

 POLITECNICO DI MILANO

Dipartimento di  
Elettronica e Informazione

# Humans Fighting Uncertainty in Top-K Scenarios

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- Rank aggregation and rank join
- Uncertain scoring
- Representative orderings
- Reducing uncertainty through human workers

- Main idea: focus on the best query answers according to some criterion, without computing the full result
  - A.k.a. “top-k” queries
- Main applications:
  - **Combination of user preferences** expressed according to various criteria
    - Example: ranking restaurants by combining criteria about culinary preference, driving distance, stars, ...
  - **Nearest neighbor** problem (e.g., similarity search)
    - Given a database  $D$  of  $n$  points in some metric space, and a query  $q$  in the same space, find the point (or the  $k$  points) in  $D$  closest to  $q$
  - **Search computing**
    - “Where can I attend an interesting conference in my field close to a sunny beach?”
  - ...

# Ranking queries: example

```
SELECT h.neighborhood, h.hid, r.rid
FROM HotelsNY h, RestaurantsNY r
WHERE h.neighborhood = r.neighborhood
RANK BY 0.4/h.price + 0.4*r.rating + 0.2*r.hasMusic
LIMIT 5
```

*Full Join Results*

Neighborhood	Hid	Rid
West Village	H89	R585
Midtown East	H248	R197
Chelsea	H427	R572
Midtown East	H248	R346
Midtown East	H597	R197
Hell's Kitchen	H662	R223
Midtown West	H141	R276
Upper East Side	H978	R137
Harlem	H355	R49
Tribeca	H381	R938
...	...	...

*Rank Join Results*

Neighborhood	Hid	Rid
East Village	H346	R738
Gramercy	H872	R822
Midtown West	H141	R276
Hell's Kitchen	H662	R498
Upper West Side	H51	R394

[Fagin, PODS 1996]

- Rank aggregation is the problem of combining **several ranked lists** of objects in a robust way to produce a **single consensus ranking** of the objects

Candidate	Candidate	Candidate	Candidate	Candidate
1	2	4	5	3
2	4	2	1	5
3	5	5	3	1
4	1	3	4	2
5	3	1	2	4

Judge 1

Judge 2

Judge 3

Judge 4

Judge 5

- What is the overall ranking?
- Who is the best candidate?

- Metric approaches are preferred over axiomatic approaches (Arrow's impossibility theorem)
- When scores are opaque, the goal is to find a new ranking  $R$  whose **total distance** to the initial rankings  $R_1, \dots, R_n$  is **minimized**
  - For several metrics, NP-hard to solve exactly
    - E.g., the **Kendall tau distance**  $K(R_1, R_2)$ , defined as the number of exchanges in a bubble sort to convert  $R_1$  to  $R_2$
  - May admit efficient approximations (e.g., median ranking)
- When scores are visible, the consensus ranking is determined by means of an **aggregation function**

# Rank aggregation – example with scores

- Aggregation function:

$$\text{Score}(\text{cand}) = 0.30 s_1 + 0.25 s_2 + 0.20 s_3 + 0.15 s_4 + 0.10 s_5$$

Cand	s <sub>1</sub>	Cand	s <sub>2</sub>	Cand	s <sub>3</sub>	Cand	s <sub>4</sub>	Cand	s <sub>5</sub>
1	.9	2	.65	4	.99	5	.6	3	.8
2	.7	1	.6	2	.97	1	.5	1	.7
3	.5	5	.55	5	.95	3	.4	5	.65
4	.3	4	.5	3	.93	4	.3	2	.63
5	.1	3	.45	1	.91	2	.2	4	.62

Judge 1

Judge 2

Judge 3

Judge 4

Judge 5

- What is the overall ranking?
- Who is the best candidate?

# Reverse top-k queries

[Vlachou et al., ICDE 2010]

- Aggregation function:

$$\text{Score}(\text{cand}) = w_1 s_1 + w_2 s_2 + w_3 s_3 + w_4 s_4 + w_5 s_5$$

Cand	s <sub>1</sub>	Cand	s <sub>2</sub>	Cand	s <sub>3</sub>	Cand	s <sub>4</sub>	Cand	s <sub>5</sub>
1	.9	2	.65	4	.99	5	.6	3	.8
2	.7	1	.6	2	.97	1	.5	1	.7
3	.5	5	.55	5	.95	3	.4	5	.65
4	.3	4	.5	3	.93	4	.3	2	.63
5	.1	3	.45	1	.91	2	.2	4	.62

Judge 1

Judge 2

Judge 3

Judge 4

Judge 5

- What weights should I convince you to use so that my preferred candidate becomes the best?
  - (point of view of the seller/product manufacturer)



- Traditionally, two ways of accessing data:
  - **Sorted access**: access, one by one, the next element (together with its score) in a ranked list, starting from top
  - **Random access**: given an element (id), retrieve its score (position in the ranked list or other associated value)
- Minimizing the accesses when determining the top k items
  - A cost is incurred for each item read from a ranking
  - Can I improve on the current best aggregate score if I read more items?
  - **Thresholds** are used to ensure that no further item needs to be read

# Ranking in the real world

[Cali & Martinenghi, ICDE 2008] [Martinenghi & Tagliasacchi, TKDE 2012]

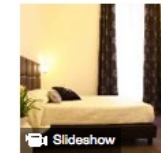
- Almost relational model, with a lot of “quirks”
  - Web interfaces with **input** and **output** fields (**access patterns**)
  - Results are typically ranked

tripAdvisor(City<sup>i</sup>, InDate<sup>i</sup>, OutDate<sup>i</sup>, Persons<sup>i</sup>, Name<sup>o</sup>, Popularity<sup>o</sup>, ranked)

- Many other needs: **joins**, dirty data, deduplication, diversification, uncertainty, incompleteness, recency, paging, access costs...

## Deko Rome

Special Offer Package Deal



Ranked #1 of 1,264 hotels in Rome

345 reviews

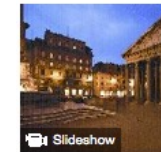
"Great atmosphere" 06/30/2013

"I only wish I could have stayed longer..." 06/30/2013

Professional photos | Traveler photos (47) | Map

## Albergo del Senato

Special Offer Package Deal



Ranked #3 of 1,264 hotels in Rome

1,688 reviews

"La Dolce Vita - WOW!" 07/02/2013

"Roman Holiday" 07/02/2013

Professional photos | Traveler photos (816) | Map

## Barocco Hotel

Offers & Announcements 10% off room rate



Ranked #5 of 1,264 hotels in Rome

1,090 reviews

"Great boutique hotel in an awesome loc..." 07/02/2013

"Wonderful Hotel in Rome" 07/02/2013

Professional photos | Traveler photos (300) | Map

Hotels ▾ Flights Vacation Rentals

Search city  
 Search hotel name

Rome, Italy

Check-in 7/9/2013

Check-out 7/10/2013

Leave dates blank

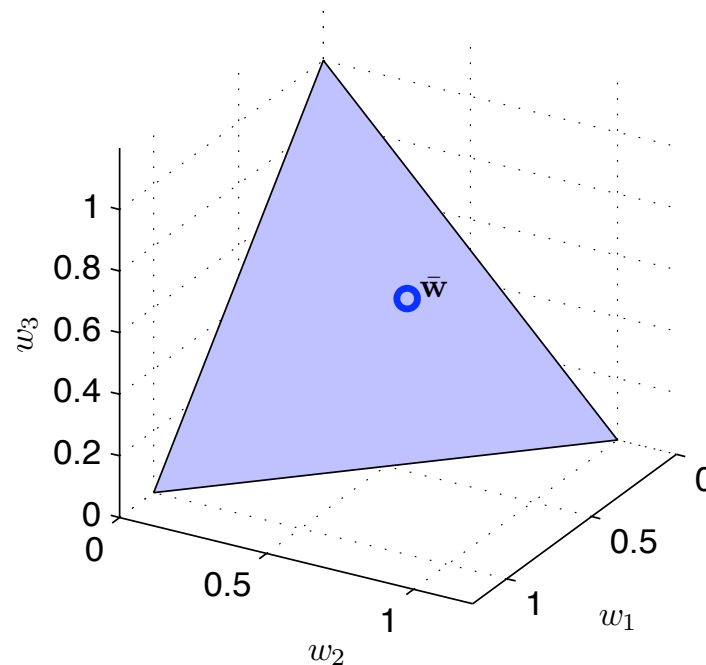
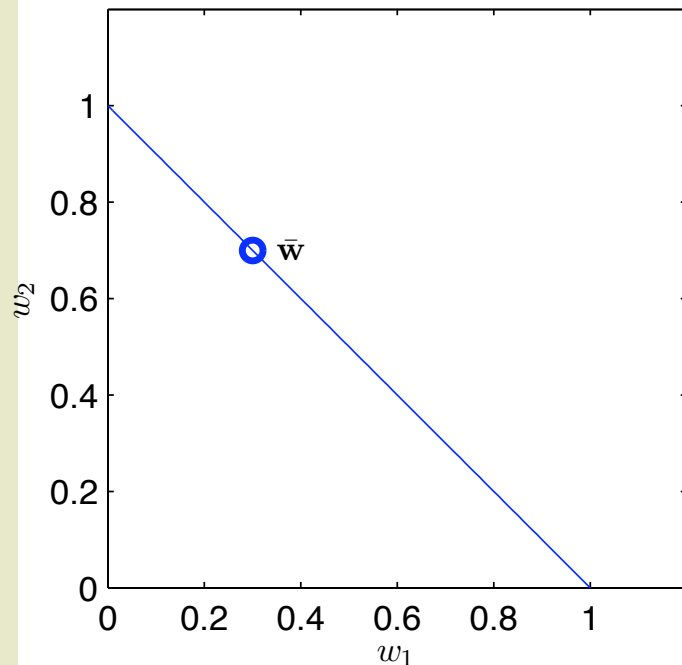
**Find Hotels**



[Soliman & Ilyas, ICDE 2009], [Soliman et al., SIGMOD 2011]

- Users are often unable to precisely specify the scoring function
- Objects may have imprecise scores, e.g., defined over intervals
  - E.g., apartment rent [\$200-\$250]
- Using trial-and-error or machine learning may be tedious and time consuming
- Even when the function is known, it is crucial to analyze the sensitivity of the computed ordering wrt. changes in the function

- Assumptions:
  - **Linear** scoring function:  $S = w_1s_1 + \dots + w_ns_n$
  - User-defined weights  $w_1, \dots, w_n$  are **uncertain**, and, w.l.o.g., **normalized** to sum up to 1
- Each point on the simplex represents a possible scoring function

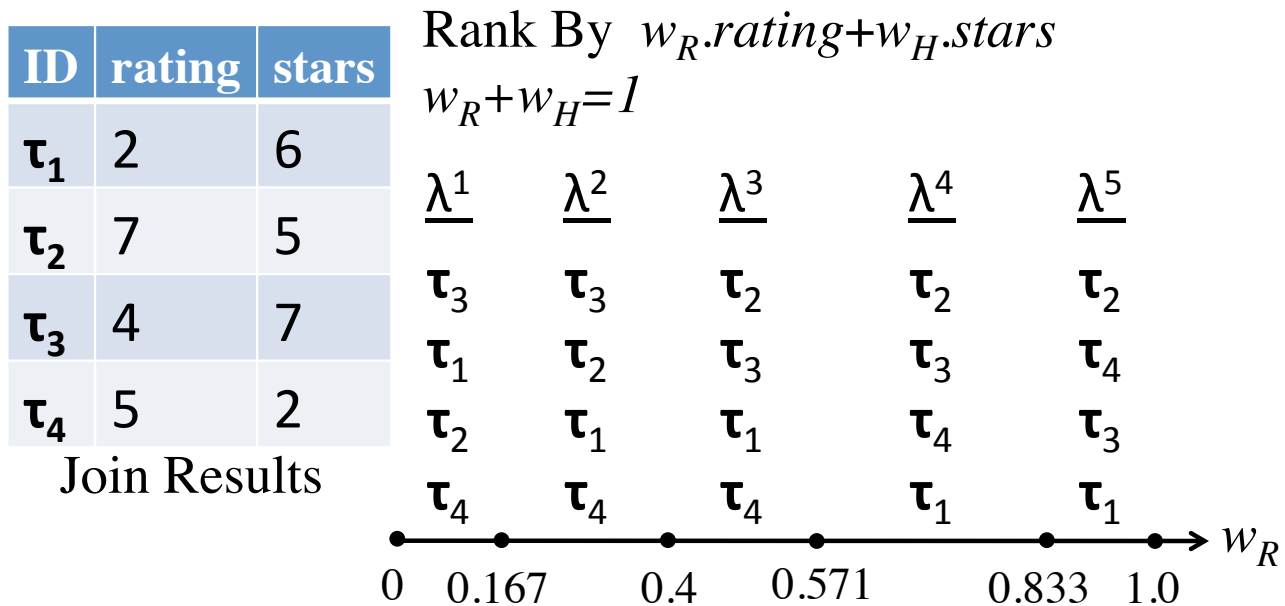


- Top-k query:

```

SELECT R.RestName, R.Street, H.HotelName
FROM RestaurantsInParis R, HotelsInParis H
WHERE distance(R.coordinates, H.coordinates) ≤ 500m
RANK BY  $w_R \cdot R.Rating + w_H \cdot H.Stars$ 
LIMIT 5
    
```

- Results and possible orderings:



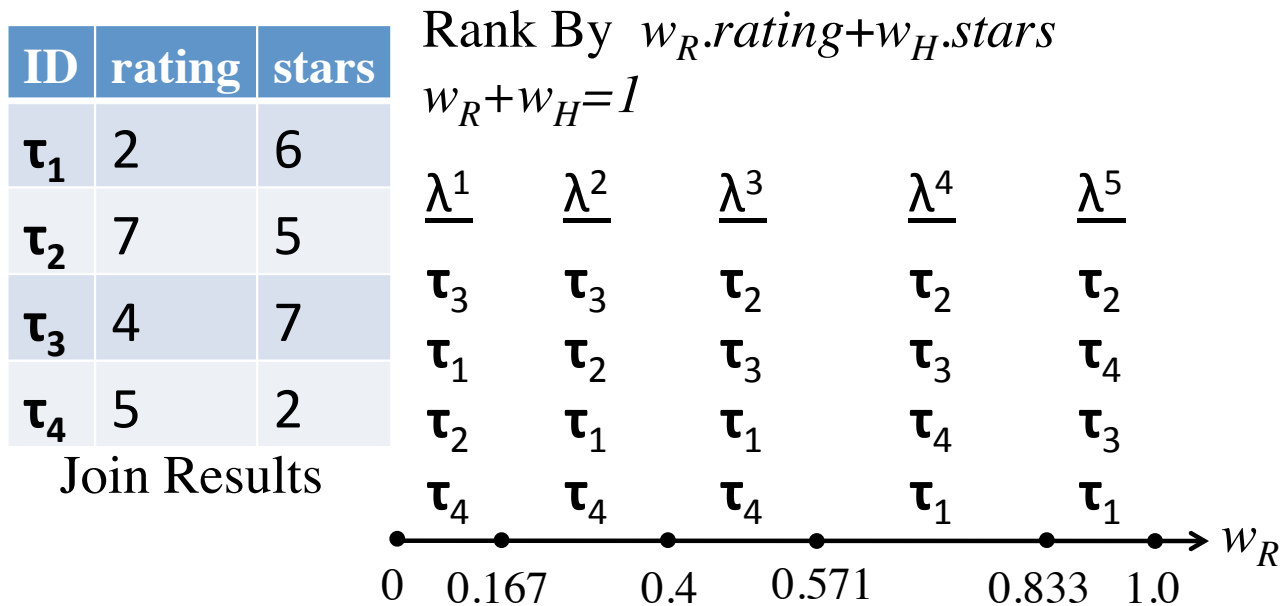
- Both value uncertainty and weight uncertainty determine **score uncertainty**
  - This induces a partial order over objects
  - we have a **space of possible** orderings
- We focus on a representative of the space
- An example is the **Most Probable Ordering**

$$\lambda_{MPO}^* = \mathit{arg.} \max_{\lambda \in \Lambda_K} p(\lambda)$$

- Other definitions of representative ordering exist, e.g., the Optimal Rank Aggregation

# Example of MPO

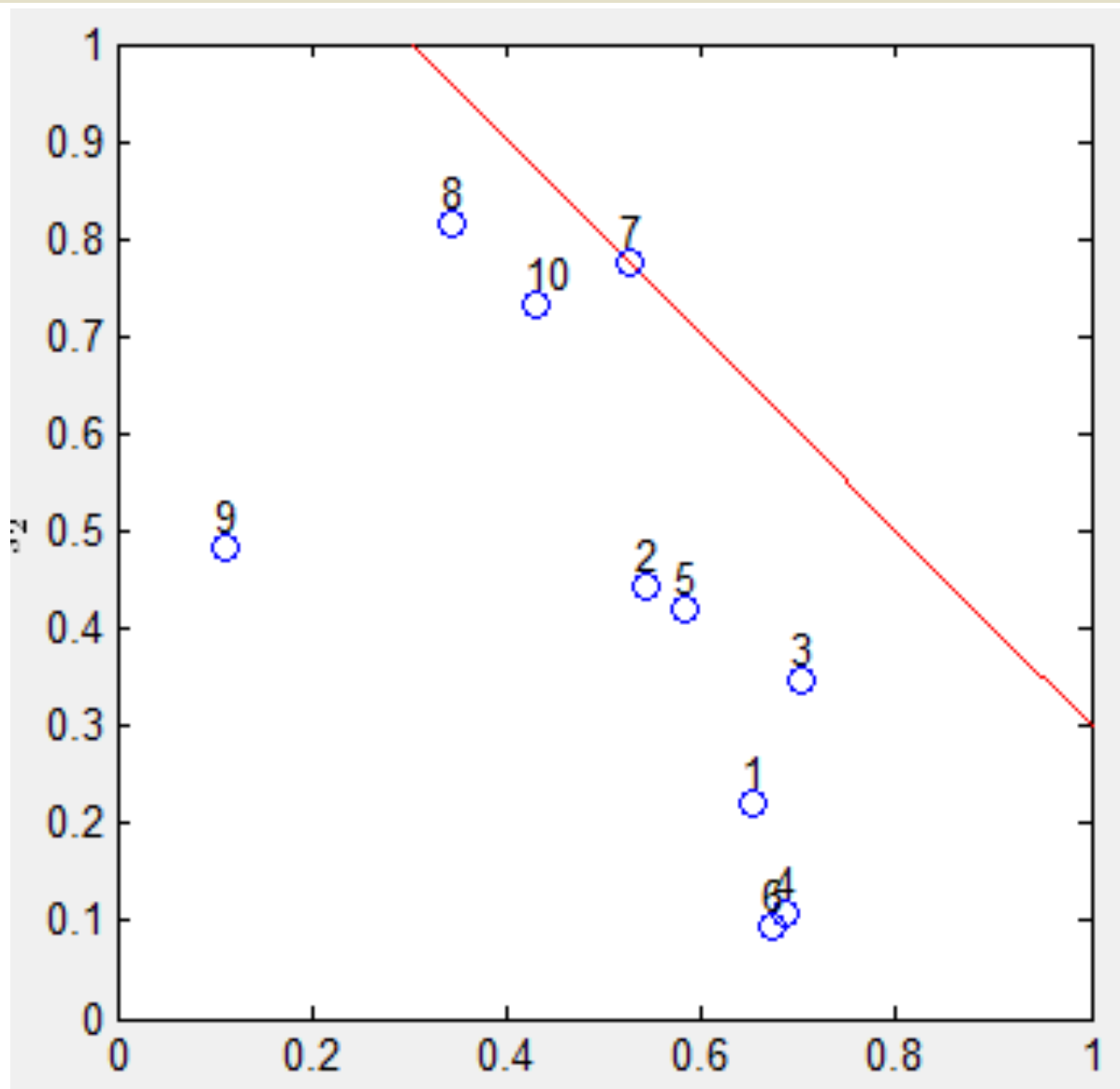
- For  $K=2$ , the MPO is  $\langle \tau_2, \tau_3 \rangle$ 
  - under the assumption of uniform probability distribution



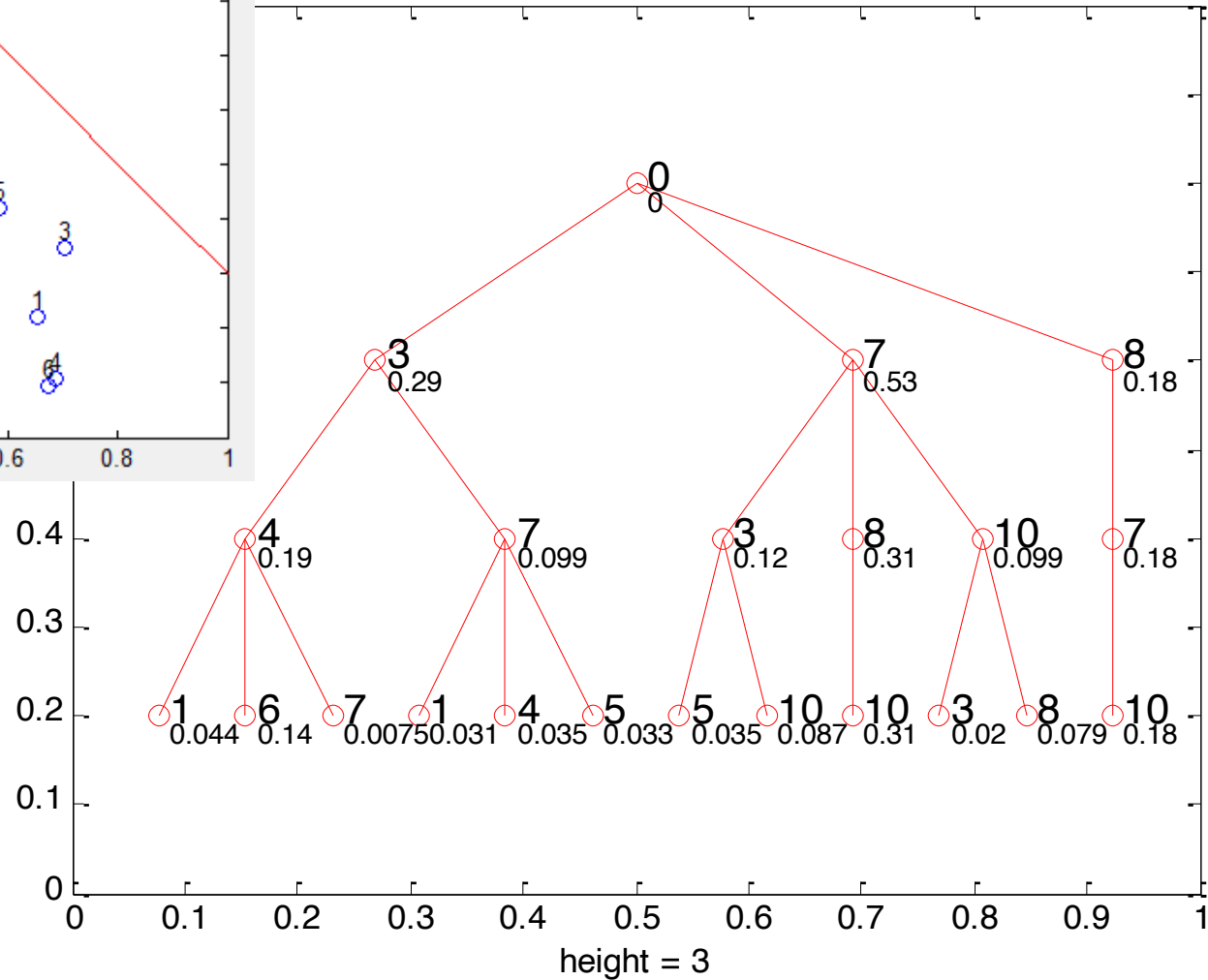
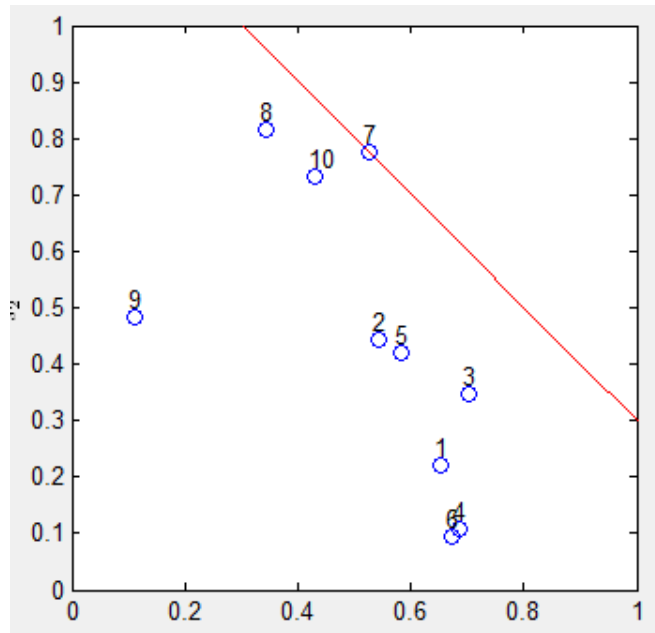
- Complex to compute:
  - exponential in the number of dimensions (weights)
  - in some cases, NP-hard already in 3D
- MPOs may fail to be truly representative:
  - often, only slightly better than the second most probable ordering
  - how stable is the ordering? would it remain the same after a slight perturbation of the weights?



# Points corresponding to join results for $d=2$



# Construction of tree of possible orderings



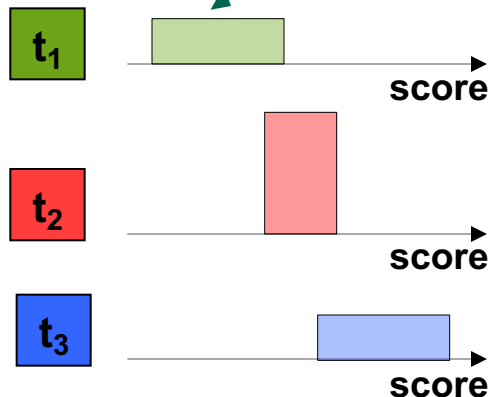
- Question answering:
  - How to use human workers to reduce the amount of uncertainty?
  - Which questions to pose?
- Task assignment:
  - Once the tasks are defined, which humans to ask?

# Uncertainty reduction via question answering

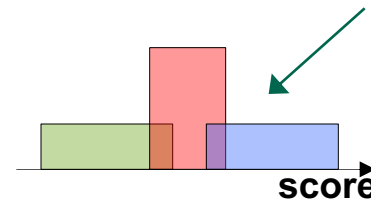
[Li & Deshpande, VLDB 2010]

- When several orderings are possible, the **space of possible orderings** compatible with the score values can be determined and represented as a tree
- Each node is associated with a probability

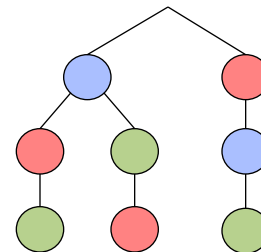
Uncertain attribute  
value: multiple  
values are  
possible



Several orderings  
are possible



Each path in the tree  
represents a possible  
ordering



# Uncertainty reduction via question answering

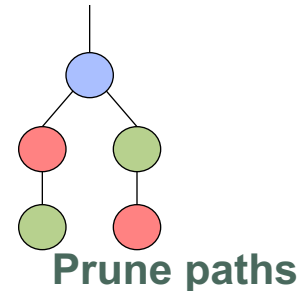
Determining the best ordering



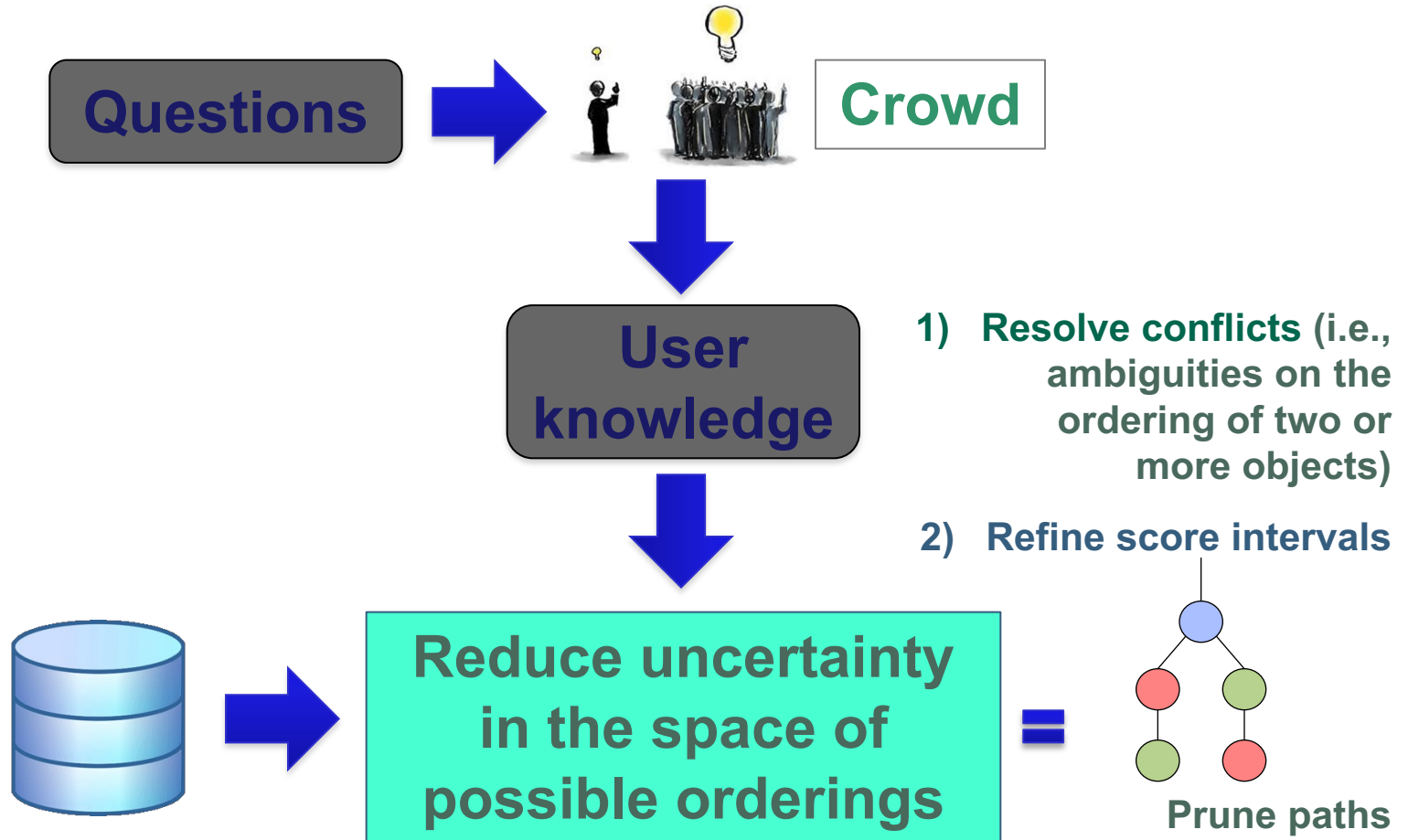
REQUIRES TO



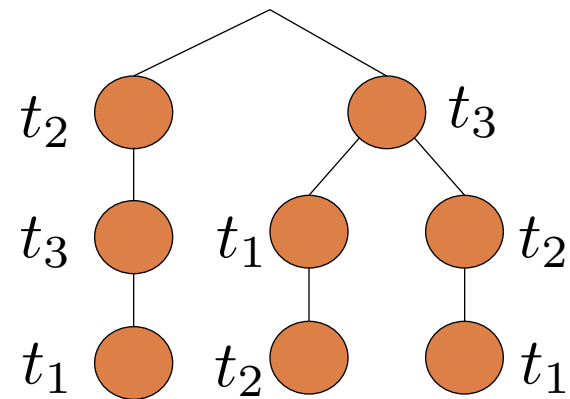
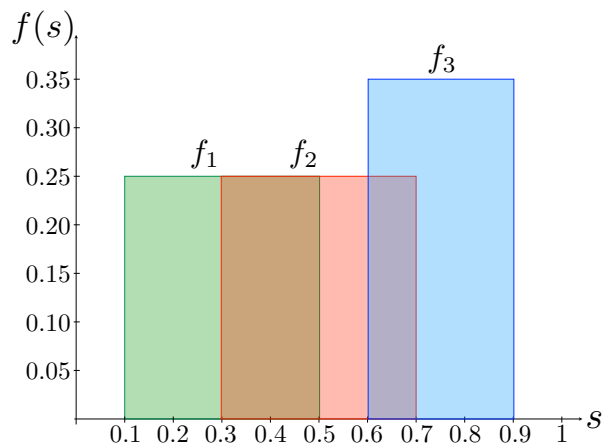
Reduce uncertainty  
in the space of  
possible orderings



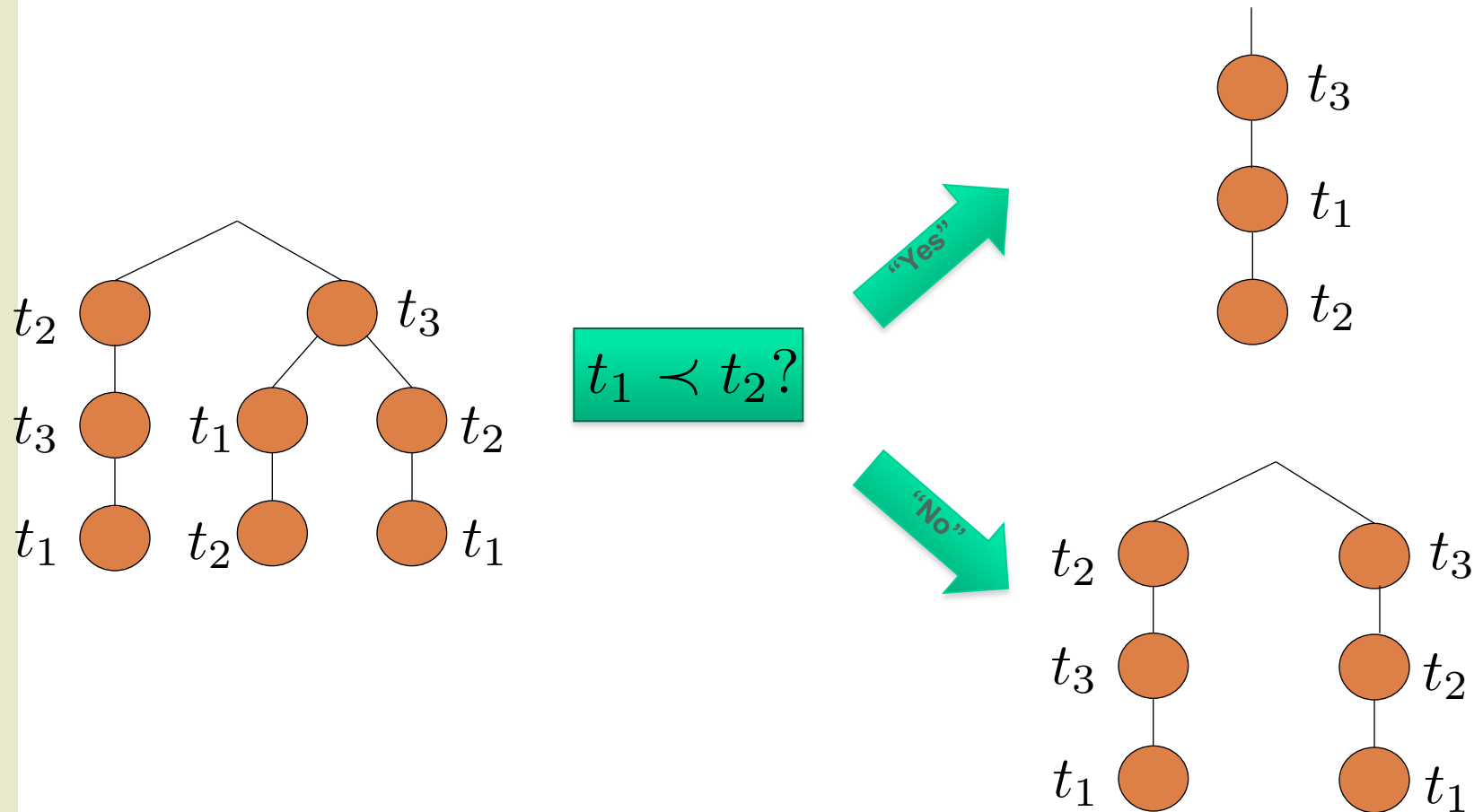
# Solution: crowdsourcing



# Showcase: tree construction



# Showcase: question answering

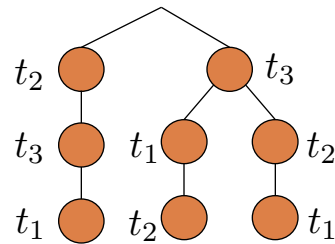




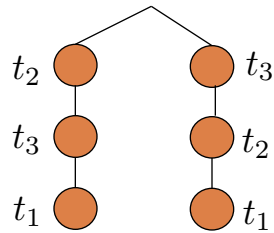
# Open issue: question types

- Questions
  - Define the **types of possible questions**
  - Define how to **measure uncertainty** in the space of possible orderings, so as to check its reduction as questions are answered
- Measuring uncertainty
  - Shannon's entropy (or some discounted version thereof)
  - Distance from a representative ordering
  - ...
- Uncertainty reduction
  - Devise the **optimal set/sequence of Q questions** that can be posed to users

# First solution: Online approach



1 Select the most promising question  $q_1$



2 Modify tree

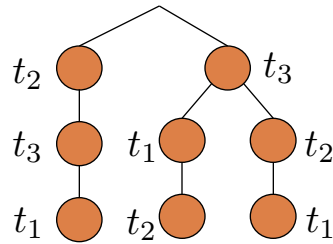
Answer

3 Select the most promising question  $q_2$  (taking into account previous tree updates)

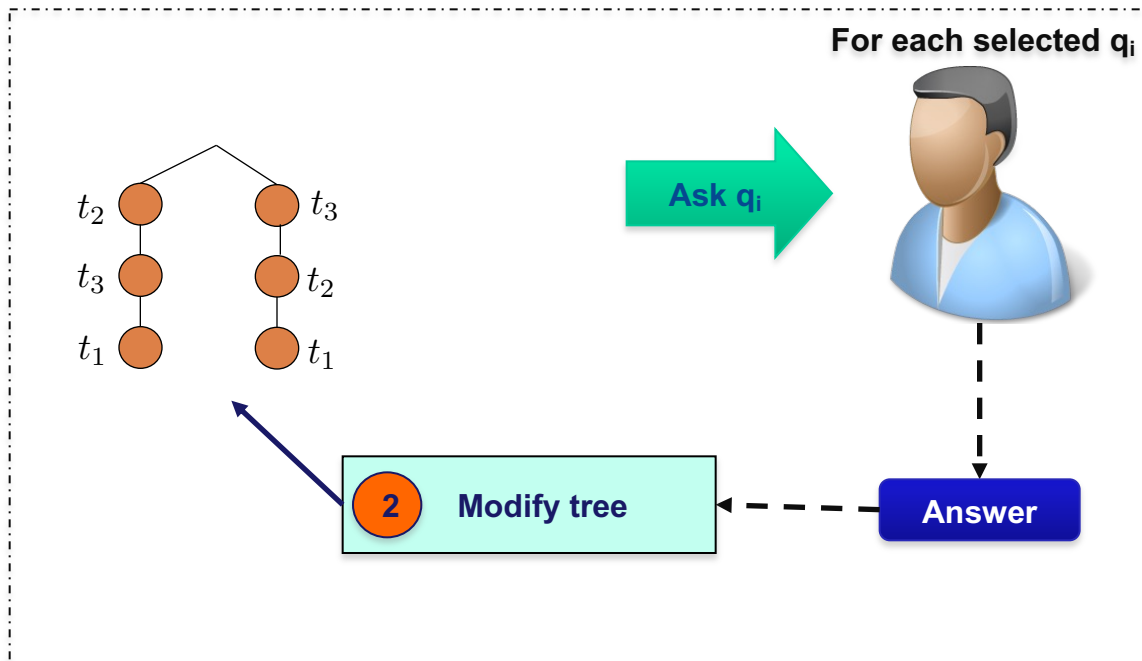


...

# Second solution: Offline approach



1 Select the  $Q$  most promising questions  $\langle q_1 \dots q_Q \rangle$



# Comparison

	Online Approach	Offline approach
PROS	Optimized with respect to the <b>actual system state</b>	<b>Fast</b> user interaction (questions are chosen before interacting with the user)
CONS	<b>Slow</b> user interaction (questions are evaluated at each step)	Questions are chosen according to the <b>initial system state</b> (+some clues about the future gains), not according to the system state at each step

## Crowdsourcing marketplaces

- **Crowdsourcing marketplaces:** Internet marketplaces that enable requesters to hire crowd workers to perform tasks



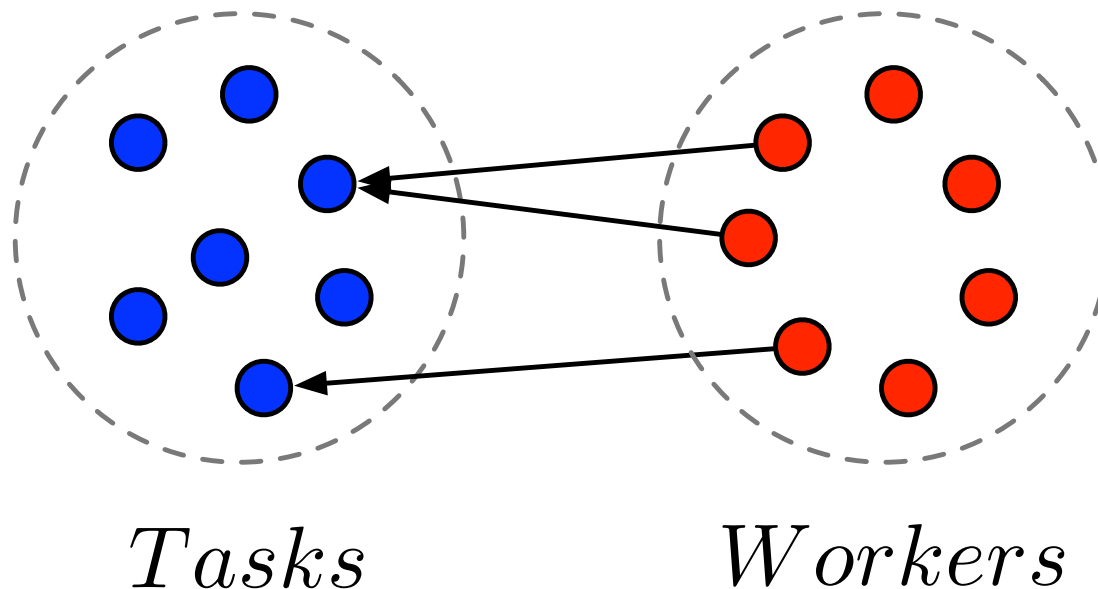
# Task assignment: Motivations

[Raykar et al., J. of Machine Learning Research 2010]

- It is often the case that a worker does not have the **appropriate knowledge** for annotating all the data, even for a particular domain
- Each worker is characterized by different parameters we should take into consideration
- Examples:
  - Expertise
  - Geocultural information
  - Past work history
- **Problem:** How to associate the most suitable task with the most appropriate worker(s)?

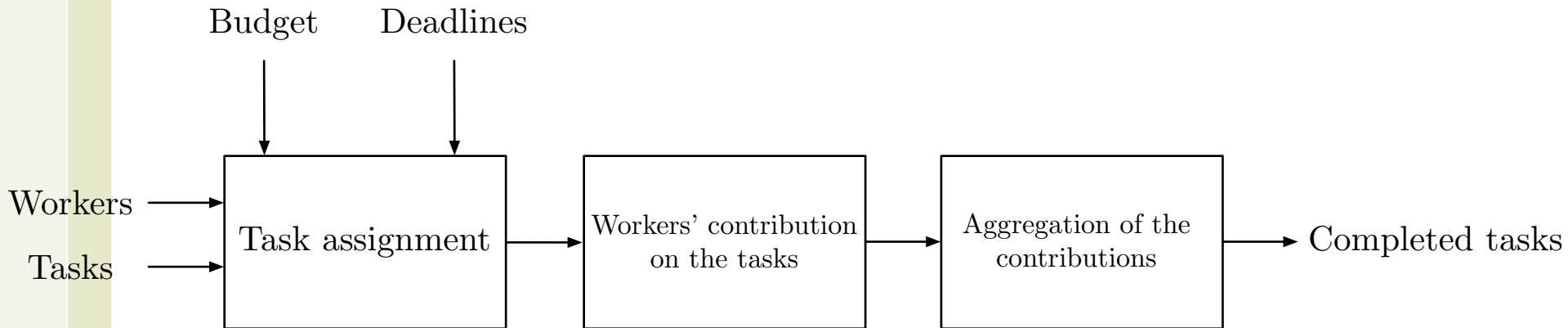
# Task assignment: Definition

- **Task assignment:** identify the best assignment configuration between workers and tasks, given an upper bound on the *number of assignments* or a *delay constraint* (i.e., *who should work on what?*)
- Expressed by means of a bipartite assignment graph
- Constrained maximization problem (maximize assignment quality over all feasible task-annotator assignments)



- Parameters of interest:
  - **Worker model:** accuracy (probability of correctly solving the task), fatigue decay, cost, correlation
  - **Task model:** uncertainty
- Optimal allocation
  - **Possible objectives:**
    - Achieving maximum quality given a target budget
    - Ensuring that tasks finish before a target deadline





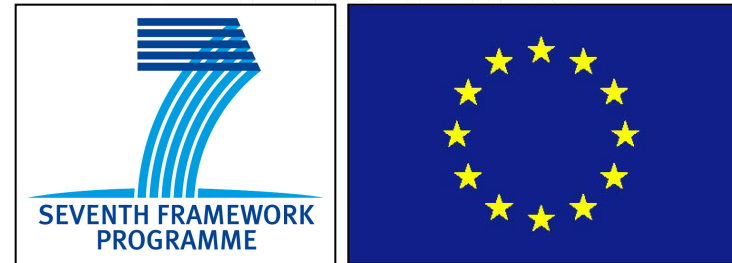
- Parameters of interest:
  - Tasks' quality and completion rate w.r.t. to workers' accuracy distributions
  - Optimal budget  $B^*$  w.r.t. expected number of workers
- Experimental assessment:
  - On publicly available data sets (e.g., UCI repository)
  - On real crowds (e.g., MicroTask)

# Acknowledgments: CUbRIK Project



- CUbRIK is a research project financed by the European Union
- **Goals:**
  - Advance the architecture of **multimedia search**
  - Exploit the **human contribution** in multimedia search
  - Use **open-source components** provided by the community
  - Start up a **search business ecosystem**

■ <http://www.cubrikproject.eu/>



# Main References

## Core contributions

- Eleonora Ciceri, Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Crowdsourcing for Top-K Query Processing over Uncertain Data. *IEEE Trans. Knowl. Data Eng.* 28(1): 41-53 (2016)
- Eleonora Ciceri, Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Humans Fighting Uncertainty: Crowdsourcing for Top-K Query Processing. *SEBD 2016*: 78-85
- Ilio Catallo, Eleonora Ciceri, Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Top-k diversity queries over bounded regions. *ACM Trans. Database Syst.* 38(2): 10 (2013)
- Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Top-k bounded diversification. *SIGMOD Conference 2012*: 421-432
- Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Efficient Diversification of Top-k Queries over Bounded Regions. *SEBD 2012*: 139-146

## Crowdsourcing applications

- Carlo Bernaschina, Ilio Catallo, Piero Fraternali, Davide Martinenghi: On the Role of Task Design in Crowdsourcing Campaigns. *HCOMP 2015*: 4-5
- Eleonora Ciceri, Ilio Catallo, Davide Martinenghi, Piero Fraternali: When Food Matters: Identifying Food-related Events on Twitter. *KDWeb 2015*: 65-76
- Carlo Bernaschina, Ilio Catallo, Piero Fraternali, Davide Martinenghi, Marco Tagliasacchi: Champagne: A Web Tool for the Execution of Crowdsourcing Campaigns. *WWW (Companion Volume) 2015*: 171-174
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# Main References

## More crowdsourcing applications

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A Draw-and-Guess Game to Segment Images. SocialCom/PASSAT 2012: 914-917
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The CUBRIK project: human-enhanced time-aware multimedia search. WWW (Companion Volume) 2012:  
259-262