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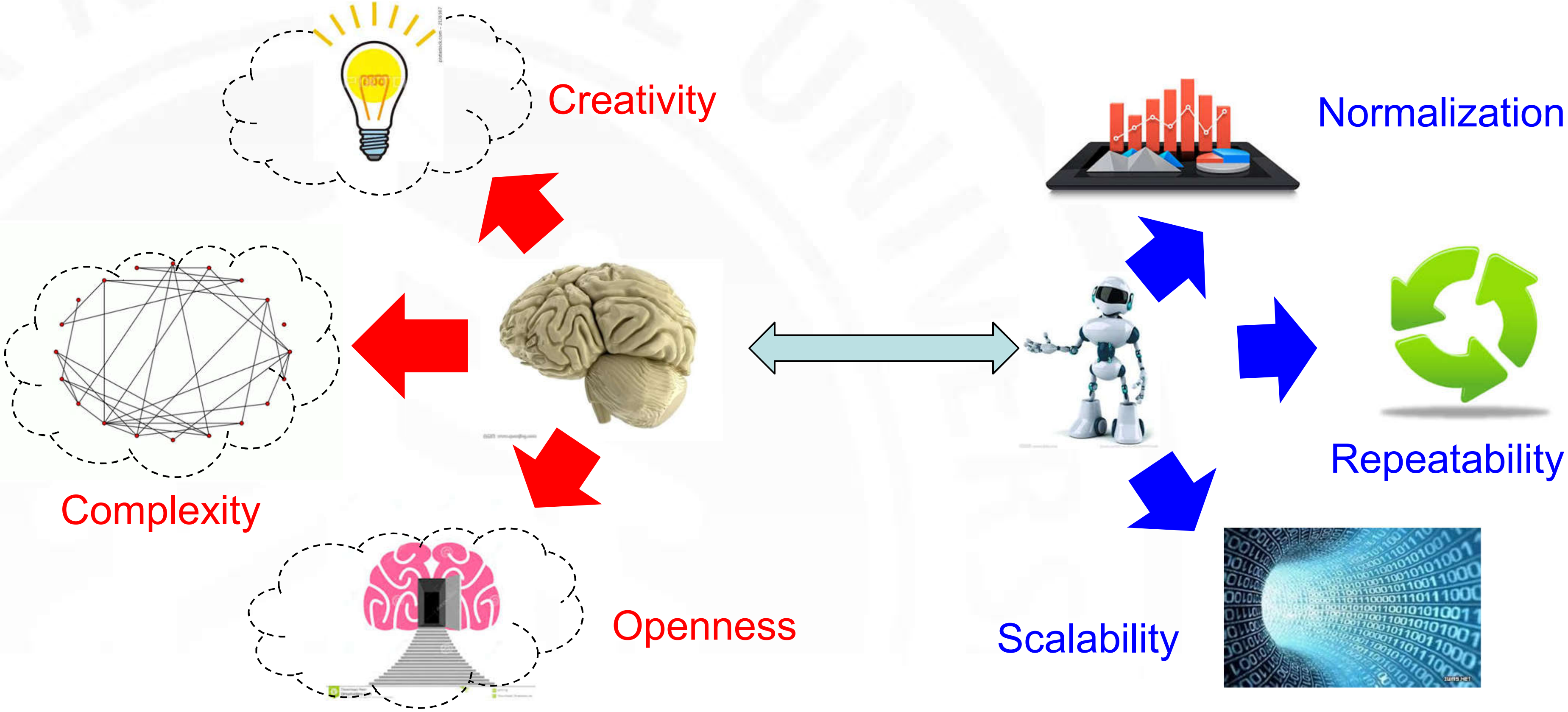
KG Refinement by Knowledge Intensive Crowdsourcing

Xin Lin
CS@Ecnu
xlin@cs.encu.edu.cn

KG Refinement

- Imperfect Data-driven KG Construction
  - Accuracy is not high enough
  - Recall is not high enough
- KG Refinement
  - Auto reasoning
  - Conflict resolution
  - Crowdsourcing

Human Brain and AI



- Human brains may help AI

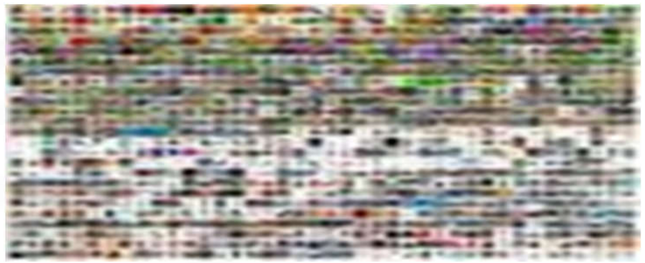
Knowledge-Intensive Crowdsourcing (KIC)

- A branch of crowdsourcing
- To achieve some knowledge-intensive task
- To bridge the gap between AI and human brain

Knowledge-Intensive Crowdsourcing

- Successful applications

CAPTCHAs



ImageNet Labeling

amazon
mechanical turk beta

Amazon MTurk

WIKIPEDIA

Issues on KIC

- What
  - to crowdsource?
- Whom
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- How
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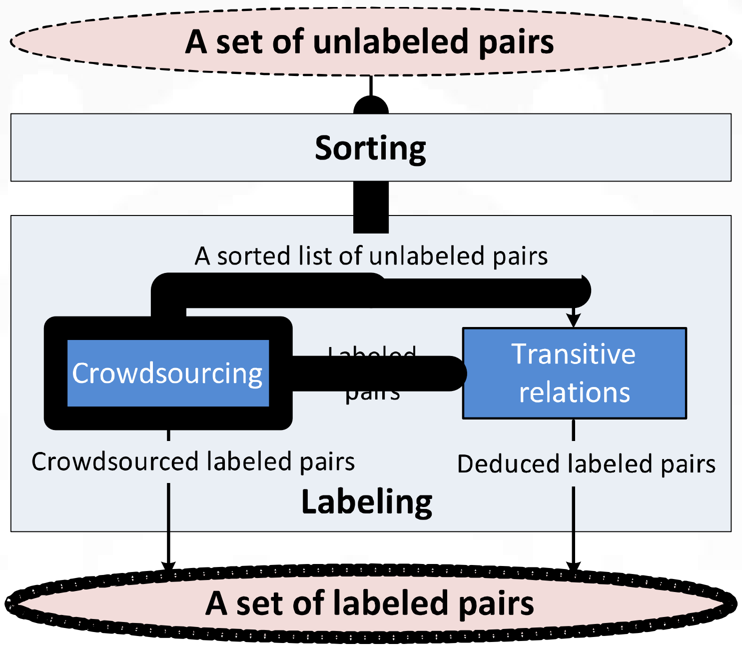
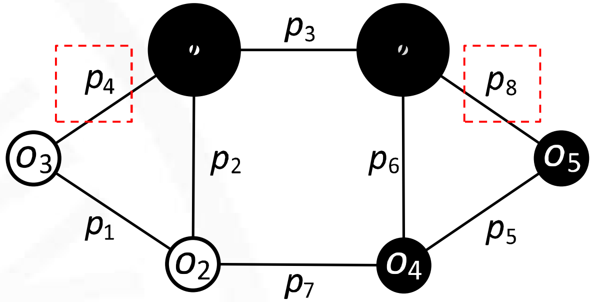
  - to incentivize worker?
  - to control quality?
  - to utilize the crowdsourcing result

What

- Task selection
  - To save monetary and time cost
  - Select the most important task
  - Select the task the human is good at but the computer is not
- Existing work
  - Entity resolution[SIGMOD13] [ICDE15]
  - Schema matching[VLDB13]

Entity Resolution [SIGMOD13]

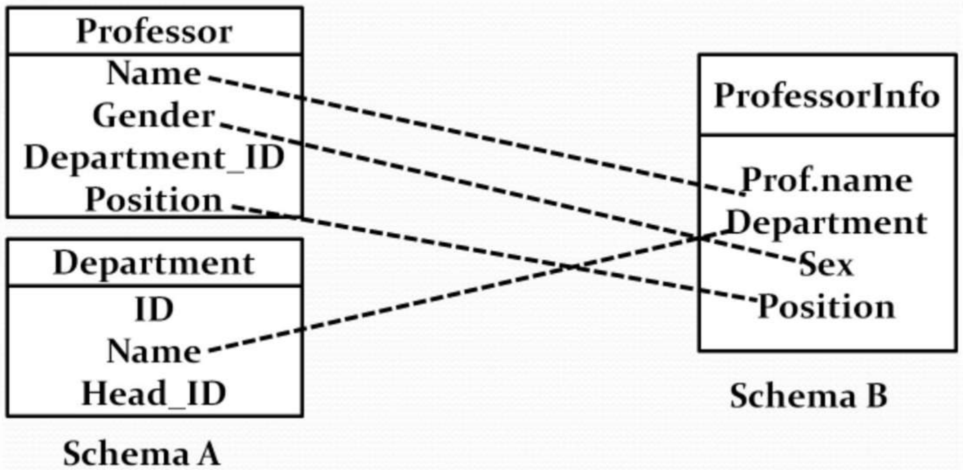




ID	Object
o_1	iPhone 2nd Gen
o_2	iPhone Two
o_3	iPhone 2
o_4	iPad Two
o_5	iPad 2
o_6	iPad 3rd Gen

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

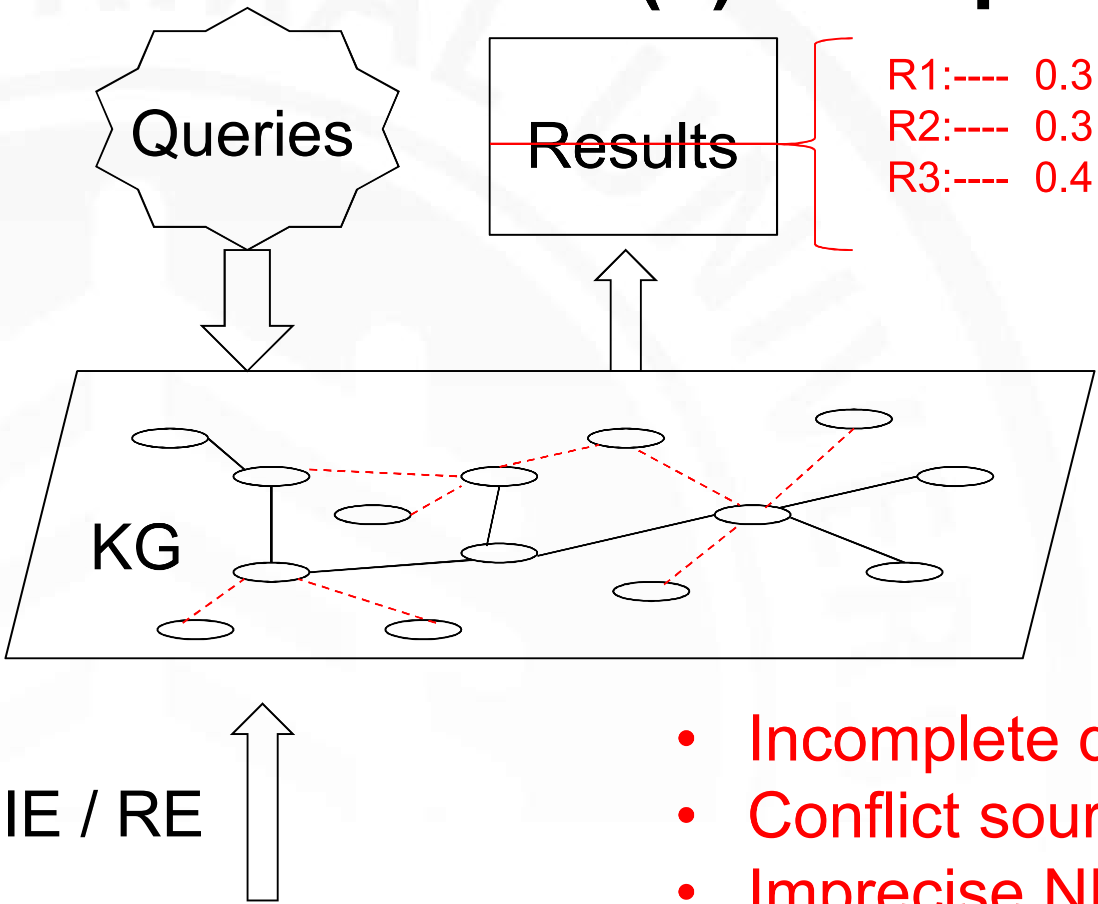
Schema Matching [VLDB13]



Correspondence	probability
c_1=<(Professor)Name,Prof.name>	.75
c_2=<Position, Position>	.7
c_3=<Gender,Sex >	1
c_4=<(Department) Name, Department>	.75
c_5=<(Department)Name,Prof.name>	.25

Possible Matchings	probability
m_1={ <(Professor)Name,Prof.name>, <Position, Position>, <Gender,Sex>, <(Department) Name, Department>}	.45
m_2={ <(Professor)Name,Prof.name>, <Gender, Sex>, <(Department) Name, Department>}	.3
m_3={ ((Department)Name,Prof.name), (Position, Position) (Gender,Sex) }	.25

What——Our work (1)：Graph Cleaning



R1:---- 0.3
R2:---- 0.3
R3:---- 0.4

Ambiguous

Could we make the results less ambiguous?

Open IE / RE

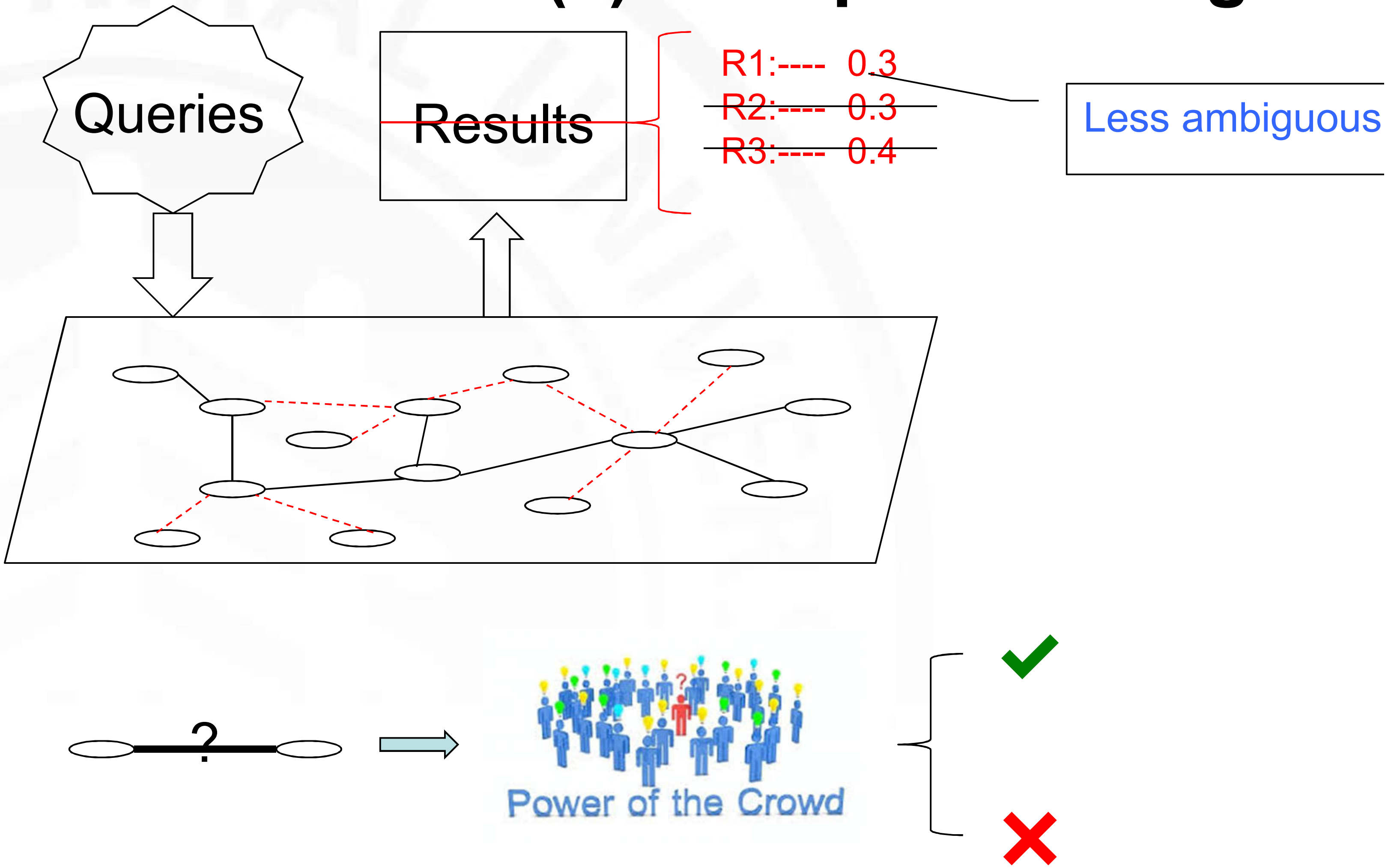
Internet Documents

- Incomplete docs
- Conflict sources
- Imprecise NLP

------------ Uncertain Relationship

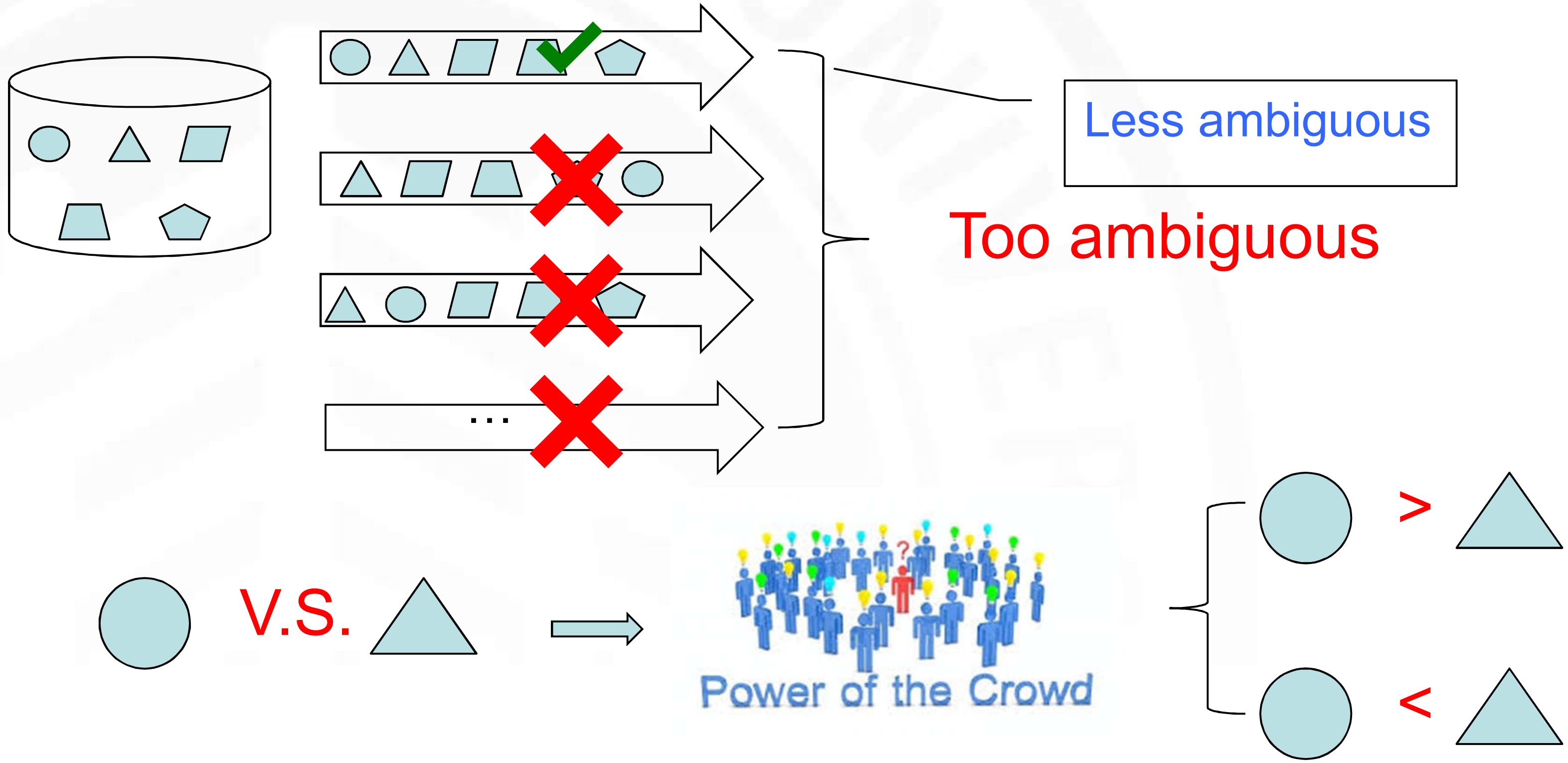
X.Lin, et.al, *Human-Powered Data Cleaning for Probabilistic Reachability Queries on Uncertain Graphs*, TKDE, 2017.

What——Our work (1): Graph Cleaning



X.Lin, et.al, *Human-Powered Data Cleaning for Probabilistic Reachability Queries on Uncertain Graphs*, TKDE, 2017.

What——Our work(2) : Pairwise Top-k cleaning



X.Lin, et.al, *Reducing Uncertainty of Probabilistic Top-k Ranking via Pairwise Crowdsourcing*, TKDE, 2017.

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Summaries of issue "what"

- Local refinement will promote the global quality
- Quantifying the influence is the key issue
- Task independent

Issues on KIC

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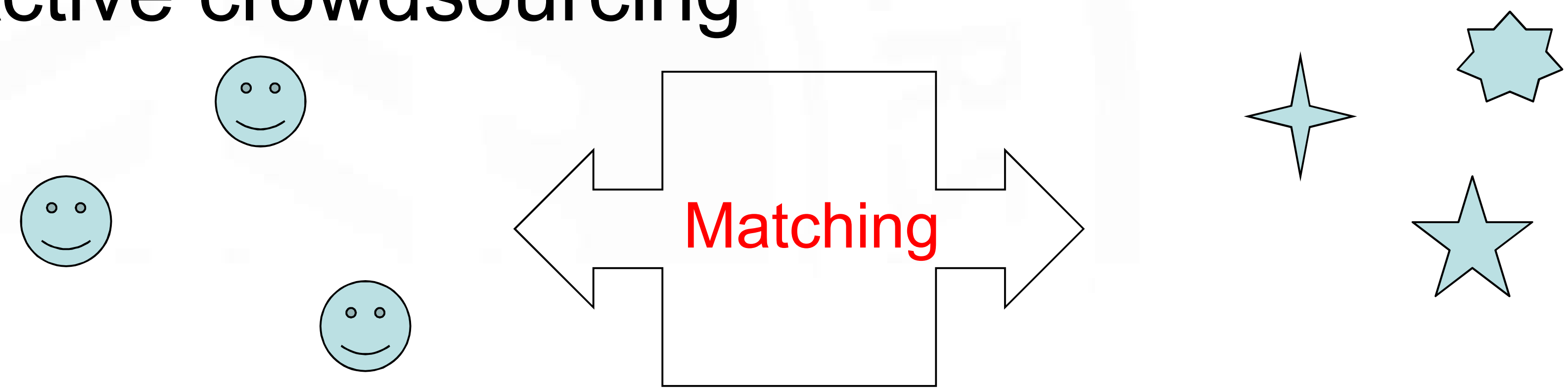
Whom

- Passive crowdsourcing
  - All tasks are *picked up* by the workers
  - Workers are qualified by some golden tasks.
- Active crowdsourcing



User Modeling

Task Modeling

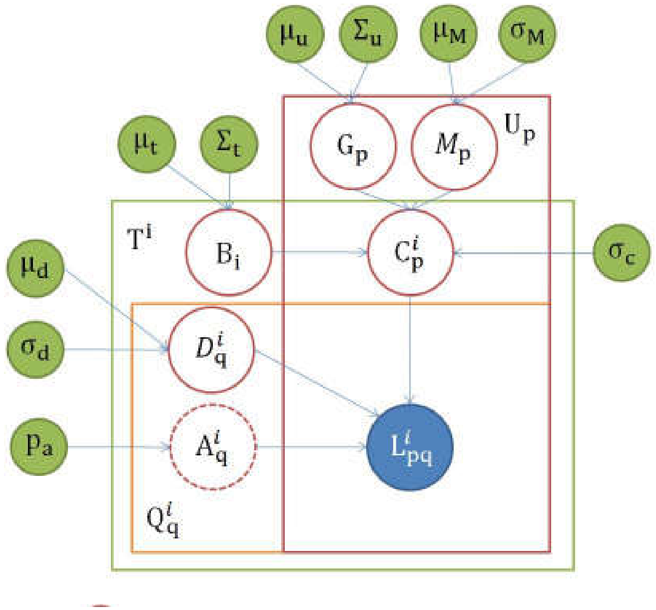
Whom: Active crowdsourcing

- User Modeling
  - Task-history-based modeling
  - Cold start problem
    - Golden task
    - Transfer learning [KDD13b]
- Matching
  - Keyword based
  - Tree based [WWW 16]
  - Vector based [VLDB 16]

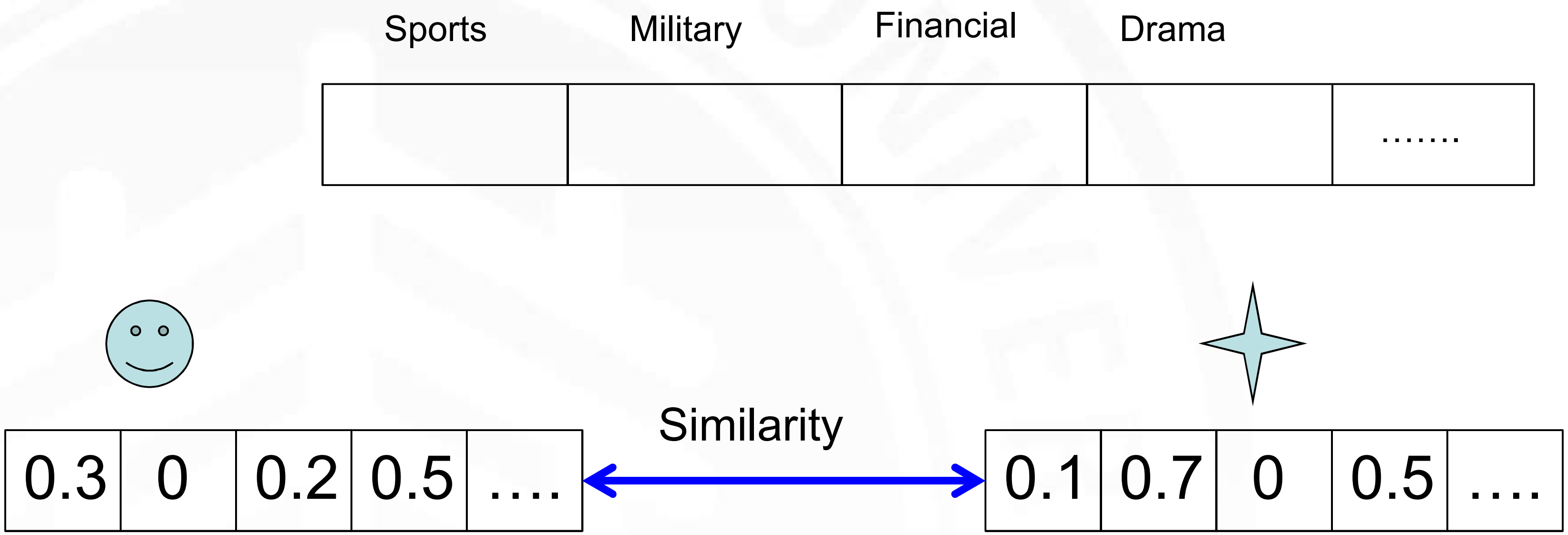
Whom: Active crowdsourcing

- **Task Assignment**
  - Randomly selected
  - Consider other factors (time, worker's quality,etc)
    - Assign the k most uncertain tasks[ICDE 12]
    - Choose the k highest quality workers[SIGMOD 15a]
    - Choose the highest improvement in quality [SIGMOD 15a]
    - …

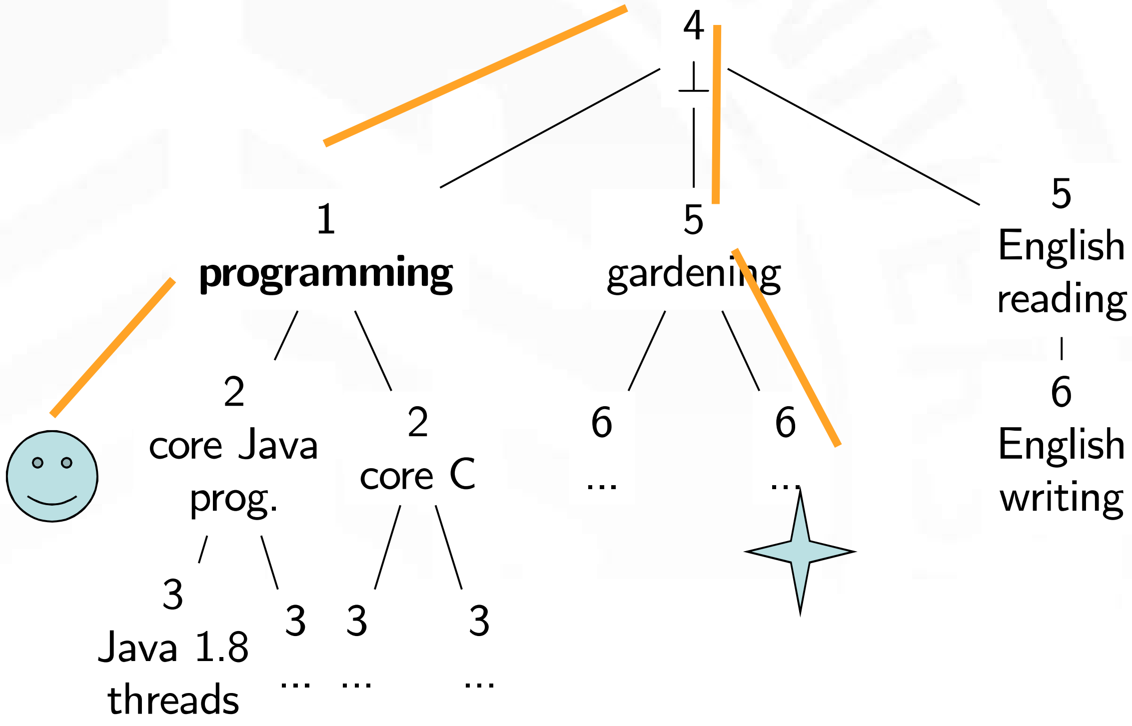
Transfer Learning in Worker Modeling [KDD2013]



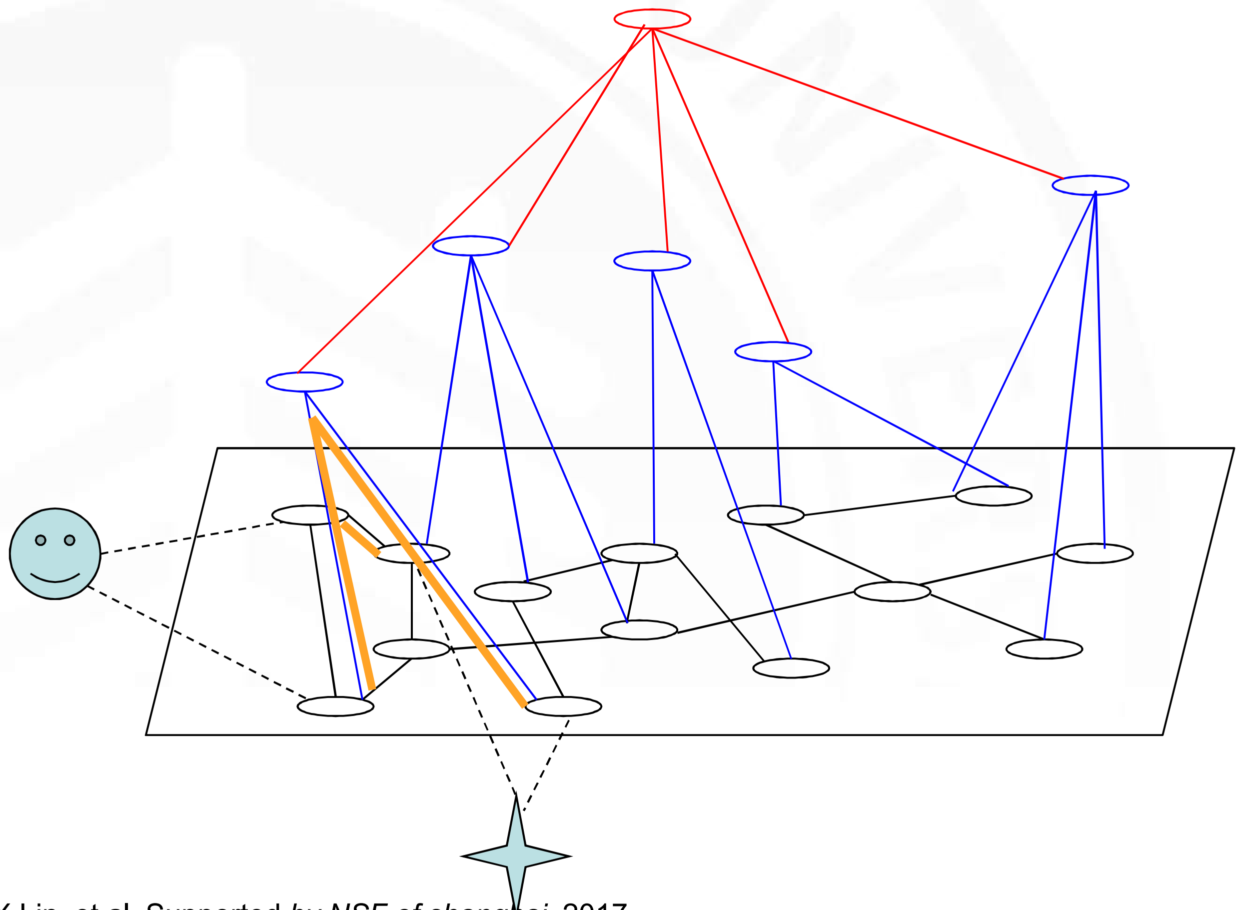
Domain-based matching [VLDB2016]



Tree-based matching [WWW16]



Whom—Our work: Graph+Tree-based



X.Lin, et.al, Supported *by NSF of shanghai*, 2017.

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How to devise question?

- Explicit crowdsourcing
- Implicit crowdsourcing

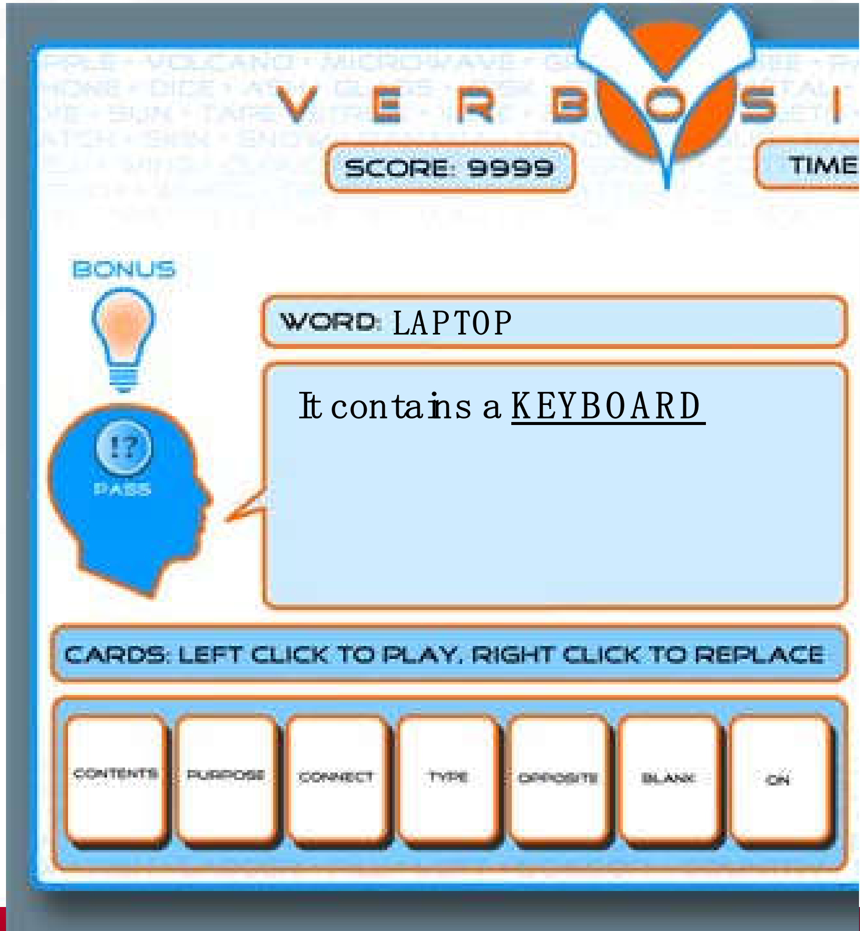
Devise questions

- Explicit crowdsourcing
  - Traditional guidelines:
    - 1. Small piece of task is preferred
    - 2. Yes-or-No > Choice >Blank filling
    - 3. Less cooperation is preferred
    - 4. Good UI is preferred
  - New research points:
    - Should tradeoff the cost and accuracy
      - Mix multi-choice and Yes-or-no [SIGMOD 17]
    - Should devise the workflow of Crowdsourcing

Devise questions

- Implicit crowdsourcing
  - **Gamification**
    - Common sense knowledge acquisition[CHI06]
    - Spatial Positions[AIIDE 14]
  - **Collecting Secretly**
    - CAPTCHAS
    - Auto Image Annotation [MTA 14]
    - Visual Focus [TMM14]
  - **Make Use of Psychological Characteristic**
    - Curiosity[CHI16]
    - Micro-diversions[CSCW 15]

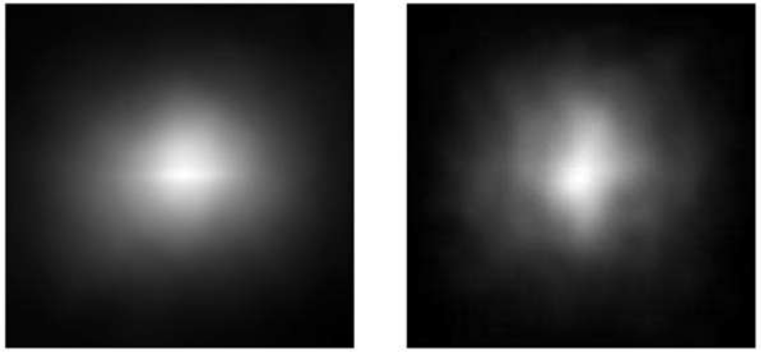
Common knowledge acquisition



Templates:

- ___ is a kind of ___.
- ___ is used for ___.
- ___ is typically near/in/on ___ .
- ___ is the opposite of ___ / ___ is related to ___ .

Touch Saliency & Visual Focus



Touch Visual

Heat Map Touch

Heat Map Visual

Implicit crowdsourcing

- Guidance of implicit crowdsourcing
  - Provide the task unconsciously
  - Workers are Users
  - First purpose should match user's demands, while second purpose should match the crowdsourced task.
  - First purpose is always the most important.
  - Motivate the crowds with Curiosity

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Taxonomy of incentives

- Incentives of crowdsourcing
  - Reputation
    - Rewards
    - Penalty
  - Joy
    - Game
  - Financial Rewards
  - Social Influence

Taxonomy of incentives

- Financial rewards
  - Static rewards
  - Dynamic rewards
  - Conditional rewards
    - Competition
    - By accuracy
    - By agreement

Taxonomy of incentives

Social Influence

Strong connection

Weak connection

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Our works

- 1. Weak connection performance better than strong connection for short-term tasks
- 2. Hybrid incentive in different phrases

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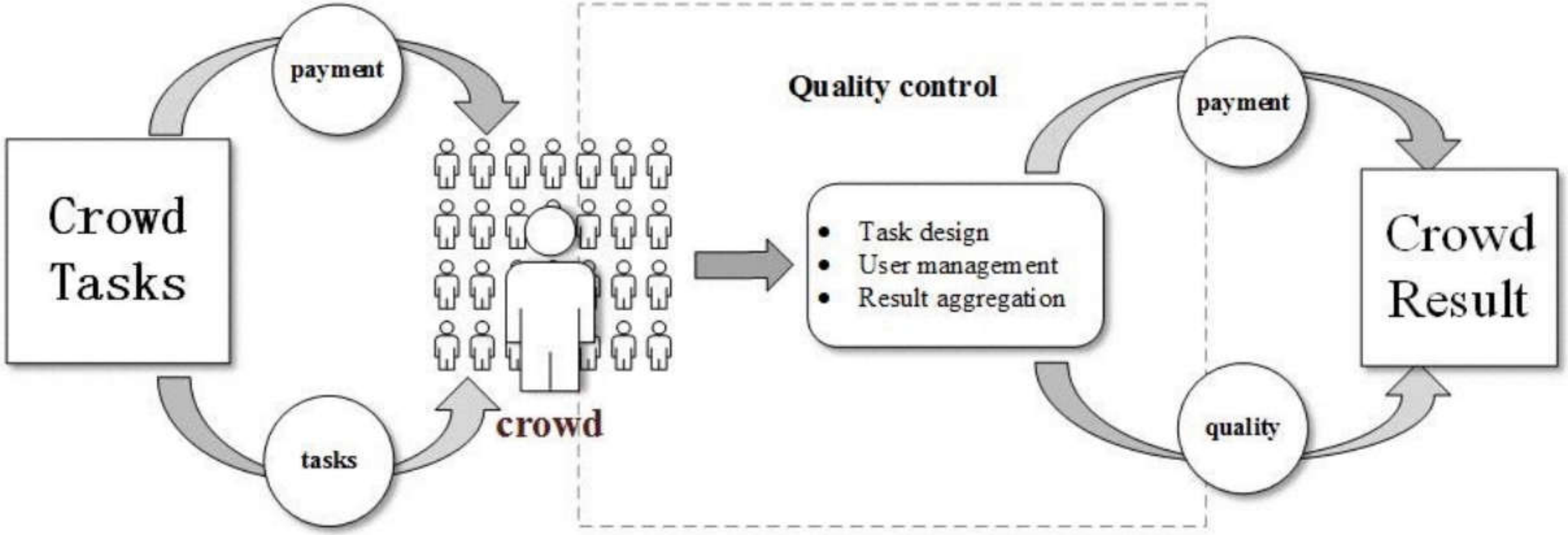
Quality Control

Overview



- Task Design
- Worker Organization Model
- Result aggregation

Quality Control

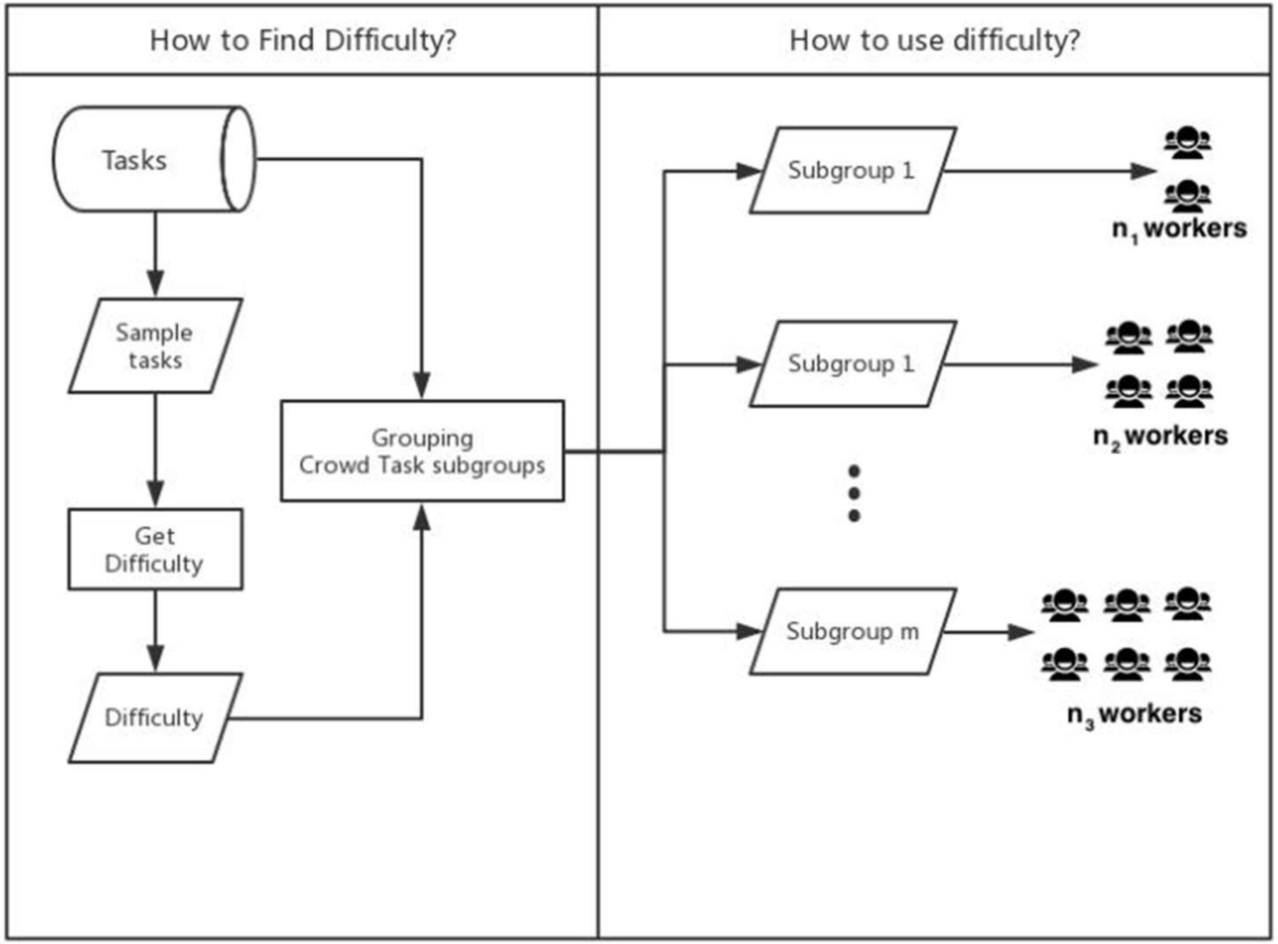
- Task design
  - Anti-malicious strategy [CHI15]
  - Add feedback mechanism[CSCW14]
- User management
  - Similar to the company management model

Quality Control

- Result Aggregation
  - Golden standard datasets
    - Dynamically insert golden tasks
    - Using golden tasks to test users
  - Redundancy-based strategy
    - Basic Majority Voting
    - Weighted Voting
  - Two-Stage strategy [KDD13a]

Our Work

- Difficulty-based task assignment [Group 2018]



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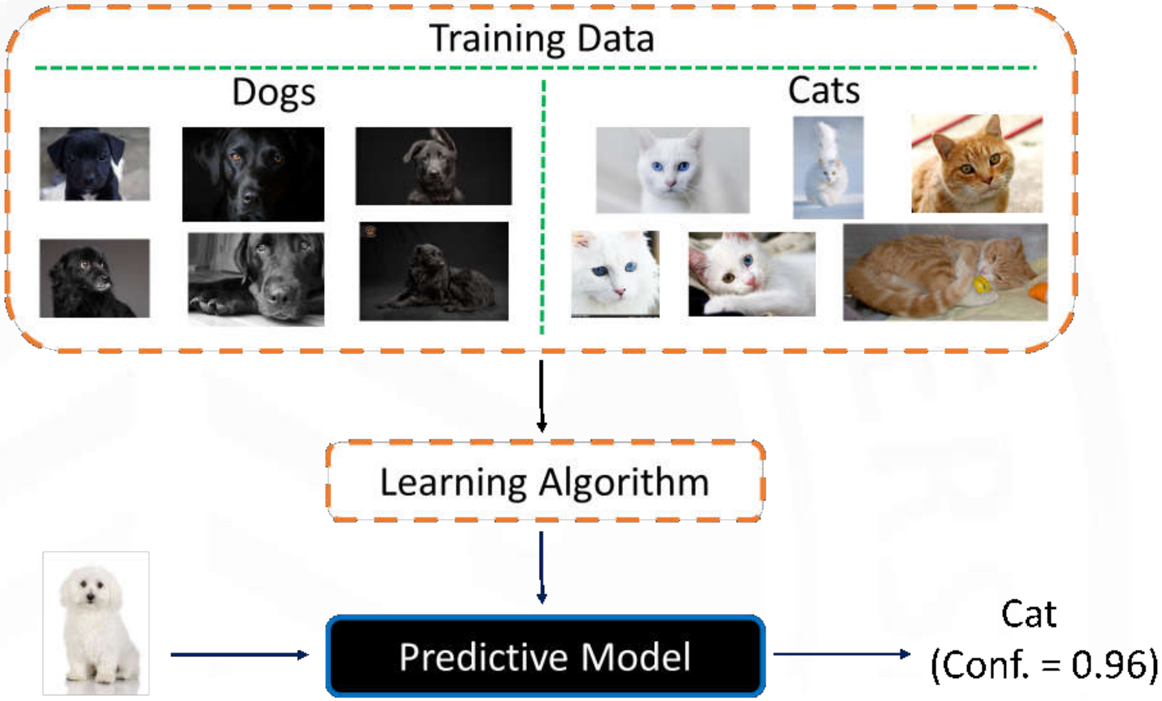
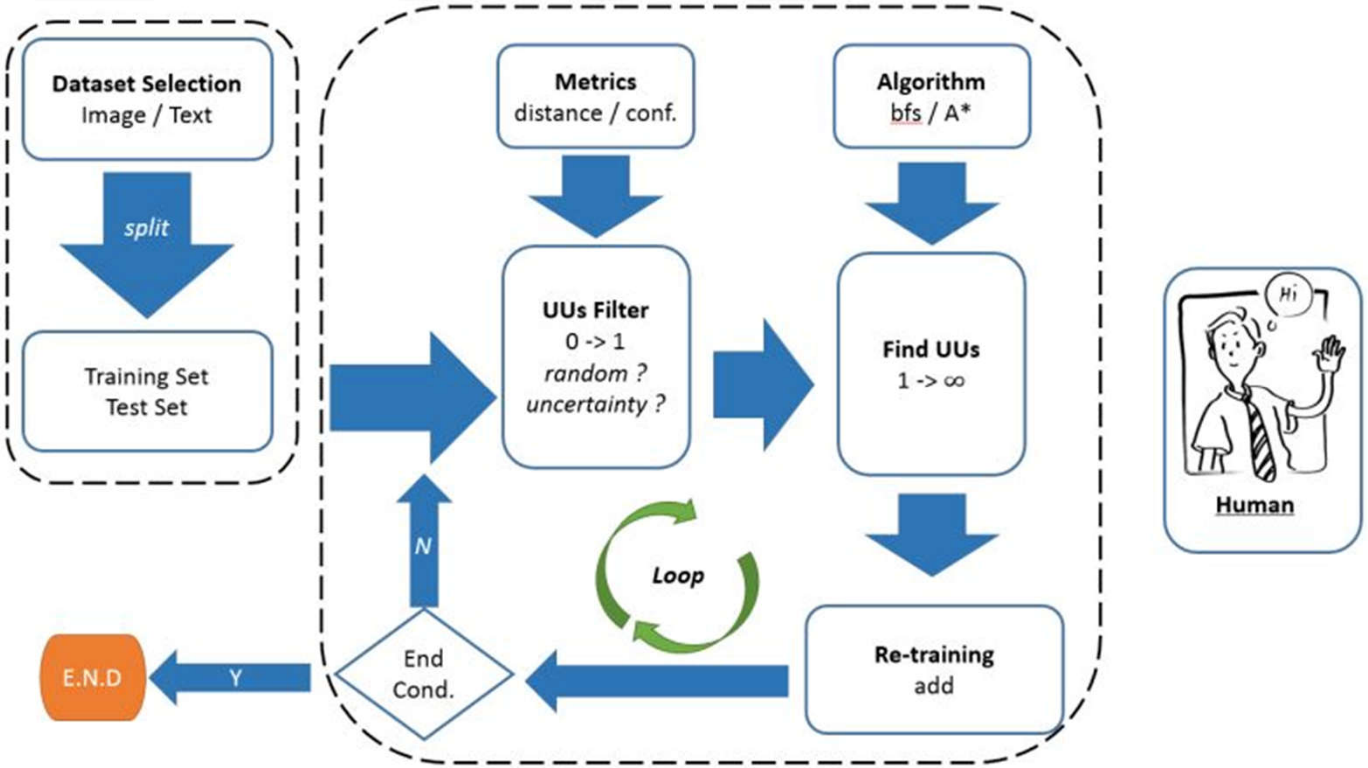
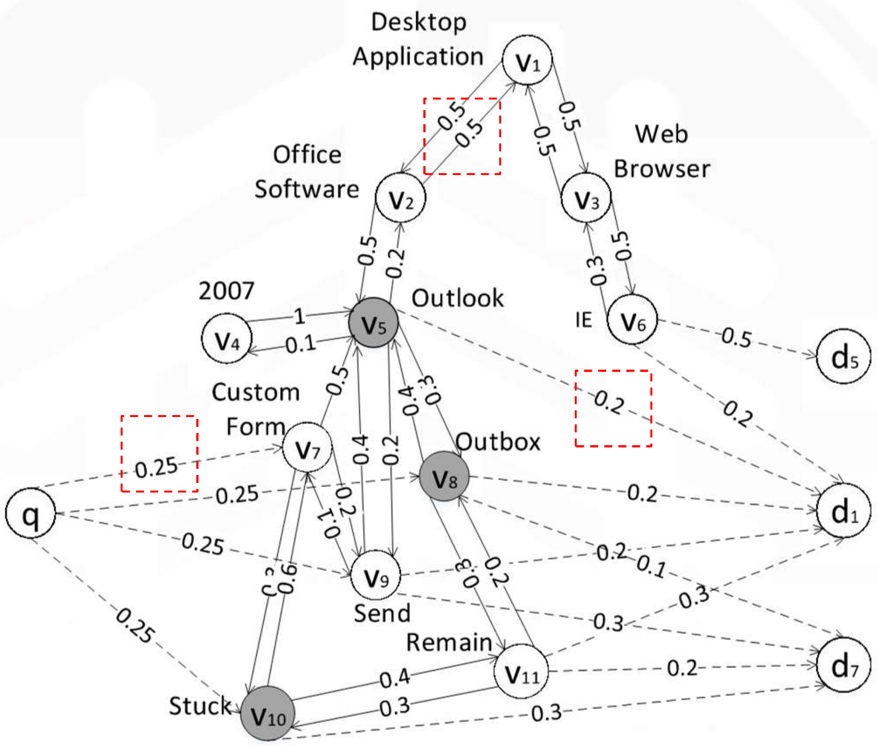
Our work (1): Finding unknown unknowns

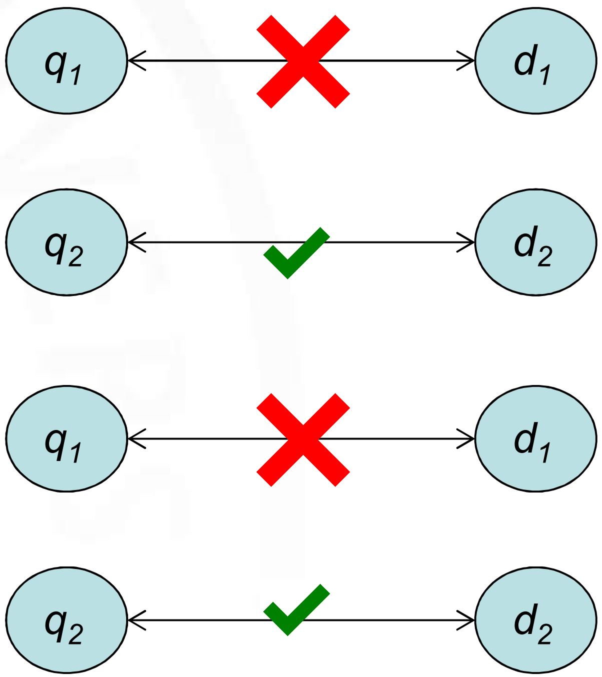


Our work (1): Finding unknown unknowns



Our work : Crafting KG via QA FeedBacks





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Thank you!

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