2017 14th IEEE International Conference on Sensing, Communication and Networking(SECON)

Incentivizing the Biased Requesters: Truthful Task Assignment Mechanisms in Crowdsourcing

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Crowdsourcing with Biased Requesters

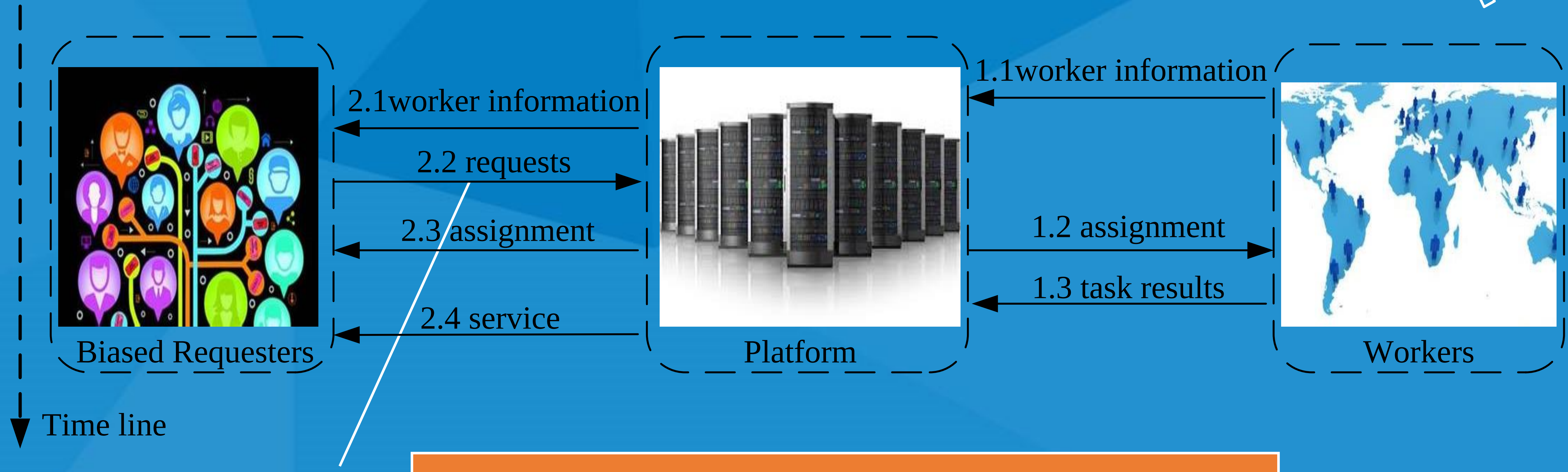
I intend to hire native Hungarian speakers to order Hungarian to English translations

I expect to assign the mobile crowdsourcing tasks to the workers who are close by the specific locations

Preference over workers!

I wish to allocate the research projects to the students who are interesting in

Crowdsourcing Process



each consists of a task and a preference set

preference set: a set of compatible workers

Designing truthful task assignment mechanisms to maximize the total value

Challenges

Compatibility

Strategic action

Workload feasibility

Contributions

first work to design truthful assignment mechanisms for the crowdsourcing systems with biased requesters

formulate the *Valuation Maximizing Assignment* (*VMA*) problem in three different models

design an assignment mechanism for each of these models to solve the *VMA* problem. We show that the designed mechanisms satisfy four desirable properties: computational efficiency, workload feasibility, preference (universal) truthfulness, and constant approximation

II-Model: Identical workload Identical value

Objective Function:

$$\max_A v(A) = \sum_{k \in W} \left|A^k\right| = \sum_{i \in R} \left|A_i\right|$$

Constraints:

$$(1)\ \left|A^k\right| \leq 1, \forall k \in W$$

$$(2)\ \left|A_i\right| \leq 1, \forall i \in R$$

$$(3)\ A \in \{(i,k) \mid i \in R, k \in P_i\}$$

It Looks So Easy?!

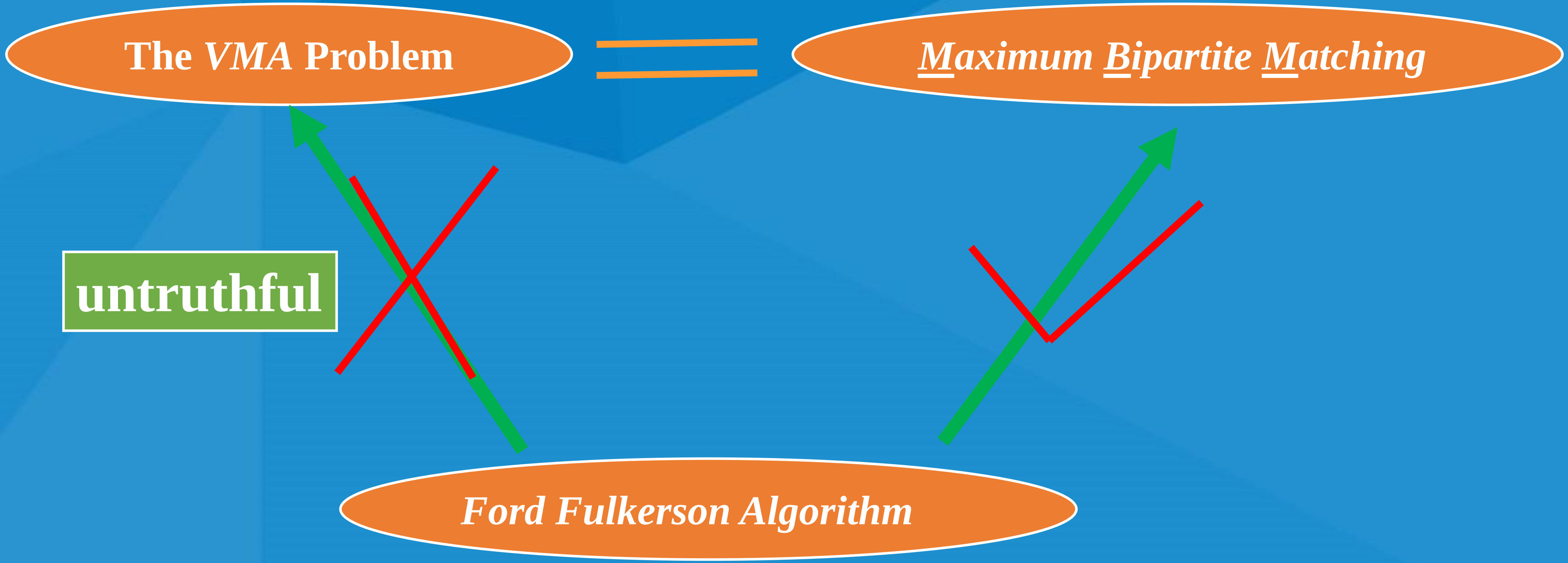
Requesters **Tasks**

… …

Maximum Bipartite Matching

Workers

However


The *VMA* Problem
Maximum Bipartite Matching
untruthful
Ford Fulkerson Algorithm

TAM-II

Sort the task-worker pairs

Compute the size of the maximum matching

Remove the allocations which cannot reduce the size of maximum matching

Input: Worker Set W, Request Set B
1: $A \leftarrow \emptyset$;
2: Represent all pairs $(i, k), i \in R, k \in P_i$ as $(1,1),(1,2),\ldots,(2,1),(2,2),\ldots,(n, m)$, and the sequence is denoted by $\mathcal{H}$;

3: $\mathcal{H}' \leftarrow \mathcal{H}$;
4: $N \leftarrow MBM(\mathcal{H})$;

5: for all $j \in \mathcal{H}$ in order do
6: $N' \leftarrow MBM(H' \setminus \{j\})$;
7: if $N' \geq N$ then
8: Remove j from $\mathcal{H}'$;
9: end if
10: end for
11: $A \leftarrow \mathcal{H}'$;
12: return(A);

Generalize to the Non-identical Value Case

Objective Function:

$$max_A v(A) = \sum_{(i,k)\in A} v_i^k = \sum_{(i,k)\in A} F(a_i) * I_k$$

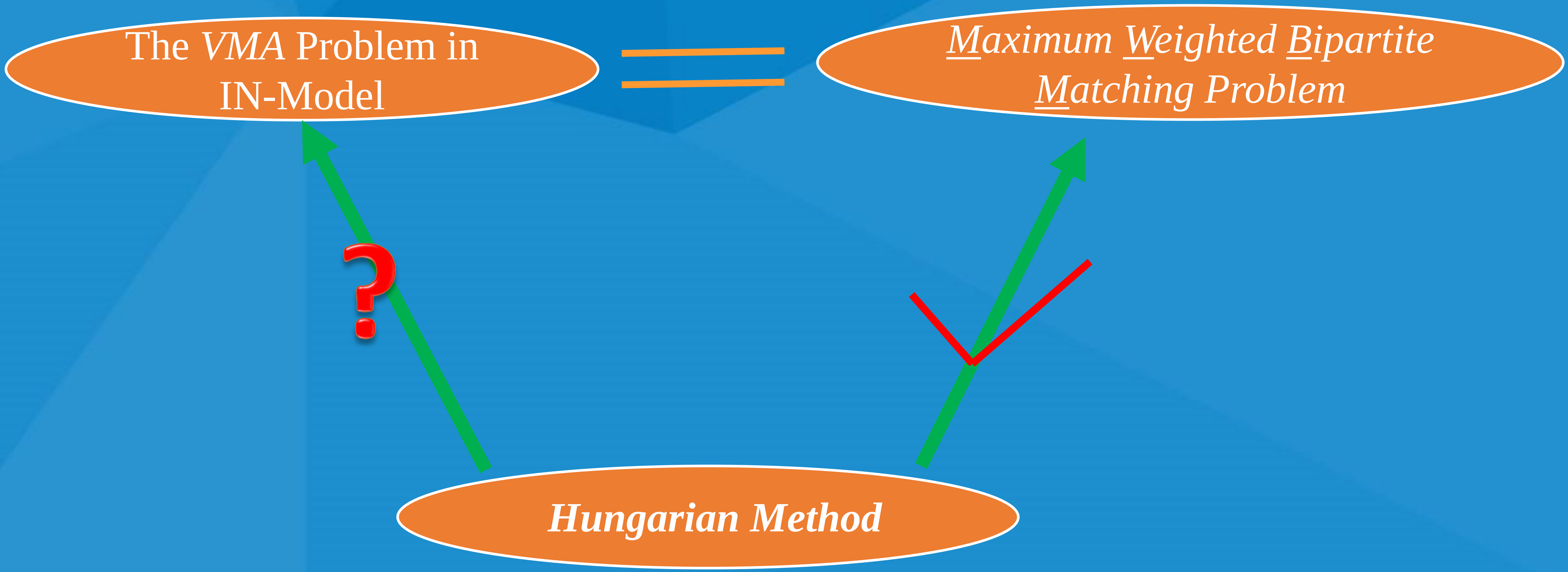
Constraints:

$$(1) \left|A^k\right| \leq 1, \forall k \in W$$

$$(2) \left|A_i\right| \leq 1, \forall i \in R$$

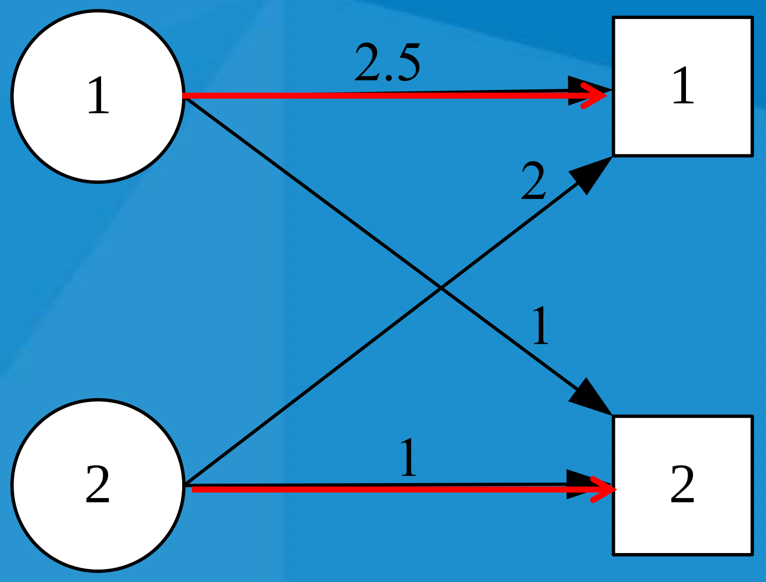
$$(3)\ A \in \{(i,k) \mid i \in R, k \in P_i\}$$

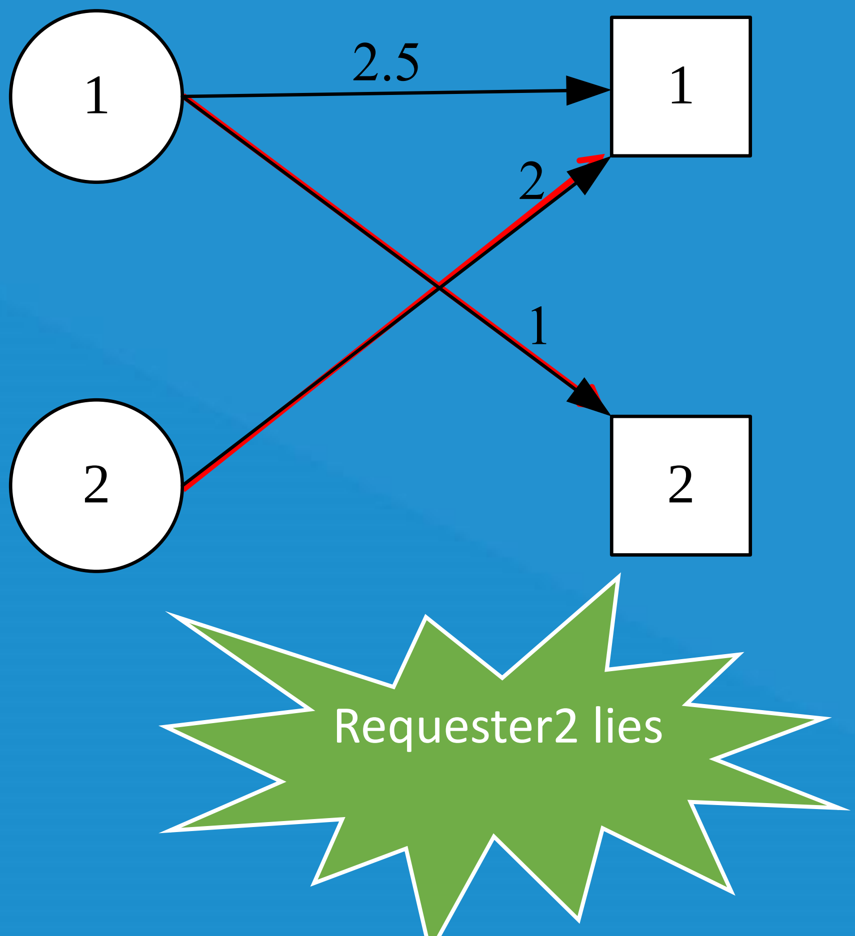
How About Hungarian Method ?



Check the Truthfulness of Hungarian Method

An Example





Hungarian method is untruthful

A Greedy Algorithm—TAM-IN

Sort all pairs

Select the pairs

Input: Worker Set W, Request Set B,Effort Indicators I

1:Sort all pairs(i,k), $i \in R$,$k \in P_i$ based on v_i^k in nonincreasing order and the sequence is denoted by $\mathcal{J}$;

2:$A \leftarrow \emptyset$;

3:**for all** $j \in \mathcal{J}$ in order **do**

4: **if** $A \cup \{j\}$ is a matching on $G(R,W,J)$ **then**

5: $A \leftarrow A \cup \{j\}$;

6: **end if**

7:**end for**

8:**return** (A);

Non-identical Workload Non-identical Value Case

Objective Function:

$$max_A v(A) = \sum_{(i,k)\in A} v_i^k$$

Constraints:

$$(1) \sum_{i\in A^k} c_i \le C_k, \forall k \in W$$

$$(2) |A_i| \le 1, \forall i \in R$$

$$(3)\ A \in \{(i,k) \mid i \in R, k \in P_i\}$$

Try greedy Assignment Mechanisms

The VMA problem in the NN-Model is NP- hard since it contains a MKP (Multiple Knapsack Problem)

GREEDY-VALUE

Select the task-worker pairs iteratively in nonincreasing order of value

GREEDY- DENSITY

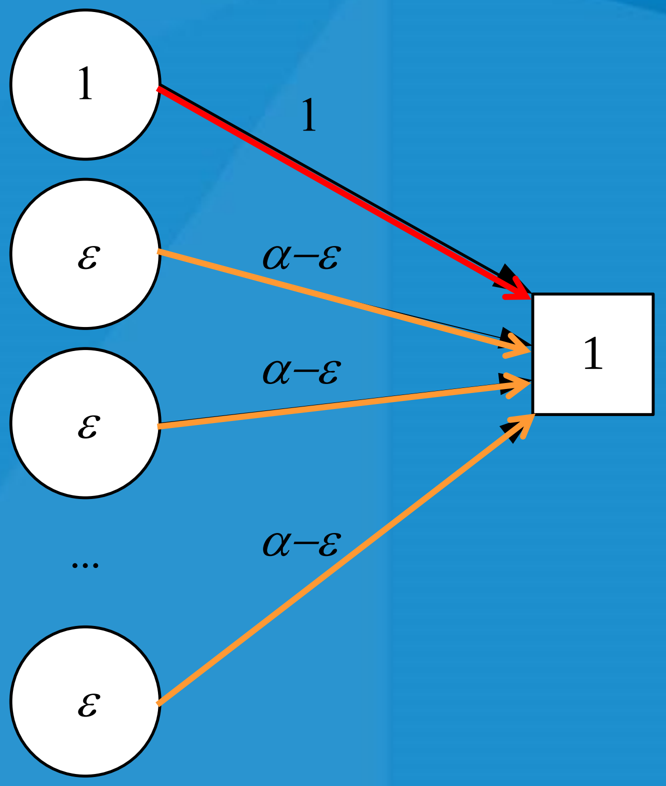
Select the task-worker pairs iteratively in nonincreasing order of the ratio of the value to the workload

How Good are Greedy Algorithms?

- Computational efficiency ✓
- Workload feasibility ✓
- Preference truthfulness ✓
- Approximation ?

Approximation Ratio of GREEDY-VALUE

A Example



Assume that $\alpha > 1, \alpha - \varepsilon < 1, \varepsilon \in (0, 1/2]$.

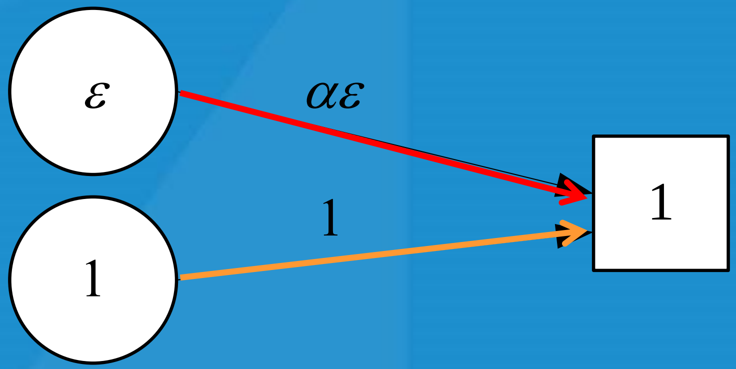
Since $1 > \alpha - \varepsilon$**,** $v(A_{value}) = 1$

$$v(A_{opt}) = \left\lfloor \frac{1}{\varepsilon} \right\rfloor (\alpha - \varepsilon).$$

Let ε **be sufficiently close to 0, the approximation ratio of GREEDY-VALUE tends to infinite.**

Approximation Ratio of GREEDY-DENSITY

A Example



Assume $\alpha > 1, \alpha\varepsilon < 1, \varepsilon \in (0,1).$

Since $\frac{\alpha\varepsilon}{\varepsilon} = \alpha > 1, \quad v(A_{density}) = \alpha\varepsilon$

Since $\alpha\varepsilon < 1, v(A_{opt}) = 1$

If we let ε be sufficiently close to 0, the approximation ratio of GREEDY-DENSITY tends to infinite.

Bad News

There is no upper bound of the approximation ratio for either GREEDY-VALUE or GREEDY-DENSITY.

A Random Methord—TAM-NN

Input: Worker Set W, Request Set B, Effort Indicators I, Workload Constraints C

1:Generate a random number o from the uniform distribution on the interval [0,1];

2: $A \leftarrow \emptyset$;

3: **if** $o \leq 1/2$ **then**

4: $A \leftarrow \text{GREEDY} - \text{V ALUE}(W, B, I, C)$;

5: **else**

6: $A \leftarrow \text{GREEDY} - \text{DENSITY}(W, B, I, C)$;

7: **end if**

8: return(A)

Summary of Theoretical Analysis

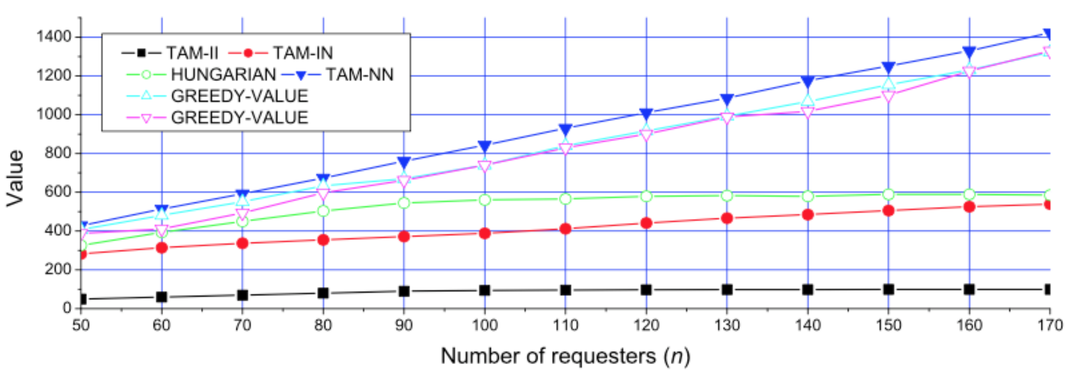
Theorem 1. ***TAM-II is computationally efficient, workload feasible, preference truthful and optimal for VMA problem in the II-Model.***

Theorem 2. ***TAM-IN is computationally efficient, workload feasible, preference truthful and 2-approximate in the IN-Model.***

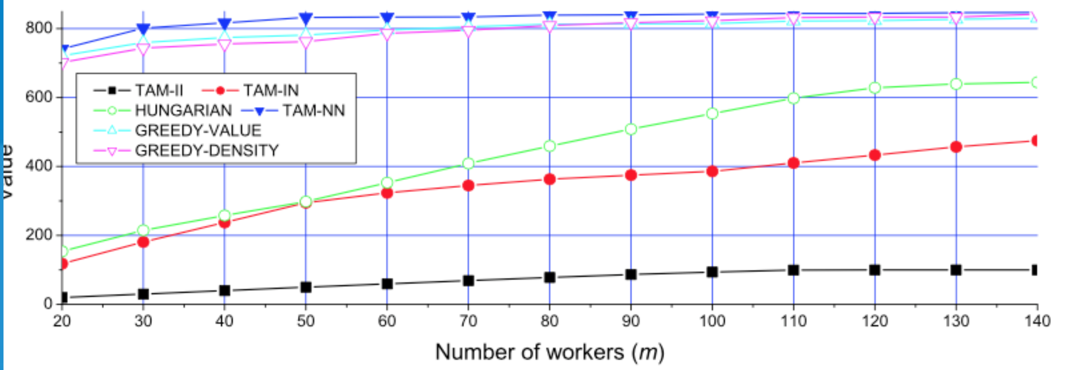
Theorem 3. ***TAM-NN is computationally efficient, workload feasible, preference truthful and 4-approximate in the NN-Model.***

Performance Evaluation

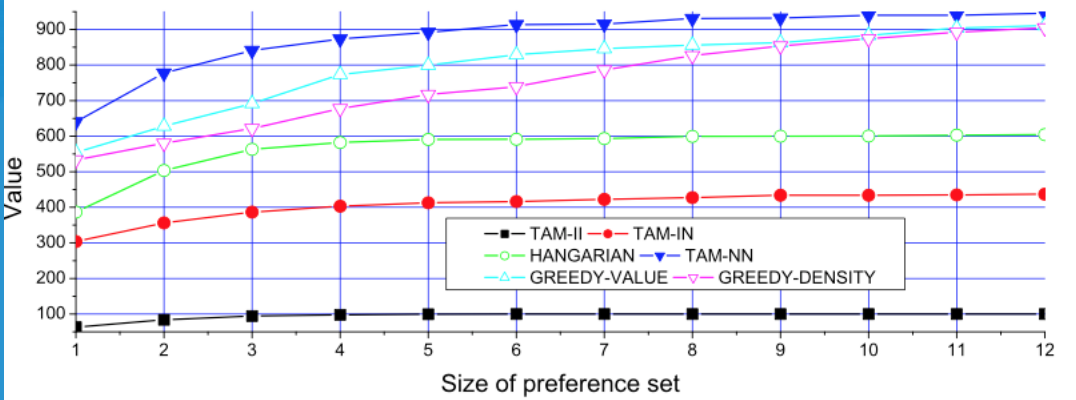
A. Value



(a) The value versus the number of requesters



(b) The value versus the number of workers



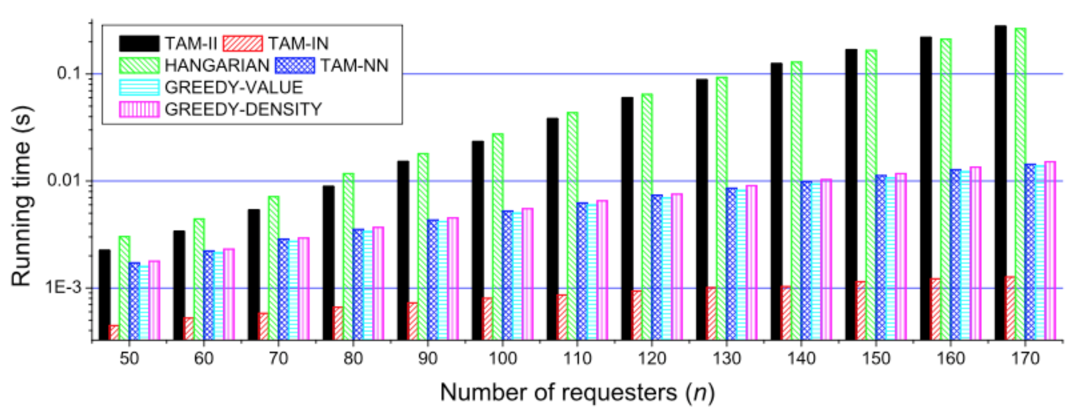
(c) The value versus the size of preference set

The average approximation ratio of TAM-IN is 1.27

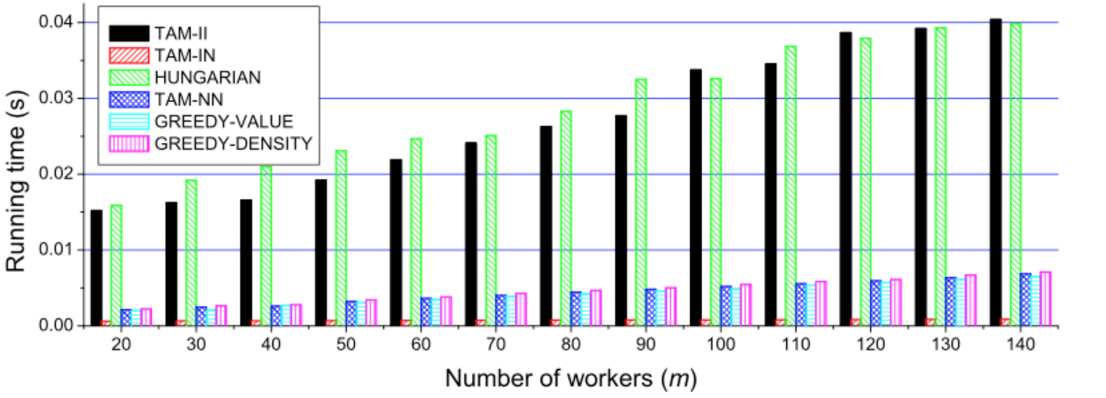
On average, TAM-NN can output 8.45% and 12.38% more value than GREEDY-VALUE and GREEDY-DENSITY, respectively

Performance Evaluation

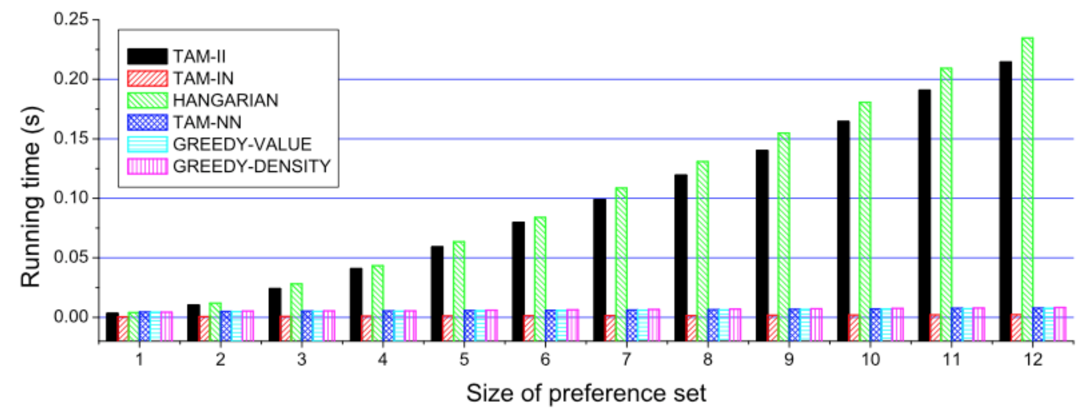
B. Running Time



(a) The running time versus the number of requesters



(b) The running time versus the number of workers



(c) The running time versus the size of preference set

TAM-IN only takes averagely 9.52% of time required by _HANGARIAN_ in all cases

Conclusion

We have investigated the task assignment incentive mechanisms for the crowdsourcing system with biased requesters.

We have studied three models of crowdsourcing and formulated the *VMA* problem for each model. We presented the task assignment mechanisms for all three models, and proved that they are computationally efficient, workload feasible, preference (universally) truthful and constant approximate.

Extensive results are presented to verify our theoretical analysis.

Thank You!

Q & A

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