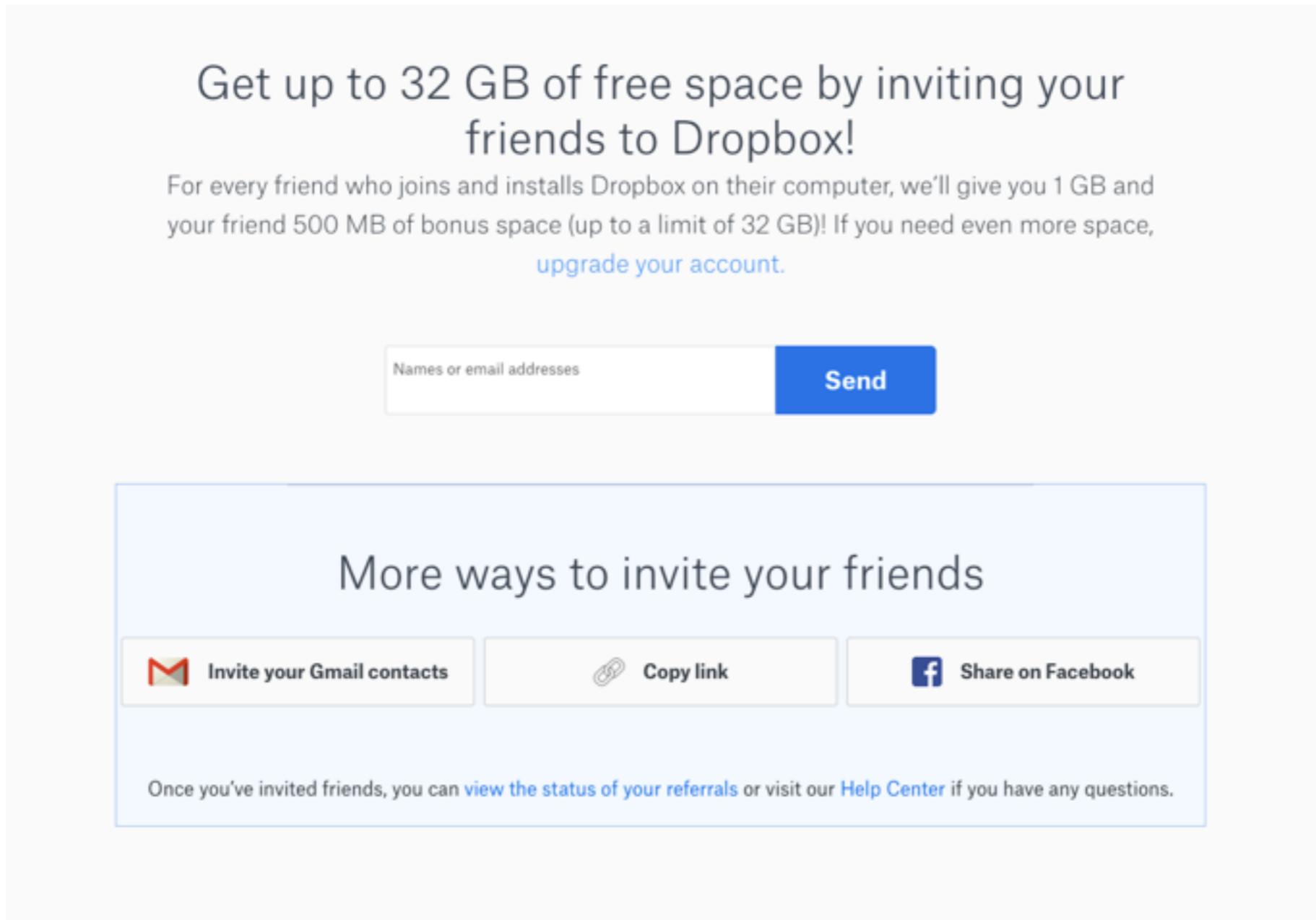


Beyond Nash Equilibrium: Mechanism Design with Thresholding Agents

Wen Shen
Sept 20, 2019

Motivating Example I

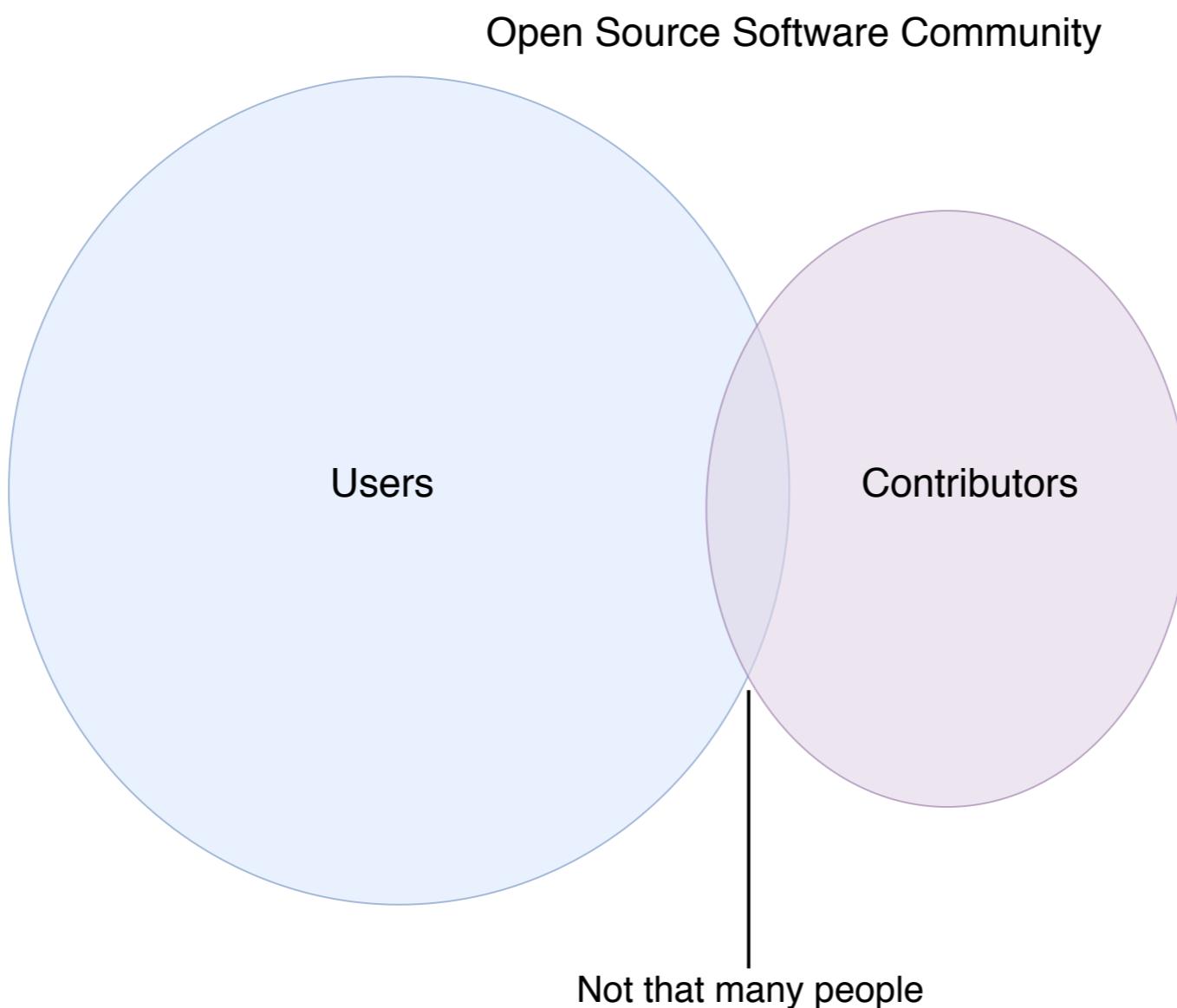


The image shows a screenshot of the Dropbox referral program landing page. At the top, it says "Get up to 32 GB of free space by inviting your friends to Dropbox!" Below that, a text block explains: "For every friend who joins and installs Dropbox on their computer, we'll give you 1 GB and your friend 500 MB of bonus space (up to a limit of 32 GB)! If you need even more space, [upgrade your account.](#)" There is a text input field labeled "Names or email addresses" and a blue "Send" button. Below this, a section titled "More ways to invite your friends" contains three buttons: "Invite your Gmail contacts" (with a Gmail icon), "Copy link" (with a link icon), and "Share on Facebook" (with a Facebook icon). A note at the bottom of this section reads: "Once you've invited friends, you can [view the status of your referrals](#) or visit our [Help Center](#) if you have any questions."

Credit: Dropbox

Dropbox VS Strategic Users

Motivating Example II



Stakeholder VS Users without Contributions

Motivating Example III



Credit: V2Gov

Transportation Authority VS Individual Commuters

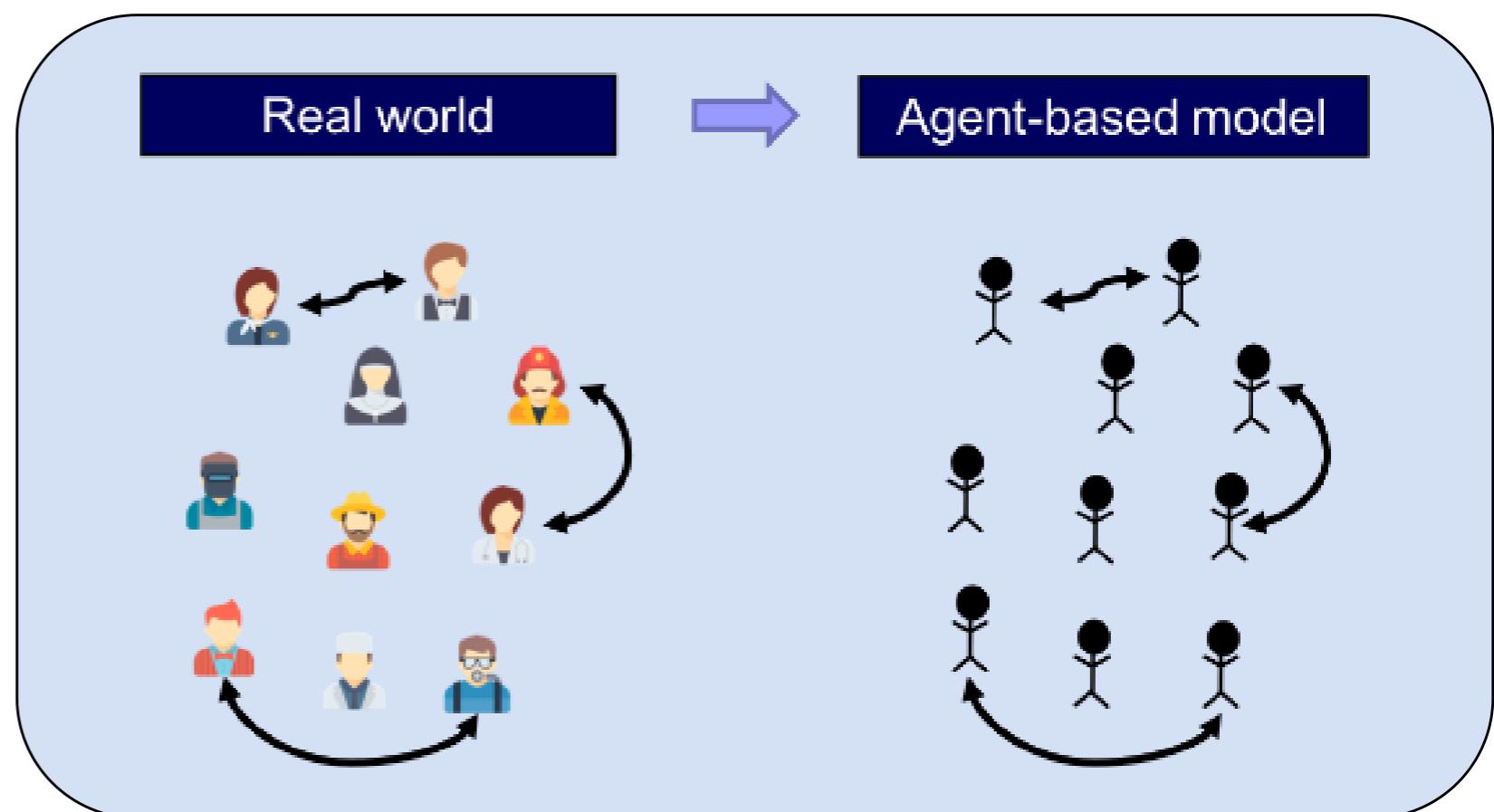
Agent-Based Modeling

- **Individual Agents**

- Autonomous
- Heterogeneous
- No global views

- **Stakeholder**

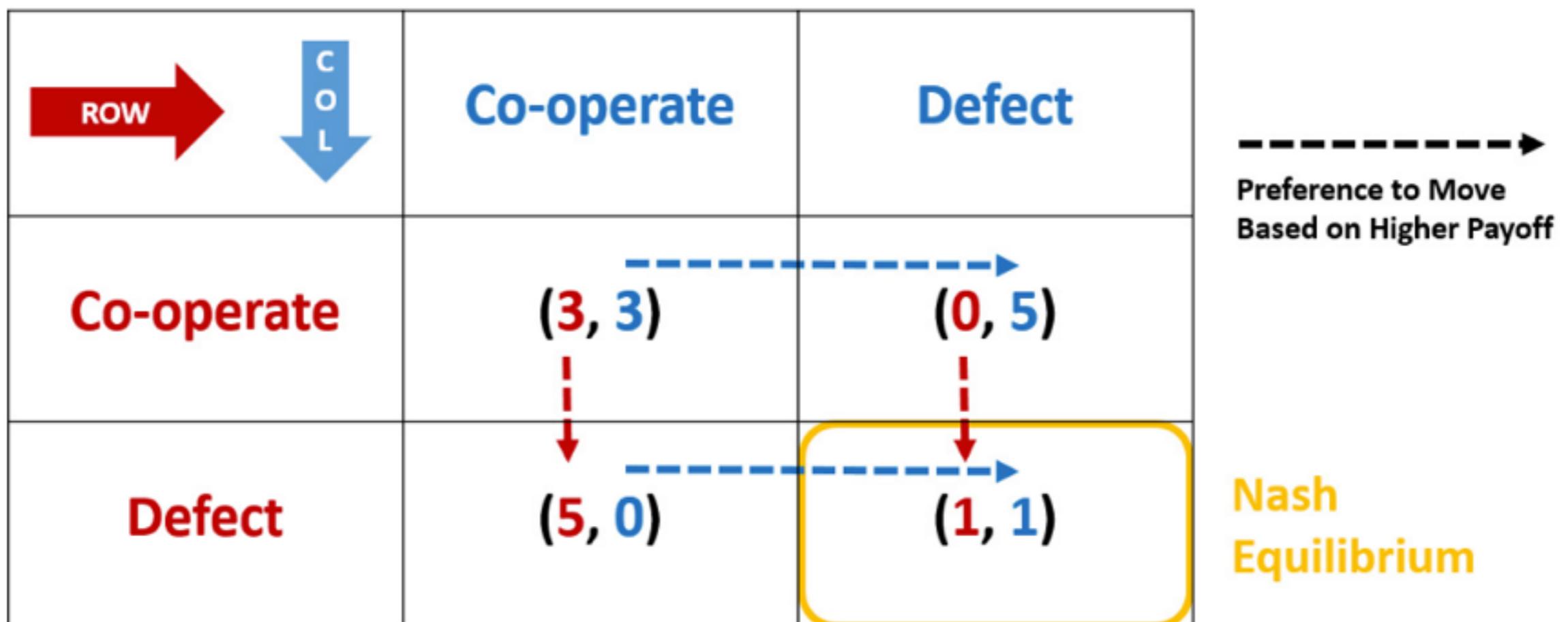
- Interested in system-wide performance



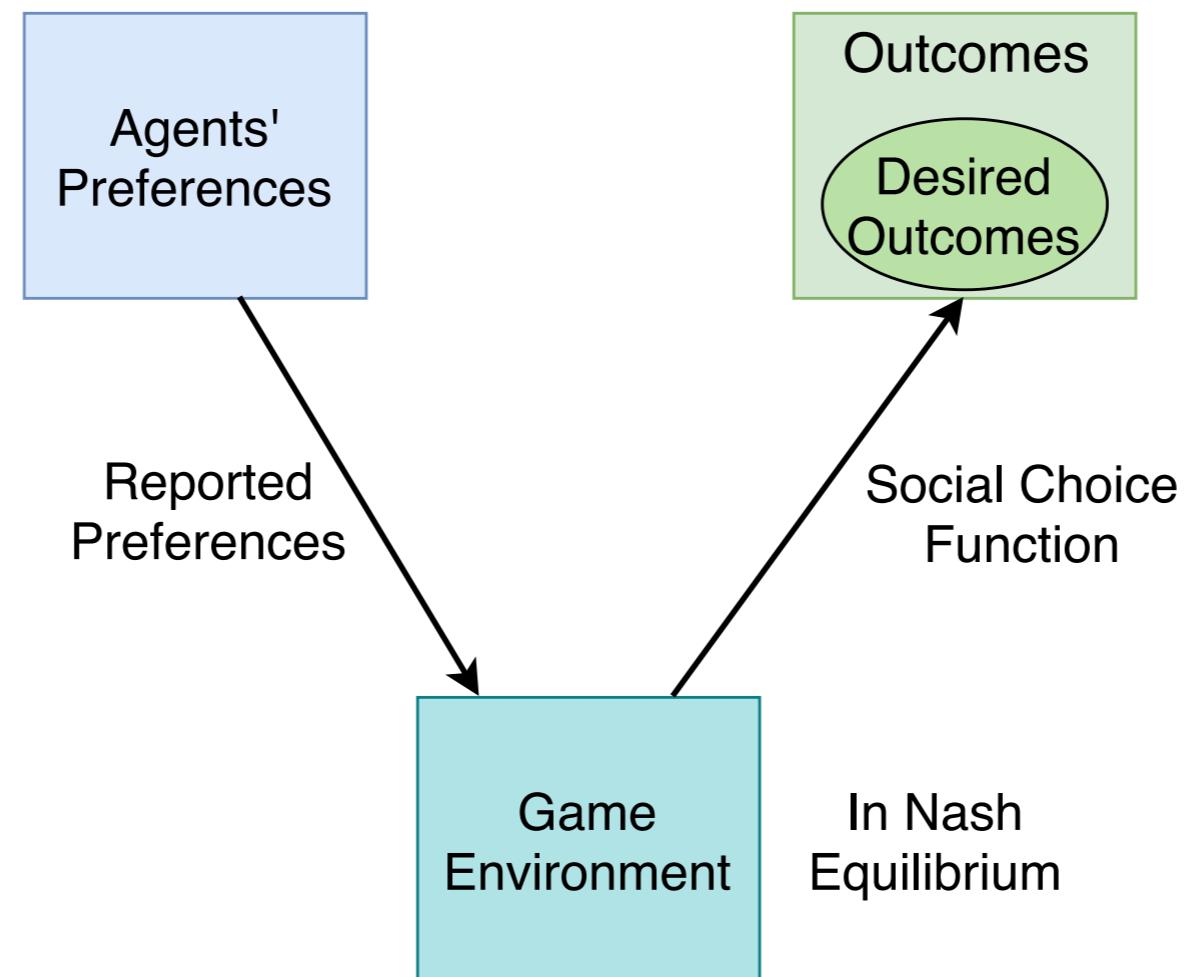
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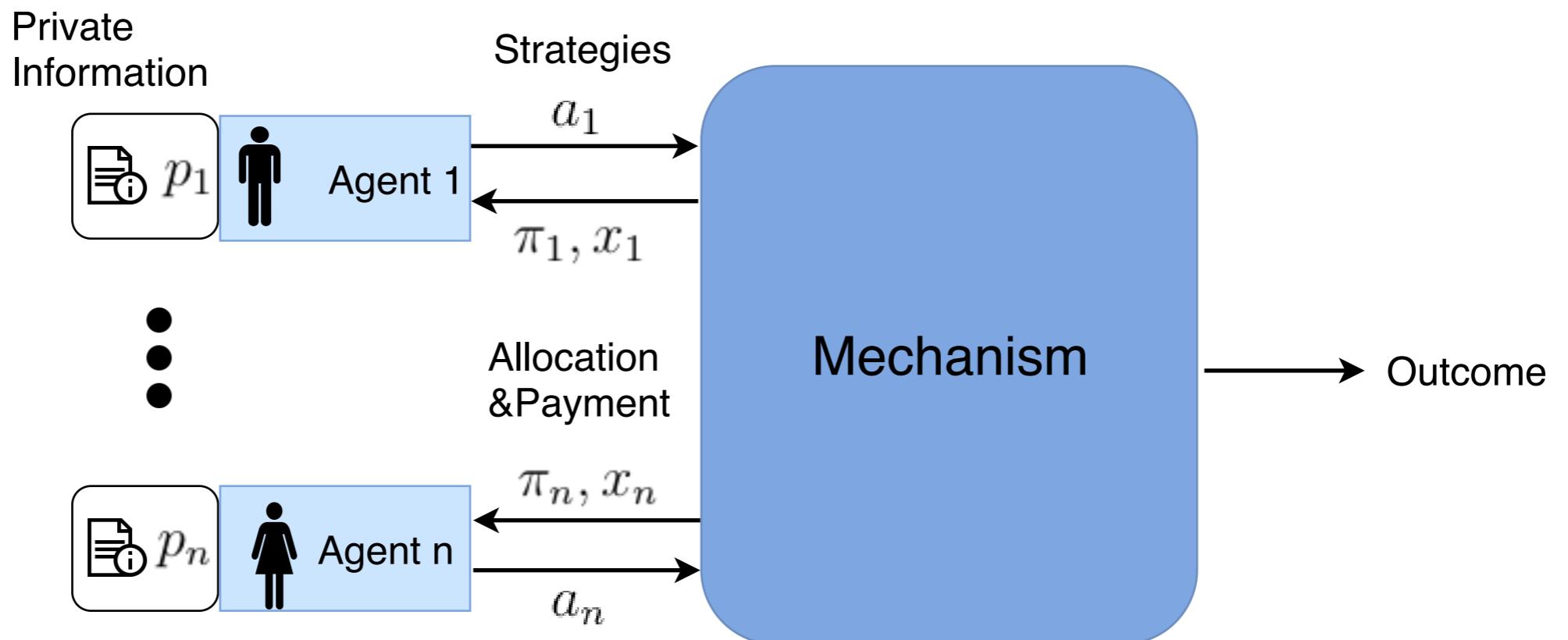
Game Theory



Mechanism Design Theory



Mechanism Design Theory



Mechanism Design for Social Good

- **Objective**

- social welfare maximization

- **Characterics**

- individual agents' interests are often partially aligned with the stakeholder's



Credit: poparide

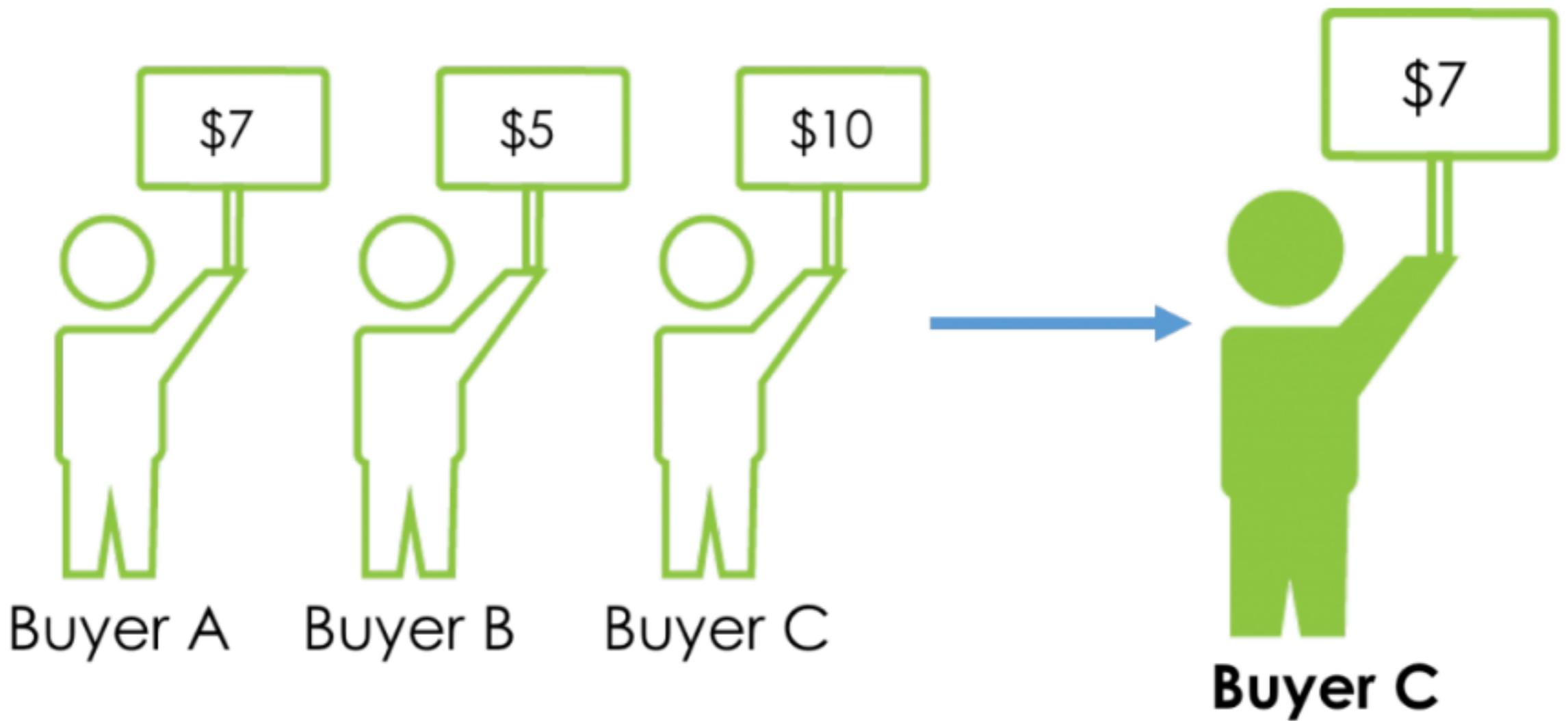
Mechanism Design for Revenue Optimization

- **Objective**
 - revenue maximization
- **Characteristics**
 - individual agents' interests are often conflicting with the stakeholder's



Credit: The balance

Second Price Auction



Benefit: incentive compatible

Challenges in Traditional Mechanism Design Theory

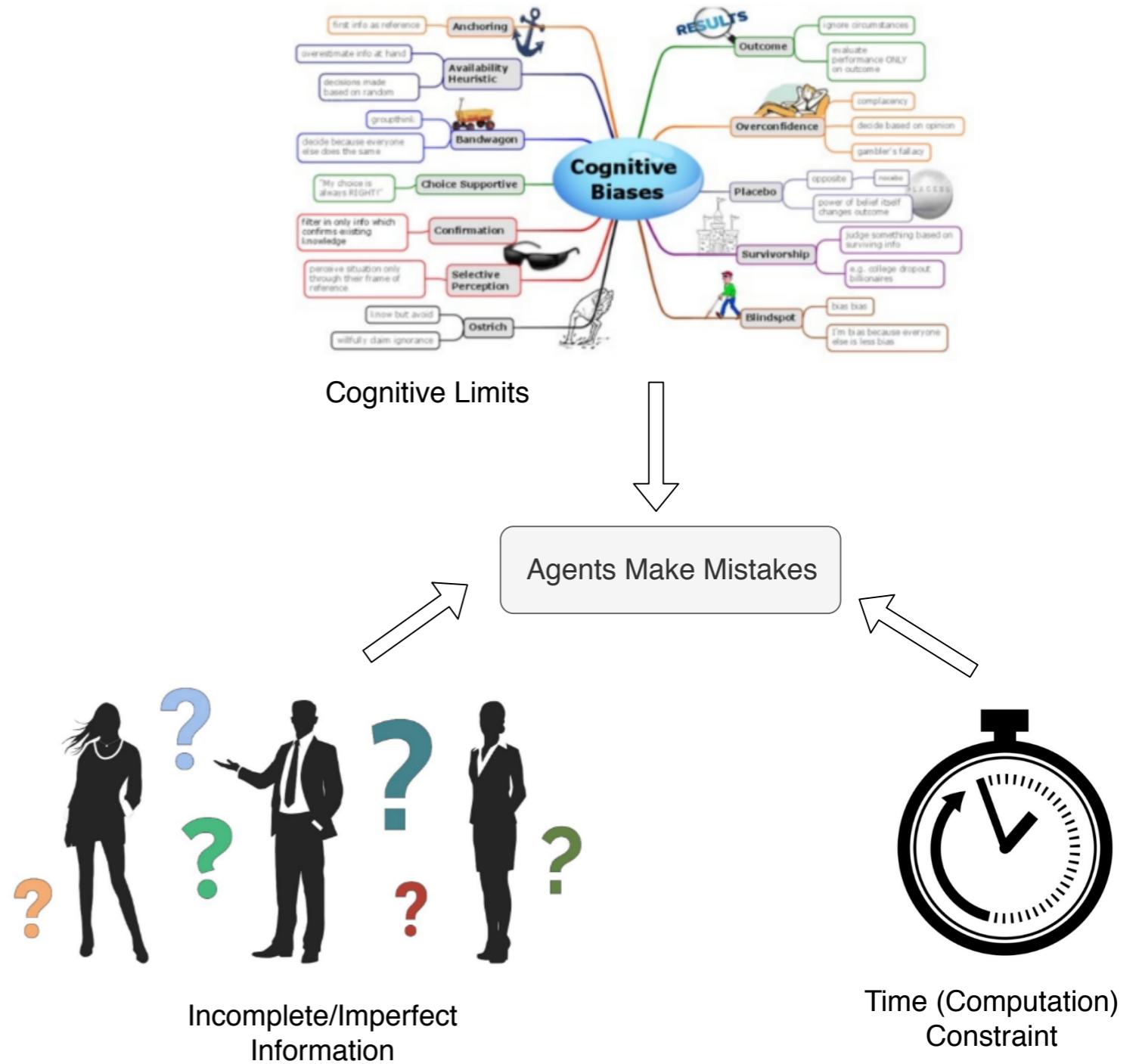
- **Full Rationality Assumption**

VS

- **Agents may make mistakes**

- Cognitive limits
- Incomplete/Imperfect information
- Computation constraints
(insufficient time to decide)

(Simon 55, Selten 90)



Challenges in Traditional Mechanism Design Theory

- **Direct Preference Revelation**
- VS
- **Agents may be unwilling to report their preference directly**
 - Privacy
 - Uncertainty



Credit: Amazon

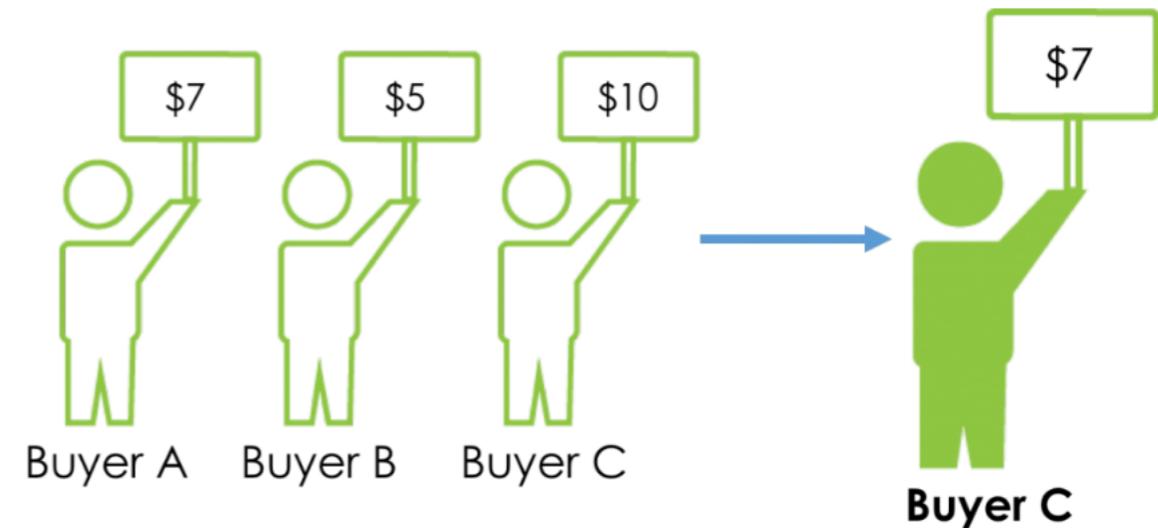
Challenges in Traditional Mechanism Design Theory

- **Vulnerability to Group Manipulations**

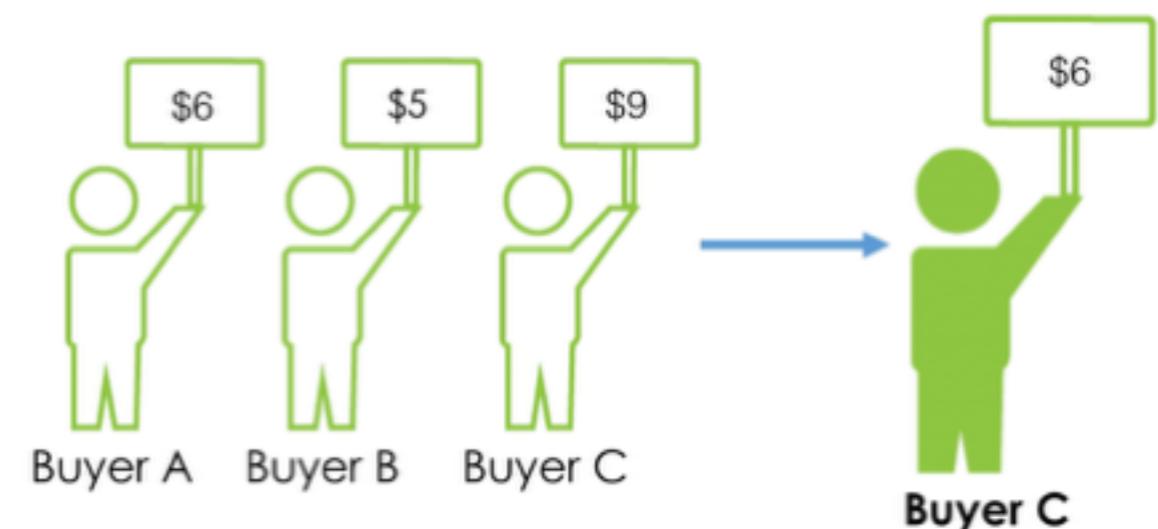
VS

- **Agents have incentives to conduct group manipulations**

- Collusion
- False-name attacks



No Collusion



Collusion (buyers A and C)

Related Work

- **Modeling Agents**

- Aspiration adaptation theory (Selten JMP'98, Rosenfeld and Kraus JAAMAS'12)
- Quantal response equilibrium (McKelvey and Palfrey GEB'95)
- Simple agents (Ghosh and Kleinberg EC'14)

- **Indirect Mechanisms**

- Post-price mechanism (Badanidiyuru, Kleinberg and Singer EC'12)

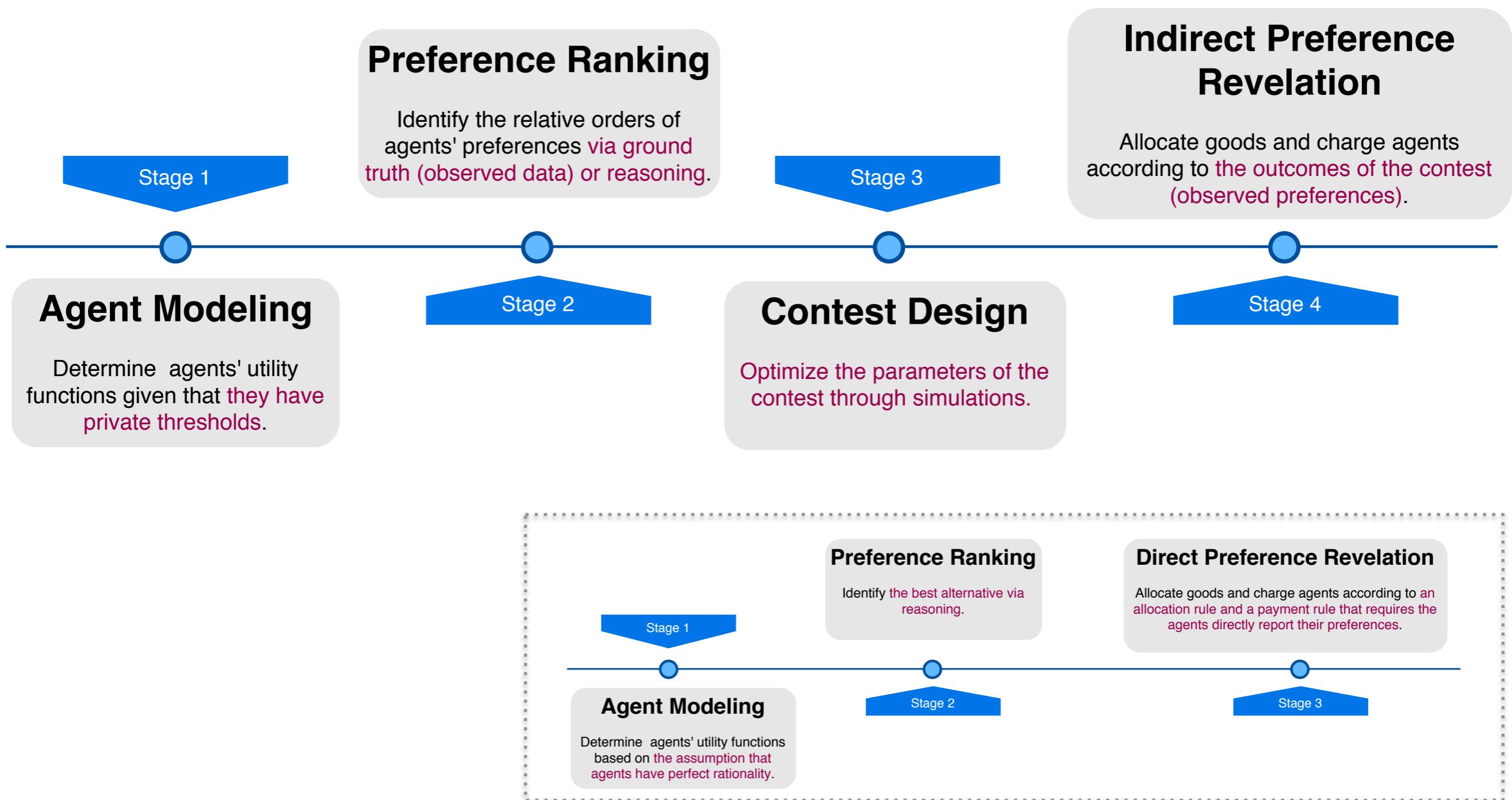
- **Manipulation-Resistant Mechanisms**

- False-name-proof mechanism (Drucker and Fletcher EC'12)
- Group-strategy-proof mechanism (Goldberg and Hardline SODA'05)

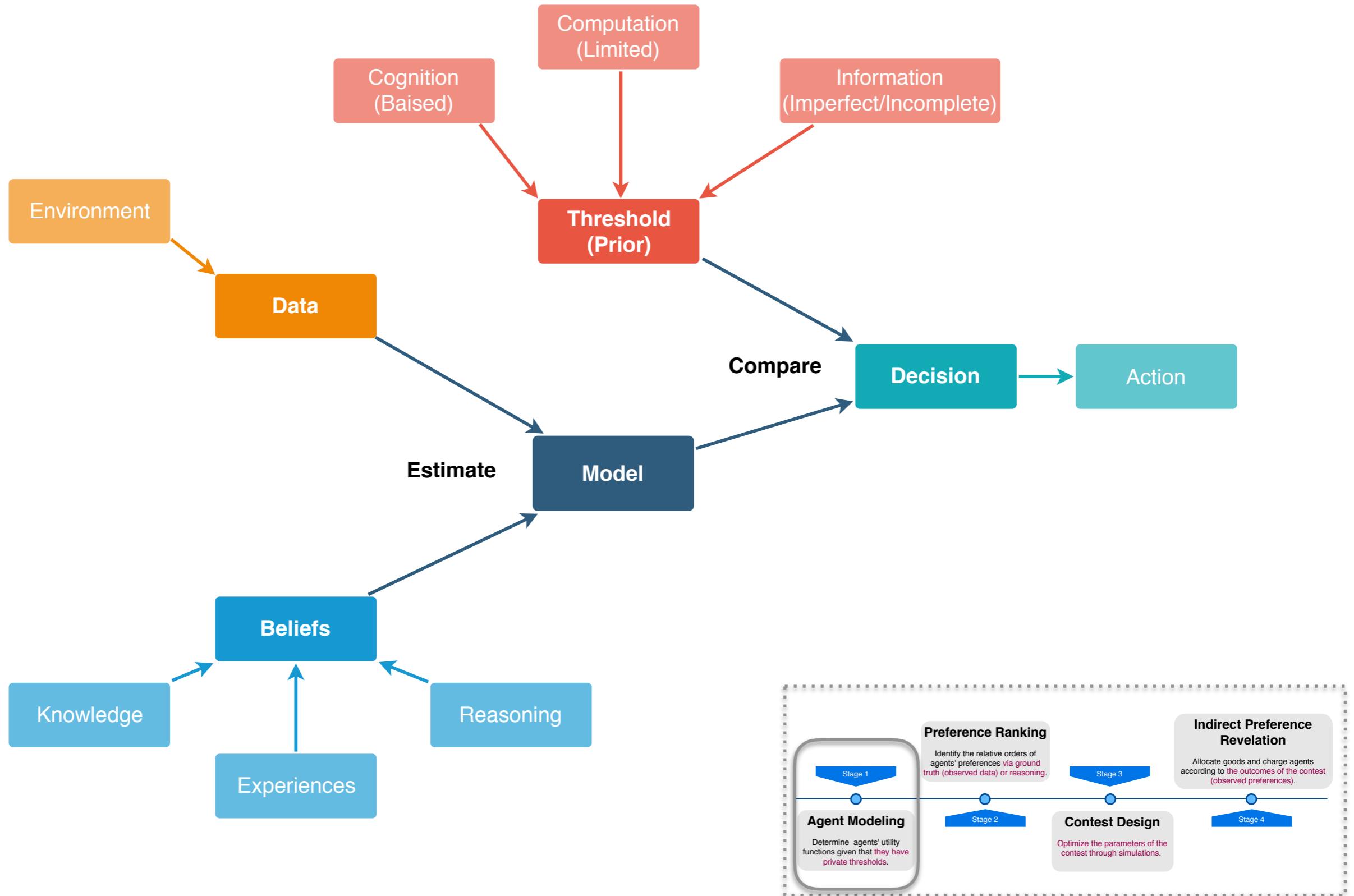
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Mechanism Design with Thresholding Agents

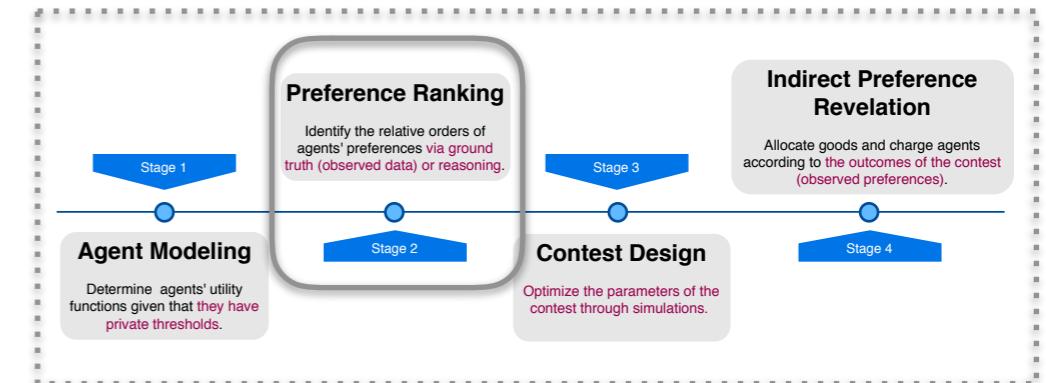
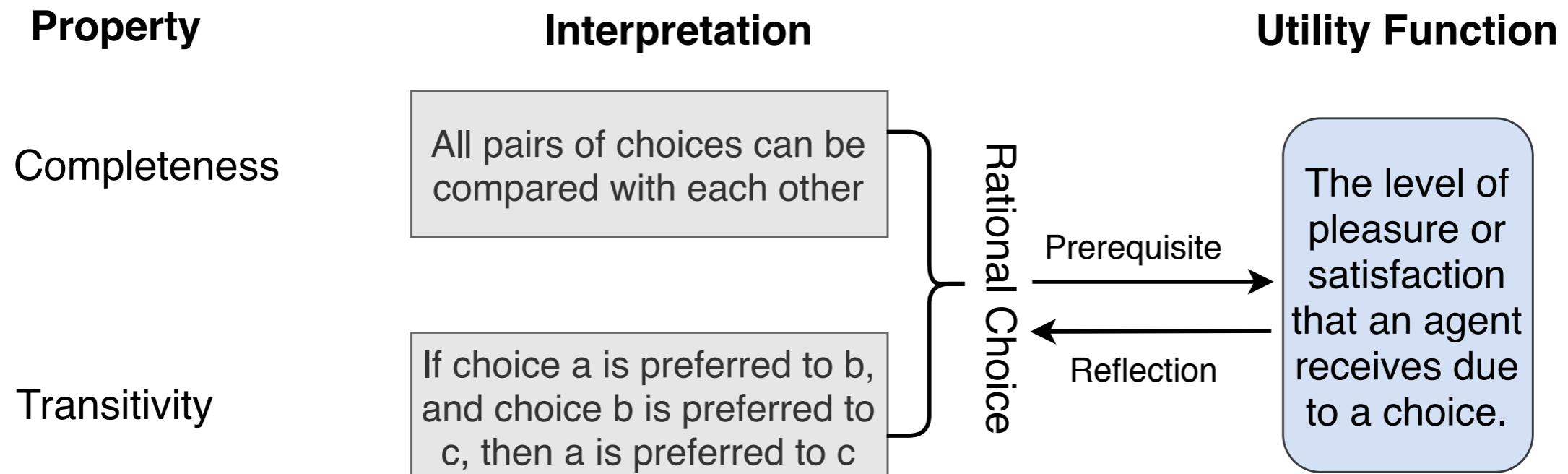


Agent Modeling

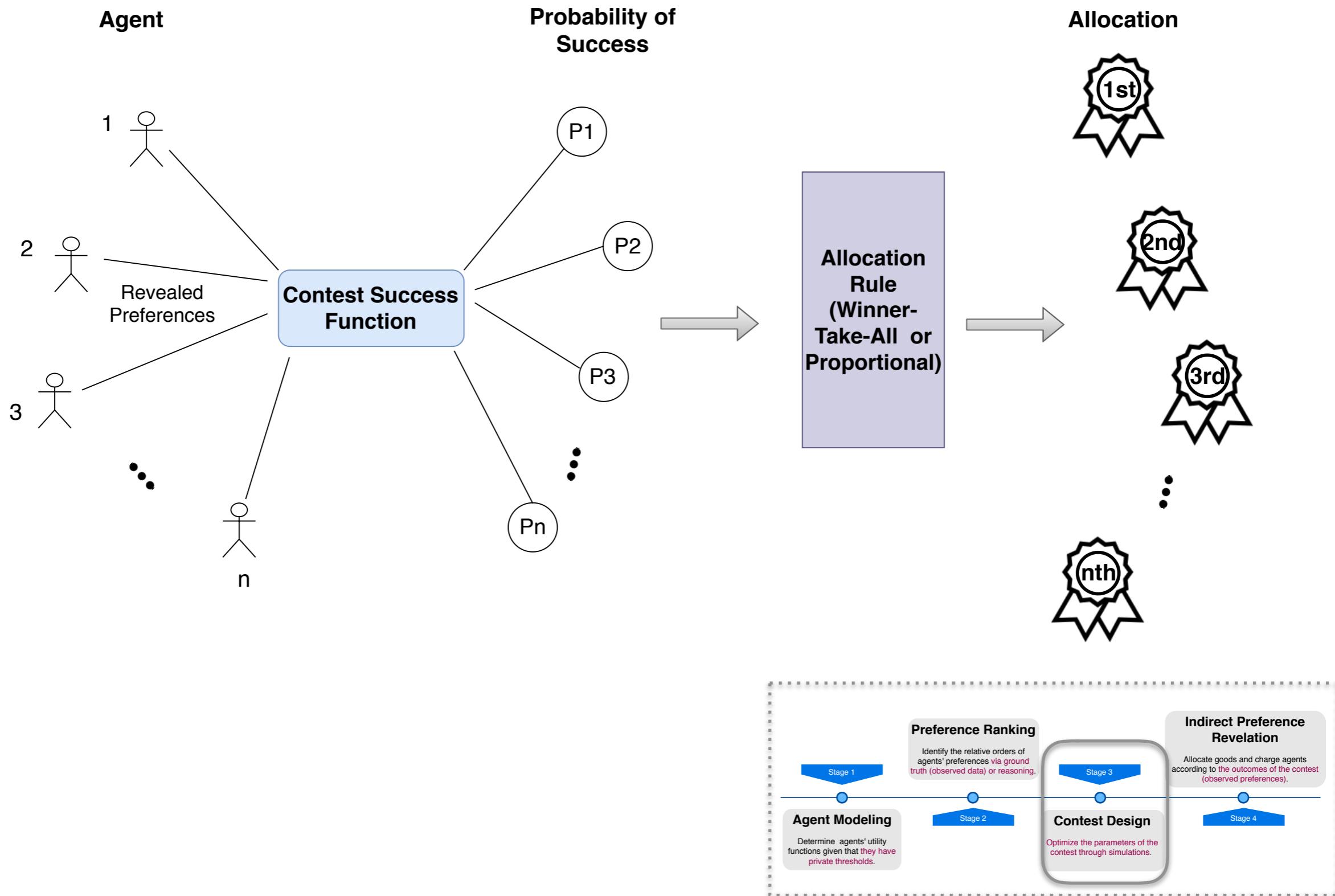


Preference Ranking

Identify the relative order of agents' preferences based on empirical data and/or reasoning



Contest Design

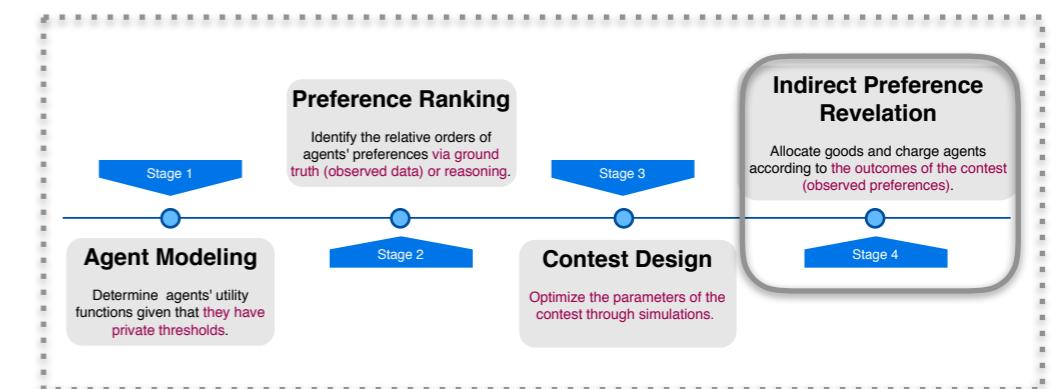
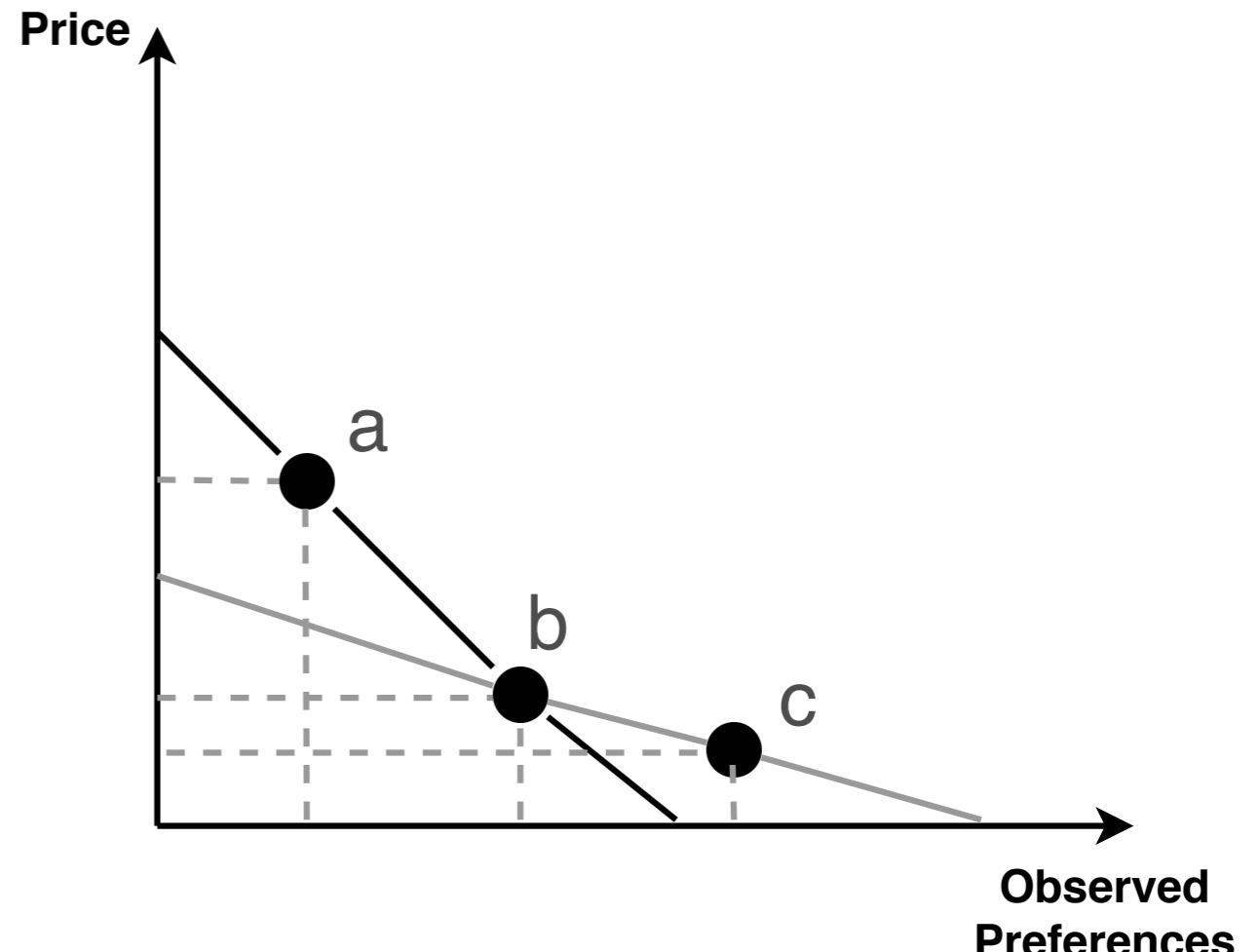


Indirect Preference Revelation

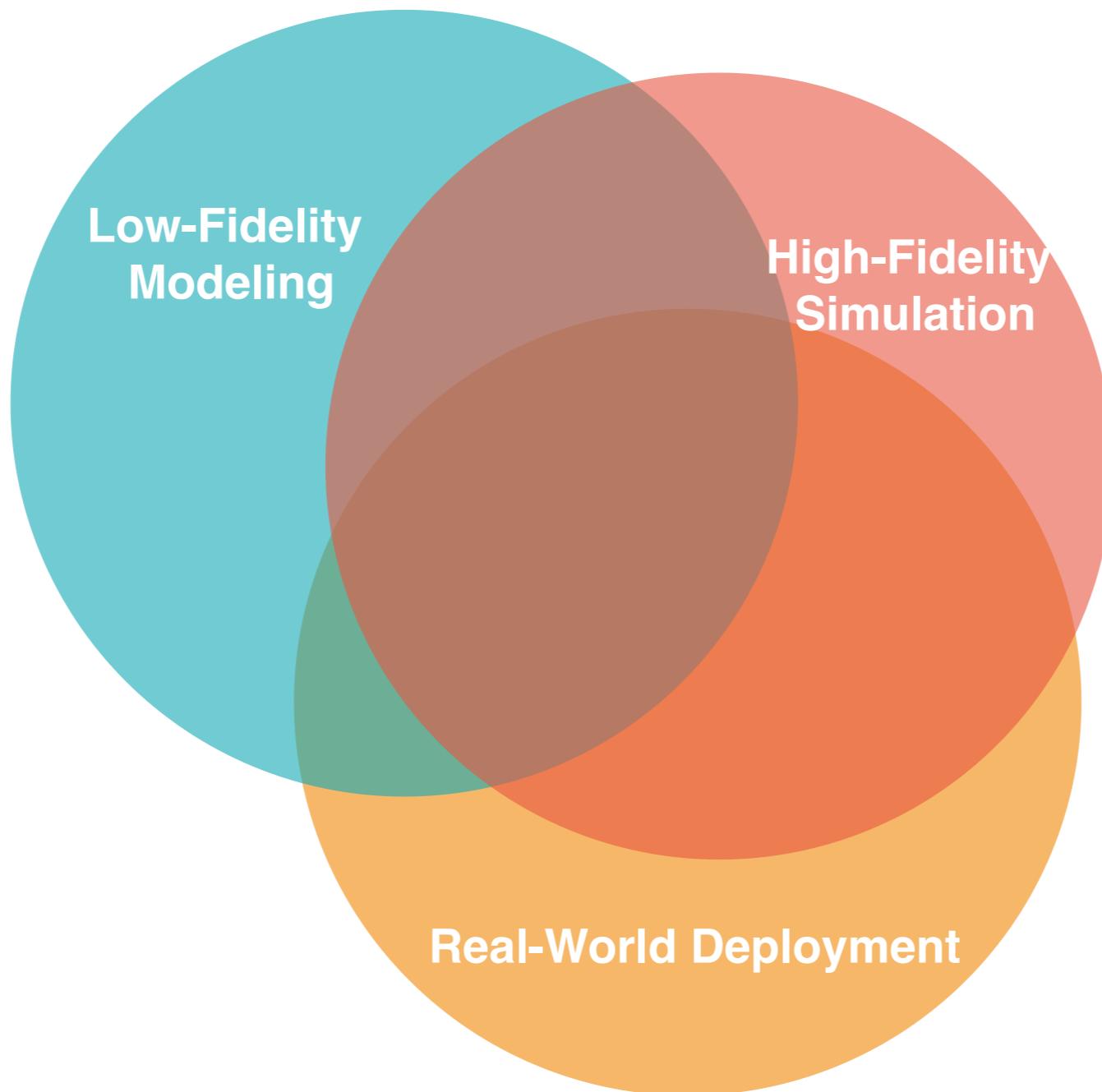
Method: Post-Price Mechanism

Benefit: allow the principal to learn agents' preferences

- If choice b is selected by an agent, then choice a is less preferred.
- If choice c is selected, then choice b is less preferred.
- Choice a and choice c cannot be directly compared. However, by transitivity, we can infer that c is preferred to a.



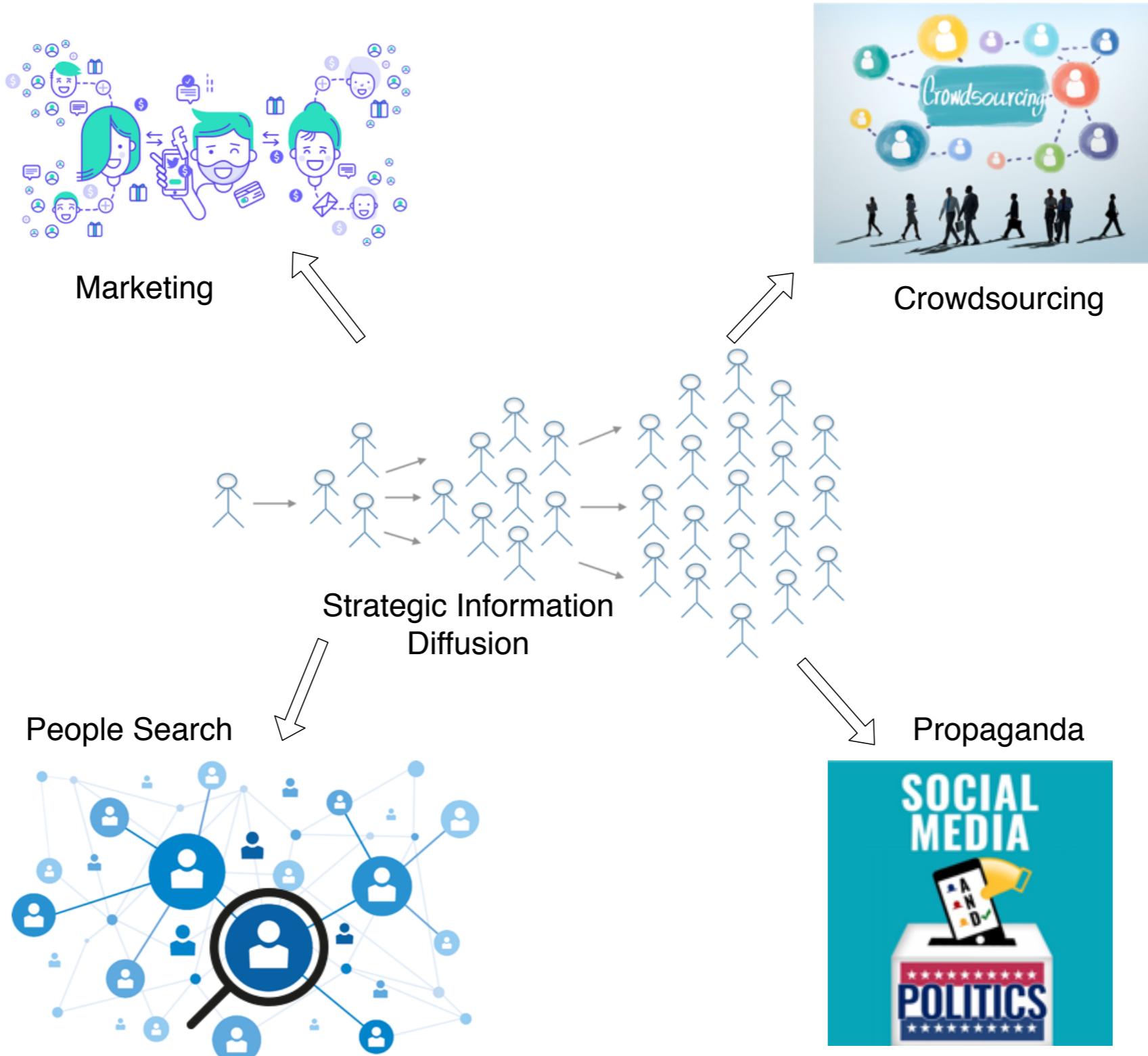
Evaluation



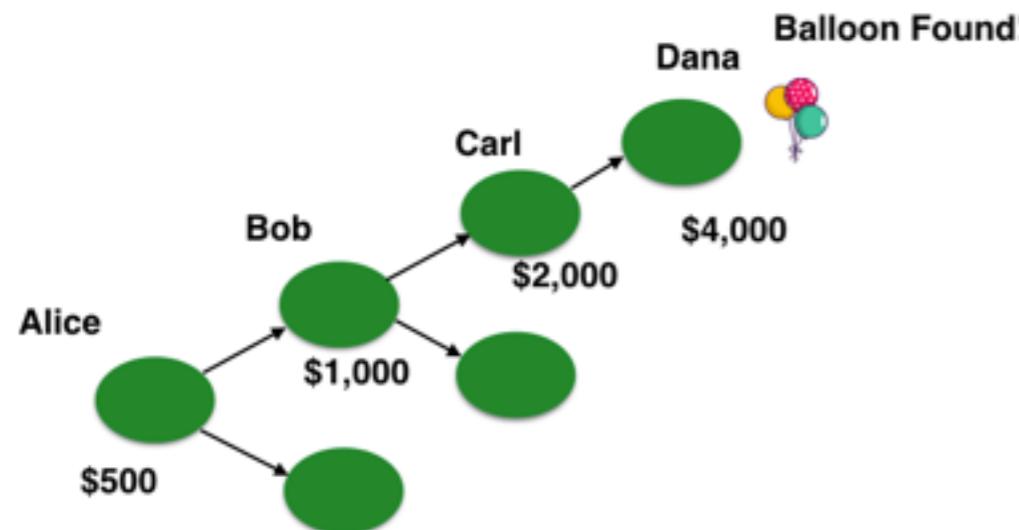
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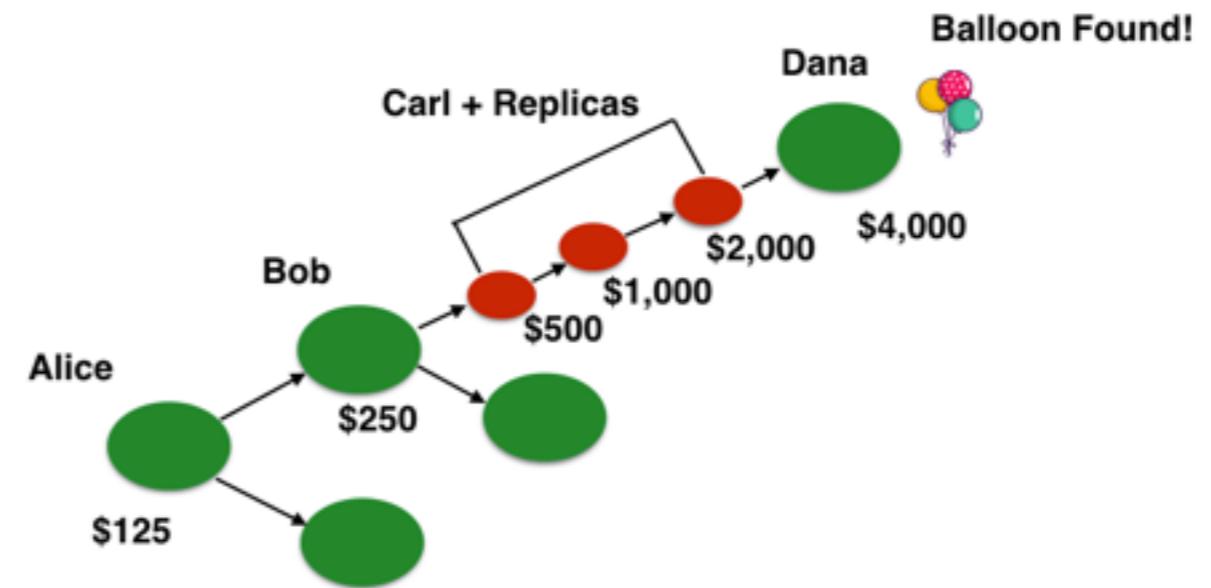
Strategic Diffusion in Social Networks



Strategic Diffusion in Social Networks



(a) Honest diffusion



(b) Diffusion with false-name attacks

- **Setting:**

- Consider a principal aims to solicit as many efforts as possible from users in a social network.

- **Challenges:**

- False-name attacks
 - Incentives for low-influential players
 - Scalability

- **Question:**

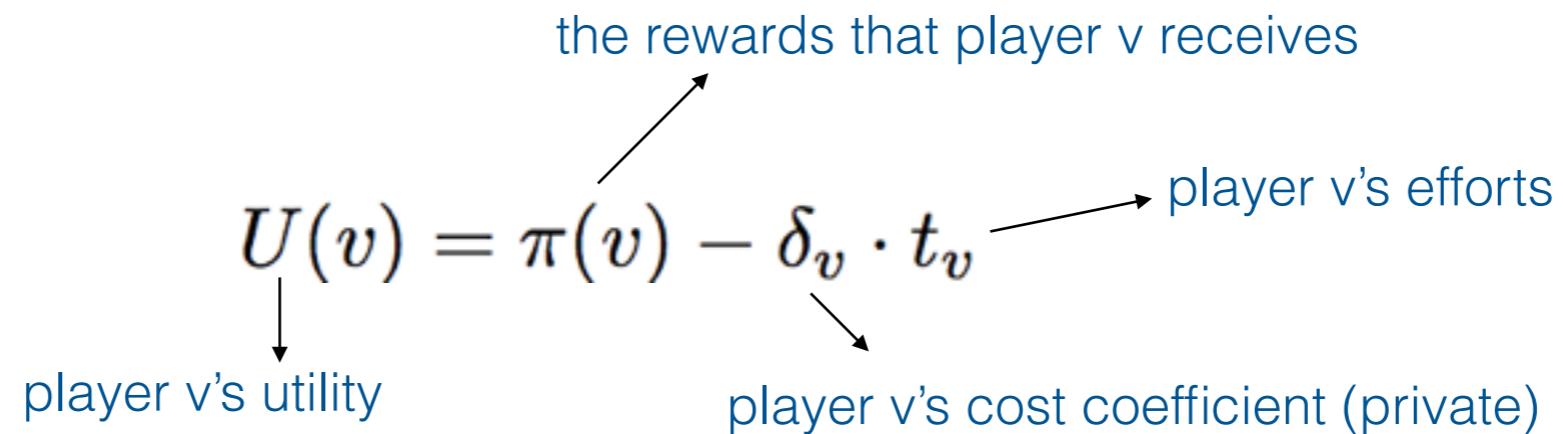
- How should a principal design the incentive mechanisms to address the challenges?

Agent Models & Preference Ranking

- **Agent Models**

$$U(v) = \pi(v) - \delta_v \cdot t_v$$

the rewards that player v receives
player v 's utility
 δ_v player v 's cost coefficient (private)
 t_v player v 's efforts



- **Preference Ranking**

Players prefer to obtain higher rewards given that they have private cost coefficients.

Multi-Winner Contests

- **Task rewards:** use the post price mechanism
- **Virtual credits:** assign a positive number of credits (quadratic in the player's task efforts) to each player that has contributed task efforts and has made successful referrals.
- **Diffusion rewards:** determine the diffusion rewards according to a ratio-form contest among players that are in the same subgraph. Allocate the rewards proportionally.

- Noise factor — captures the marginal increase in the probability of winning caused by a higher effort: with a low noise factor, players with different efforts may have a similar level of chance to win; with a high noise factor, players with higher efforts have a greater chance to win.

$$\text{prob}(v) = \frac{(b_v)^\sigma}{\sum_{u \in V'} (b_u)^\sigma}$$

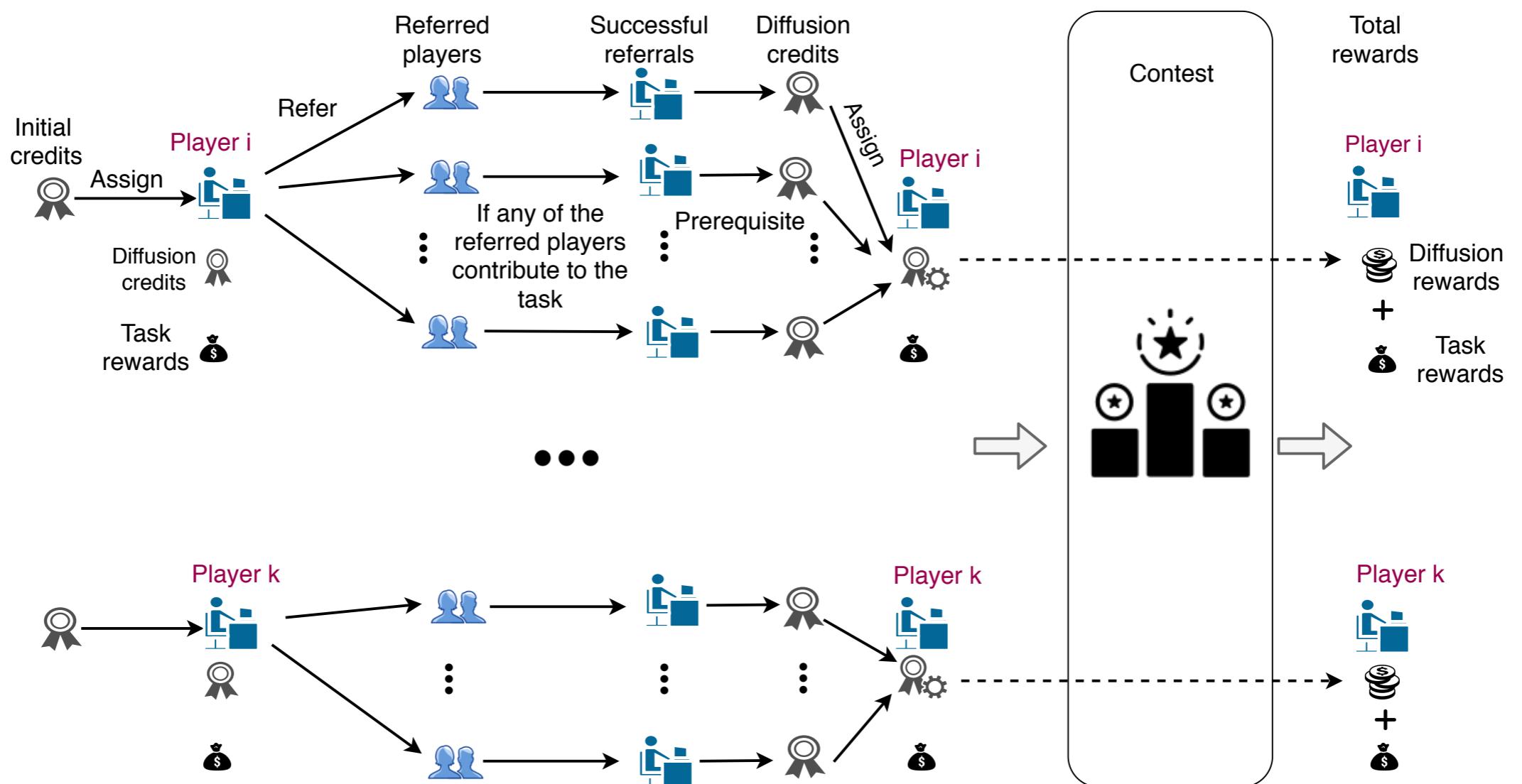
player v's virtual credits

noise factor

player v's probability of winning

players in the same subgraph of player v

Multi-Winner Contests



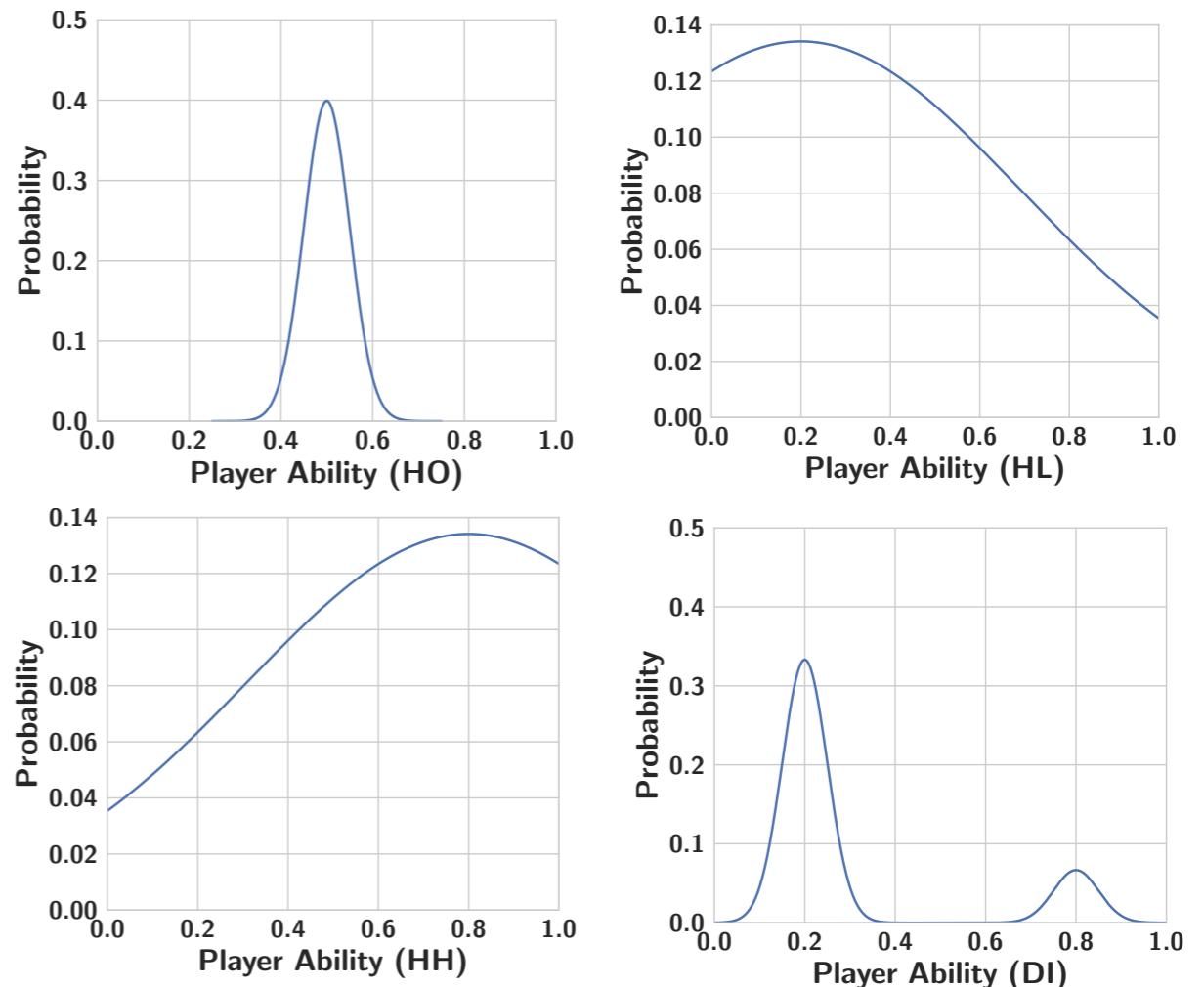
Experimental Settings

Dataset	#Nodes	#Edges	#Seeds	M.D.	A.D.
Twitter	323,185	2,148,717	1,715	8,822	52
Flickr	145,305	2,149,882	768	6,731	34
Flixster	95,969	484,865	502	3,109	27
Digg	17,817	128,587	107	1,375	20

Dataset configuration: M.D.- maximum degree
A.D.- average degree

Experimental Settings

- We conducted experiments with four groups of players on the four datasets and measured the total contributions
- Each group was run 20 times on the same 3.7 GHz linux machine; only the average numbers were reported.



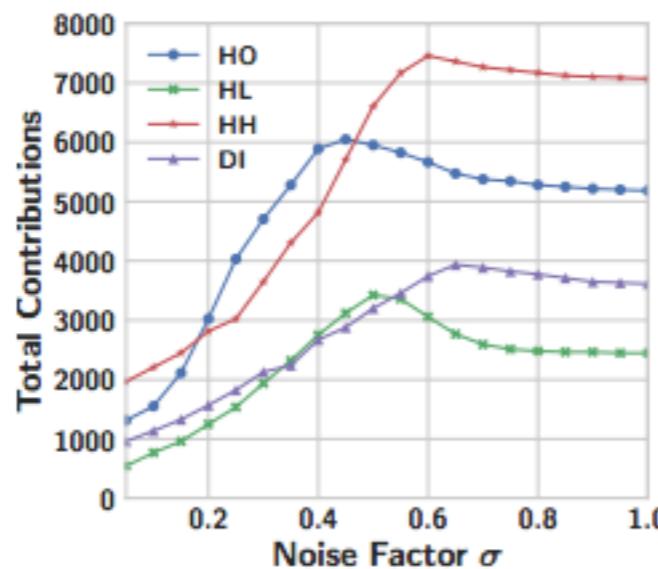
HO- homogeneous; HL- heterogeneously low;
HH -heterogeneously high; DI-distinctive

$$\delta_v = 1 - \rho_v$$

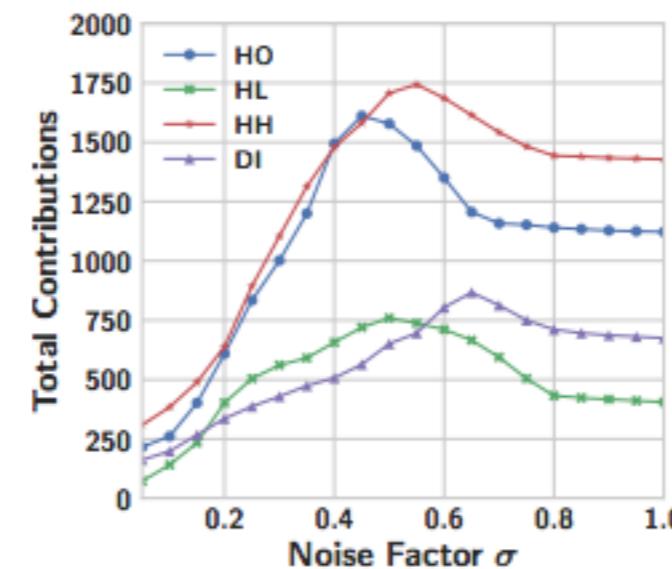
player v's
cost coefficient

player v's
ability

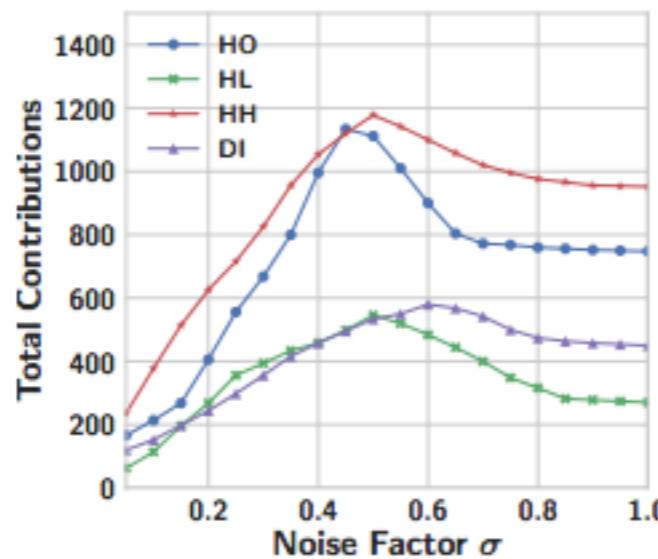
Total Contributions



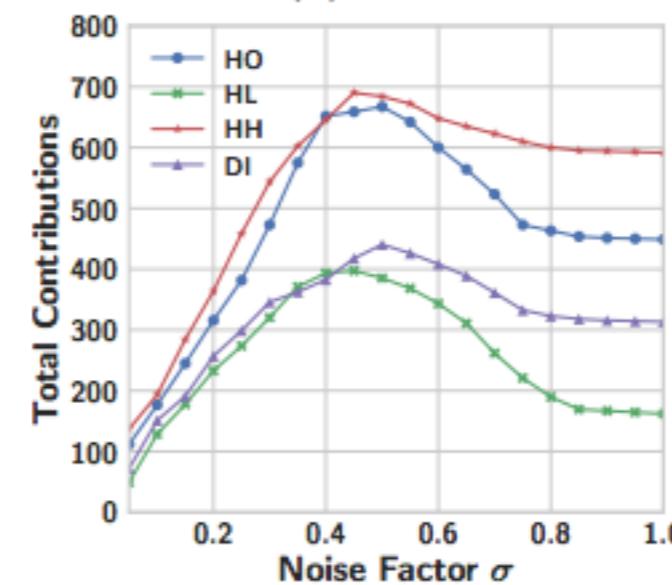
(a) Twitter.



(b) Flickr.



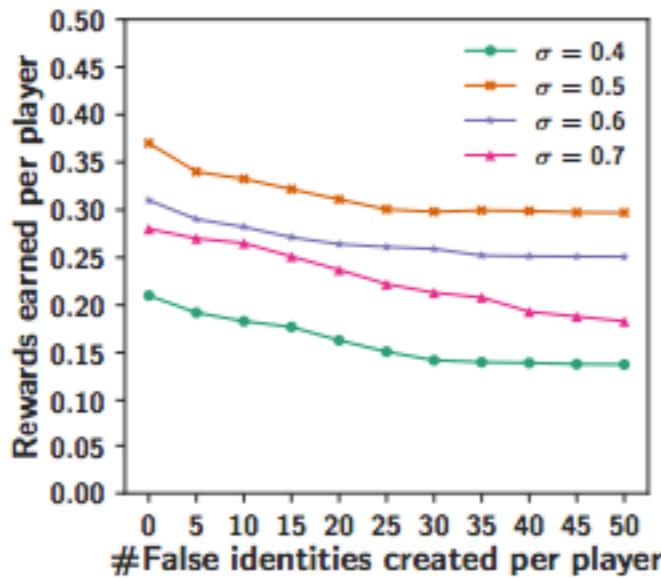
(c) Flixster.



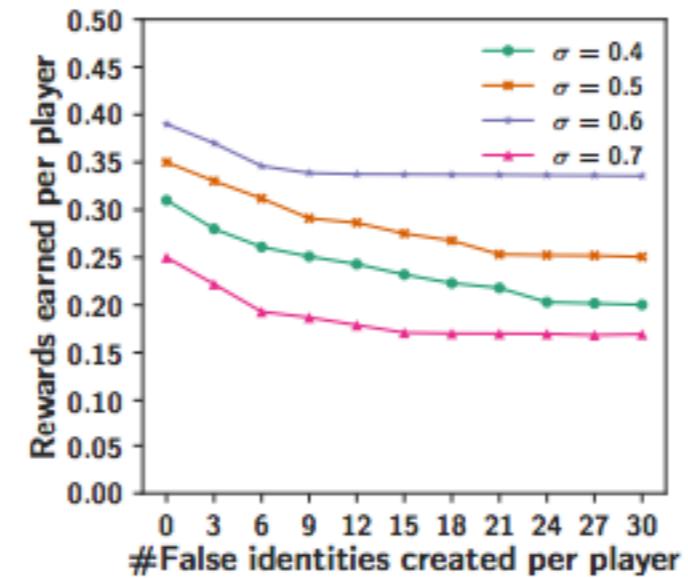
(d) Digg.

MWC with moderate noise factors performed consistently the best among groups with different player compositions

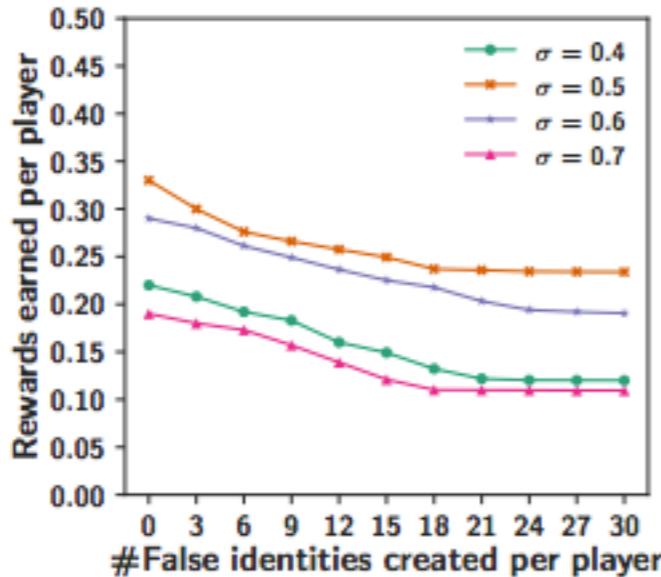
Robustness



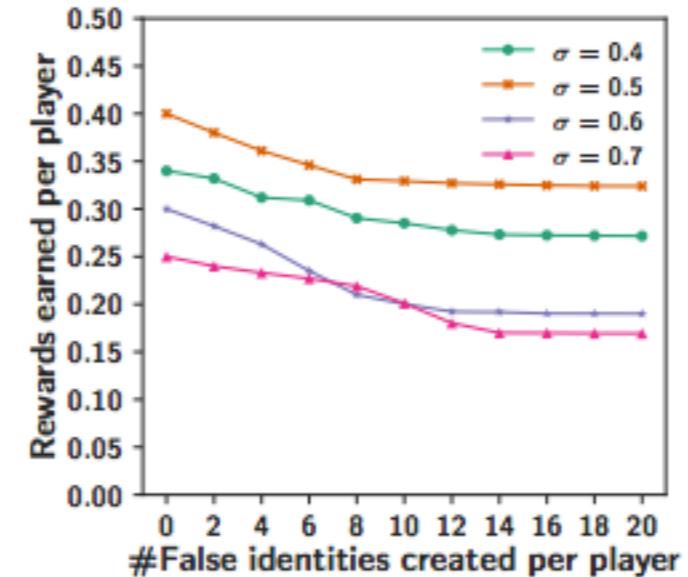
(a) Twitter.



(b) Flickr.



(c) Flixster.



(d) Digg.

Players received fewer rewards when they created more false identities.

Discussion

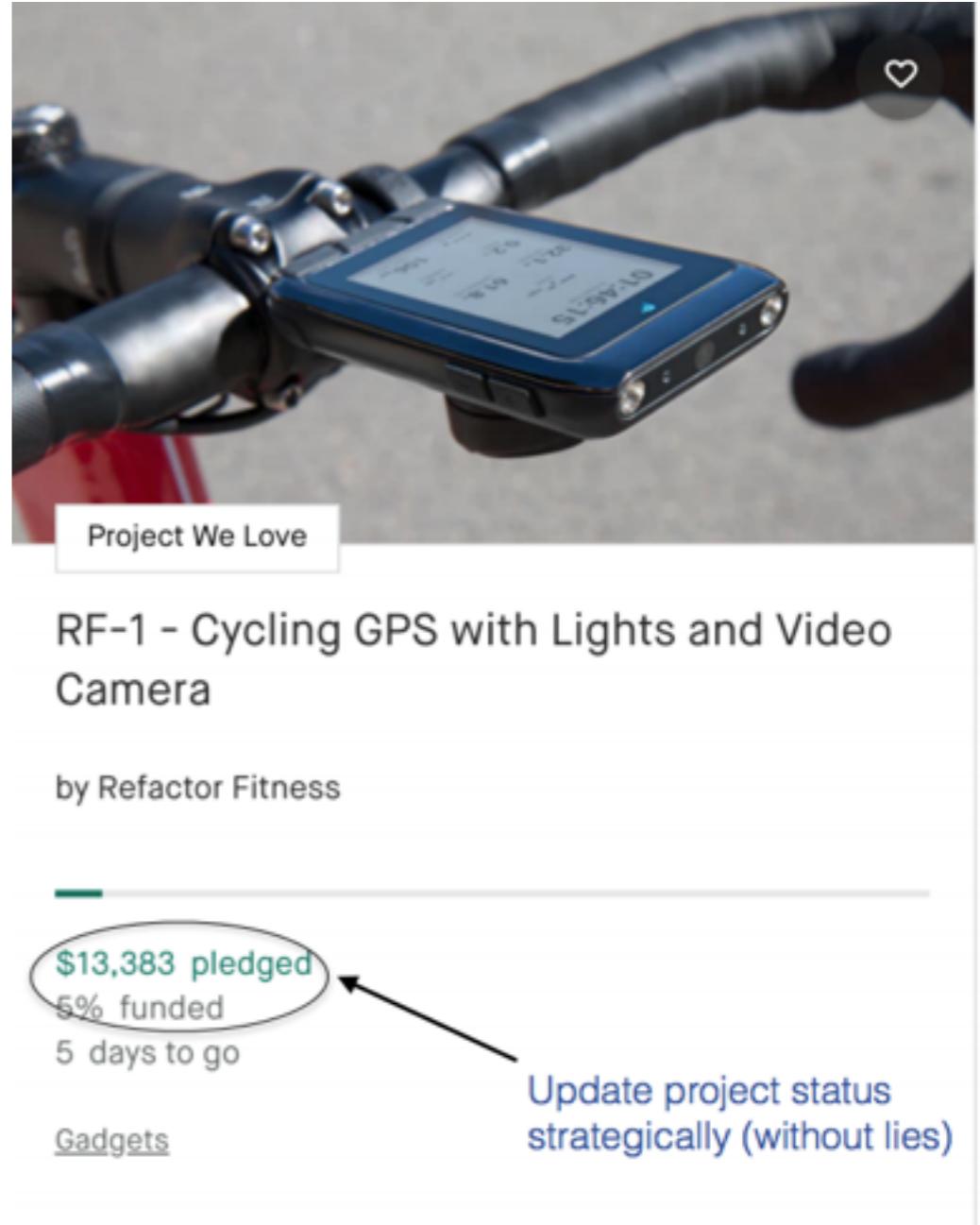
- **The MWC mechanism:**
 - Satisfies desirable properties: false-name-proofness, individual rationality, budget constraint, etc.
 - Can be applied to large graphs with tens of thousands of nodes.
- **Extended work:**
 - Counteracting collusion (Shen, Yan and Lopes, Working Paper 2019)
 - Counteracting free riding (Shen and Lopes, Working Paper 2019)

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Information Design for Crowdfunding

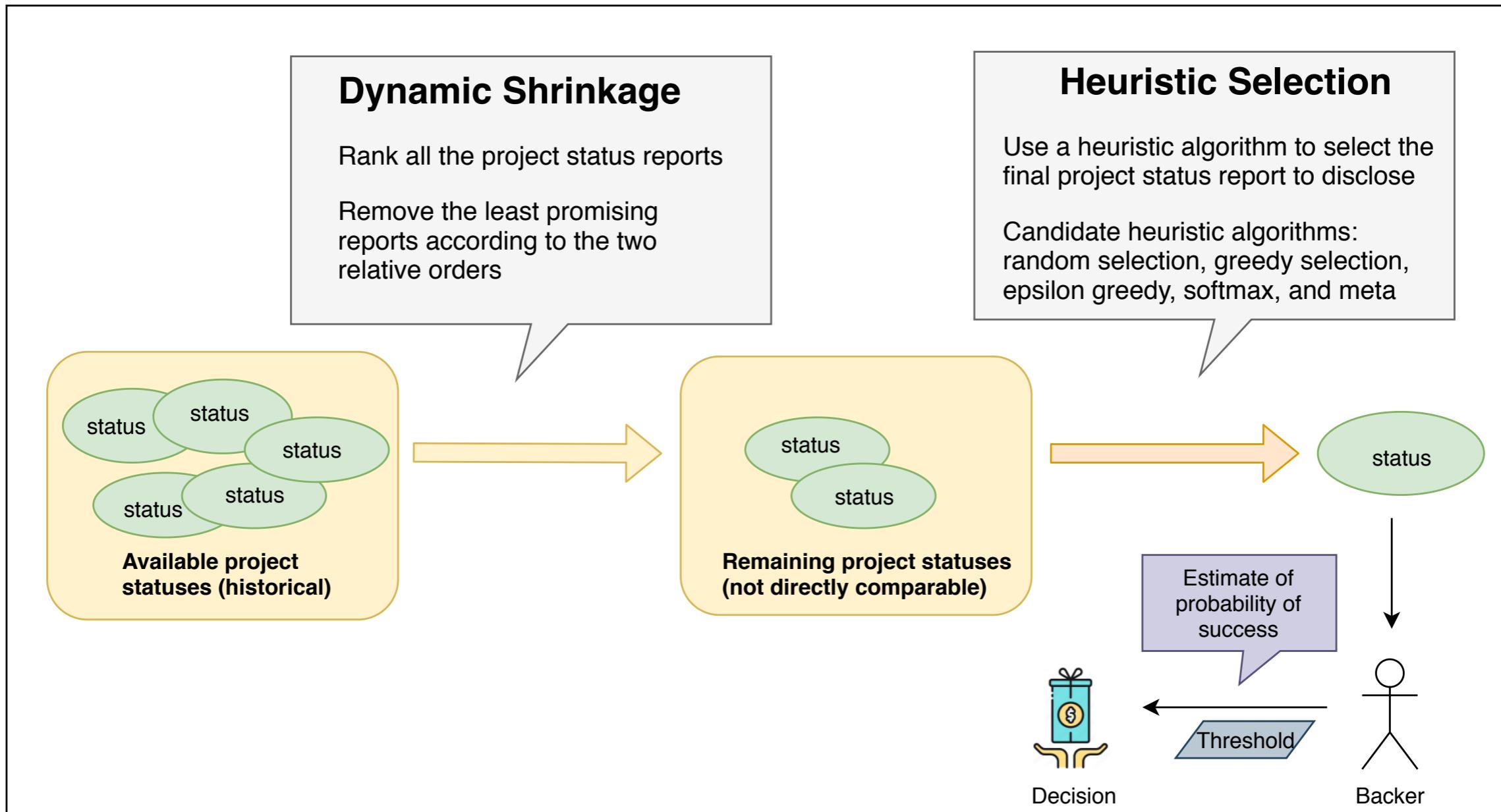
- **Objective:** to solicit contributions from early backers to generate revenue
- **Intuition:** to influence agents' beliefs by designing information disclosure policies (i.e. information structures that determine which pieces of information are disclosed to whom for desirable outcomes)



Credit: Kickstarter

Dynamic Information Design

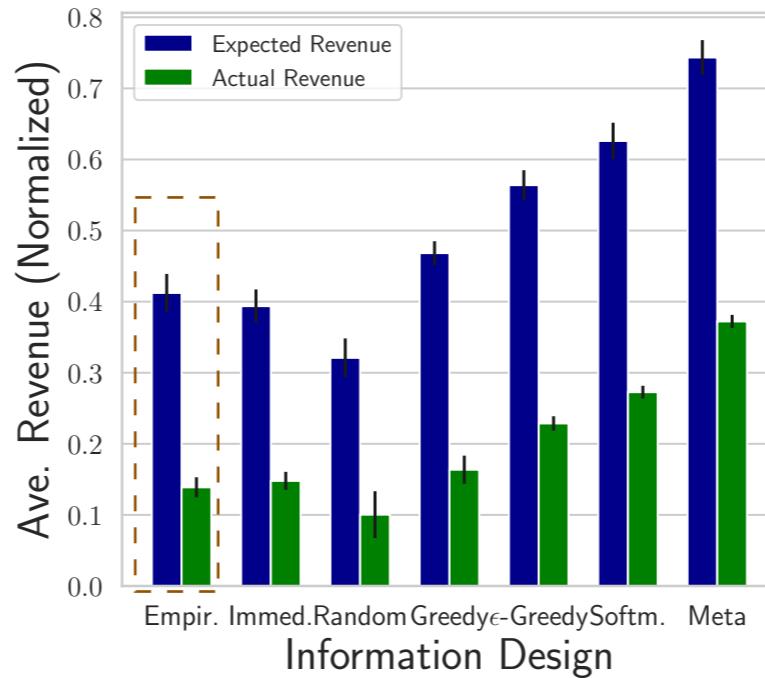
Dynamic Shrinkage with Heuristic Selection



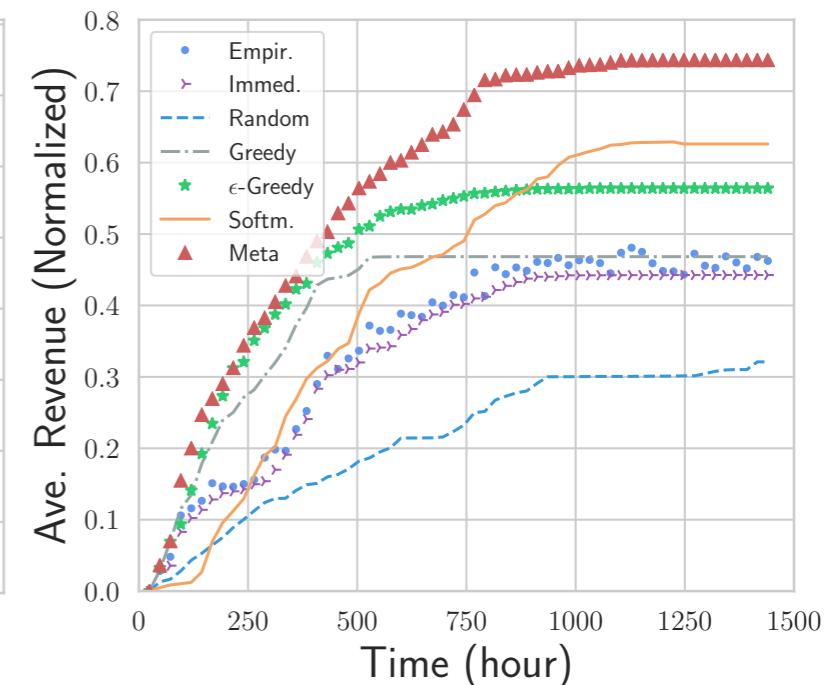
Simulation Results

• Observations

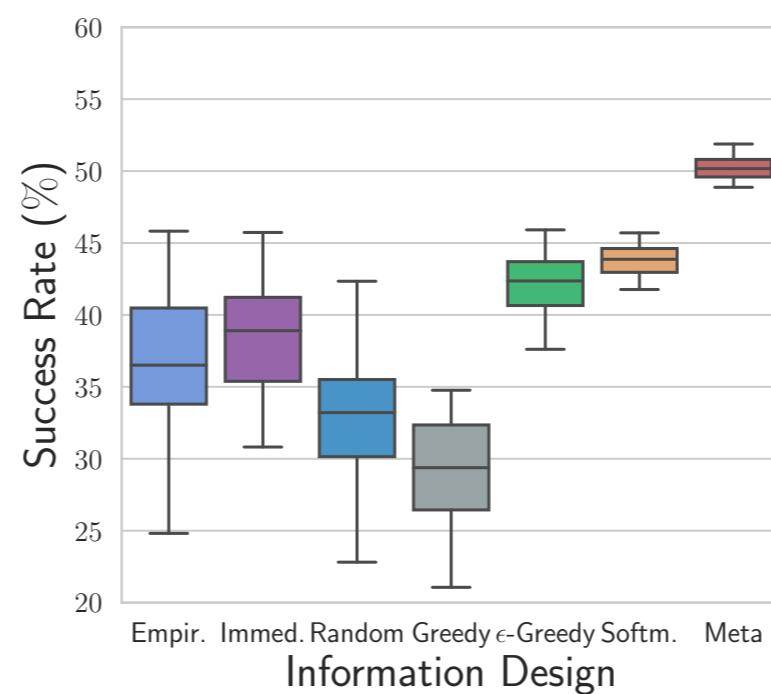
- Meta group performed consistently the best among all the groups in terms of both actual and expected revenue.
- Meta group had the highest project success rate.
- Meta group required the most computational time.



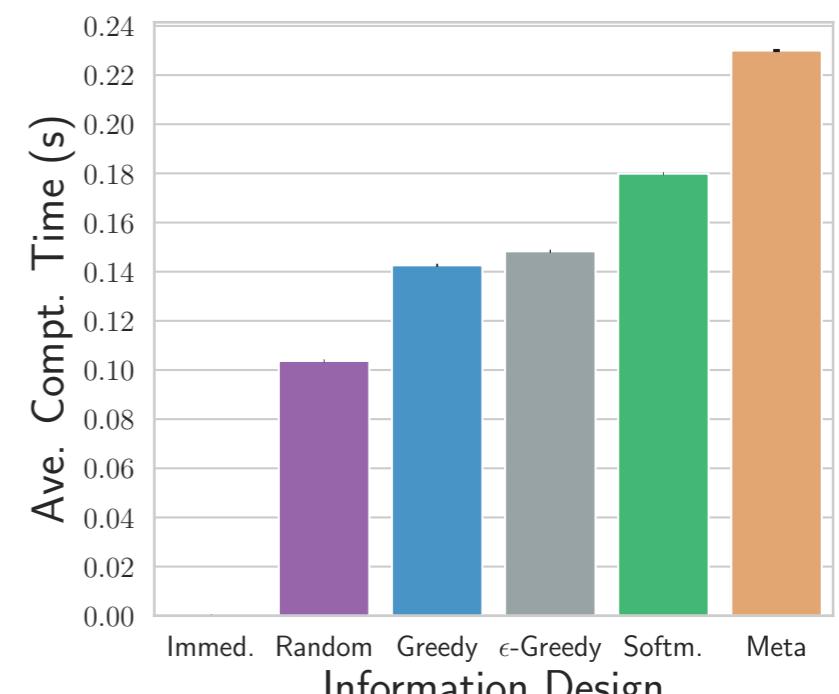
(a) Overall revenue ($t = 1440$)



(b) Expected revenue over time



(c) Project success rate (%)



(d) Computation time

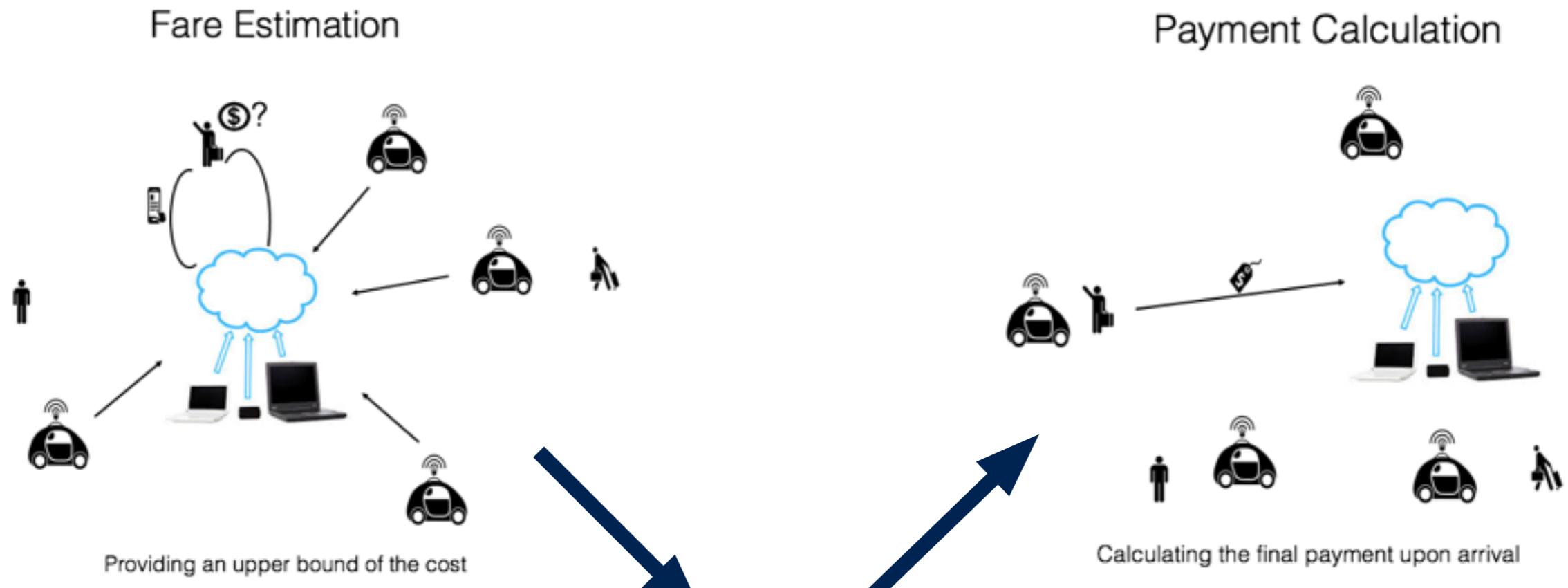
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Autonomous Mobility-on-Demand Systems



An Online Post-Price Mechanism for Autonomous Ridesharing Systems



Objective:

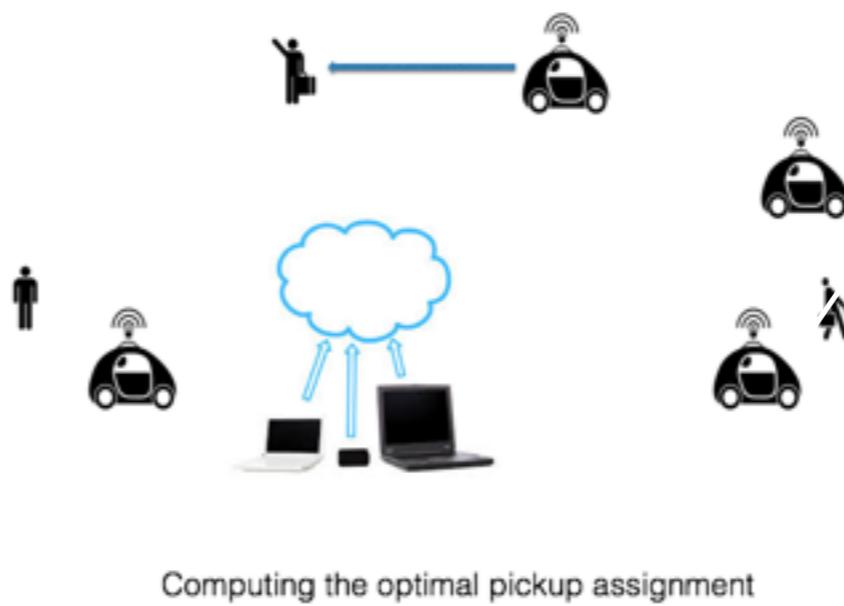
To minimize the operational cost per unit demand (i.e. to maximize the serviced demand per unit cost).

Method:

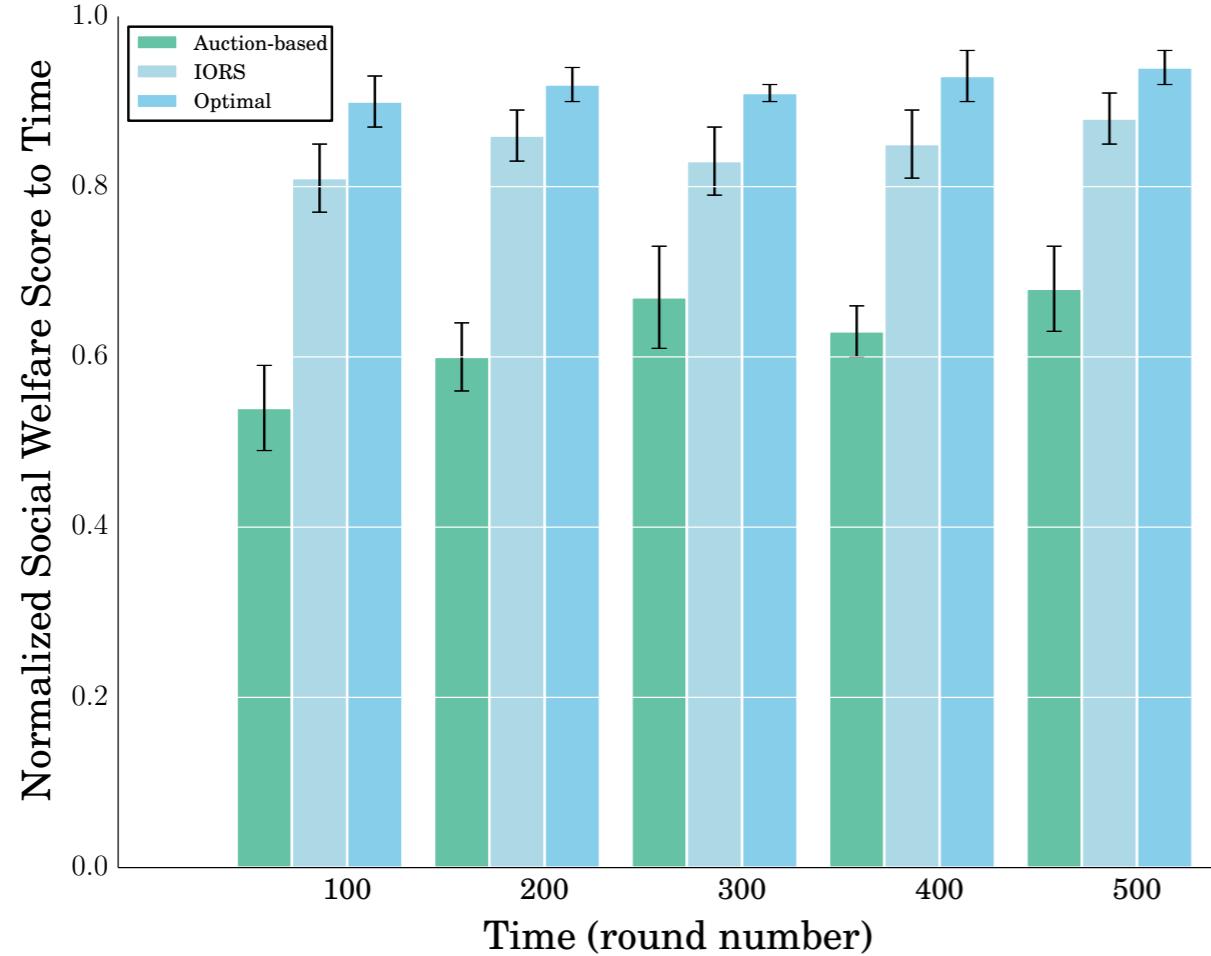
Integrated Online RideSharing (IORS) mechanism

Properties:

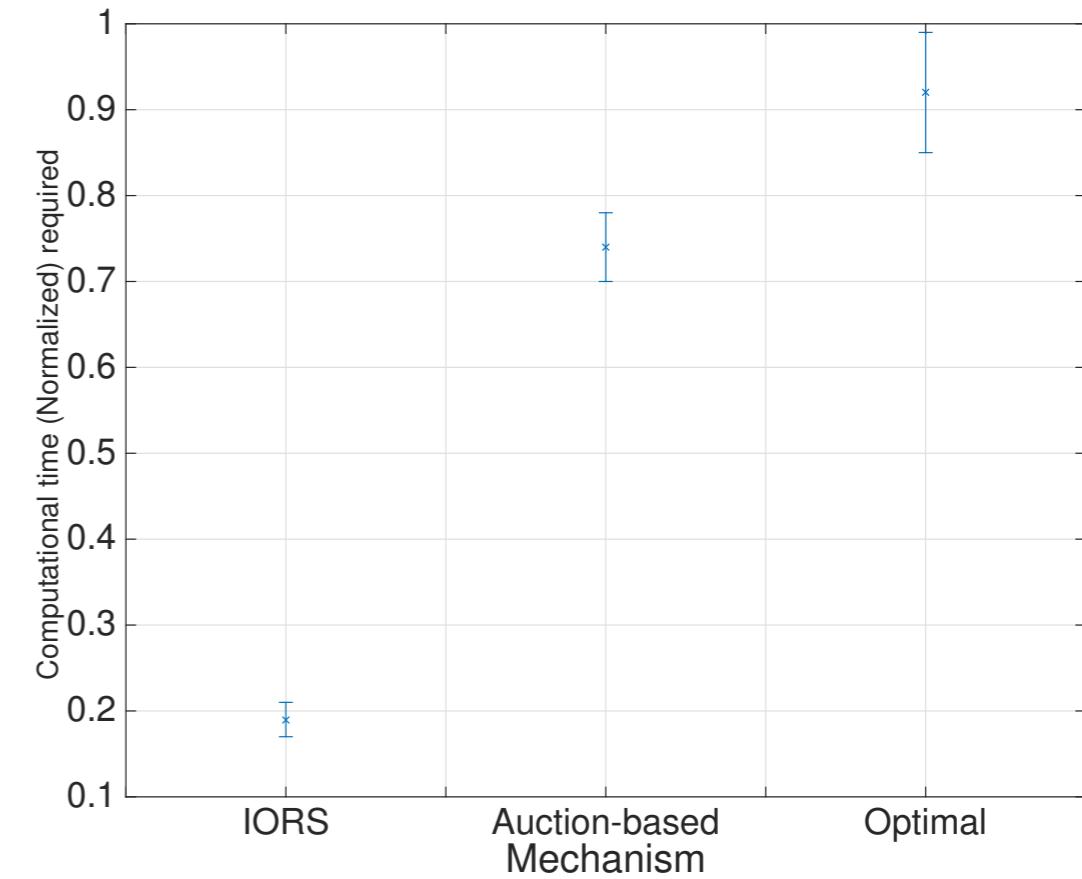
- Ex-post incentive compatibility
- Individual rationality
- Budget constraint



IORS is Competitive



Social welfare scores to time.



Computational time.

Benchmarks: Optimal offline, Auction-based mechanism (Cheng et al. 2014)

Observations:

- IORS outperforms the auction-based mechanism
- Close to the optimal solution with less computation time

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Mechanism Design with Thresholding Agents

Motivation: how to counter manipulations

Approach: using contests to increase competitions

Results: robust to false-name attacks, collusion, free riding

Motivation: how to attract early donations

Approach: dynamic information design

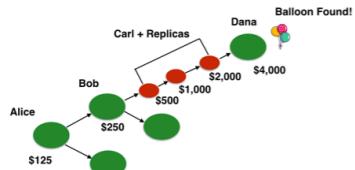
Results: outperforms immediate disclosure

Motivation: how to promote ridesharing

Approach: post-price online mechanism

Results: outperforms the auction-based mechanism, comparable to the optimal approach

Countering Manipulation



Shen, Feng, Lopes AAAI'19
Shen, Yan, Lopes Working Paper
Shen, Lopes Working Paper

Crowdfunding



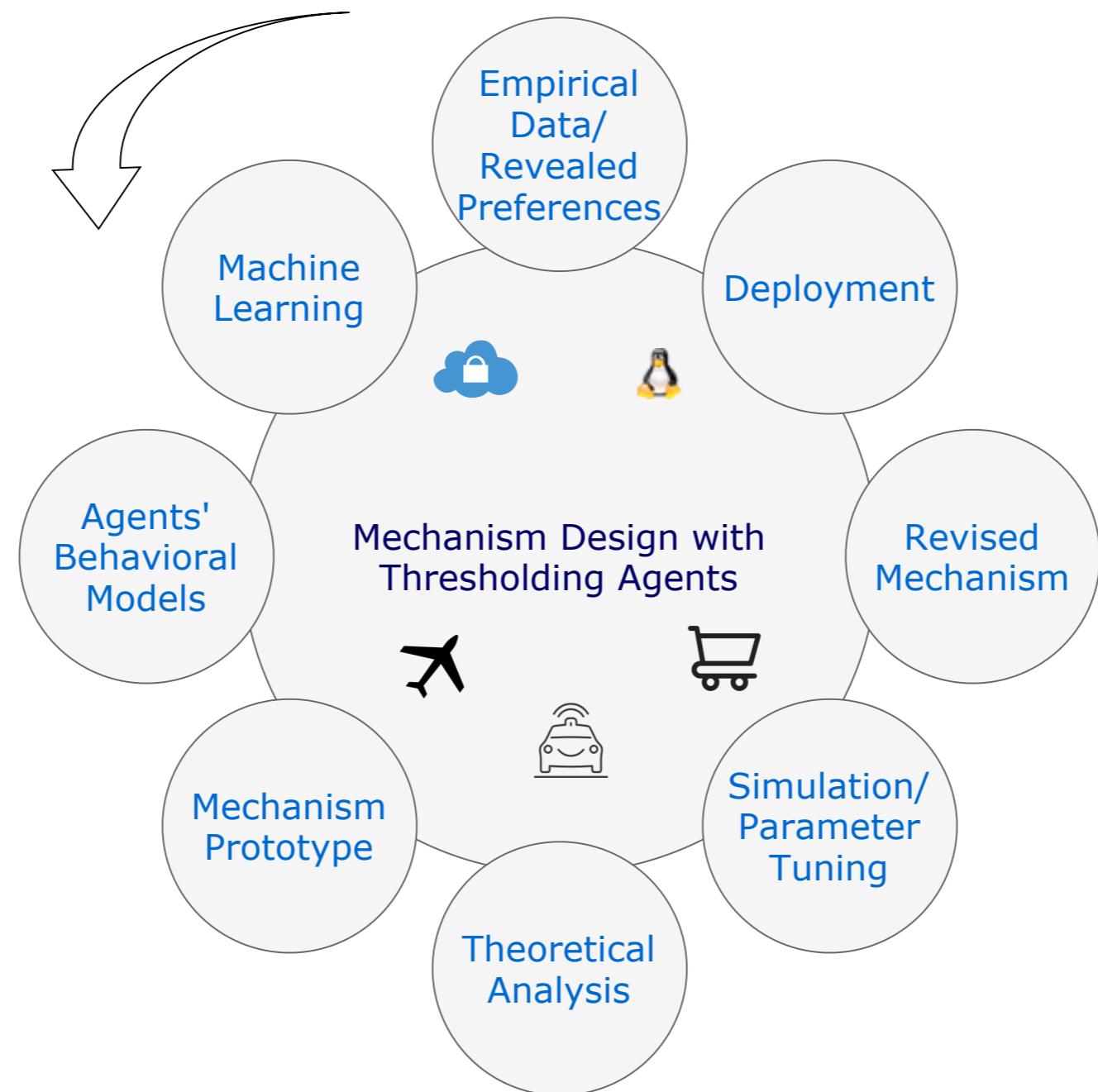
Shen, Crandall, Yan, Lopes AAMAS'18

Ridesharing



Shen, Lopes, Crandall IJCAI'16

Future Directions



References

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- W. Shen**, Y. Feng, C.V. Lopes: Multi-Winner Contests for Strategic Diffusion in Social Networks. In Proc. of the 33rd AAAI Conference on Artificial Intelligence (*AAAI 2019*).
- W. Shen**, R. Achar, C. V. Lopes: Toward Understanding the Impact of User Participation in Autonomous Ridesharing Systems. In Proc. of the 50th Winter Simulation Conference (*WinterSim 2018*).
- W. Shen**, J.W. Crandall, K. Yan, C. V. Lopes: Information Design in Crowdfunding under Thresholding Policies. In Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (*AAMAS 2018*).
- W. Shen**, A. A. Khemeiri, A. Almehrezi, W. Al-Enezi, I. Rahwan, J.W. Crandall: Regulating Highly Automated Robot Ecologies. In Proc. of the Fifth International Conference on Human-Agent Interaction (*HAI 2017*). Best Student Paper Award.
- W. Shen**, C. V. Lopes, J. W. Crandall: An Online Mechanism for Ridesharing in Autonomous Mobility-on-Demand Systems. In Proc. of the 25th International Joint Conference on Artificial Intelligence (*IJCAI 2016*).
- W. Shen**, C. V. Lopes: Managing Autonomous Mobility on Demand Systems for Better Passenger Experience. In Proc. of the 18th International Conference on Principles and Practice of Multi-Agent Systems (*PRIMA 2015*).

Q & A

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