Crowdsourcing in Information and Knowledge Management

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Slide available @ http://is.gd/7Vxetk

CIKM 2014 Tutorial



TOC

- Part 1
 - Crowdsourcing Database Systems



- Part 2
 - Human Powered Database Operations

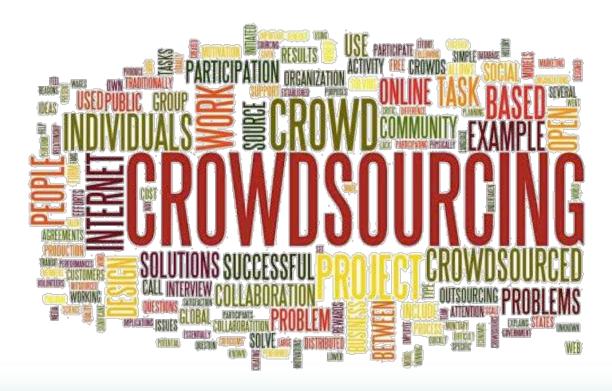


- Part 3
 - Quality Control



Part 1 CROWDSOURCING DATABASE SYSTEMS

Crowdsourcing – What is it?



Crowdsourcing is a process that involves outsourcing tasks to a distributed group of people. The difference between crowdsourcing and ordinary outsourcing is that a task or problem is outsourced to an undefined public rather than a specific body, such as paid employees.

Crowdsourcing on Web 2.0

Coordinates: @ 31°12'N 121°30'E



YAHOO! ANSWERS

Shanghai

From Wikipedia, the free encyclopedia

For other uses, see Shanghai (disambiguation).

Shanghai is the largest Chinese city by population[8][9] and the largest city proper by population in the world.[10] It is one of the four direct-controlled municipalities, with a population of more than 24 million as of 2013.[5] It is a global financial center,[11] and a transport hub with the world's busiest container port.[12] Located in the Yangtze River Delta in East China, Shanghai sits at the mouth of the Yangtze in the middle portion of the Chinese coast. The municipality borders the provinces of Jiangsu and Zhejiang to the north, south and west, and is bounded to the east by the East China Sea.[13]

For centuries a major administrative, shipping, and trading town, Shanghai grew in importance in the 19th century due to European recognition of its favorable port location and economic potential. The city was one of five opened to foreign trade following the British victory over China in the First Opium War while the



Shanghai Municipality



signs on Nanjing Road, and The Bund



Is there a difference between Hongqiao Airport and Pudong Airport in Shanghai? *

I'm flying domestically in China (Guangzhou-Baiyun to Shanghai) and is there any difference between these 2 airports? They're both same price? Which airport is better?

Best Answer Asker's Choice



Marcela P answered 5 months ago

Pudong (PVG) is normally used by international traffic while Honggiao (SHA) normally used by domestic flights. PVG is quite far from the city, while SHA is close to downtown.

Asker's rating & comment

Crowdsourcing on Image Tagging

















Crowdsourcing over the Internet



- Human workers are better at some complex jobs than the machines
 - Creating content
 - Image tagging
 - Digitizing paper work
 - Data verification
 - Data cleansing
 - Classification
 - Rating
 - Sentiment analysis
 - More ...

jobs than The New-York State Yacht Squadron, on its The New-York State Yacht Squadron, on its came into the harbor yes- Human workers are better at annual cruise to Newport, came into the harbor yesterday afternoon. The following are the names of the boats that came to anchor here: Jessie, Geraldine, Evelyn, Annie, Mannering, Julia, Bonila, Magie, Widgeon, Rambler, Florede-Lis, Henrietta, ked-Drift and

Maria, with the Steamer America as a tender. On anchoring, each boat fired a gun, according to custom.

The reports were heard distinctly in the city, causing considerable inquiry as to a what was up," and quite a number of sanguine individuals came into our office to inquire if the guns were not annunciatory signals

or the succession laying of the Atlantic Cable. We in-variably replied in the negative. The squadron will leave to-day for Newport. The yachts Washington and Ranter, of this city, start with it, with parties of New-Haven neonle.

of the successful laying of the Atlantic Cable.

Creatin

Image ta

Digitizing

Data veri

Data cleansing

Haven people.

Class

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Rating

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Sentir

More ...

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Data veri

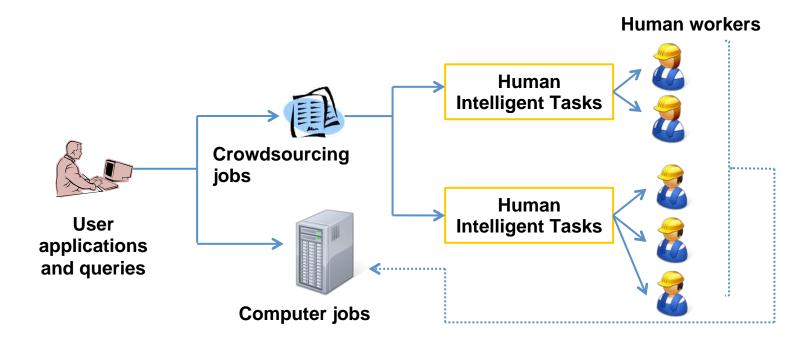
Data (**CAPTCHA_Transcription

Haven people.

- Class
- Ratino
- Sentir
- More

The New-York State yacht Squadron, on its annual cruise to Newport came into the harbor vesterday afternoon. The following are the names of the boats that came to anchor here: Jessie, gera loliv erelun Annie, Mannering, Julia, Bonita, Magic wut. Rambler, floumblie, Henrietta, Sea-Drift and Maria, with the steamer America as a tender. On anchoring each boat fired a gun, according to custom. The reports were heard distinctly in the city, causing considerable inquiry as to "what was up," and quite a number of sanguine individuals came into our office to inquire if the guns were not annunciatory signals of the successful laying of the Atlantic Cable. We invariably replied in the negative. The squadron will leave to-day for Newport. The yachts Washington and buub r of this city, start with it, with parties of New Haven people.

Work flow of crowdsourcing applications



Crowdsourcing Platforms





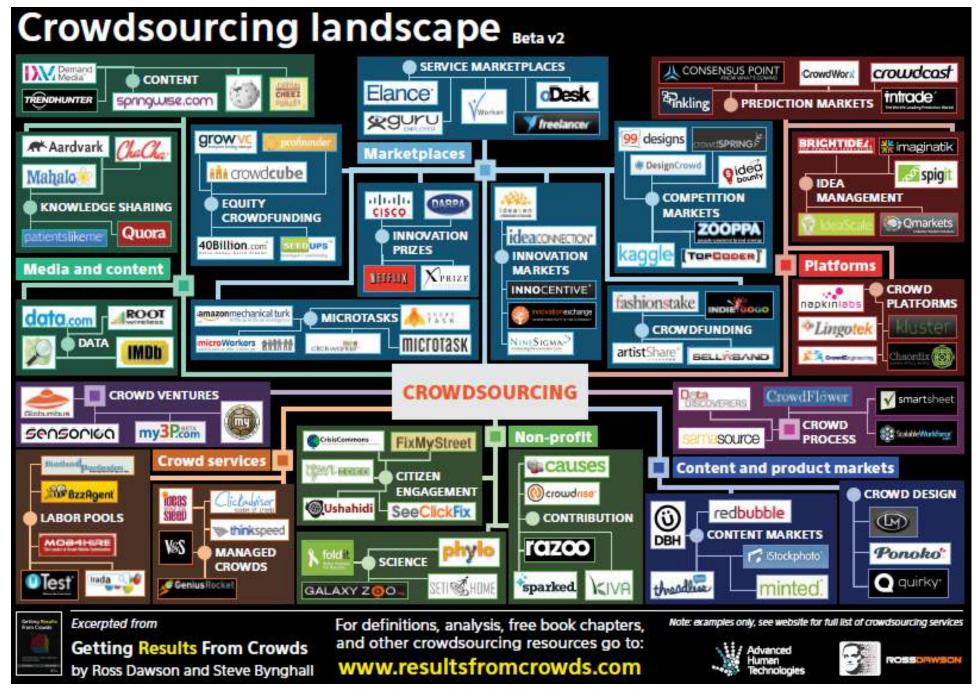












../features/crowdsourcing-landscape/

../features/crowdsourcing-services/

Amazon Mechanical Turk (AMT)

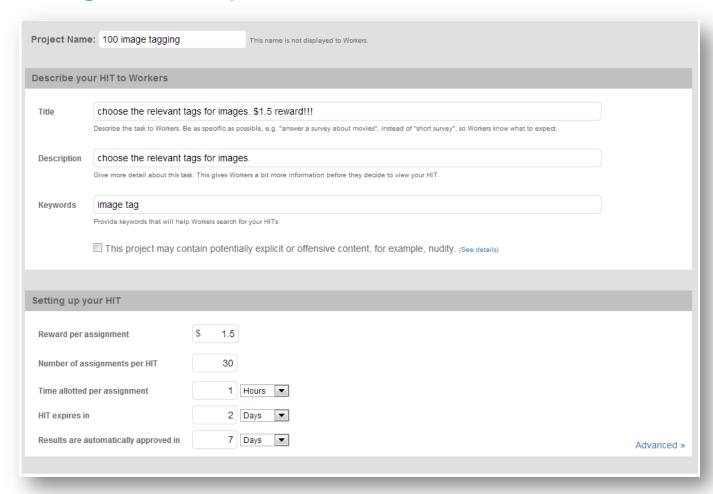
worker





requester

- Set up your HIT
 - Assignment # per HIT



- Set up your HIT
 - Assignment # per HIT
- Design layout
 - Question # per HIT

```
Select all the words that are relevant to the given image.

1. $\inv \$\{\text{img1_opt1}\} \Bigcup \$\{\text{img1_opt2}\} \Bigcup \$\{\text{img1_opt3}\} \Bigcup \$\{\text{img1_opt4}\}
```

```
Format
                              THE B THE COLOR FOR THE THE SOURCE
</script>
<div style="font-family: Arial, Helvetica; font-size: 14px">
<h3>Select all the words that are relevant to the given image.</h3>
<form onsubmit="return validate checkbox()">
   <div class="image" style="margin-bottom: 25px">
   1. <img alt="image url" style="margin-right: 20px; border: none" src="${img1}" />
   <div class="options" style="margin-left: 10px; margin-top: 5px"><input type="checkbox" value="${img1 opt1}" name="img1" /> ${img1 opt1} &nbsp; <input type="checkbox"</pre>
value="${img1 opt2}" name="img1" /> ${img1 opt2}   <input type="checkbox" value="${img1 opt3}" name="img1" /> ${img1 opt3} &nbsp; <input type="checkbox"
value="${img1 opt4}" name="img1" /> ${img1 opt4}  </div>
   <div class="image" style="margin-bottom: 25px">
   2. <img alt="image url" style="margin-right: 20px; border: none" src="${img2}" />
   <div class="options" style="margin-left: 10px; margin-top: 5px"><input type="checkbox" value="${img2 opt1}" name="img2" /> ${img2 opt1} &nbsp; <input type="checkbox"</pre>
value="${img2 opt2}" name="img2" /> ${img2 opt3}   <input type="checkbox" value="${img2 opt3}" name="img2" /> ${img2 opt3} &nbsp; <input type="checkbox"
value="${img2_opt4}" name="img2" /> ${img2_opt4}  </div>
   <div class="image" style="margin-bottom: 25px">
   3. <img alt="image_url" style="margin-right: 20px; border: none" src="${img3}" />
   <div class="options" style="margin-left: 10px; margin-top: 5px"><input type="checkbox" value="${img3 opt1}" name="img3" /> ${img3 opt1} &nbsp; <input type="checkbox"</pre>
value="${img3 opt2}" name="img3" /> ${img3 opt2}   <input type="checkbox" value="${img3 opt3}" name="img3" /> ${img3 opt3} &nbsp; <input type="checkbox"
value="${img3_opt4}" name="img3" /> ${img3_opt4}  </div>
   <div class="image" style="margin-bottom: 25px">
   4. <img alt="image url" style="margin-right: 20px; border: none" src="${img4}" />
   <div class="options" style="margin-left: 10px; margin-top: 5px"><input type="checkbox" value="${img4 opt1}" name="img4" /> ${img4 opt1} &nbsp; <input type="checkbox"</pre>
value="${img4 opt2}" name="img4" /> ${img4 opt3}   <input type="checkbox" value="${img4 opt3}" name="img4" /> ${img4 opt3} &nbsp; <input type="checkbox"
value="${img4 opt4}" name="img4" /> ${img4_opt4}  </div>
```

- Set up your HIT
 - Assignment # per HIT
- Design layout
 - Question # per HIT
- Prepare and upload data file

- Set up your HIT
 - Assignment # per HIT
- Design layout
 - Question # per HIT
- Prepare and upload data file
- Wait for the result



- Set up your HIT
 - Assignment # per HIT

	Answer.m1_r1	Answer.m1_r2	Answer.m1_r3	Answer.m1_r4	Answer.m1_r5
	Negative	Negative	Positive	Positive	Positive
	Negative	Positive	Positive	Positive	Positive
• P	Positive	Negative	Positive	Negative	Positive
	Positive	Positive	Positive	Positive	Positive
\ \	Negative	Negative	Positive	Positive	Positive

- Download, parse and analyze the result
 - Conflicting answers

Need from Crowdsourcing

- A "smarter" system that takes care of
 - Layout design
 - HIT generation
 - Worker assignment
 - Result analysis
 - Declarative query
 - Optimization
 - More...



Data

ID	lmag e	Tag s
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Need from DB Systems

Find CEO and HQ for a list of companies?

Company CEO Headquarter

IBM

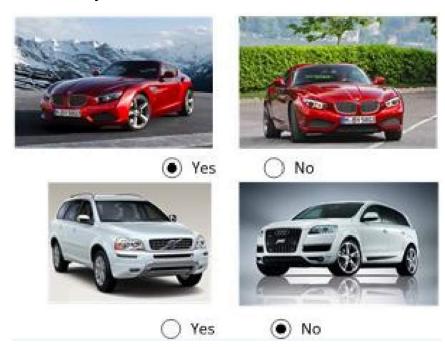
Google

Microsoft

Apple

Oracle

Are they the same car?



- Crowd helps on DB-hard queries
 - Seeking information
 - Adding intelligence

- Add crowd functionality into traditional databases for processing queries that cannot be easily answered by machines
- Automate certain tasks and provide higherlevel services than existing platforms

Challenges of Crowdsourcing

Quality

- Human workers are prone to errors, and crowdsourcing results are inevitably noisy
 - Maliciousness, worker skills, task difficulty

Cost

- Very expensive to publish a huge amount of tasks
 - E.g., Finding matched pairs from 1000 records
 - Straightforward: 1000 * 1000 = 1M tasks
 - \$ 0.01 per task * 1M tasks = \$ 10000 !

Latency

- It depends on worker pool and job attractiveness
- Dependency among tasks

New Challenges to DB Systems

- Closed world → open world
 - Unbounded amount of data available
- Non-deterministic nature
 - Human factors → uncertainty
- Trade-off among cost, latency and quality
 - Optimizations

Qurk – MIT

- [Marcus-CIDR2011]
- [Marcus-SIGMOD2011]
- [Marcus-VLDB2012]

CrowdDB – Berkeley and ETH

- [Feng-VLDB2011]
- [Franklin-SIGMOD2011]

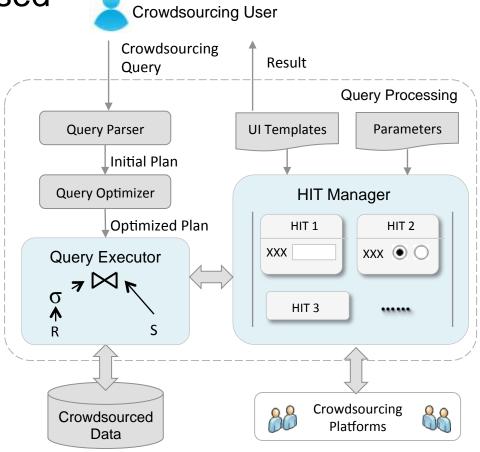
Deco – Stanford and UCSC

- [Parameswaran-CIKM2012]
- [Park-VLDB2013]

CDAS – NUS

- [Liu-VLDB2012]
- [Gao-SIGMOD2013]
- [Ooi-SIGKDD2014]

- Data model
 - Relational model based
- Query language
 - Declarative
 - SQL-like
- Query processing and optimization



System Architecture

Qurk – MIT

- [Marcus-CIDR2011]
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Qurk: Data Model

Relational model + a few "twists"

- Qurk allows multi-valued attributes
 - Different responses to the same HIT
- Qurk provides functions to convert multivalued attributes to usable single-valued fields
 - E.g, majorityVote

Qurk: Query Language

- SQL-based query language with user-defined functions (UDFs)
- Predefined task templates for UDF:
 - Filter: produces tuples that satisfy the conditions specified in the UDF
 - Sort: ranks the input tuples according to the UDFs specified in the ORDER BY clause
 - Join: compares input tuples and performs join according to the UDF; extends syntax with a POSSIBLY keyword
 - Generative: allows workers to generate data

Qurk: Filter Example

```
SELECT image
FROM car_image
WHERE isBlack(image)
TASK isBlack(field) TYPE Filter:
 Prompt: " \
     <img src='%s'> \
     Is the car in the image in black color?
     ", tuple[field]
 YesText: "Yes"
 NoText: "No"
 Combiner: MajorityVote
```

Qurk: Sort Example

```
SELECT squares.label
FROM squares
ORDER BY squareSort(img)
TASK squareSort(field) TYPE Rank:
 SingularName: "square"
 PluralName: "squares"
 OrderDimensionName: "area"
 LeastName: "smallest"
 MostName: "largest"
 Html: "<img src='%s' class=lgImg>",tuple[field]
```

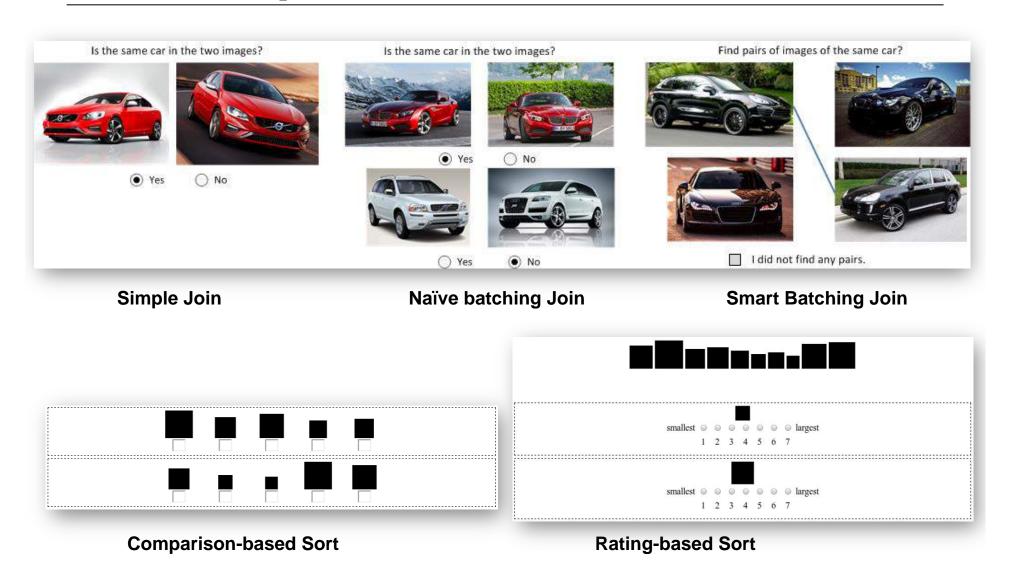
Qurk: Join Example

```
SELECT c.name
FROM celeb c JOIN photos p
ON samePerson(c.img,p.img)
TASK samePerson(f1, f2) TYPE EquiJoin:
 SingluarName: "celebrity"
 PluralName: "celebrities"
 LeftPreview: "<img src='%s' class=smImg>",tuple1[f1]
 LeftNormal: "<imq src='%s' class=lqImq>",tuple1[f1]
 RightPreview: "<imq src='%s'class=smImq>",tuple2[f2]
 RightNormal: "<img src='%s' class=lgImg>",tuple2[f2]
 Combiner: MajorityVote
```

Qurk: Generative Example

```
SELECT c.name
FROM celeb c JOIN photos p
ON samePerson(c.img,p.img)
AND POSSIBLY gender(c.img) = gender(p.img)
AND POSSIBLY hairColor(c.img) = hairColor(p.img)
AND POSSIBLY skinColor(c.img) = skinColor(p.img)
TASK gender(field) TYPE Generative:
 Prompt: " \
                <img src='%s'> \
                What is this person's gender? \
          ", tuple[field]
 Response: Radio("Gender",["Male","Female",UNKNOWN])
```

Qurk: Operators



Adam Marcus, Eugene Wu, David R. Karger, Samuel Madden, Robert C. Miller: Human-powered Sorts and Joins. PVLDB 5(1): 13-24 (2012)

Qurk: Optimizations

- Runtime pricing
- Input sampling
- Batch predicates
- Operator implementations
- Join heuristics
- Task result cache
- Model training

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CrowdDB: Query Language

- CrowdSQL: a new keyword CROWD
- Crowdsourced column:

```
CREATE TABLE car_review (
review STRING,
make CROWD STRING,
model CROWD STRING,
sentiment CROWD STRING);
```

Crowdsourced table:

```
CREATE CROWD TABLE car (
make STRING,
model STRING,
color STRING,
style STRING,
PRIMARY KEY (make, model));
```

CrowdDB: Query Language

CrowdSQL: two new built-in functions

CROWDEQUAL: ~= symbol

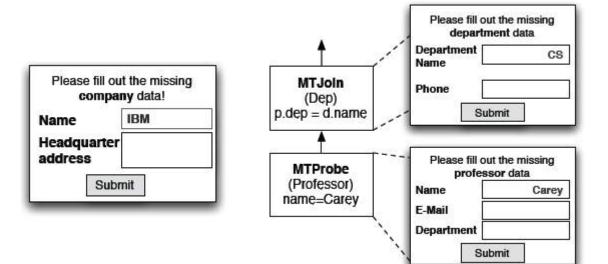
```
SELECT review FROM car_review
WHERE sentiment ~= "pos";
```

• CROWDORDER:

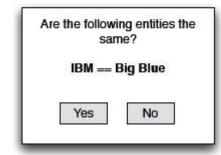
```
SELECT image i FROM car_image
WHERE subject = "Volvo S60"
ORDER BY CROWDORDER(i, "Which image visualizes
better %subject");
```

CrowdDB: Operators

- CrowdProbe
 - Collects missing information
- CrowdJoin
 - Inner relation is a CROWD table
- CrowdCompare
 - Implements CROWDEQUAL and CROWDORDER



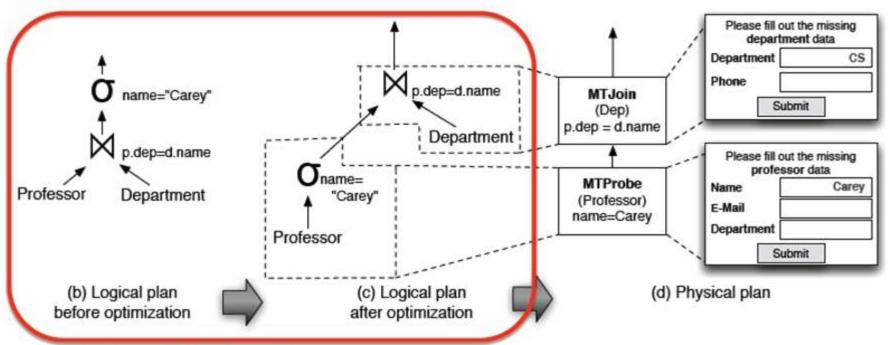




CrowdDB: Example

SELECT *
FROM PROFESSOR p, DEPARTMENT d
WHERE d.name = p.dep
AND p.name ="Michael J. Carey"

CREATE CROWD TABLE professor (
name STRING PRIMARY KEY
e-mail STRING
dep STRING
REF department(name)
);
CREATE CROWD TABLE department (
name STRING PRIMARY KEY
phone_no STRING);



Rule based optimizer

Michael J. Franklin, Donald Kossmann, Tim Kraska, Sukriti Ramesh, Reynold Xin: CrowdDB: answering queries with crowdsourcing. SIGMOD Conference 2011: 61-72

CrowdDB: Optimizations

- Rule-based optimizer
 - Predicate push-down
 - Join ordering
 - Bounded plan
- Simple heuristics to set the crowd parameters
 - Price per HIT
 - Batch size
 - Replication factor

Crowdsourcing DB Systems

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- [Ooi-SIGKDD2014]

Deco: Data Model

- Conceptual relation: user view
 - Anchor attributes (entities)
 - Dependent attributes (properties of entities)
 - Country(country, [language], [capital])
- Raw schema: system view
 - RDBMS as back-end
 - Anchor table containing anchor attributes
 - Dependent table for each dependent attribute
 - CountryA(country),
 - CountryD1(country, language)
 - CountryD2(country, captital)

Deco: Rules

• Fetch rules $A \downarrow 1 \Rightarrow A \downarrow 2 : P$

```
\emptyset \Rightarrow country: Ask for a new country name country \Rightarrow capital: Ask for the captital given a country name
```

Resolution rules

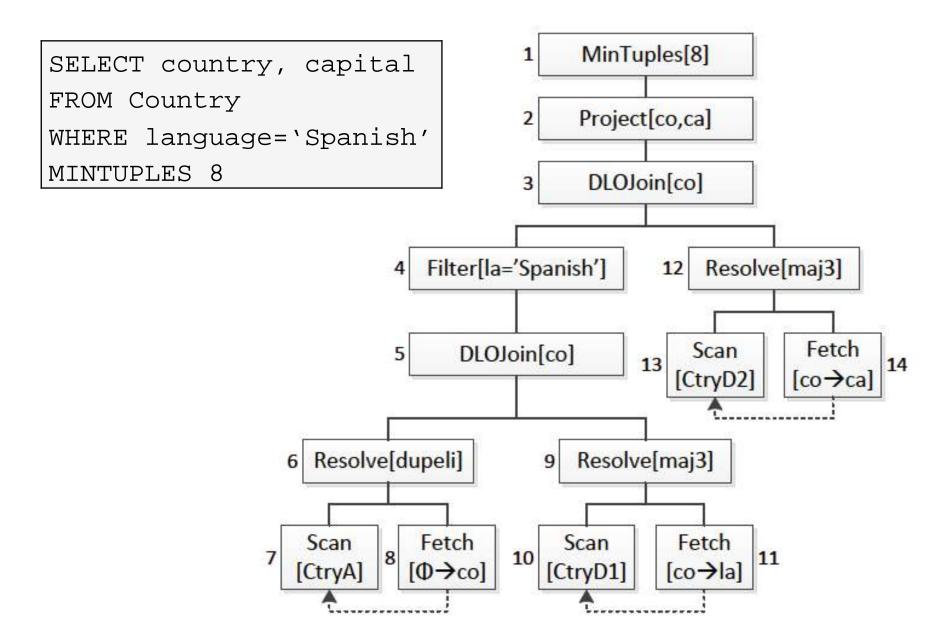
```
Ø ⇒ country: dupElim
country ⇒ capital: majority-of-3
```

- "MinTuples n" to avoid empty-answer
 - MaxCost c
 - MaxTime t

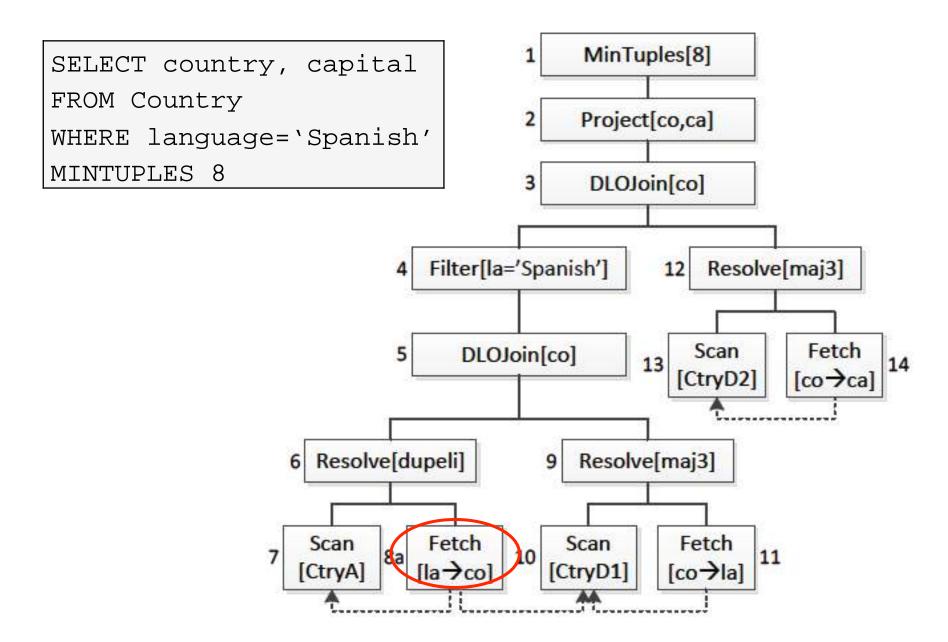
Deco: Operators

- Scan
- Project
- Filter
- Dependent left outer join
- Fetch
- Resolve
- MinTuples

Deco: Example



Deco: Example



Deco: Optimizations

- Existing vs. new data
 - Fetch only if raw tables do not have sufficient data
- Statistical information
 - Existing data: maintained by RDBMS
 - New data: provided by schema designer/user
- Search space
 - Possible join ordering
 - Available fetch rules

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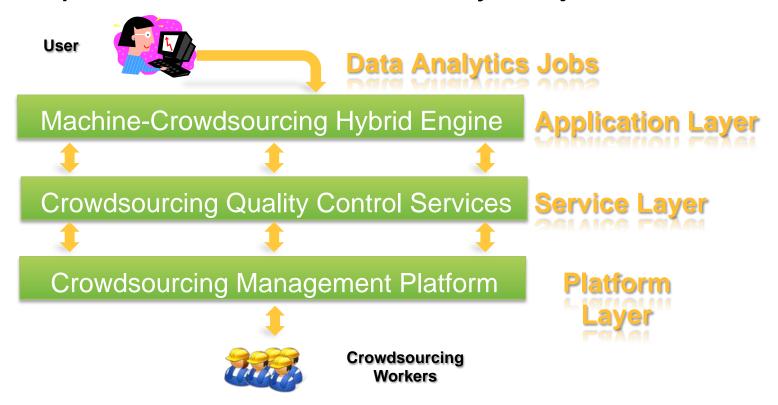
- [Parameswaran-CIKM2012]
- [Park-VLDB2013]

• CDAS - NUS

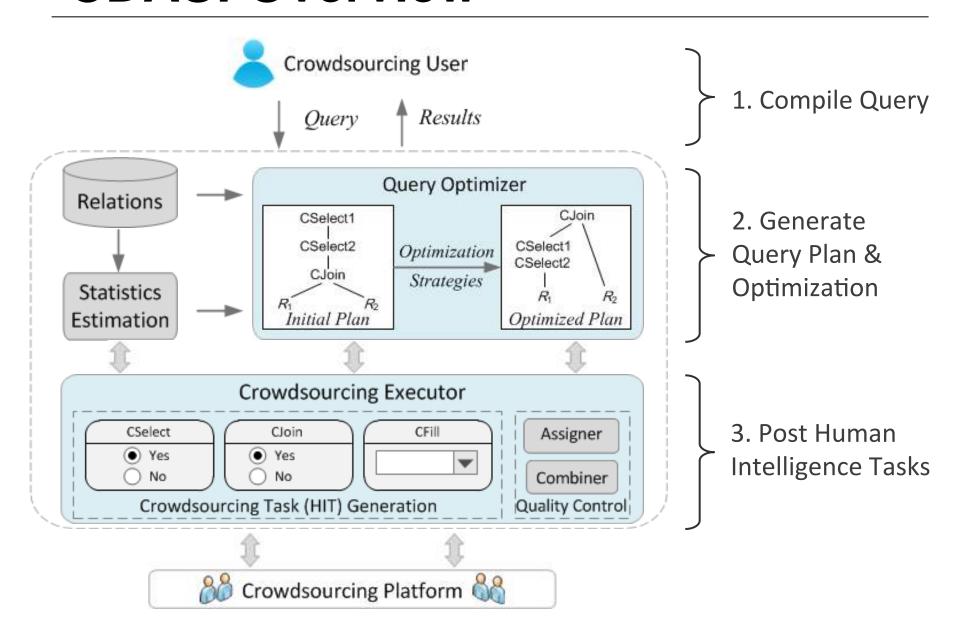
- [Liu-VLDB2012]
- [Gao-SIGMOD2013]
- [Ooi-SIGKDD2014]

CDAS: Overview

- CDAS: Crowdsourcing Data Analytics System
- http://www.comp.nus.edu.sg/~cdas/
- Aim: exploit the crowd intelligence for improving the performance of data analytics jobs



CDAS: Overview



CDAS: Query Language

Selection query

```
SELECT i.image

FROM car_image i

WHERE make = "Volvo" AND color = "black" AND quality = "high"
```

Join query

```
SELECT c.*, i.image

FROM car c, car_image i

WHERE c.make = i.make AND c.model = i.model

JoinFilter c.style = i.style
```

Complex query

```
SELECT c.*, i.image, r.review

FROM car c, car_image i, car_review r

WHERE r.sentiment = "pos" AND i.color = "black"

AND c.make = i.make AND c.model = i.model

AND c.make = r.make AND c.model = r.model
```

CDAS: Operators

- CrowdSelect (CSelect)
 - Leverage the crowd to select the items satisfying certain constraints



Operator Input

- A set of items
- Some constraints

Operator Output

 The subset of items satisfying the constraints

CDAS: Operators

- CrowdJoin (CJoin)
 - Solicit the crowd to match the items according to some matching criteria



Operator Input

- Two sets of items
- Matching criteria

Operator Output

 The item pairs satisfying the criteria

CDAS: Operators

- CrowdFill (CFill)
 - Ask the crowd to fill in missing values for some item attributes



Operator Input

- A set of items
- An attribute of interest

Operator Output

 The filled values for the attributes of the items

CDAS: Example

SQL Statement

 Q_1 :

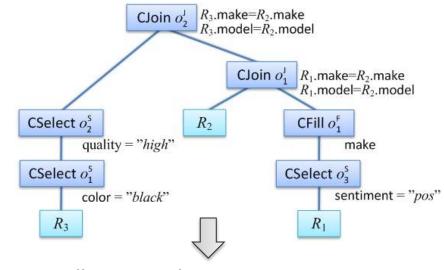
SELECT $R_{2.*}, R_{1.}$ review, $R_{3.}$ image

FROM REVIEW R_1 , AUTOMOBILE R_2 , IMAGE R_3

WHERE R_1 .sentiment ="pos"

AND $R_3.\text{color} = \text{``black''} \text{ AND } R_3.\text{quality} = \text{``high''}$ AND $R_1.\text{make} = R_2.\text{make} \text{ AND } R_1.\text{model} = R_2.\text{model}$

AND R_2 .make = R_3 .make AND R_2 .model = R_3 .model



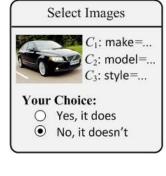
Crowdsourcing Result

Make	Model	Revie w	
Volvo	S80		
		•••	



Human Intelligence Tasks

Query Plan







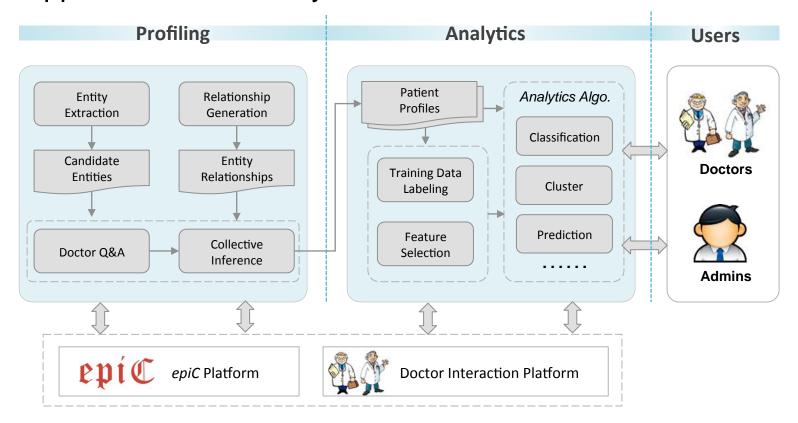


CDAS: Optimizations

- Objective I: Cost Minimization
 - Find the query plan that minimizes the overall cost for evaluating a crowdsourcing query
- Objective II: Latency Bounded Cost Minimization
 - Latency cannot exceed a constraint
 - Minimizing the query plan with latency bound and minimum overall monetary cost

GEMINI: **GE**neralizable Medical Information aNalysis and Integration System

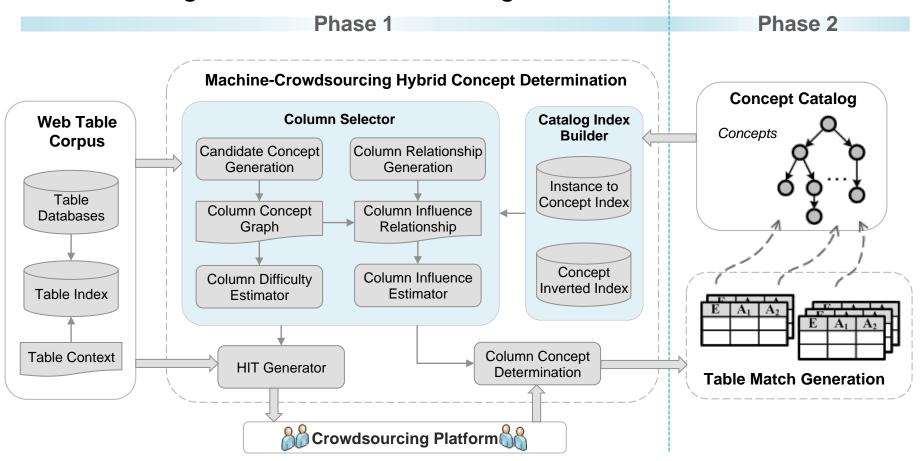
- Hybrid human-machine intelligent data management system optimized for healthcare domain
- To provide comprehensive holistic views of patients and supports real-time analytics



B. C. Ooi, K.-L. Tan, Q.T. Tran, J.W.L. Yip, G. Chen, Z.J. Ling, T. Nguyen, A.K.H. Tung, M. Zhang: Contextual Crowd Intelligence. SIGKDD Exploration, 2014.

A Hybrid Machine-Crowdsourcing Solution for Web Table Integration

- Hybrid human-machine intelligent system optimized for web table integration
- Knowledge base + Crowdsourcing



Ju Fan, Meiyu Lu, Beng Chin Ooi, Wang-Chiew Tan, Meihui Zhang: A hybrid machine-crowdsourcing system for matching web tables. ICDE 2014: 976-987

Part 1 Summary

- Crowdsourcing is a novel paradigm to help solve DB-hard problems
- Crowdsourcing database systems
 - Qurk, CrowdDB, Deco, CDAS
 - Data model
 - Query language
 - Crowd operators
 - Optimization issues

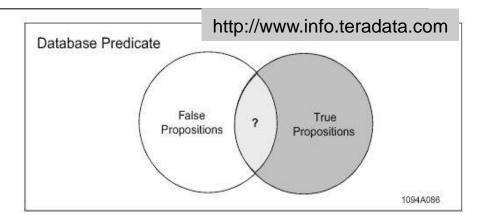
Reference

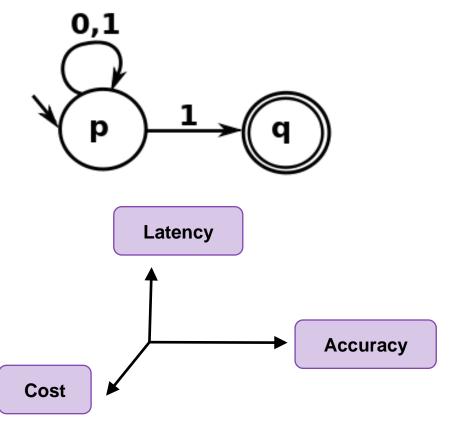
- **[Fan-ICDE2014]** A hybrid machine-crowdsourcing system for matching web tables, J. Fan et al., ICDE 2014
- [Feng-VLDB2011] CrowdDB: Query Processing with the VLDB Crowd, A. Feng et al., VLDB 2011
- [Franklin-SIGMOD11] CrowdDB: answering queries with crowdsourcing, Michael J. Franklin et al, SIGMOD 2011
- [Gao-SIGMOD2013] An online cost sensitive decision-making method in crowdsourcing systems, J. Gao et al., SIGMOD 2013
- [Liu-VLDB2012] CDAS: A Crowdsourcing Data Analytics System, X. Liu et al., VLD B 2012
- [Marcus-CIDR2011] Crowdsourced Databases: Query Processing with People, A. M. arcus et al., CIDR 2011
- [Marcus-SIGMOD2011] Demonstration of Qurk: a query processor for human operat ors, A. Marcus et al., SIGMOD 2011
- [Marcus-VLDB2012] Human-powered Sorts and Joins, A. Marcus et al., VLDB 2011
- [Parameswaran-CIKM2012] Deco: declarative crowdsourcing, A. G. Parameswaran et al., CIKM 2012
- [Park-VLDB2013] Query Optimization over Crowdsourced Data, H. Park et al., VLDB 2013
- [Ooi-SIGKDD14] Contextual Crowd Intelligence, B. C. Ooi et al., SIGKDD 2014

Part 2 HUMAN POWERED DATABASE OPERATIONS

New Challenges

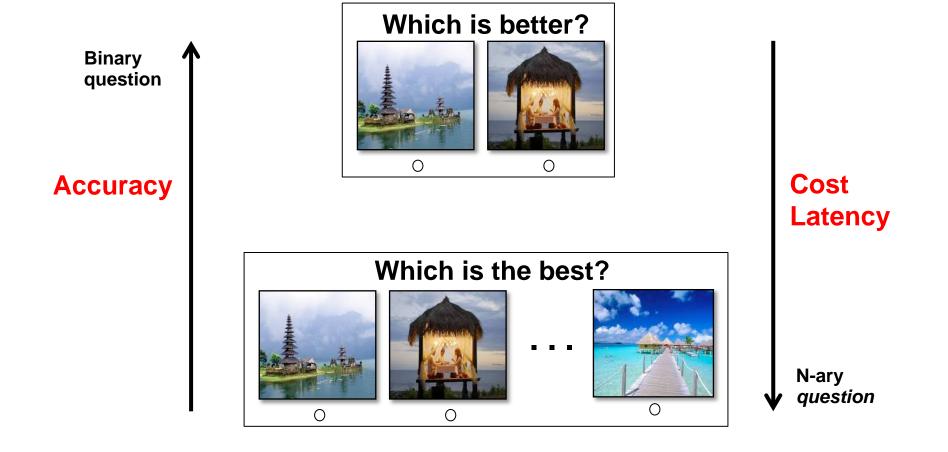
- Open-world assumption (OWA)
 - Eg, workers suggest a new relevant image
- Non-deterministic algorithmic behavior
 - Eg, different answers by the same workers
- Trade-off among cost, latency, and accuracy





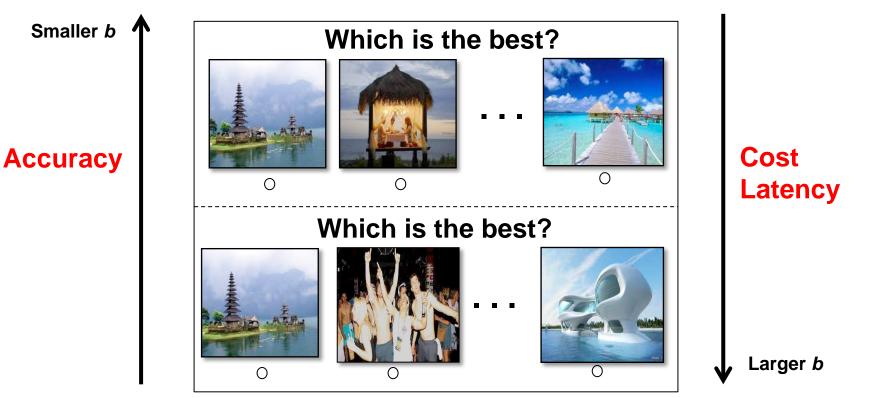
Size of Comparison

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



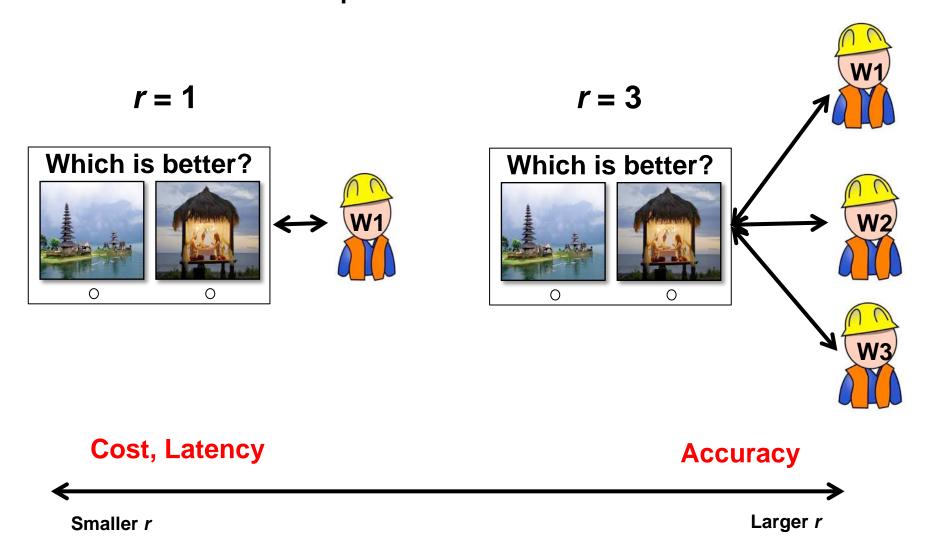
Size of Batch

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



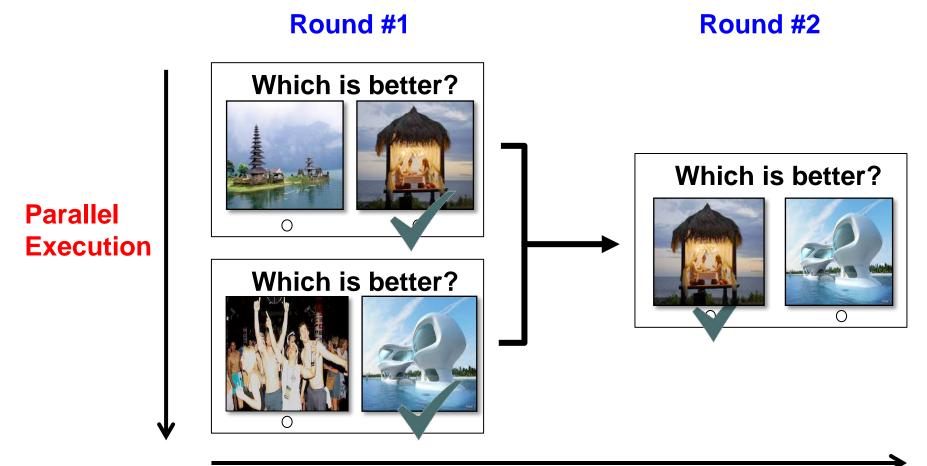
Response (r)

of human responses seeked for a HIT



Round (= Step)

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



DB Operations

- The focus of Part 2
 - Top-1 (= Max)
 - Top-k
 - Sort
 - Demo
 - Select
 - Count
 - Join

Top-1 Operation

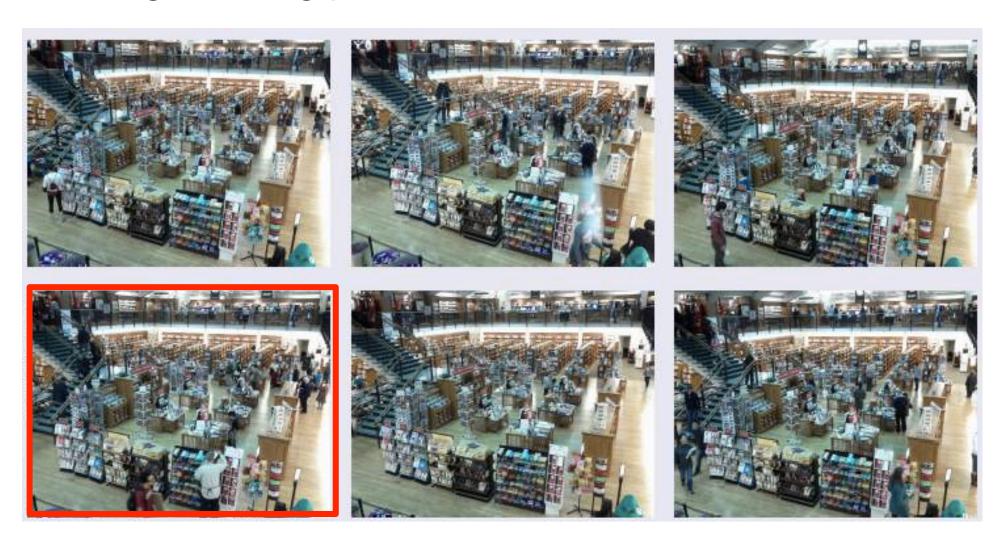
- Find the top-1, either MAX or MIN, among N items w.r.t. a predicate P
- Often P is subjective, fuzzy, ambiguous, and/or difficult-for-machines-to-compute
 - Which is the most "representative" image of Shanghai?
 - Which animal is the most "dangerous"?
 - Which soccer player is the most "valuable"?
- Note
 - 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

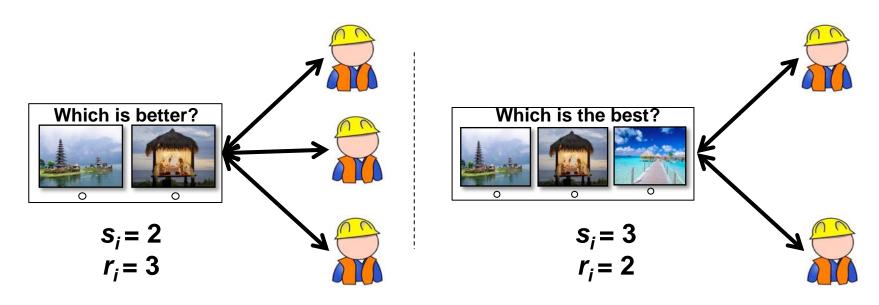
Max [Venetis-WWW12]

• Eg, Finding peak hours

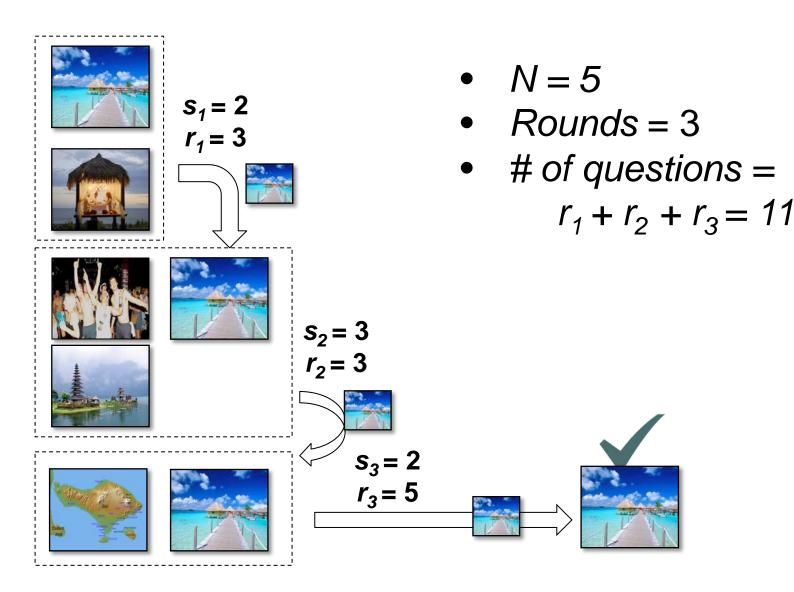


Max [Venetis-WWW12]

- 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



Bubble Max Case #1



Bubble Max Case #2









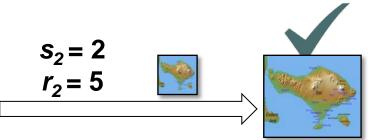
$$s_1 = 4$$

$$r_1 = 3$$

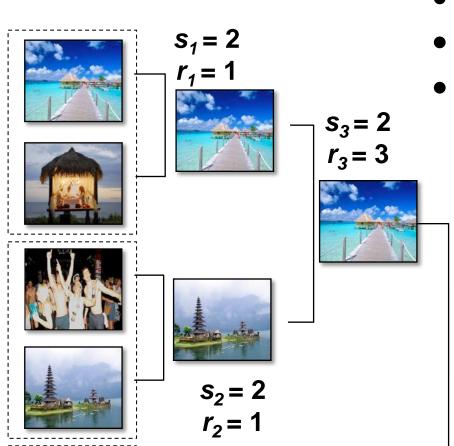




- Rounds = 2
- # of questions = $r_1 + r_2 = 8$



Tournament Max

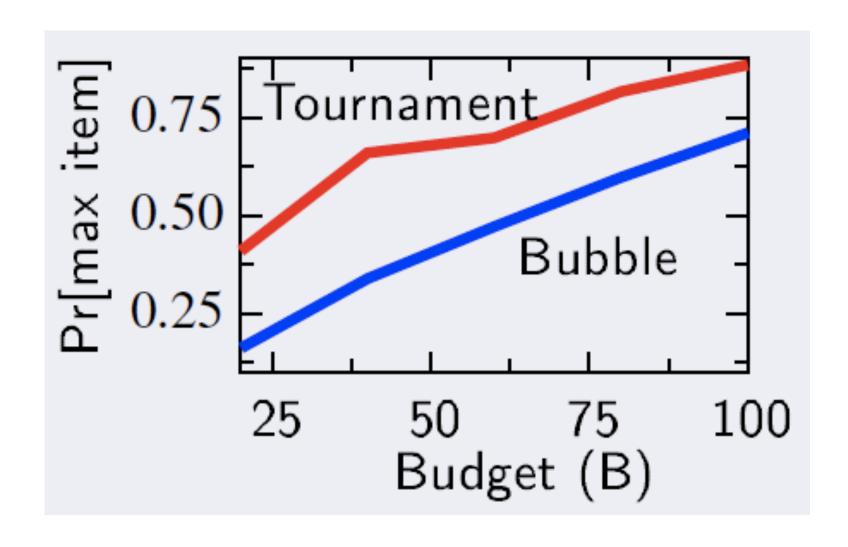


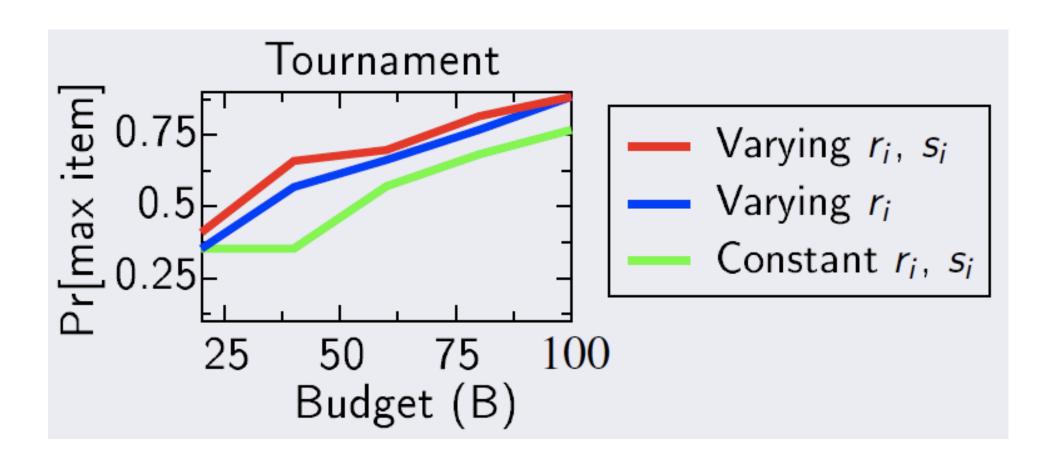
- N=5
- Rounds = 3
- # of questions = $r_1 + r_2 + r_3 + r_4 = 10$



$$s_4 = 2$$
$$r_4 = 5$$

- 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





Top-k Operation

 Find top-k items among N items w.r.t. a predicate P

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





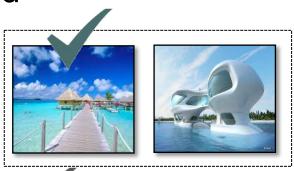






Top-k: Tournament Solution (k = 2)

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



Round 3





Round 2

Total, 4 questions with 3 rounds







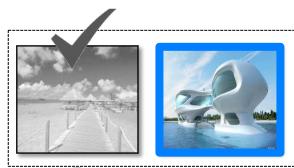


Round 1



Top-k: Tournament Solution (k = 2)

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



Round 3





Round 2









Round 1



Top-k: Tournament Solution (k = 2)

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



Round 5





Round 4

Total, 6 questions With 5 rounds











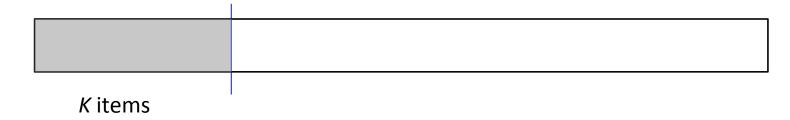
Top-k: Tournament Solution

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



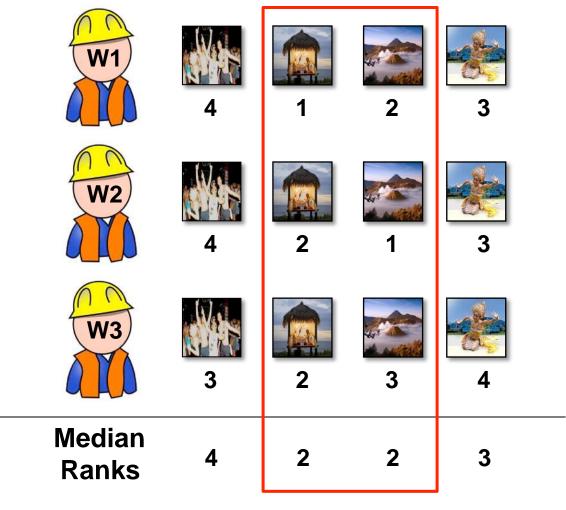
- Tournament-based approach
- Can become a Top-k list algorithm
 - Eg, Top-k set algorithm, followed by [Marcus-VLDB11] to sort k items

- Algorithm
 - Input: N items, integer k and s (ie, s > k)
 - Output: top-k set
 - Procedure:
 - \circ O \leftarrow 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

• Eg, N=10, s=4, k=2**Top-2 items** s-rank() s-rank(s-rank(s-rank() s-rank() s-rank()

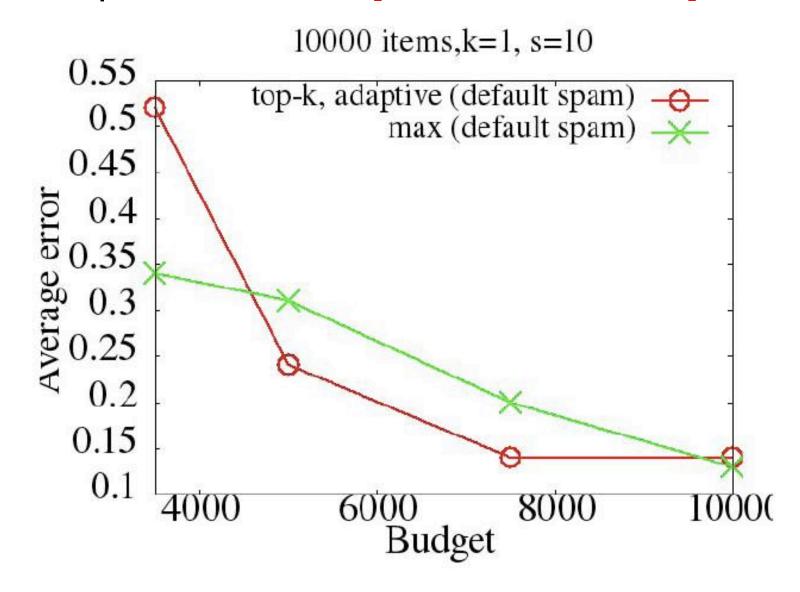
- s-rank(s)
 - // workers rank s items and aggregate
 - Input: s items, integer k (ie, s > k), w workers
 - Output: top-k items among s items
 - Procedure:
 - For each of w workers
 - Rank s items ≈ comparison-based sort [Marcus-VLDB11]
 - Merge w rankings of s items into a single ranking
 - Use median-rank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

• Eg, s-rank(): *s*=4, *k*=2, *w*=3

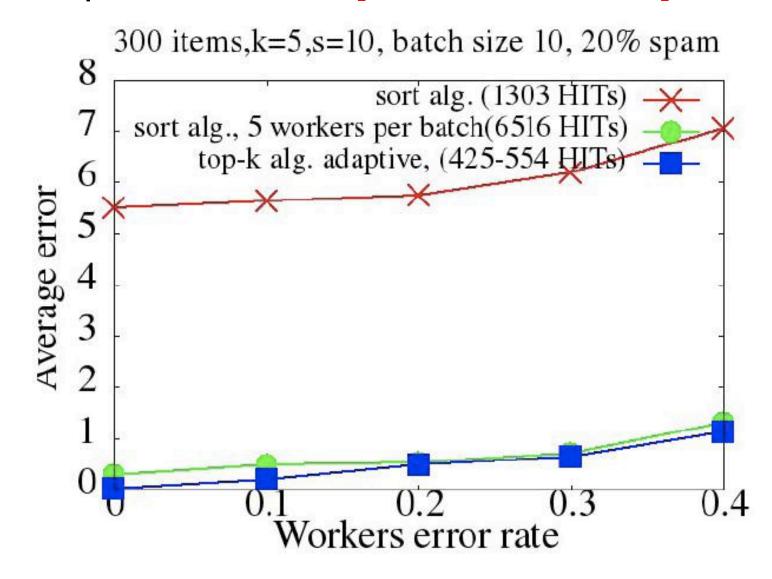


Top-2

Comparison to Max [Venetis-WWW12]



Comparison to Sort [Marcus-VLDB11]



Sort Operation

Rank N items w.r.t. a predicate P

SELECT *

FROM SoccerPlayers AS P

WHERE P.WorldCupYear = '2014'

ORDER BY CrowdOp('most-valuable')



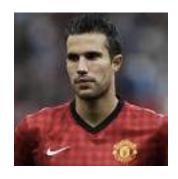
















. . .

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)









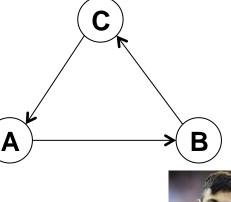




Naïve Sort

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





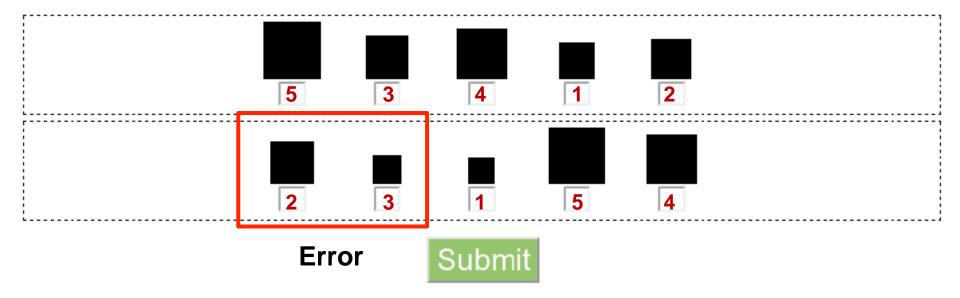
- If no cycle occurs
 - Naïve all pair-wise comparisons takes comparisons
- If cycle exists
 - More comparisons from workers
 - Break cycle



- 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
 - o 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

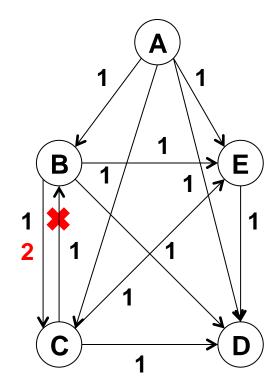
There are 2 groups of squares. We want to order the squares in each group from smallest to largest.

- 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.

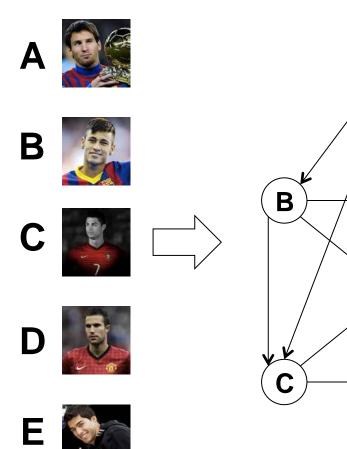


• N=5, S=3





• N=5, S=3



Sorted Result



Topological

Sort

Ε

DAG

- #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







3.6

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	1		

Worker	Rating
W1	1
W2	2
W3	1

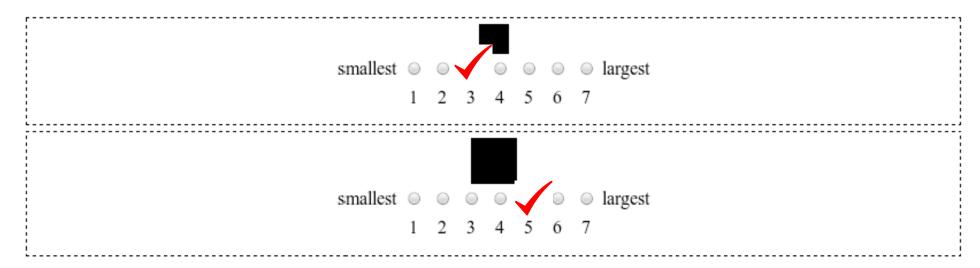


8.2

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:





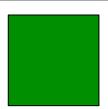


- #3: Hybrid Sort
 - First, do rating-based sort → sorted list L
 - Second, do comparison-based sort on $S(S \subset L)$
 - S may not be accurately sorted
 - How to select the size of S
 - Random
 - Confidence-based
 - Sliding window

Q1: squares by size



VS.



Q2: adult size



VS.



Q3: dangerousness



VS.



- Q4: how much animal belongs to Saturn
 - Non-sensical question

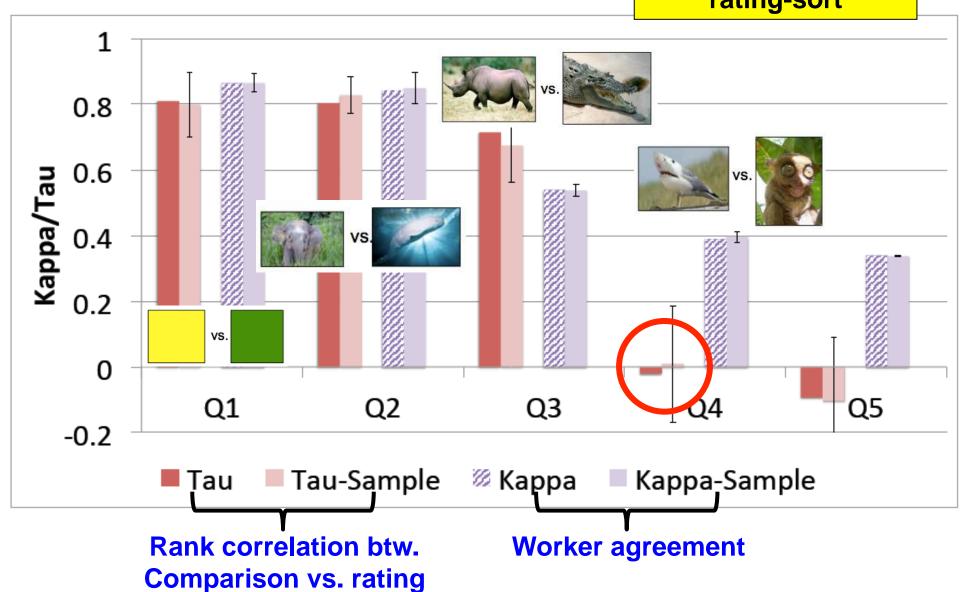


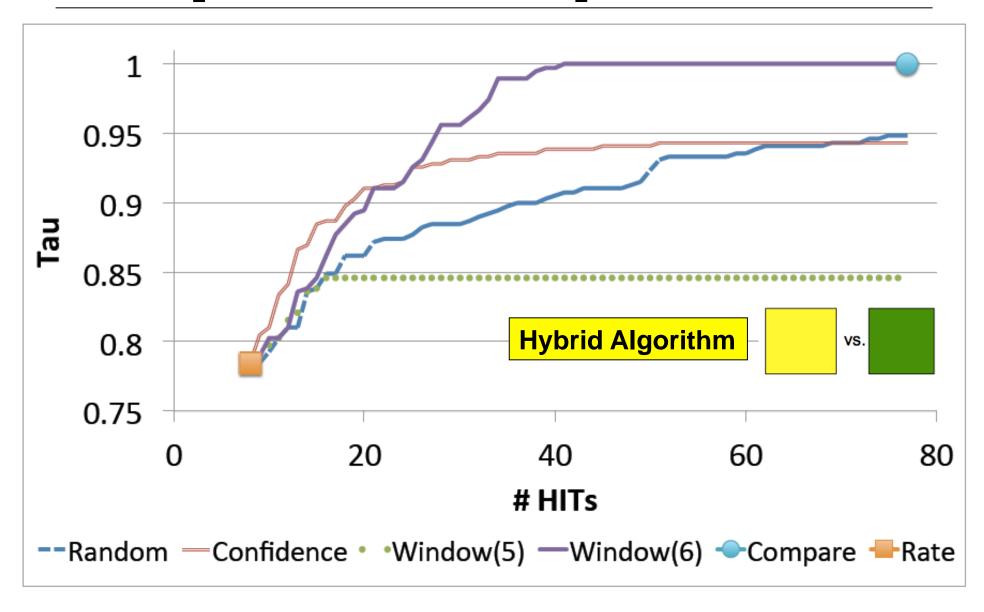


VS.



Finds that in general comparison-sort > rating-sort





Demo: Human-Powered Sorting

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

http://is.gd/Eju2nU



Select Operation

 Given N items, select m items that satisfy a predicate P

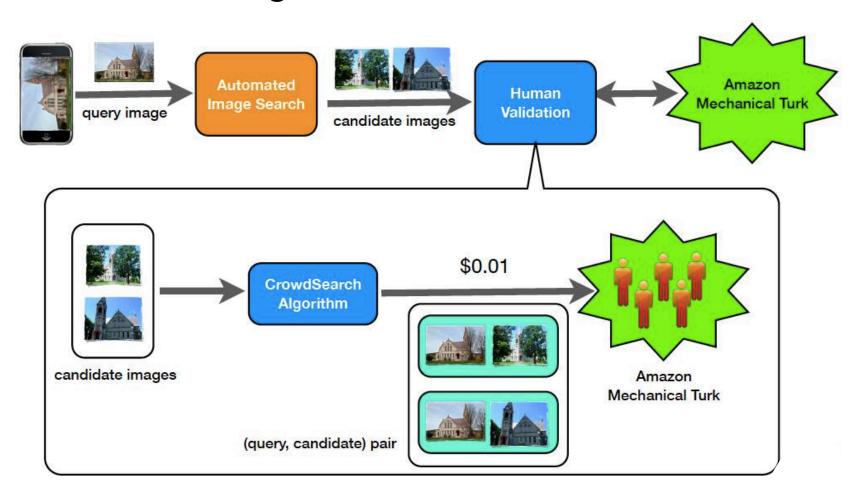
≈ Filter, Find, Screen, Search



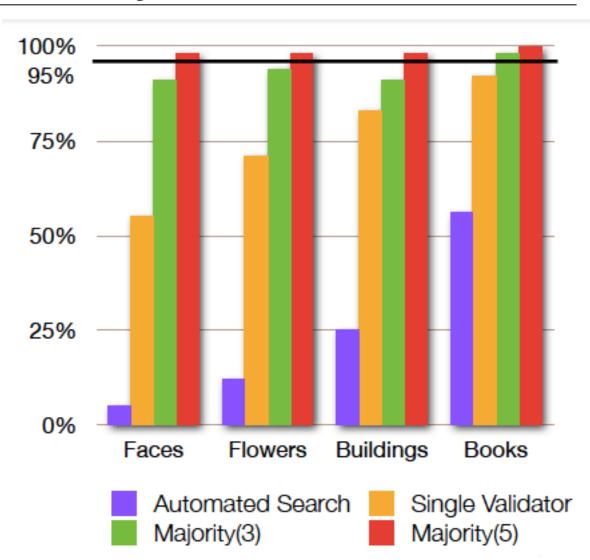
Select Operation

- Examples
 - [Yan-MobiSys10] uses crowds to search an image relevant to a query
 - [Parameswaran-SIGMOD12] develops humanpowered 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

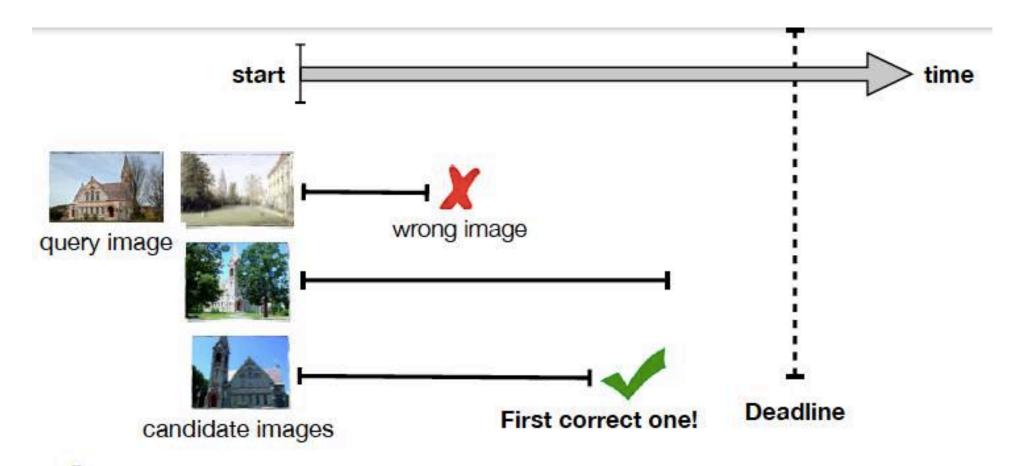
 Improving mobile image search using crowdsourcing



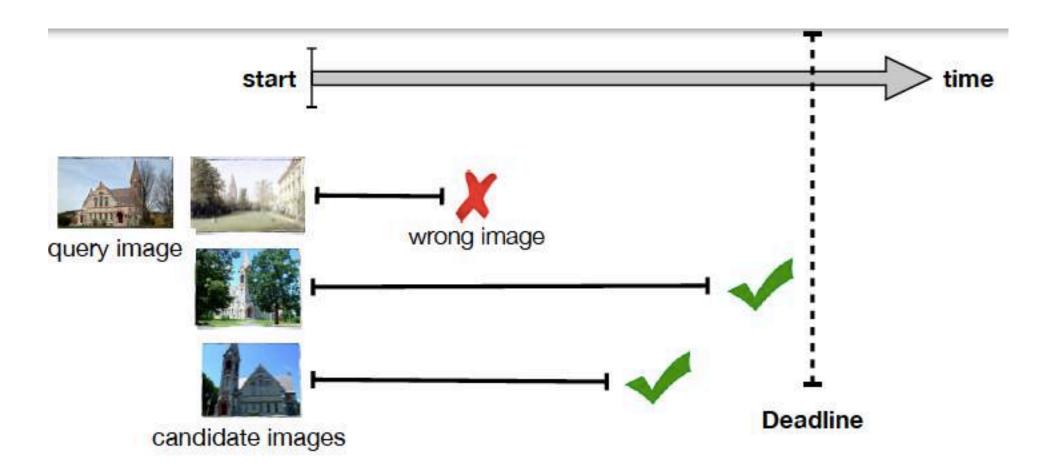
- Ensuring accuracy with majority voting
- Given accuracy, optimize cost and latency
- Deadline as latency in mobile phones



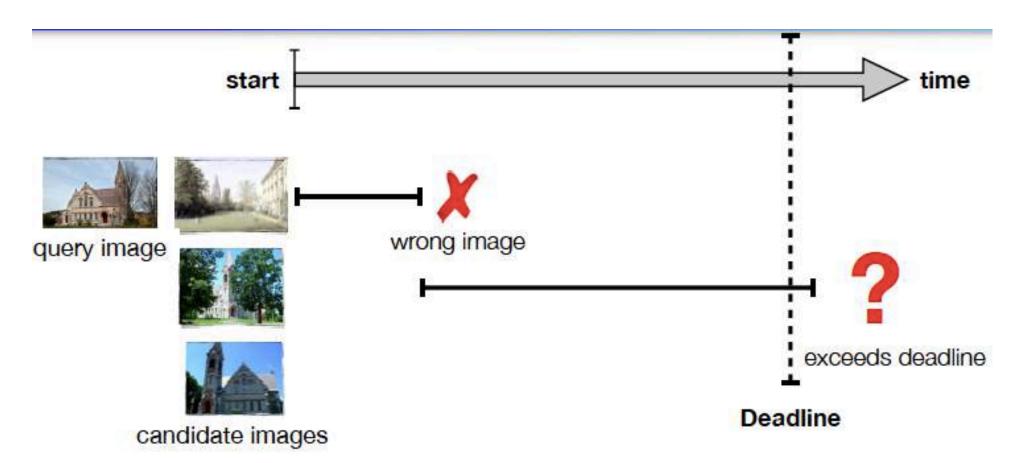
 Goal: For a query image Q, find the first relevant image I with min cost before the deadline



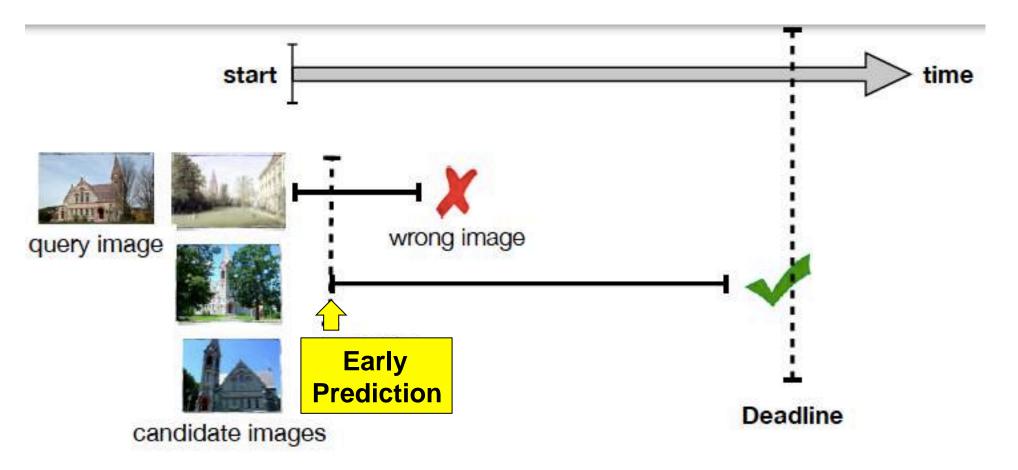
Parallel crowdsourced validation



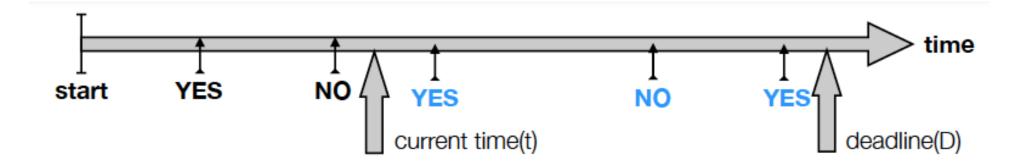
Sequential crowdsourced validation

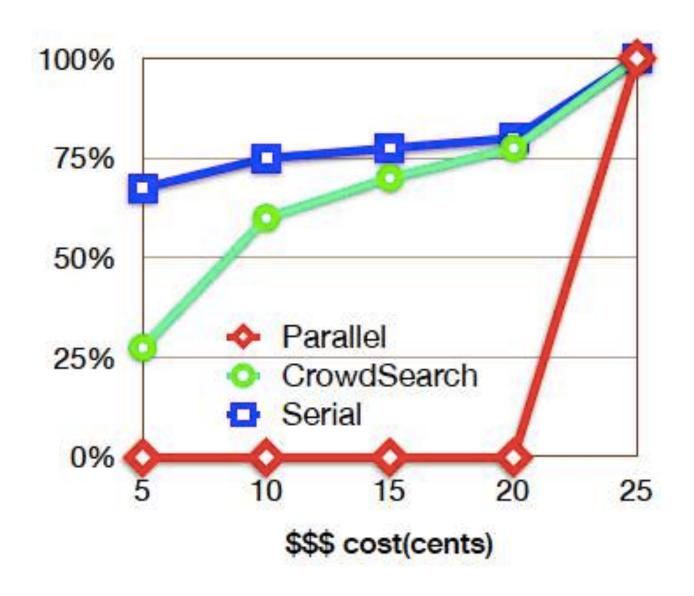


 CrowdSearch: using early prediction on the delay and outcome to start the validation of next candidate early



- Predicting accuracy
- Eg, at time t
 - 2 responses so far (1 Yes, and 1 No)
 - From training data, list all majority-vote(5)=Yes
 - Determine probability





Count Operation

- Given N items, estimate the number of m items that satisfy a predicate P
- Selectivity estimation in DB → crowdpowered 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

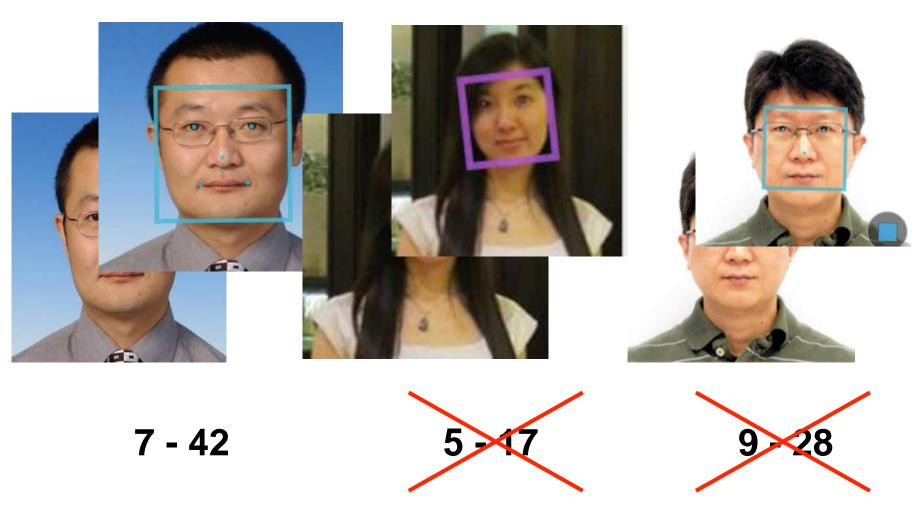
Count Operation

 Q: "How many teens are participating in the Hong Kong demonstration?"



Count Operation

Using Face++, guess the age of a person

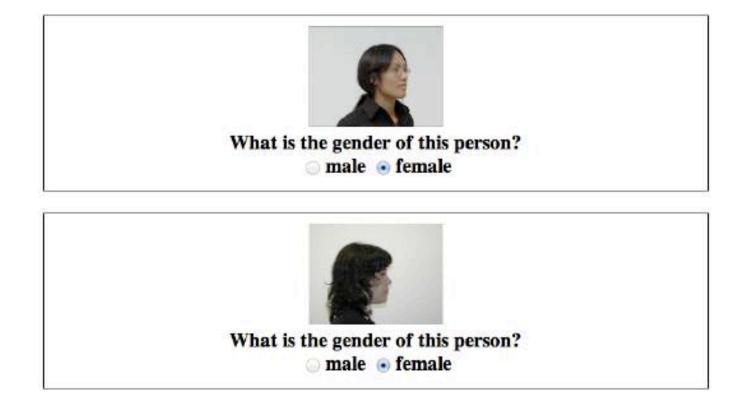


http://www.faceplusplus.com/demo-detect/

- 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

Label Count (via sampling)

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



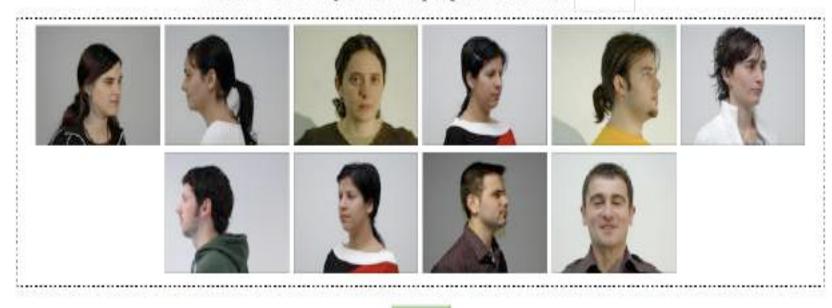


Batch Count

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?





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

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
 - $R \text{ JOIN}_p S$, 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

- 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

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

#1 Simple Join









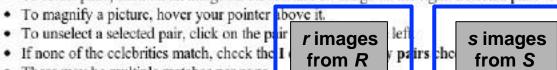
Is the same celebrity in the image on the left and the image on the right?

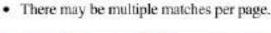
#2 Naïve Batching Join



Find pairs of images with the same celebrity

To select pairs, click on an image on the left and an image on the right. Selected pairs will appear in the Matched Celebrities list on the left.

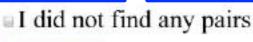














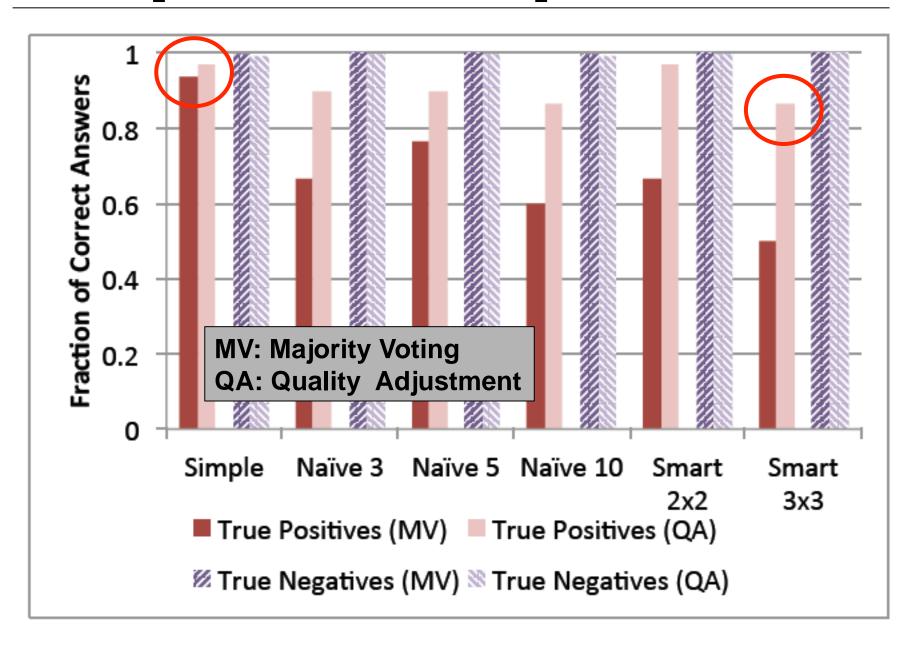
Matched Celebrities

To remove a pair added in error, click on the pair in the list below.





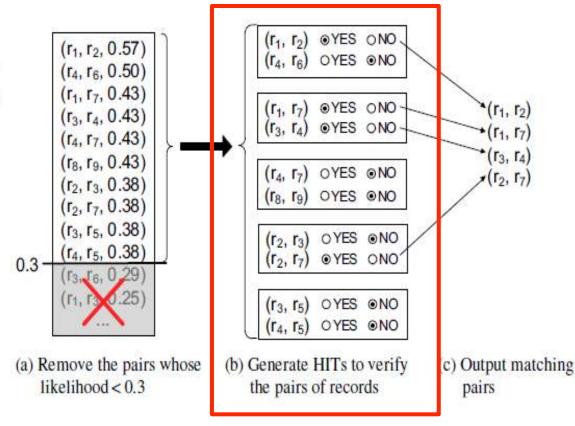
#3 Smart Batching Join



- [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
 - Algorithm to generate min # of HITs for step #2

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

Product Name Price iPad Two 16GB WiFi White \$490 iPad 2nd generation 16GB WiFi White \$469 \$545 iPhone 4th generation White 16GB Apple iPhone 4 16GB White \$520 \$375 Apple iPhone 3rd generation Black 16GB iPhone 4 32GB White \$599 Apple iPad2 16GB WiFi White \$499 Apple iPod shuffle 2GB Blue \$49 Apple iPod shuffle USB Cable \$19



Main Issue: HIT Generation Problem

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

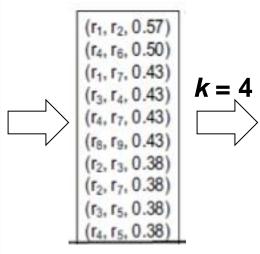
roduct Pair #1	
Product Name	Price
iPad Two 16GB WiFi White	\$490
iPad 2nd generation 16GB WiFi White	\$469
Your Choice (Required) They are the same product They are different products Reasons for Your Choice (Option	al)
Product Pair #2	
Product Pair #2 Product Name	Price
	0000000
Product Name	0000000
Product Name iPad 2nd generation 16GB WiFi White	\$469
Product Name iPad 2nd generation 16GB WiFi White iPhone 4th generation White 16GB	\$469
Product Name iPad 2nd generation 16GB WiFi White iPhone 4th generation White 16GB Your Choice (Required) They are the same product They are different products	\$469 \$545
Product Name iPad 2nd generation 16GB WiFi White iPhone 4th generation White 16GB Your Choice (Required) They are the same product	\$469 \$545
Product Name iPad 2nd generation 16GB WiFi White iPhone 4th generation White 16GB Your Choice (Required) They are the same product They are different products	\$469 \$545
Product Name iPad 2nd generation 16GB WiFi White iPhone 4th generation White 16GB Your Choice (Required) They are the same product They are different products	\$469 \$545

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

you can	(1) SORT the table by clicking headers; (2) MOVE a row by dragging and dropping it	
Label	Product Name	Price -
•	iPad 2nd generation 16GB WiFi White	\$469
•	iPad Two 16GB WiFi White	\$490
•	Apple iPhone 4 16GB White	\$520
•	iPhone 4th generation White 16GB	\$545
	Reasons for Your Answers (Optional)	

- 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
 - Each pair $(p_i, p_i) \in P$ 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

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



Cluster-based HIT #1

 r_1, r_2, r_3, r_7

Cluster-based HIT #2

 r_3, r_4, r_5, r_6

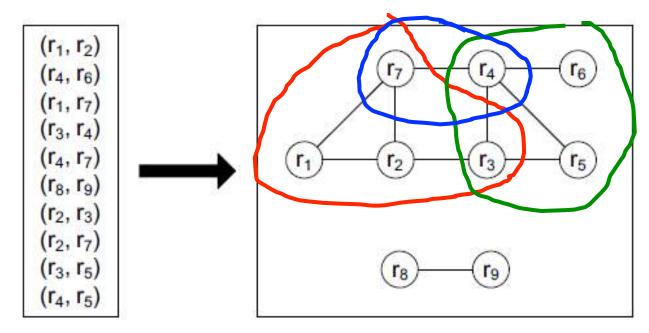
Cluster-based HIT #3

 r_4, r_7, r_8, r_9

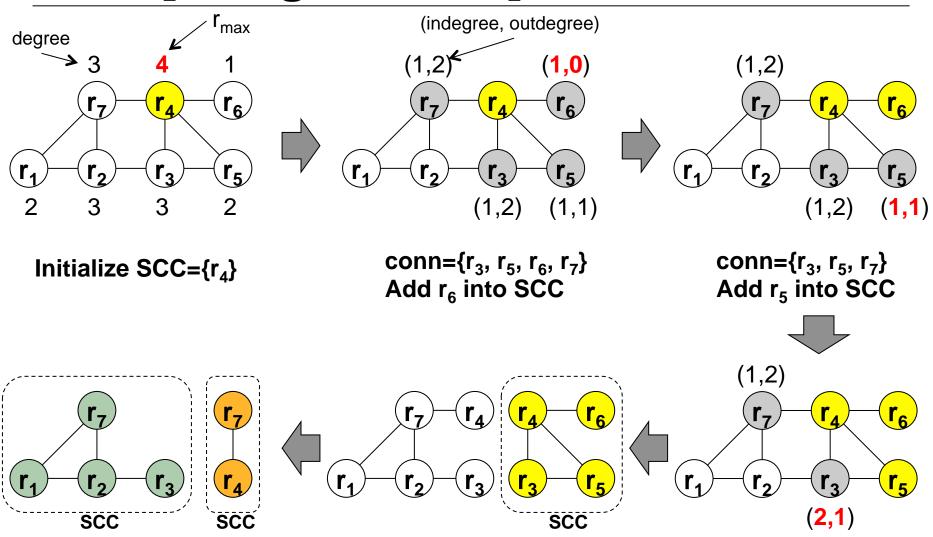
This is the minimal # of cluster-based HITs satisfying previous two conditions

- 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

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



- Step 1: Partition
 - Input: LCC, kOutput: SCCs
 - r_{max} ← node in LCC with the max degree
 - $scc \leftarrow \{r_{max}\}$
 - 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



Output other SCC

Output SCC

conn={r₃, r₇} Add r₃ into SCC

Part 2 Summary

- New opportunities and challenges
 - Open-world assumption
 - Non-deterministic algorithmic behavior
 - Trade-off among cost, latency, and accuracy
- Human-Powered DB → "Human-in-theloop" DB
 - Machines process majority of operations
 - Humans process a small fraction of challenging

operations in big data



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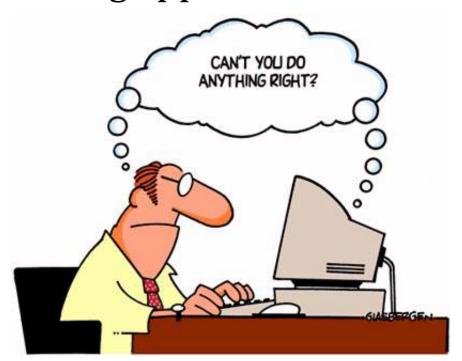
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Part 3 QUALITY CONTROL

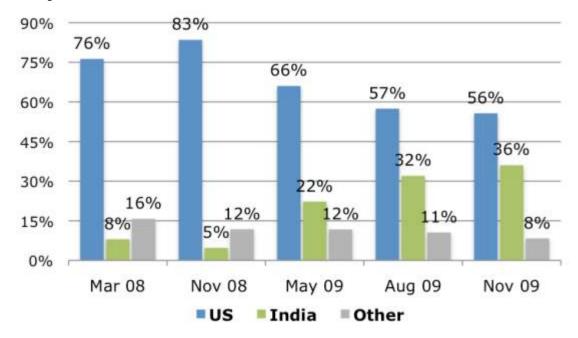
Challenges

 Data Quality is always the first concern in crowdsourcing applications



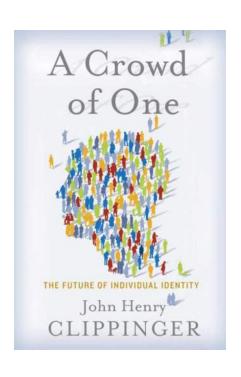
Challenges

- Bias
 - Narrowed Demographics
 - Mainly women in U.S. and India



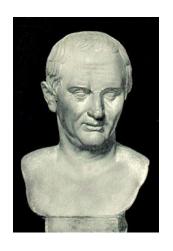
Workers on AMT

Challenges



- Wisdom is within the human.
- We need to dig it out, and manage them.
- Well, it is difficult, because the humans are ...

Humans



Erroneous"To err is human"

—Marcus Tullius Cicero

Greedy

"...my more-having would be a sauce to make me hunger more"

—Macbeth act 4, sc. 3, Shakespeare



Challenges

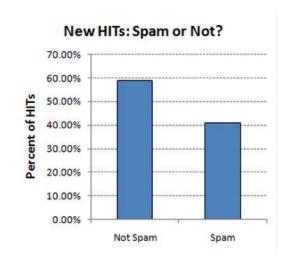
Spammers

- Spam Worker
 - Finish tasks simply for rewards
 - Low quality of the answers



Spam HITs

- Some tasks are to spamming "social media" metrics
- Some tricks the worker by refuse to pay for their answers



Quality Control

- Qualification Tests
- Aggregation Methods (Majority, Rasch)
- Golden Tests and Estimation
- Task Design
- Feedback
- Reputation (trustworthy crowdsourcing)

Task Design Example

- ESP Game(Luis von Ahn)
 - Object: Images Labeling
 - Human task: online game, two players guessing one common item



PLAYER 1



GUESSING: CAR

GUESSING: HAT

GUESSING: KID

SUCCESS!
YOU AGREE ON CAR

PLAYER 2



GUESSING: BOY

GUESSING: CAR

SUCCESS! YOU AGREE ON CAR

Quality Control

- Whom to Ask
- WiseMarket
- COPE

Social Network/Media services the virtualization and digitalization of people's social activities



calebcc

lf take a cab, can I get to Gyeongbokgung(경복궁) from 63 Building in one hour? @zhiyangsu @童咏昕 @SeoulHeart @ocar_liv @刘工bong

10秒前 来自新浪微博 粉丝头条 | 🖒 | 转发 | 收藏 | 评论

- Minor as dressing for a banquet
- Major as prediction of macro economy trends

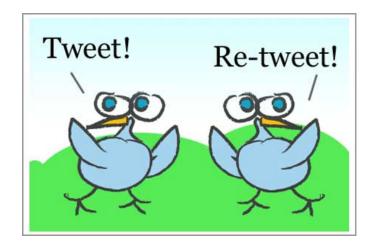
"two-option decision making tasks"



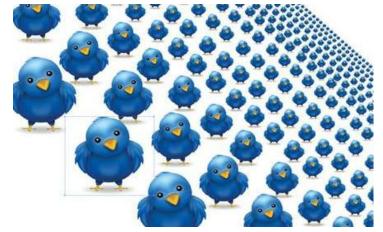
Can we extend the magic power of **Crowdsourcing** onto **social network**?

Microblog Users

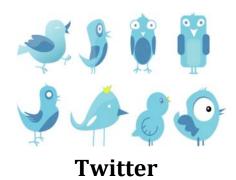
- Simple
 - 140 characters
 - 'RT' + '@'

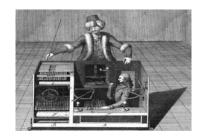


- But comprehensive
 - Large network
 - Various



Why Microblog Platform?





AMT

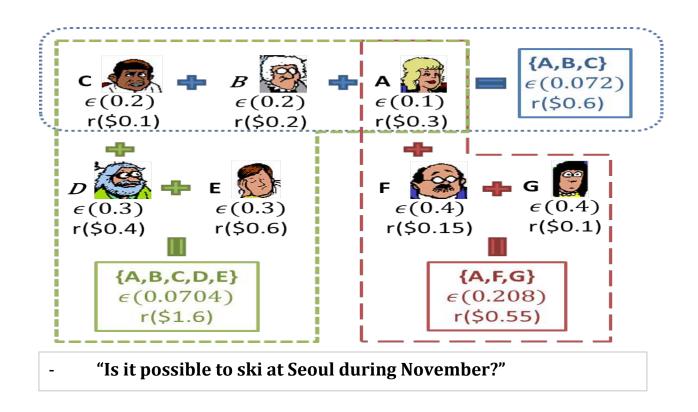
Accessibility	Highly convenient, on all kinds of mobile devices	Specific online platform
Incentive	Altruistic or payment	Mostly monetary incentive
Supported tasks	Simple task as decision making	Various types of tasks
Communication Infrastructure	'Tweet' and 'Reply' are enough	Complex workflow control mechanism
Worker Selection	Active, Enabled by '@'	Passively, No exact selection

Running Example

 "Is it possible to ski at Seoul during November?"

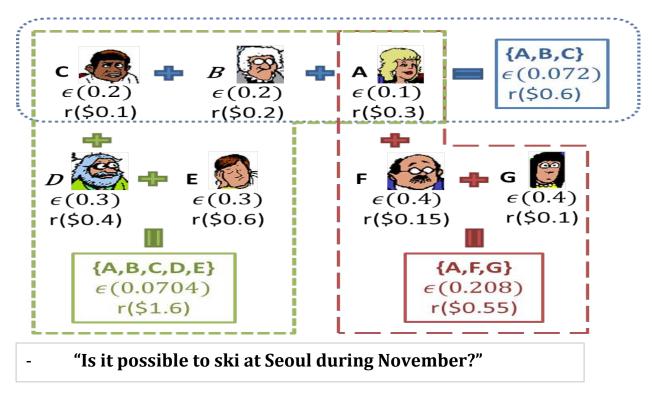


Motivation – Jury Selection Problem Running Case(1)

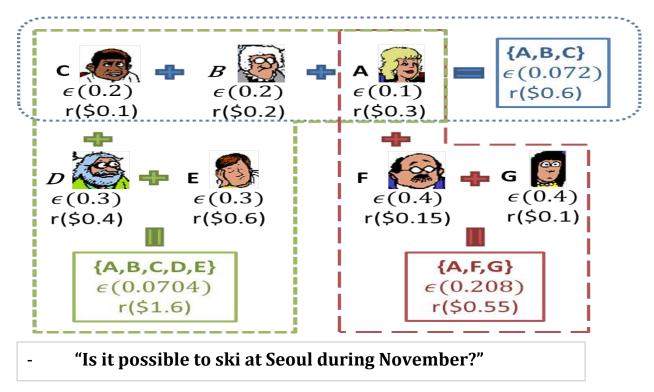


• Given a decision making problem, with budget \$1, whom should we ask?

Motivation – Jury Selection Problem Running Case(2)

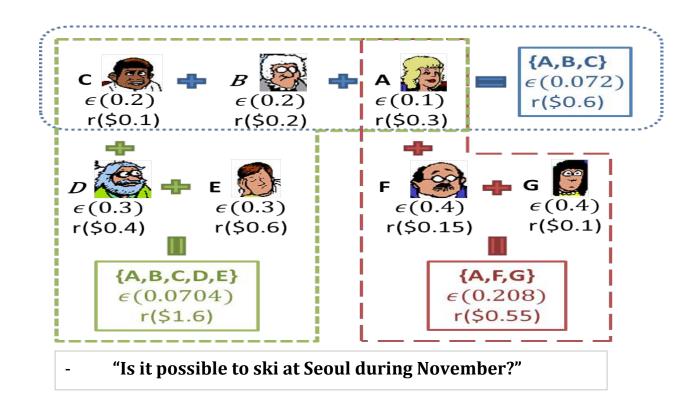


- Worker: Juror
- Crowds : Jury
- Data Quality: Jury Error Rate



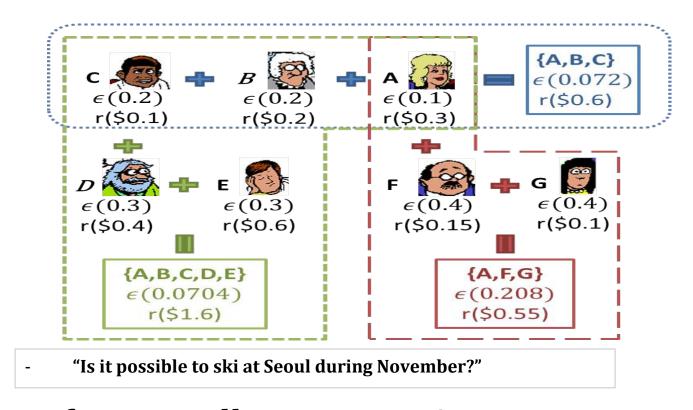
- If (A, B, C) are chosen(Majority Voting)
 - ▶ JER(A,B,C) = 0.1*0.2*0.2 + (1 0.1)*0.2*0.2 + 0.1*(1 0.2)*0.2 + 0.1*0.2*(1 0.2) = 0.072
 - ▶ Better than A(0.1), B(0.2) or C(0.2) individually

Motivation – Jury Selection Problem Running Case(4)



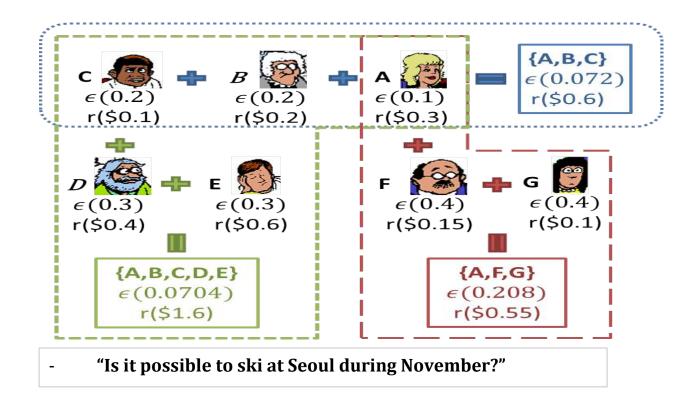
- What if we enroll more
 - JER(A,B,C,D,E) = 0.0704 < JER(A,B,C)
 - The more the better?

Motivation – Jury Selection Problem Running Case(5)



- What if we enroll even more?
 - JER(A,B,C,D,E,F,G) = 0.0805 > JER(A,B,C,D,E)
 - Hard to calculate JER

Motivation – Jury Selection Problem Running Case(6)



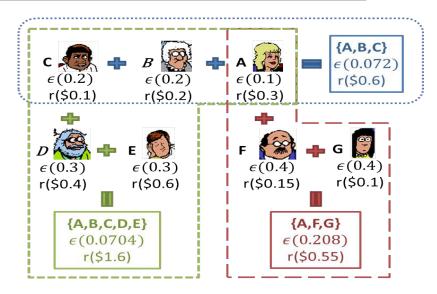
- So just pick up the best combination?
 - JER(A,B,C,D,E)=0.0704
 - R(A,B,C,D,E) = \$1.6 > budget(\$1.0)

Motivation – Jury Selection Problem Running Case(7)

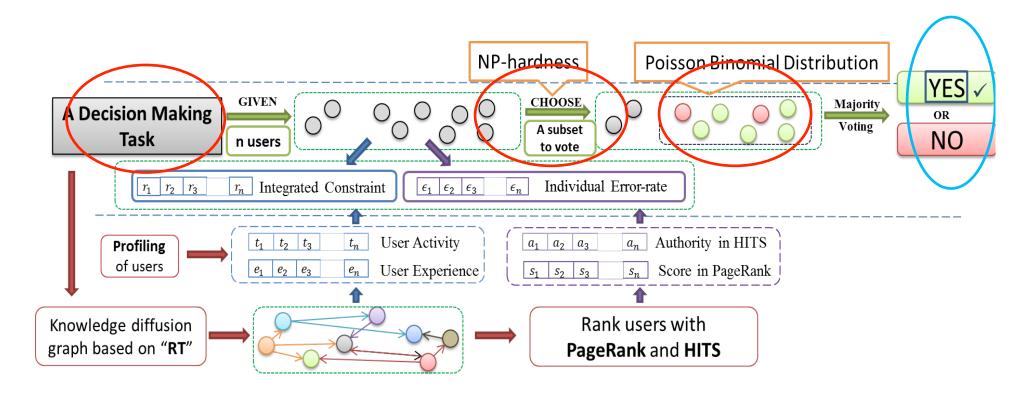
Crowd	Individual Error-rate	Jury Error-rate
С	0.2	0.2
A	0.1	0.1
$_{\mathrm{C,D,E}}$	0.2,0.2,0.3	0.174
A,B,C	0.1, 0.2, 0.2	0.072
A,B,C,D,E	0.1,0.2,0.2,0.3,0.3	0.0703
A,B,C,D,E,F,G	0.1,0.2,0.2,0.3,0.3,0.4,0.4	0.0805

Worker selection for maximize the quality of a particular type of product:

the reliability of voting.



Framework

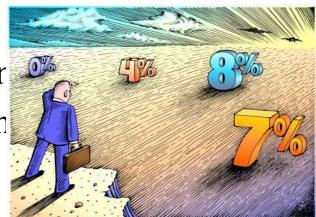


 Any structured method to manage the crowds?

- A Market

Market

- Humans are investors
 - They have (partial)information
 - They invest to maximize incom



- A market consists of investors
 - Some of them win
 - Some of them lose
- A market can
 - Make Decisions/Show Preference
 - Based on Majority Voting

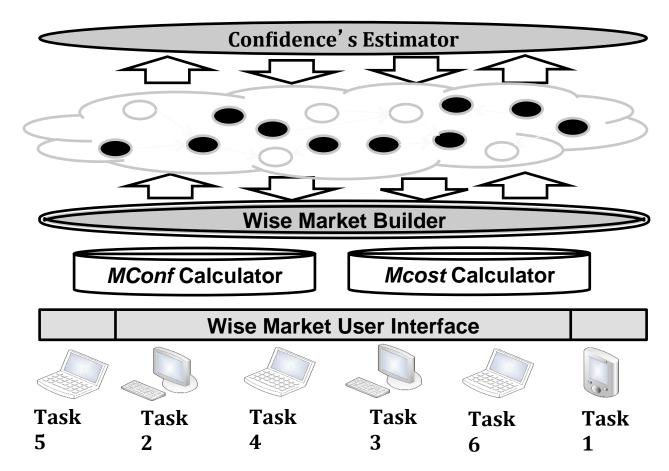


Only winning investors get rewards

Why WiseMarket?

- Worriers in crowdsourcing, human computation services
 - Low Answers Quality
 - Spam Workers
 - Otiose Expenditure
- Drawbacks in survey samplings, online review aggregation
 - Vulnerable Quality Guarantee
 - Uncontrolled Demographic
- So How Does it Run?

How Does it Run?



Choose the best investors to build a market

Investors

DEFINITION 1 (INVESTOR CONFIDENCE). For each investor ι_i , the Investor Confidence c_i is the probability that ι_i chooses the same option as the ground truth. Respectively, given a ground truth G, the confidence

$$c_i = \Pr\{\iota_i \text{chooses correctly}\}$$

$$= \Pr\{G = 0\} \cdot \Pr\{v_i = 0 | G = 0\}$$

$$+ \Pr\{G = 1\} \cdot \Pr\{v_i = 1 | G = 1\}$$

$$= \Pr\{v_i = G | G\}$$

- v_i is the actual invest choice of the investor
- The two options are assumed to have equal prior preference

Wise Market

DEFINITION 2 (Wise Market). A Wise Market is a set of investors $WM_n = \{\iota_1, \iota_2, \dots, \iota_n\} \subseteq I$ with size n, where each ι_i is associated with an individual confidence c_i and actual voting v_i .

Market Opinion

DEFINITION 3 (MARKET OPINION). Given a Wise Market WM, the Market Opinion $OP(WM_n)$ is the aggregated result according to the following equation:

$$OP(WM_n) = \begin{cases} 1 & \text{if } \sum v_i \ge \left[\frac{n}{2}\right] \\ 0 & \text{if } \sum v_i \le \left[\frac{n}{2}\right] \end{cases}$$

Market Confidence

DEFINITION 4 (MARKET CONFIDENCE). The Market Confidence MC is defined as the probability that the Market Opinion is the same as ground truth G:

$$MC(WM_n) = \Pr(OP(WM_n) = G|G)$$

$$= \Pr(|C| \ge \lceil \frac{n}{2} \rceil) = \Pr(|C| \ge \frac{n+1}{2})$$

$$= \sum_{k=\lceil \frac{n}{2} \rceil}^{n} \sum_{A \in F_k} \prod_{i \in A} c_i \prod_{j \in A^c} (1 - c_j)$$

- $F_k = \{A | |A| = k, A \subseteq WM_n\}$ is all the subsets of WM_n with size k
- A^c is the complementary set of A

Market Cost

DEFINITION 5 (MARKET COST). Given a Wise Market WM_n , the Market Cost $Cost(WM_n)$ is defined as the size of the Winning Set:

$$Cost(WM_n) = |W| = |\{\iota_i | \iota_i \in WM_n \text{ s.t. } v_i = OP(WM_n)\}|$$

Expected Market Cost

$$E[Cost(WM_n)]$$

$$= \sum_{k=\lceil \frac{n}{2} \rceil}^{n} k \cdot \Pr(|W| = k)$$

$$= \sum_{k=\lceil \frac{n}{2} \rceil}^{n} k \cdot \left[\sum_{A \in F_k} \prod_{i \in A} c_i \prod_{j \in A^c} (1 - c_j) + \sum_{A \in F_k} \prod_{i \in A} (1 - c_i) \prod_{j \in A^c} c_j \right]$$

Effective Market Problem

DEFINITION 6 (EFFECTIVE MARKET PROBLEM). Given a set of investors $I = \{\iota_1, \ldots, \iota_N\}$ with size N, a Market Confidence threshold θ , the Effective Market Problem(EMP) is to find a subset of all investors $WM_n \subseteq I$, so that:

minimize
$$E[Cost(WM_n)]$$

subject to $MC(WM_n) \ge \theta$

- A market BUILDER for tasks holders

Market Building

Overall Algorithm

```
Algorithm 6: Effective Market Algorithm (EMA)
   Input: A set of candidate investors I = \{\iota_1, \iota_2, \dots, \iota_N\}, an market
           confidence threshold \theta
   Output: the effective market EM
1 if (Max(c_i) \geq \theta) then
        return EM \leftarrow c \in WM_n s.t. minimized{E[Cost(c)]} and
        MC(c) \geq \theta;
3 else
        for i \leftarrow 1 to n-1 do
             if EM \leq [AEC(min(s_{i+2}), \theta)] then
              return EM;
 6
             M_{i+2} \leftarrow RankMerge(M_i);
             for s_i \in M_{i+2} do
 8
                 if MC(s_j) \ge \theta \&\& AEC(s_j, \theta) \le EM then
                   EM \leftarrow AEC(s_j, 0);
10
             else
11
                  continue;
12
```

COPE-Motivation

- Q: "What's your opinion about the game between Brazil and Germany tonight?"
- C1: "I vote for Germany, it will definitely win."
- C2: "I also vote for Germany. There's <u>no doubt</u>, since T. Silva and Neymar cannot play."
- C3: "There is still a **slight hope** that Brazil will win. I vote for Brazil."
- C4: "I know nothing about football. I'll **give it a shot** on Brazil."
- Judge: "2 v.s. 2. The crowds don't have an opinion."

Motivation

We need more than simple Binary Votes to capture the true opinion from the crowds.

From Labor to Trader: Motivation

- Opinion Elicitation
 - Opinion: numerical statements expressing individual's degrees of belief about certain events
 - Normally expressed as distribution
- Applications
 - Probabilistic Risk Analysis
 - Event Tree for industrial risk analysis
 - Causality Determination
 - PGM structure and probability

From Labor to Trader: Motivation

• Industrial Example

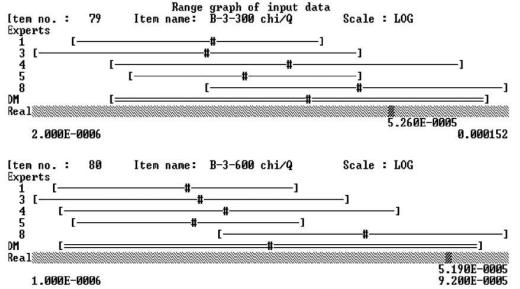


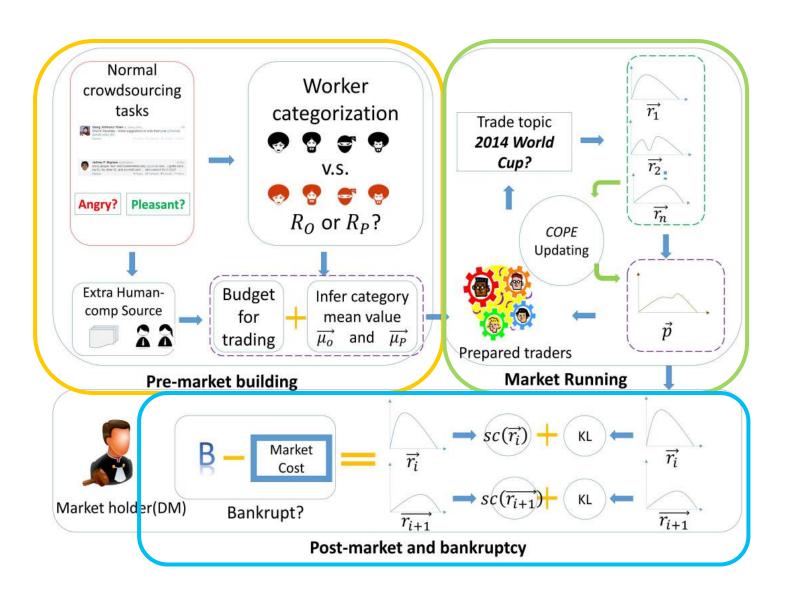
Figure 1: Example of Opinion Elicitation of five participants over two variables(NRC-EU accident uncertainty analysis [4])

- Specifying (uniform) variable distribution over a range
- Multiple workers are involved to express their

Solution

- We propose COPE to tackle the challenges
- <u>Crowd-powered OPinion Elicitation</u>
 - General crowd workforce from any labor markets
 - Form an invest market situation
 - Payments are connected to their contribution

COPE Framework



COPE – The Design

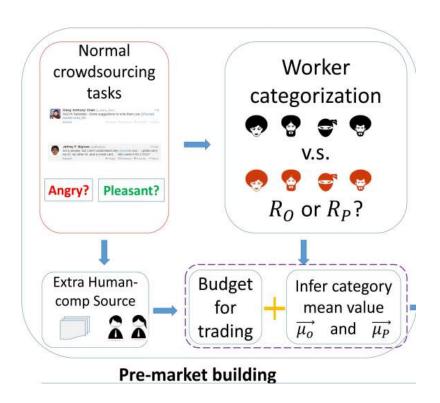
Trader

- A trader will present a report that maximize his/her payoff according to a payoff rule
- Traders are assumed as Risk-neutral
 - i.e. expected payoff oriented
 - Risk aversion enhances sincerity but introduces bias

COPE – The Design

- Pre-market Building
 - Generate Seed Capital
 - Promised Salaries as initial funds
 - Tendency Evaluation
 - Optimistic
 - Pessimistic
 - Group Mean
 - For bias adjustment during Bayesian updating

$$\vec{\mu_o} = \frac{\sum_i \vec{r_i^o}}{|R_o|} \qquad \qquad \vec{\mu_p} = \frac{\sum_i \vec{r_i^p}}{|R_p|}$$

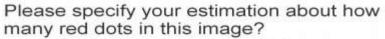


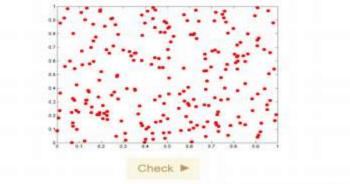
COPE – The Design

- Bayesian Updating Scheme
 - The design of COPE indicates the existence of a latent decision maker, as in the case of probabilistic risk analysis
 - Bayesian Updating is the best practice for such scenario*
 - Two principles for a normative Bayesian Updating
 - Unanimity: info-less report don't update global distribution
 - Compromise: global distribution is between the two extremes

$$p^* = \Pr(\vec{p}|\vec{r}) \propto \frac{\Pr(\vec{p})L(\vec{r}|\vec{p})}{\Pr(\vec{r})}$$

COPE – The Implementation



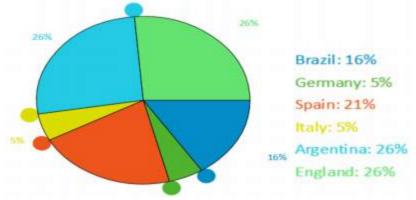


Please specify on the pie chart, which team will win the FIFA World Cup?

Note: Your reward will depend on the answers from others:

 If your answer is the same as the aggregated opinion of others, you will be granted a reward 10 times of the given reward;

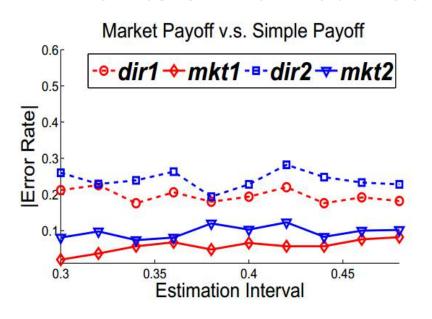
If your answer is too far from the aggregated opinion of others, you may receive no reward.

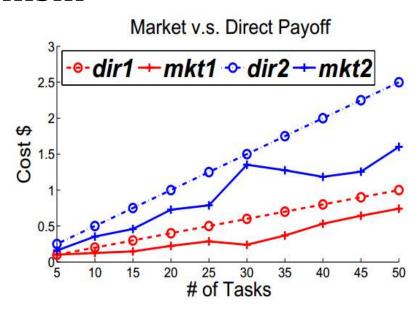


- Premarket Tasks
- Opinion Elicitation
 - Dynamic Chart
 - Kill probability-phobia
 - Unwilling or uncomfortable to give numerical probability
 - Workers are informed the payoff method
- Payoff Dispatch
 - Special "payoff tasks" are generated with workerID

COPE – The Evaluation

Merits of Market Mechanism





- task: estimate man's age according to a photo
- dir means Direct Pay, mkt means market-based payoff

Summary

- Quality Control is a difficult problem
 Because we are dealing with human and we are...
- Possible Solutions:
 - Task Design
 - Reward Design
 - Aggregation Design
 -

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