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

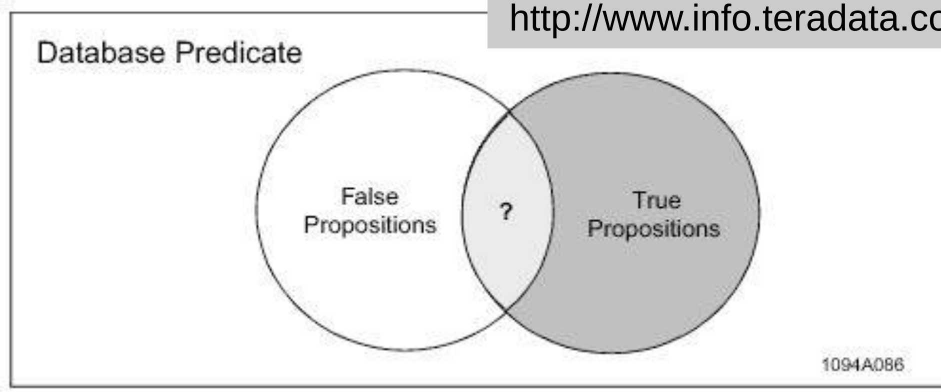
Part 2: Crowdsourced Algo. in DB

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

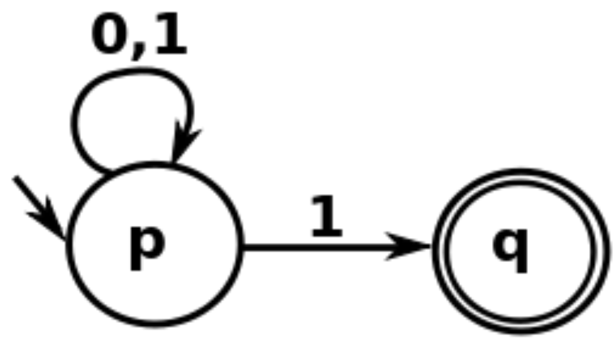
New Challenges

- Open-world assumption (OWA)

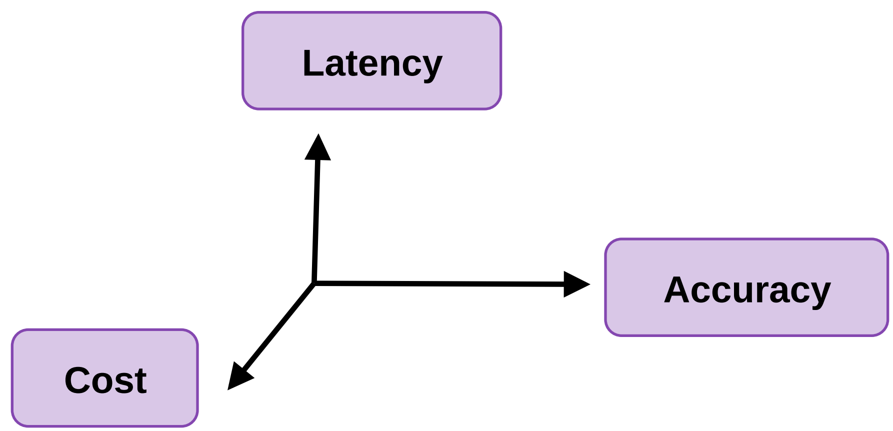
http://www.info.teradata.com



- Non-deterministic algorithmic behavior

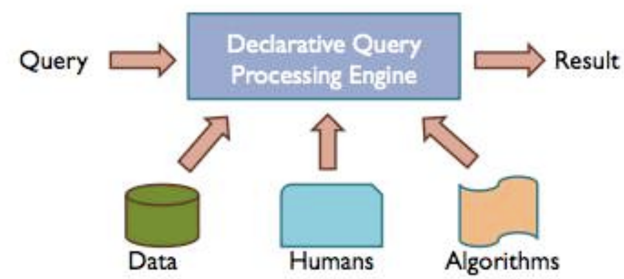


- Trade-off among cost, latency, and accuracy



Crowdsourcing DB Projects

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

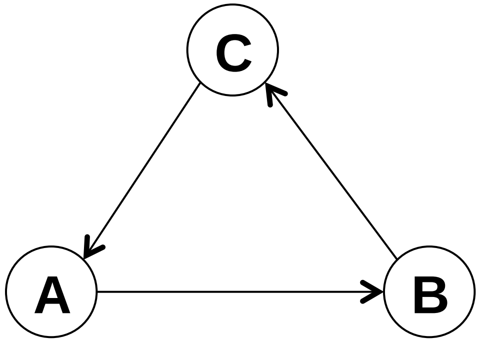


Part 2: Crowdsourced Algo. in DB

- 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



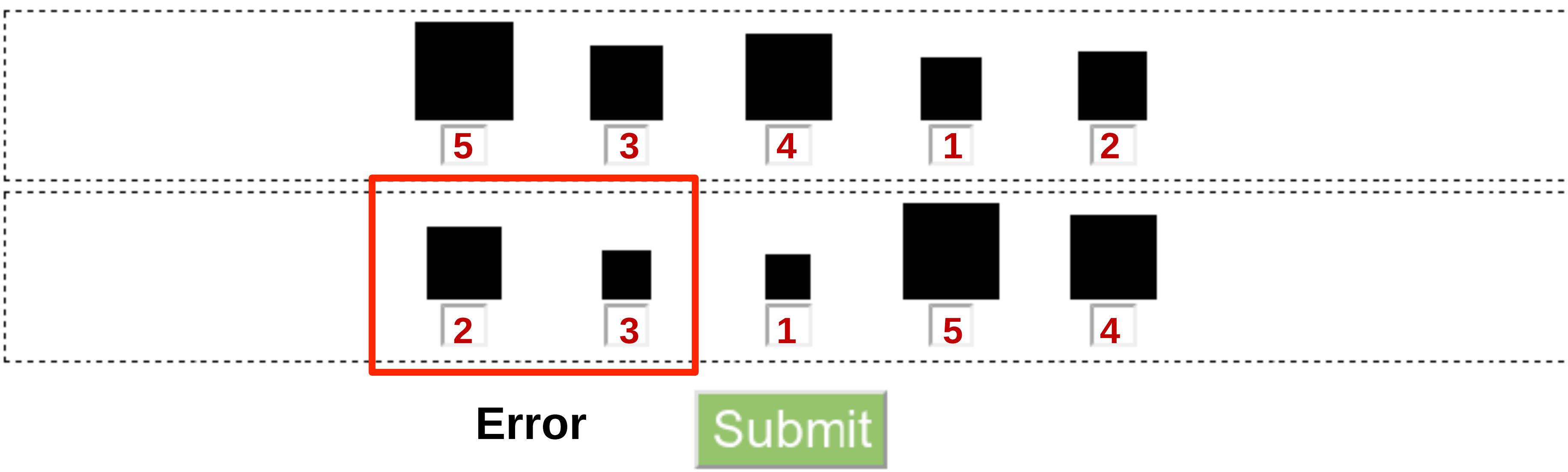
Sort [Marcus-VLDB11]

- 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]

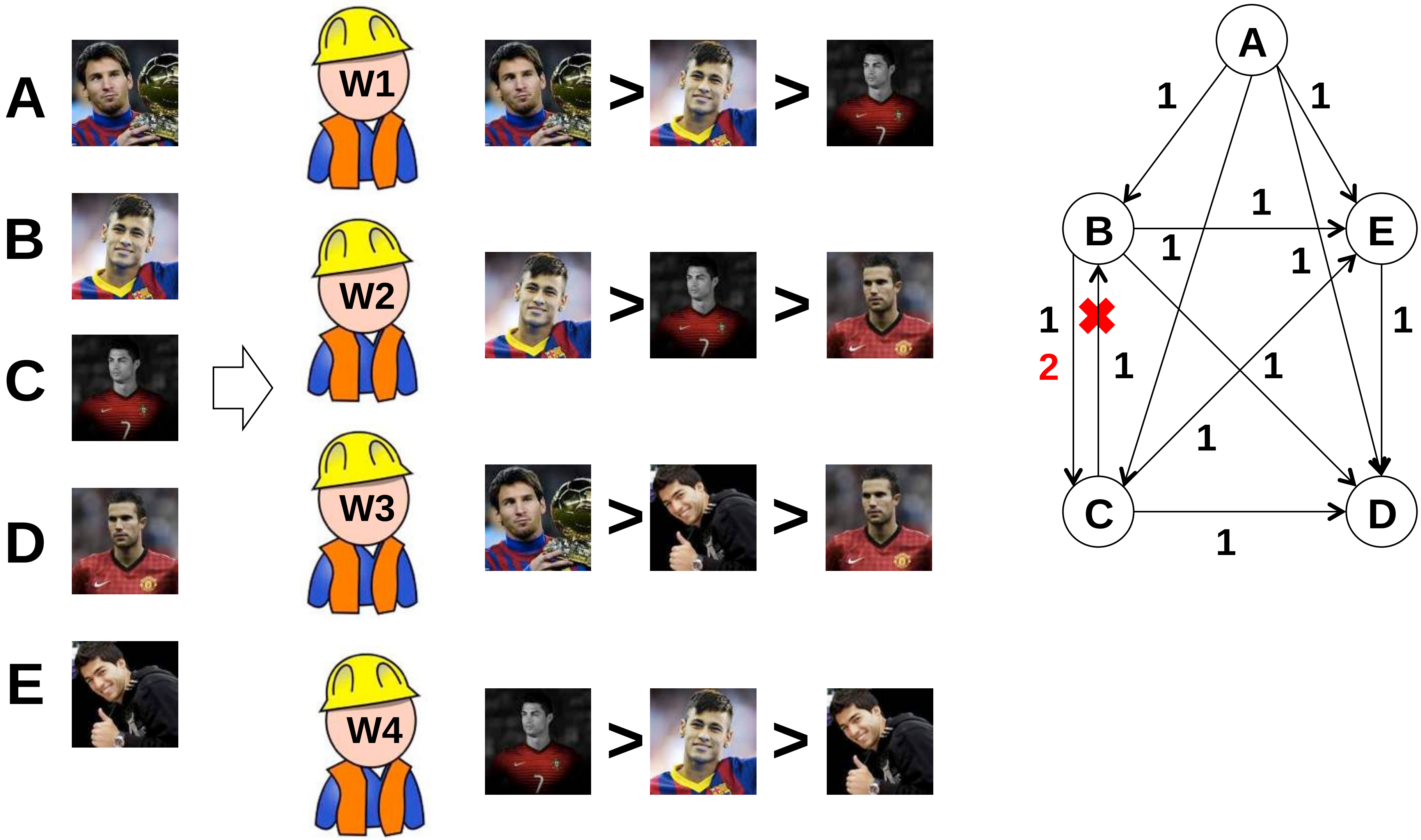
There are 2 groups of squares. We want to order the squares in each group from smallest to largest.

- 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]

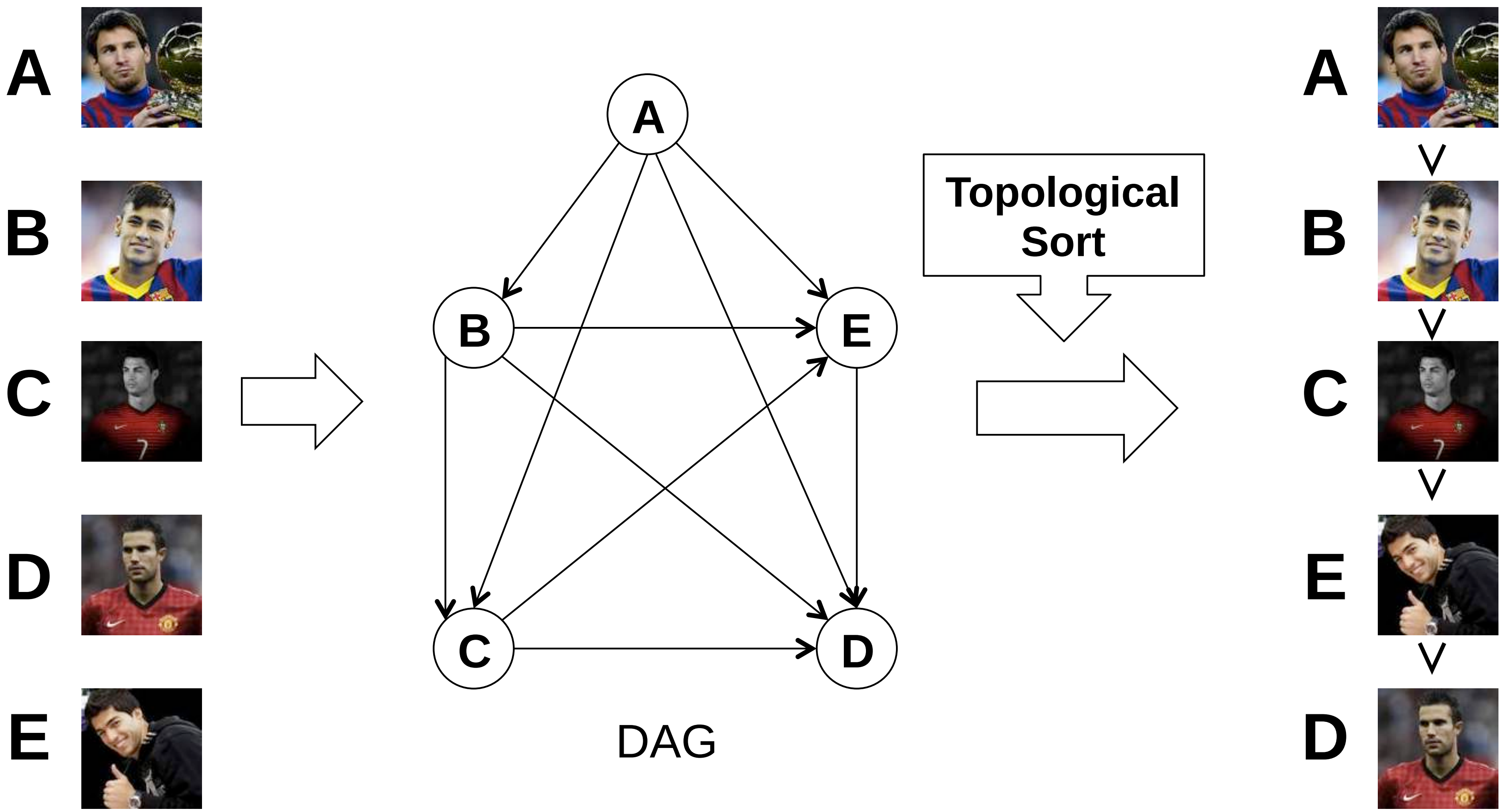
- N=5, S=3



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

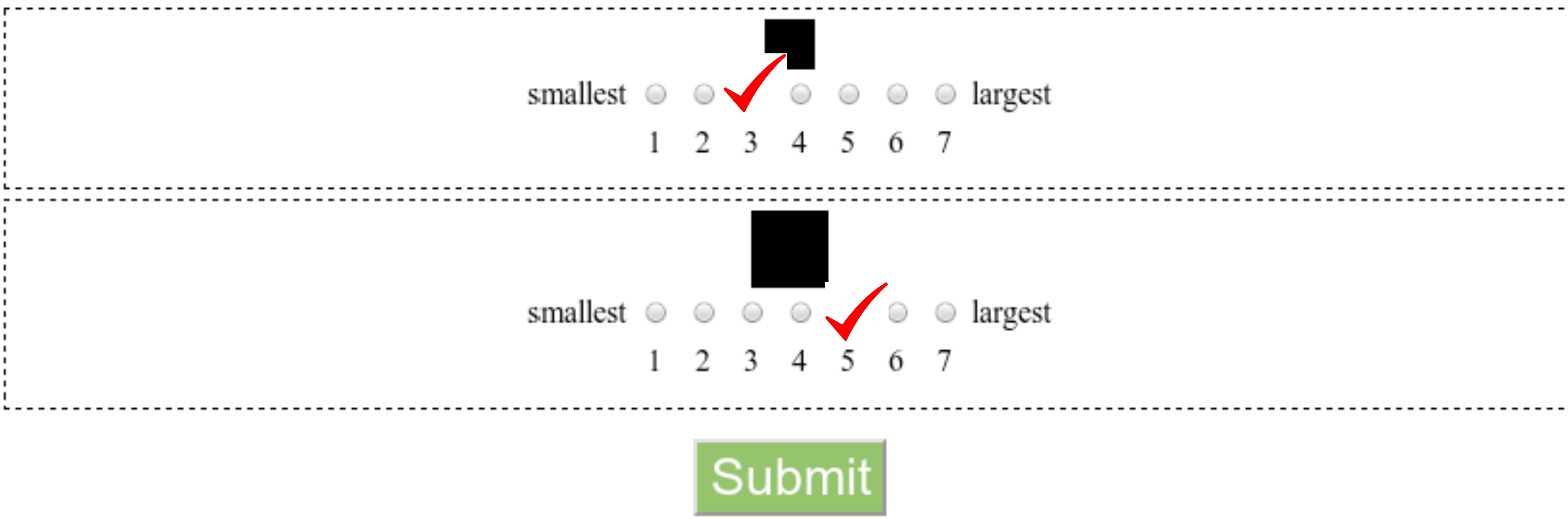
. . .

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:

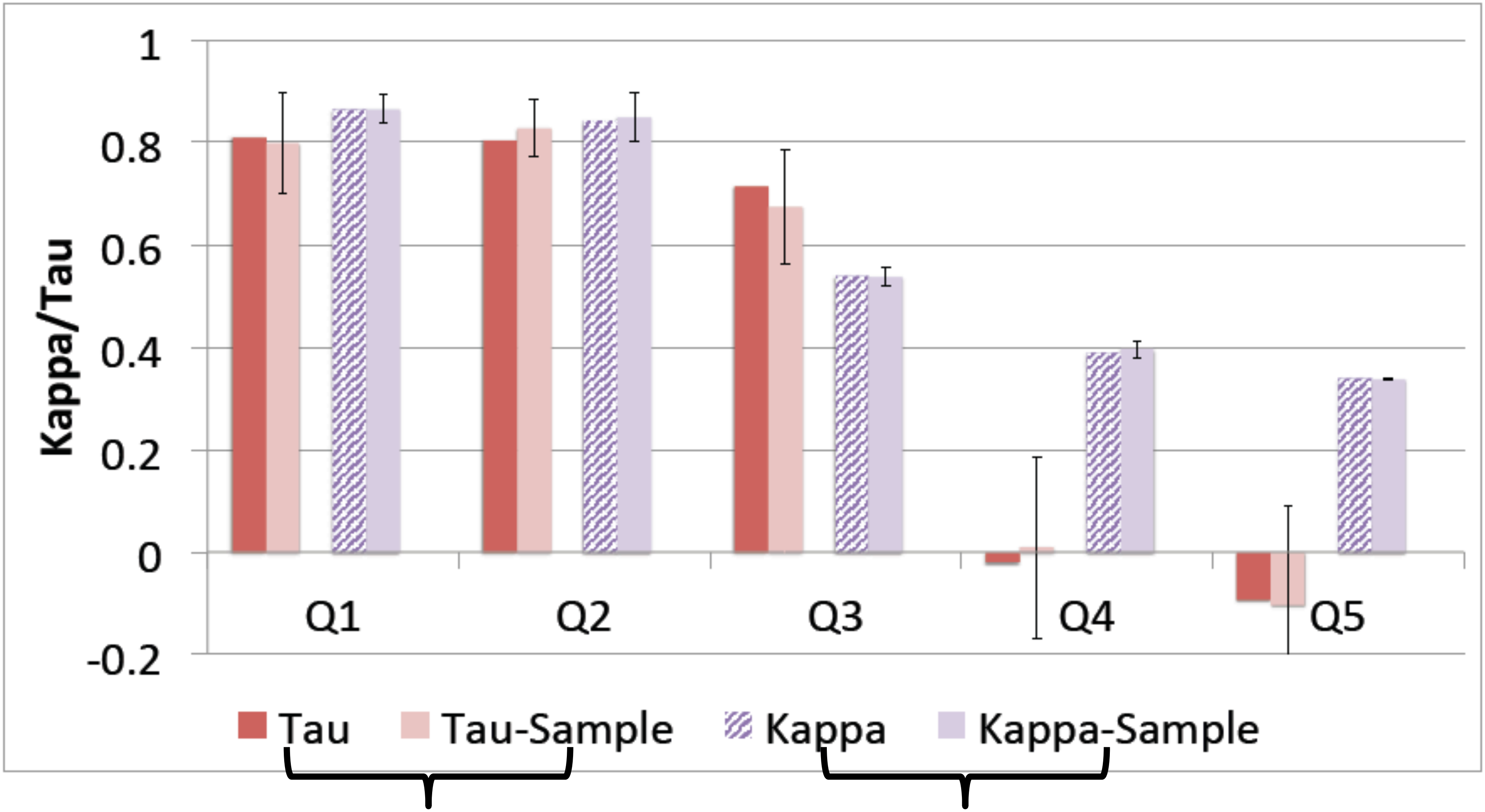


Sort [Marcus-VLDB11]

- #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

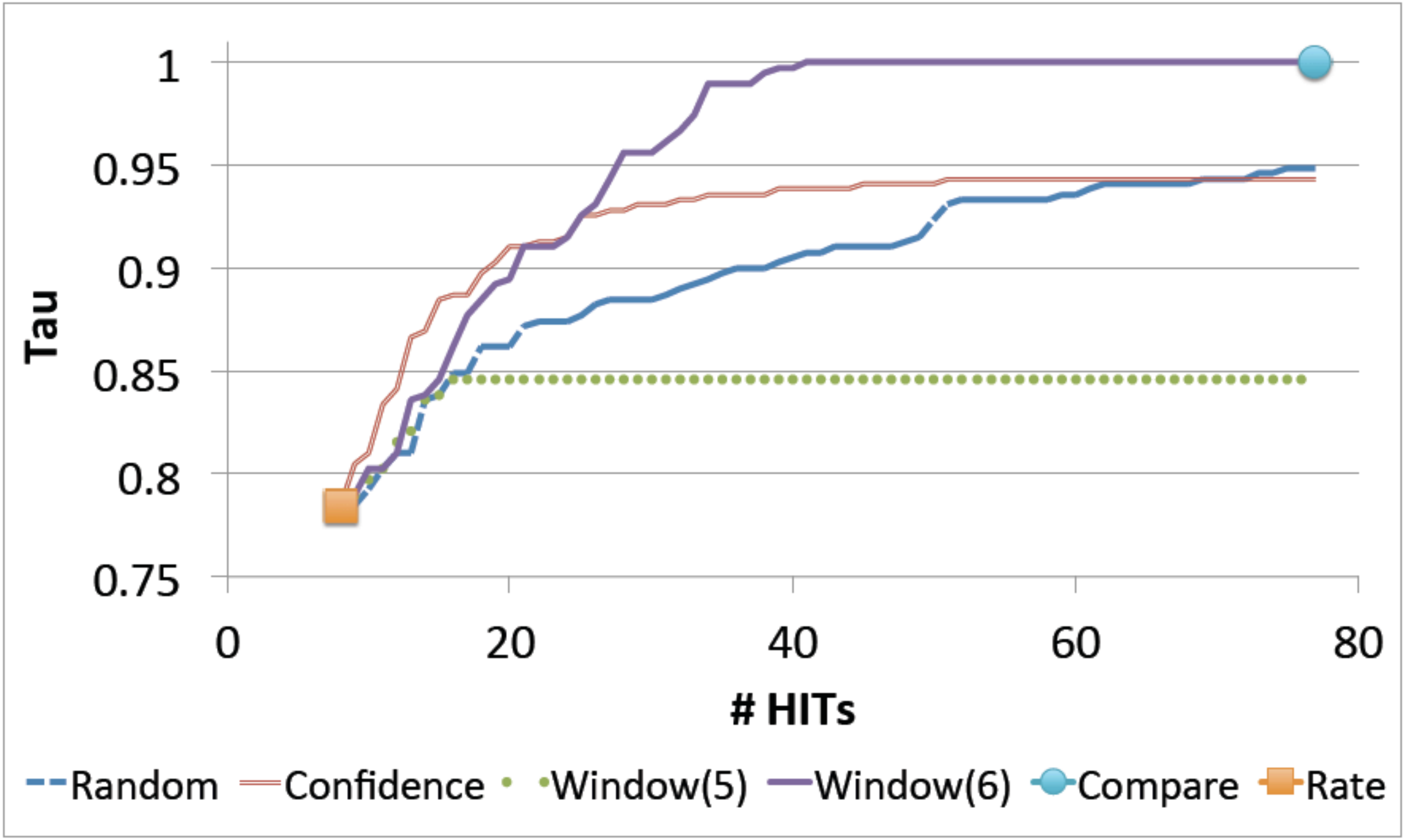
Sort [Marcus-VLDB11]



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

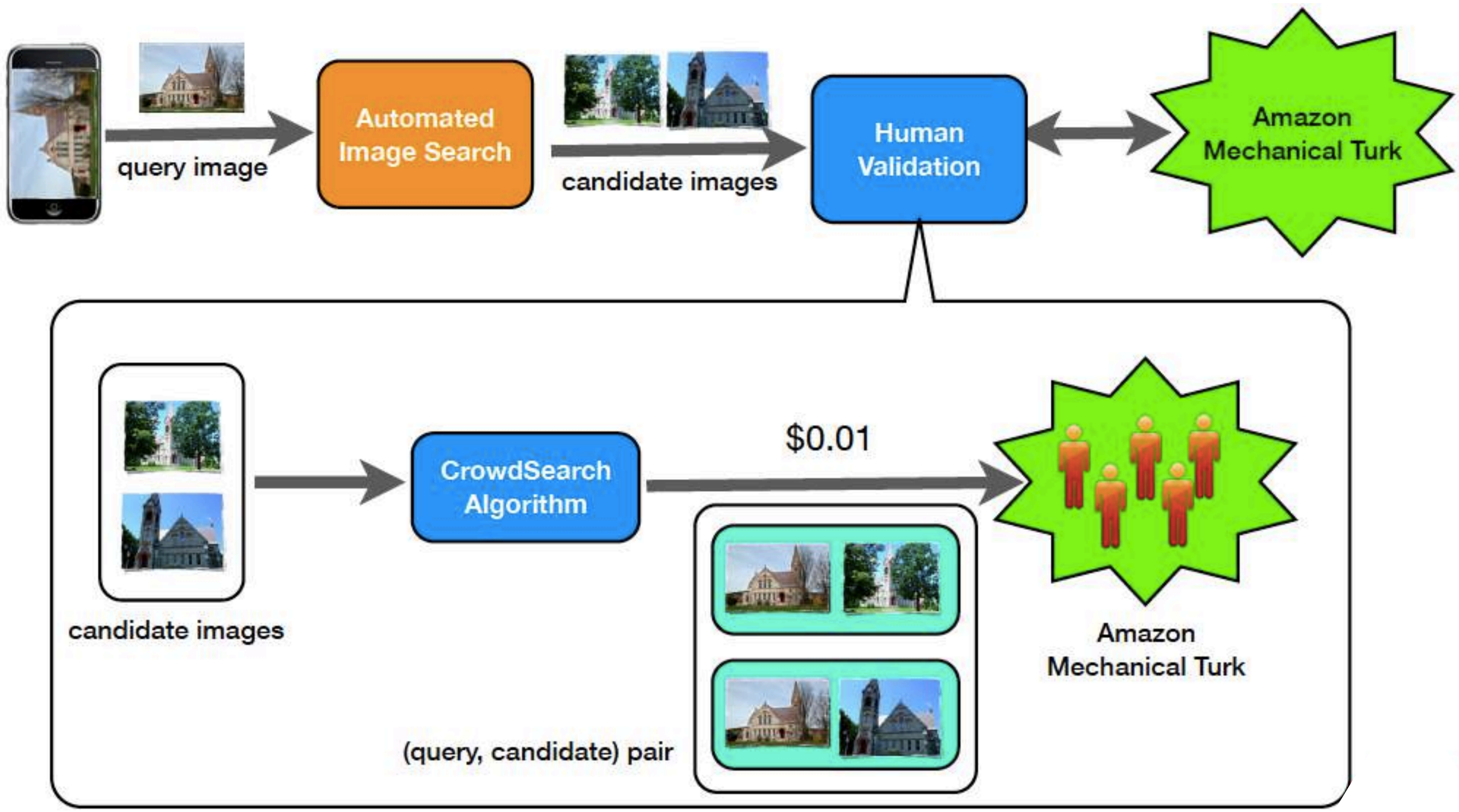
- Given *N* items, select *k* items that satisfy a predicate *P*
- ≈ Filter, Find, Screen, Search

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

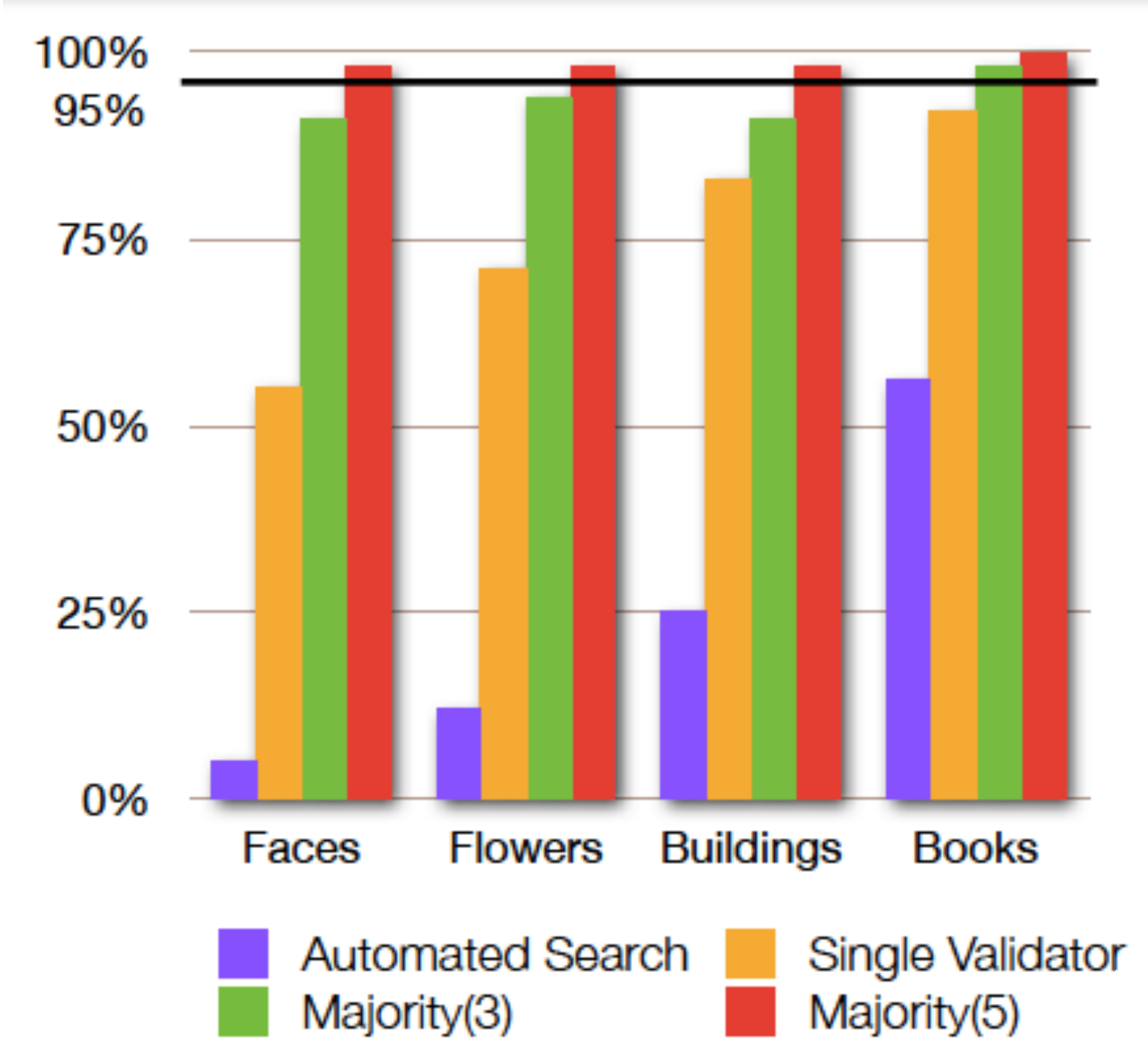
Select [Yan-MobiSys10]

- Improving mobile image search using crowdsourcing



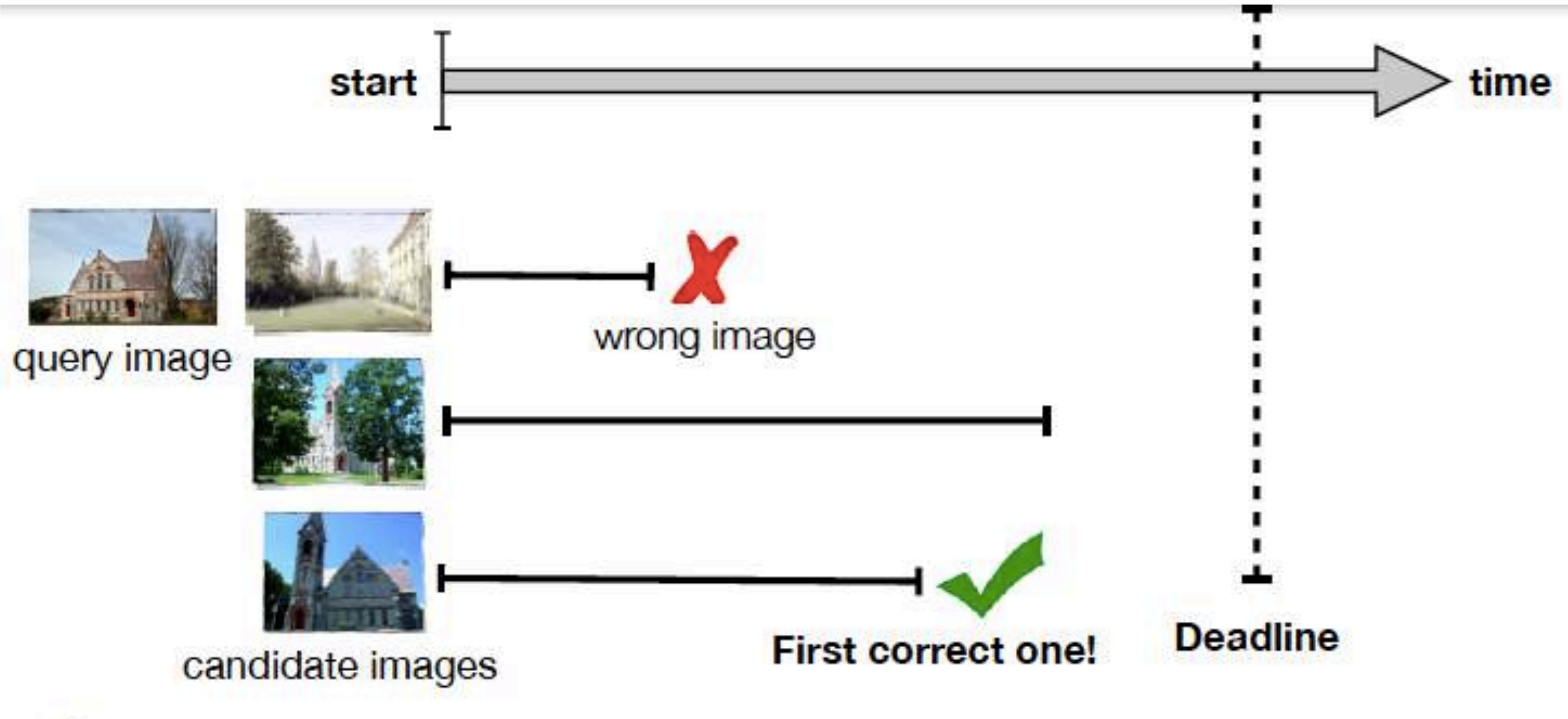
Select [Yan-MobiSys10]

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



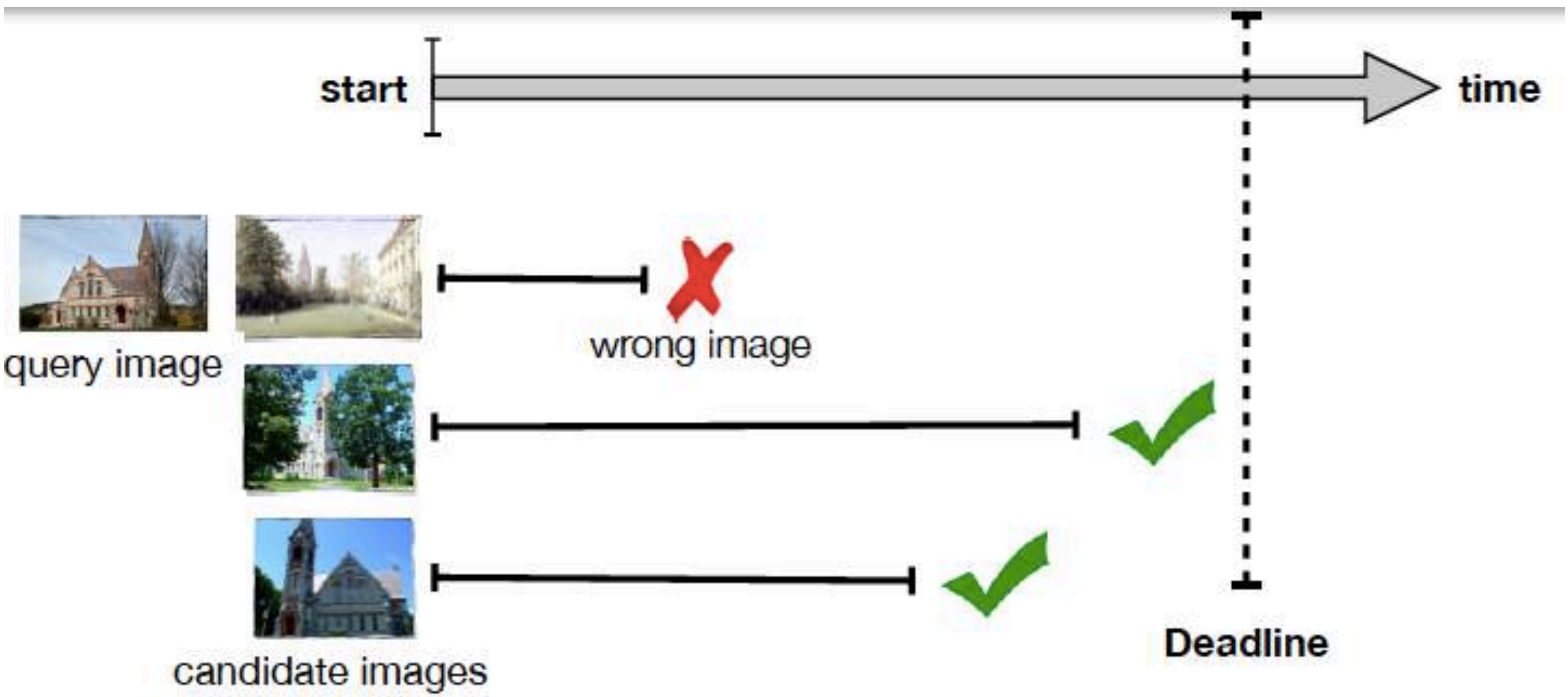
Select [Yan-MobiSys10]

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



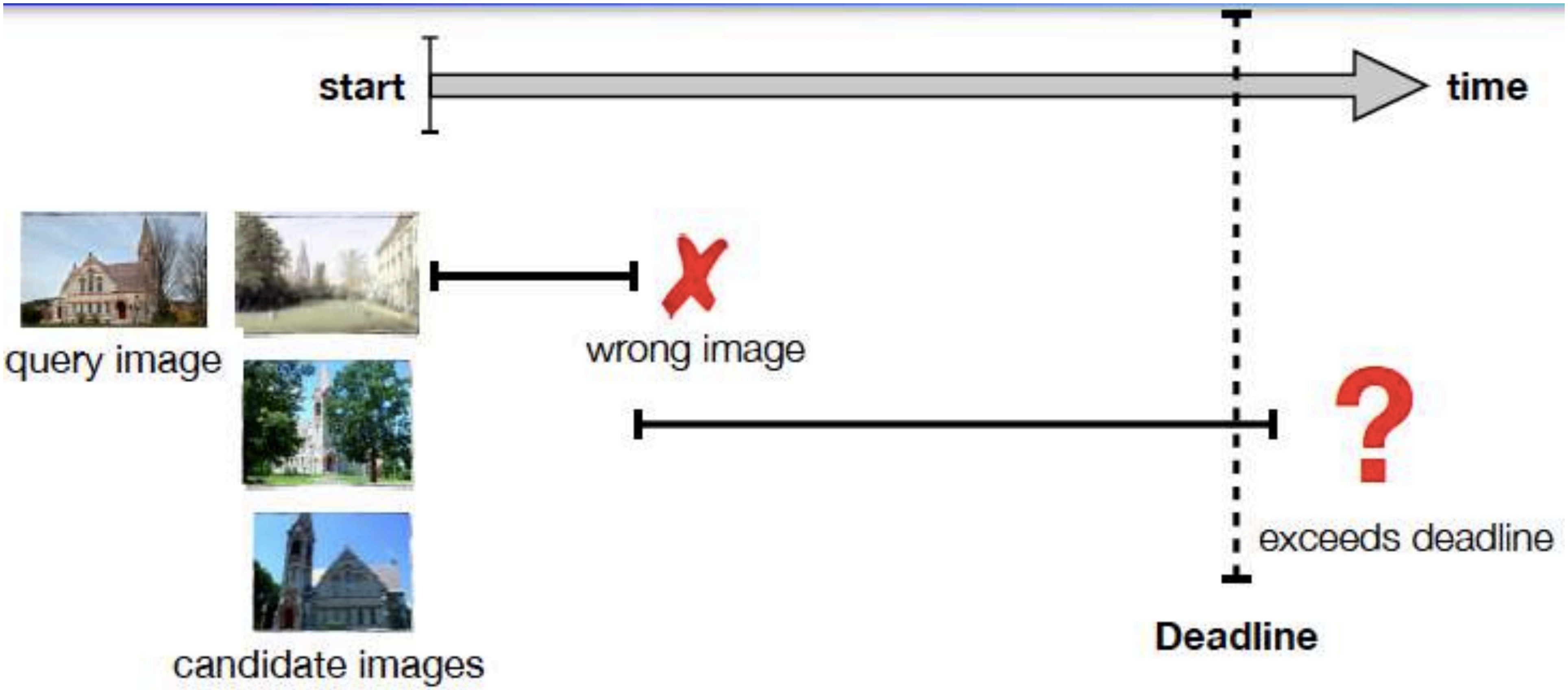
Select [Yan-MobiSys10]

- Parallel crowdsourced validation



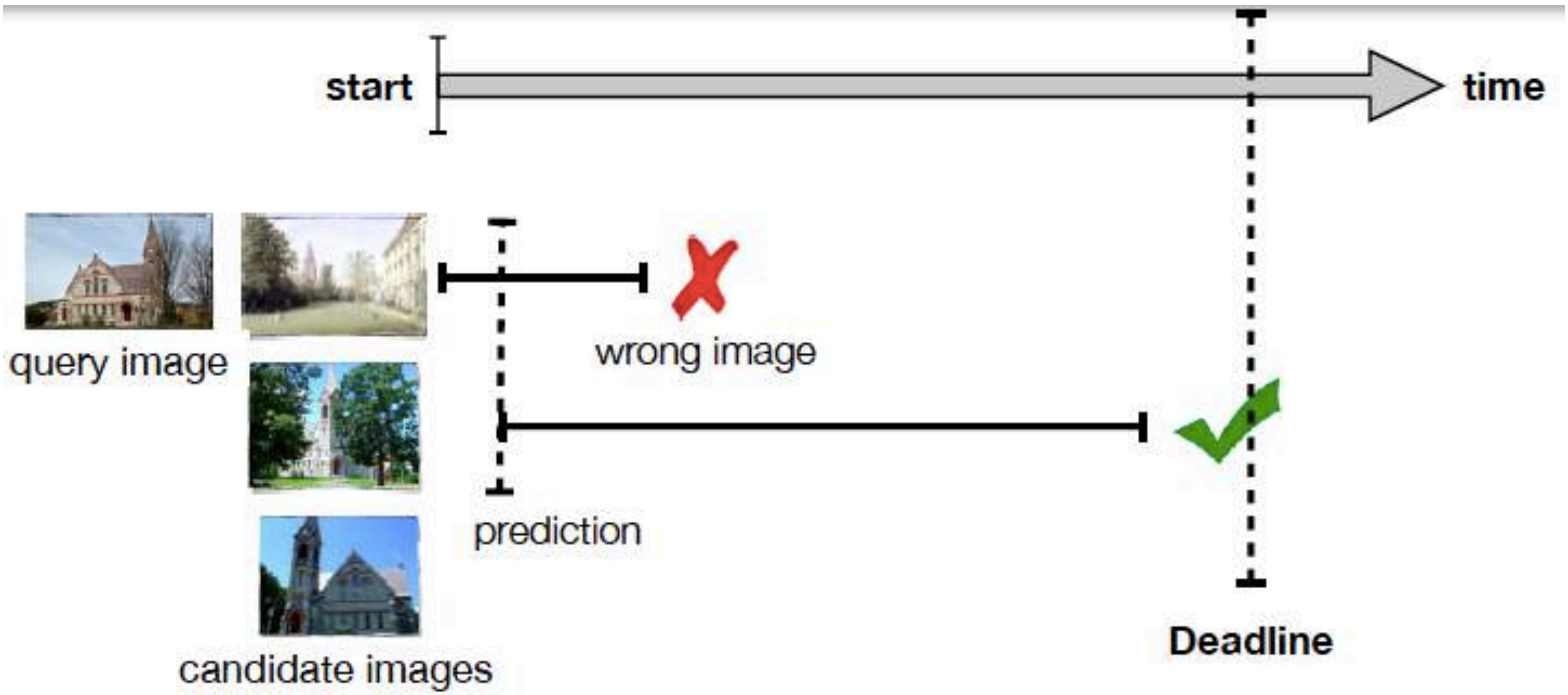
Select [Yan-MobiSys10]

- Sequential crowdsourced validation

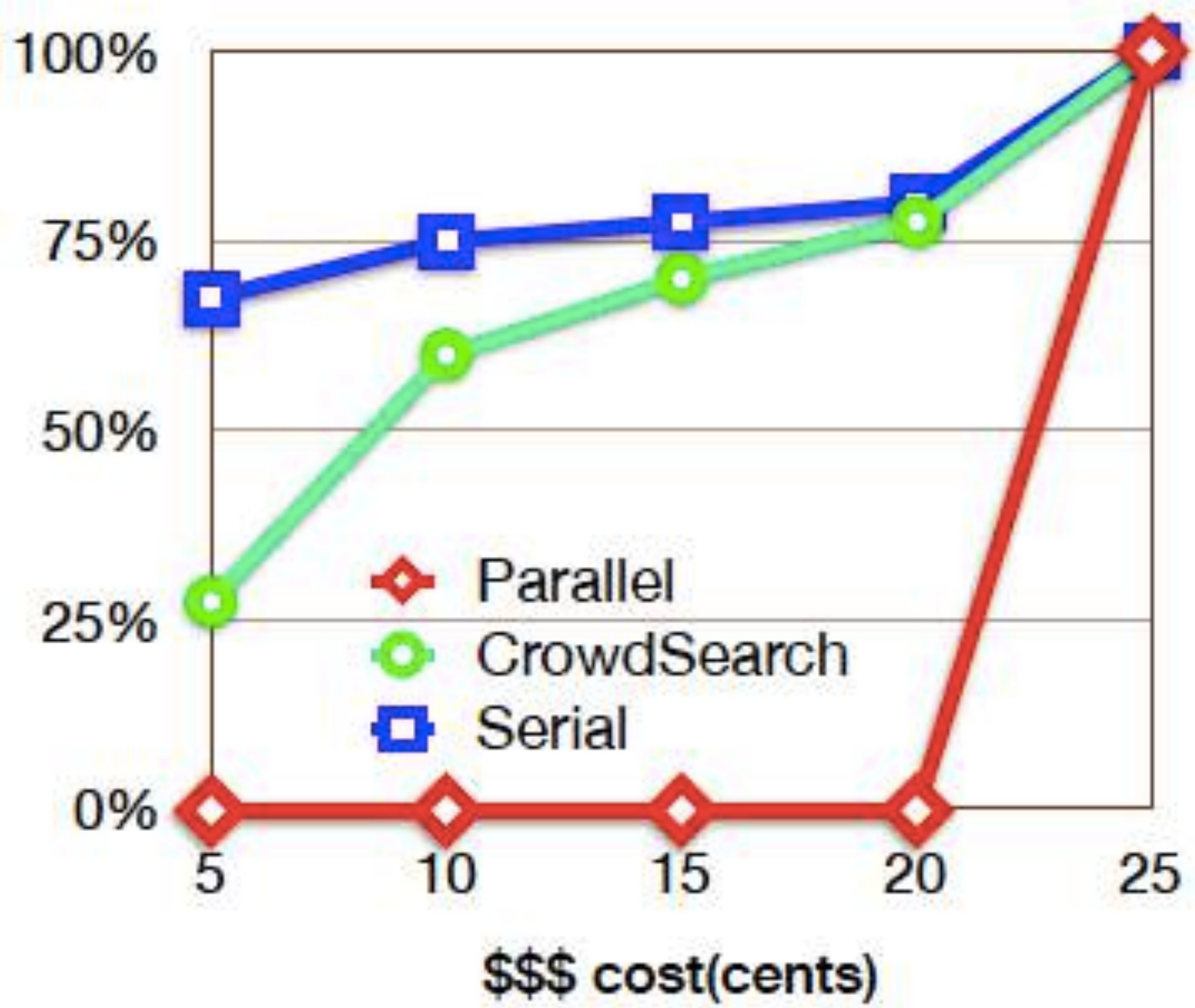


Select [Yan-MobiSys10]

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



Select [Yan-MobiSys10]

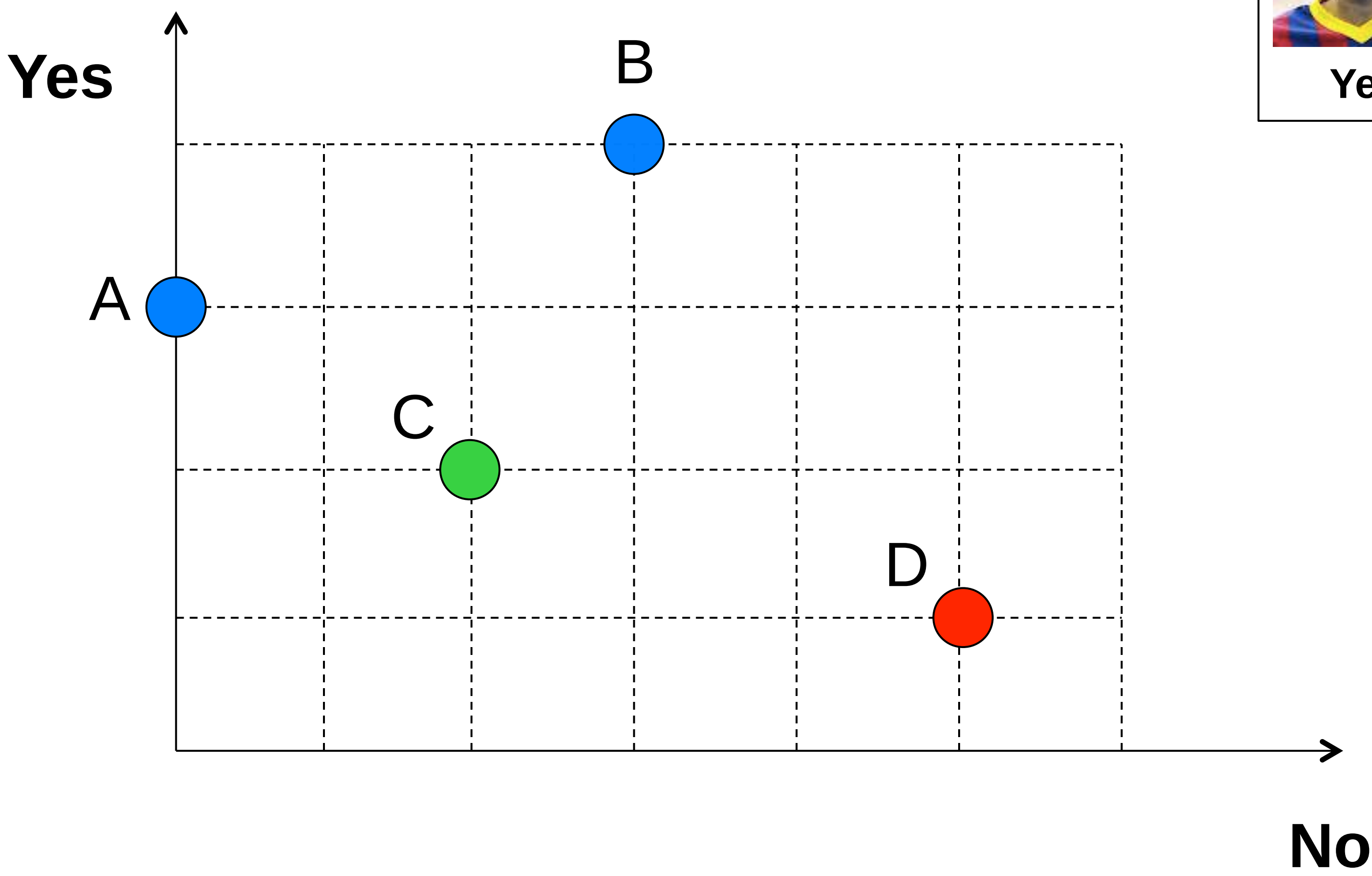


Select [Parameswaran-SIGMOD12]

- Novel grid-based visualization

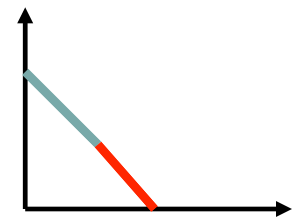
Same person?

Yes ○ **No** ○



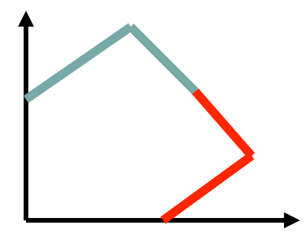
Select [Parameswaran-SIGMOD12]

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



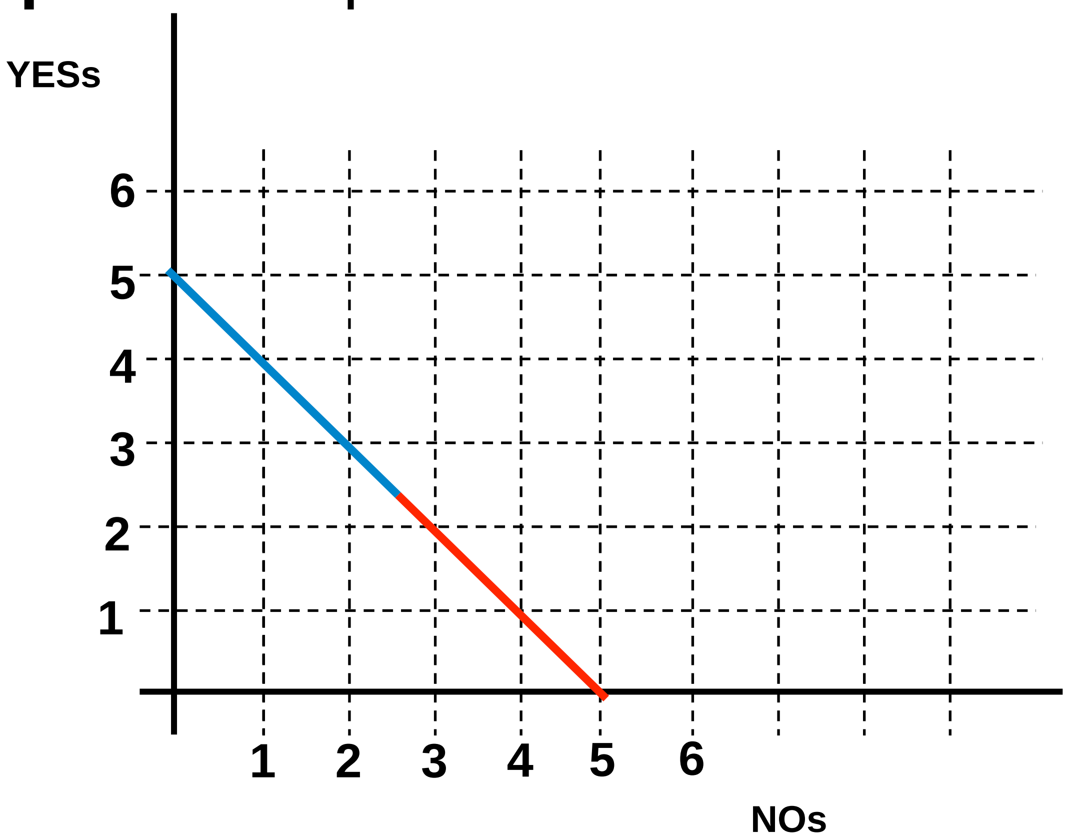
  - If X YES return “Pass”, Y NO return “Fail”, else keep asking → Rectangular strategy

  - 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*

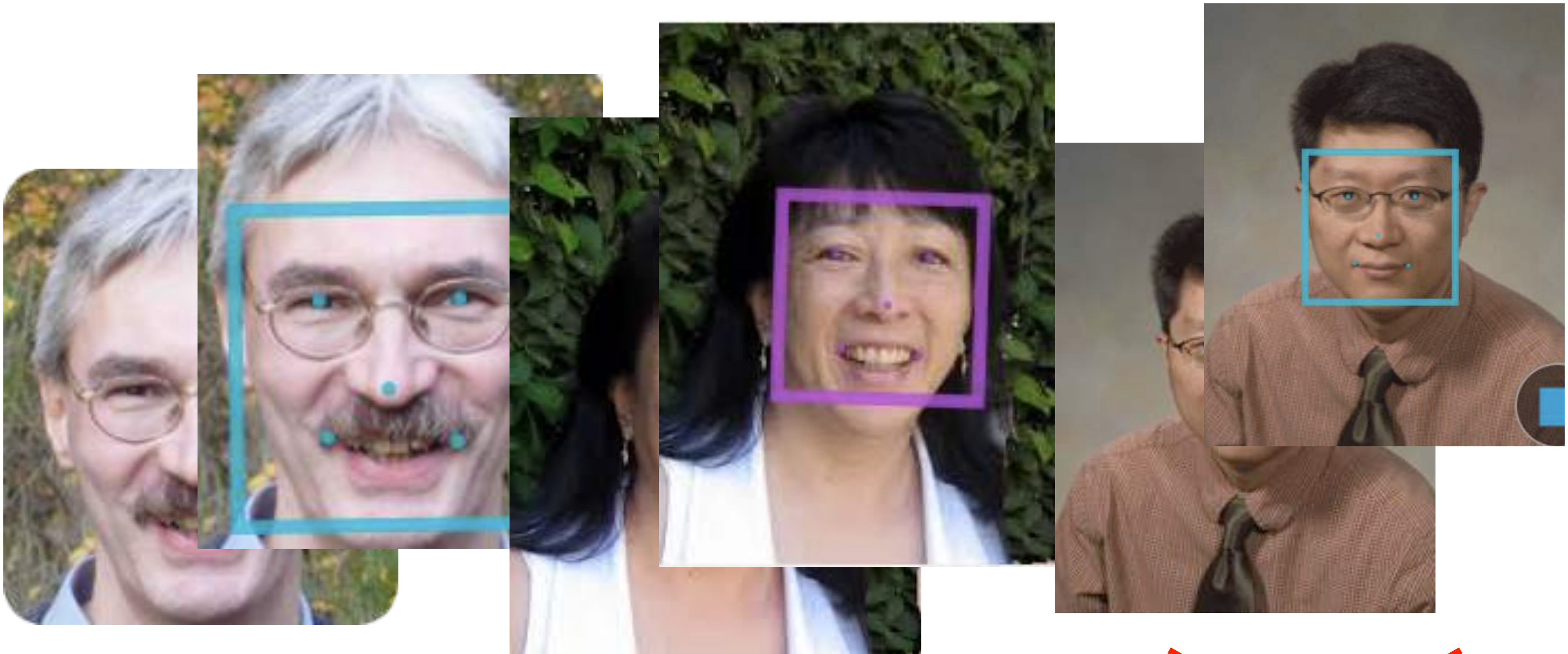
- Selectivity estimation in DB → crowd-powered query optimizers
- Evaluating queries with GROUP BY + COUNT/AVG/SUM operators
- Eg, “Find photos of females with red hairs”
  - Selectivity(“female”) ≈ 50%
  - Selectivity(“red hair”) ≈ 2%
  - Better to process predicate(“red hair”) first

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

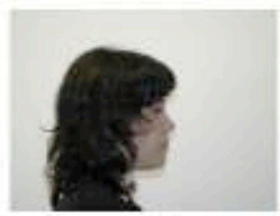
Count [Marcus-VLDB13]

- Label Count (via sampling)

There are 2 people below. Please identify the gender of each.

What is the gender of this person?

○ male ◉ female



What is the gender of this person?

○ male ◉ female

Submit

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

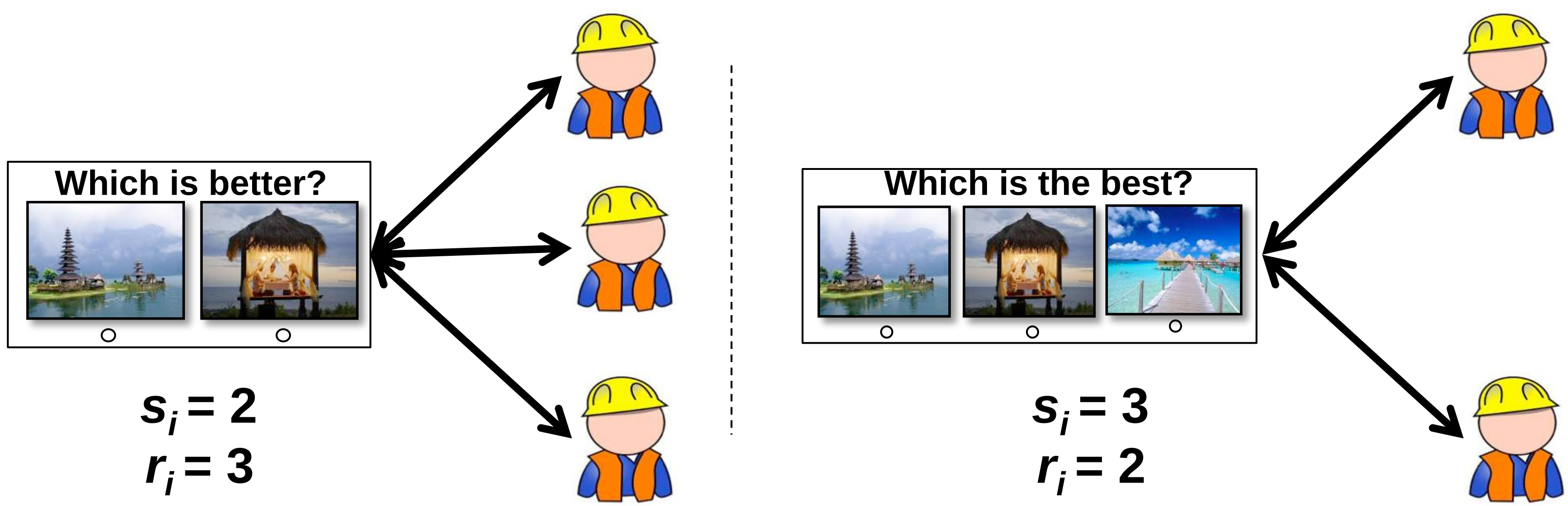
- Objective
  - Avoid sorting all *N* items to find top-1

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

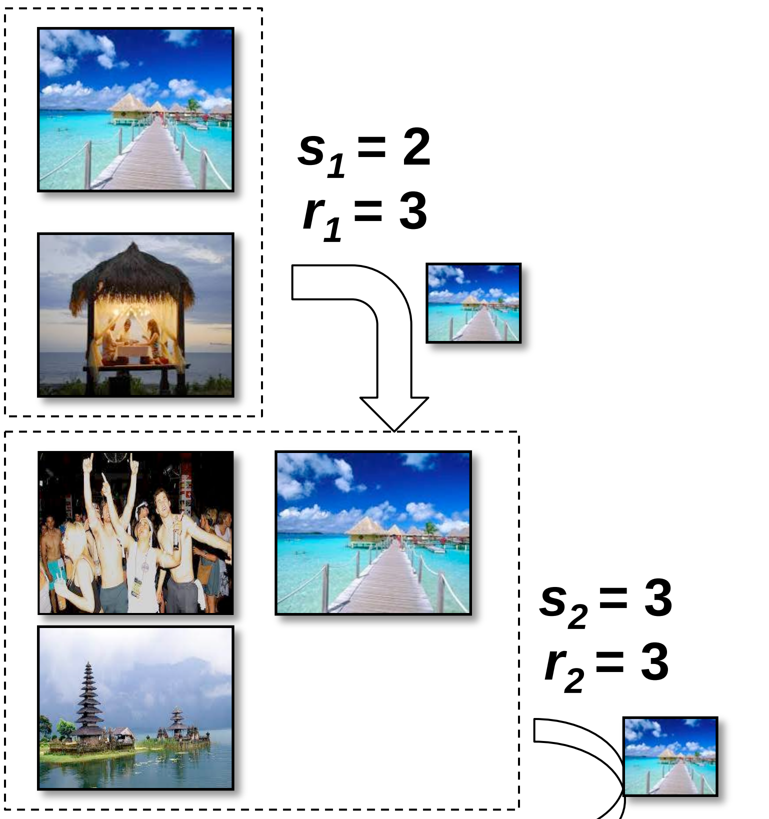
Max [Venetis-WWW12]

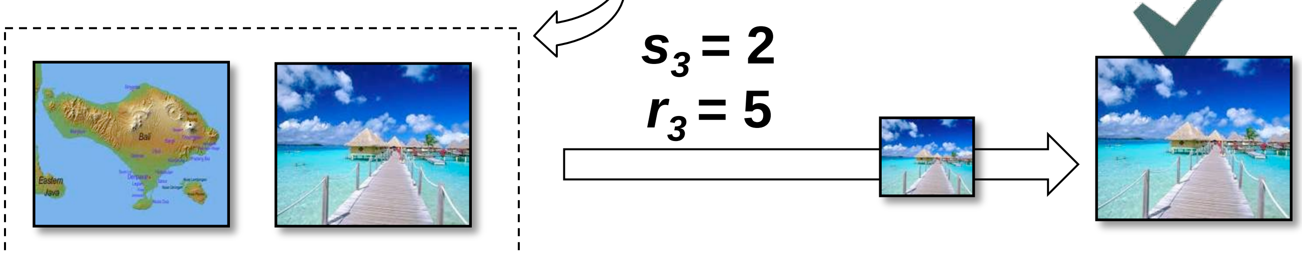
- Introduced two Max algorithms
  - Bubble Max
  - Tournament Max
- Parameterized framework
  - s_i: size of sets compared at the i-th round
  - r_i: # of human responses at the i-th round



Max [Venetis-WWW12]

- Bubble Max Case #1



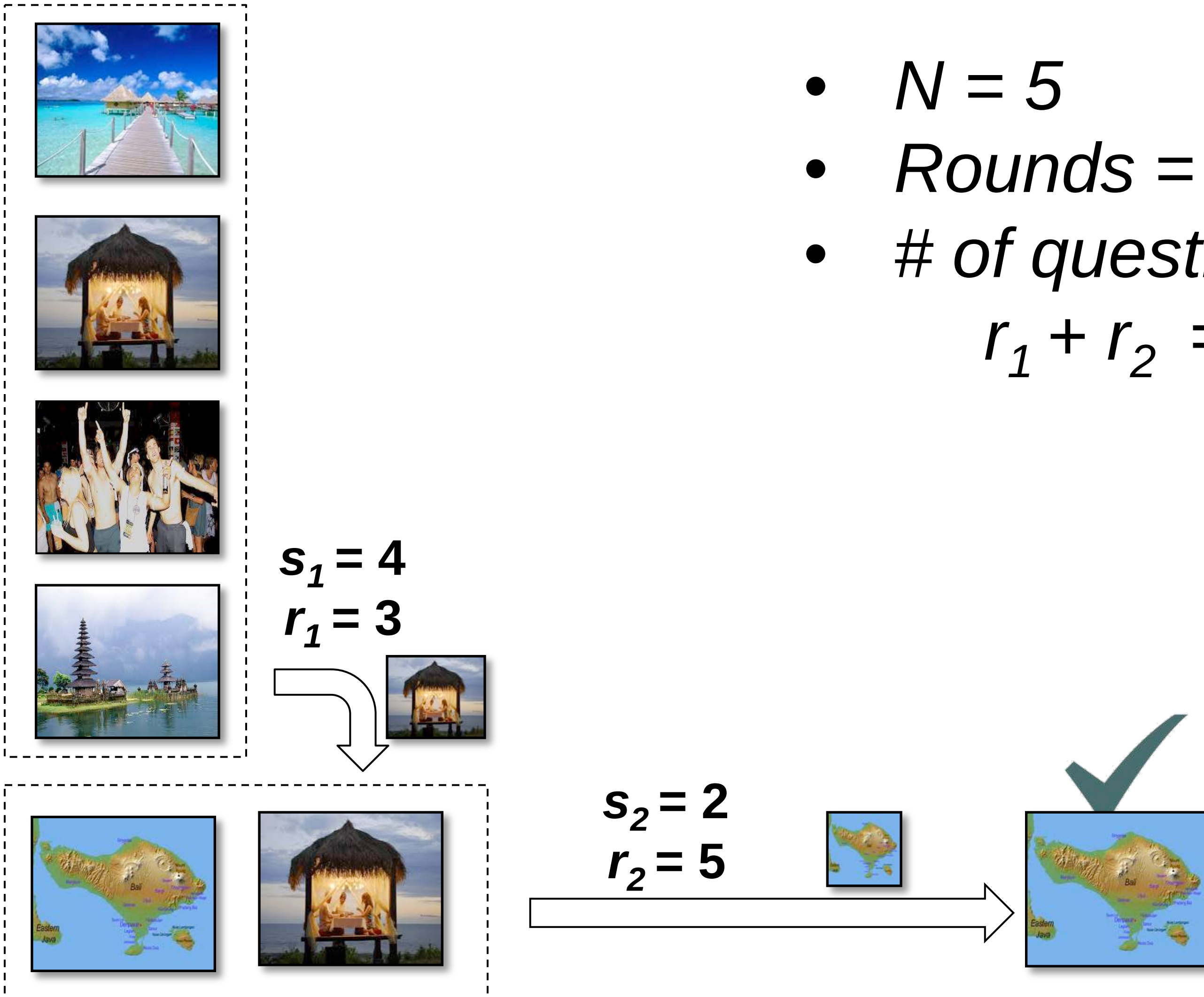


- $N = 5$
- *Rounds* = 3
- *# of questions* =
  $r_1 + r_2 + r_3 = 11$

Max [Venetis-WWW12]

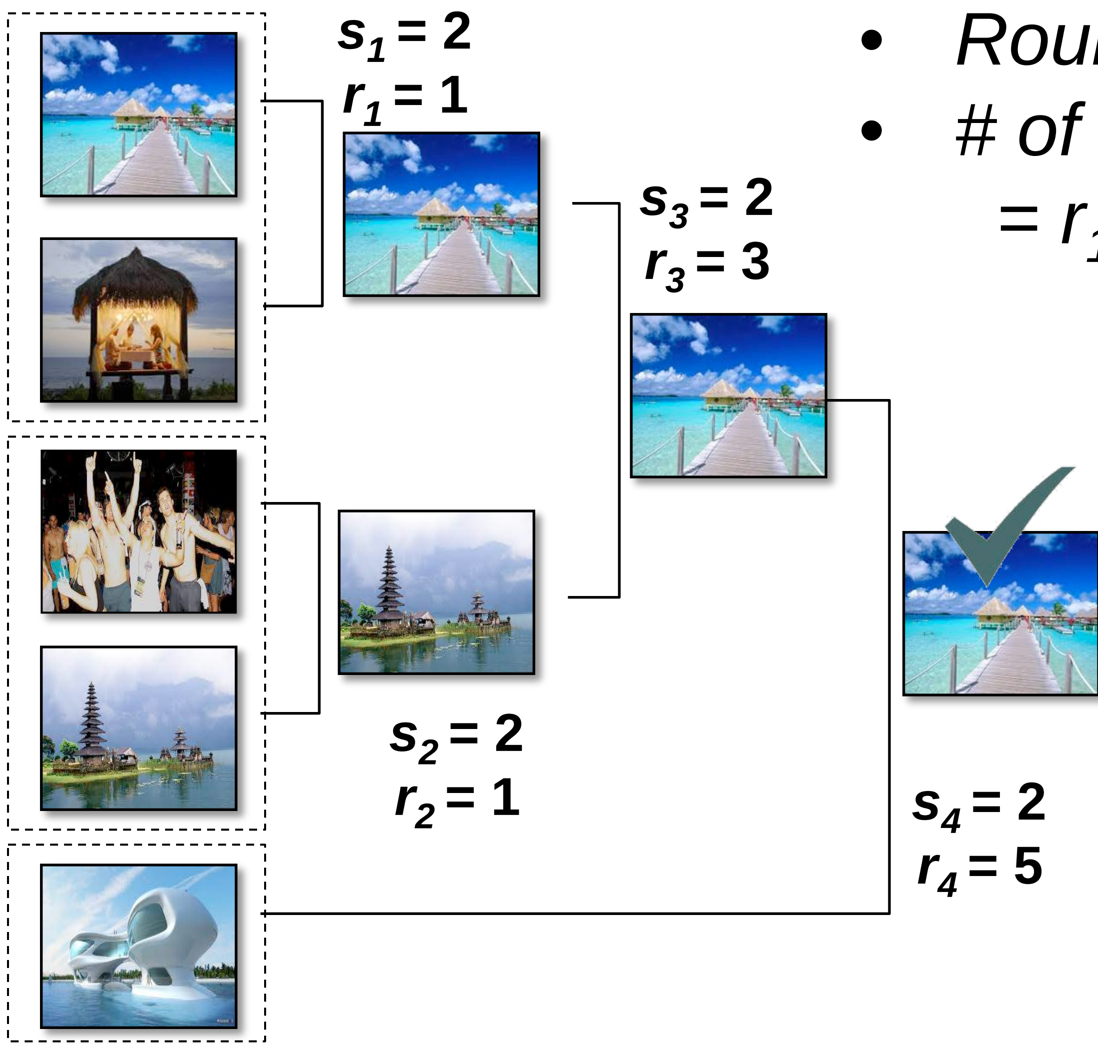
- Bubble Max Case #2

  - $N = 5$
  - *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]

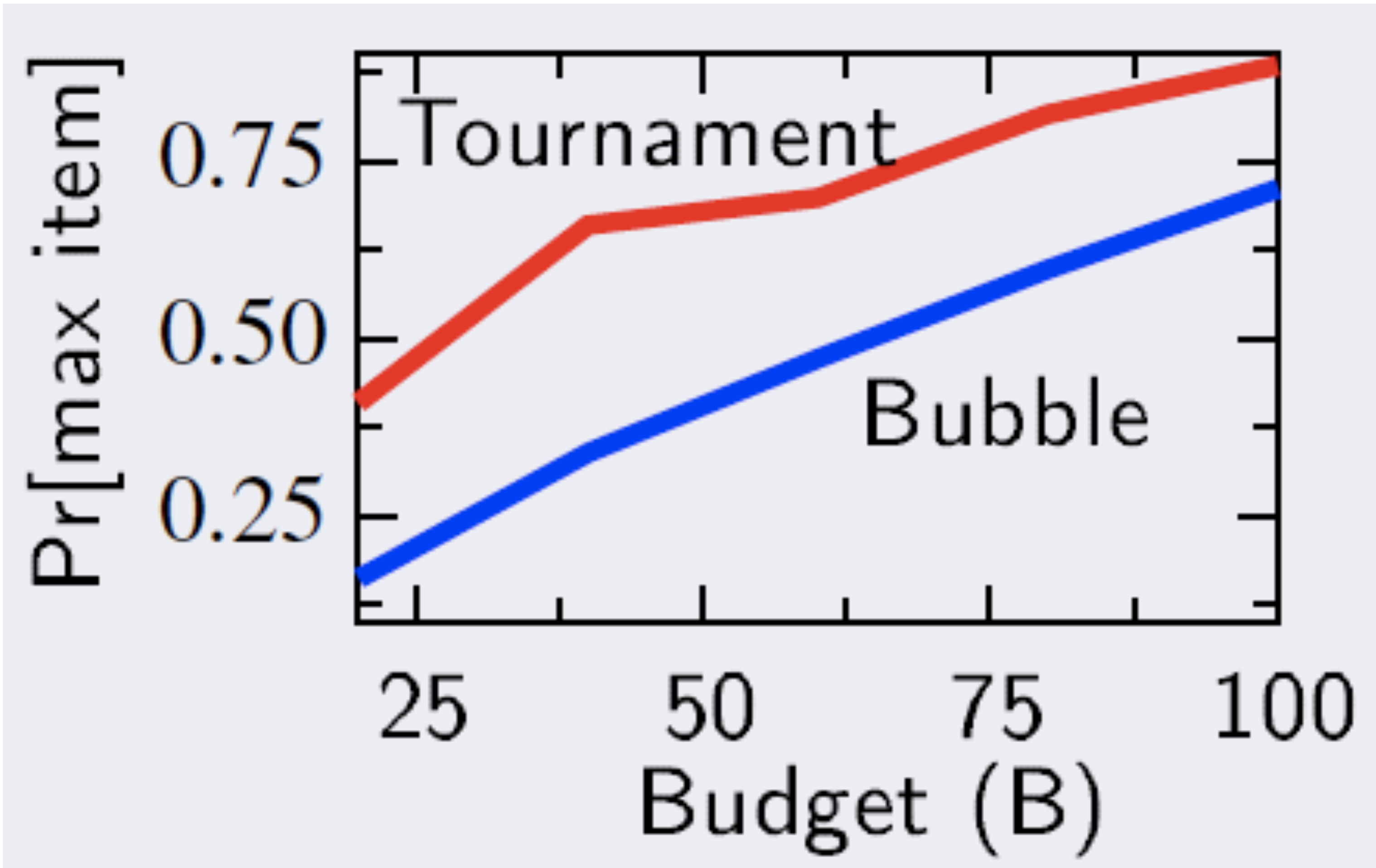
- How to find optimal parameters?: s_i and r_i
- Tuning Strategies (using Hill Climbing)
  - Constant s_i and r_i
  - Constant s_i and varying r_i
  - Varying s_i and r_i

Max [Venetis-WWW12]

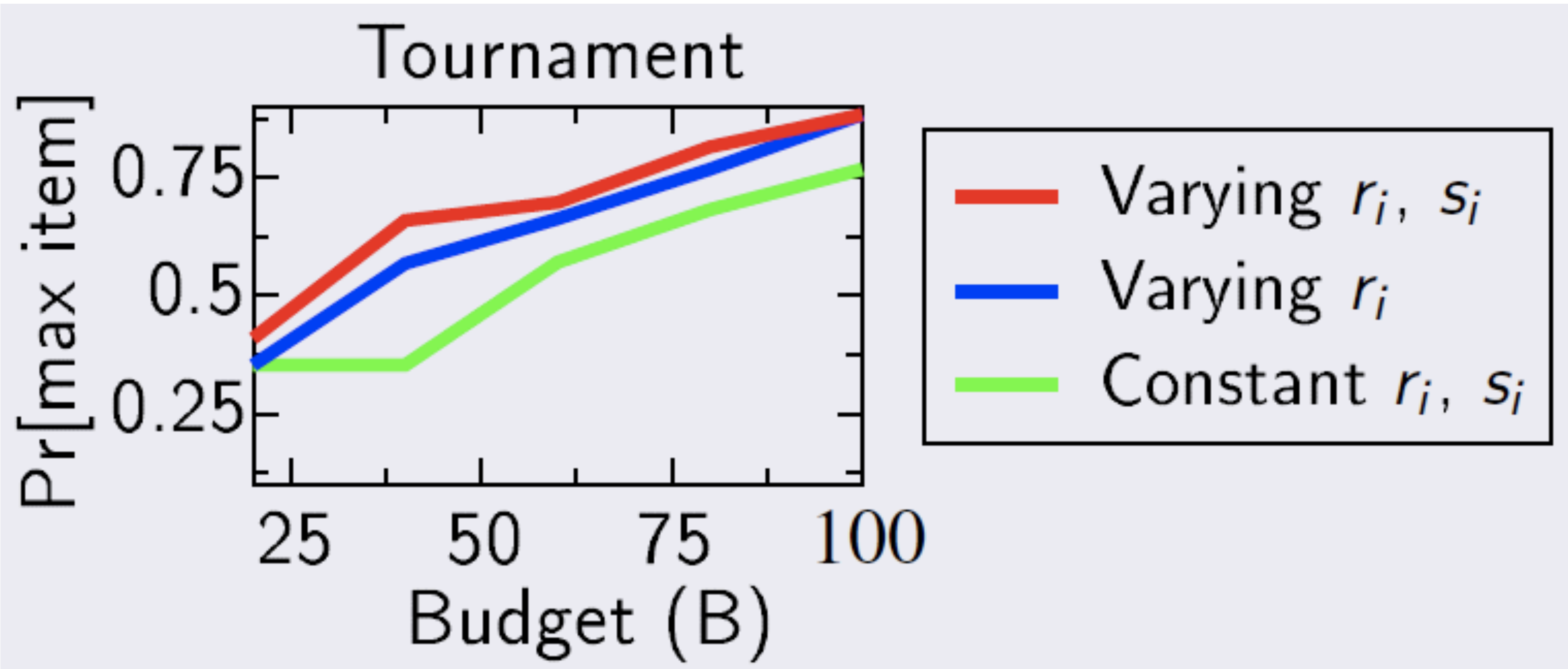
- Bubble Max
  - Worst case: with s_i=2, O(N) comparisons needed
- Tournament Max
  - Worst case: with s_i=2, O(N) comparisons needed

- 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

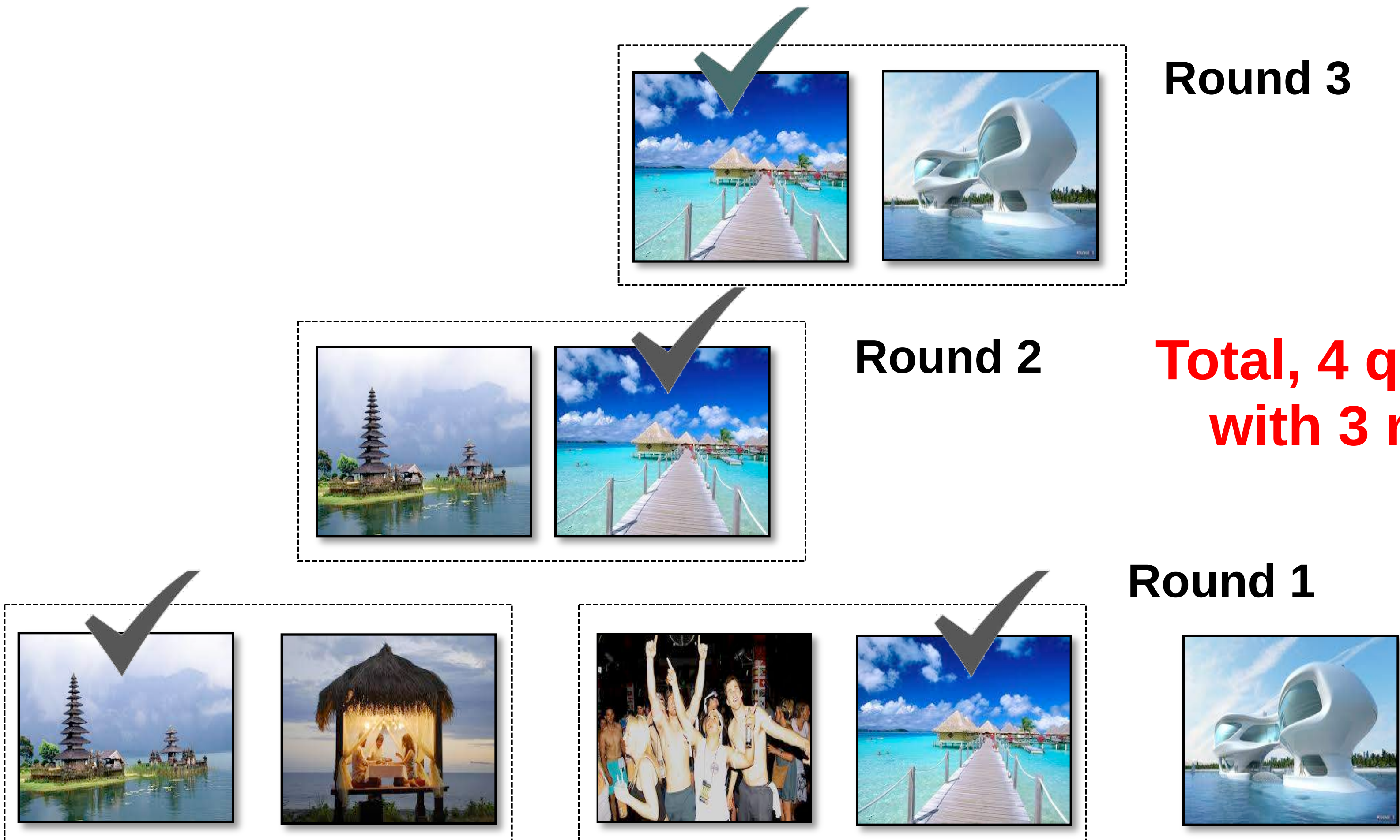
- Examples
  - **[Davidson-ICDT13]** investigates the variable user error model in solving top-*k* list problem
  - **[Polychronopoulous-WebDB13]** proposes tournament-based top-*k* set solution

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)

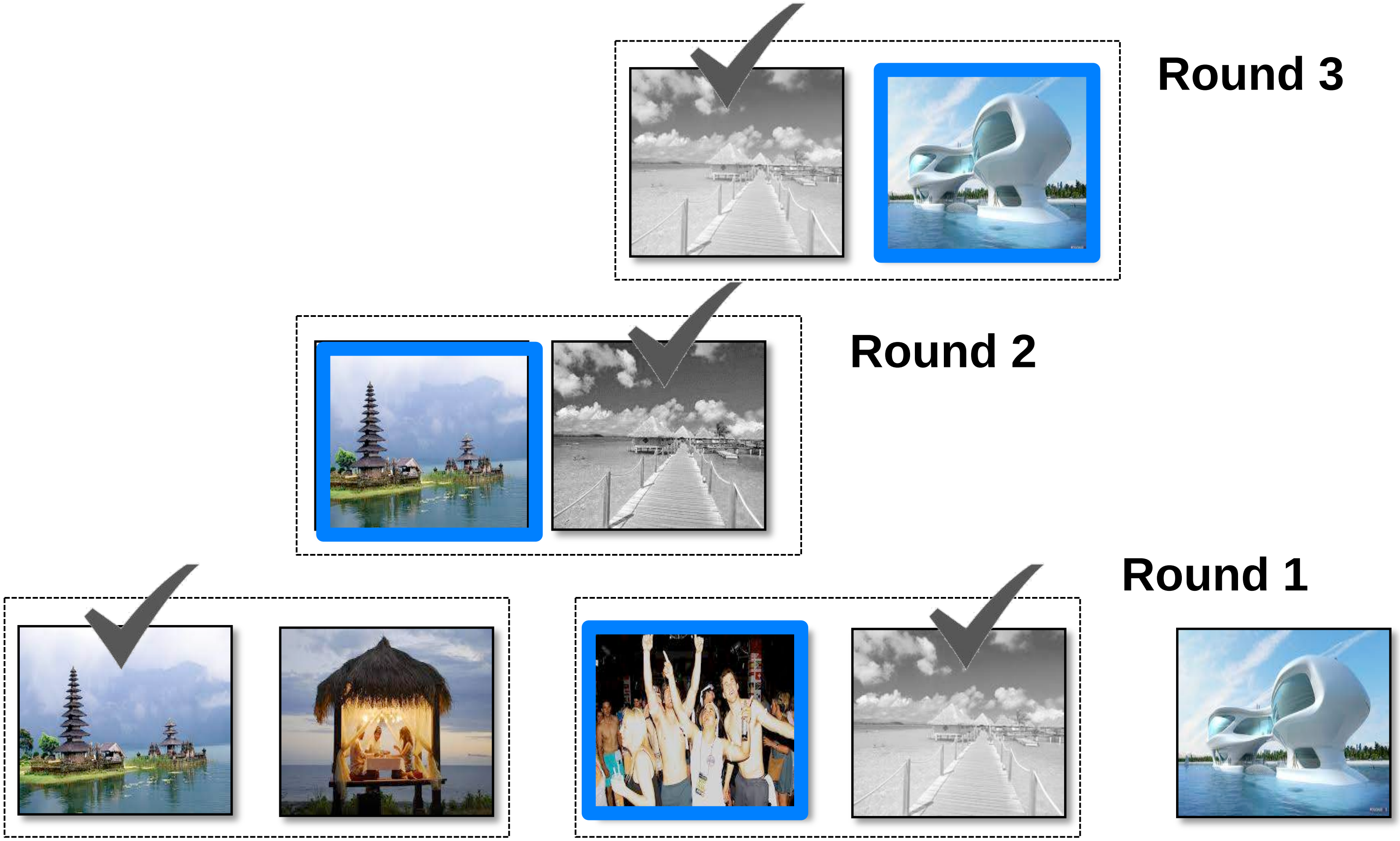
- Phase 1: **Building a tournament tree**
  - For each comparison, only winners are promoted to the next round



Total, 4 questions with 3 rounds

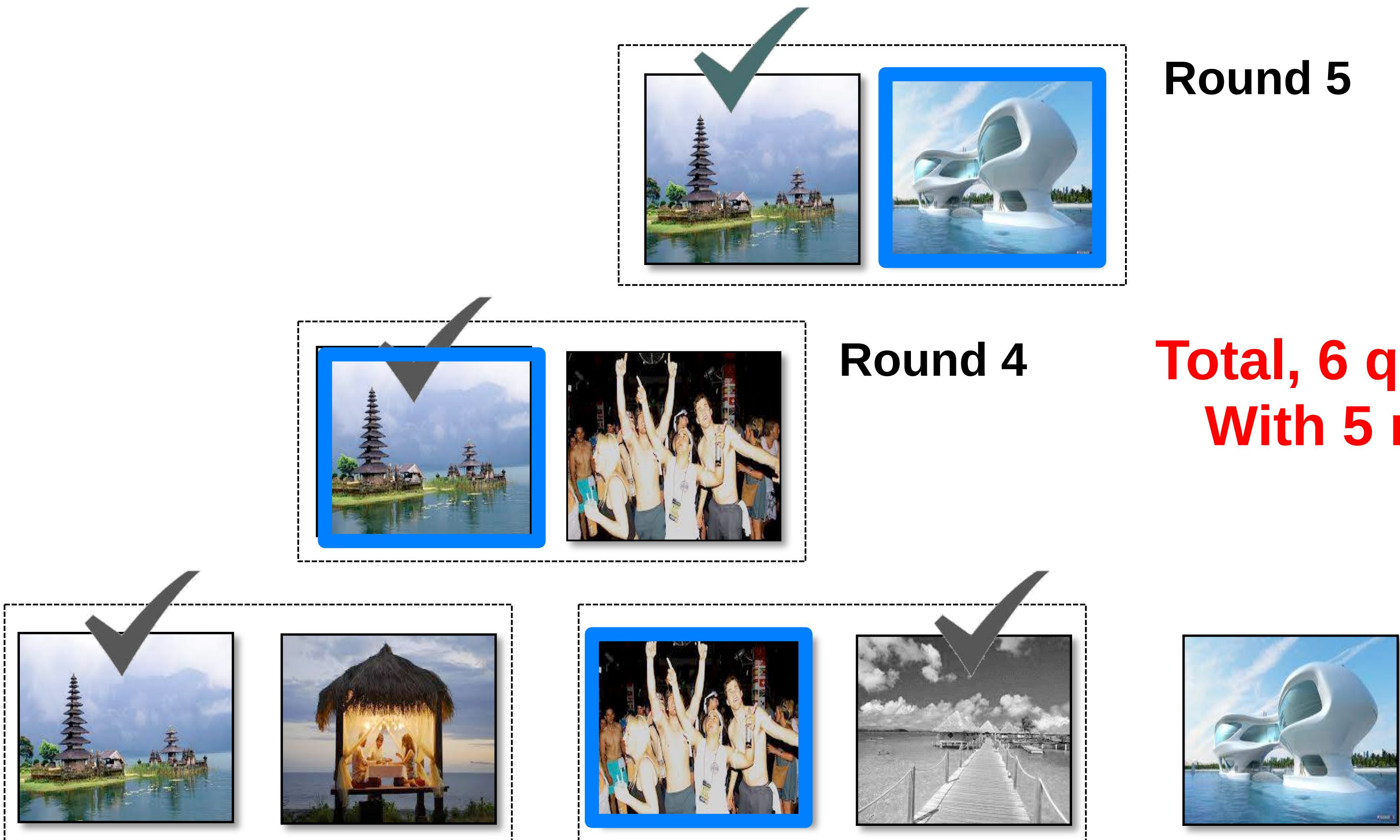
Top-*k*: Tournament Solution (*k* = 2)

- 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

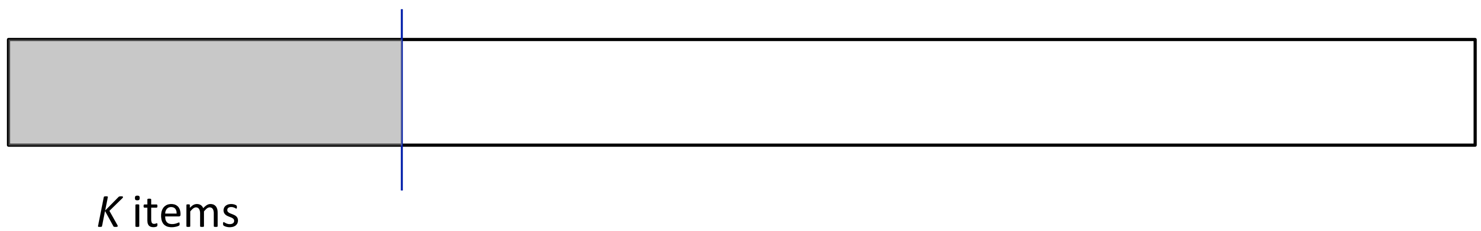
- This is a top-*k* **list** algorithm
- Analysis

	$k = 1$	$k \geq 2$
# 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

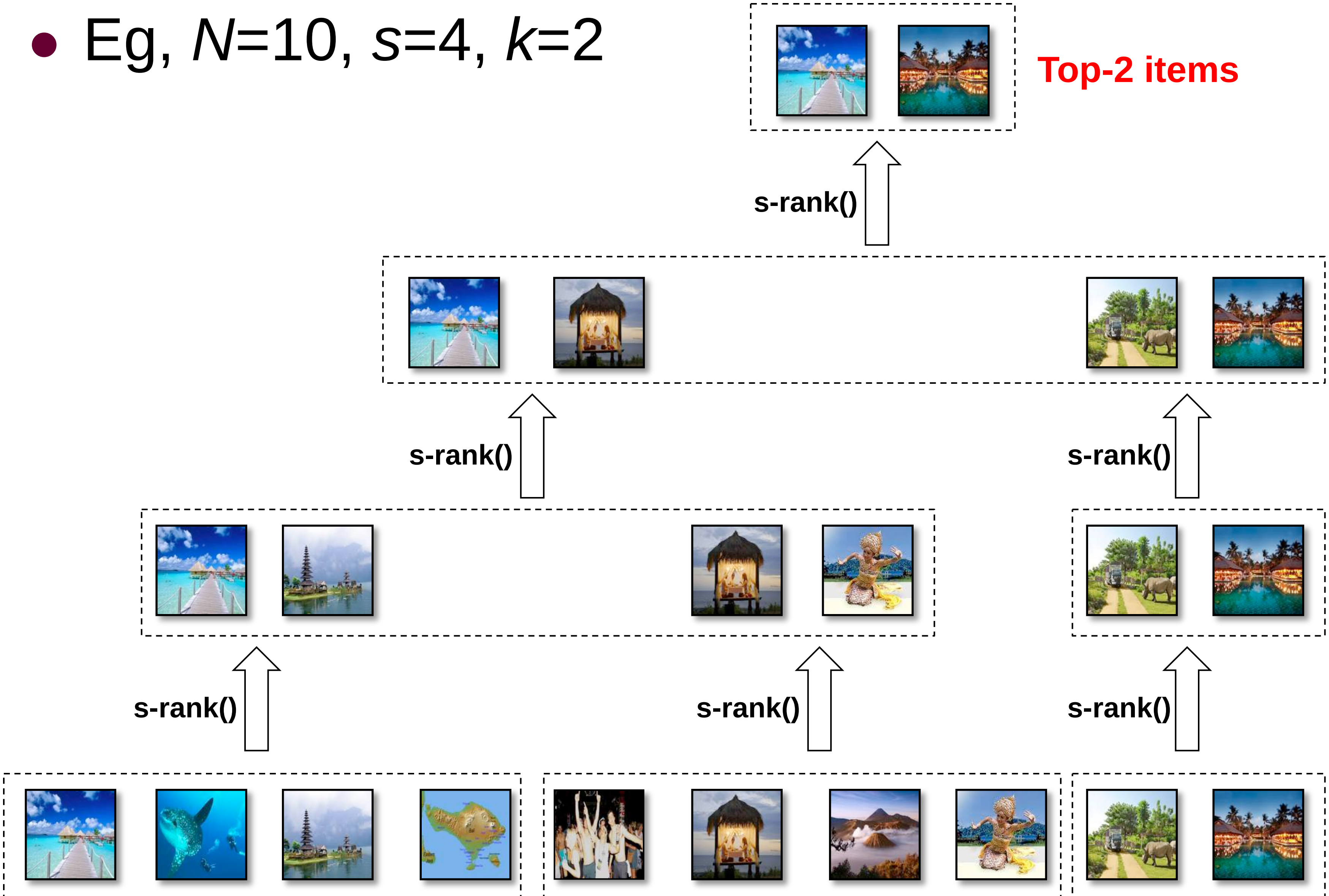
Top-*k* [Polychronopoulous-WebDB13]

- 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]

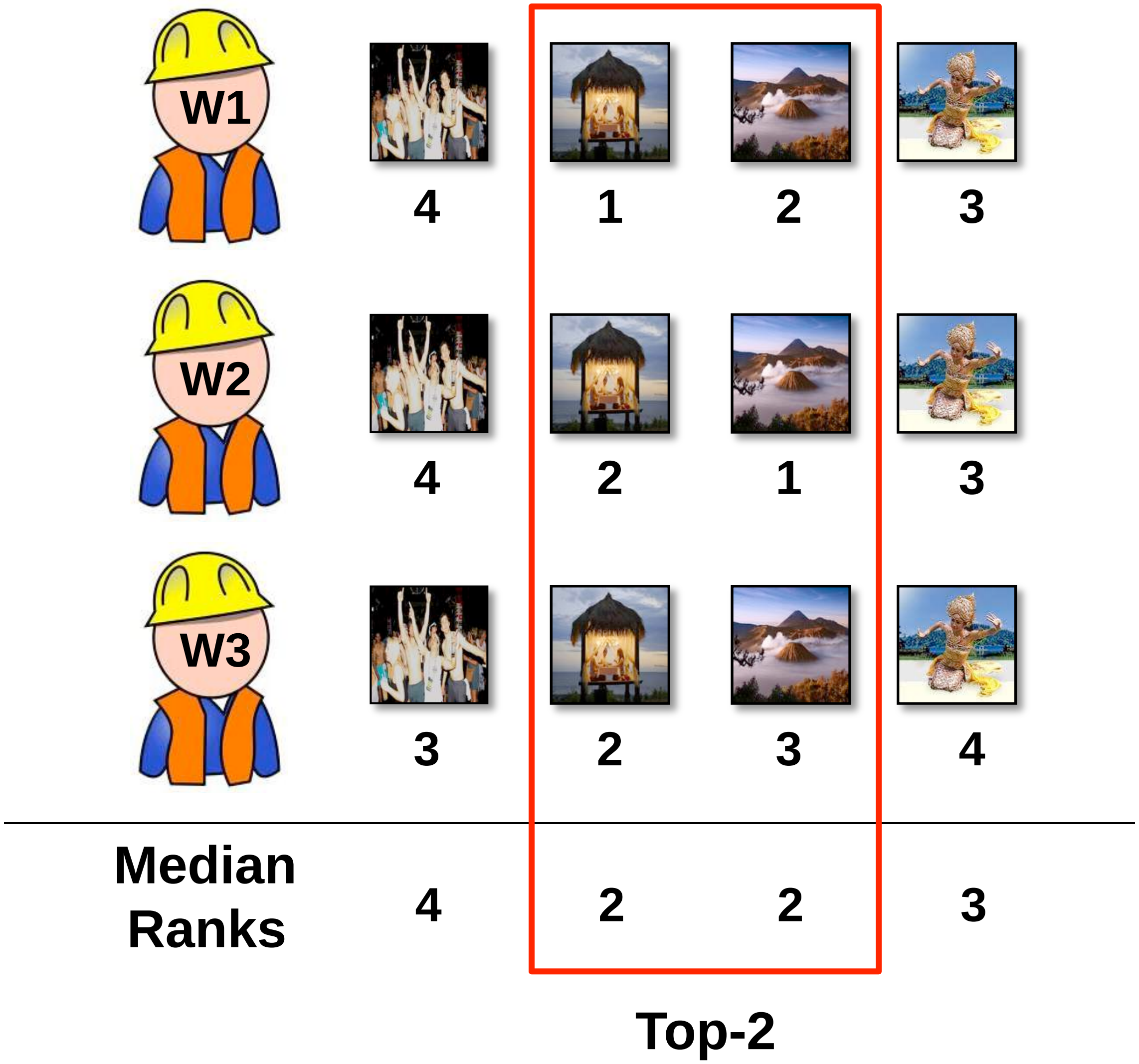
- s-rank(s)

  // 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

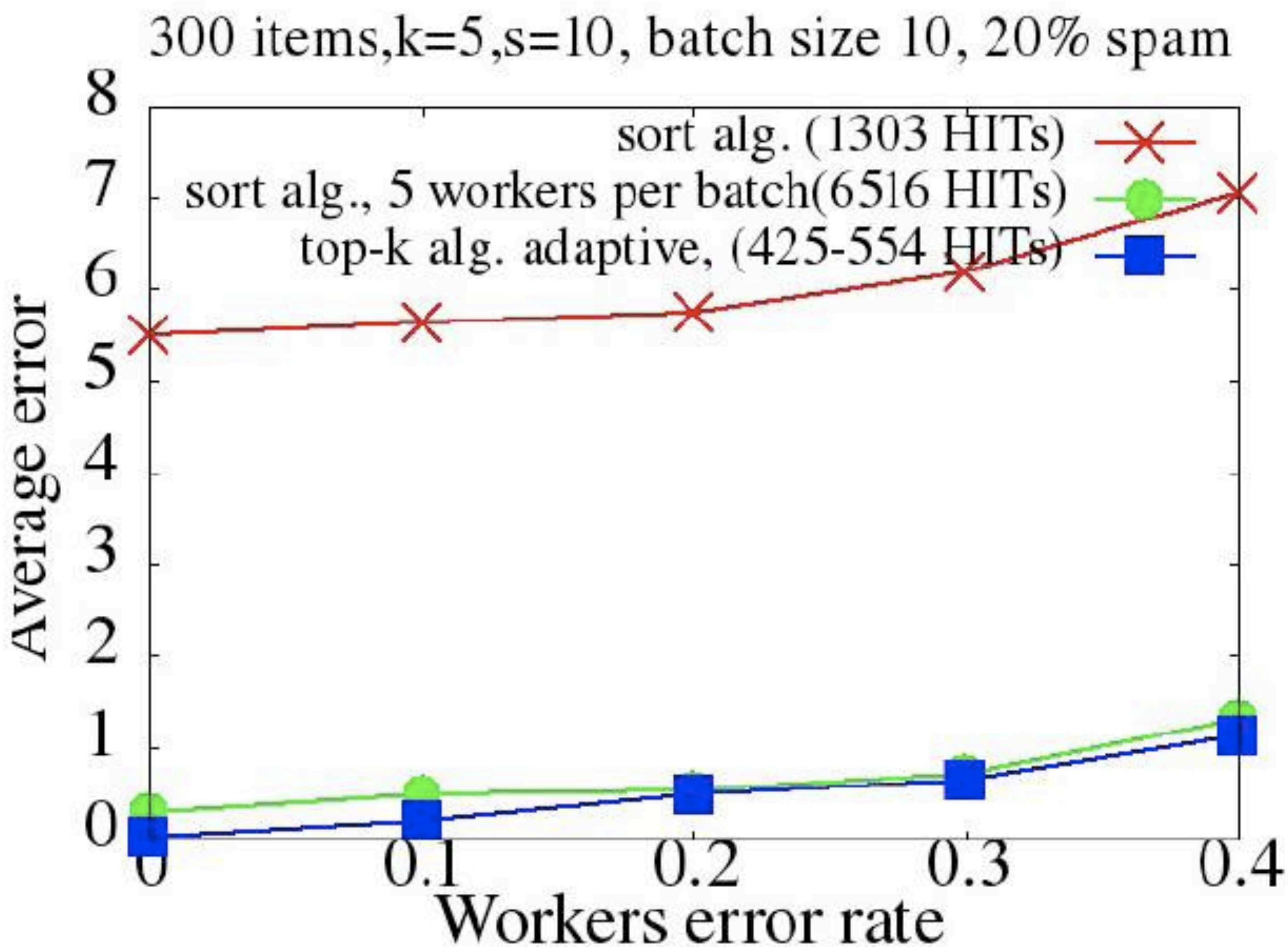
Top-*k* [Polychronopoulous-WebDB13]

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



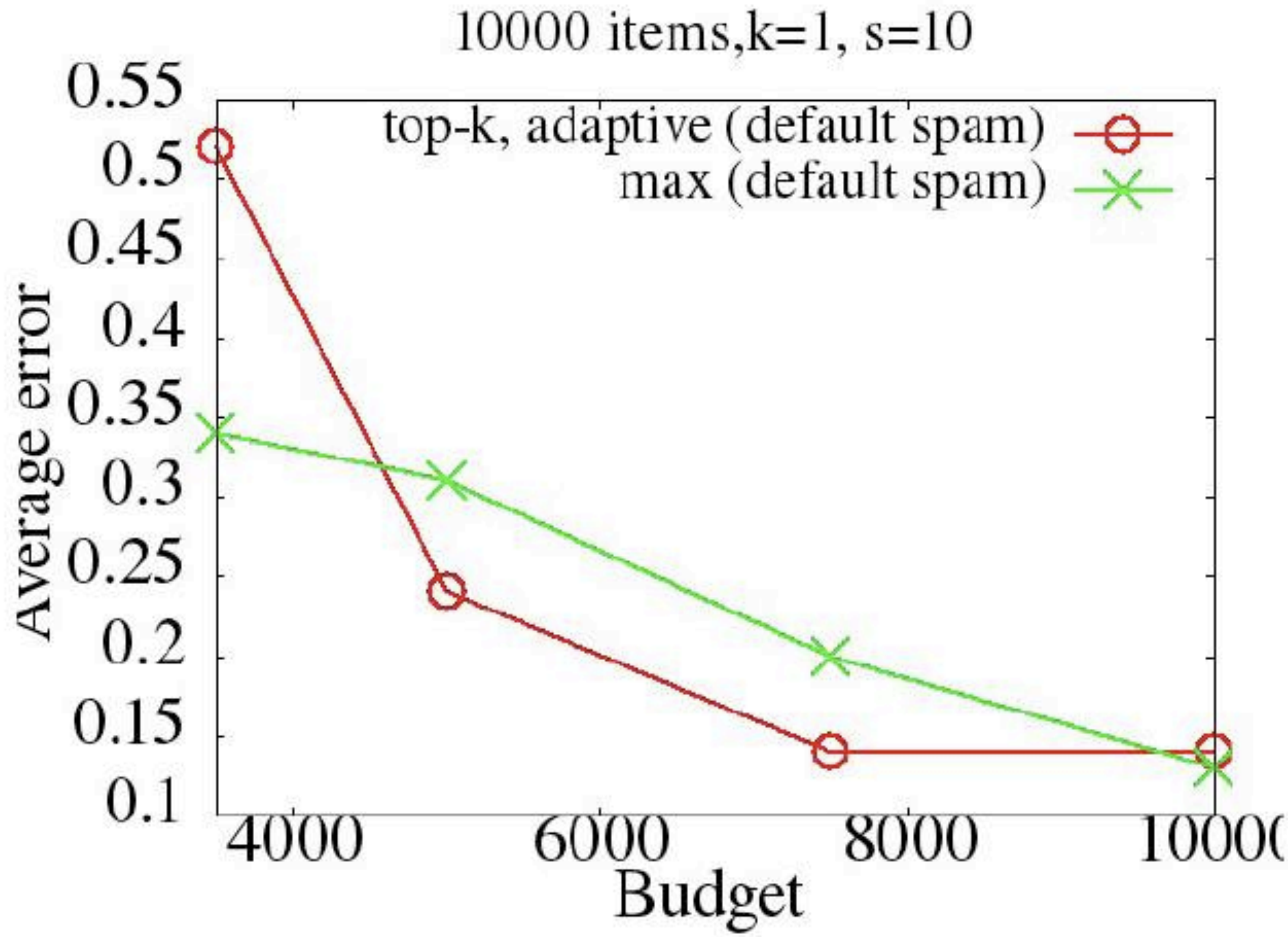
Top-*k* [Polychronopoulous-WebDB13]

- Comparison to Sort [Marcus-VLDB11]



Top-*k* [Polychronopoulous-WebDB13]

- Comparison to Max [Venetis-WWW12]



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- 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

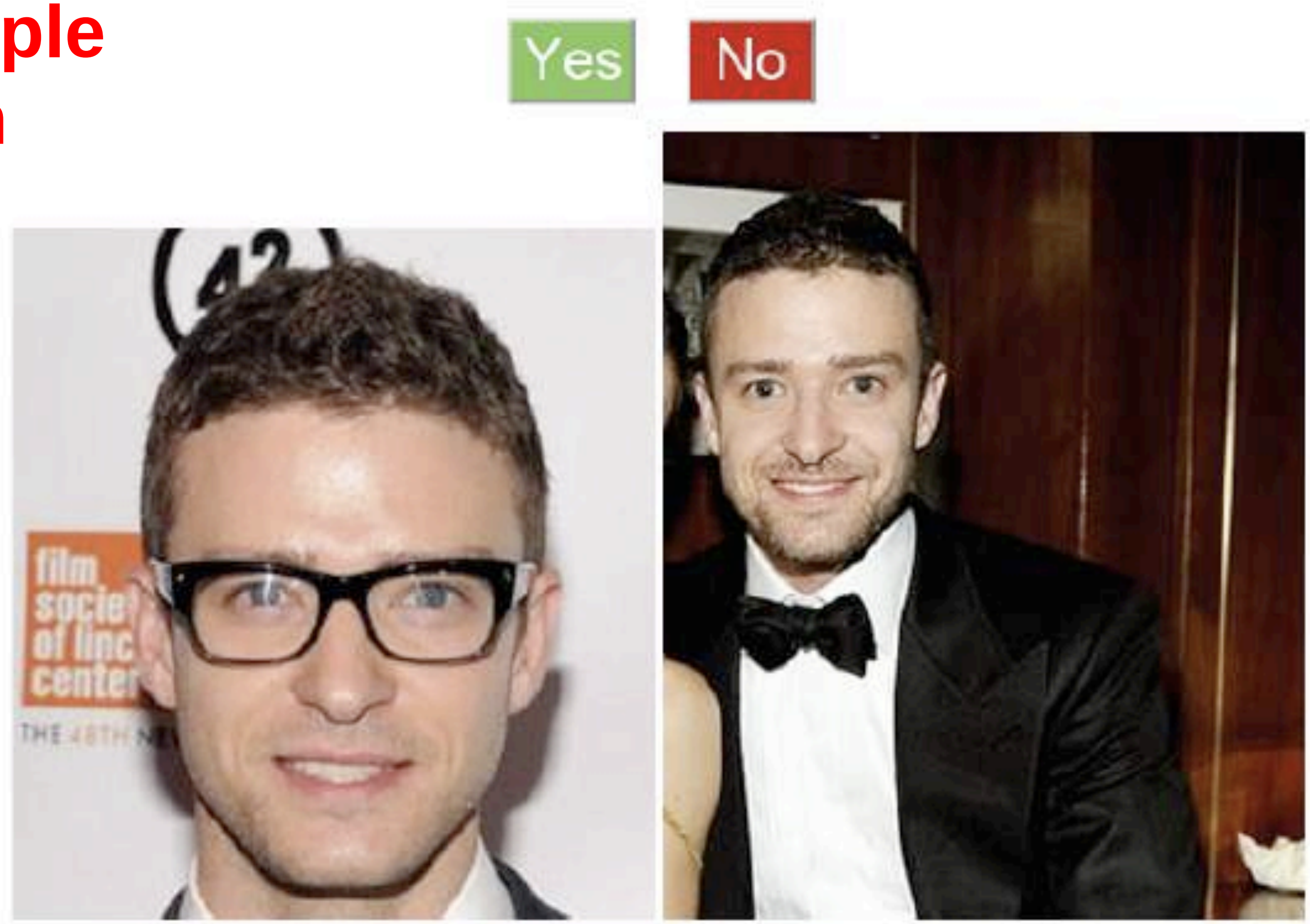
Join [Marcus-VLDB11]

- 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



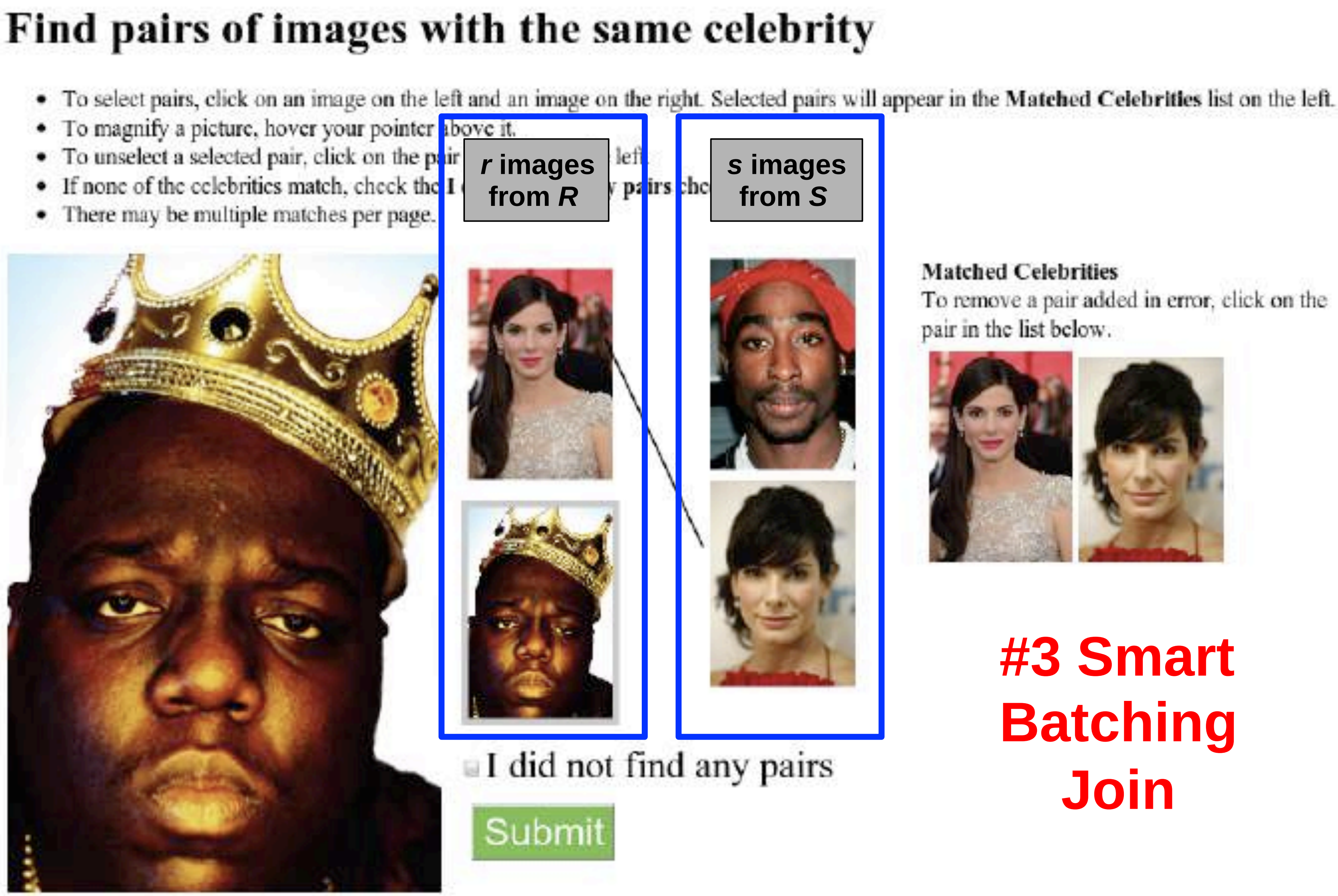
Join [Marcus-VLDB11]

#2 Naïve Batching Join

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

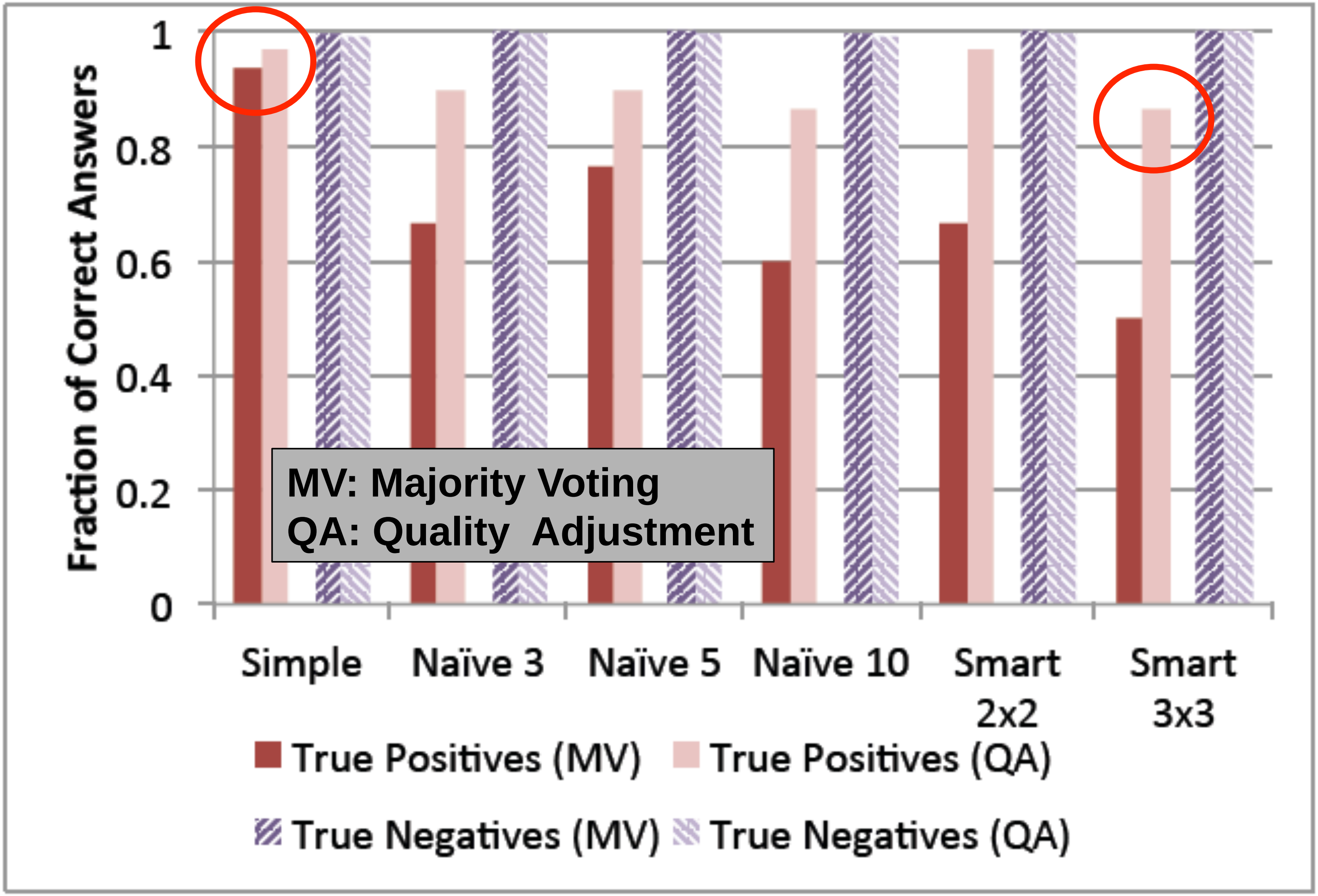
Batch factor
***b* = 2**

Join [Marcus-VLDB11]

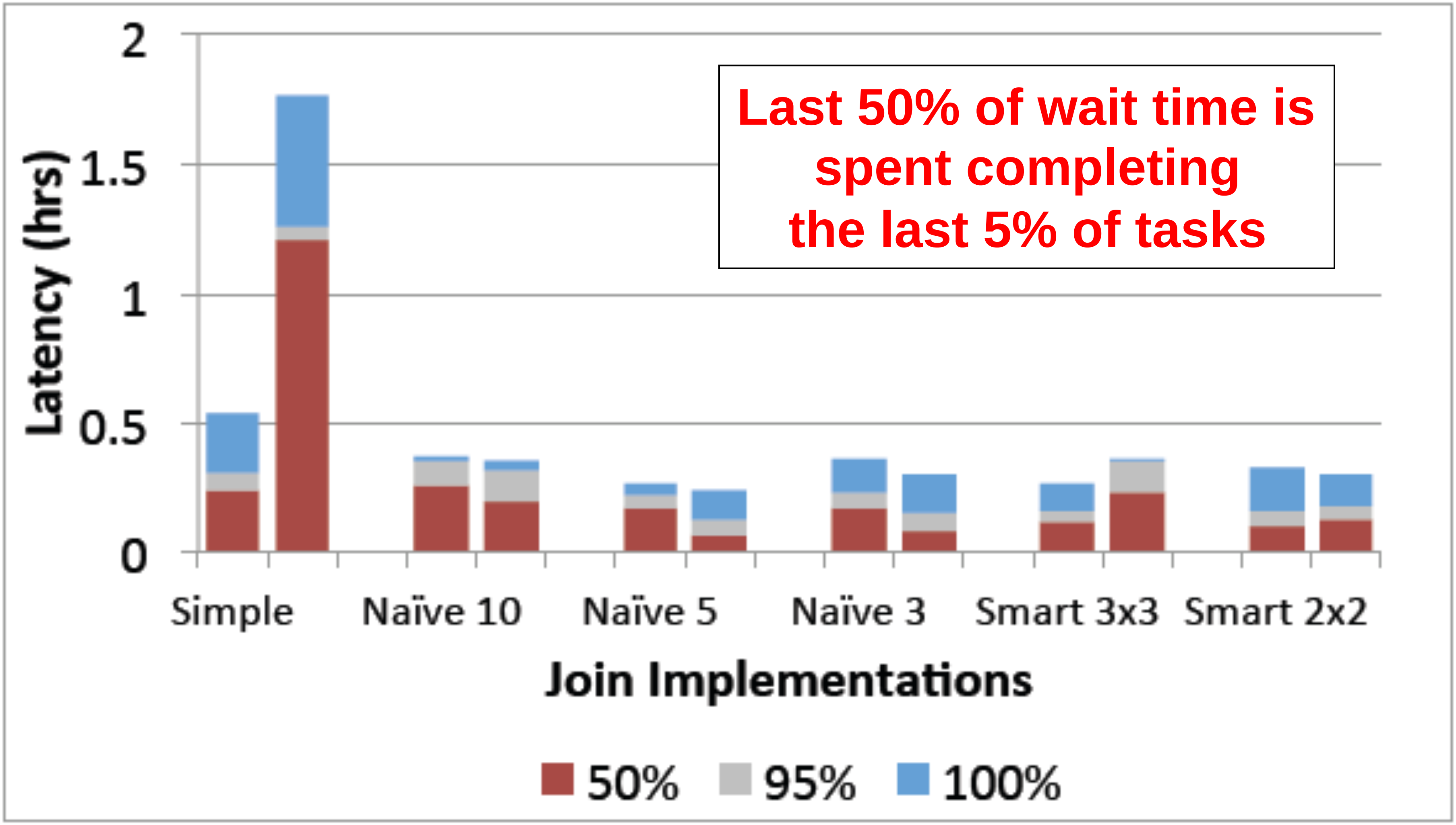


#3 Smart Batching Join

Join [Marcus-VLDB11]



Join [Marcus-VLDB11]



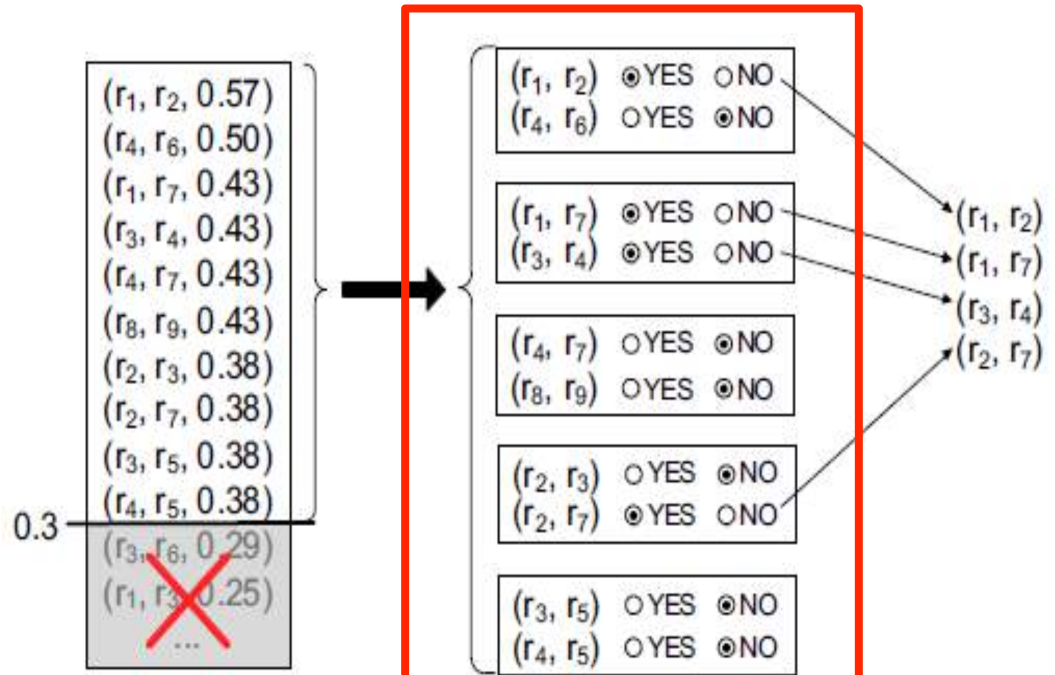
Join [Wang-VLDB12]

- [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

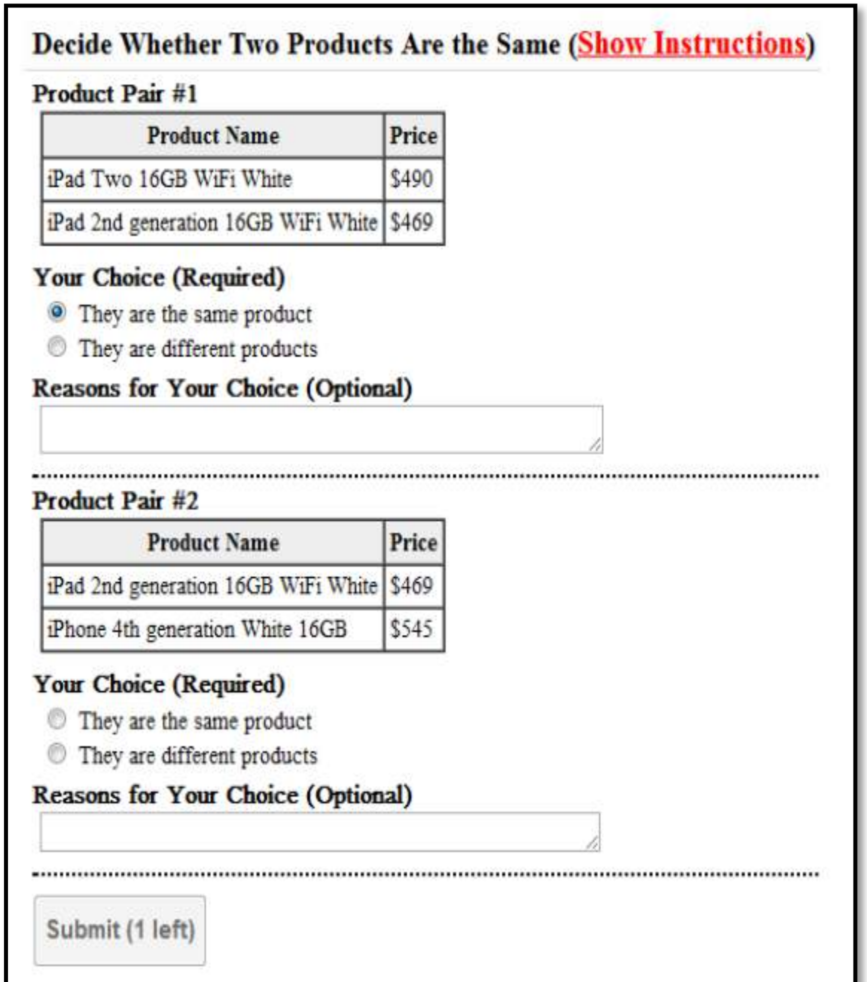
(b) Generate HITs to verify the pairs of records

(c) Output matching pairs

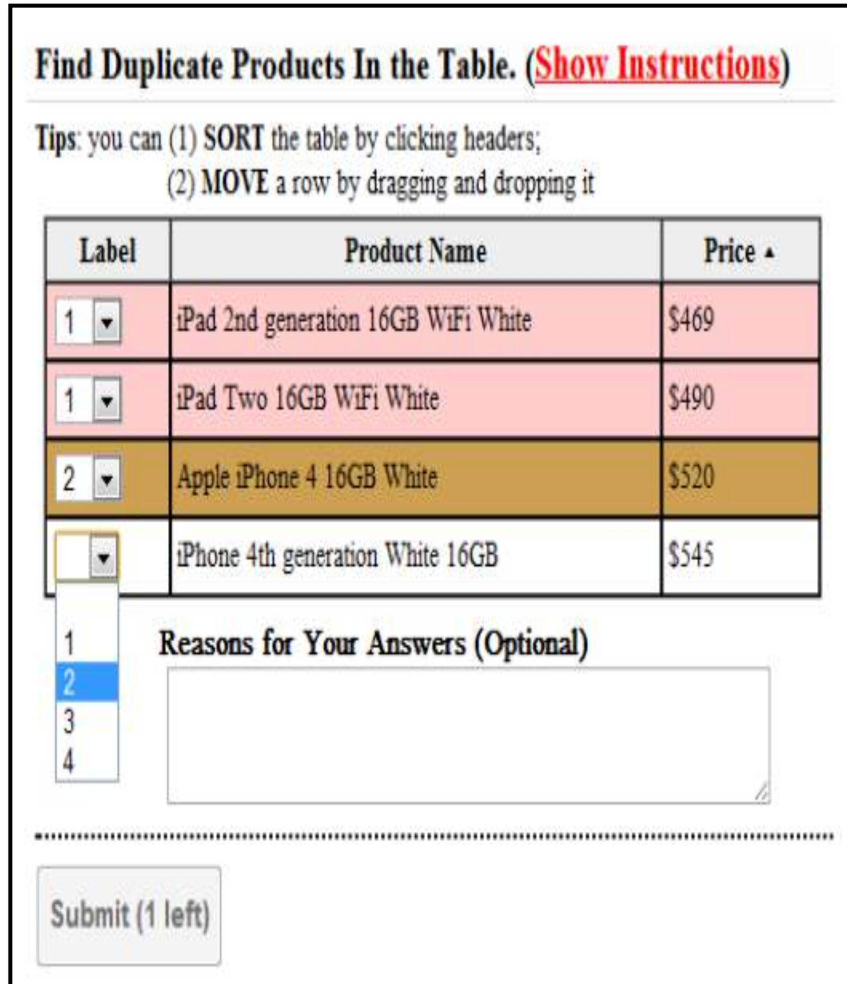
Main Issue: HIT Generation Problem

Join [Wang-VLDB12]

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



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



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

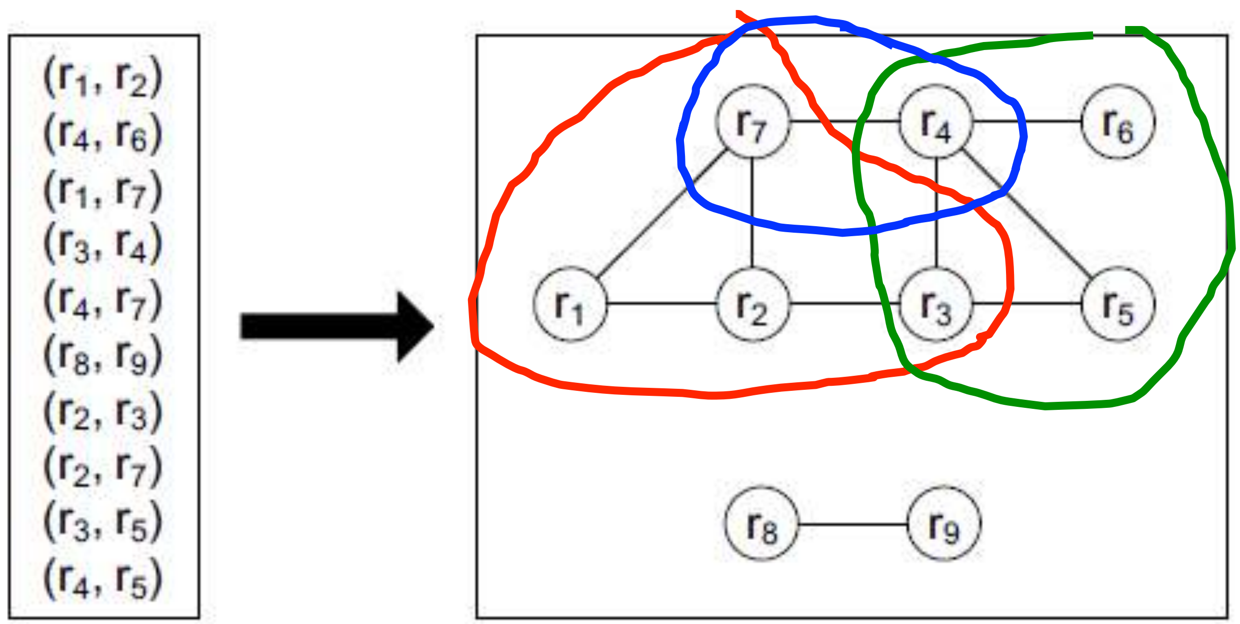
This is the minimal # of cluster-based HITs satisfying previous two conditions

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]

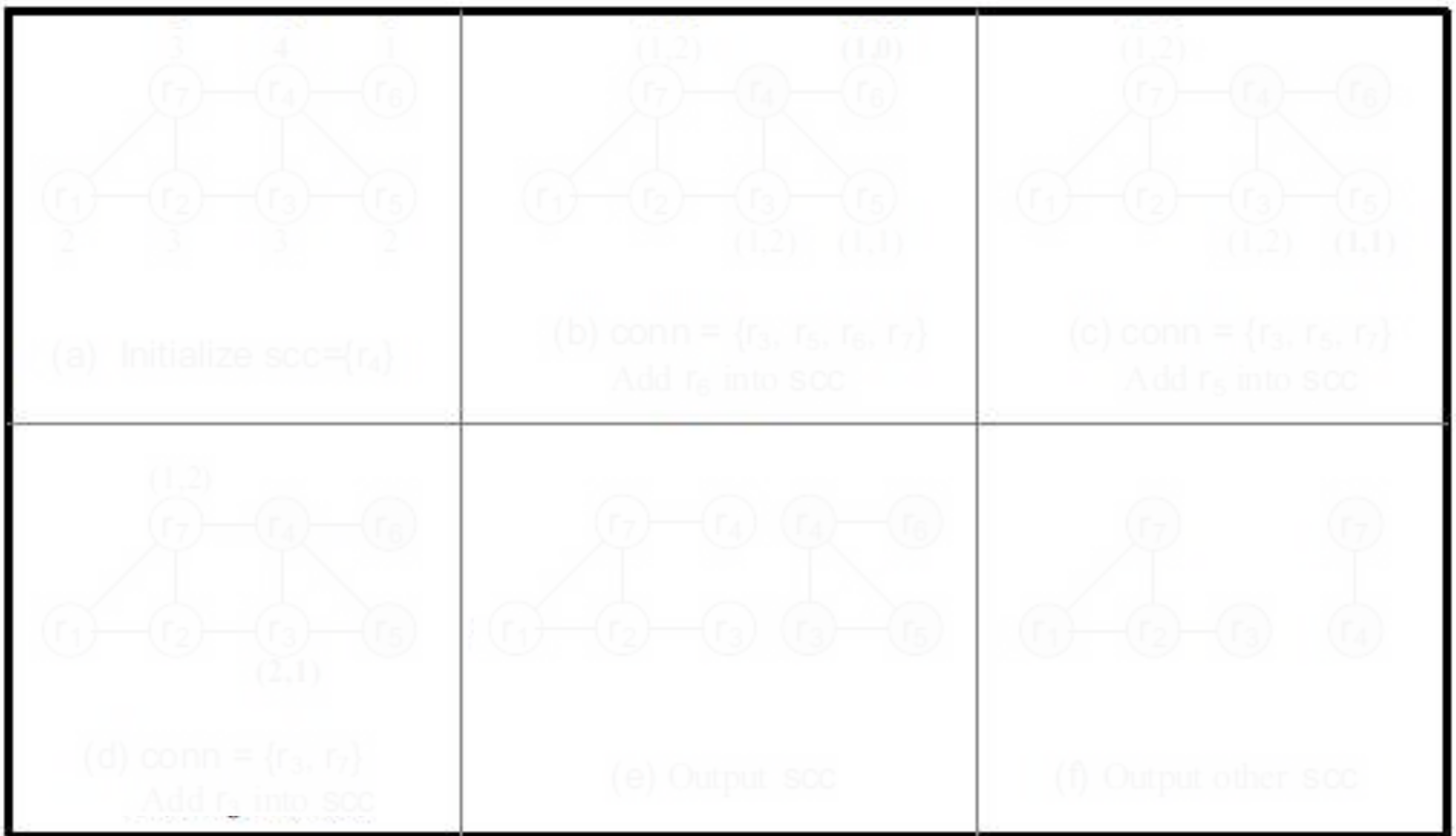
- Eg, Generate cluster-based HITs (k = 4)
  1. Partition the LCC into 3 SCCs
     - $\{r_1, r_2, r_3, r_7\}$, $\{r_3, r_4, r_5, r_6\}$, $\{r_4, r_7\}$
  2. Pack SCCs into HITs
     - A single HIT per $\{r_1, r_2, r_3, r_7\}$ and $\{r_3, r_4, r_5, r_6\}$
     - Pack $\{r_4, r_7\}$ and $\{r_8, r_9\}$ into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



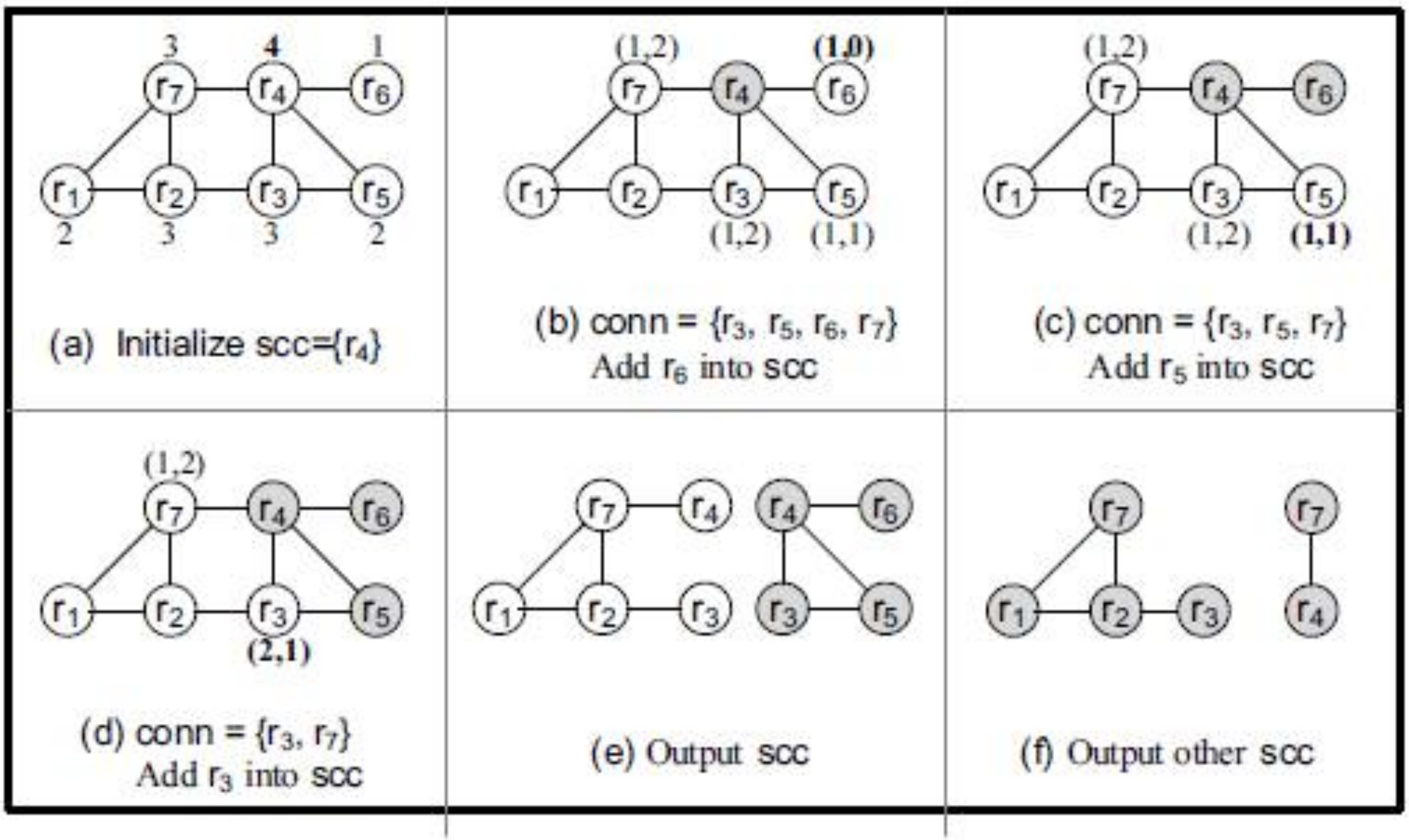
Join [Wang-VLDB12]

- 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

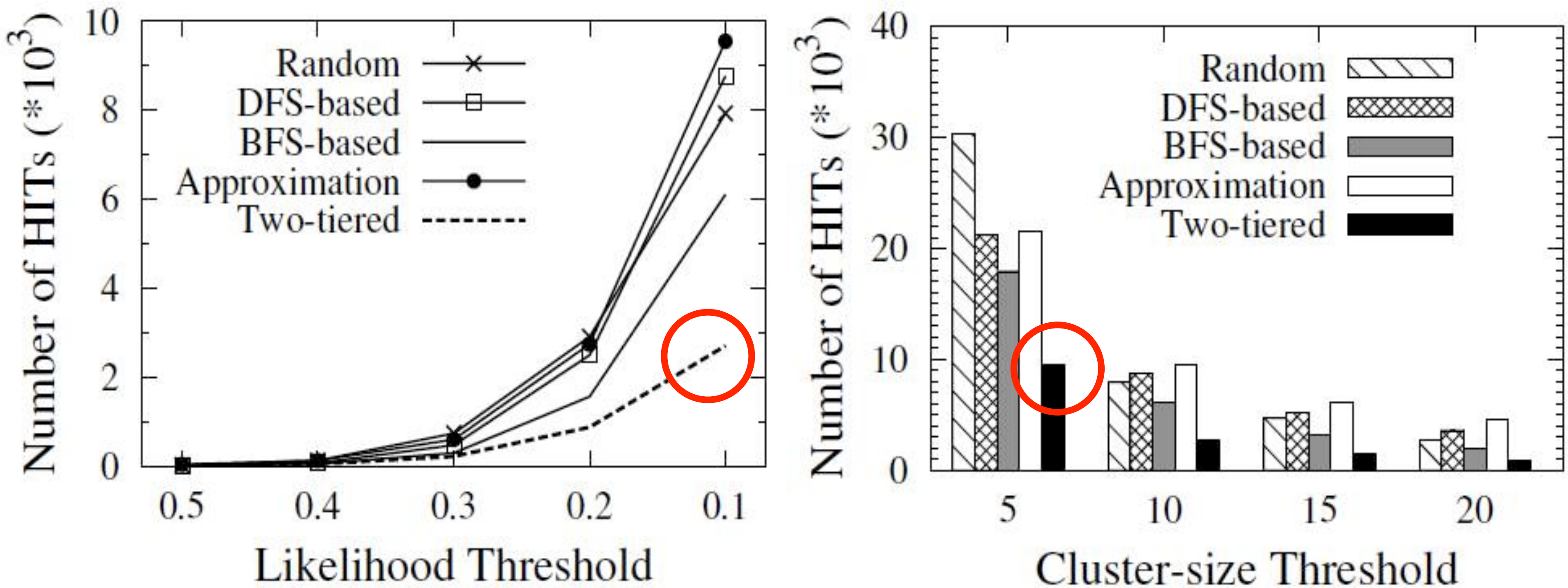
Join [Wang-VLDB12]



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 2nd Gen = iPad Two

iPad Two = iPad 2

$\Rightarrow$ *iPad 2nd Gen = iPad 2*

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

iPad 2nd Gen = iPad Two

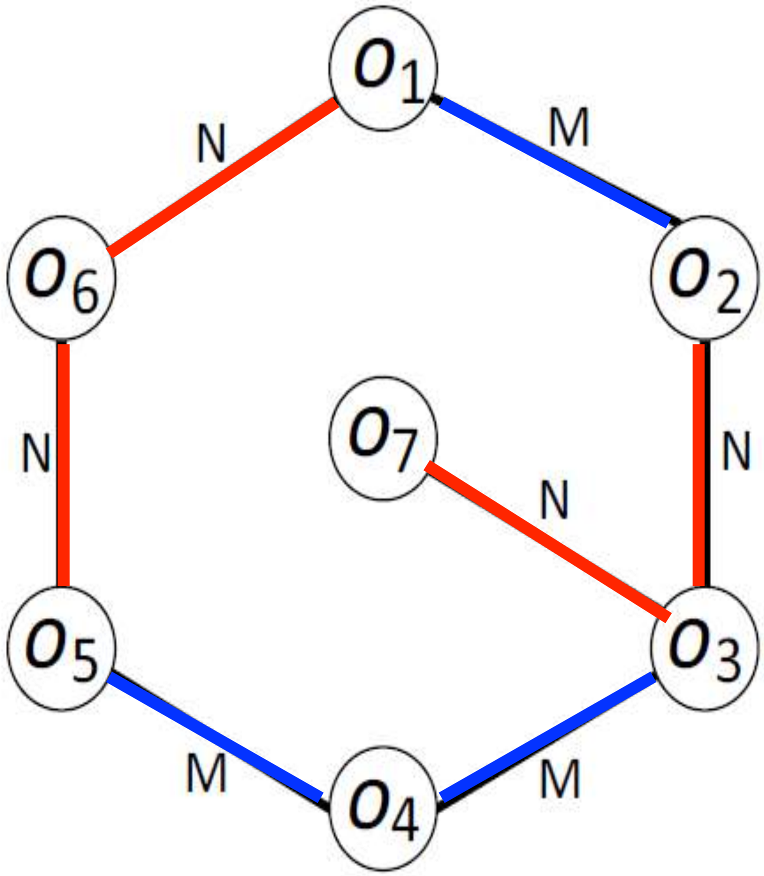
iPad Two ≠ iPad 3

$\Rightarrow$ *iPad 2nd 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]



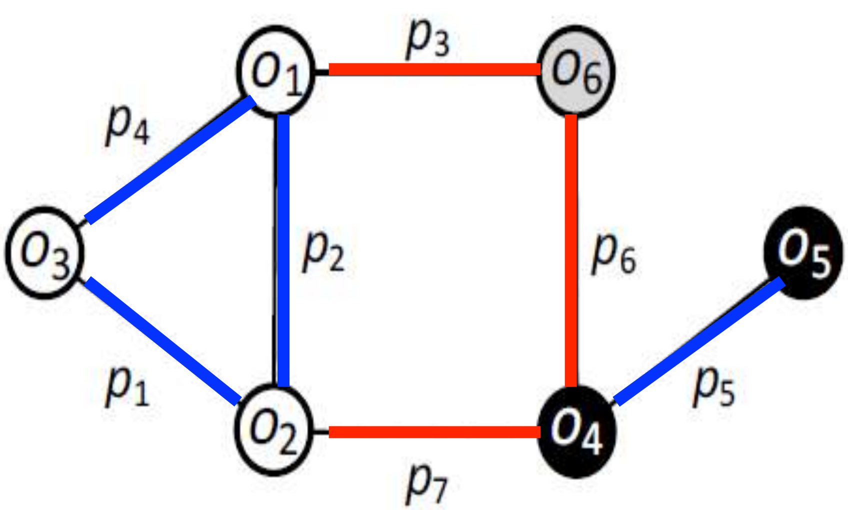
$(o_3, o_5) \rightarrow$ match

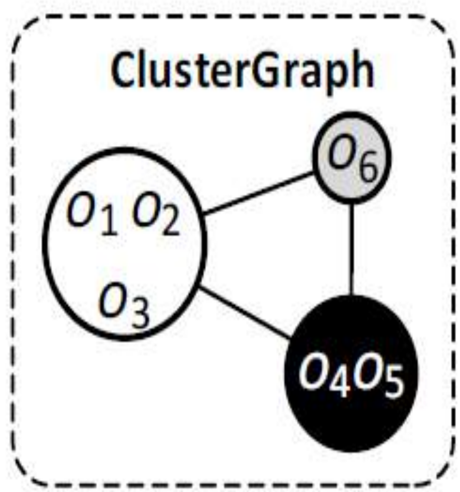
$(o_5, o_7) \rightarrow$ non-match

$(o_1, o_7) \rightarrow$?

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**

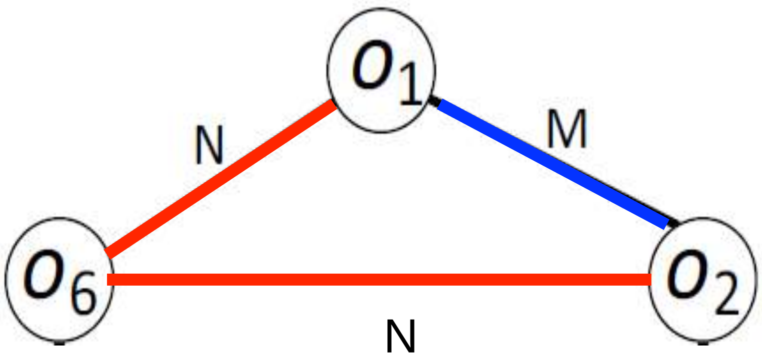
ID	Object
o_1	iPhone 2nd Gen
o_2	iPhone Two
o_3	iPhone 2
o_4	iPad Two
o_5	iPad 2
o_6	iPad 3rd Gen

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

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

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

  - 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
  - $w = <p_1, p_2, ..., p_n>$
  - $C(w)$ = # of crowdsourced pairs required for w

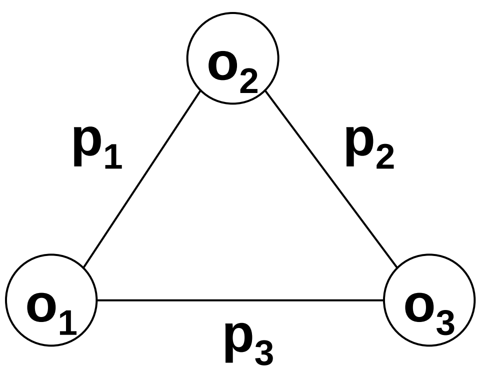
$$\mathrm{E}[\mathcal{C}(\omega)] = \sum_{i=1}^{n} \mathbb{P}(p_i = \text{crowdsourced})$$

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

Join [Wang-SIGMOD13]

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

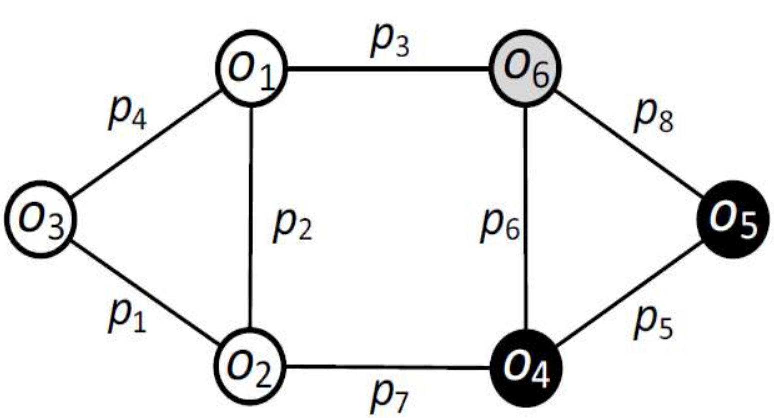
Probability of matching	
P_1	0.9
P_2	0.5
P_3	0.1



Expected value	
$w_1 = \langle p_1, p_2, p_3 \rangle$	**2.05**
$w_2 = \langle p_1, p_3, p_2 \rangle$	2.09
$w_3 = \langle p_2, p_3, p_1 \rangle$	2.45
$w_4 = \langle p_2, p_1, p_3 \rangle$	**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
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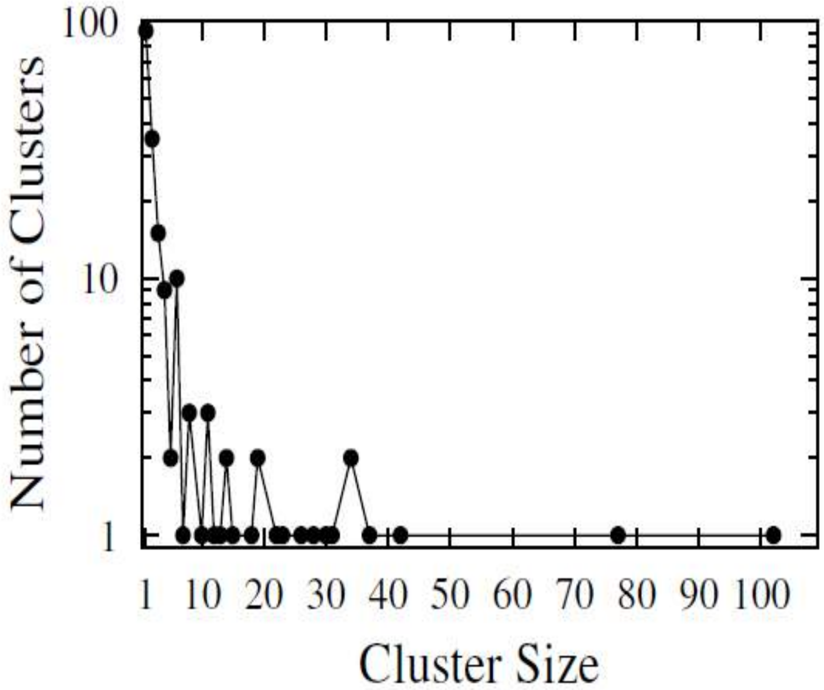
p_6	(o_4, o_6)	0.48
p_7	(o_2, o_4)	0.45
p_8	(o_5, o_6)	0.42

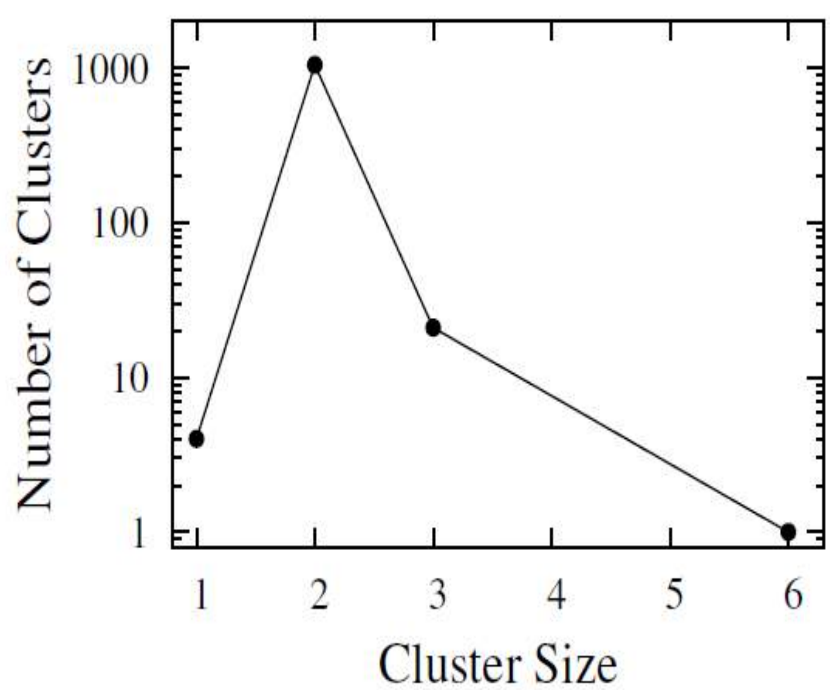
High

Join [Wang-SIGMOD13]

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



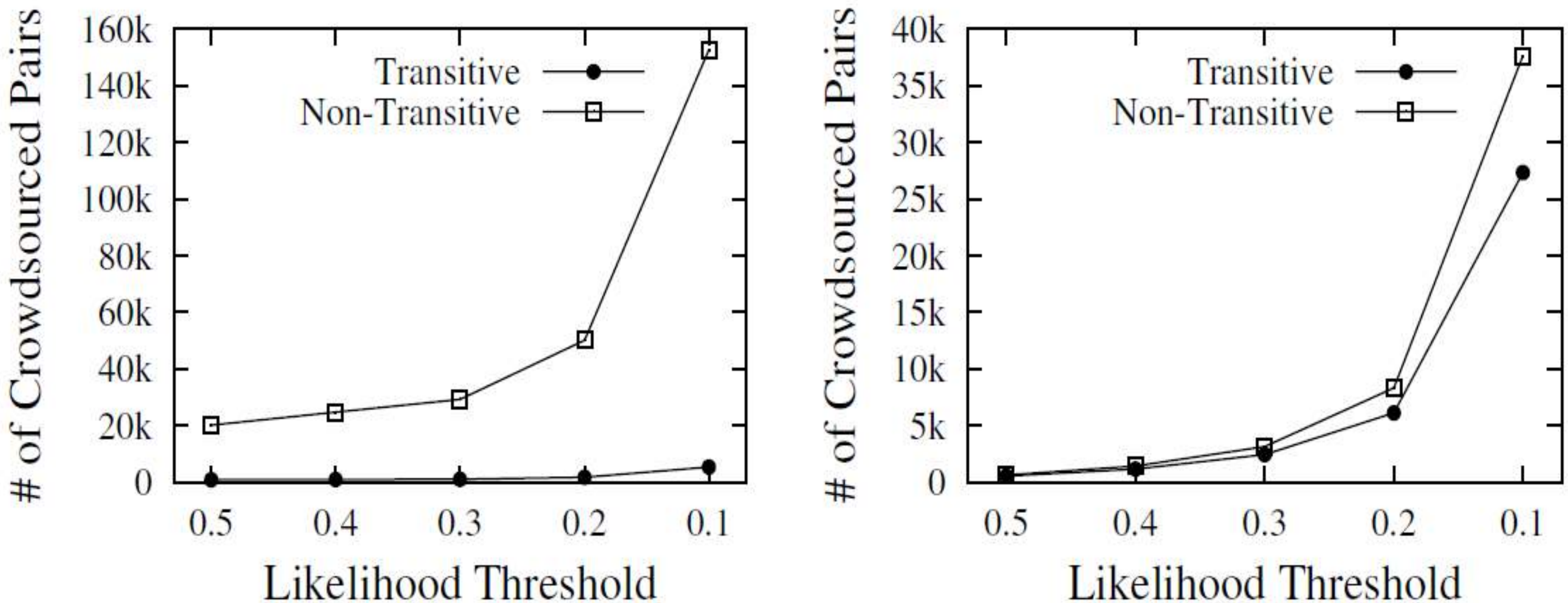
(a) Paper



(b) Product

Join [Wang-SIGMOD13]

- Transitivity



(a) Paper (b) Product

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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