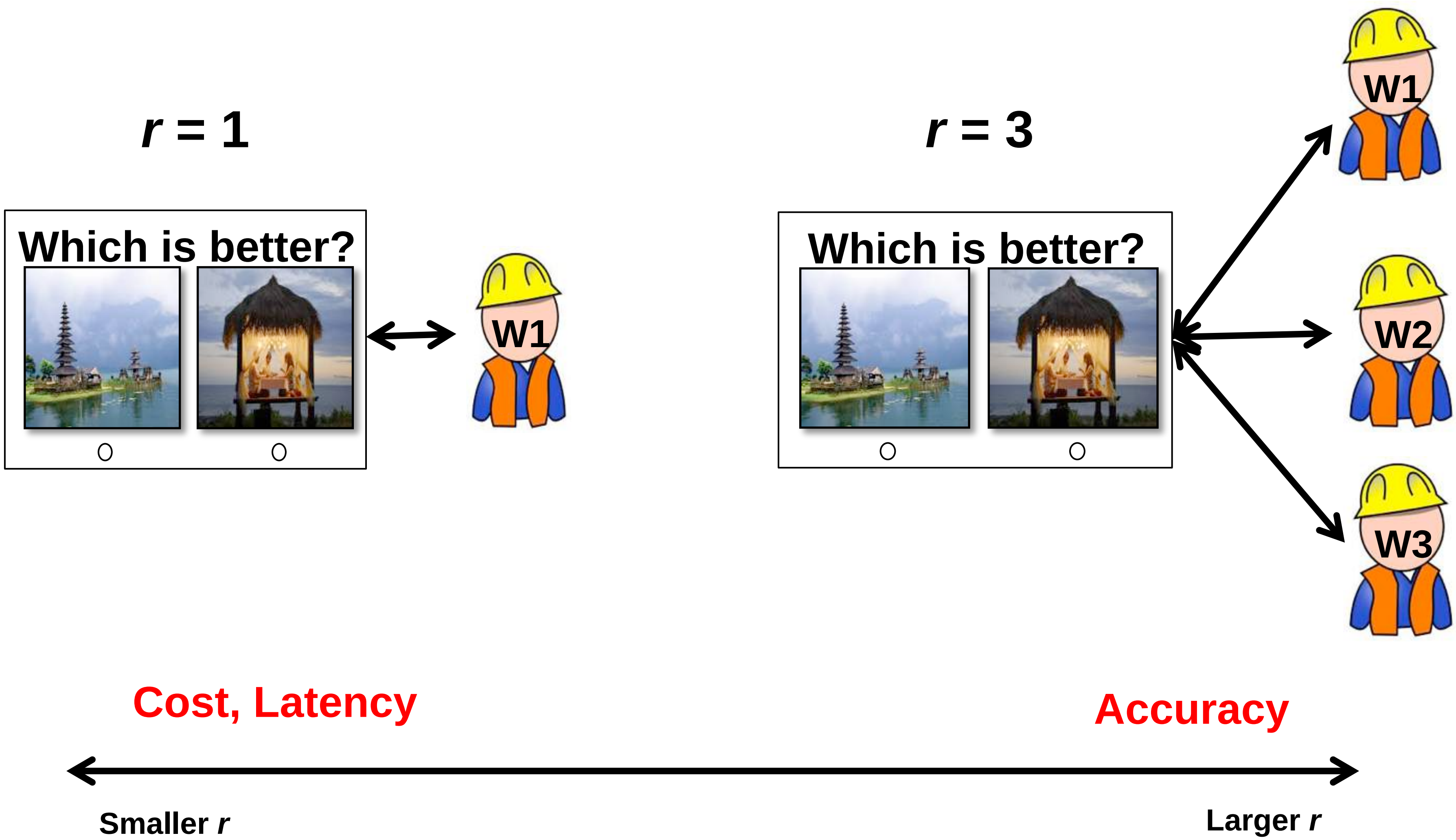
Size of Batch

- Repetitions of questions within a HIT
- Eg, two *n*-ary questions (batch factor *b*=2)



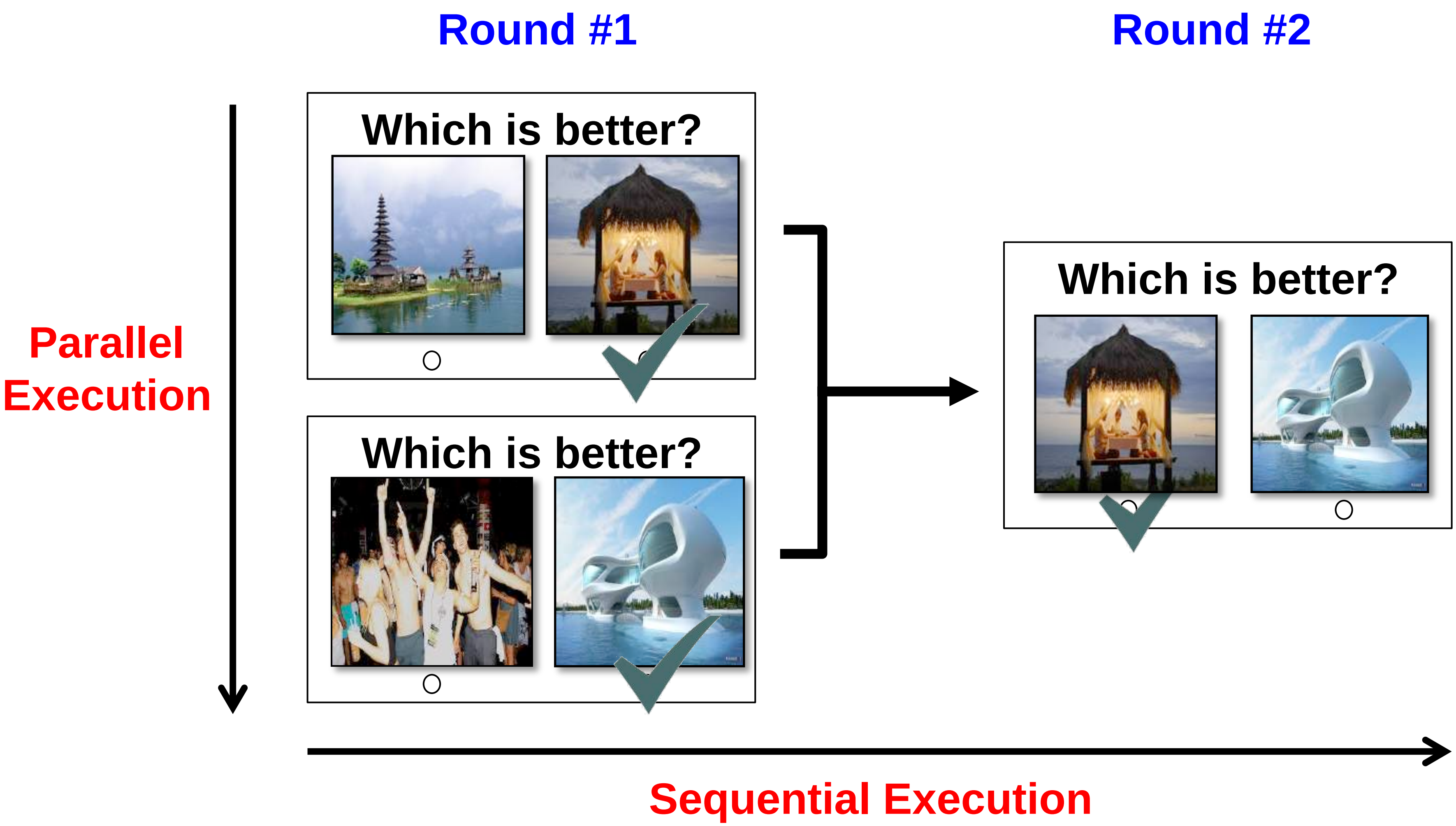
Response (*r*)

- # of human responses seeked for a HIT



Round (= Step)

- Algorithms are executed in rounds
- # of rounds ≈ latency



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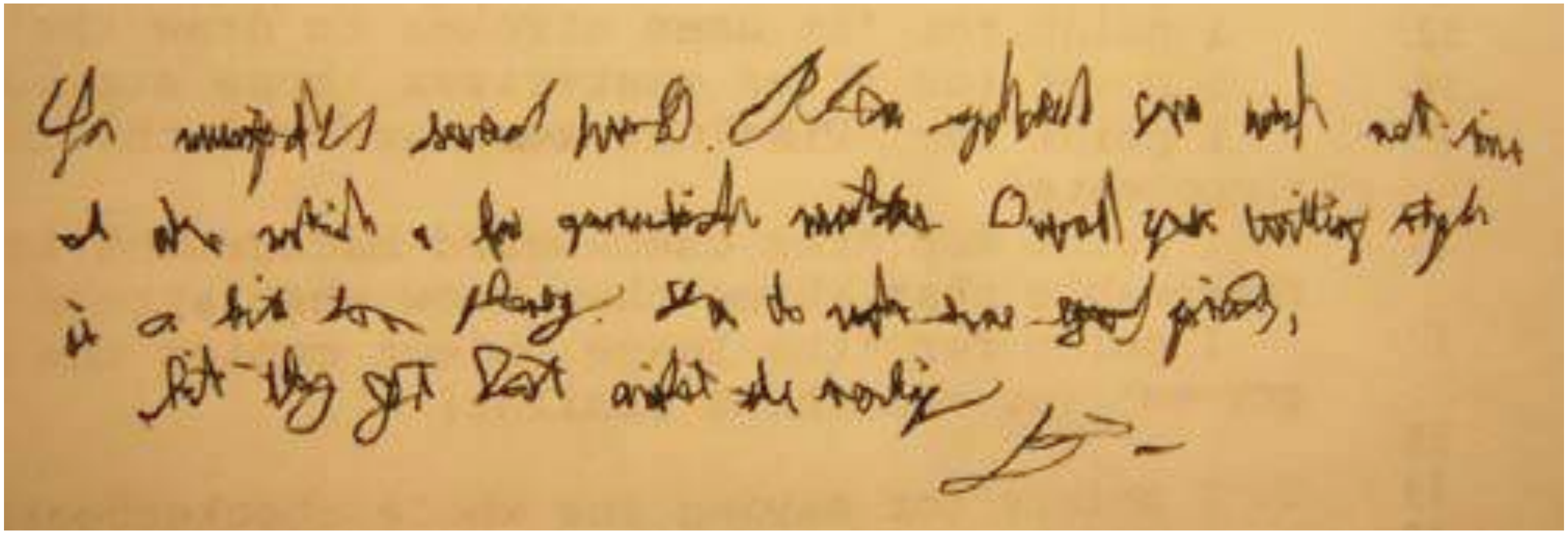
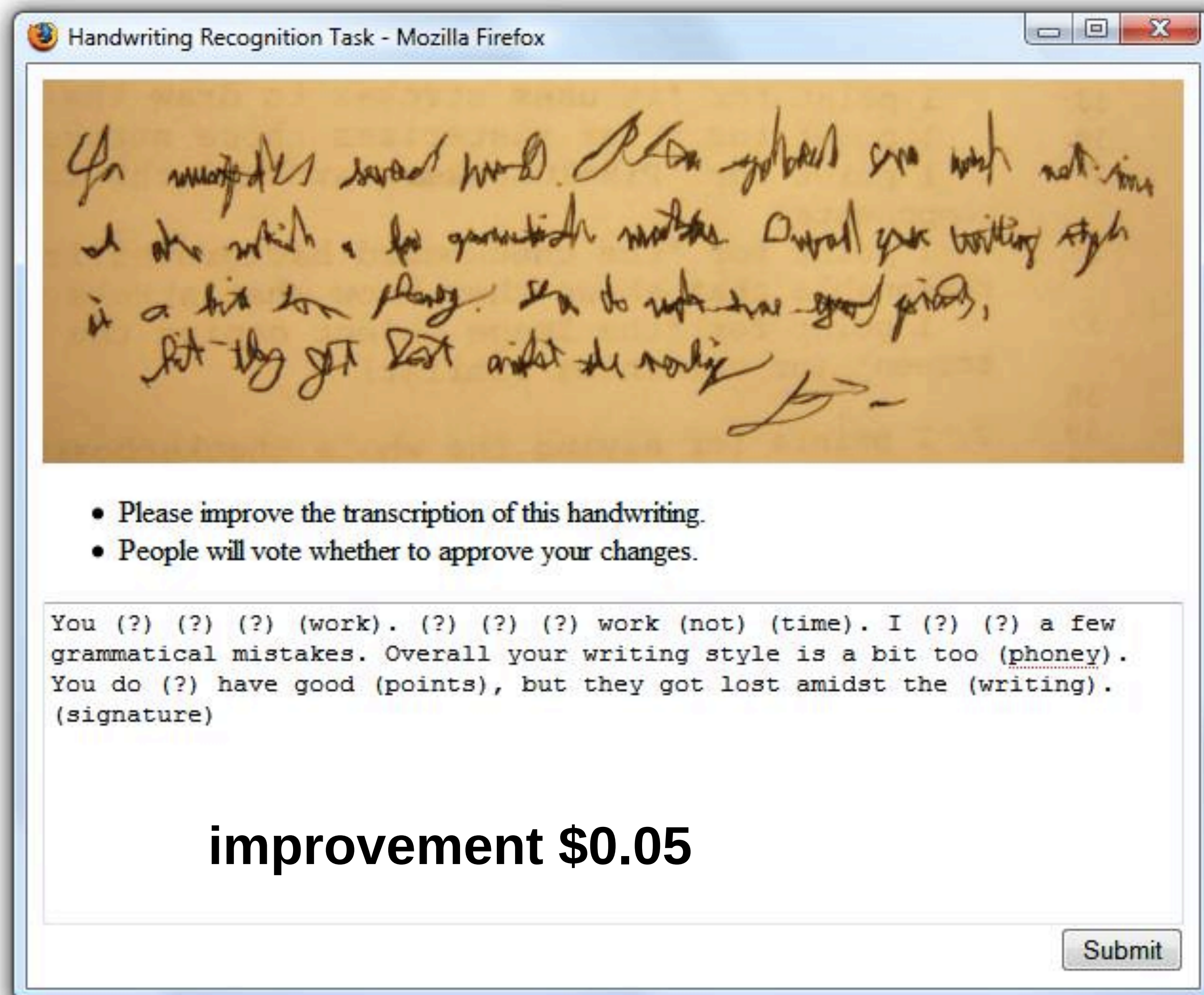
Eg, Text Transcription [Miller-13]



- **Problem**: one person cannot do a good transcription
- **Key idea**: iterative improvement by many workers

Greg Little *et al*. “Exploring iterative and parallel human computation processes.” HCOMP 2010

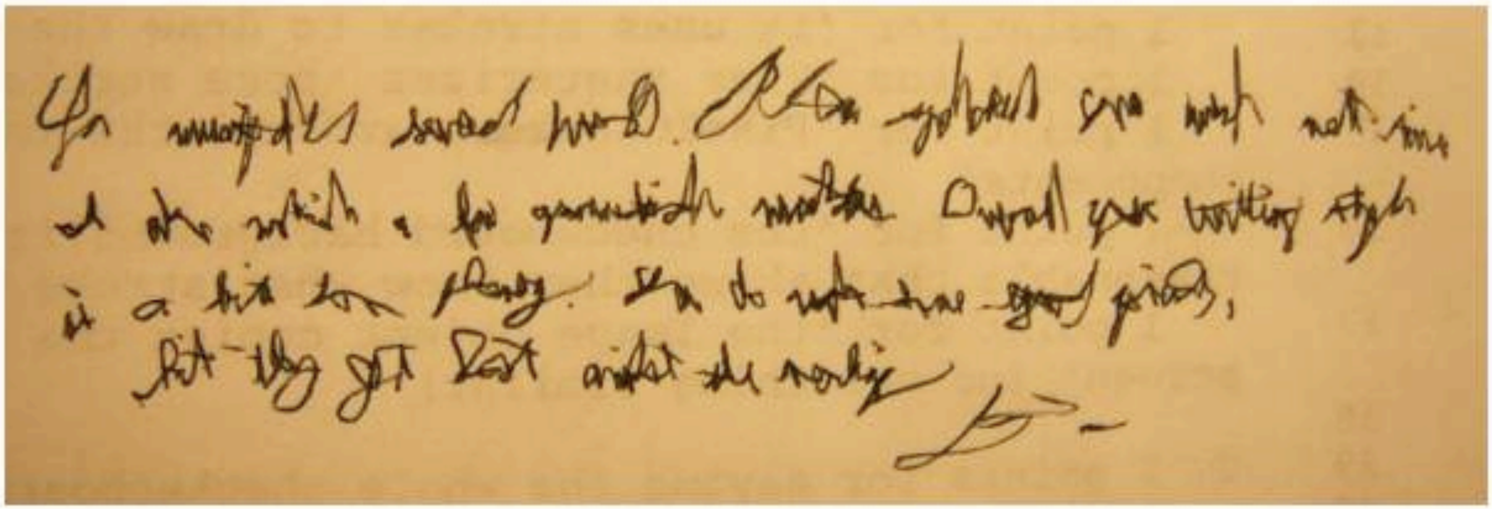
Eg, Text Transcription [Miller-13]



improvement $0.05

Eg, Text Transcription [Miller-13]

MTurk Task - Mozilla Firefox



- Please select the better transcription for this handwriting.
- Differences are highlighted in yellow.

3 votes @ $0.01

\> You (misspelled) (several) (words) (work). (?) (?) (?) work next (time). I also notice a few grammatical mistakes. Overall your writing style is a bit too (phoney). You do (?) have good (points), but they got lost amidst the (writing). (signature)

\> You (?) (?) (?) (work). (?) (?) (?) work (not) (time). I (?) (?) a few grammatical mistakes. Overall your writing style is a bit too (phoney). You do (?) have good (points), but they got lost amidst the (writing). (signature)

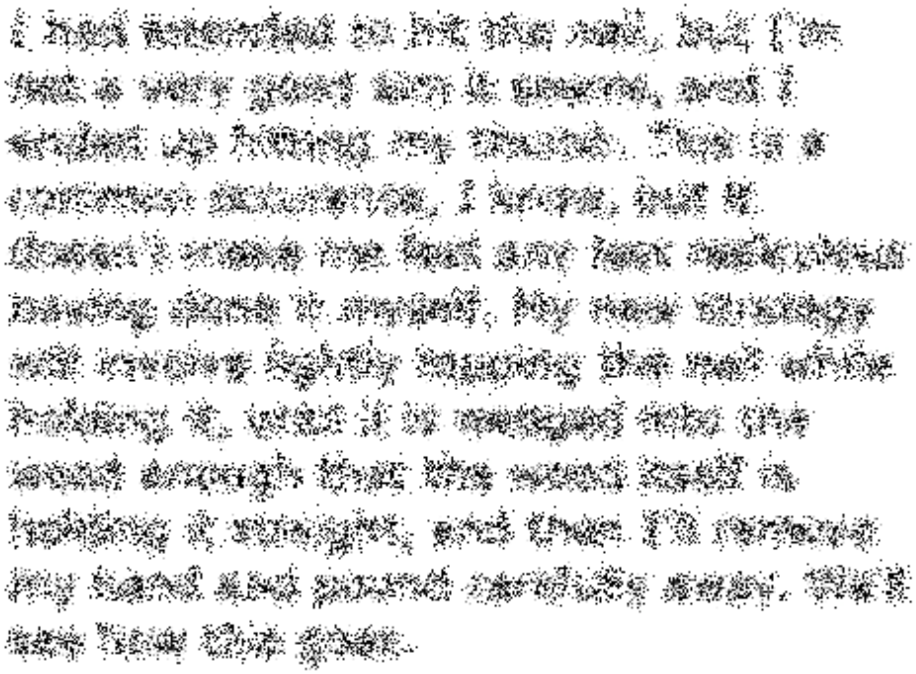
Eg, Text Transcription [Miller-13]

"You (misspelled) (several) (words). Please spellcheck your work next time. I also notice a few grammatical mistakes. Overall your writing style is a bit too phoney. You do make some good (points), but they got lost amidst the (writing). (signature)"

According to our ground truth, the highlighted words should be "flowery", "get", "verbiage" and "B-" respectively.

After 9 iterations

Eg, Text Transcription [Miller-13]



I had intended to hit the nail, but I’m not a very good aim it seems and I ended up hitting my thumb. This is a common occurrence I know, but it doesn’t make me feel any less ridiculous having done it myself. My new strategy will involve lightly tapping the nail while holding it until it is embedded into the wood enough that the wood itself is holding it straight and then I’ll remove my hand and pound carefully away. We’ll see how this goes.

After 8 iterations
with thousands of crowds

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Human-Powered Sort

- Rank *N* items using crowdsourcing with respect to the constraint *C*
- Often *C* is subjective, fuzzy, ambiguous, and/or difficult-for-machines-to-compute
- Eg,
  - Which image is the most “representative” one of Brazil?
  - Which animal is the most “dangerous”?
  - Which actress is the most “beautiful”?

Human-Powered Sort

```
SELECT     *
FROM       SoccerPlayers AS P
WHERE      P.WorldCupYear = ‘2014’
ORDER BY   CrowdOp(‘most-valuable’)
```









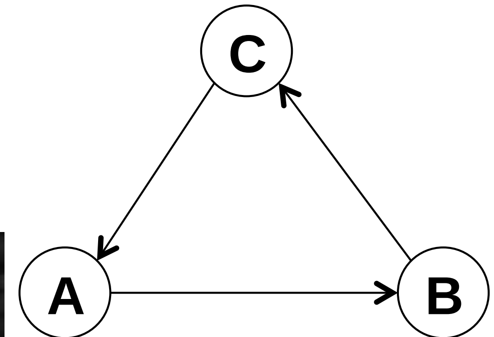
...

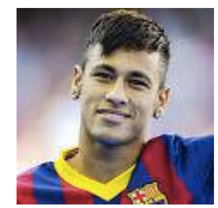
Naïve Sort

- Eg, "Which of two players is better?"
- Naïve all pair-wise comparisons takes $\binom{N}{2}$ comparisons
  - Optimal # of comparison is *O(N log N)*

Naïve Sort

- Conflicting opinions may occur
  - Cycle: A > B, B > C, and C > A





- If no cycle occurs
  - Naïve all pair-wise comparisons takes $\binom{N}{2}$ comparisons
- If cycle exists
  - More comparisons are required

Sort [Marcus-VLDB11]

- N=5, S=3

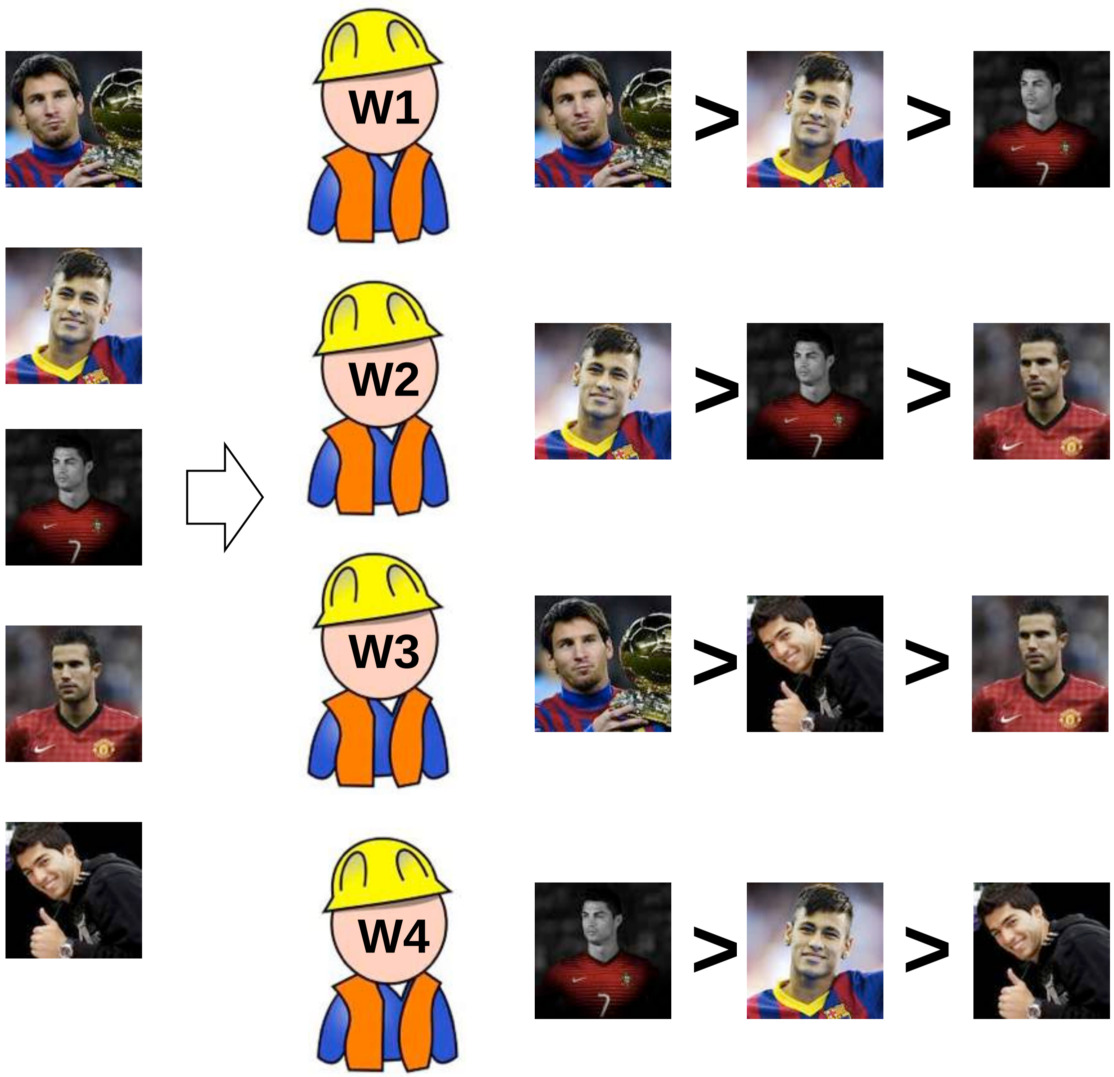
A

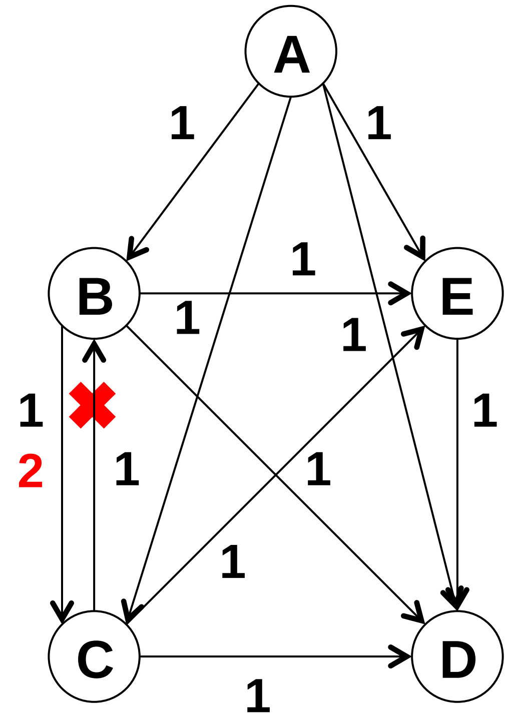
B

C

D

E

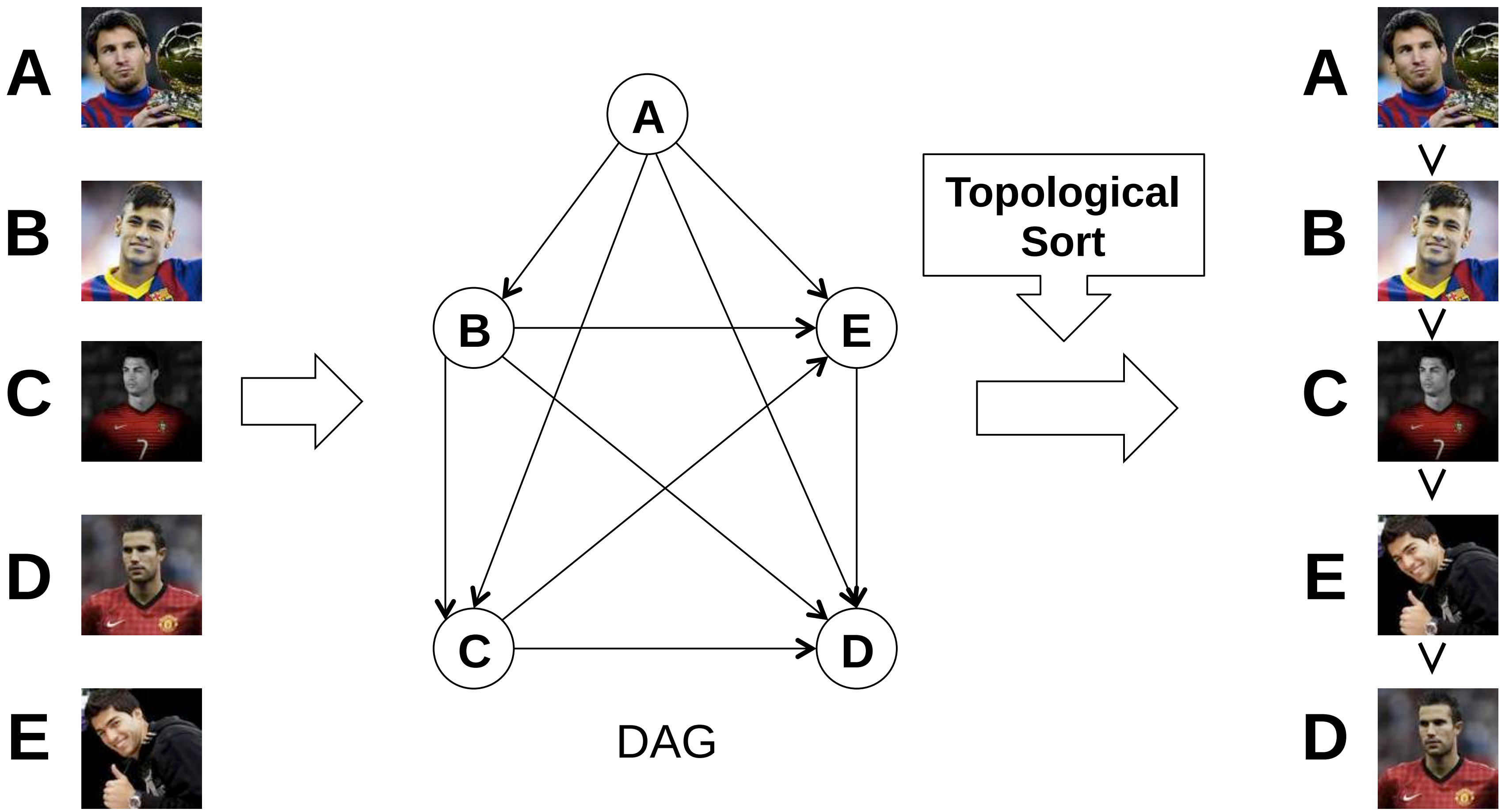




Sort [Marcus-VLDB11]

- N=5, S=3

Sorted Result



Part 1: Crowdsourcing Basics

- Examples
- Definitions
- Marketplaces
- Computational Crowdsourcing
  - Preliminaries
  - Transcription
  - Sorting
- **Demo**

Demo: Human-Powered Sorting

- From your smartphone or laptop, access the following URL or QR code:

`http://goo.gl/3tw7b5`

Part 1 Conclusion

- Crowdsourcing ≈ Human Computation
- Academia: novel paradigm to solve the challenging problems in Computer Science
- Industry: novel entrepreneurial opportunities
  - Eg, Brazil-version Mechanical Turk?

This slide is available at

http://goo.gl/4pNUhB

Reference

- **[Brabham-13]** *Crowdsourcing*, Daren Brabham, 2013
- **[Franklin-SIGMOD11]** *CrowdDB: answering queries with crowdsourcing*, Michael J. Franklin et al, SIGMOD 2011
- **[Howe-08]** *Crowdsourcing*, Jeff Howe, 2008
- **[LawAhn-11]** *Human Computation*, Edith Law and Luis von Ahn, 2011
- **[Li-HotDB12]** *Crowdsourcing: Challenges and Opportunities*, Guoliang Li, HotDB 2012
- **[Marcus-VLDB11]** *Human-powered Sorts and Joins*, Adam Marcus et al., VLDB 2011
- **[Miller-13]** *Crowd Computing and Human Computation Algorithms*, Rob Miller, 2013
- **[Shirky-08]** *Here Comes Everybody*, Clay Shirky, 2008

Human-Powered Database Operations: Part 2

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Slide available @ **http://goo.gl/UEUEBh**

SBBD 2014 Tutorial

Part 1: Crowdsourcing Basics

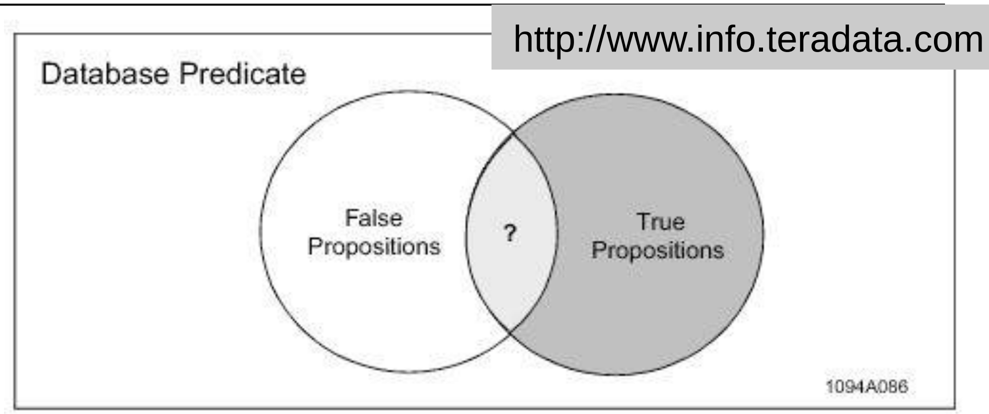
- Examples
- Definitions
- Marketplaces
- Computational Crowdsourcing
  - Preliminaries
  - Transcription
  - Sorting
- Demo

Part 2: Crowdsourced Algo. in DB

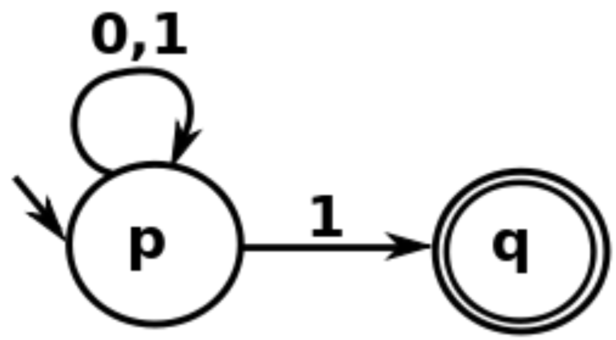
- **Preliminaries**
- Sort
- Select
- Count
- Top-1
- Top-*k*
- Join

New Challenges

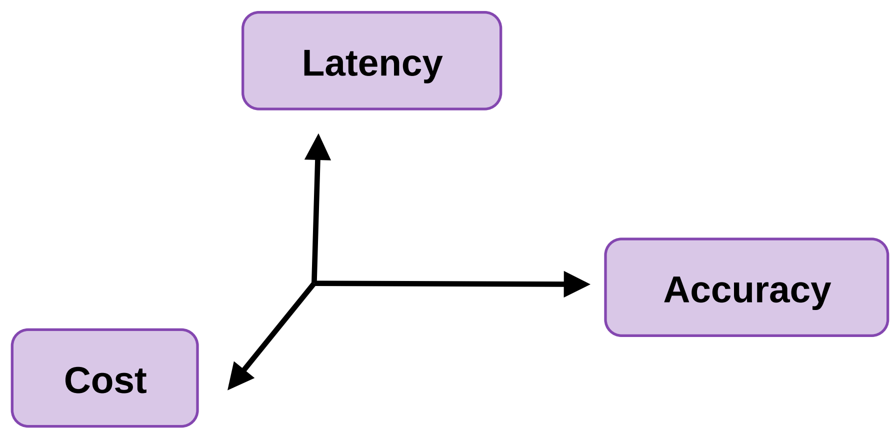
- Open-world assumption (OWA)



- Non-deterministic algorithmic behavior



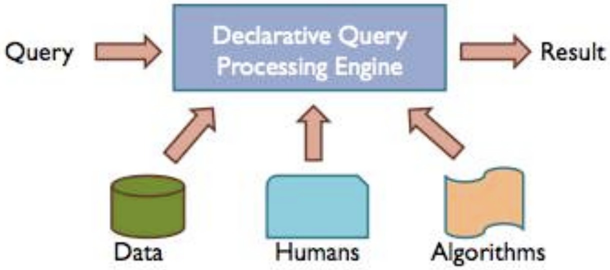
- Trade-off among cost, latency, and accuracy



Crowdsourcing DB Projects

- CDAS @ NUS
- CrowdDB @ UC Berkeley
  & ETH Zurich
- MoDaS @ Tel Aviv U.
- Qurk @ MIT

- sCOOP @ Stanford & UCSC

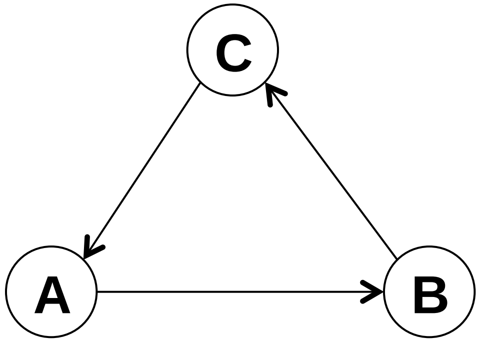


Part 2: Crowdsourced Algo. in DB

- Preliminaries
- **Sort**
- Select
- Count
- Top-1
- Top-*k*
- Join

Sort Operation

- Rank *N* items using crowdsourcing w.r.t some criteria
- Assuming pair-wise comparison of 2 items
  - Eg, “Which of two images is better?”
- Cycle: A > B, B > C, and C > A
- If no cycle occurs
  - Naïve all pair-wise comparisons takes $\binom{N}{2}$ comparisons
- If cycle exists
  - More comparisons are required



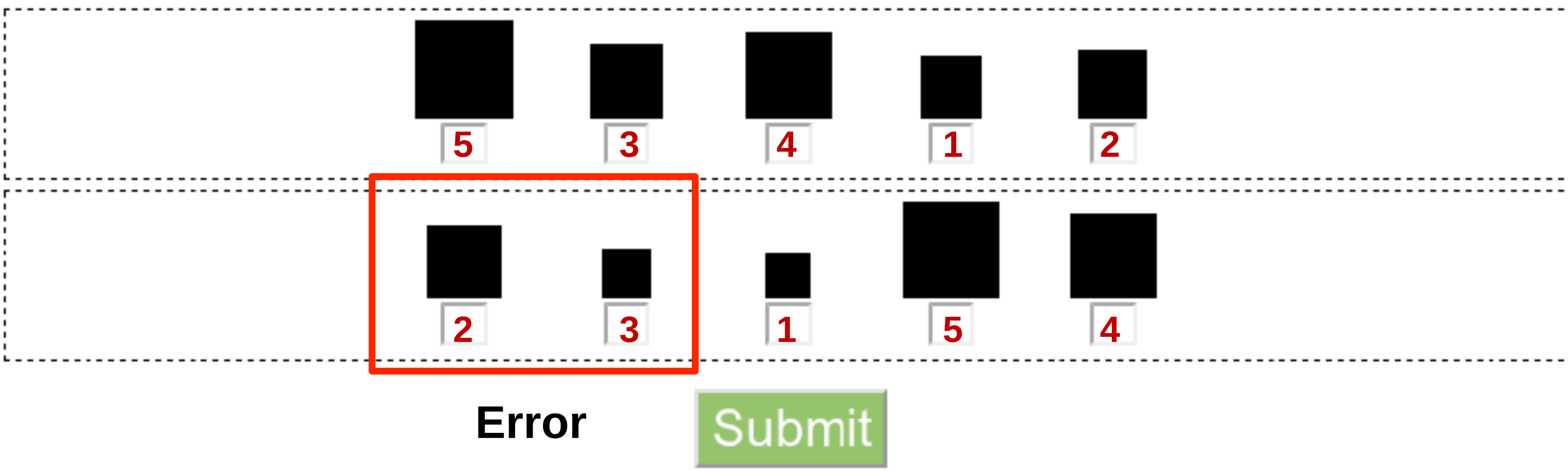
Sort [Marcus-VLDB11]

- Proposed 3 crowdsourced sort algorithms
- #1: Comparison-based Sort
  - Workers rank *S* items ($S \subset N$) per HIT
  - Each HIT yields $\binom{S}{2}$ pair-wise comparisons
  - Build a directed graph using all pair-wise comparisons from all workers
    - If *i* > *j*, then add an edge from *i* to *j*
  - Break a cycle in the graph: "head-to-head"
    - Eg, If *i* > *j* occurs 3 times and *i* < *j* occurs 2 times, keep only *i* > *j*
  - Perform a topological sort in the DAG

Sort [Marcus-VLDB11]

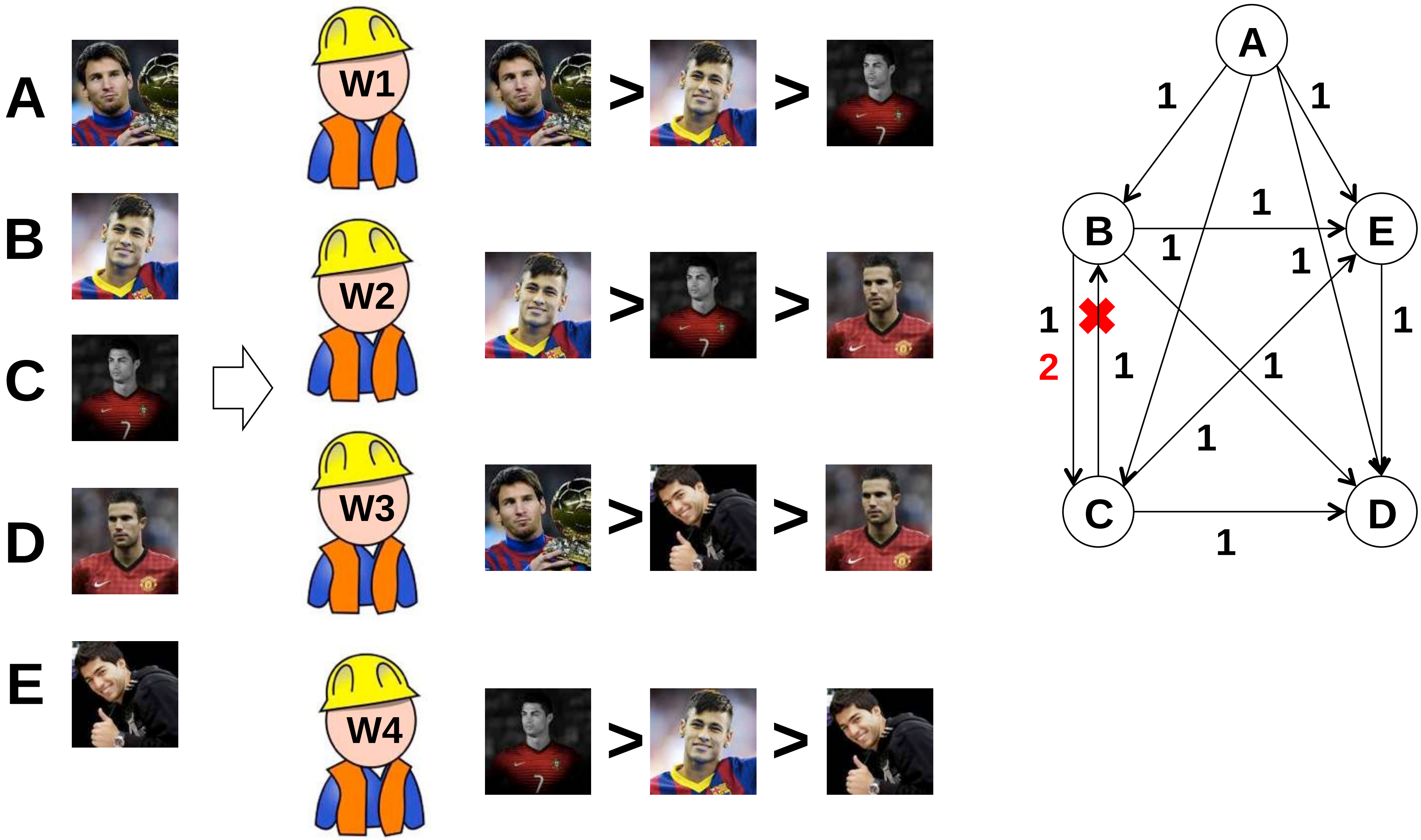
There are 2 groups of squares. We want to order the squares in each group from smallest to largest.

- Each group is surrounded by a dotted line. Only compare the squares within a group.
- Within each group, assign a number from 1 to 7 to each square, so that:
  - 1 represents the smallest square, and 7 represents the largest.
  - We do not care about the specific value of each square, only the relative order of the squares.
  - Some groups may have less than 7 squares. That is OK: use less than 7 numbers, and make sure they are ordered according to size.
  - If two squares in a group are the same size, you should assign them the same number.



Sort [Marcus-VLDB11]

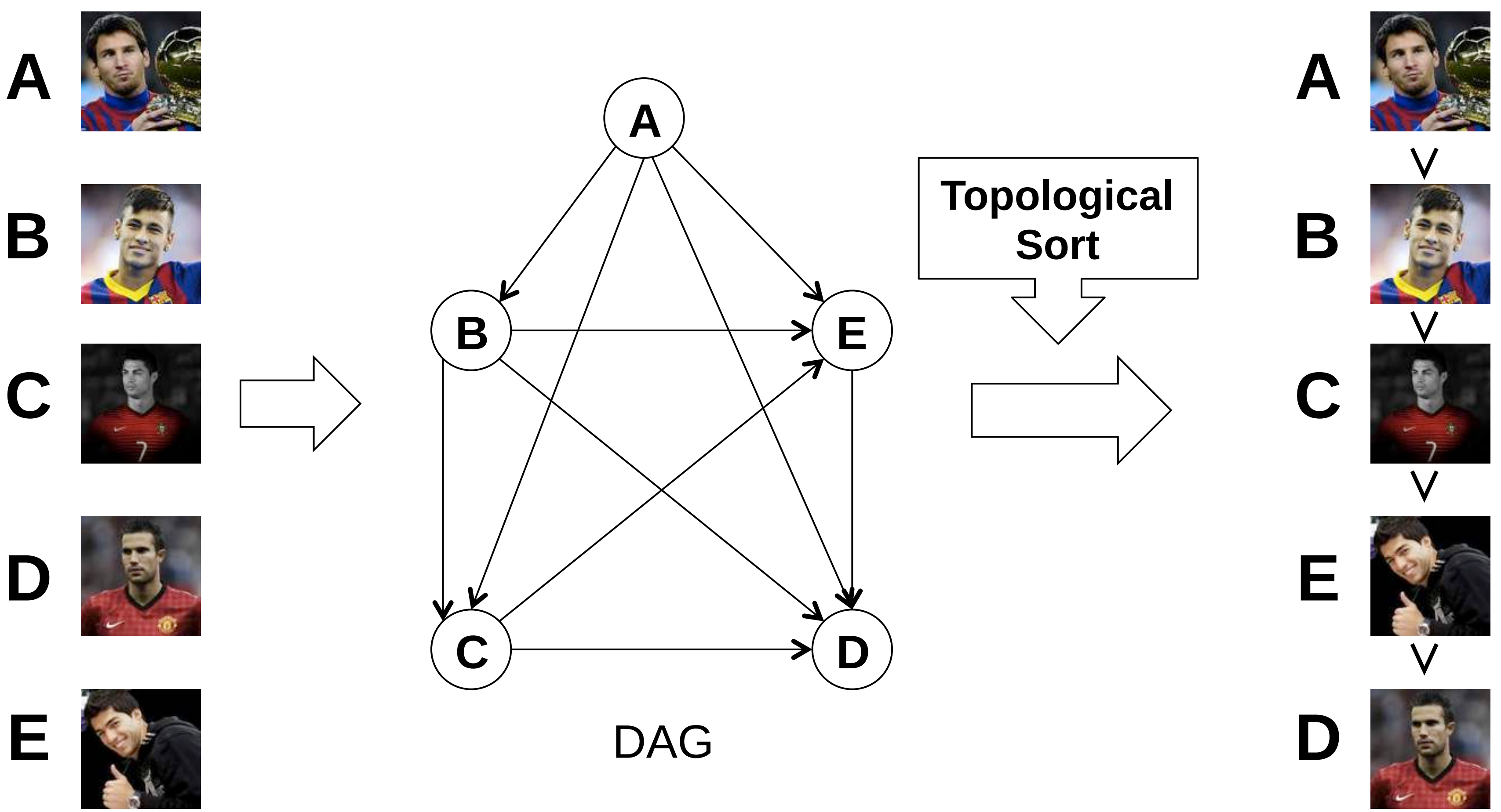
- N=5, S=3



Sort [Marcus-VLDB11]

- N=5, S=3

Sorted Result



Sort [Marcus-VLDB11]

- #2: Rating-based Sort
  - *W* workers rate each item along a numerical scale
  - Compute the mean of *W* ratings of each item
  - Sort all items using their means
  - Requires *W**N* HITs: *O(N)*

Worker	Rating
W1	4
W2	3
W3	4

. . .

Worker	Rating
W1	1
W2	2
W3	1

Mean rating

1.3

3.6

. . .

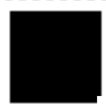
8.2

Sort [Marcus-VLDB11]

There are 2 squares below. We want to rate squares by their size.

- For each square, assign it a number from 1 (smallest) to 7 (largest) indicating its size.
- For perspective, here is a small number of other randomly picked squares:

smallest ○ ○ ✓ ○ ○ ○ ○ largest
1 2 3 4 5 6 7



smallest ○ ○ ○ ○ ✓ ○ ○ largest
1 2 3 4 5 6 7

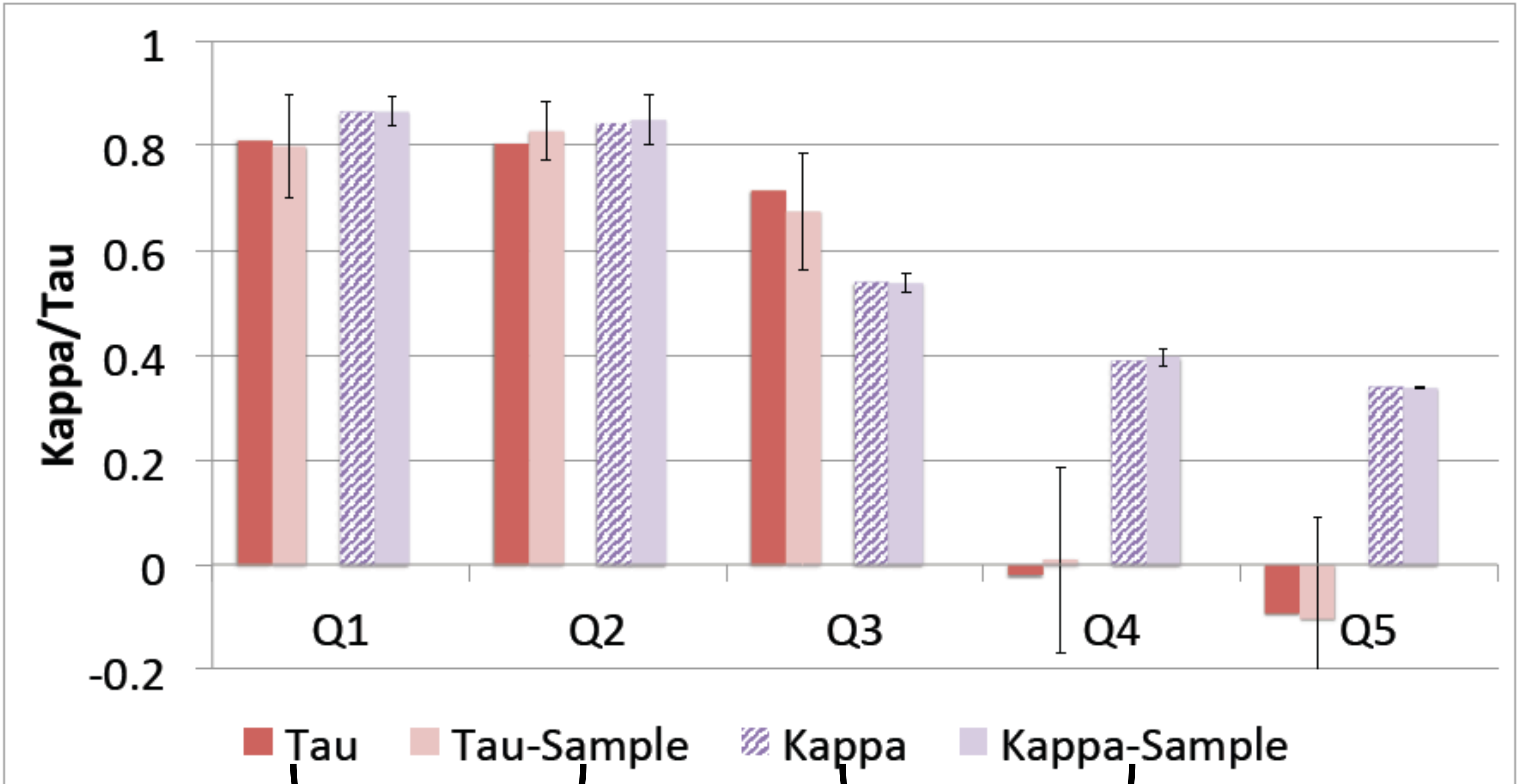
Submit

Sort [Marcus-VLDB11]

- #3: Hybrid Sort
  - First, do rating-based sort → sorted list *L*
  - Second, do comparison-based sort on *S* ($S \subset L$)

  - How to select the size of S
    - Random
    - Confidence-based
    - Sliding window

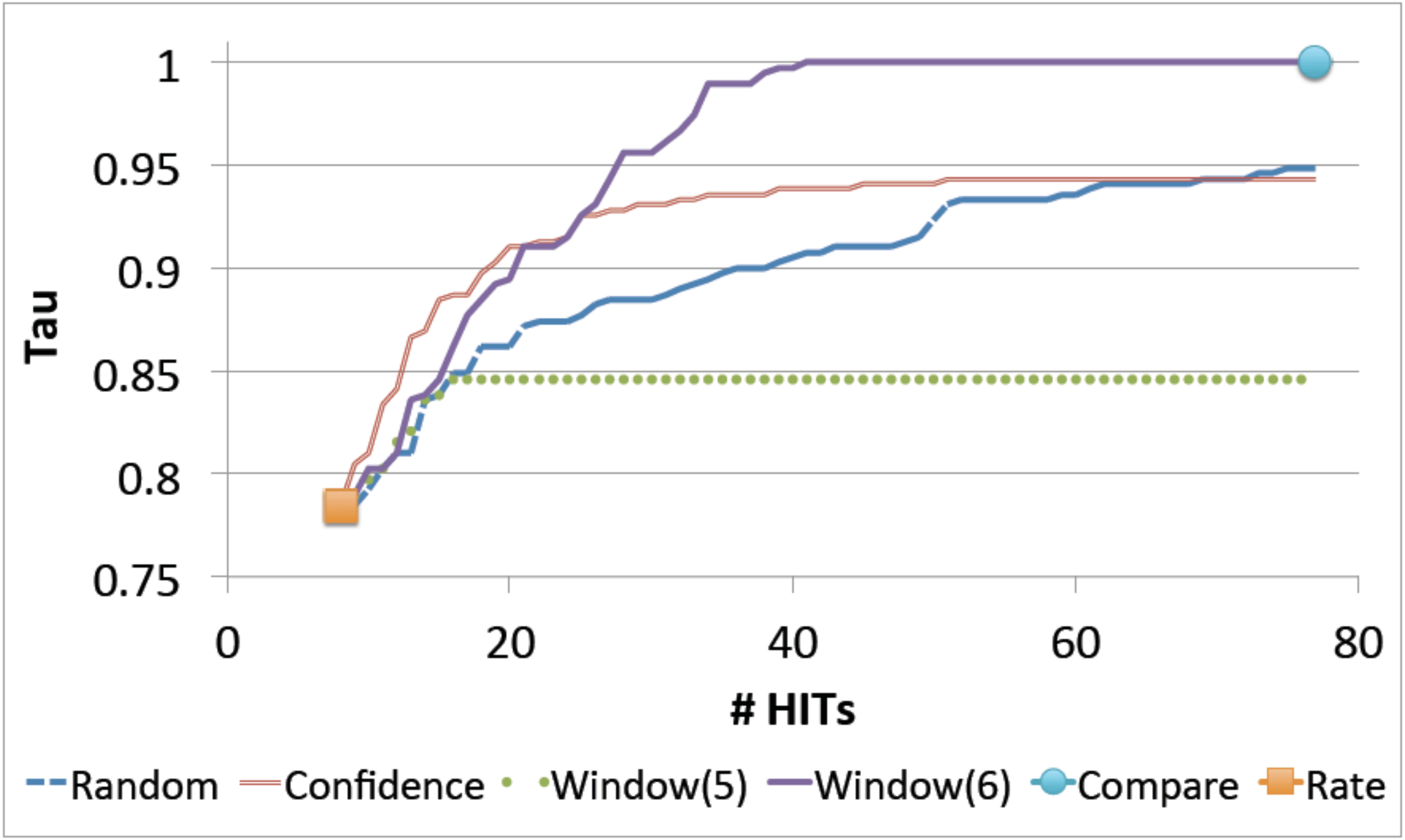
Sort [Marcus-VLDB11]



Rank correlation btw. Comparison vs. rating

Worker agreement

Sort [Marcus-VLDB11]



Part II: Crowdsourced Algo. in DB

- Preliminaries
- Sort
- **Select**
- Count
- Top-1
- Top-*k*
- Join

Select Operation

- Given *N* items, select *k* items that satisfy a predicate *P*

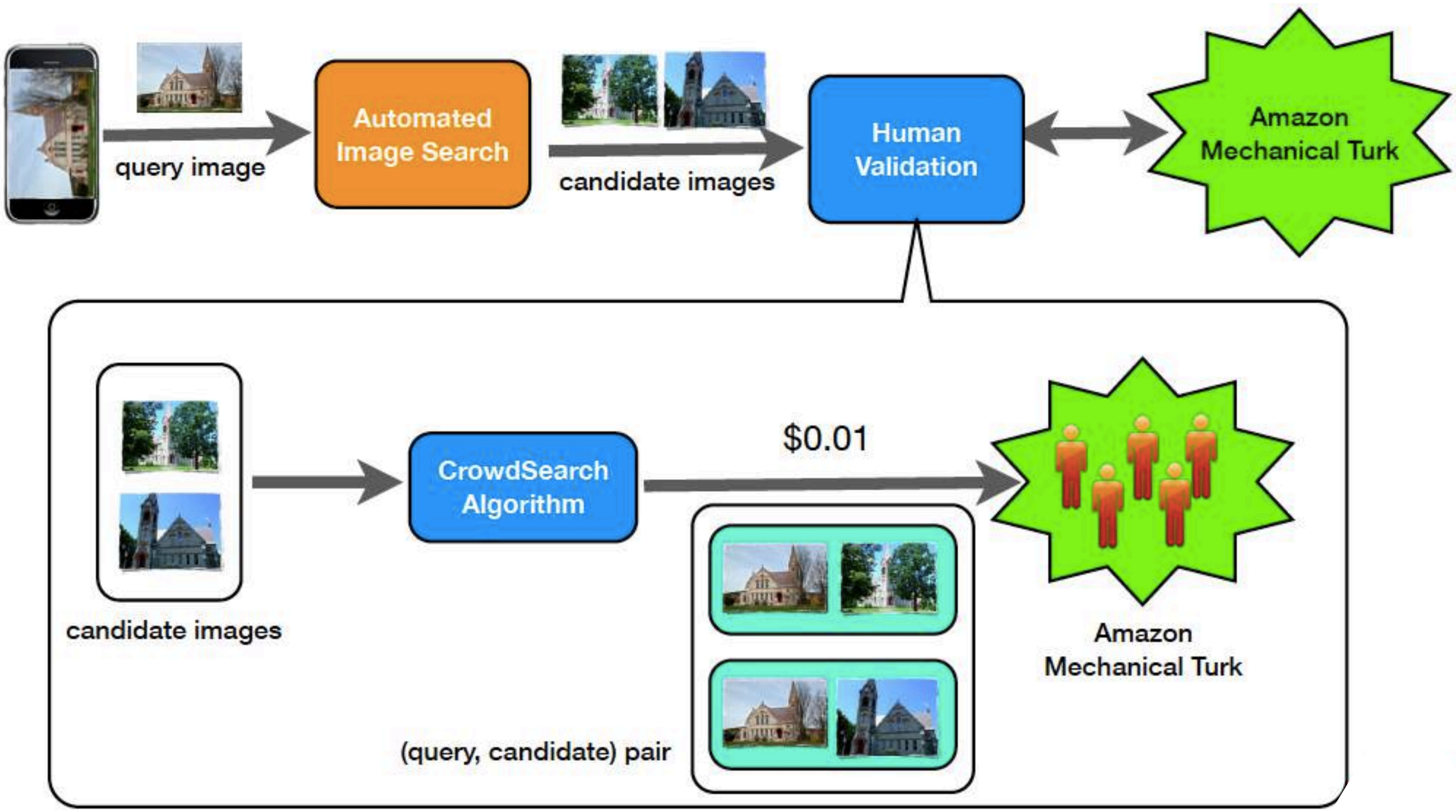
- ≈ Filter, Find, Screen, Search

Select Operation

- Examples
  - **[Yan-MobiSys10]** uses crowds to search an image relevant to a query
  - **[Parameswaran-SIGMOD12]** develops human-powered filtering algorithms
  - **[Franklin-ICDE13]** efficiently enumerates items satisfying conditions via crowdsourcing
  - **[Sarma-ICDE14]** finds a bounded number of items satisfying predicates using the optimal solution by the skyline of cost and time

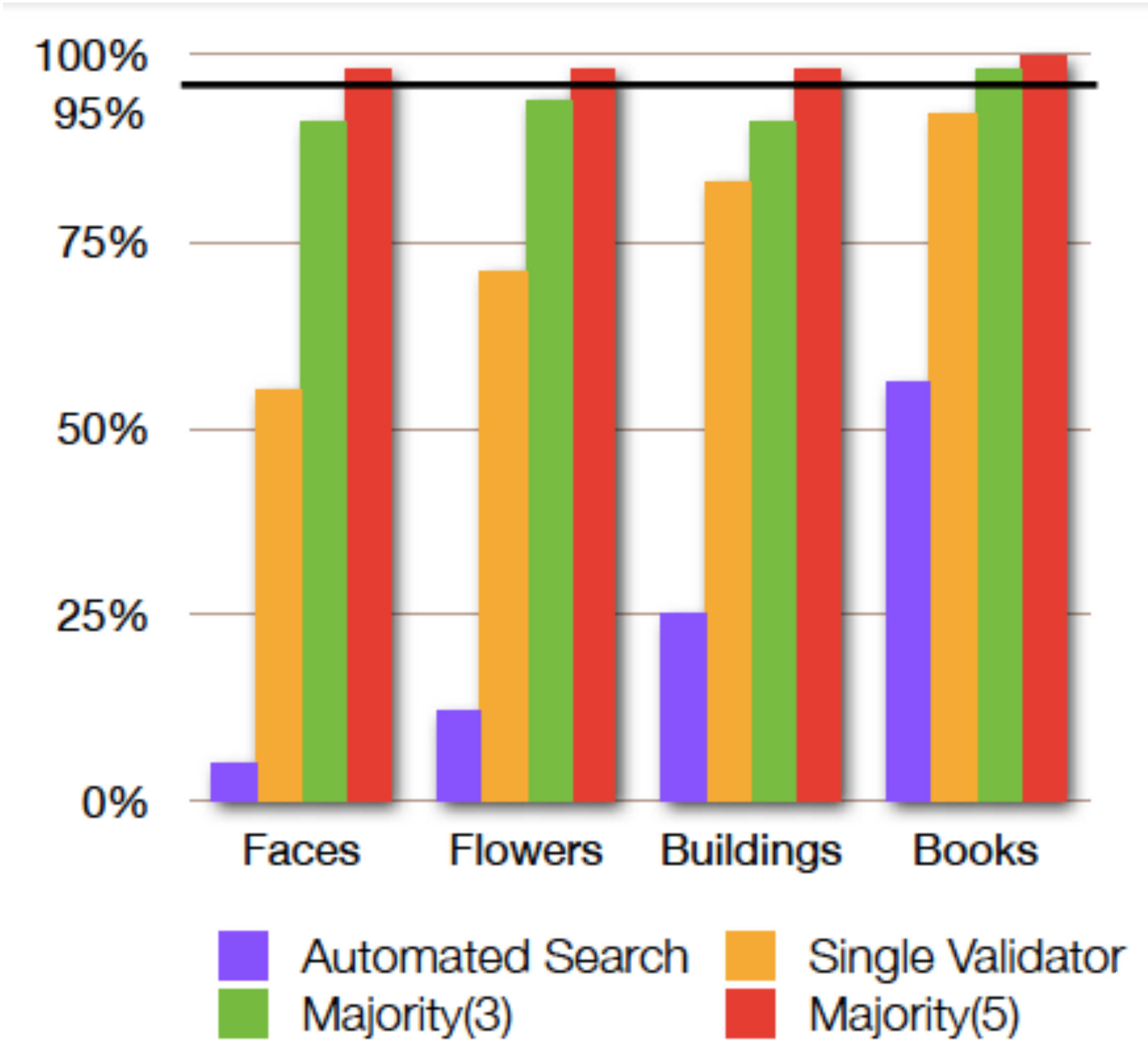
Select [Yan-MobiSys10]

- Improving mobile image search using crowdsourcing



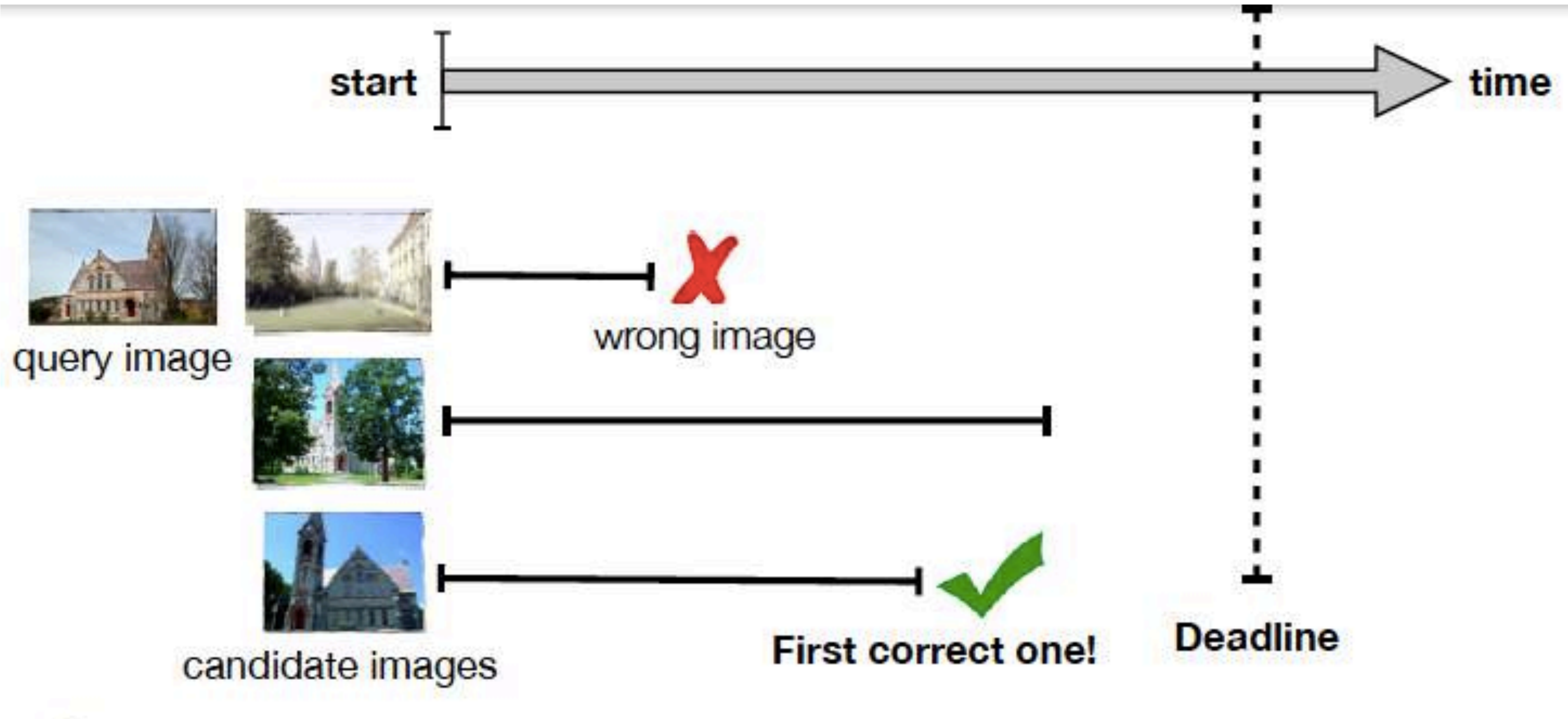
Select [Yan-MobiSys10]

- Ensuring accuracy with majority voting
- Given accuracy, optimize cost and latency
- Deadline as latency in mobile phones



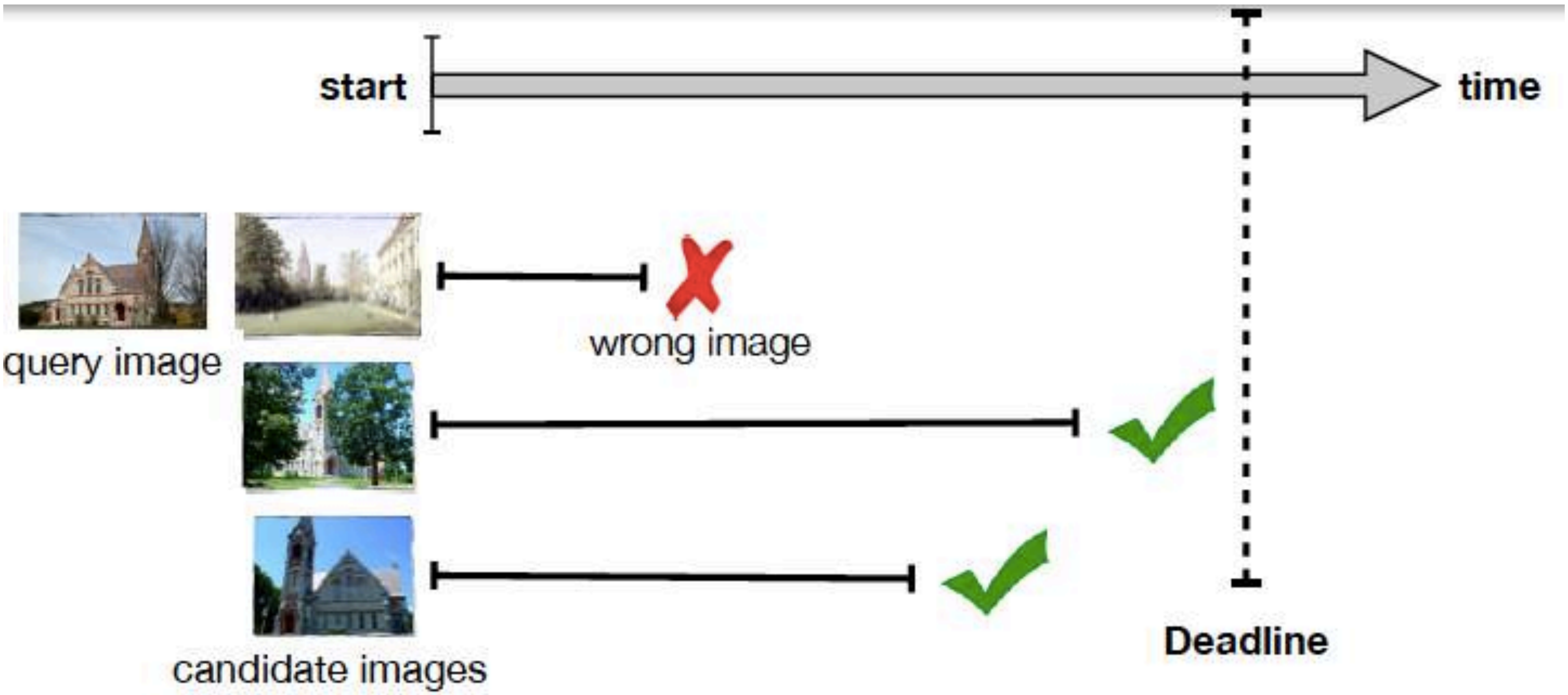
Select [Yan-MobiSys10]

- Goal: For a query image *Q*, find the first relevant image *I* with **min cost** before the **deadline**



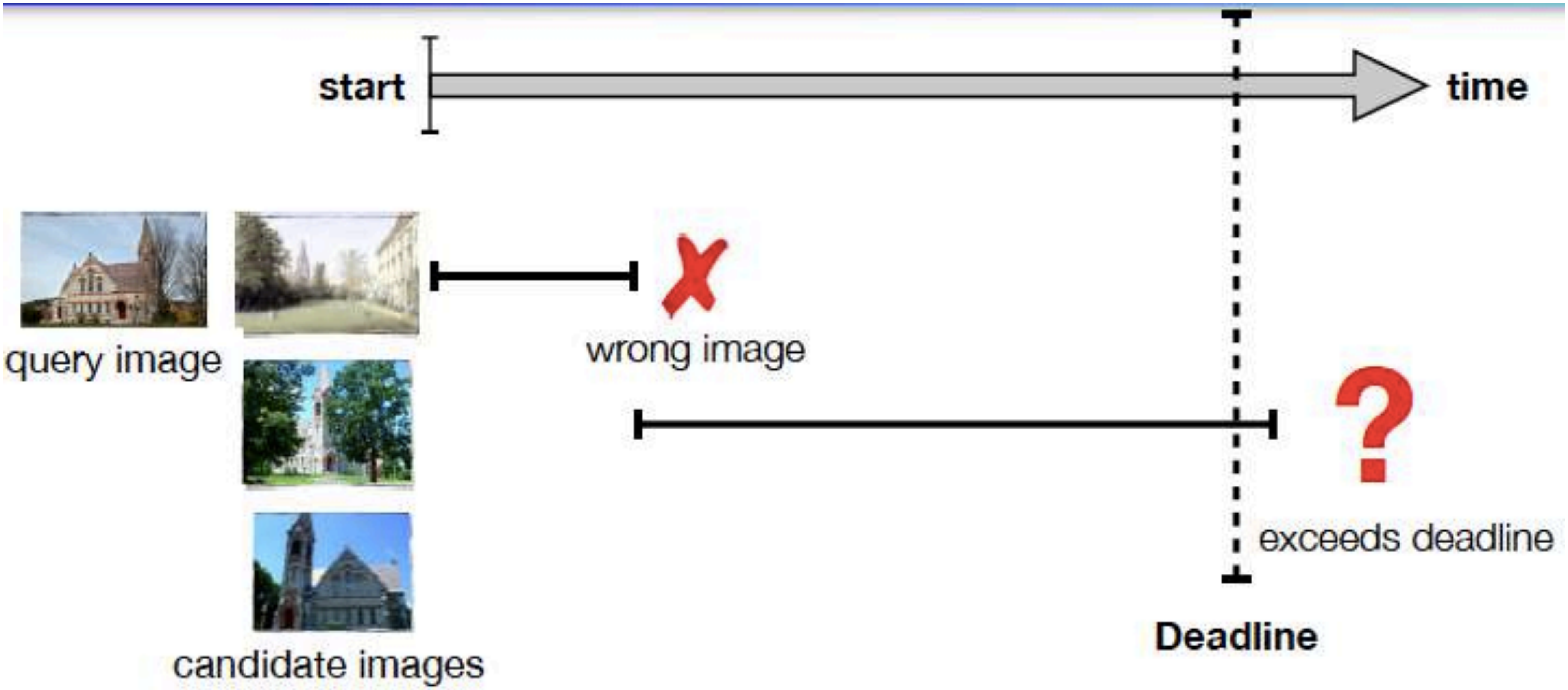
Select [Yan-MobiSys10]

- Parallel crowdsourced validation



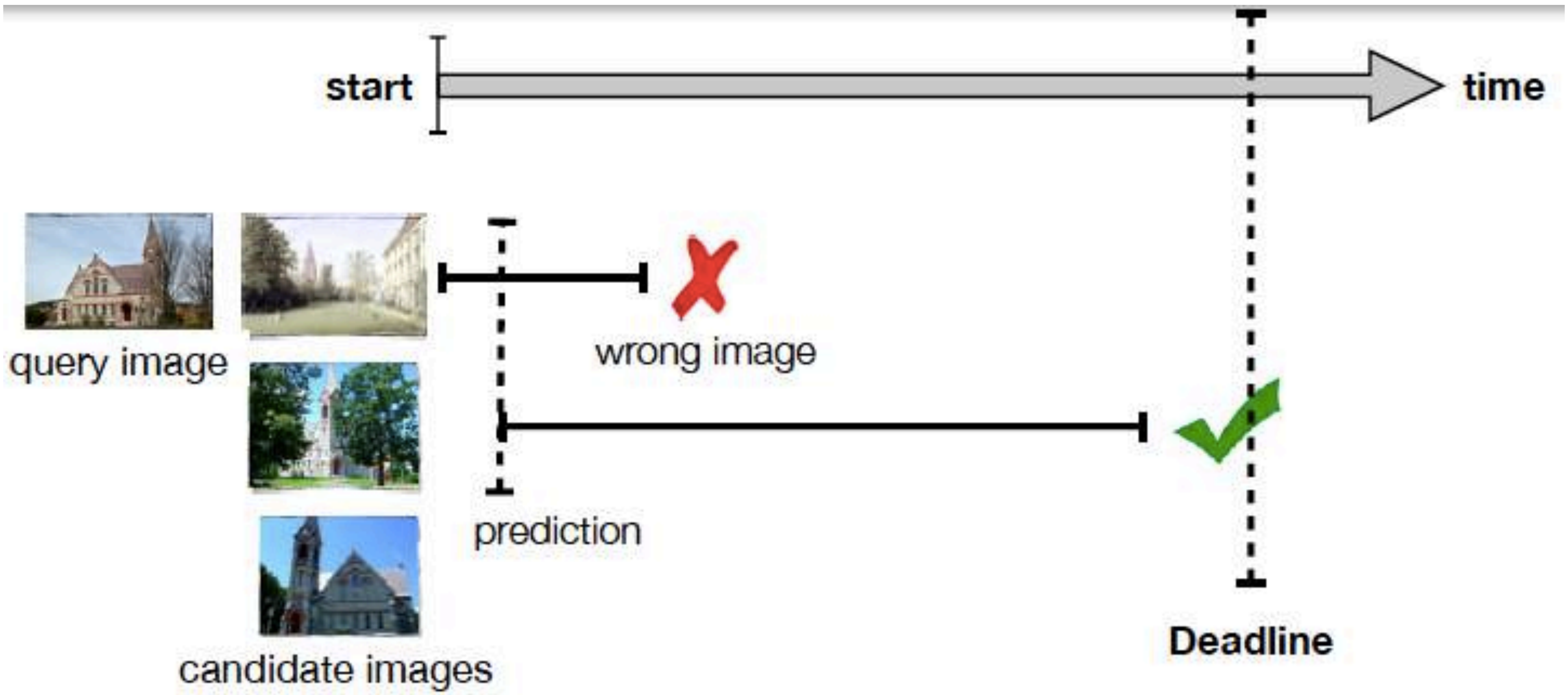
Select [Yan-MobiSys10]

- Sequential crowdsourced validation

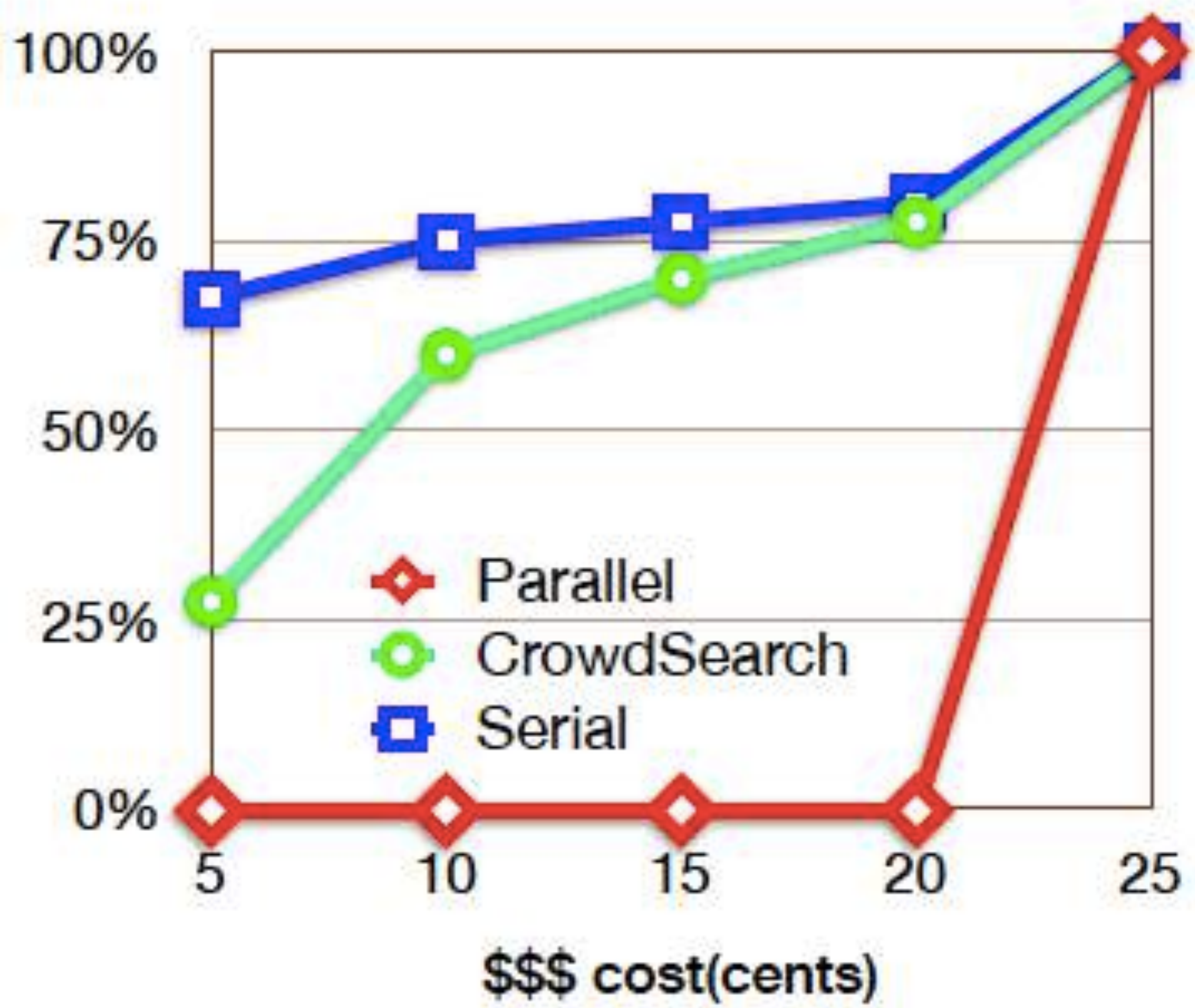


Select [Yan-MobiSys10]

- CrowdSearch: using early prediction on the delay and outcome to start the validation of next candidate early

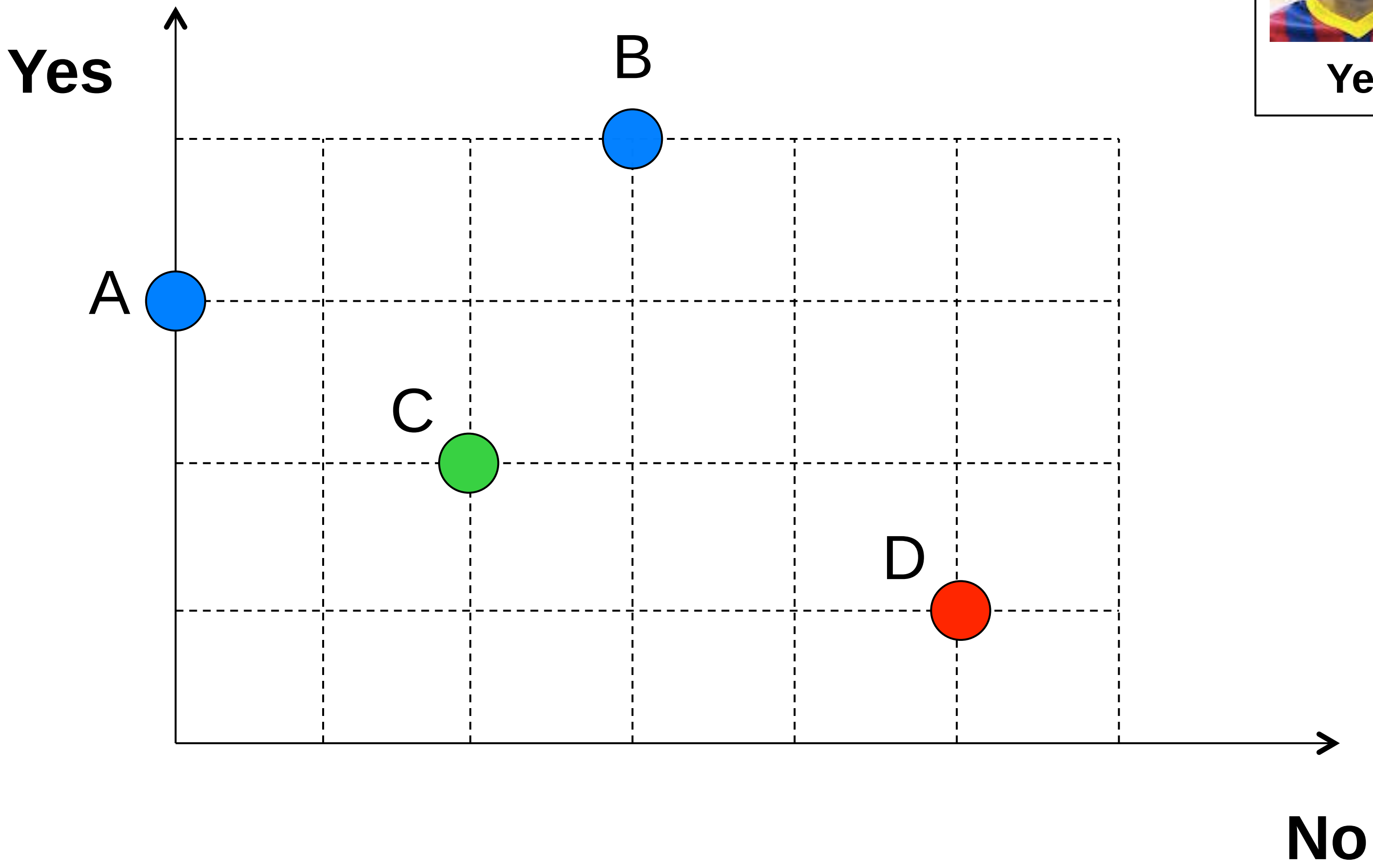


Select [Yan-MobiSys10]



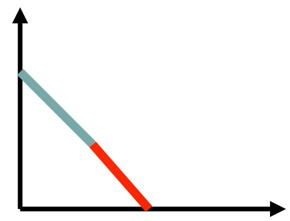
Select [Parameswaran-SIGMOD12]

- Novel grid-based visualization



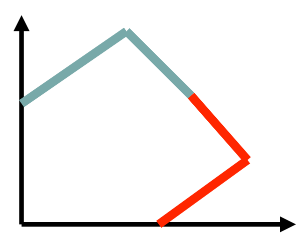
Select [Parameswaran-SIGMOD12]

- Common strategies
  - Always ask X questions, return most likely answer → Triangular strategy



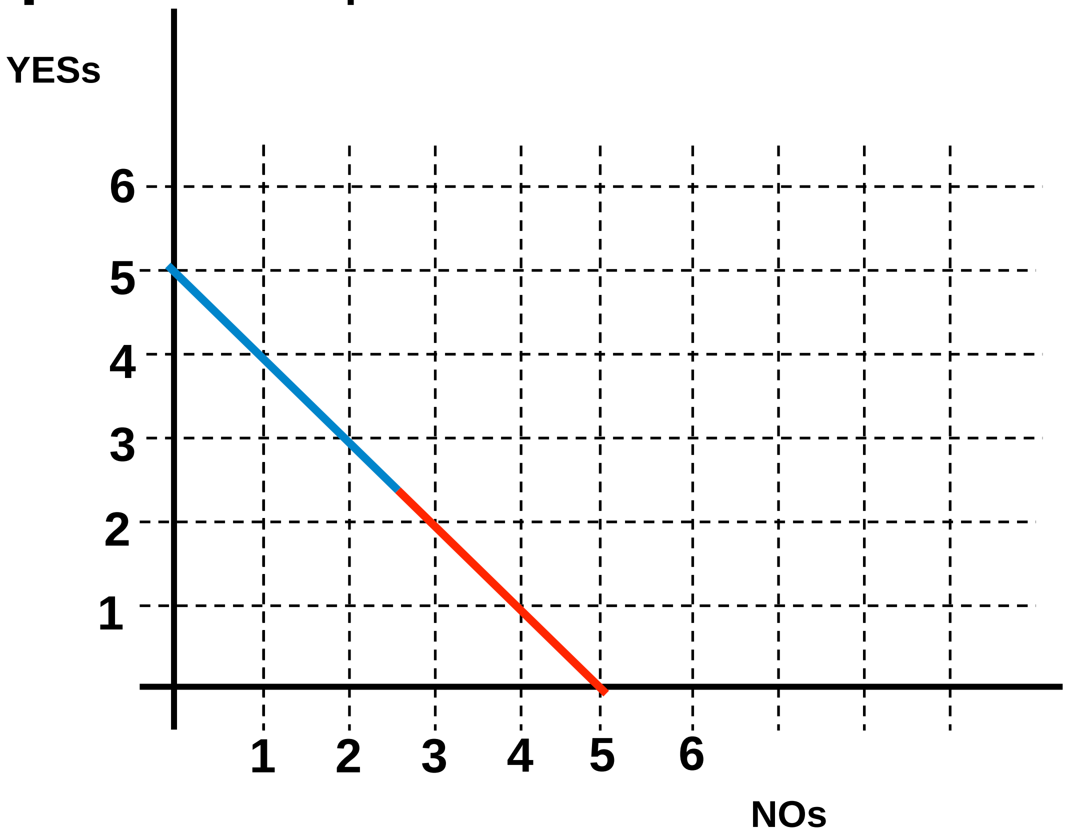
  - If X YES return “Pass”, Y NO return “Fail”, else keep asking → Rectangular strategy

  - Ask until |#YES - #NO| > X, or at most Y questions → Chopped off triangle



Select [Parameswaran-SIGMOD12]

- What is the best strategy? Find strategy with minimum overall expected cost s.t.
  1. **Overall expected error** is less than threshold
  2. **# of questions** per item never exceeds **m**



Part 2: Crowdsourced Algo. in DB

- Preliminaries
- Sort
- Select
- **Count**
- Top-1
- Top-*k*
- Join

Count Operation

- Given *N* items, estimate a fraction of items *M* that satisfy a predicate *P*

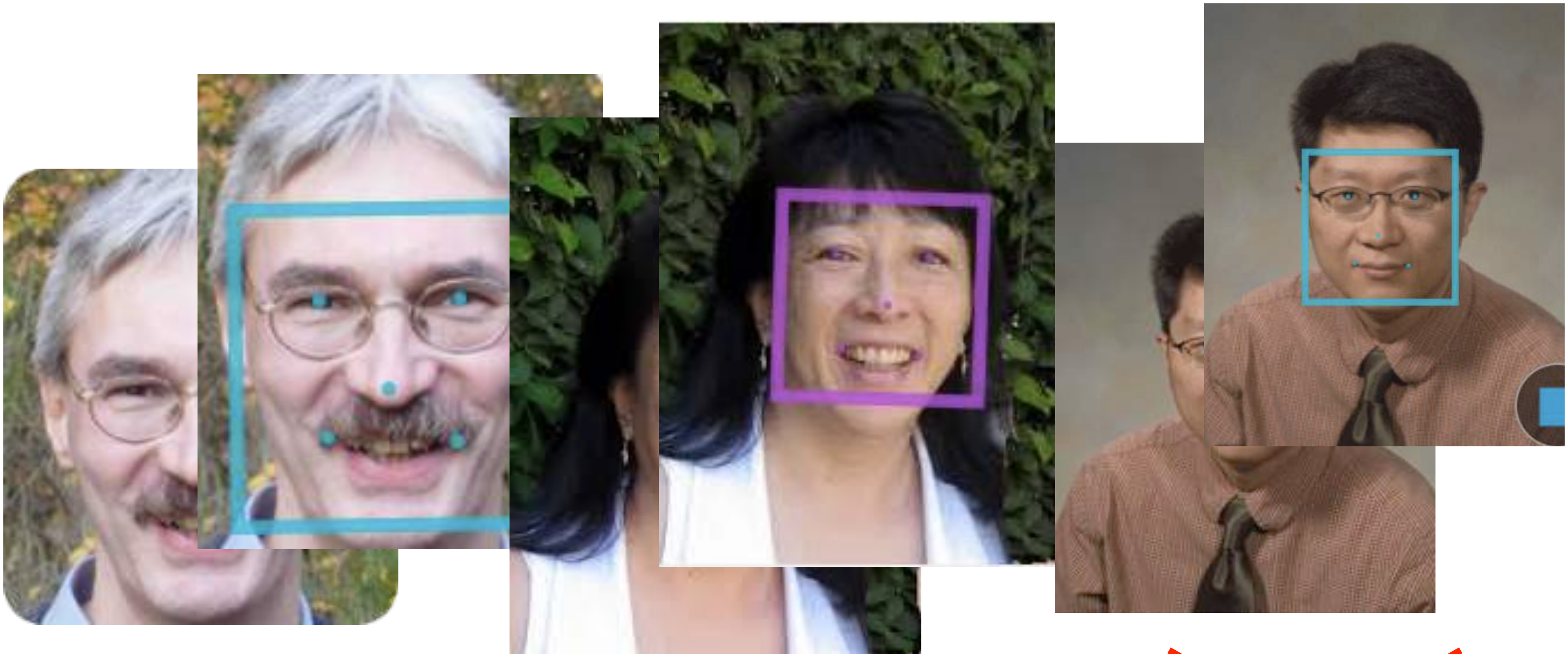
- Selectivity estimation in DB → crowd-powered query optimizers
- Evaluating queries with GROUP BY + COUNT/AVG/SUM operators
- Eg, "Find photos of females with red hairs"
  - Selectivity("female") ≈ 50%
  - Selectivity("red hair") ≈ 2%
  - Better to process predicate("red hair") first

Count Operation

- Q: “How many teens are participating in the Hong Kong demonstration?”

Count Operation

- Using Face++, guess the age of a person



10 - 56 **20 - 30** ~~**15 - 29**~~

http://www.faceplusplus.com/demo-detect/

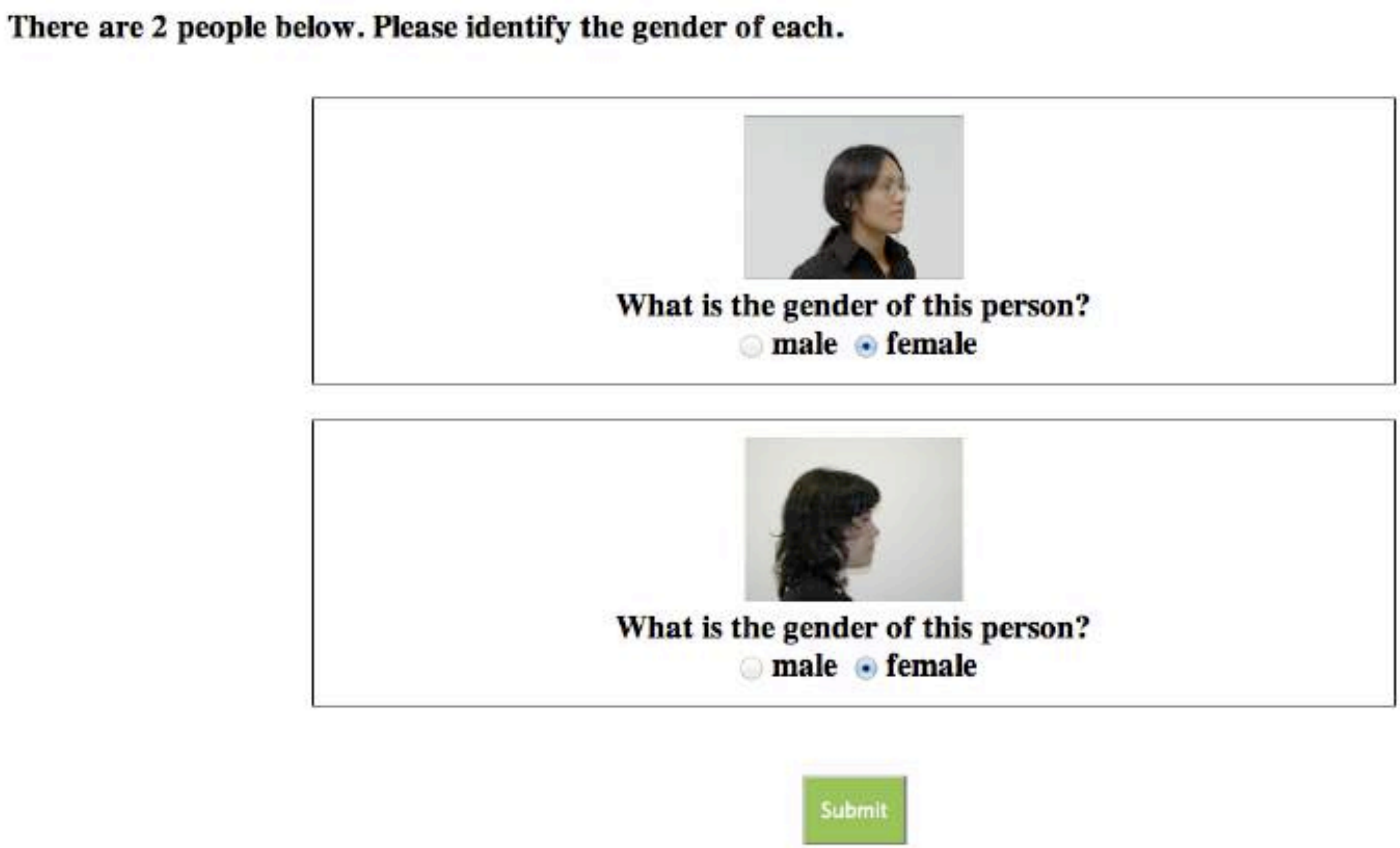
Count [Marcus-VLDB13]

- Hypothesis: Humans can estimate the frequency of objects' properties in a batch without having to explicitly label each item

- Two approaches
  - #1: Label Count
    - Sampling based
    - Have workers label samples explicitly
  - #2: Batch Count
    - Have workers estimate the frequency in a batch

Count [Marcus-VLDB13]

- Label Count (via sampling)



Count [Marcus-VLDB13]

- Batch Count

There are 10 people below. Please provide rough estimates for how many of the people have various properties.

About how many of the 10 people are male? 4

About how many of the 10 people are female?

Submit

Count [Marcus-VLDB13]

- Findings on accuracy
  - Images: Batch count **>** Label count
  - Texts: Batch count **<** Label count
- Further Contributions
  - Detecting spammers
  - Avoiding coordinated attacks

Part 2: Crowdsourced Algo. in DB

- Preliminaries
- Sort
- Select
- Count
- **Top-1**
- Top-*k*
- Join

Top-1 Operation

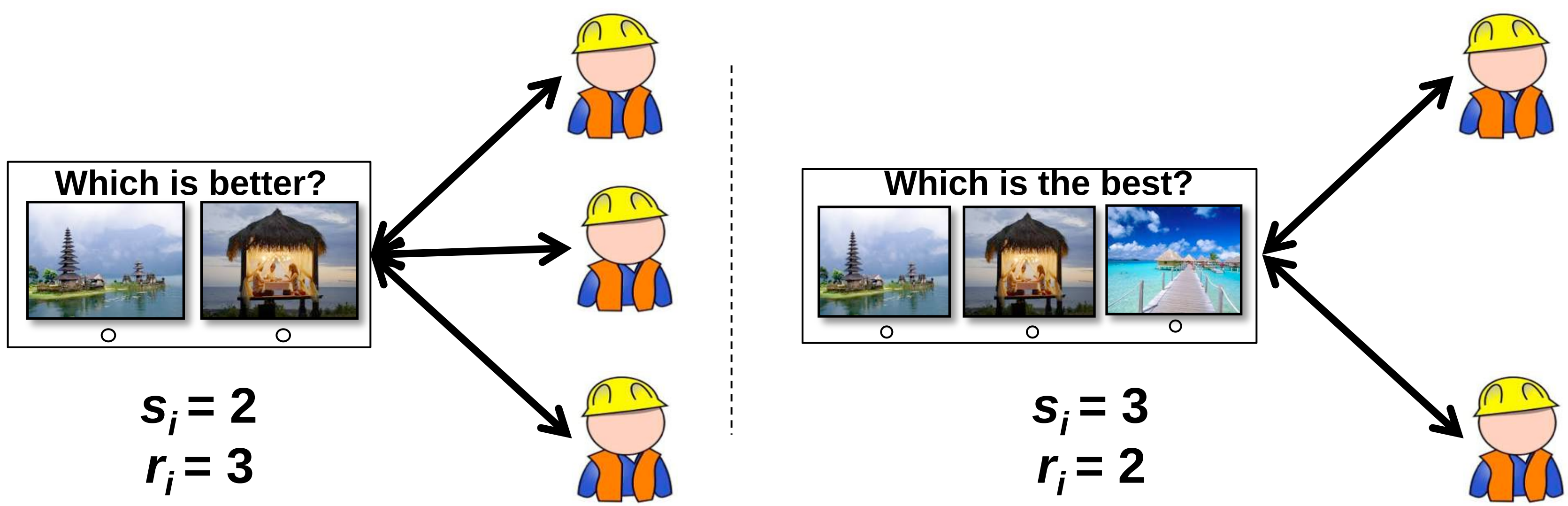
- Find the top-1, either MAX or MIN, among *N* items w.r.t. some criteria
- Objective
  - Avoid sorting all *N* items to find top-1

Top-1 Operation

- Examples
  - **[Venetis-WWW12]** introduces the bubble max and tournament-based max in a parameterized framework
  - **[Guo-SIGMOD12]** studies how to find max using pair-wise questions in the tournament-like setting and how to improve accuracy by asking more questions

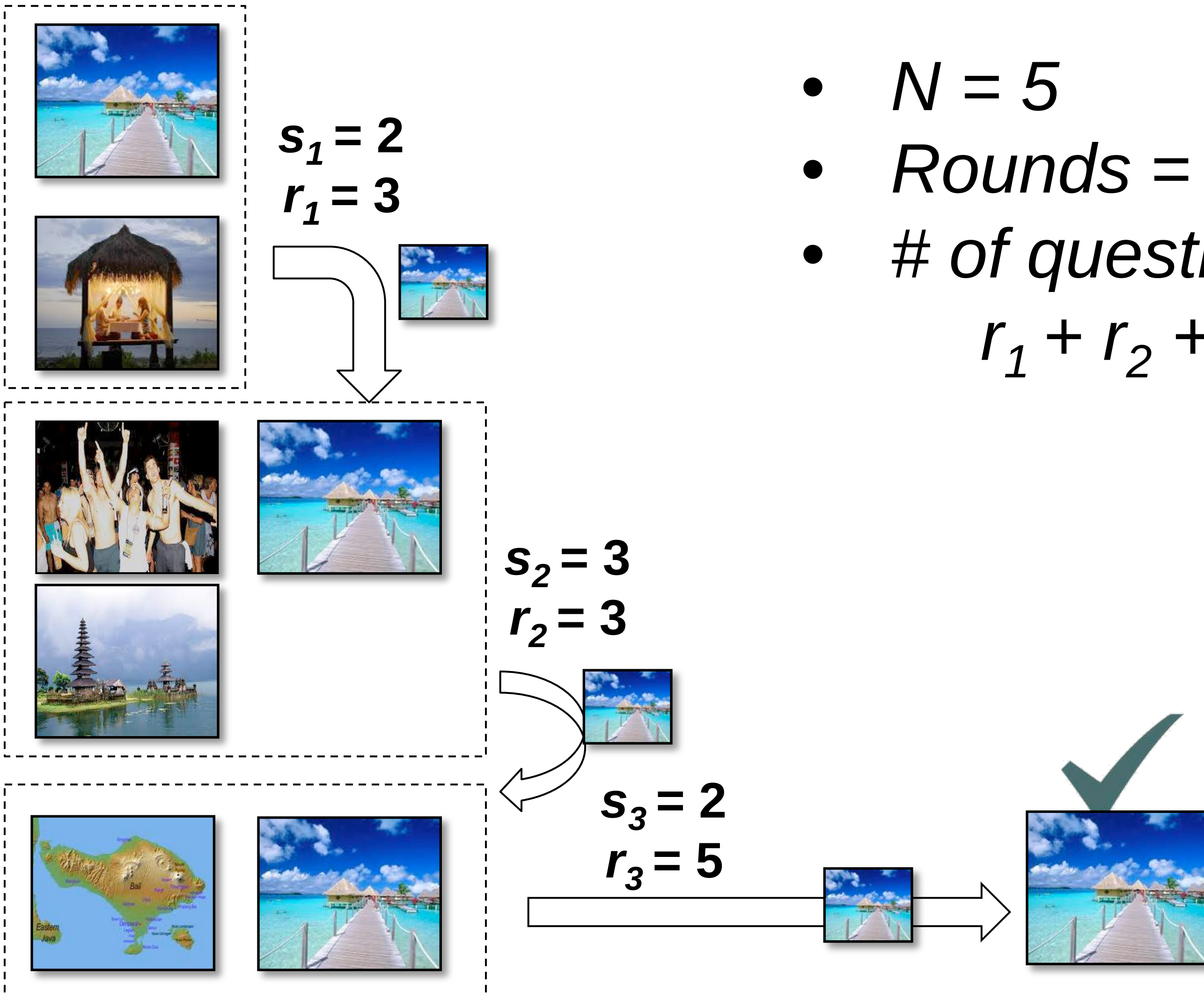
Max [Venetis-WWW12]

- Introduced two Max algorithms
  - Bubble Max
  - Tournament Max
- Parameterized framework
  - s_i: size of sets compared at the i-th round
  - r_i: # of human responses at the i-th round



Max [Venetis-WWW12]

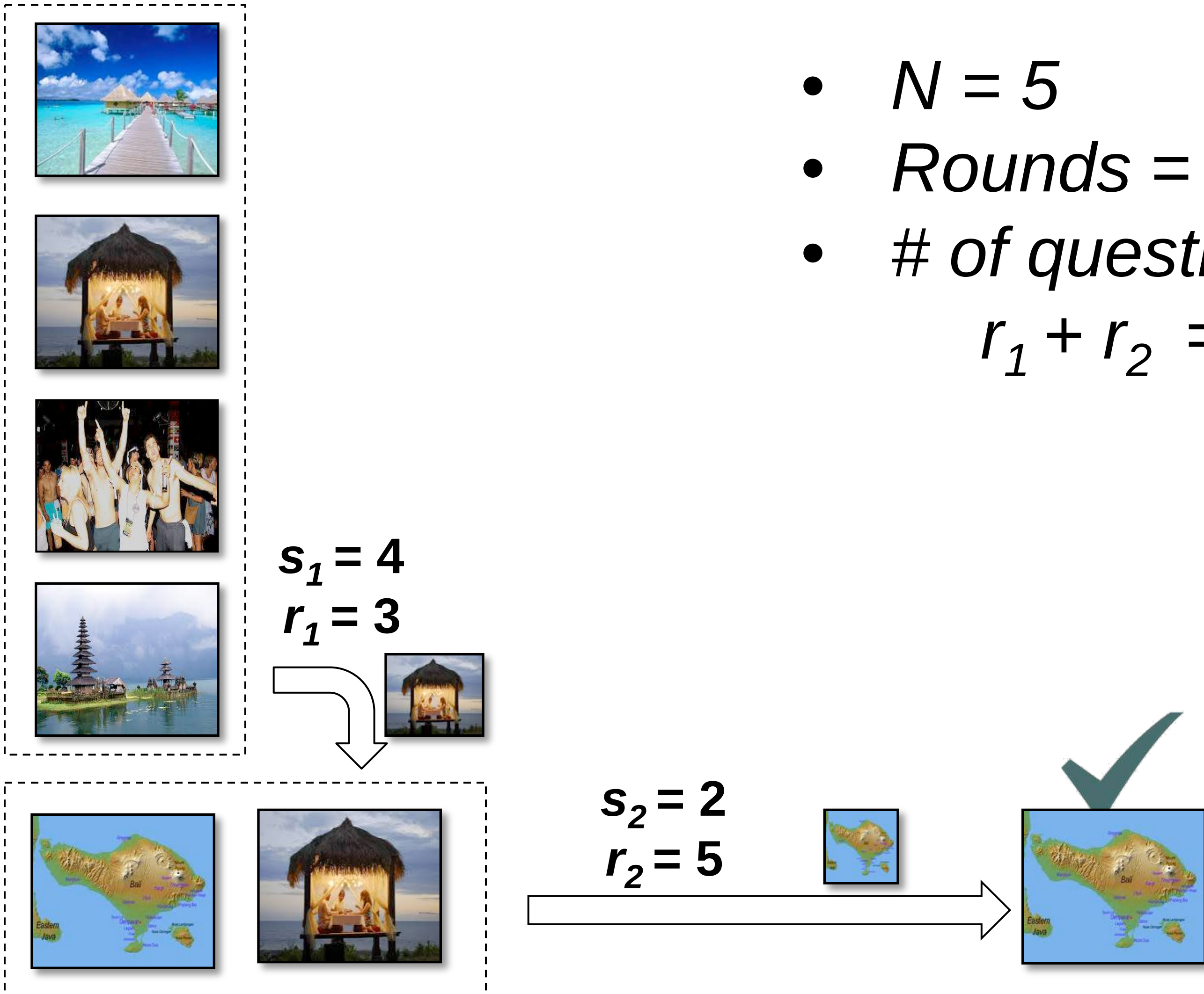
- Bubble Max Case #1



- *N = 5*
- *Rounds = 3*
- *# of questions =* $r_1 + r_2 + r_3 = 11$

Max [Venetis-WWW12]

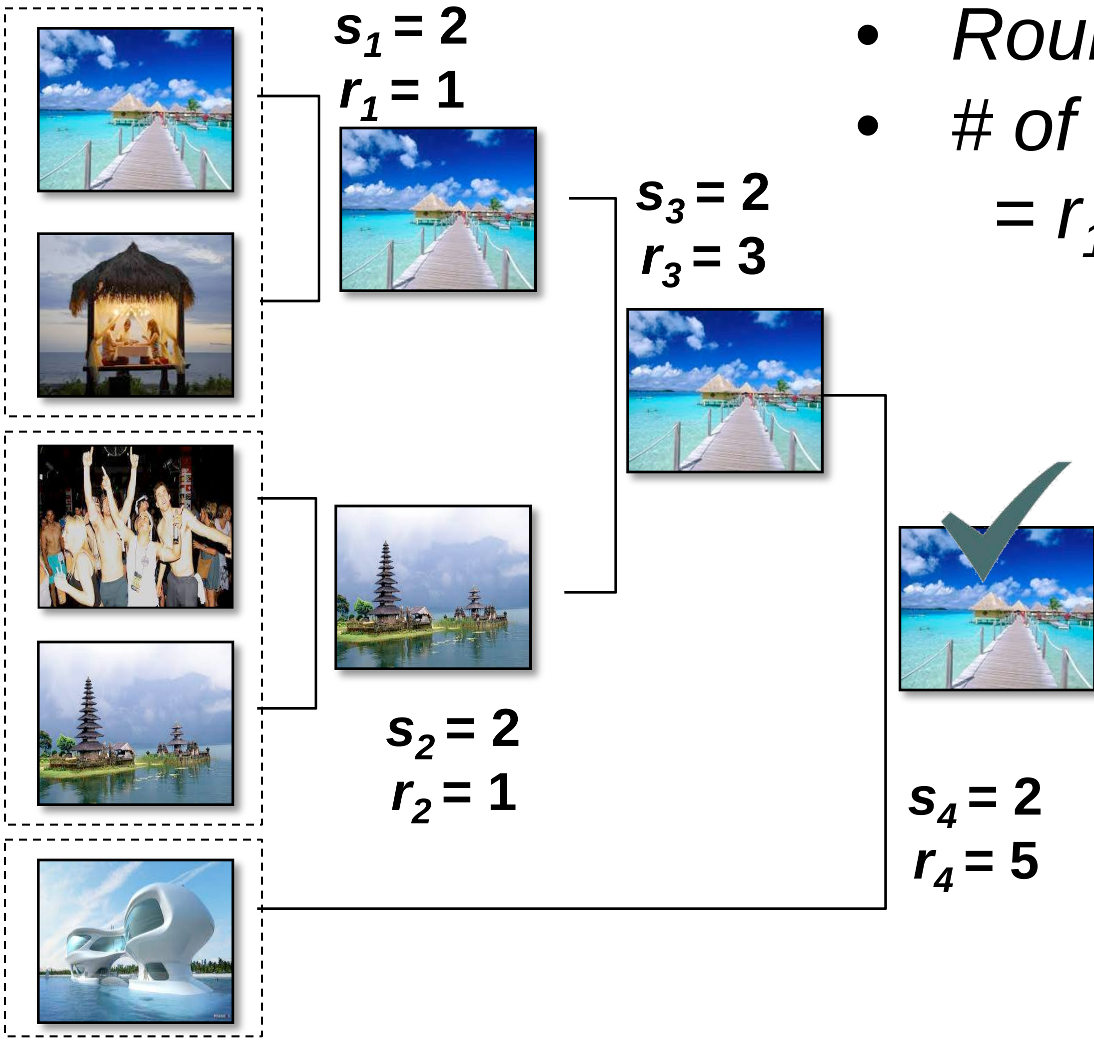
- Bubble Max Case #2



- $N = 5$
- *Rounds* = 2
- *# of questions* = $r_1 + r_2 = 8$

Max [Venetis-WWW12]

- Tournament Max



- $N = 5$
- *Rounds* $= 3$
- *# of questions*
  $= r_1 + r_2 + r_3 + r_4 = 10$

Max [Venetis-WWW12]

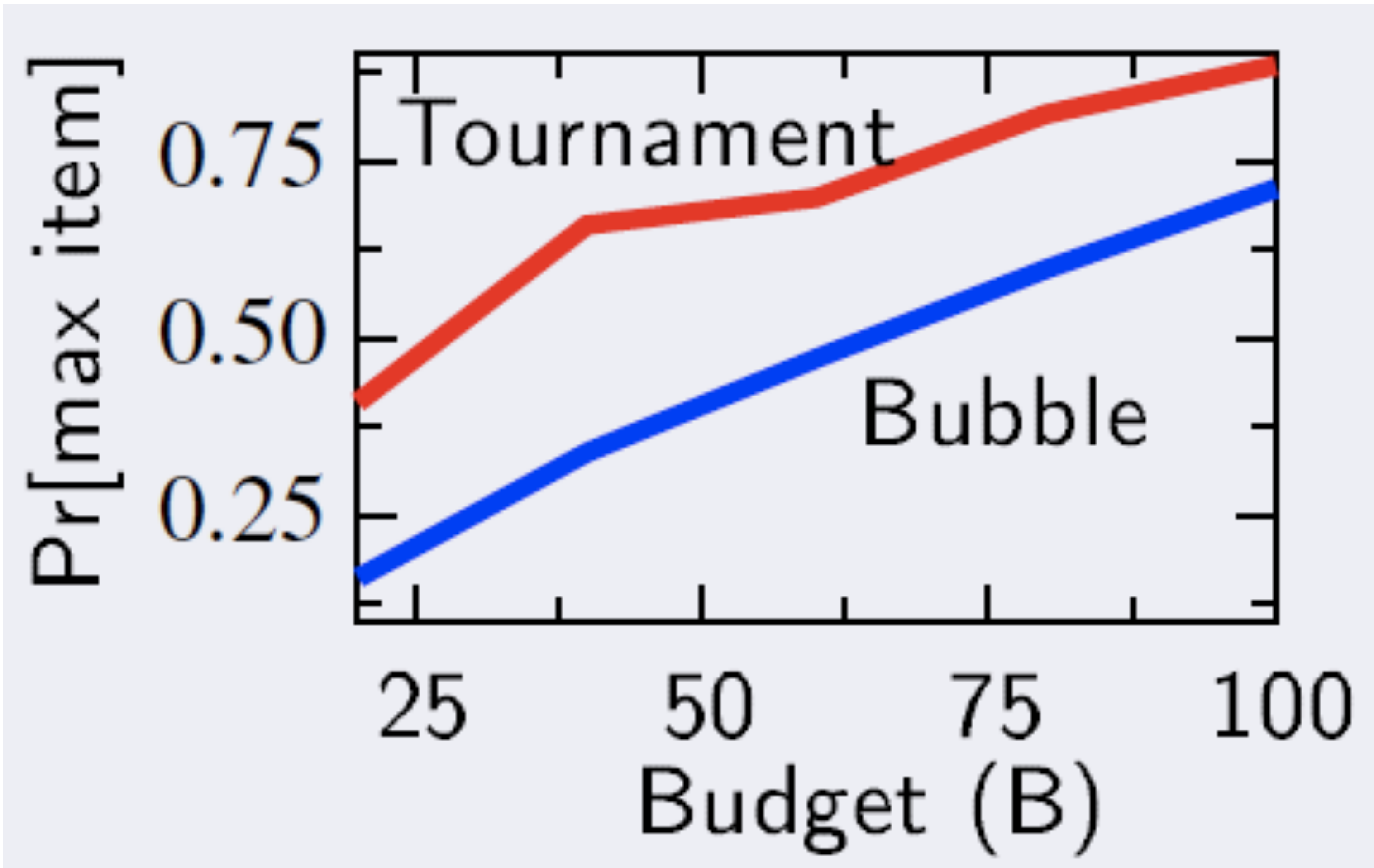
- How to find optimal parameters?: s_i and r_i
- Tuning Strategies (using Hill Climbing)
  - Constant s_i and r_i
  - Constant s_i and varying r_i
  - Varying s_i and r_i

Max [Venetis-WWW12]

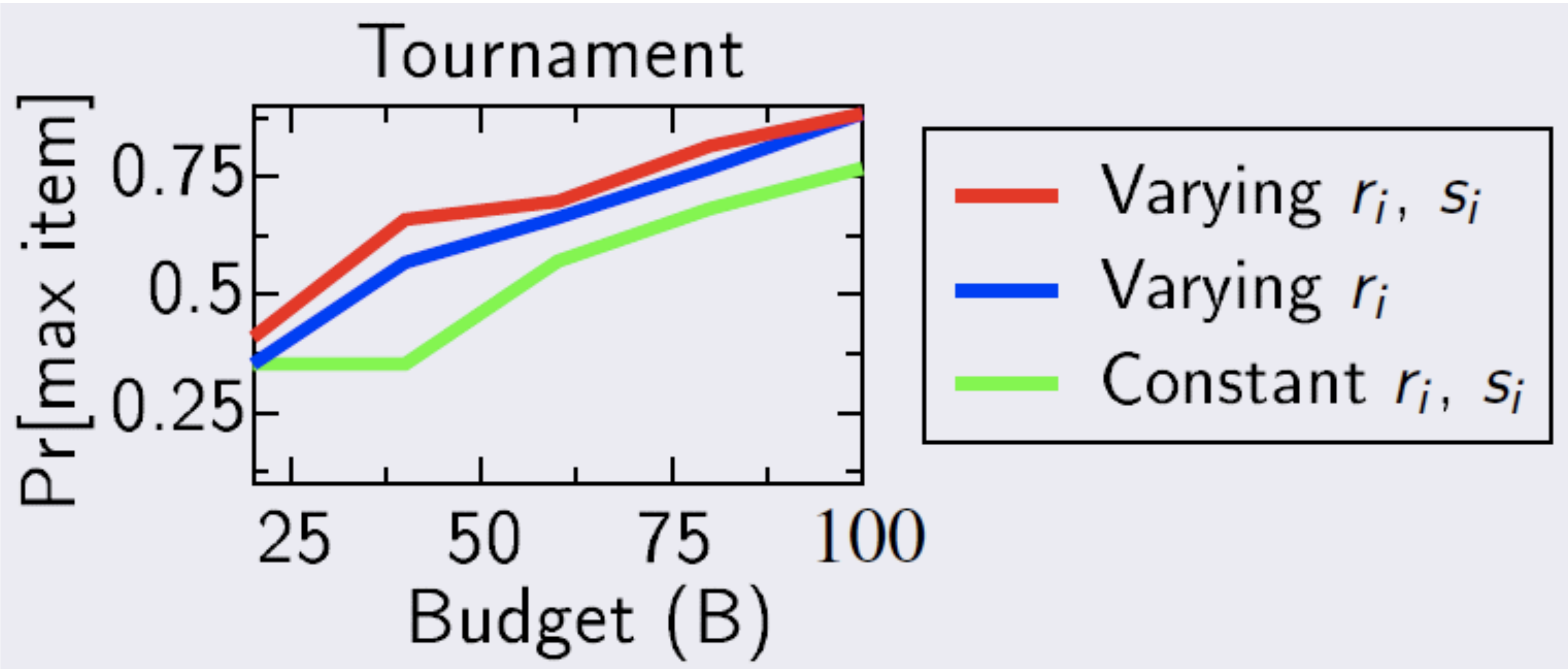
- Bubble Max
  - Worst case: with s_i=2, O(N) comparisons needed
- Tournament Max
  - Worst case: with s_i=2, O(N) comparisons needed

- Bubble Max is a special case of Tournament Max

Max [Venetis-WWW12]



Max [Venetis-WWW12]



Part 2: Crowdsourced Algo. in DB

- Preliminaries
- Sort
- Select
- Count
- Top-1
- **Top-*k***
- Join

Top-*k* Operation

- Find top-*k* items among *N* items w.r.t. some criteria
- Top-*k* list vs. top-*k* set
- Objective
  - Avoid sorting all *N* items to find top-*k*

Top-*k* Operation

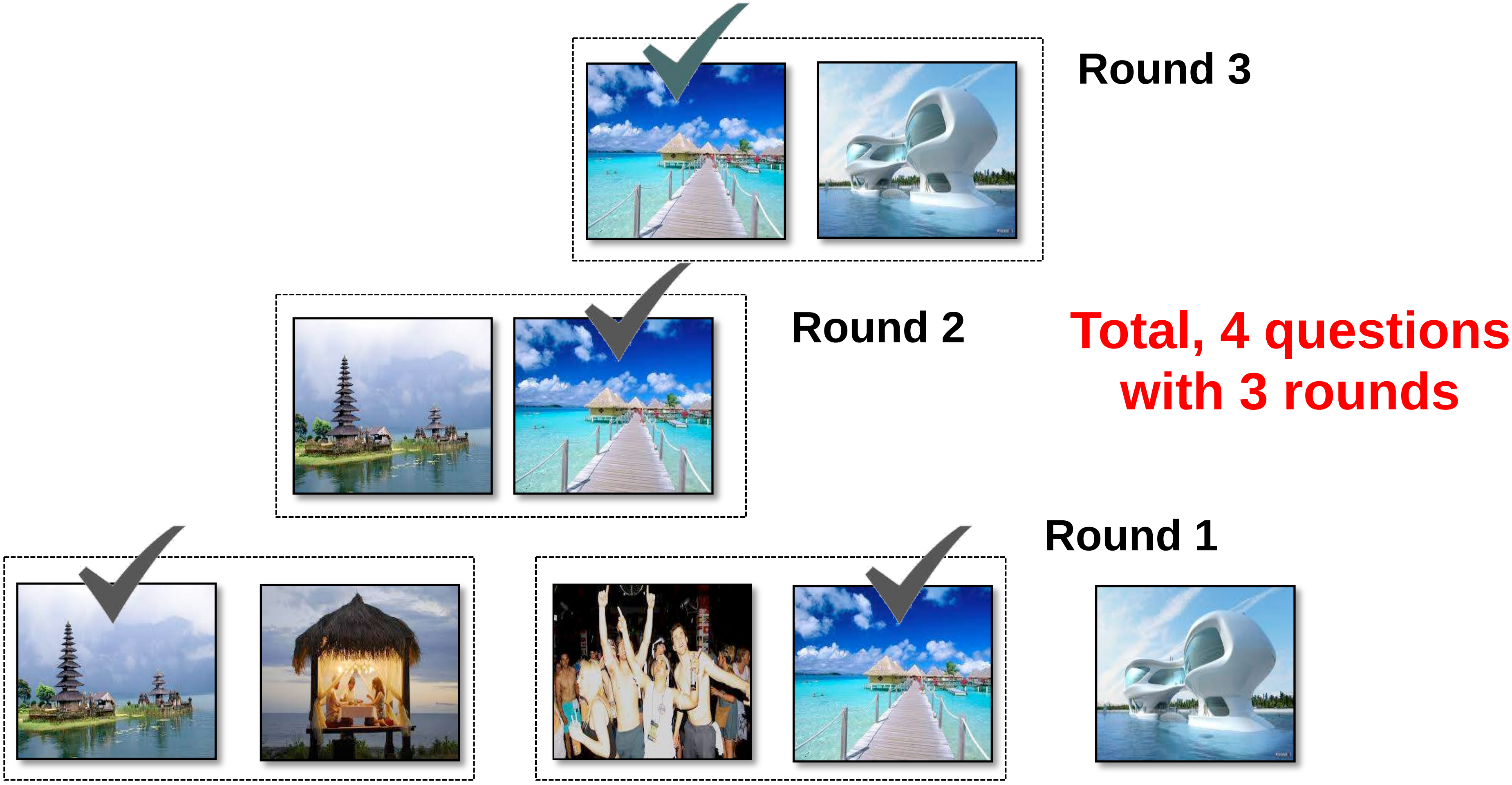
- Examples
  - **[Davidson-ICDT13]** investigates the variable user error model in solving top-*k* list problem
  - **[Polychronopoulous-WebDB13]** proposes tournament-based top-*k* set solution

Top-*k* Operation

- Naïve solution is to "sort" *N* items and pick top-*k* items
- Eg, *N*=5, *k*=2, "Find two best Bali images?"
  - Ask $\binom{5}{2}$ = 10 pair-wise questions to get a total order
  - Pick top-2 images

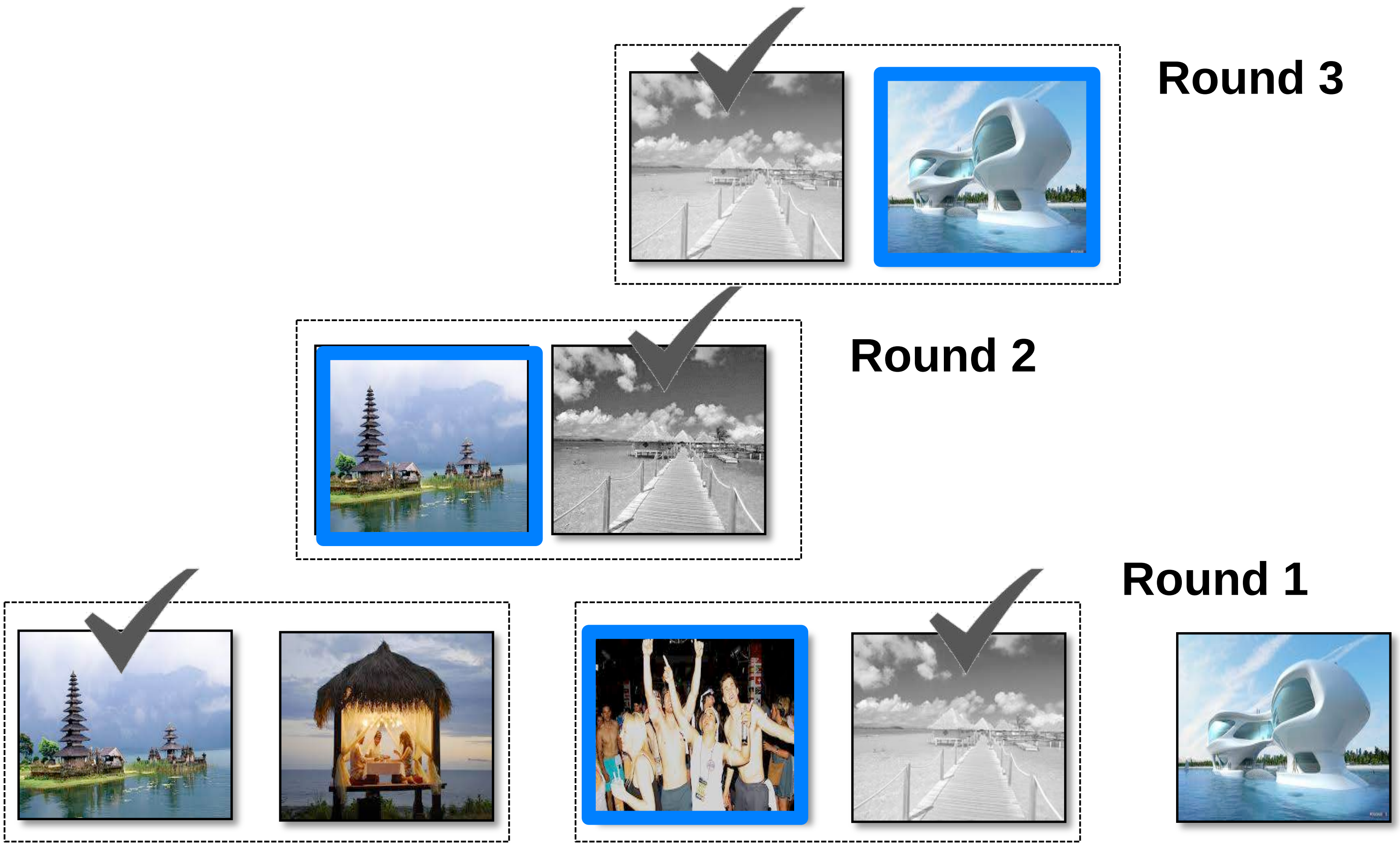
Top-*k*: Tournament Solution (*k* = 2)

- Phase 1: **Building a tournament tree**
  - For each comparison, only winners are promoted to the next round



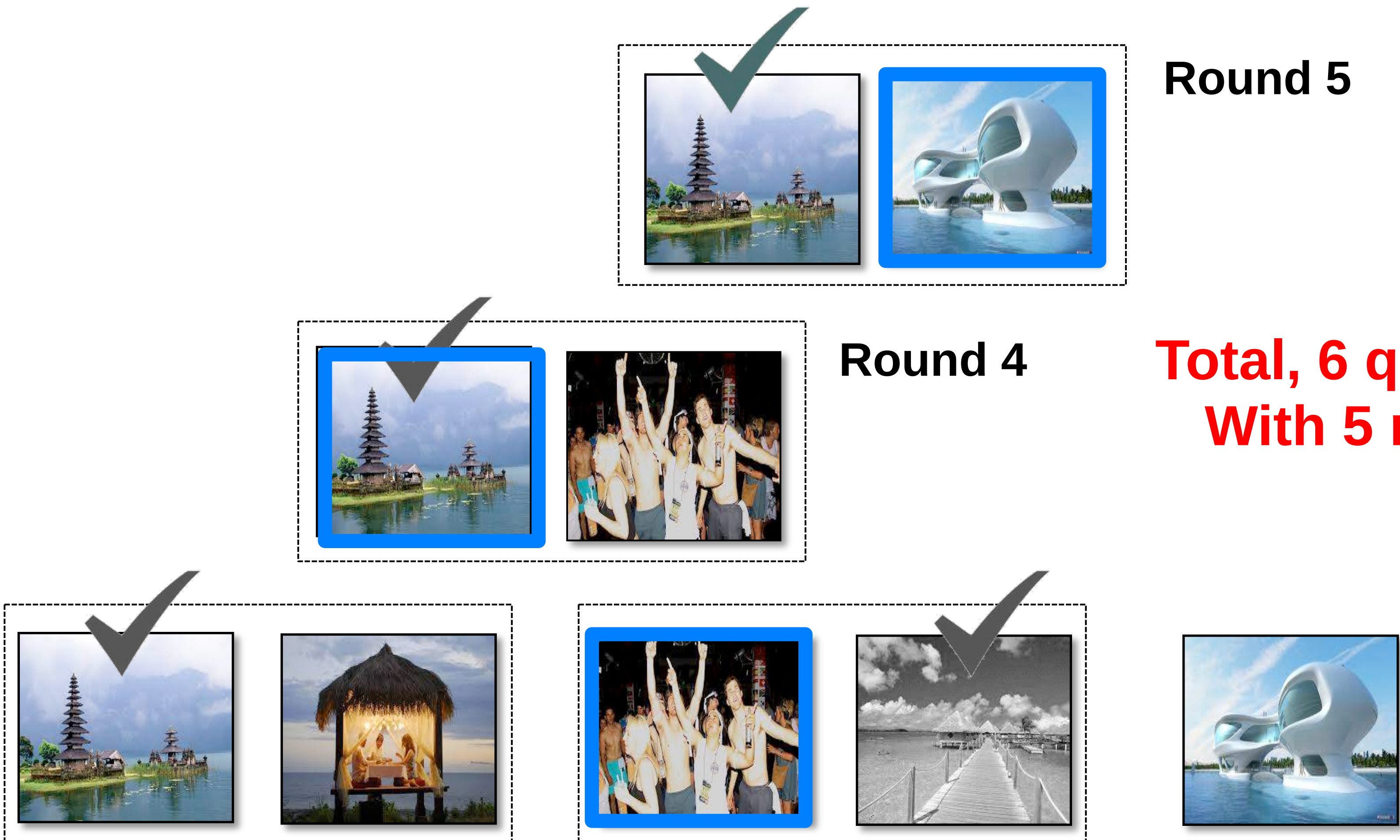
Top-*k*: Tournament Solution (*k* = 2)

- Phase 2: **Updating a tournament tree**
  - **Iteratively** asking pair-wise questions from the bottom level



Top-*k*: Tournament Solution (*k* = 2)

- Phase 2: **Updating a tournament tree**
  - **Iteratively** asking pair-wise questions from the bottom level



Total, 6 questions
With 5 rounds

Top-*k*: Tournament Solution

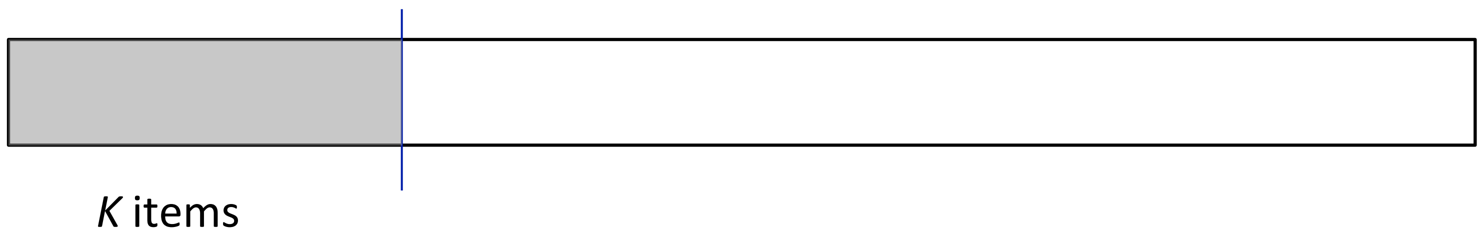
- This is a top-*k* **list** algorithm
- Analysis

	k = 1	k ≥ 2
# of questions	$O(n)$	$O(n + k \lceil \log_2 n \rceil)$
# of rounds	$O(\lceil \log_2 n \rceil)$	$O(k \lceil \log_2 n \rceil)$

- If there is no constraint for the number of rounds, this tournament sort based top-*k* scheme yields the optimal result

Top-*k* [Polychronopoulous-WebDB13]

- Top-*k* **set** algorithm
  - Top-k items are "better" than remaining items
  - Capture NO ranking among top-*k* items



  - Tournament-based approach
- Can become a Top-*k* **list** algorithm
  - Eg, Top-*k* **set** algorithm, followed by [Marcus-VLDB11] to sort *k* items

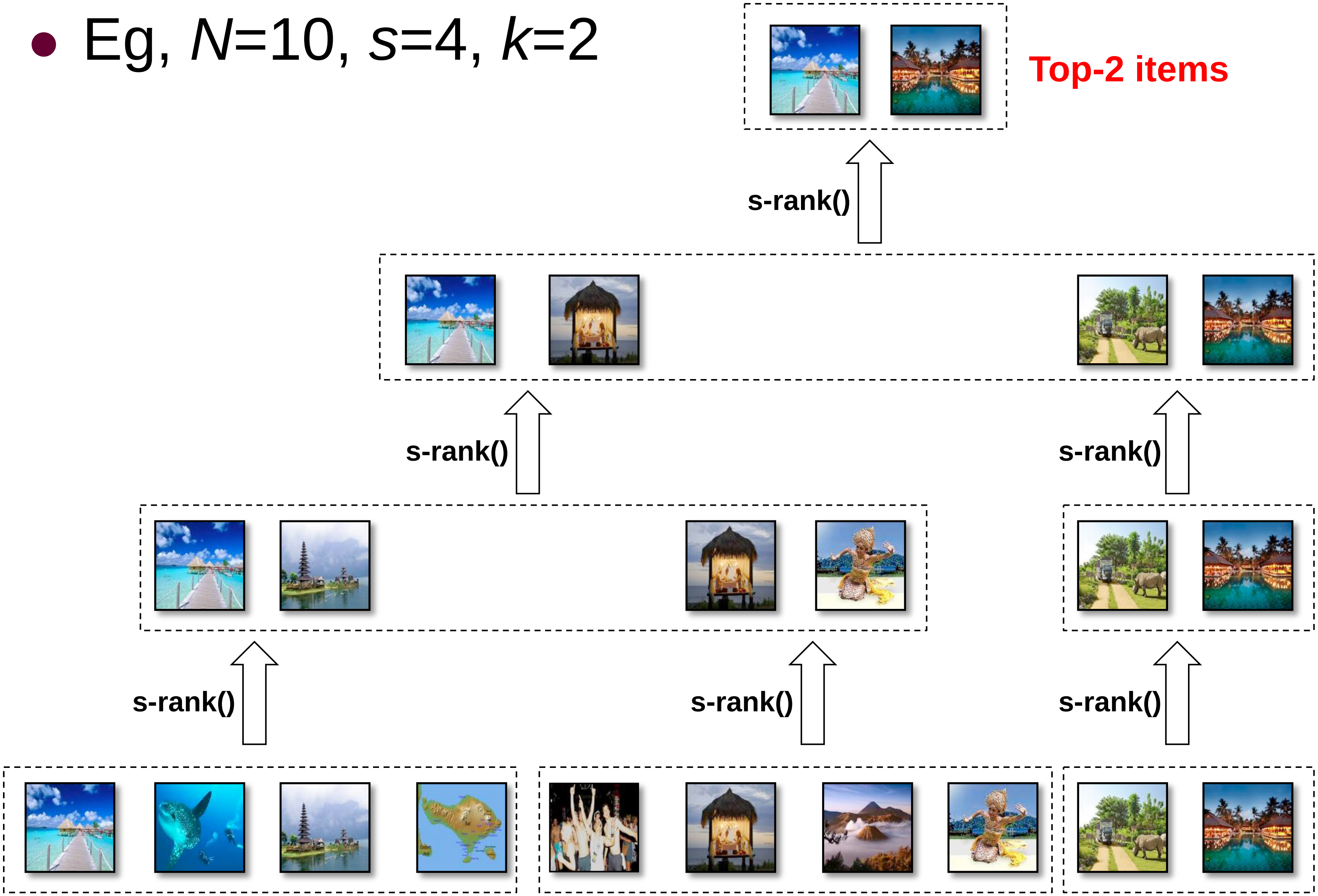
Top-*k* [Polychronopoulous-WebDB13]

- Algorithm
  - Input: *N* items, integer *k* and *s* (ie, *s* > *k*)
  - Output: top-*k* set
  - Procedure:
    - *O* ← *N* items
    - While |*O*| > *k*
      - Partition *O* into disjoint subsets of size *s*
      - Identify top-*k* items in each subset of size *s*: *s-rank(s)*
      - Merge all top-*k* items into *O*
    - Return *O*

- More effective when *s* and *k* are small
  - Eg, *s-rank*(20) with *k*=10 may give poor accuracy

Top-*k* [Polychronopoulous-WebDB13]

- Eg, N=10, s=4, k=2



Top-*k* [Polychronopoulous-WebDB13]

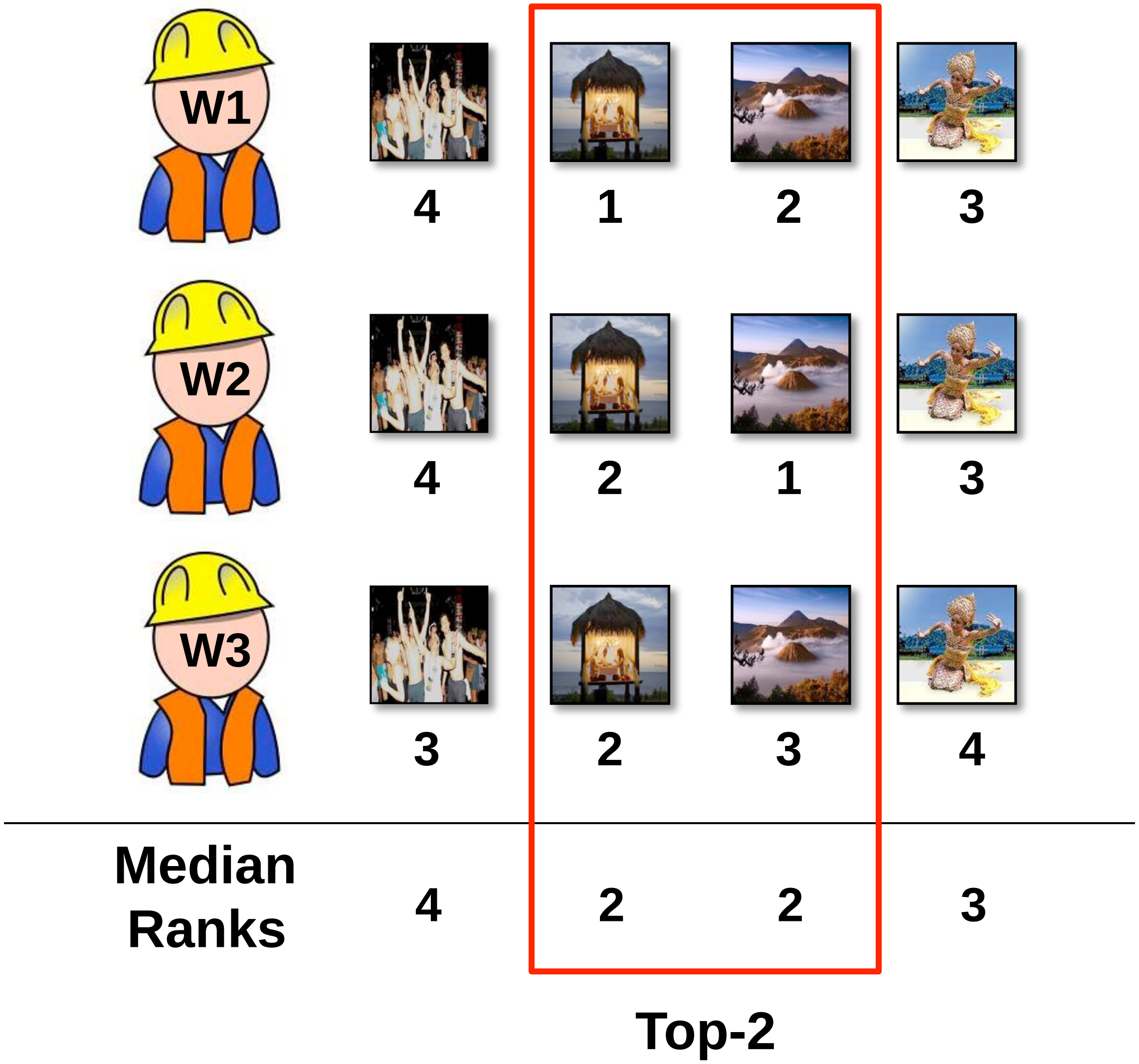
- s-rank(s)

  // workers rank *s* items and aggregate

  - Input: *s* items, integer *k* (ie, *s* > *k*), *w* workers
  - Output: top-*k* items among *s* items
  - Procedure:
    - For each of *w* workers
      - Rank *s* items ≈ comparison-based sort [Marcus-VLDB11]
    - Merge *w* rankings of *s* items into a single ranking
      - Use median-rank aggregation [Dwork-WWW01]
    - Return top-*k* item from the merged ranking of *s* items

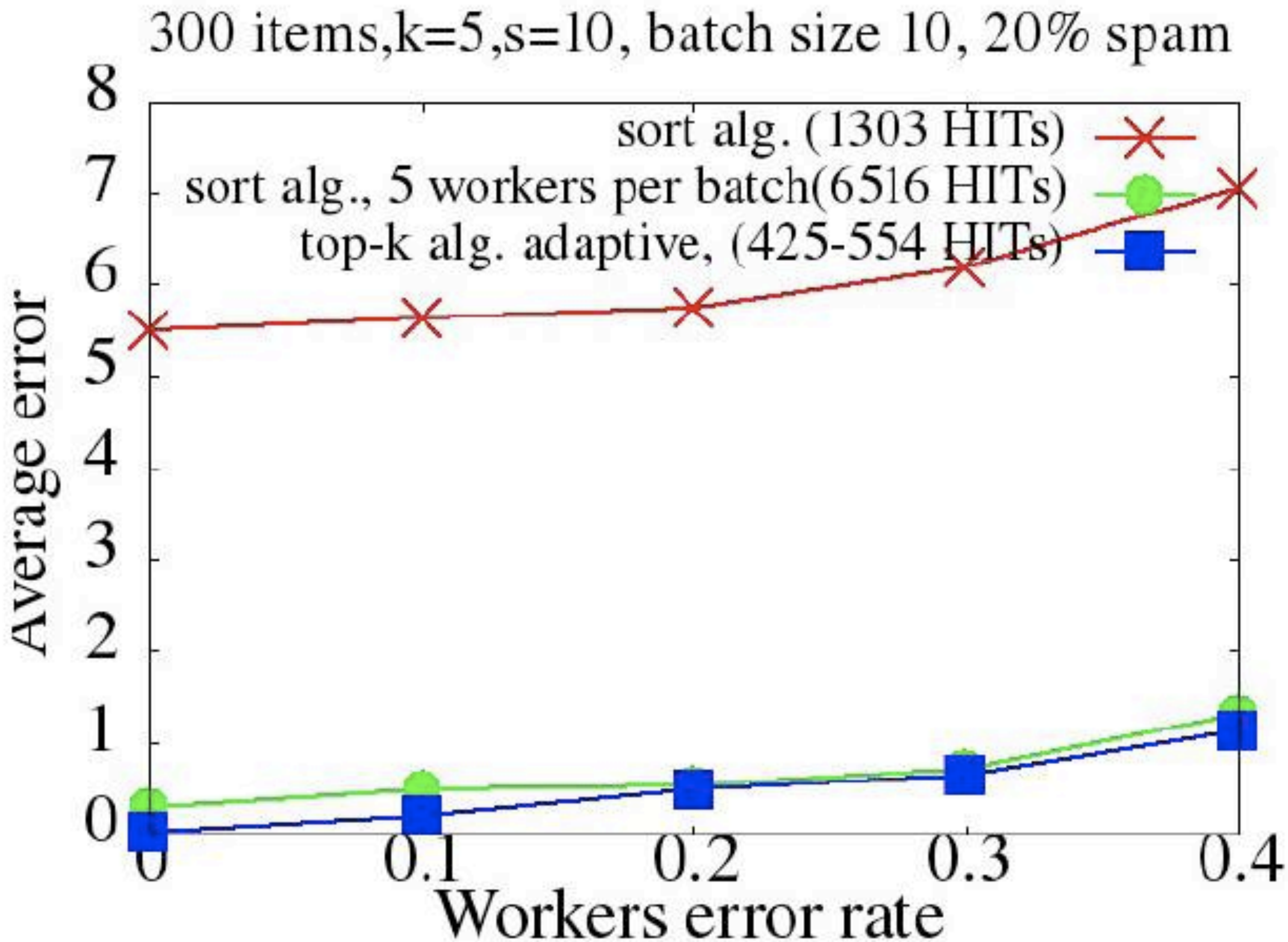
Top-*k* [Polychronopoulous-WebDB13]

- Eg, s-rank(): s=4, k=2, w=3



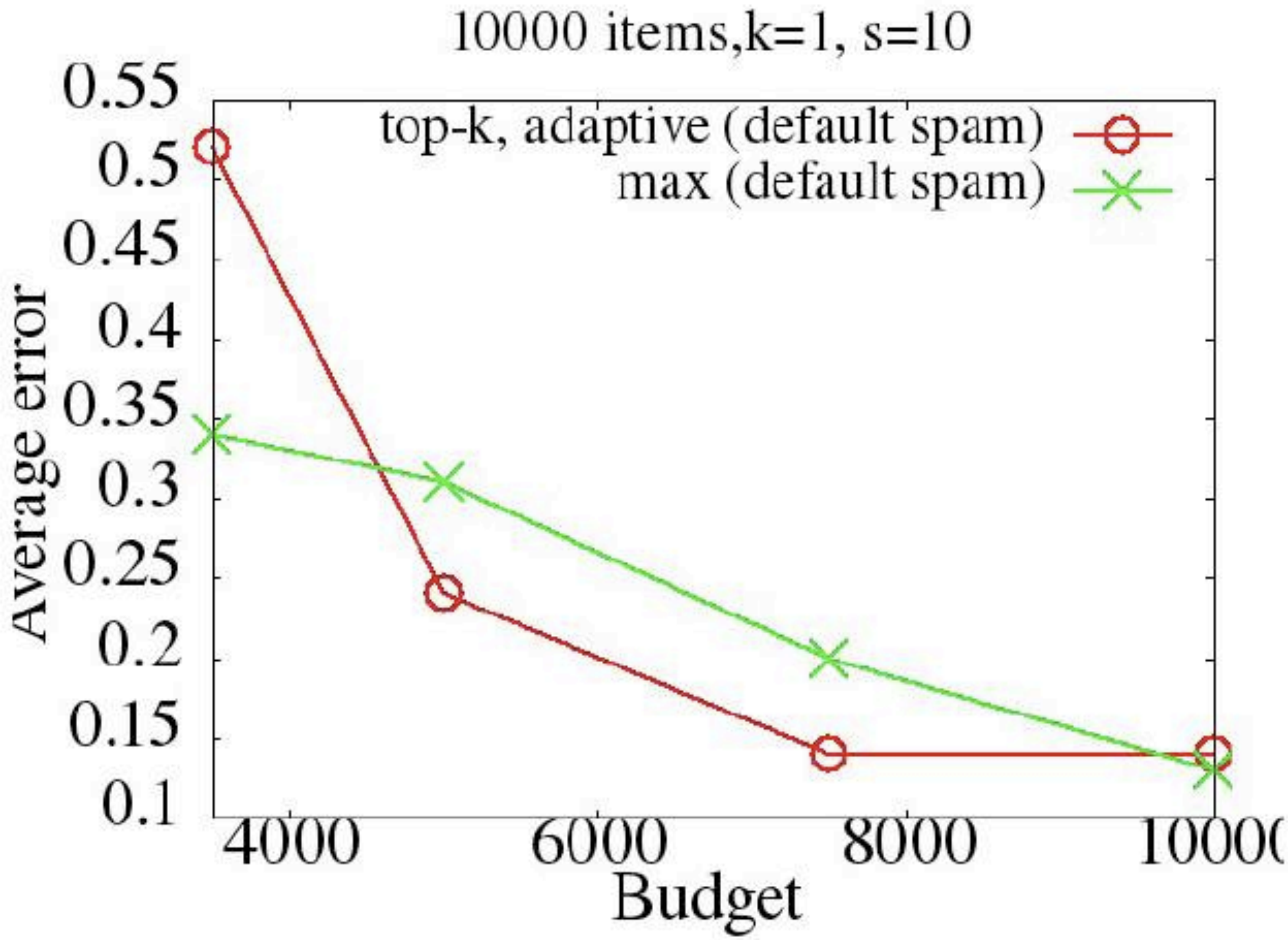
Top-*k* [Polychronopoulous-WebDB13]

- Comparison to Sort [Marcus-VLDB11]



Top-*k* [Polychronopoulous-WebDB13]

- Comparison to Max [Venetis-WWW12]



Part 2: Crowdsourced Algo. in DB

- Preliminaries
- Sort
- Select
- Count
- Top-1
- Top-*k*
- **Join**

Join Operation

- Identify matching records or entities within or across tables
  - ≈ similarity join, entity resolution (ER), record linkage, de-duplication, …
  - Beyond the exact matching
- [Chaudhuri-ICDE06] similarity join
  - R JOIN$_p$ S, where p=$sim(R.A, S.A) > t$
  - *sim()* can be implemented as UDFs in SQL
  - Often, the evaluation is expensive
    - DB applies UDF-based join predicate after Cartesian product of R and S

Join Operation

- Examples
  - **[Marcus-VLDB11]** proposes 3 types of joins
  - **[Wang-VLDB12]** generates near-optimal cluster-based HIT design to reduce join cost
  - **[Wang-SIGMOD13]** reduces join cost further by exploiting transitivity among items
  - **[Whang-VLDB13]** selects right questions to ask to crowds to improve join accuracy
  - **[Gokhale-SIGMOD14]** proposes the hands-off crowdsourcing for join workflow

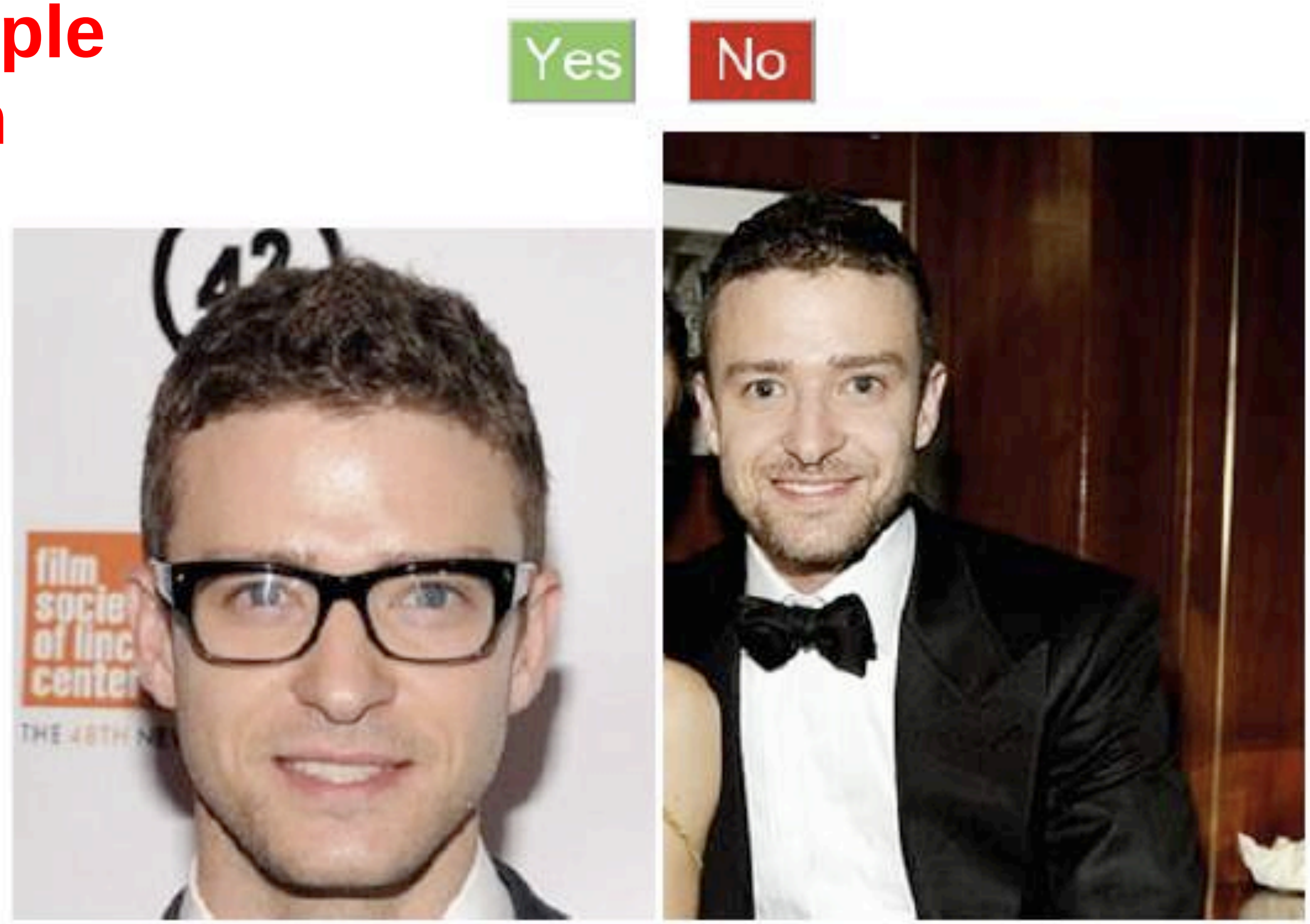
Join [Marcus-VLDB11]

- To join tables *R* and *S*
- #1: Simple Join
  - Pair-wise comparison HIT
  - $|R||S|$ HITs needed
- #2: Naïve Batching Join
  - Repetition of #1 with a batch factor *b*
  - $|R||S|/b$ HITs needed
- #3: Smart Batching Join
  - Show *r* and *s* images from *R* and *S*
  - Workers pair them up
  - $|R||S|/rs$ HITs needed

Join [Marcus-VLDB11]

Is the same celebrity in the image on the left and the image on the right?

#1 Simple Join



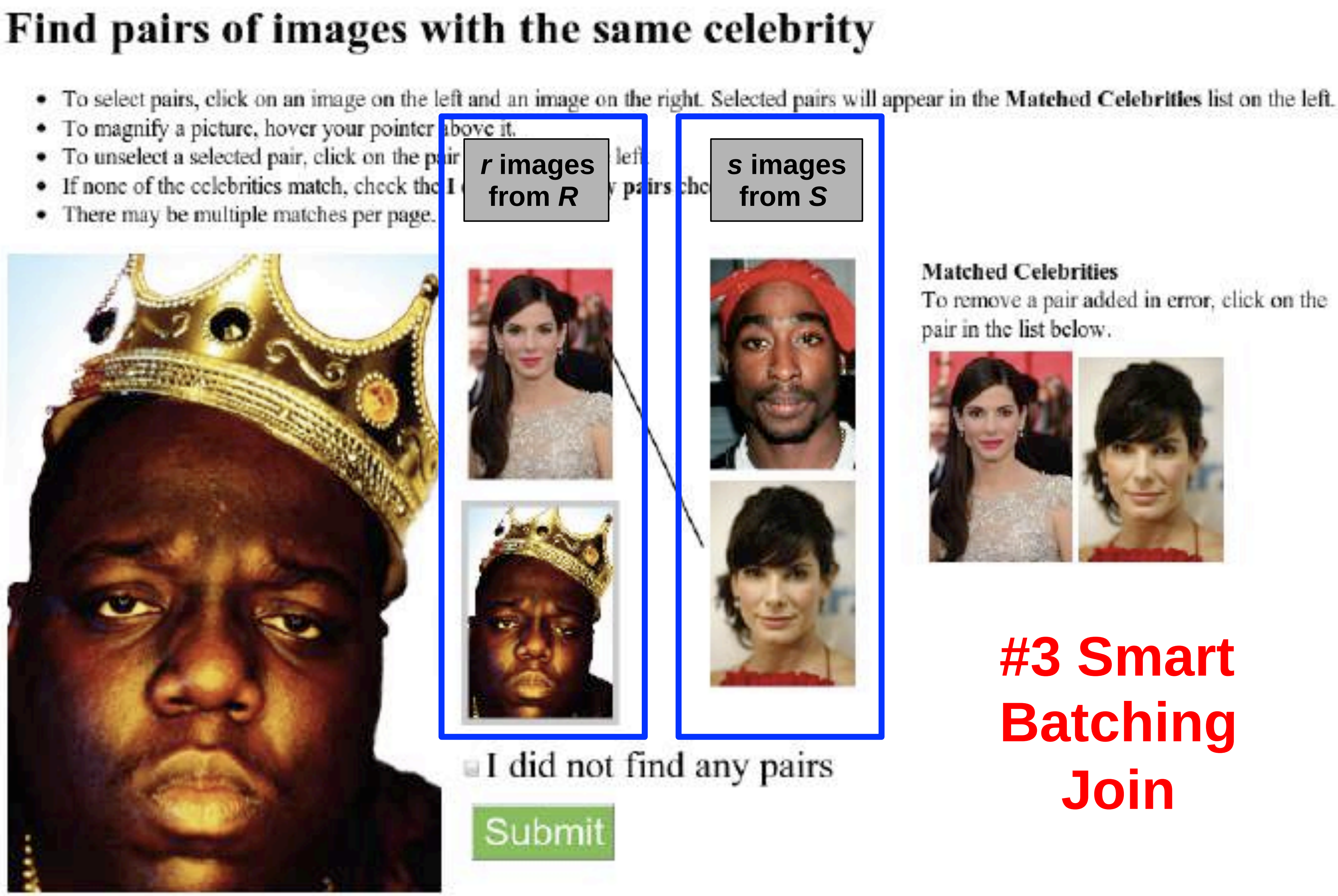
Join [Marcus-VLDB11]

Is the same celebrity in the image on the left and the image on the right?

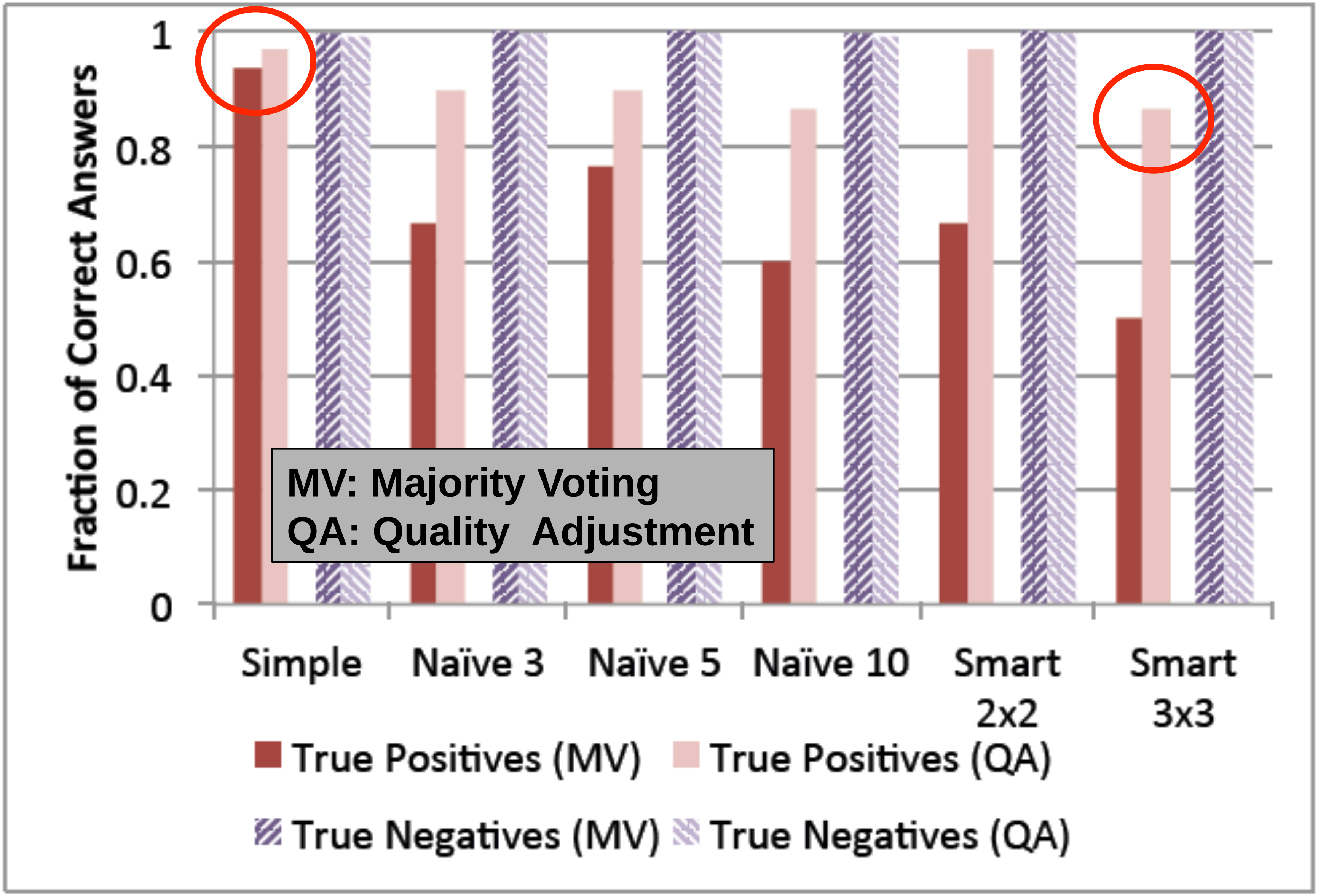
#2 Naïve Batching Join

Batch factor
***b* = 2**

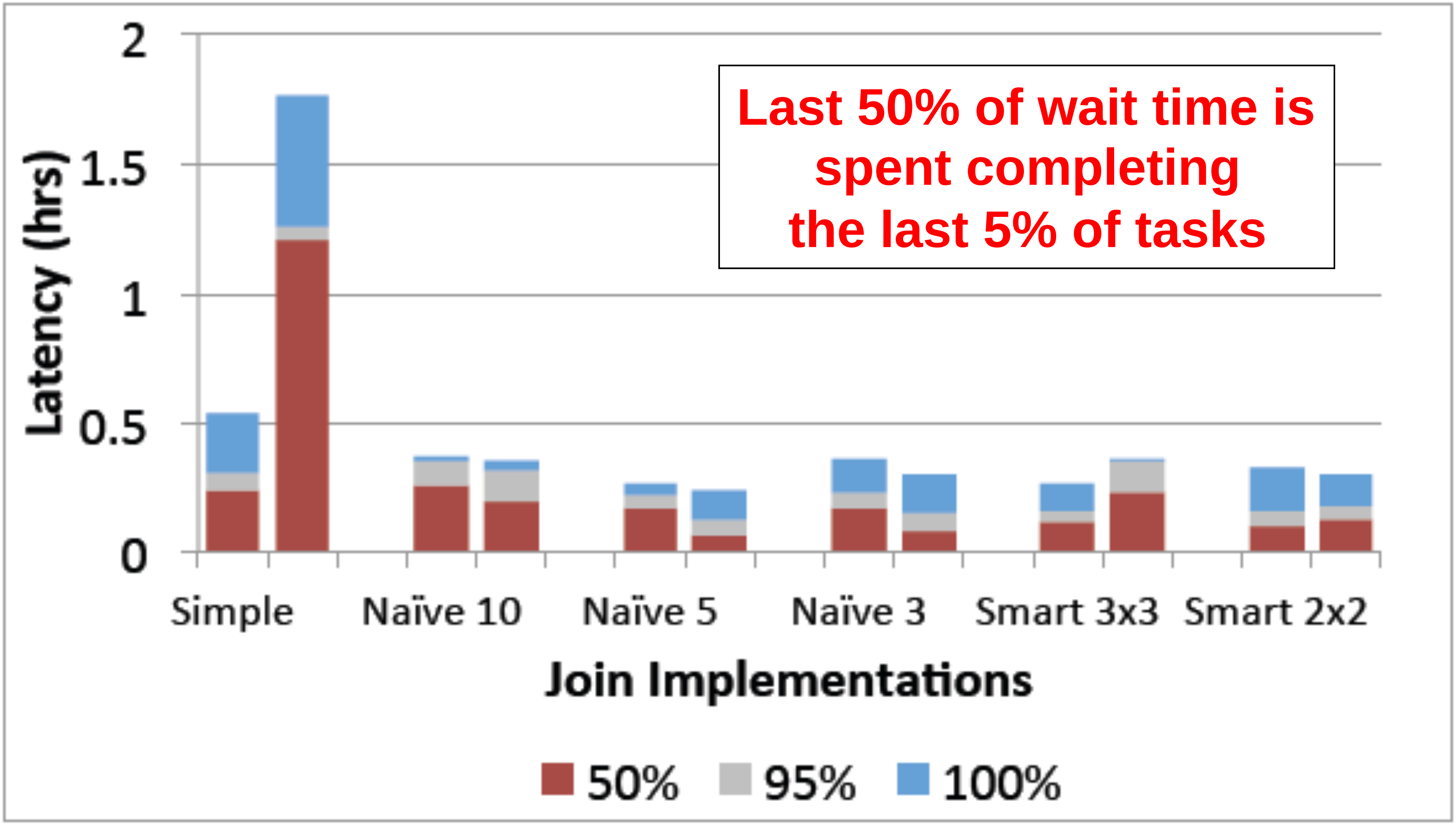
Join [Marcus-VLDB11]



Join [Marcus-VLDB11]



Join [Marcus-VLDB11]



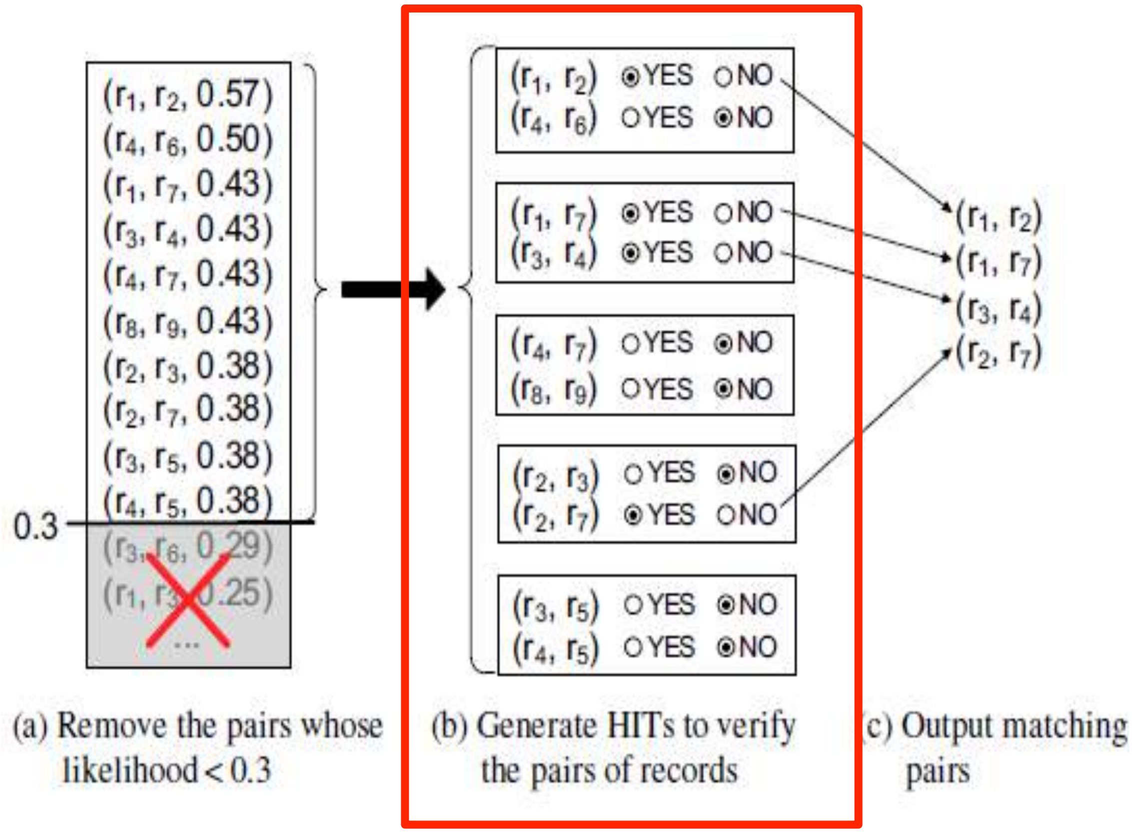
Join [Wang-VLDB12]

- [Marcus-VLDB11] proposed two batch joins
  - More efficient smart batch join still generates $|R||S|/rs$ # of HITs
  - Eg, (10,000 X 10,000) / (20 x 20) = 250,000 HITs → Still too many !
- [Wang-VLDB12] contributes CrowdER:
  1. A hybrid human-machine join
     - #1 machine-join prunes obvious non-matches
     - #2 human-join examines likely matching cases
       - Eg, candidate pairs with high similarity scores
  2. Algorithm to generate min # of HITs for step #2

Join [Wang-VLDB12]

- Hybrid idea: generate candidate pairs using existing similarity measures (eg, Jaccard)

ID	Product Name	Price
r_1	iPad Two 16GB WiFi White	$490
r_2	iPad 2nd generation 16GB WiFi White	$469
r_3	iPhone 4th generation White 16GB	$545
r_4	Apple iPhone 4 16GB White	$520
r_5	Apple iPhone 3rd generation Black 16GB	$375
r_6	iPhone 4 32GB White	$599
r_7	Apple iPad2 16GB WiFi White	$499
r_8	Apple iPod shuffle 2GB Blue	$49
r_9	Apple iPod shuffle USB Cable	$19

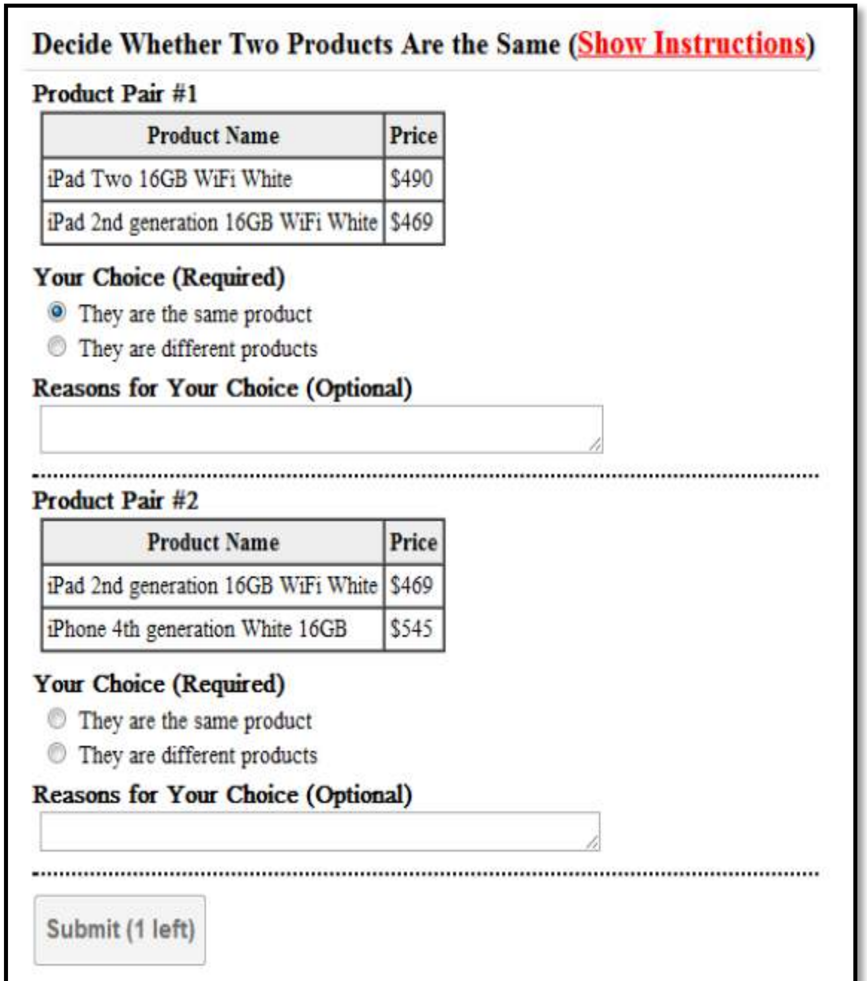


(a) Remove the pairs whose likelihood < 0.3 (b) Generate HITs to verify the pairs of records (c) Output matching pairs

Main Issue: HIT Generation Problem

Join [Wang-VLDB12]

Pair-based HIT Generation ≈ Naïve Batching in [Marcus-VLDB11]



Decide Whether Two Products Are the Same (Show Instructions)

Product Pair #1

Product Name	Price
iPad Two 16GB WiFi White	$490
iPad 2nd generation 16GB WiFi White	$469

Your Choice (Required)

- They are the same product
- They are different products

Reasons for Your Choice (Optional)

Product Pair #2

Product Name	Price
iPad 2nd generation 16GB WiFi White	$469
iPhone 4th generation White 16GB	$545

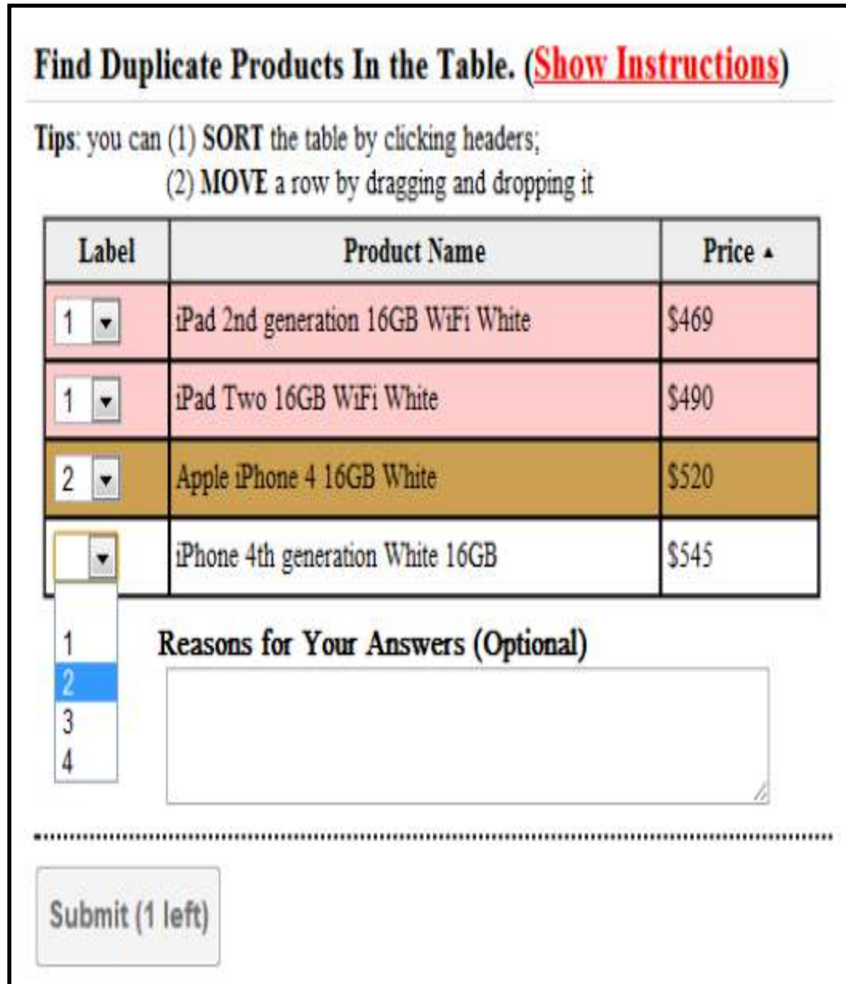
Your Choice (Required)

- They are the same product
- They are different products

Reasons for Your Choice (Optional)

Submit (1 left)

Cluster-based HIT Generation ≈ Smart Batching in [Marcus-VLDB11]



Find Duplicate Products In the Table. (Show Instructions)

Tips: you can (1) SORT the table by clicking headers;
(2) MOVE a row by dragging and dropping it

Label	Product Name	Price ▲
1	iPad 2nd generation 16GB WiFi White	$469
1	iPad Two 16GB WiFi White	$490
2	Apple iPhone 4 16GB White	$520
	iPhone 4th generation White 16GB	$545

1
2
3
4

Reasons for Your Answers (Optional)

Submit (1 left)

Join [Wang-VLDB12]

- HIT Generation Problem
  - Input: pairs of records *P*, # of records in HIT *k*
  - Output: minimum # of HITs s.t.
    1. All HITs have at most *k* records
    2. Each pair $(p_i, p_j) \in P$ must be in at least one HIT

1. Pair-based HIT Generation
   - Trivial: *P/k* # of HITs s.t. each HIT contains *k* pairs in *P*
2. Cluster-based HIT Generation
   - NP-hard problem → approximation solution

Join [Wang-VLDB12]

ID	Product Name	Price
r_1	iPad Two 16GB WiFi White	$490
r_2	iPad 2nd generation 16GB WiFi White	$469
r_3	iPhone 4th generation White 16GB	$545
r_4	Apple iPhone 4 16GB White	$520
r_5	Apple iPhone 3rd generation Black 16GB	$375
r_6	iPhone 4 32GB White	$599
r_7	Apple iPad2 16GB WiFi White	$499
r_8	Apple iPod shuffle 2GB Blue	$49
r_9	Apple iPod shuffle USB Cable	$19

(r_1, r_2, 0.57)
(r_4, r_6, 0.50)
(r_1, r_7, 0.43)
(r_3, r_4, 0.43)
(r_4, r_7, 0.43)
(r_8, r_9, 0.43)
(r_2, r_3, 0.38)
(r_2, r_7, 0.38)
(r_3, r_5, 0.38)
(r_4, r_5, 0.38)

***k* = 4**

Cluster-based HIT #1

r_1, r_2, r_3, r_7

Cluster-based HIT #2

r_3, r_4, r_5, r_6

Cluster-based HIT #3

r_4, r_7, r_8, r_9

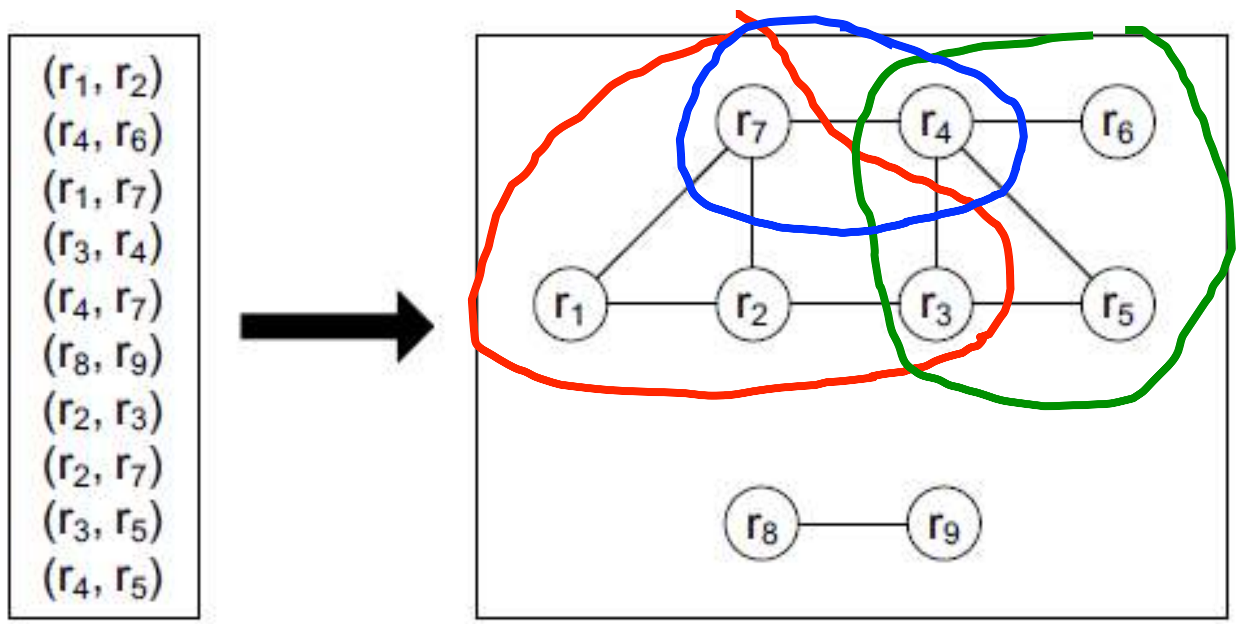
This is the minimal # of cluster-based HITs satisfying previous two conditions

Join [Wang-VLDB12]

- Two-tiered Greedy Algorithm
  - Build a graph *G* from pairs of records in *P*
  - CC ← connected components in *G*
    - LCC: large CC with more than *k* nodes
    - SCC: small CC with no more than *k* nodes
  - Step 1: Partition LCC into SCCs
  - Step 2: Pack SCCs into HITs with *k* nodes
    - Integer programming based

Join [Wang-VLDB12]

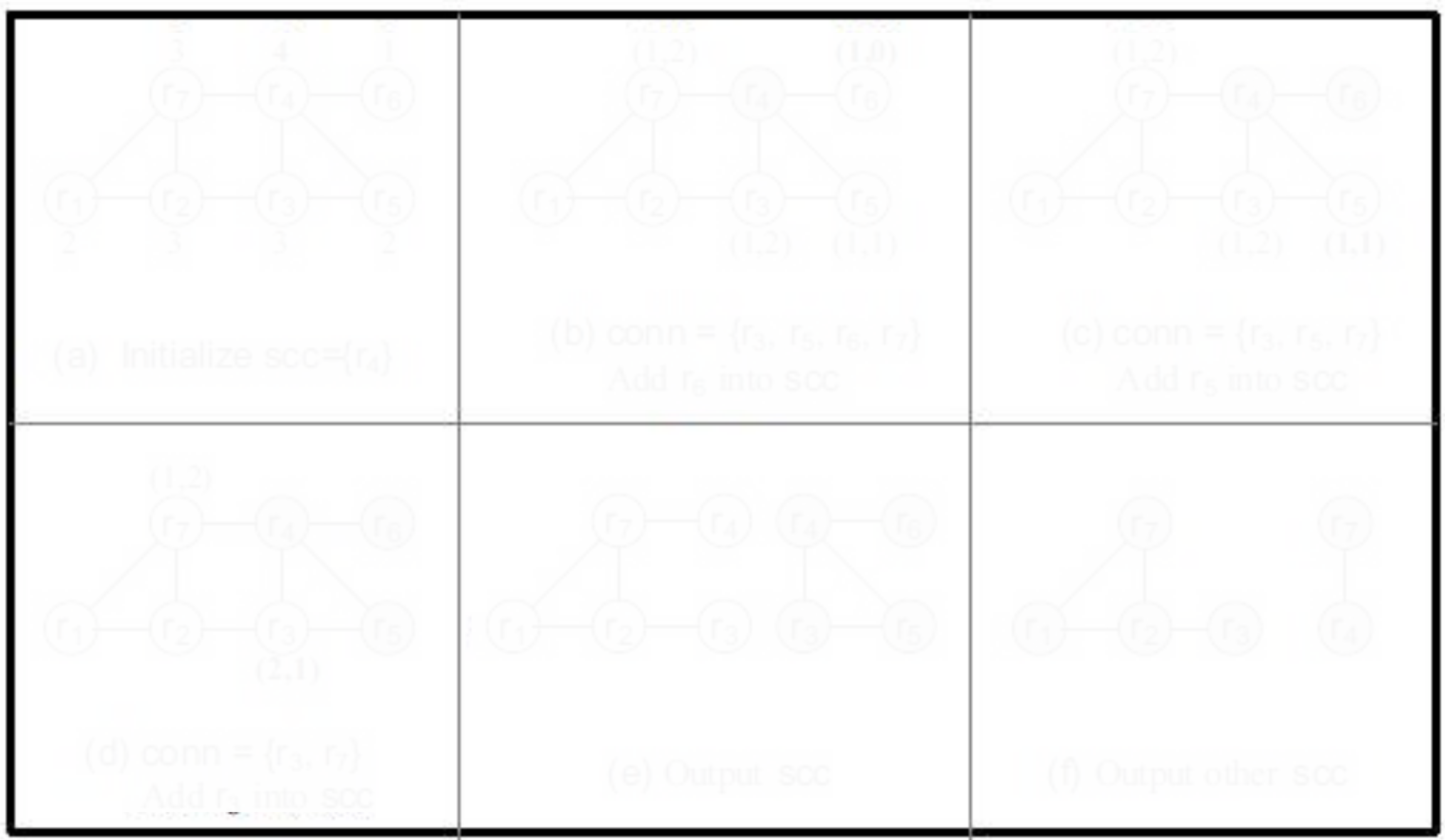
- Eg, Generate cluster-based HITs (*k* = 4)
  1. Partition the LCC into 3 SCCs
     - {r_1, r_2, r_3, r_7}, {r_3, r_4, r_5, r_6}, {r_4, r_7}
  2. Pack SCCs into HITs
     - A single HIT per {r_1, r_2, r_3, r_7} and {r_3, r_4, r_5, r_6}
     - Pack {r_4, r_7} and {r_8, r_9} into a HIT



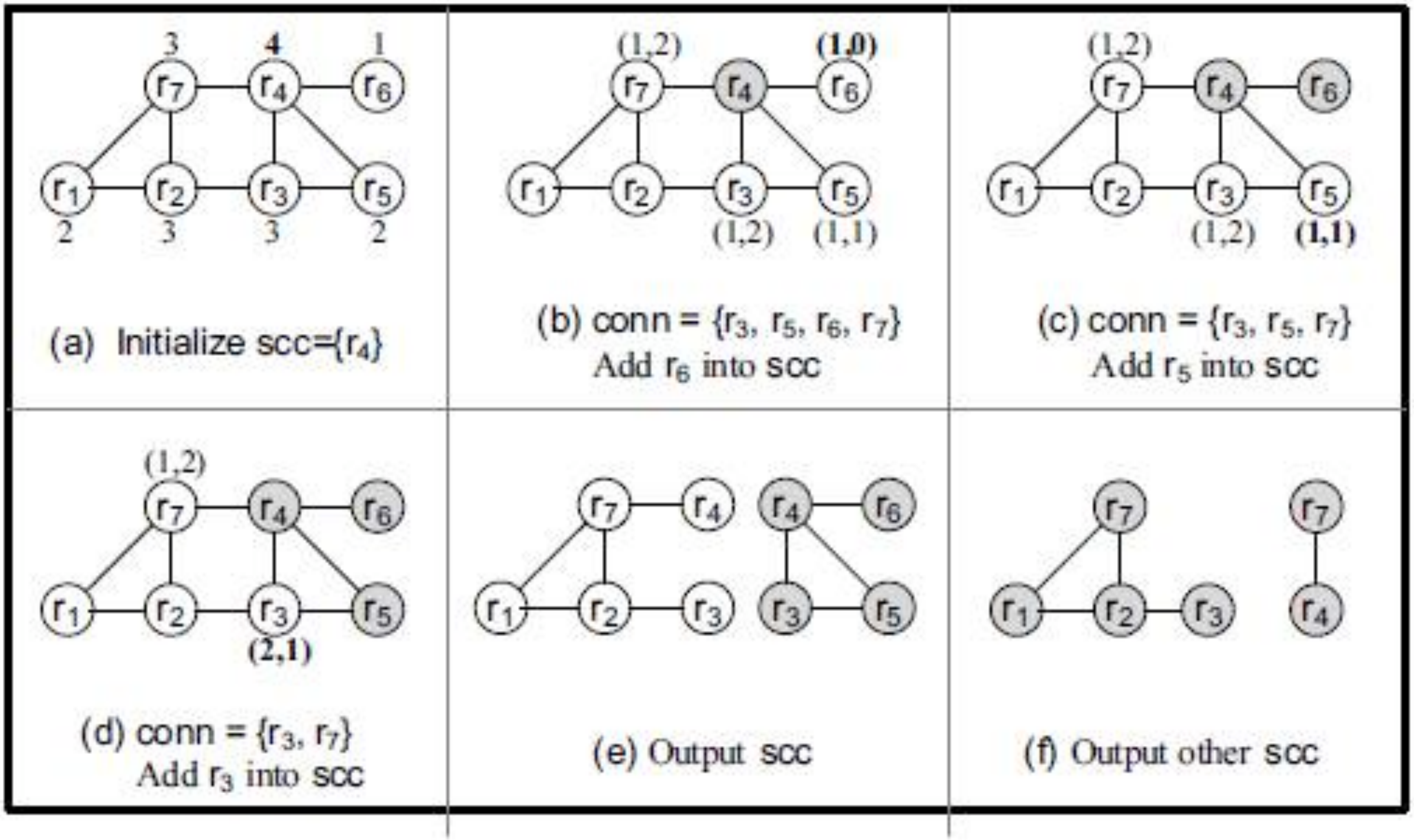
Join [Wang-VLDB12]

- Step 1: Partition
  - Input: LCC, *k*   Output: SCCs
  - r_{max} ← node in LCC with the max degree
  - scc ← $\{r_{max}\}$
  - conn ← nodes in LCC directly connected to r_{max}
  - while |scc| < k and |conn| > 0
    - r_{new} ← node in conn with max indegree (# of edges to scc) and min outdegree (# of edges to non-scc) if tie
    - move r_{new} from conn to scc
    - update conn using new scc
  - add scc into SCC

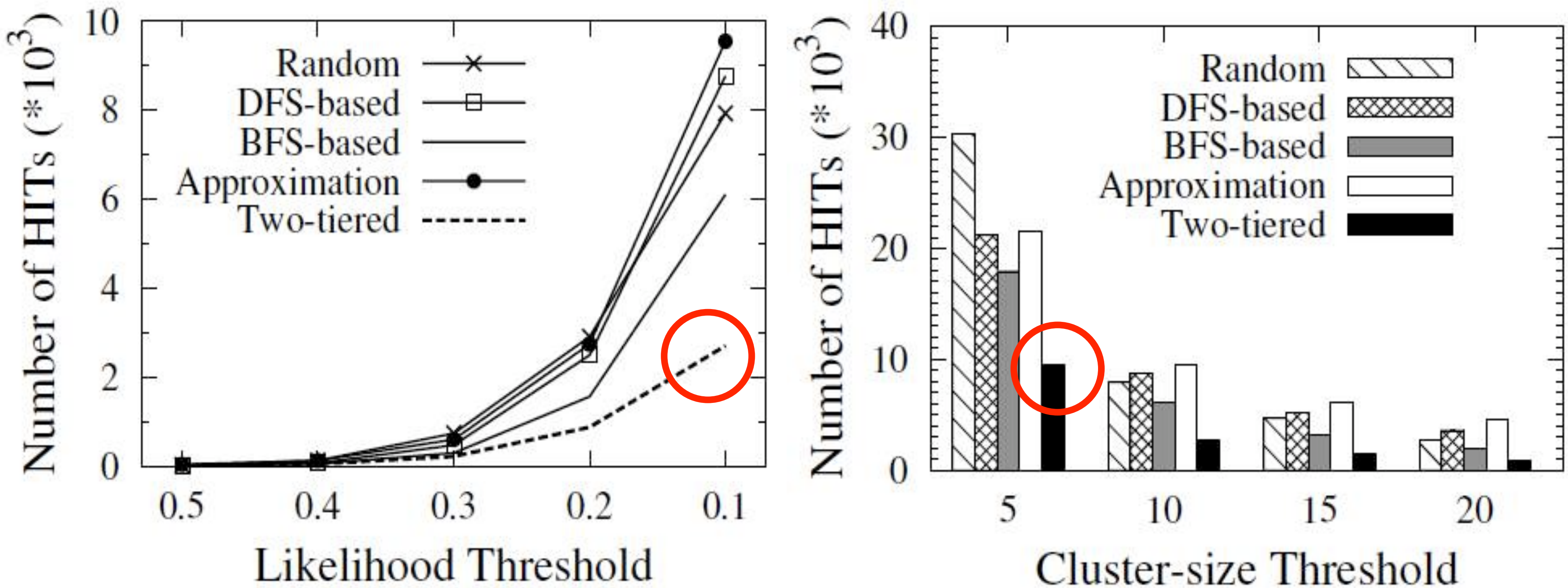
Join [Wang-VLDB12]



Join [Wang-VLDB12]



Join [Wang-VLDB12]



Join [Wang-SIGMOD13]

- Use the same hybrid machine-human framework as [Wang-VLDB12]
- Aim to reduce # of HITs further

- Exploit transitivity among records

http://blogs.oc.edu/ece/transitivity/

Join [Wang-SIGMOD13]

- Positive transitive relation
  - If a=b, and b=c, then a=c

iPad 2^{nd} Gen = iPad Two

iPad Two = iPad 2

➡ *iPad 2^{nd} Gen = iPad 2*

- Negative transitive relation
  - If a = b, b ≠ c, then a ≠ c

iPad 2^{nd} Gen = iPad Two

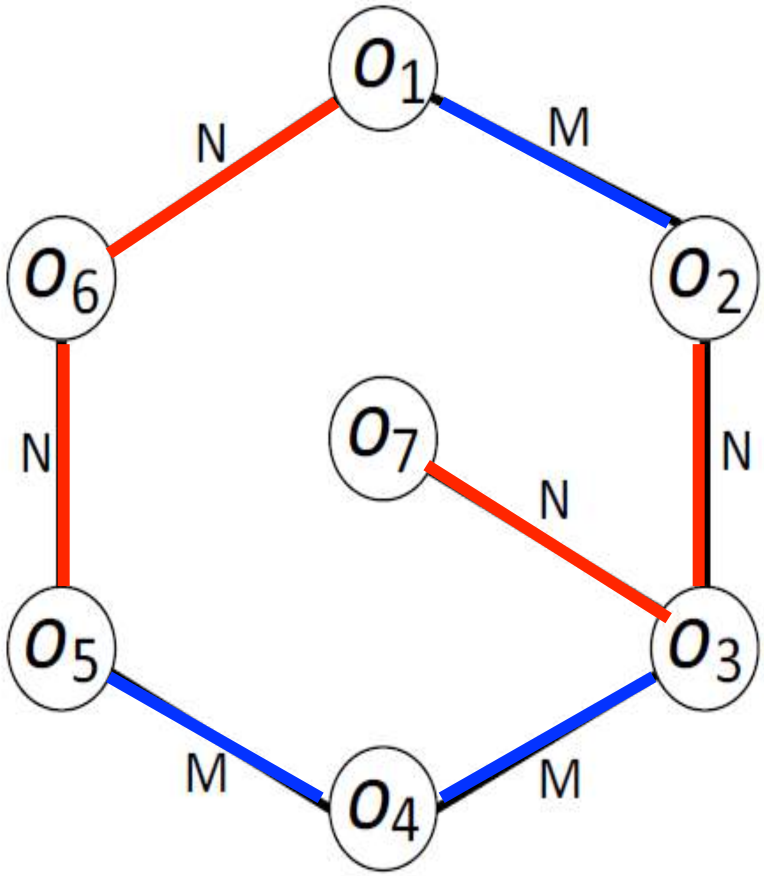
iPad Two ≠ iPad 3

➡ *iPad 2^{nd} Gen ≠ iPad 3*

Join [Wang-SIGMOD13]

- Three transitive relations
  - If there exists a path from o to o' which only consists of **matching pairs**, then (o, o') can be deduced as a **matching pair**
  - If there exists a path from o to o' which only contains **a single non-matching pair**, then (o, o') can be deduced as a **non-matching pair**
  - If any path from o to o' contains **more than one non-matching pairs**, (o, o') **cannot** be deduced.

Join [Wang-SIGMOD13]



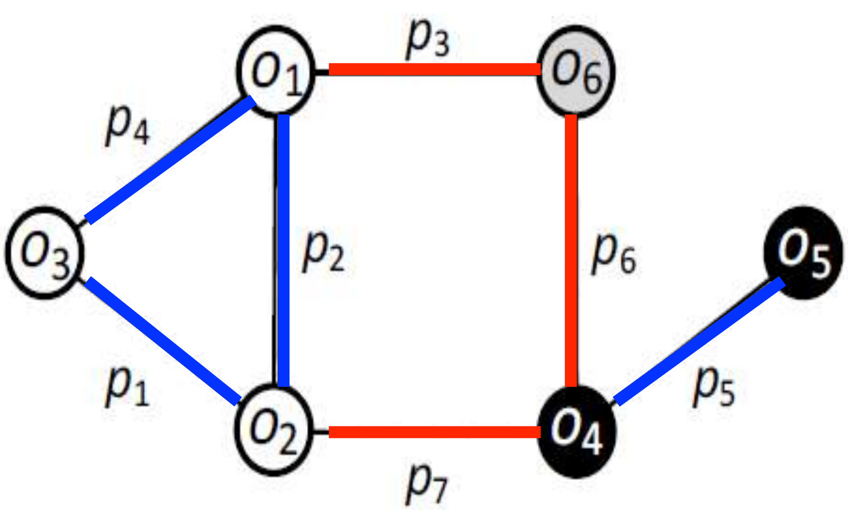
$(o_3, o_5) \rightarrow$ match

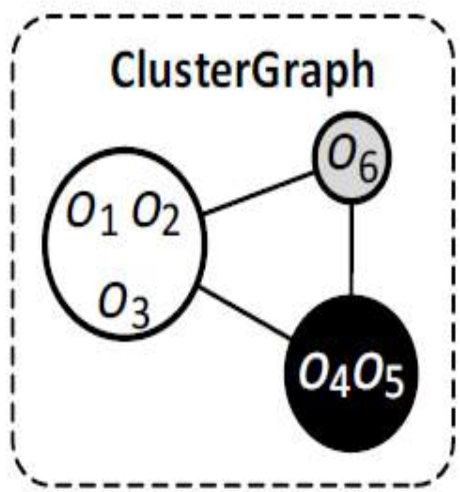
$(o_5, o_7) \rightarrow$ non-match

$(o_1, o_7) \rightarrow$?

Join [Wang-SIGMOD13]

- Given a pair (o_i, o_j), to check the transitivity
  - Enumerate path from o_i to o_j → exponential !
  - Count # of non-matching pairs in each path
- Solution: Build a cluster graph
  - Merge matching pairs to a cluster
  - Add inter-cluster edge for non-matching pairs





(o_5, o_6) → ?

(o_1, o_5) → ?

Join [Wang-SIGMOD13]

- Problem Definition:
  - Given a set of pairs that need to be labeled, **minimize the # of pairs** requested to crowd workers based on **transitive relations**

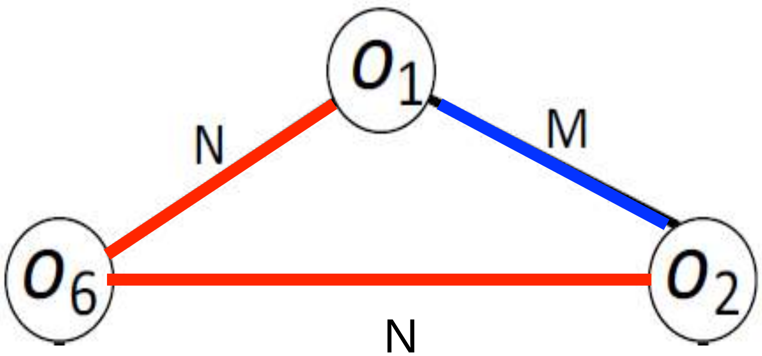
ID	Object
o_1	iPhone 2nd Gen
o_2	iPhone Two
o_3	iPhone 2
o_4	iPad Two
o_5	iPad 2
o_6	iPad 3rd Gen

ID	Object Pairs	Likelihood
p_1	(o_2, o_3)	0.85
p_2	(o_1, o_2)	0.75
p_3	(o_1, o_6)	0.72
p_4	(o_1, o_3)	0.65
p_5	(o_4, o_5)	0.55
p_6	(o_4, o_6)	0.48
p_7	(o_2, o_4)	0.45
p_8	(o_5, o_6)	0.42

?

Join [Wang-SIGMOD13]

- Labeling order matters !



$(o_1, o_2), (o_1, o_6), (o_2, o_6)$

vs.

$(o_1, o_6), (o_2, o_6), (o_1, o_2)$

➔ Given a set of pairs to label, how to order them affects the # of pairs to deduce using the transitivity

Join [Wang-SIGMOD13]

- Theorem: Optimal labeling order

  $w = <p_1, \ldots, p_{i-1}, p_i, p_{i+1}, \ldots, p_n>$

  $w' = <p_1, \ldots, p_{i-1}, p_{i+1}, p_i, \ldots, p_n>$

  - If p_i is a matching pair and p_{i+1} is a non-matching pair, then $C(w) \leq C(w')$
    - *C(w)*: # of crowdsourced pairs required for *w*
- That is, always better to first label a matching pair and then a non-matching pair
- In reality, optimal label order cannot be achieved

Join [Wang-SIGMOD13]

- Expected optimal labeling order
  - $w = <p_1, p_2, \ldots, p_n>$
  - $C(w)$ = # of crowdsourced pairs required for w

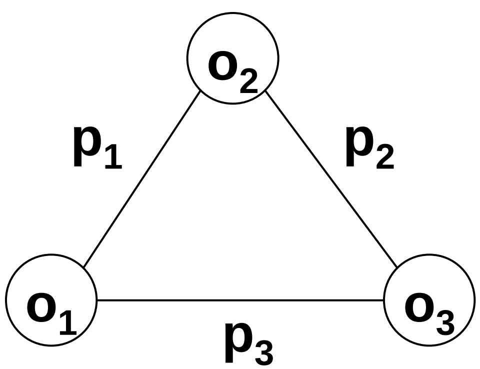
$$\mathrm{E}[\mathcal{C}(\omega)] = \sum_{i=1}^{n} \mathbb{P}(p_i = \text{crowdsourced})$$

  - $P(p_i$ = crowdsourced)
    - o Enumerate all possible labels of $<p_1, p_2, \ldots, p_{i-1}>$, and for each possibility, derive whether p_i is crowdsourced or not
    - o Sum of the probability of each possibility that whether p_i is crowdsourced

Join [Wang-SIGMOD13]

- Expected optimal labeling order
  - $w_1 = <p_1, p_2, p_3>$
  - $E[C(w_1)] = 1 + 1 + 0.05 = \mathbf{2.05}$
    - P_1: $P(P_1 = crowdsourced) = 1$
    - P_2: $P(P_2 = crowdsourced) = 1$
    - P_3: $P(P_3 = crowdsourced) = P(both\ P_1\ and\ P_2\ are\ non\text{-}matching) = (1\text{-}0.9)(1\text{-}0.5) = 0.05$

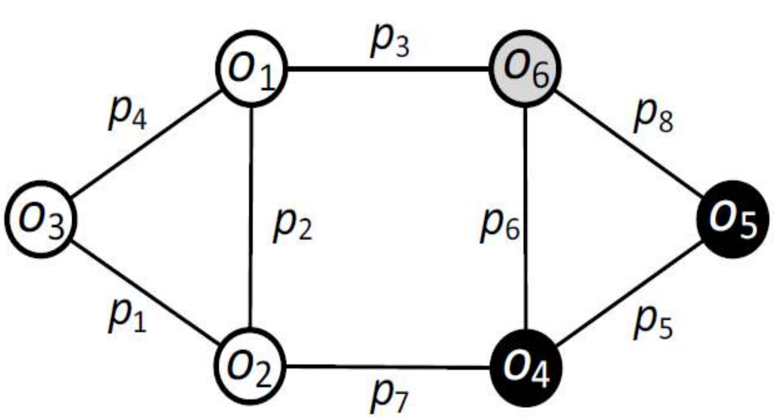
Probability of matching	
P_1	0.9
P_2	0.5
P_3	0.1



Expected value	
$w_1 = <p_1, p_2, p_3>$	**2.05**
$w_2 = <p_1, p_3, p_2>$	2.09
$w_3 = <p_2, p_3, p_1>$	2.45
$w_4 = <p_2, p_1, p_3>$	**2.05**
…	…

Join [Wang-SIGMOD13]

- Theorem: Expected optimal labeling order
  - Label the pairs in **the decreasing order of the probability** that they are a matching pair
  - Eg, p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8



$$\mathrm{E}[\mathcal{C}(\omega)] = \sum_{i=1}^{n} \mathbb{P}(p_i = \text{crowdsourced})$$

ID	Object Pairs	Likelihood
p_1	(o_2, o_3)	0.85
p_2	(o_1, o_2)	0.75
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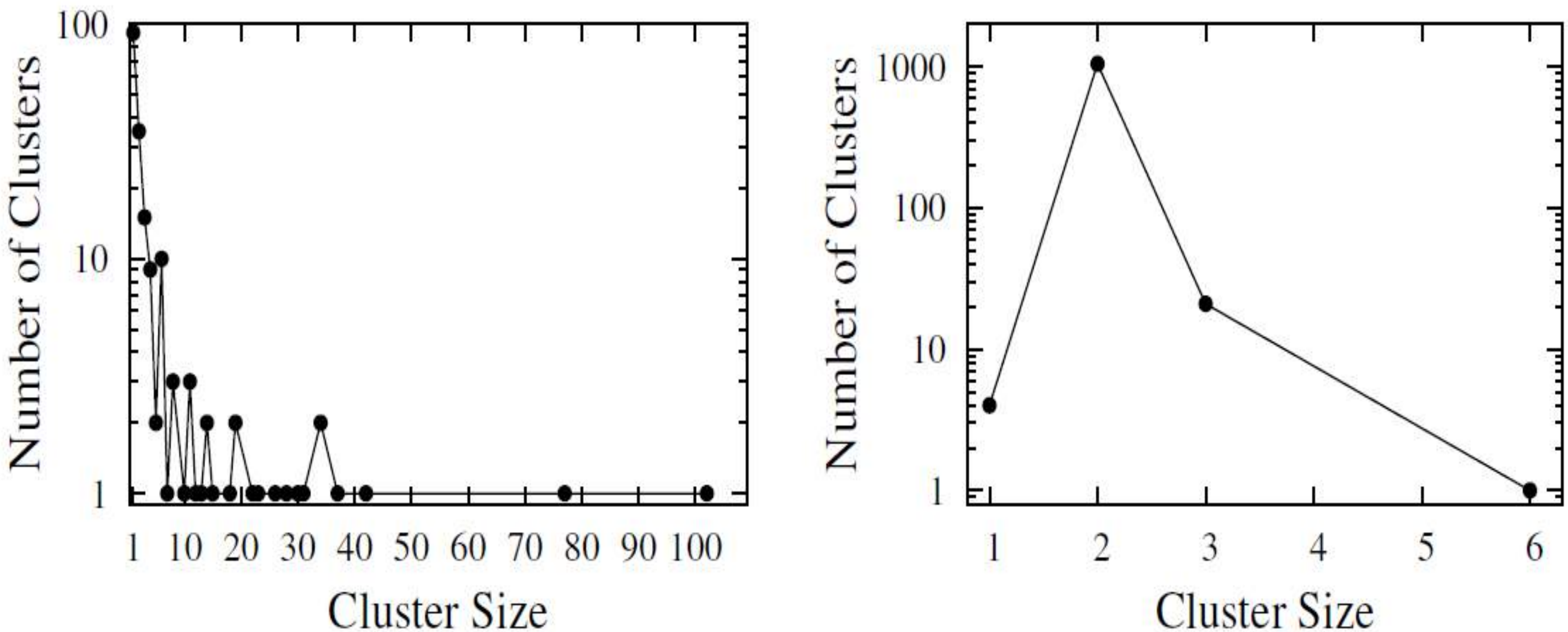
p_5	(o_4, o_5)	0.55
p_6	(o_4, o_6)	0.48
p_7	(o_2, o_4)	0.45
p_8	(o_5, o_6)	0.42

High

Join [Wang-SIGMOD13]

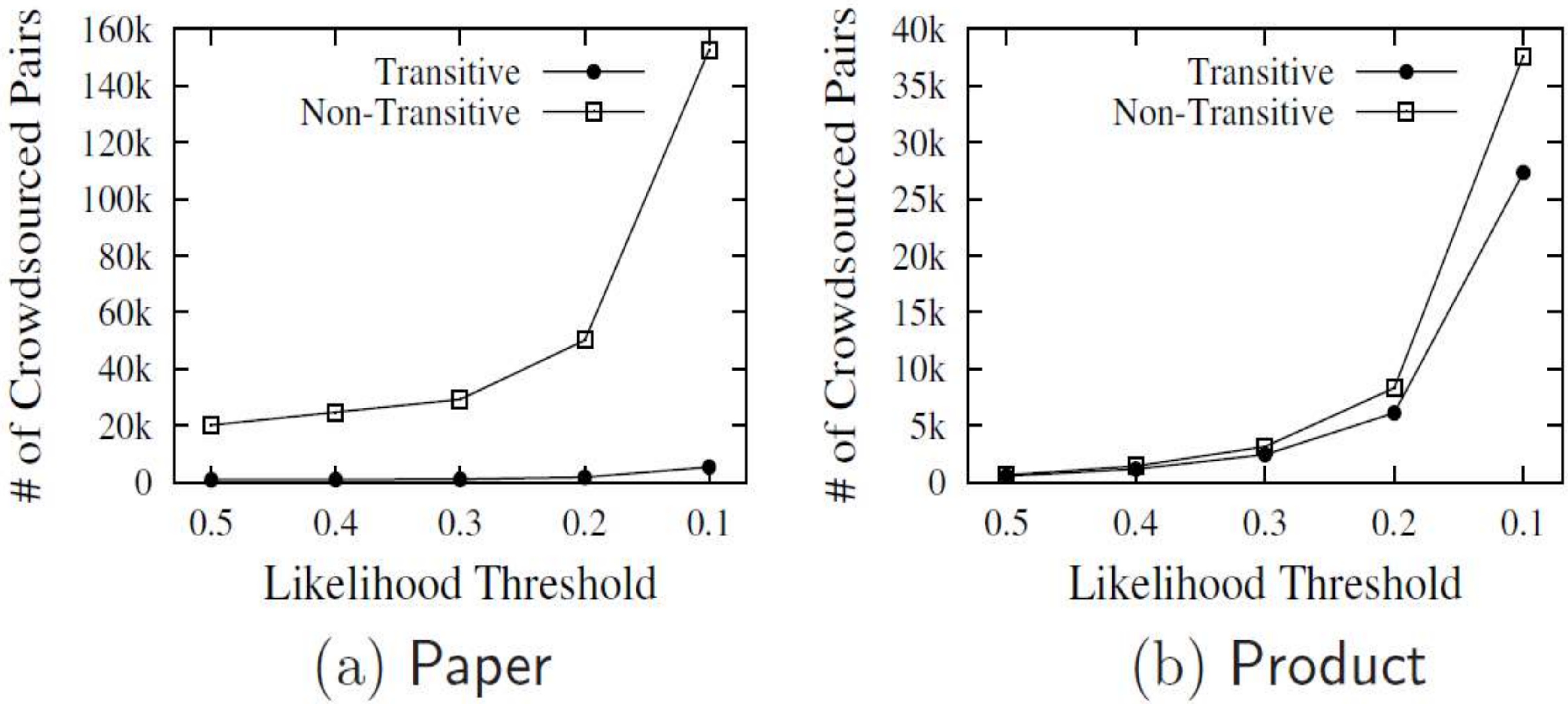
- Two data sets
  - Paper: 997 (author, title, venue, date, and pages)
  - Product: 1081 product (abt.com), 1092 product (buy.com)



(a) Paper (b) Product

Join [Wang-SIGMOD13]

- Transitivity



Machine vs. Human

- Human-Powered Crowdsourcing → "**Human-in-the-loop**" Crowdsourcing
  - Should use machine to process majority of big data
  - Should use human to process a small fraction of challenging cases in big data
- How to split tasks and combine results for machines and human automatically is an open issue

http://www.theoddblog.us/2014/02/21/damienwaltershumanloop/

Conclusion

- New opportunities
  - Open-world assumption
  - Non-deterministic algorithmic behavior
  - Trade-off among cost, latency, and accuracy
- Crowdsourcing for Big Data?

This slide is available at

http://goo.gl/UEUEBh

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