

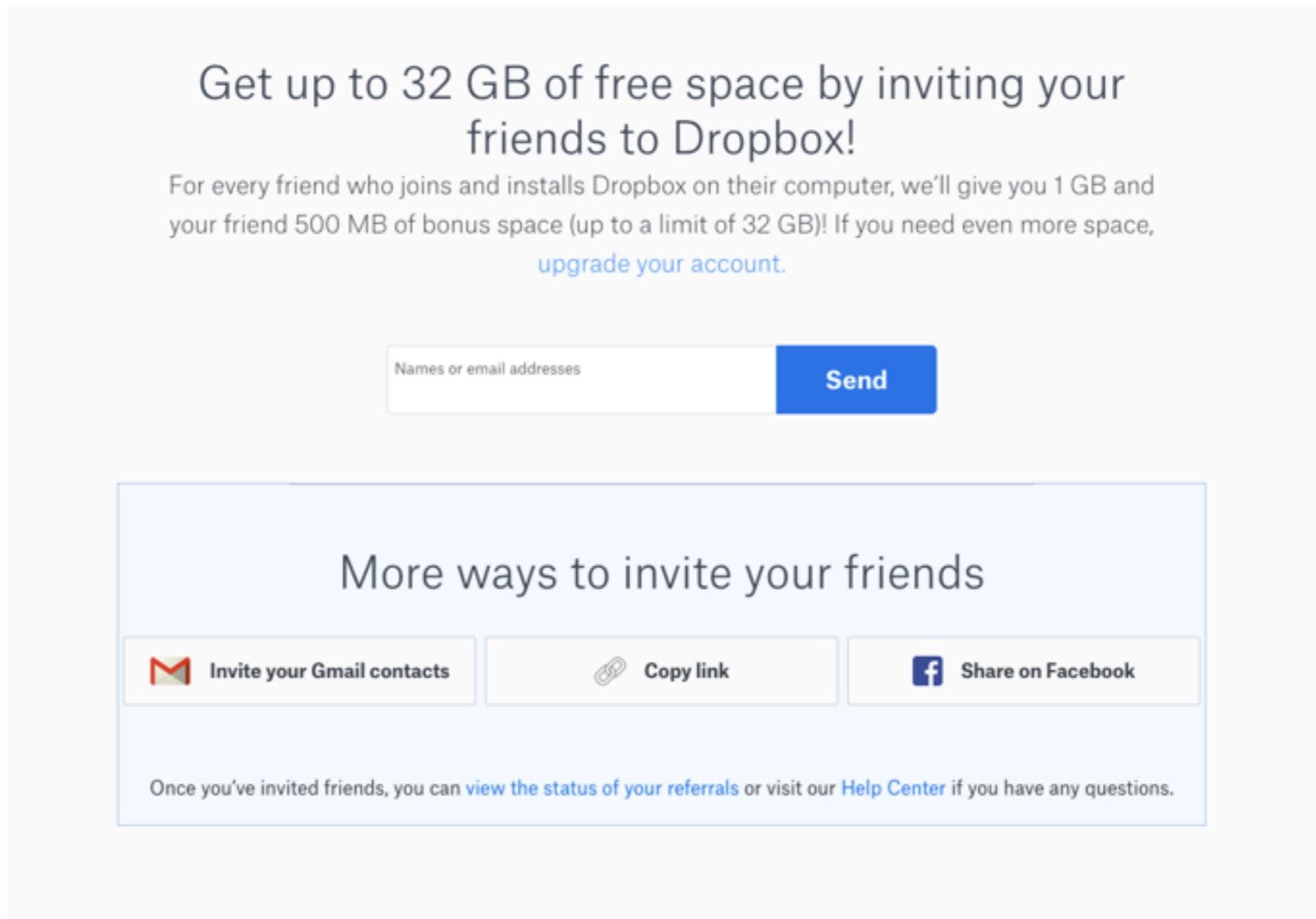
# Beyond Nash Equilibrium: Mechanism Design with Thresholding Agents

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June 5, 2019

Committee Prof. Cristina Lopes (Chair)  
Prof. Amelia Regan  
Prof. David Redmiles

# Motivating Example I

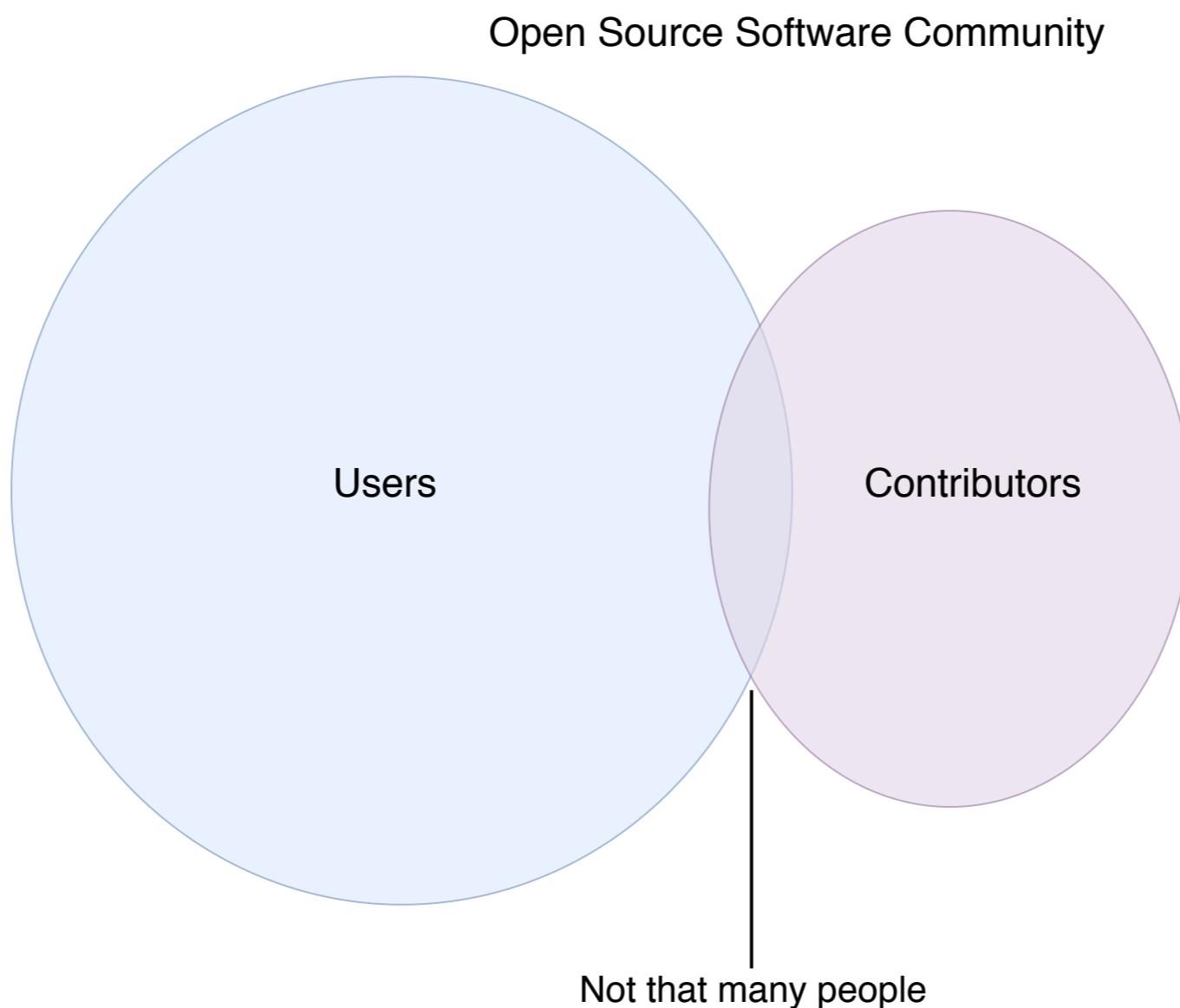


The image shows a screenshot of the Dropbox referral program landing page. At the top, it says "Get up to 32 GB of free space by inviting your friends to Dropbox!" Below that, a text block explains: "For every friend who joins and installs Dropbox on their computer, we'll give you 1 GB and your friend 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

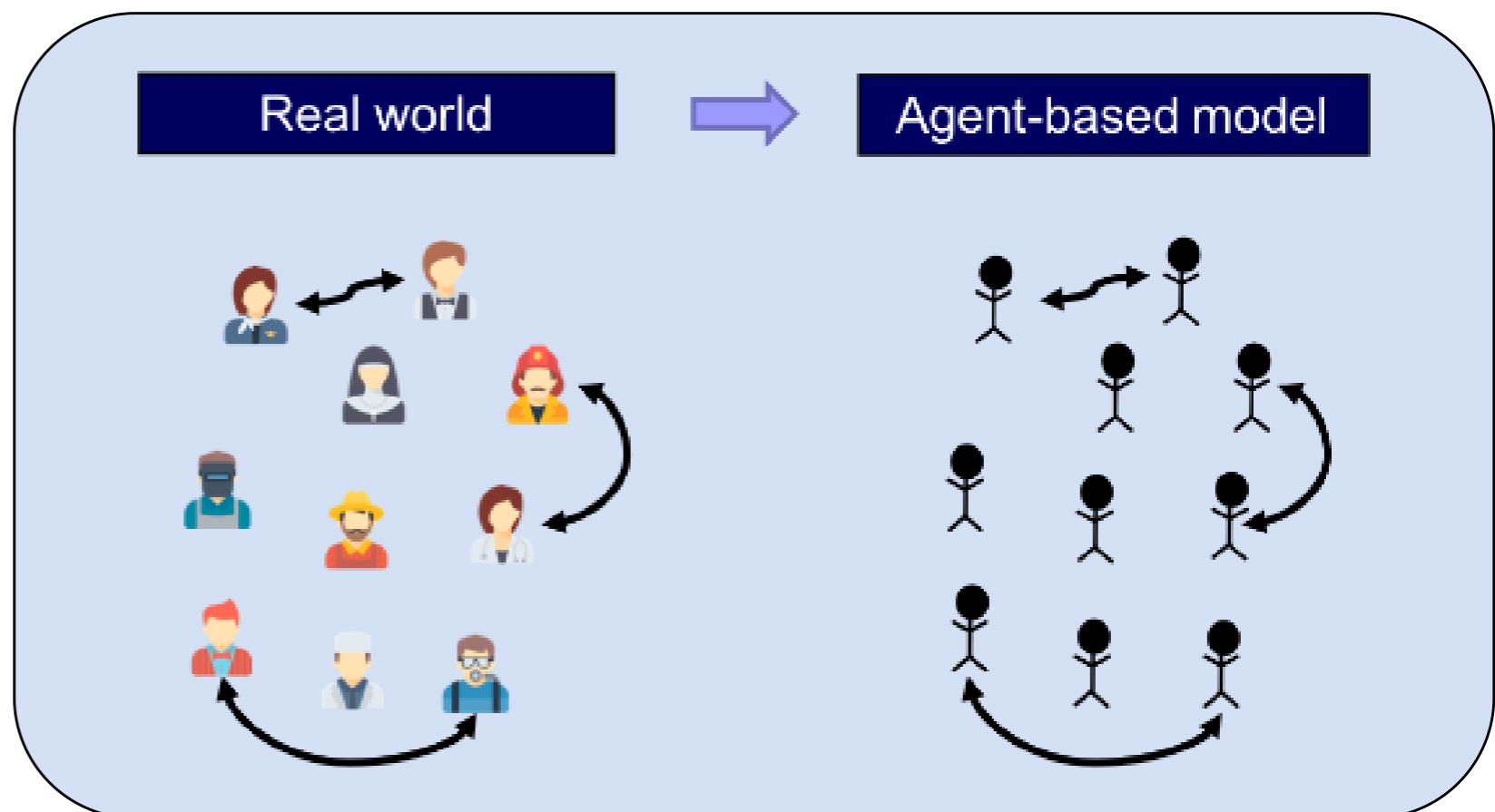
# Agent-Based Modeling

- **Individual Agents**

- Autonomous
- Heterogeneous
- No global views

- **Stakeholder**

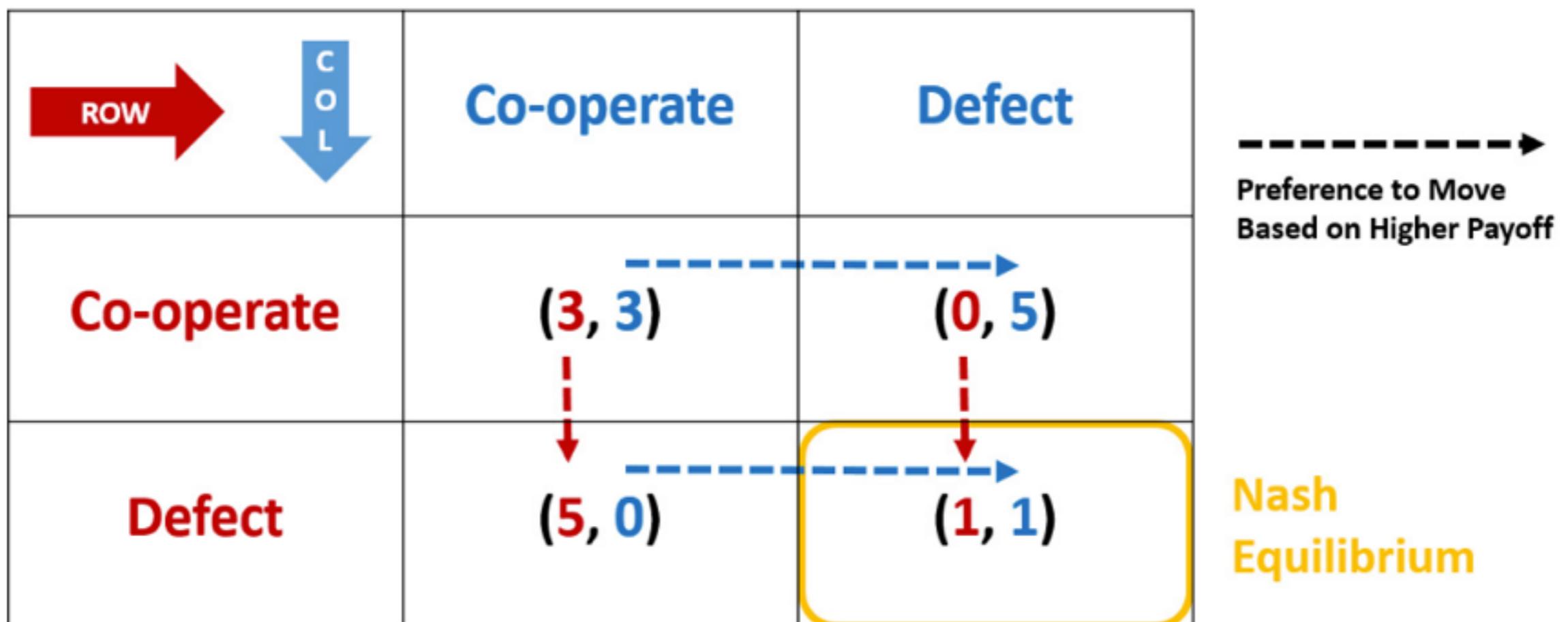
- Interested in system-wide performance



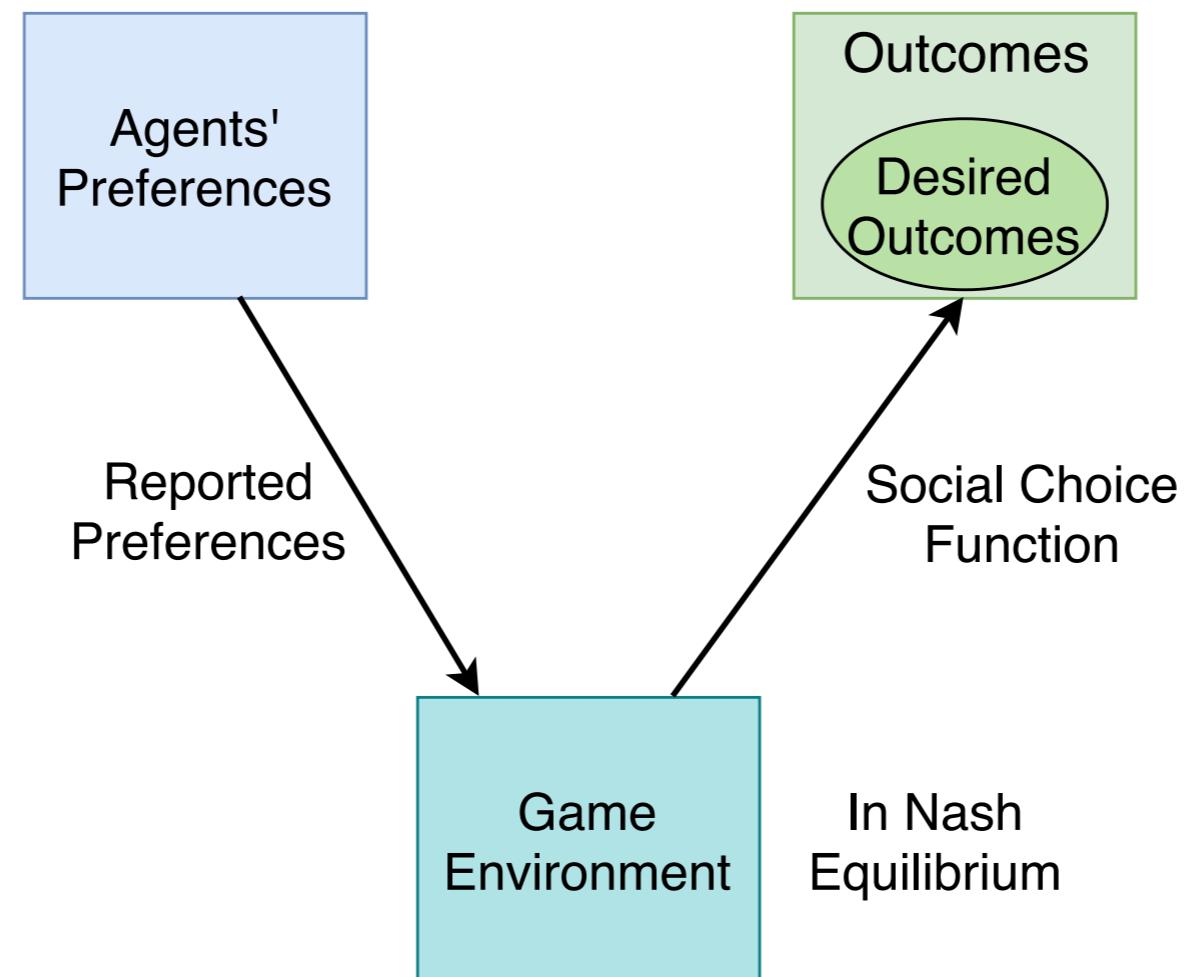
# Outline

- Traditional Mechanism Design and Its Challenges
- Theory of Mechanism Design with Thresholding Agents
- Case Study I: Contest Mechanism for Countering Manipulations
- Case Study II: Information Design for Crowdfunding
- Case Study III: Mechanism Design for Ridesharing
- Conclusion and Future Directions

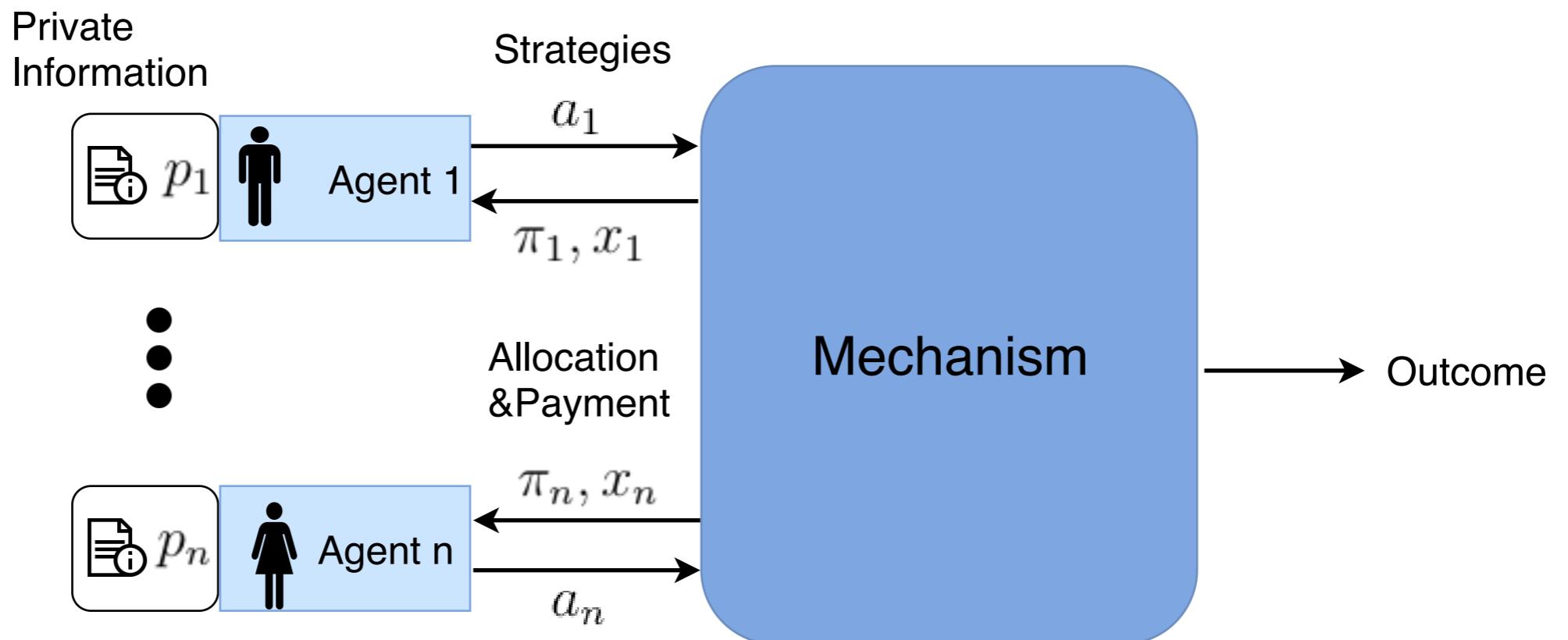
# Game Theory



# Mechanism Design Theory



# Mechanism Design Theory



# Mechanism Design for Social Good

- **Objective**

- social welfare maximization

- **Characterics**

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



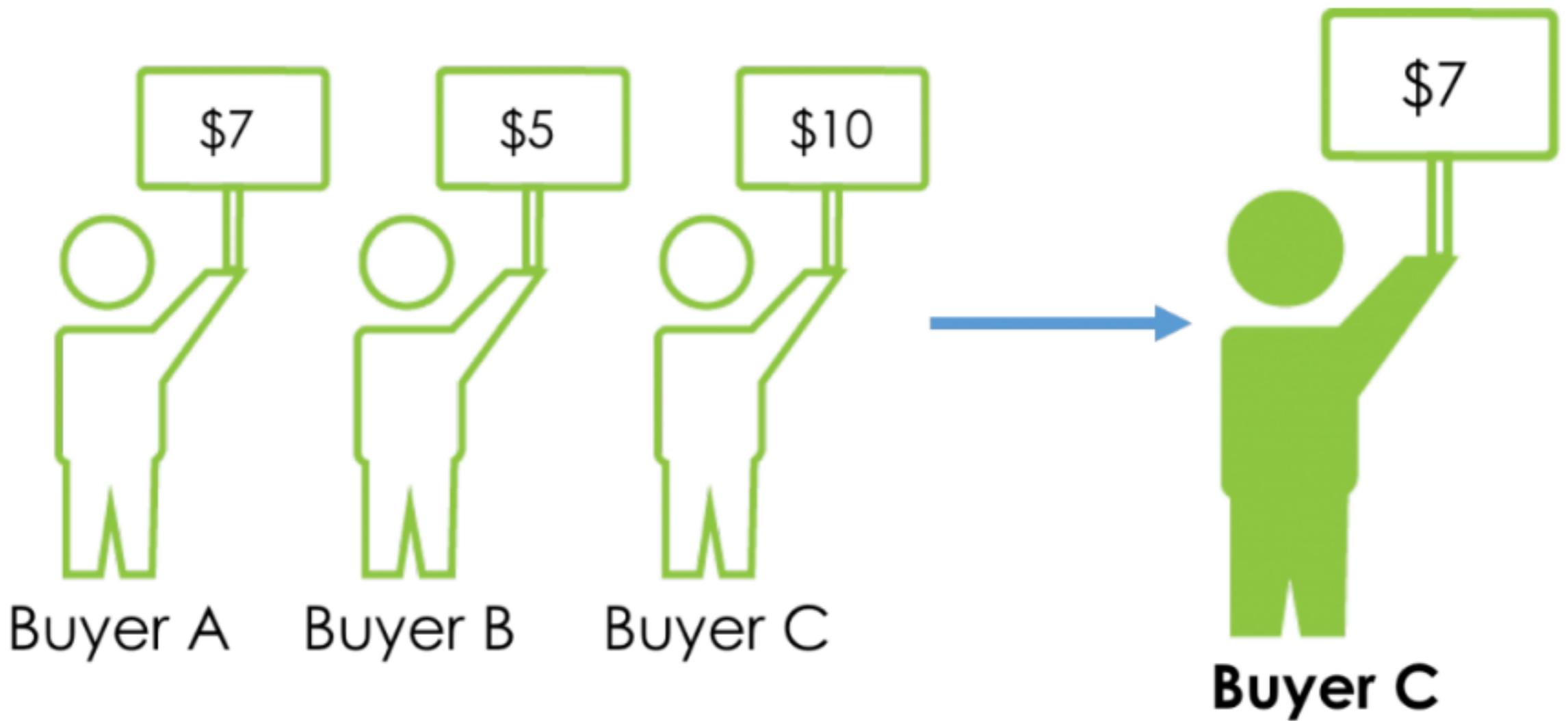
# Mechanism Design for Revenue Optimization

- **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

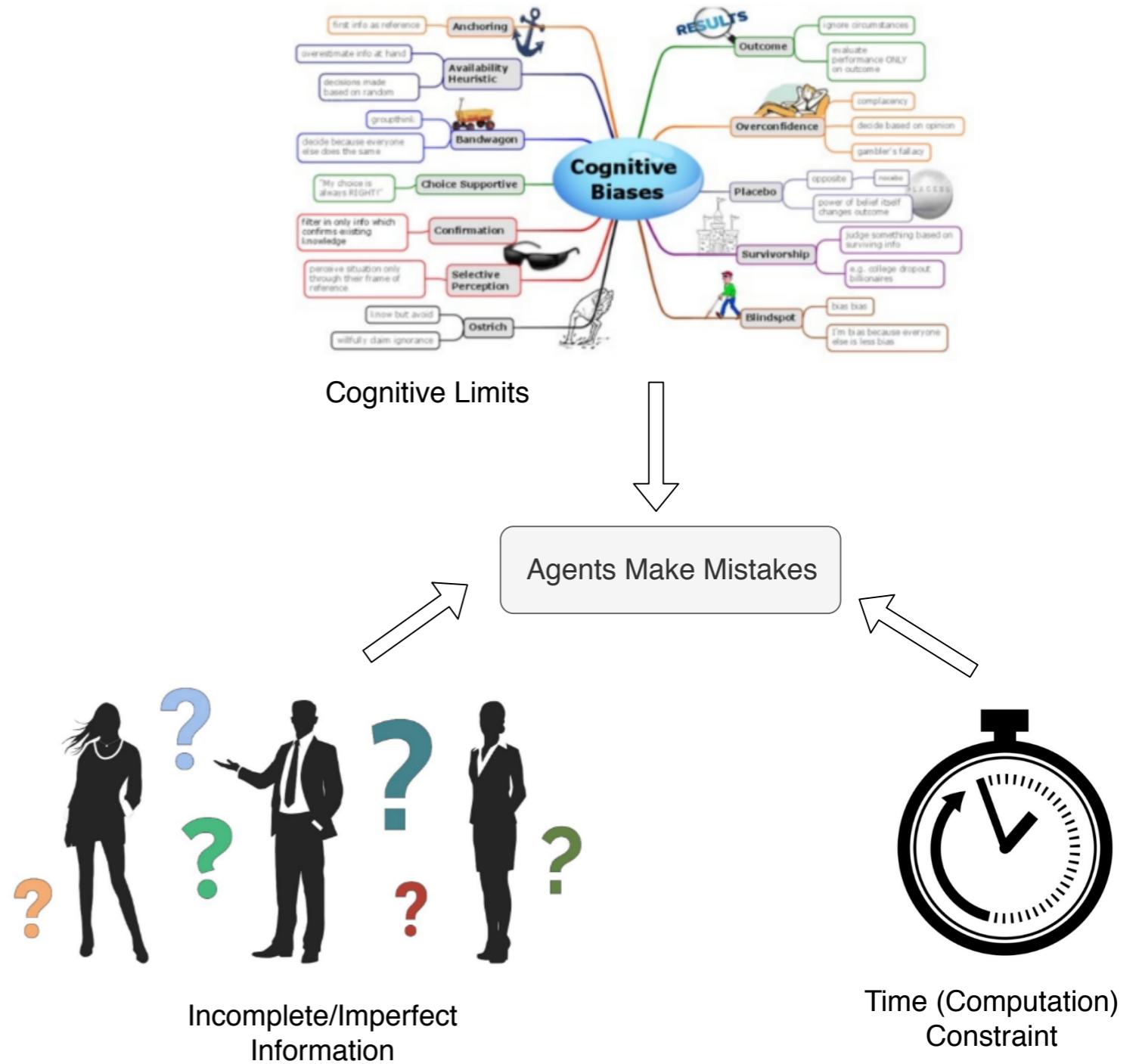
- **Full Rationality Assumption**

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

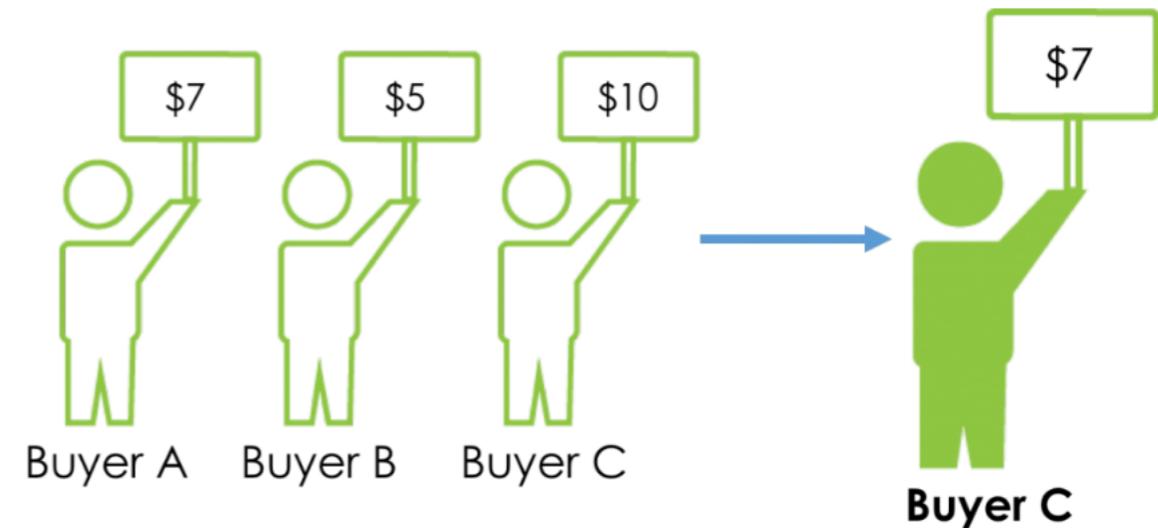
# Challenges in Traditional Mechanism Design Theory

- **Vulnerability to Group Manipulations**

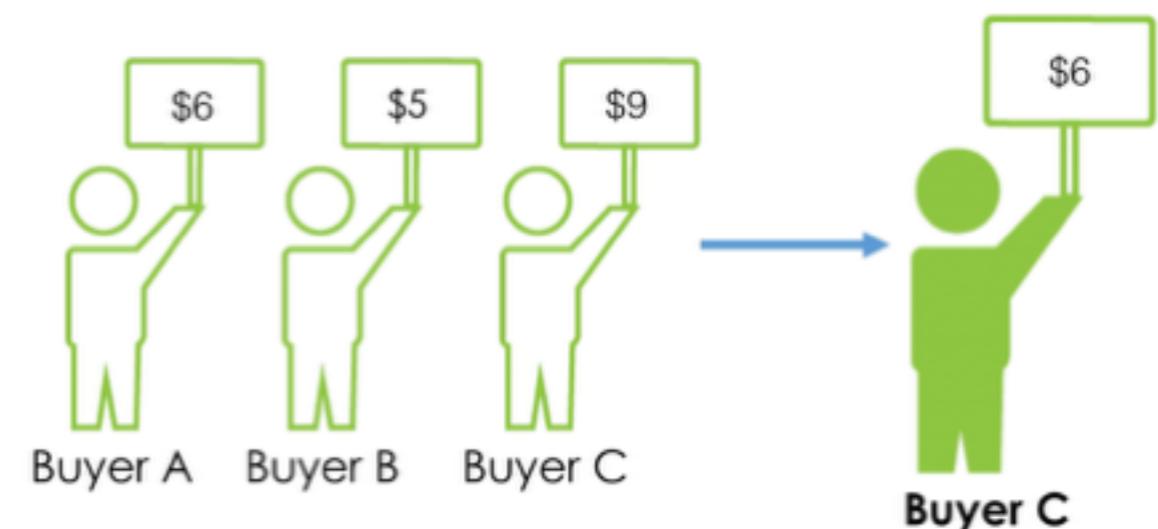
VS

- **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)

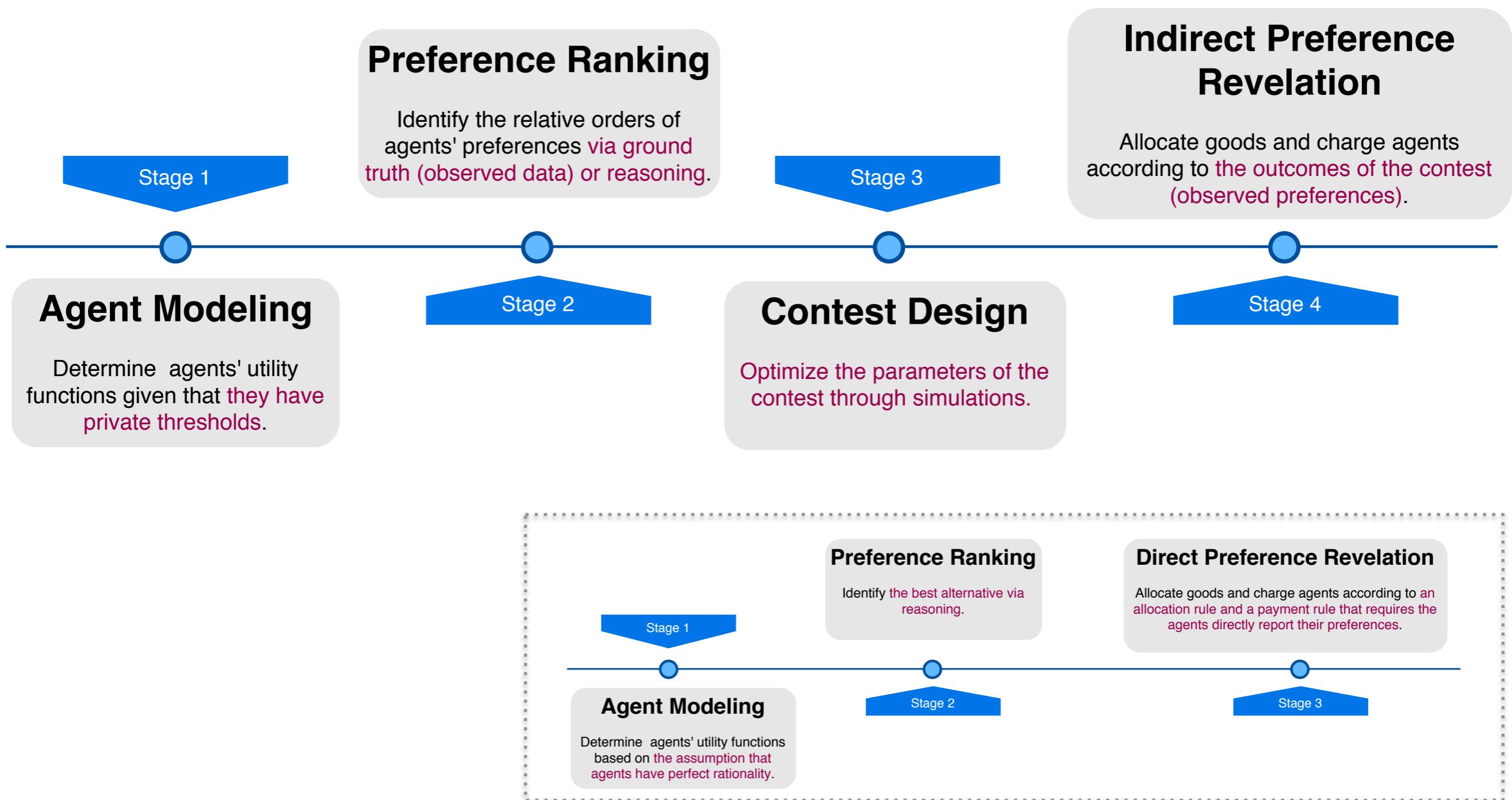
- **Manipulation-Resistant Mechanisms**

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

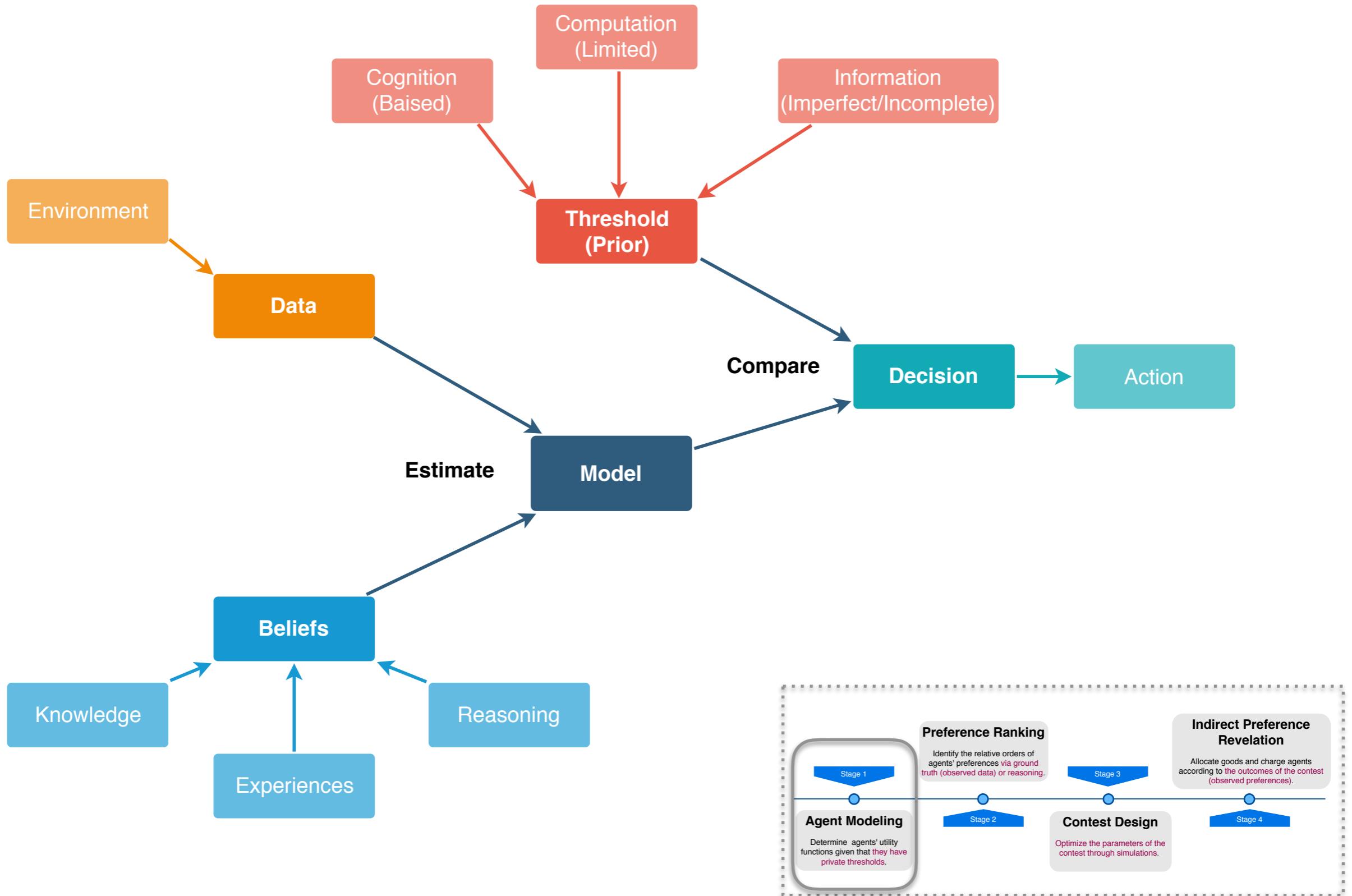
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# Mechanism Design with Thresholding Agents

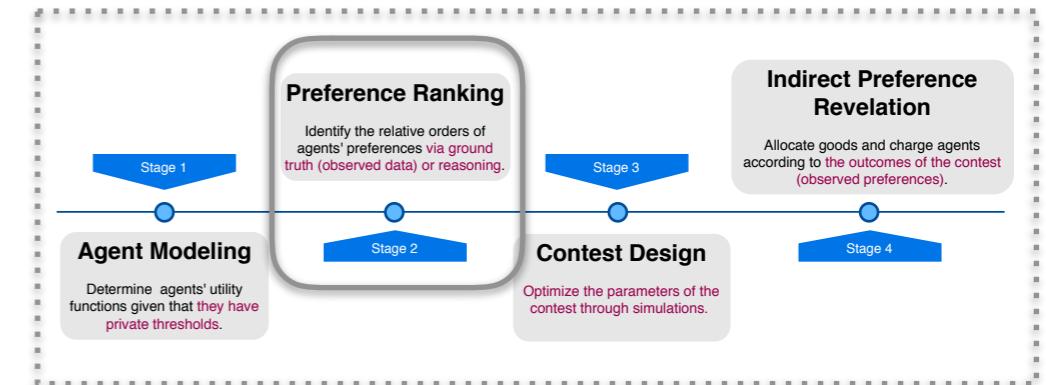
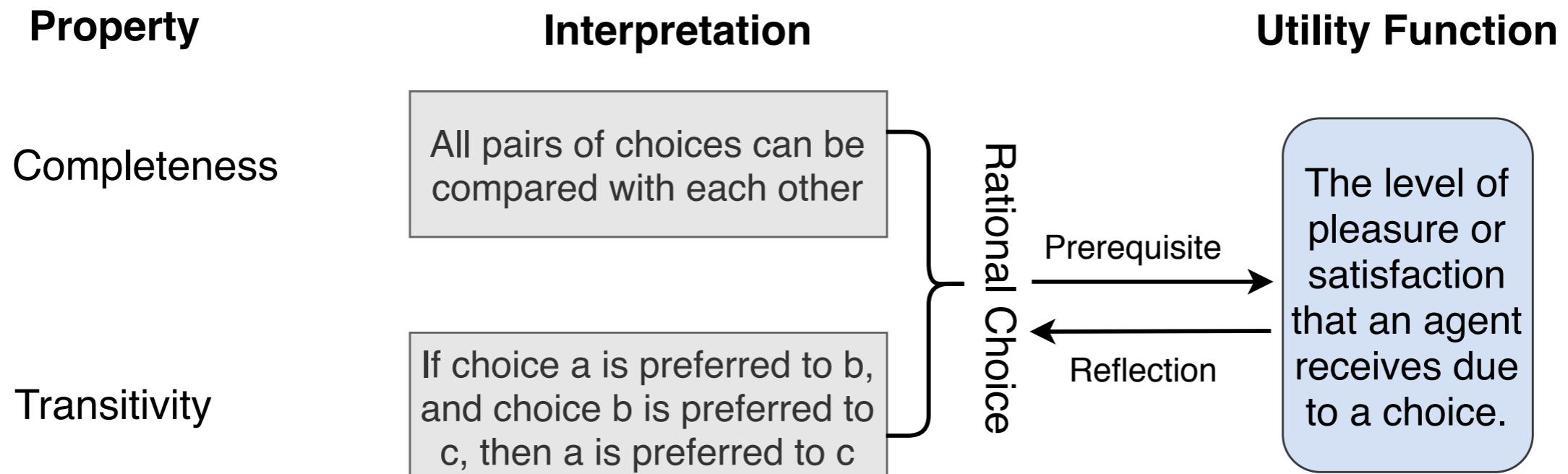


# Agent Modeling

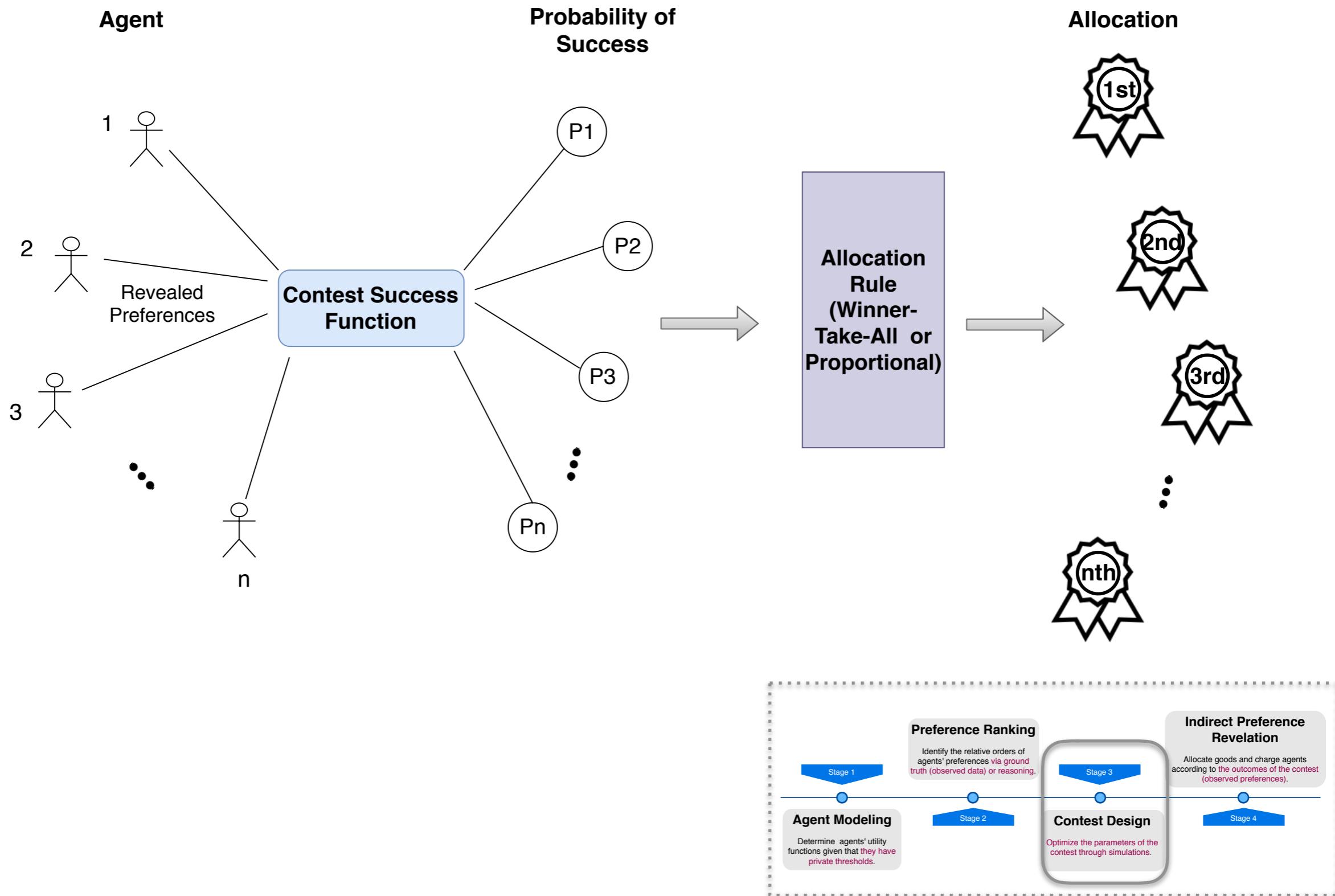


# Preference Ranking

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



# Contest Design

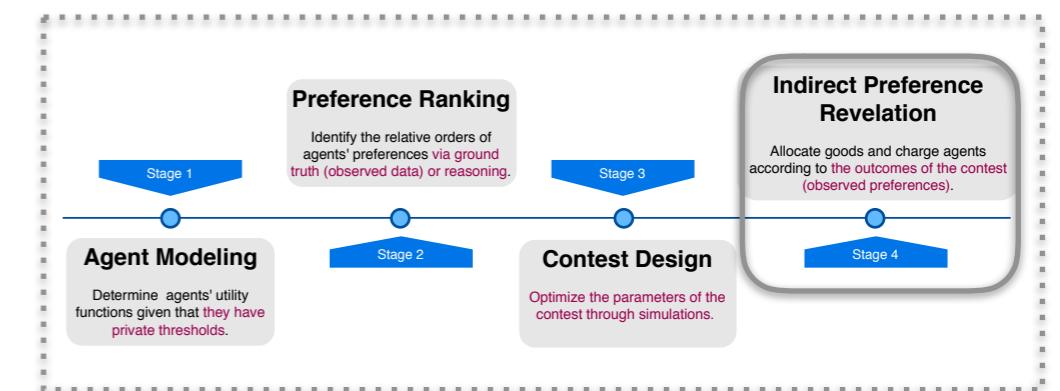
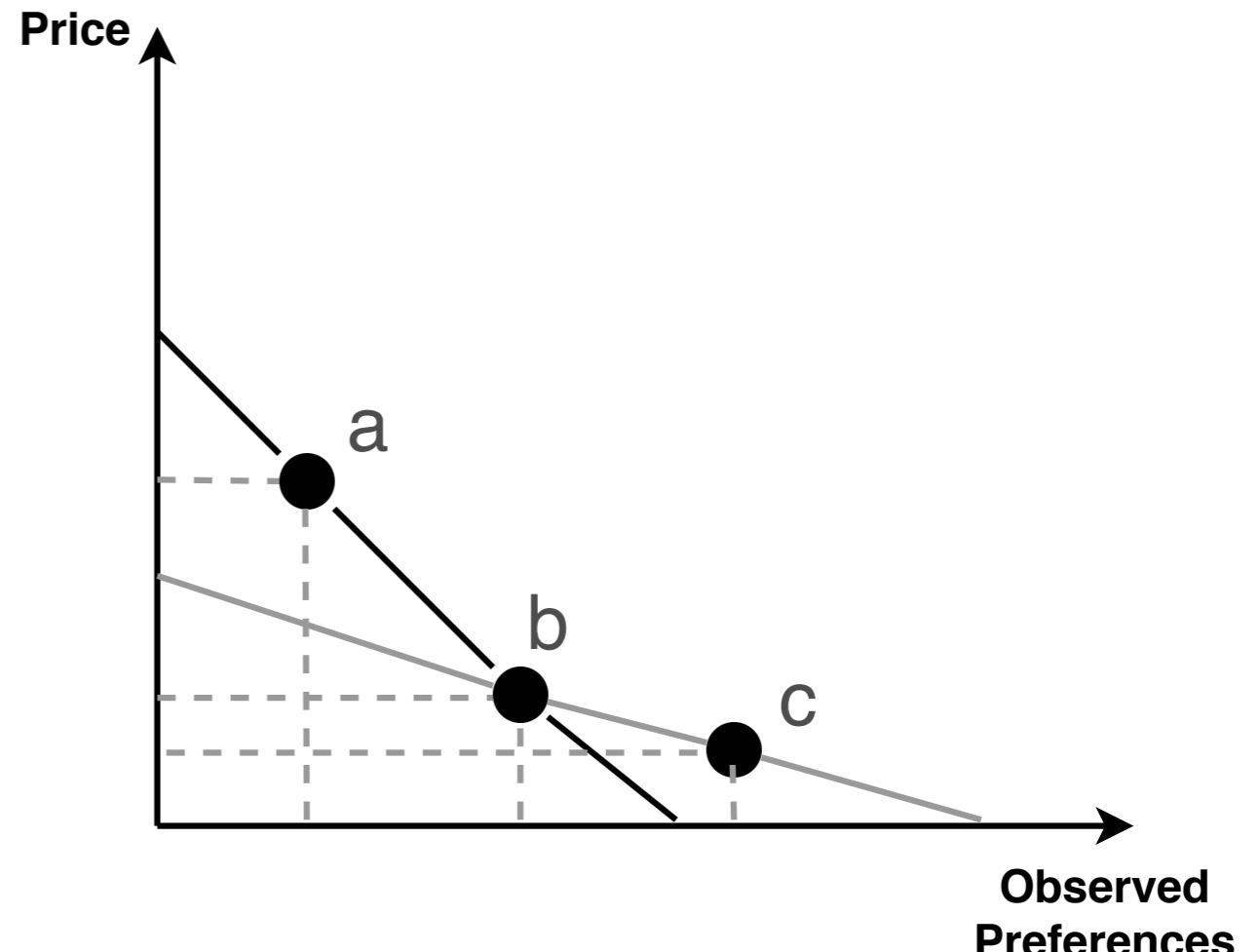


# Indirect Preference Revelation

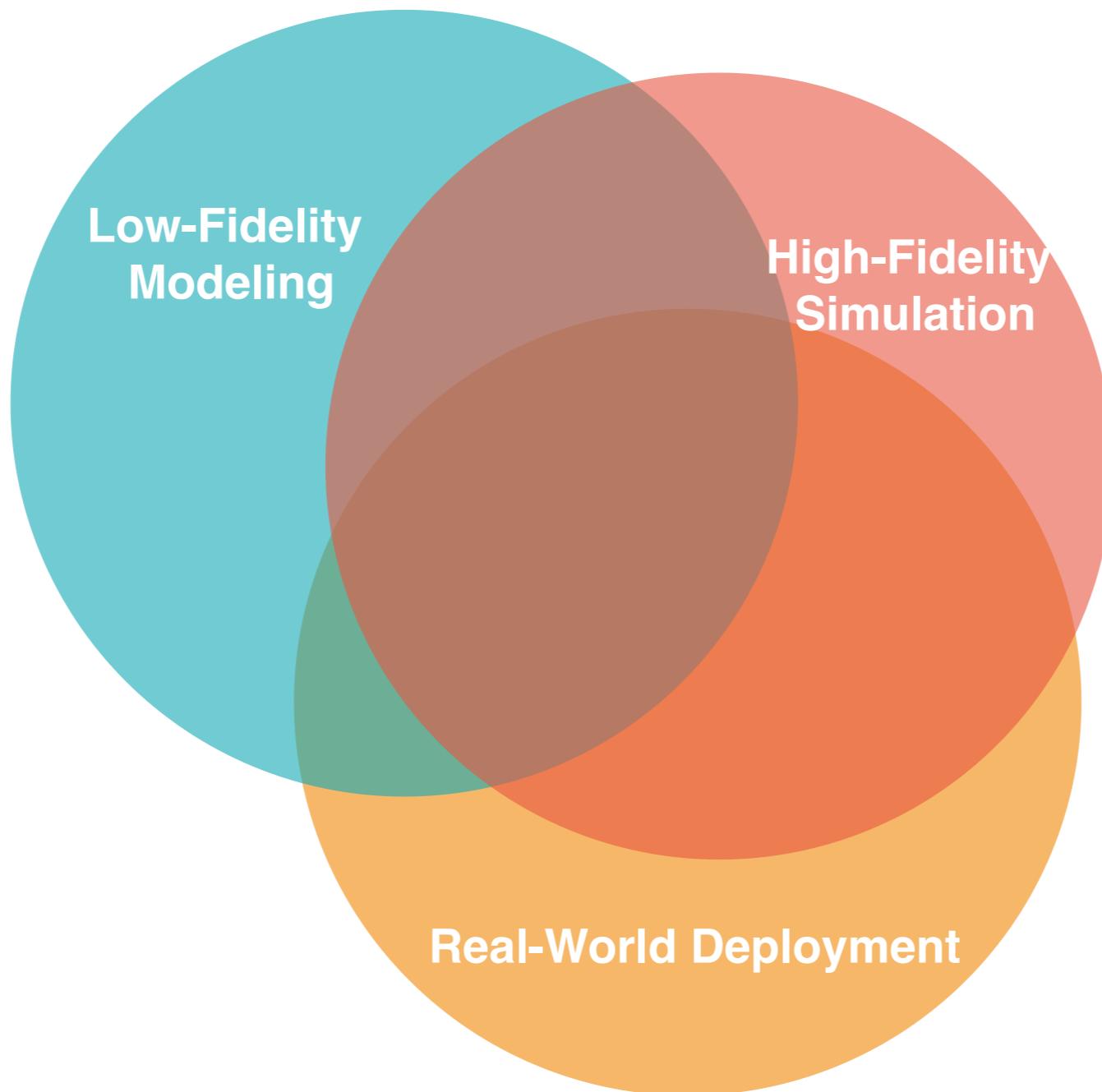
**Method:** Post-Price Mechanism

**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



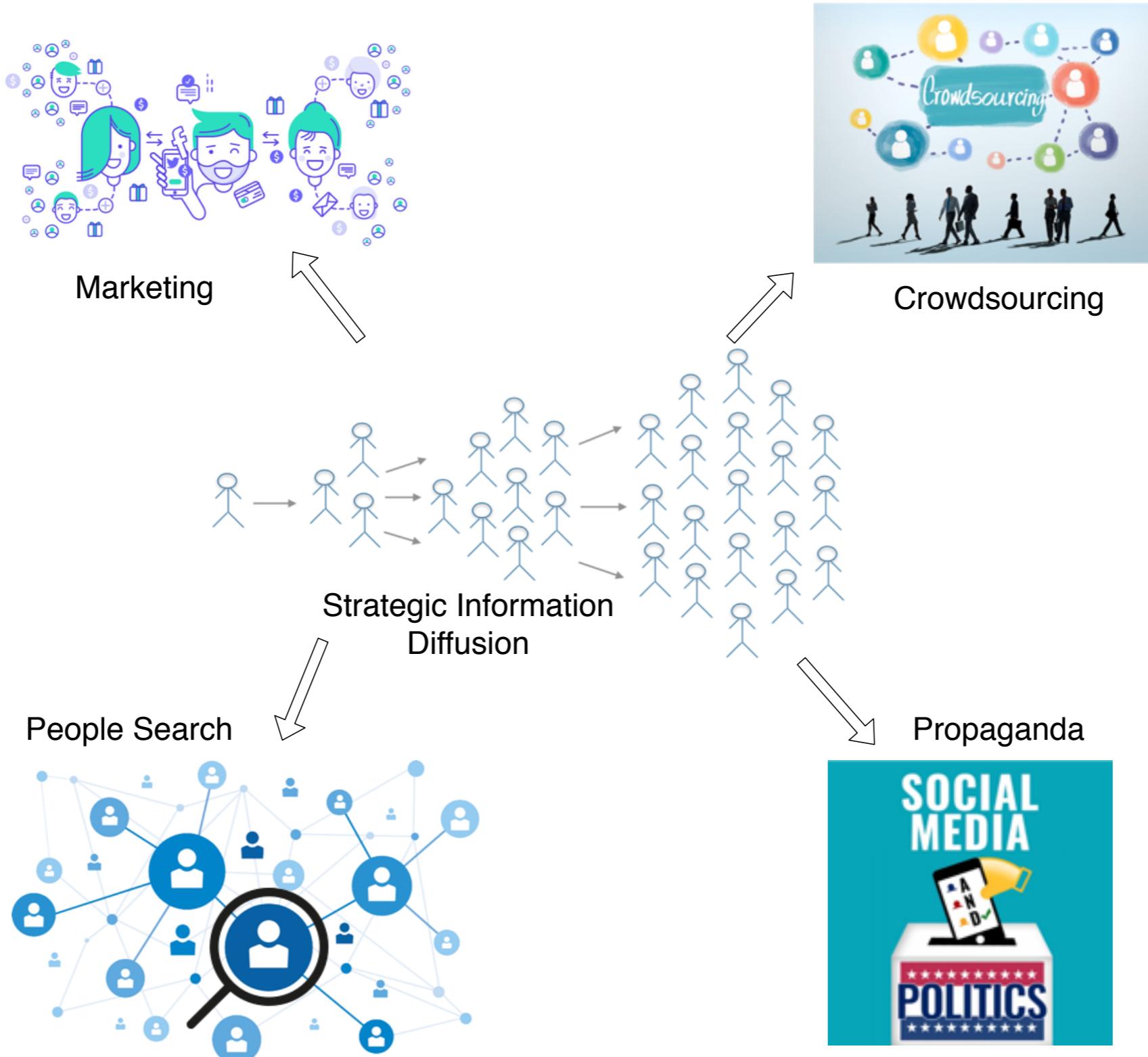
# Thesis Statement

- Mechanism design with thresholding agents is more realistic and performs better than traditional approaches. Furthermore, it is robust with respect to group manipulations.

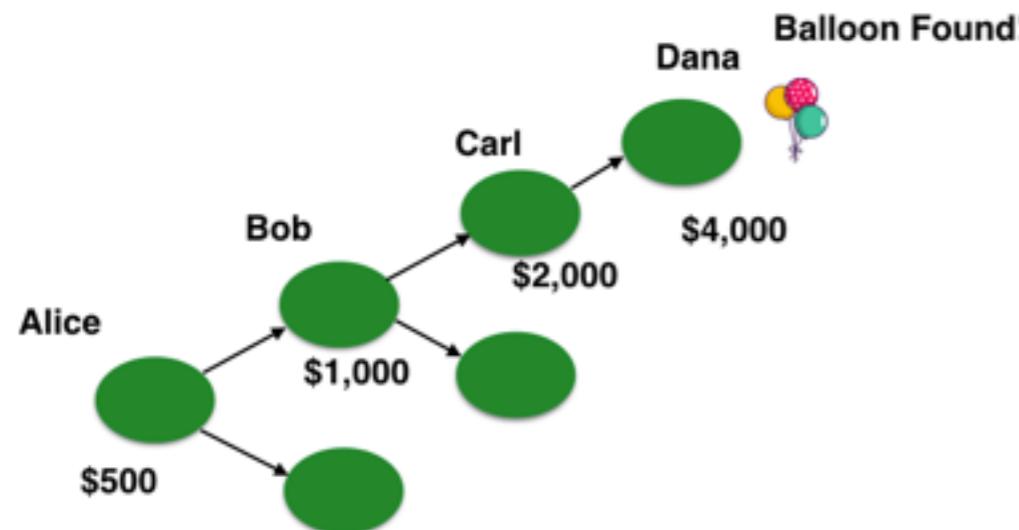
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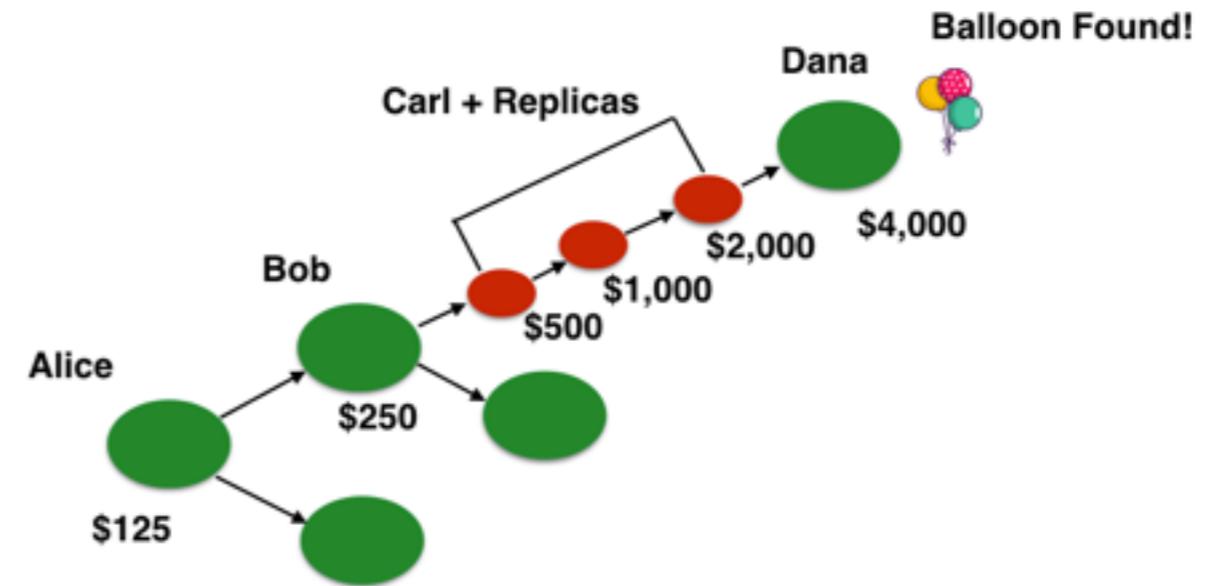
# Strategic Diffusion in Social Networks



# 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:**

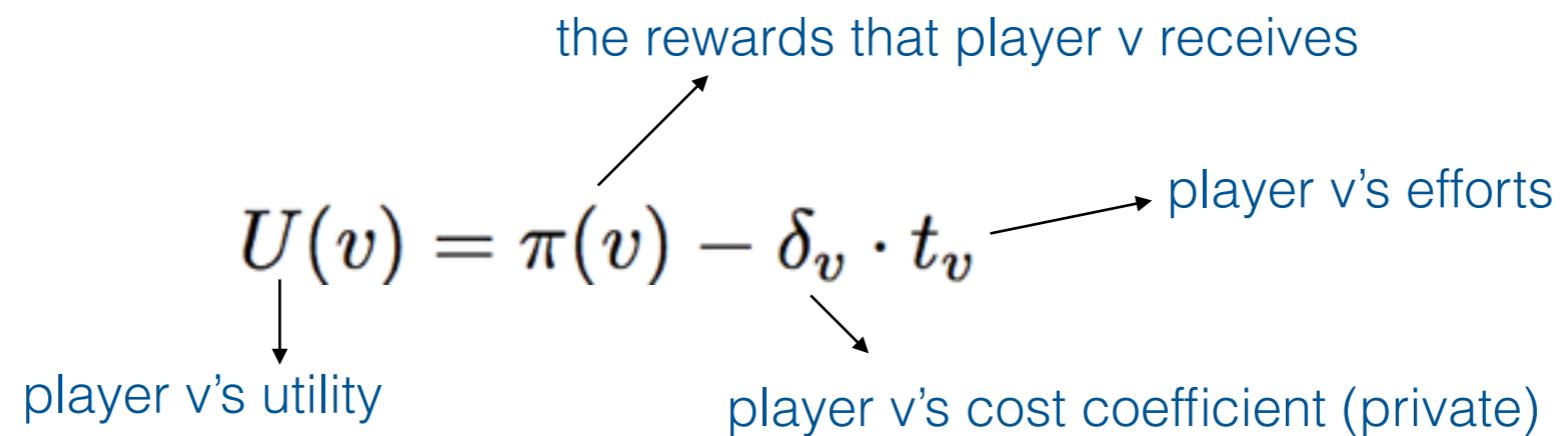
- How should a principal design the incentive mechanisms to address the challenges?

# 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  
 $\delta_v$  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

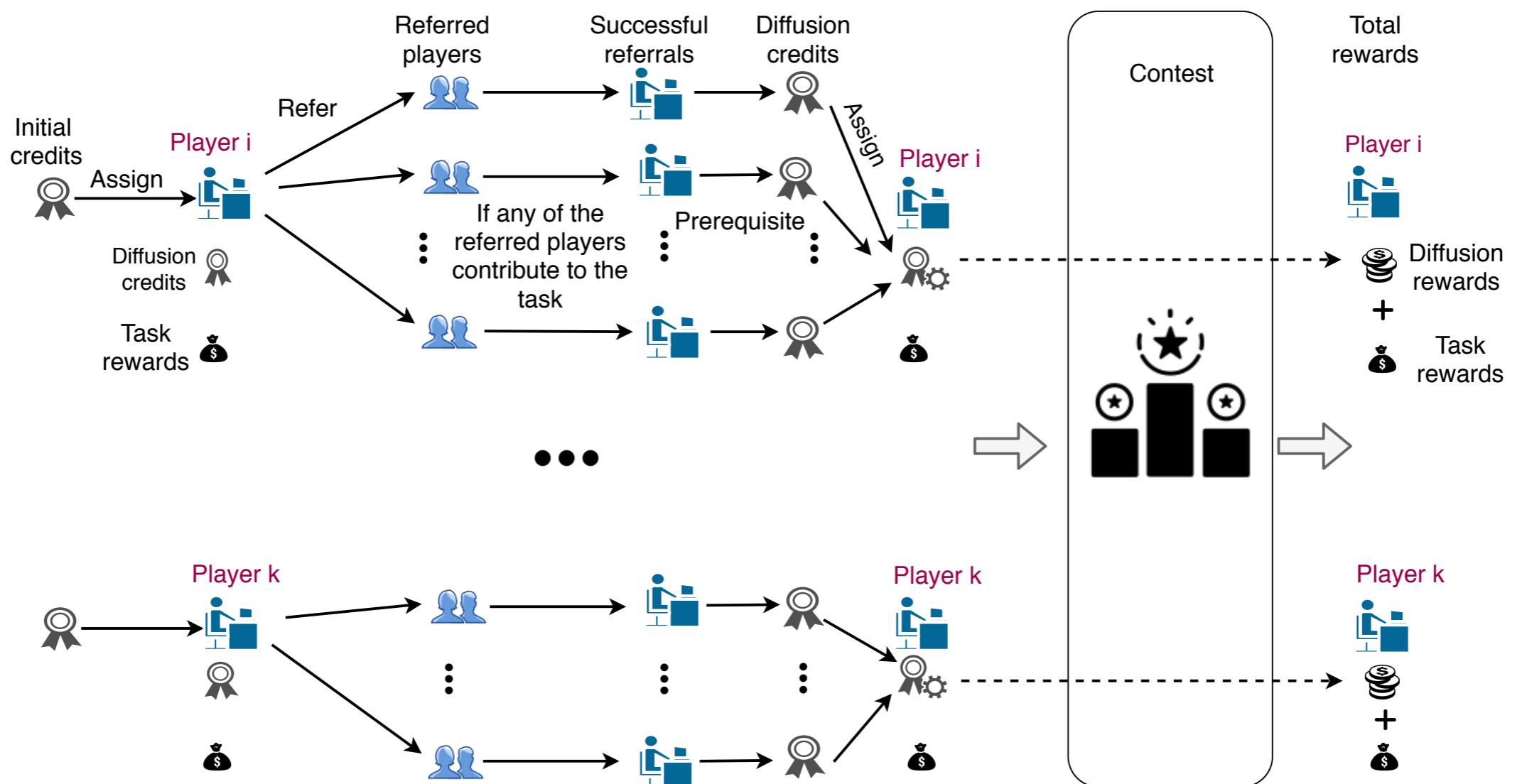
noise factor

player v's probability of winning

players in the same subgraph of player v

```
graph TD; A[player v's virtual credits] --> Top((b_v)^σ); B[noise factor] --> Top; C[player v's probability of winning] --> Bottom((b_u)^σ); D[players in the same subgraph of player v] --> Bottom;
```

# Multi-Winner Contests



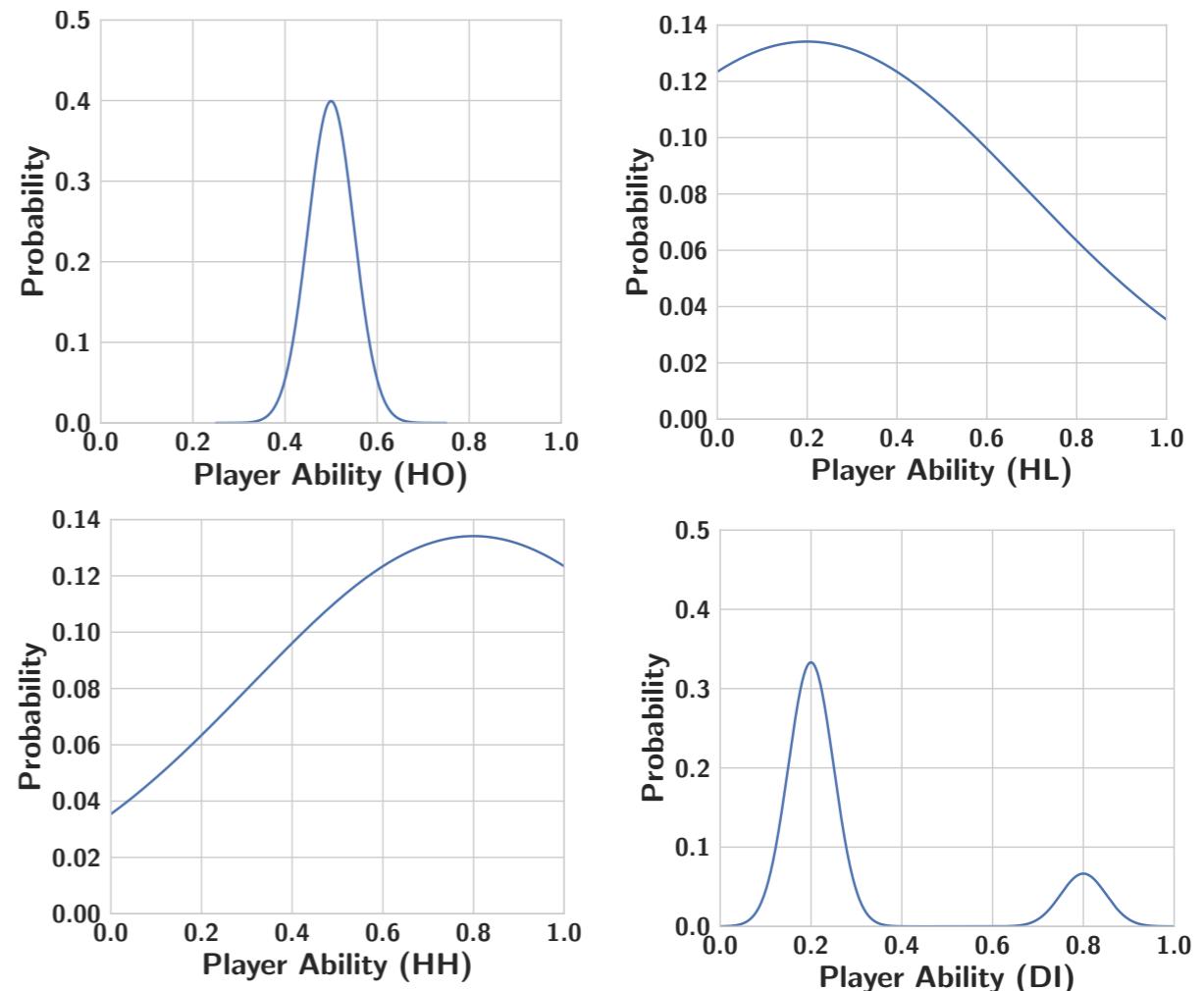
# Experimental Settings

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.



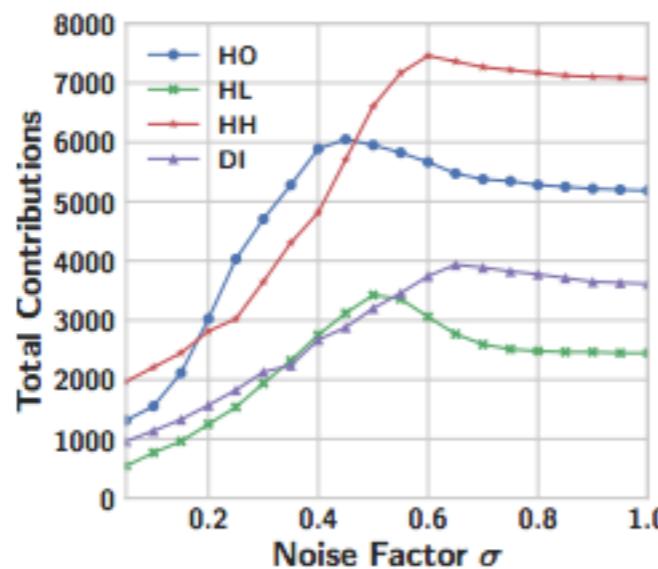
HO- homogeneous; HL- heterogeneously low;  
HH -heterogeneously high; DI-distinctive

$$\delta_v = 1 - \rho_v$$

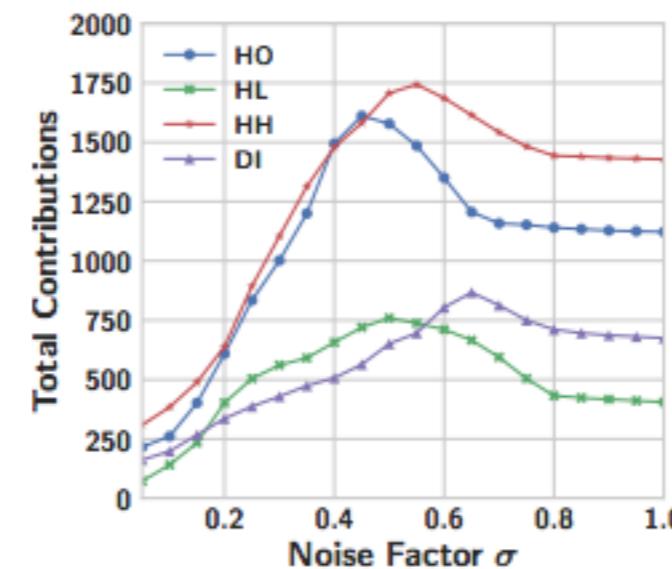
player v's  
cost coefficient

player v's  
ability

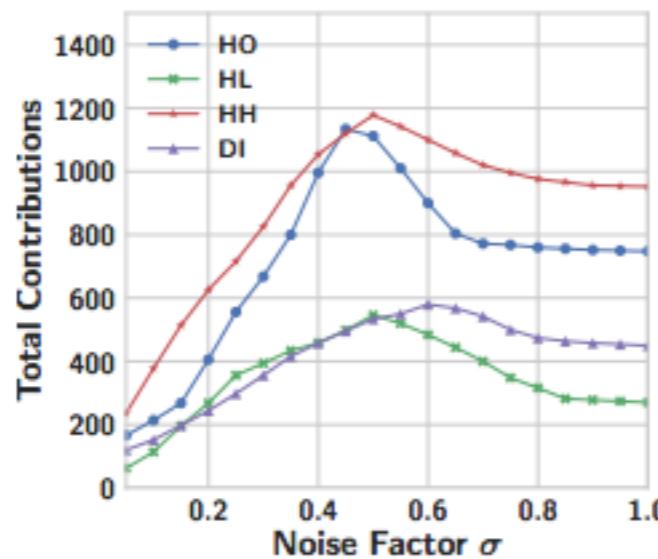
# Total Contributions



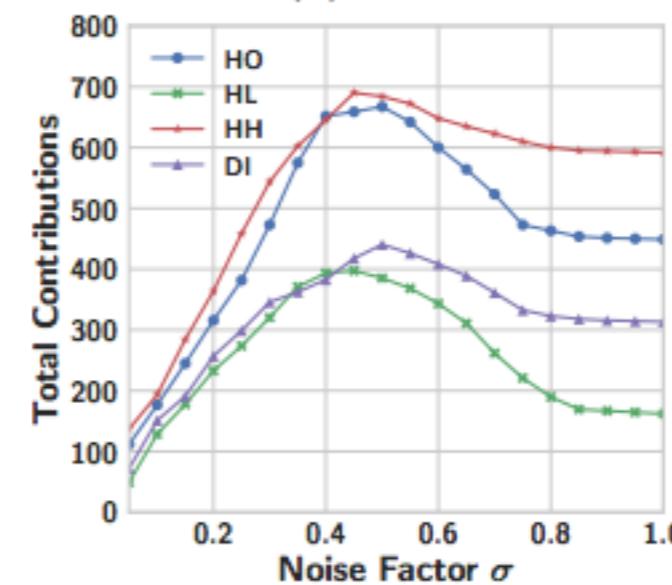
(a) Twitter.



(b) Flickr.



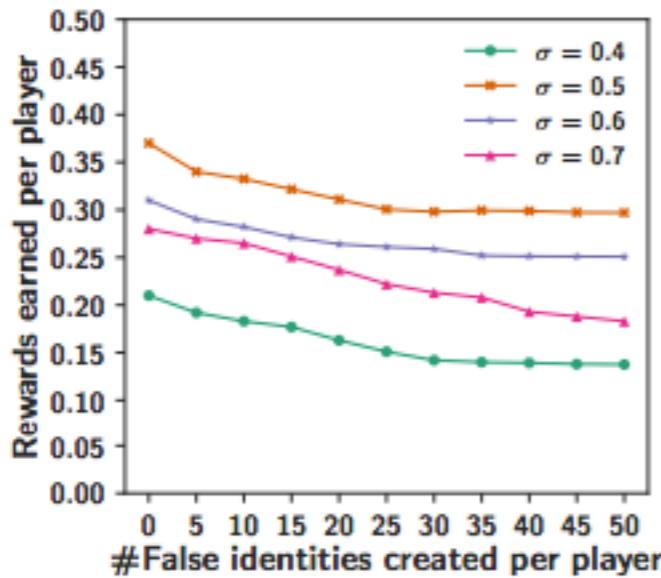
(c) Flixster.



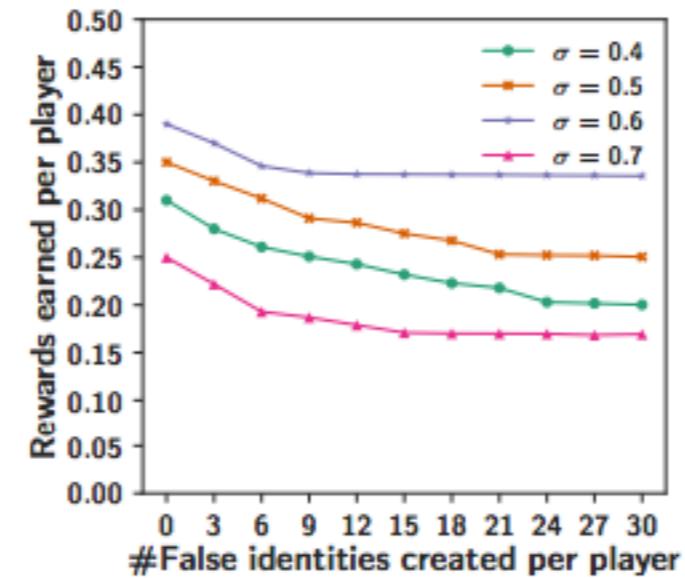
(d) Digg.

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

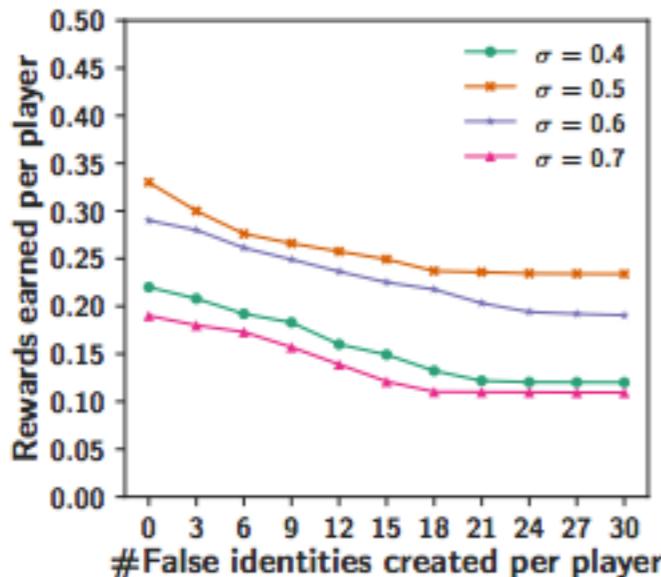
# Robustness



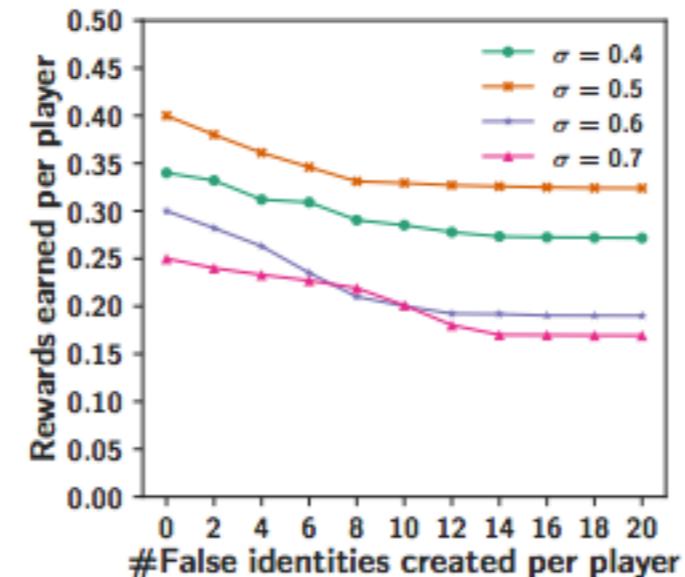
(a) Twitter.



(b) Flickr.



(c) Flixster.



(d) Digg.

Players received fewer rewards when they created more false identities.

# Discussion

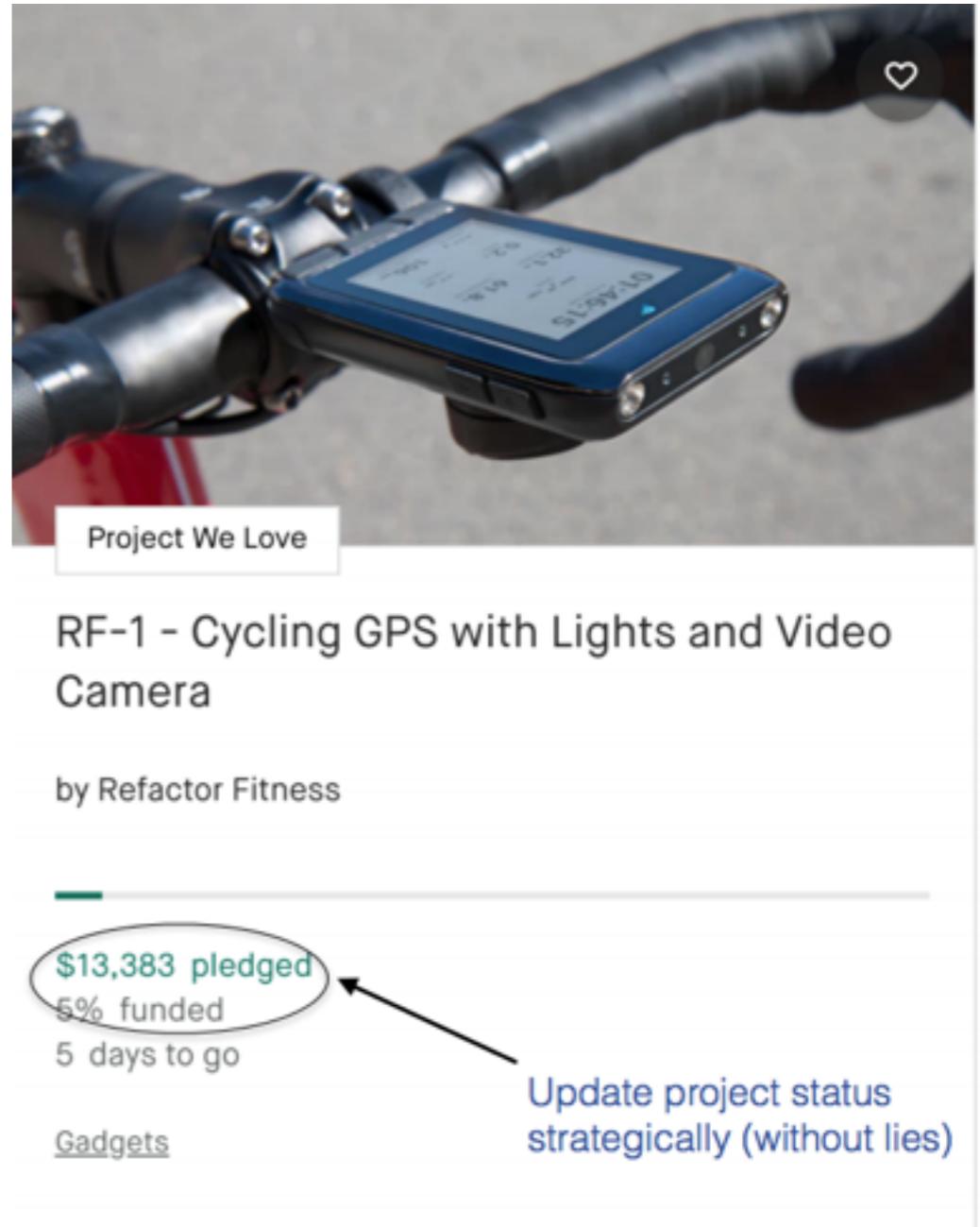
- **The MWC mechanism:**
  - Satisfies desirable properties: false-name-proofness, individual rationality, budget constraint, etc.
  - Can be applied to large graphs with tens of thousands of nodes.
- **Extended work:**
  - Counteracting collusion (Shen, Yan and Lopes, Working Paper 2019)
  - Counteracting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

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# Information Design for Crowdfunding

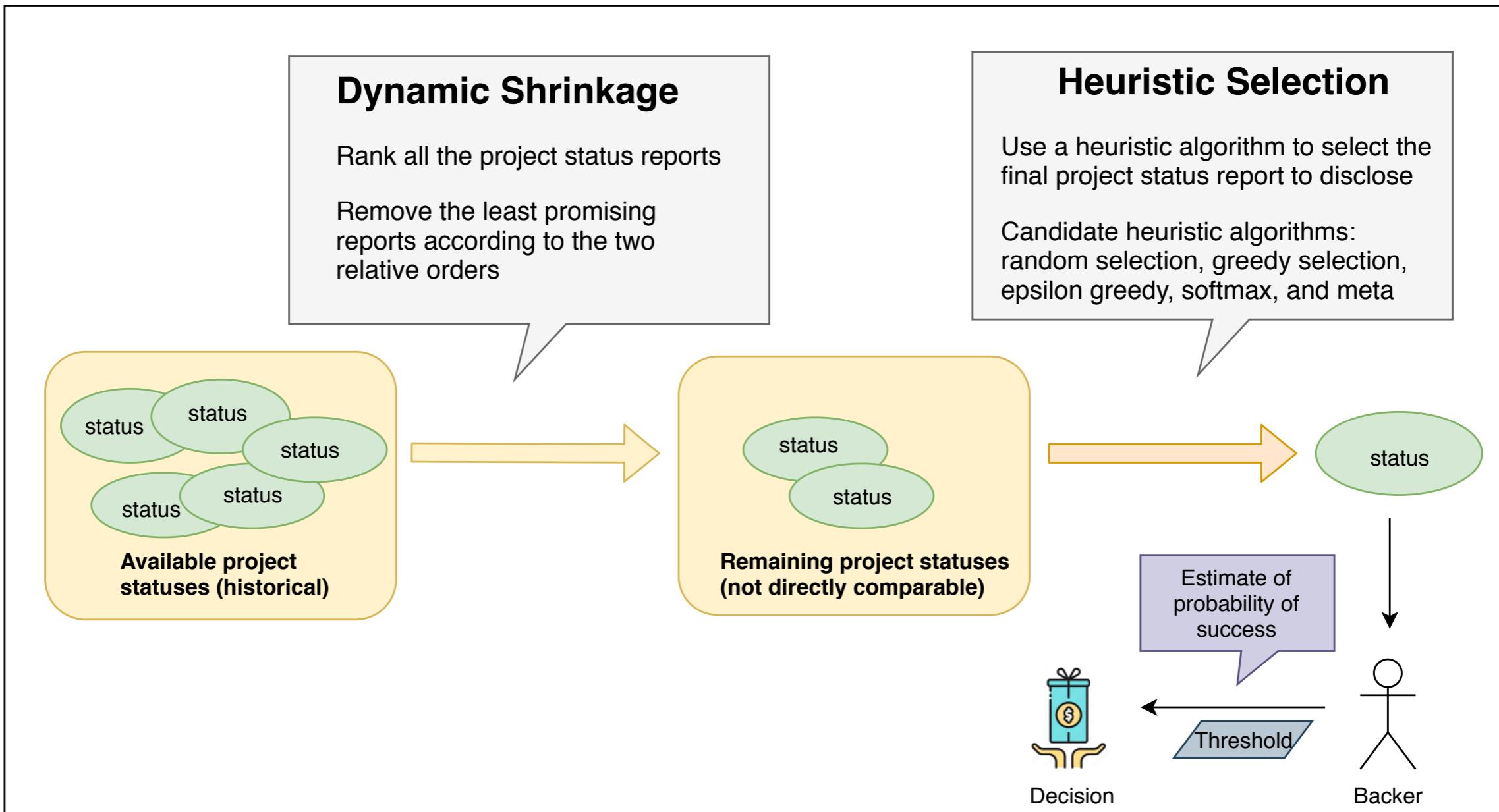
- **Objective:** to solicit contributions from early backers to generate revenue
- **Intuition:** to influence agents' beliefs by designing information disclosure policies (i.e. information structures that determine which pieces of information are disclosed to whom for desirable outcomes)



Credit: Kickstarter

# Dynamic Information Design

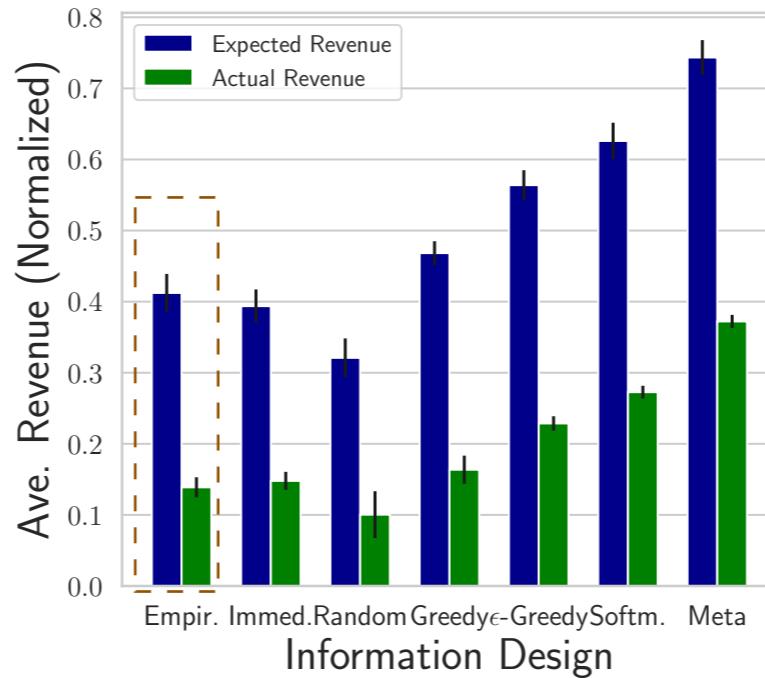
## Dynamic Shrinkage with Heuristic Selection



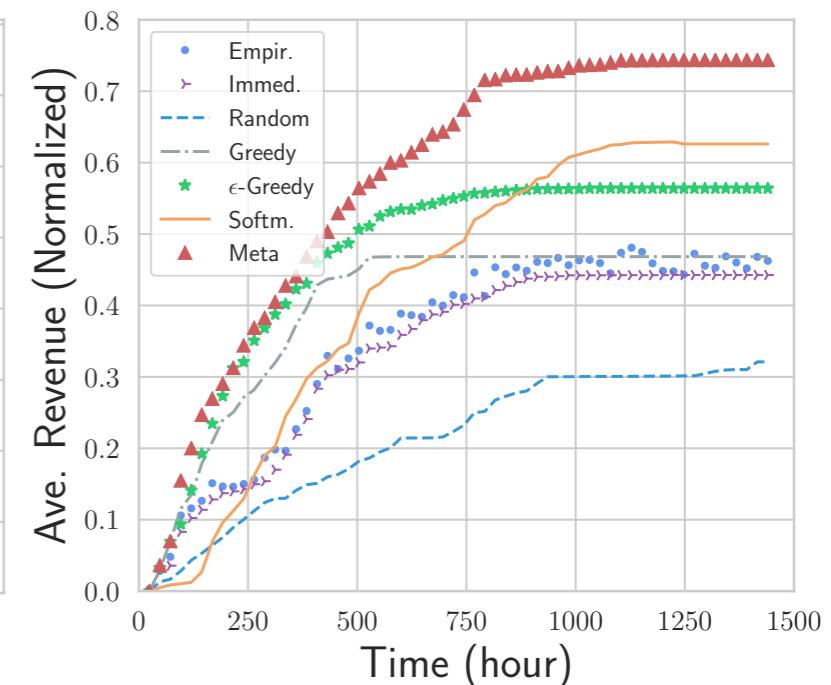
# Simulation Results

## • Observations

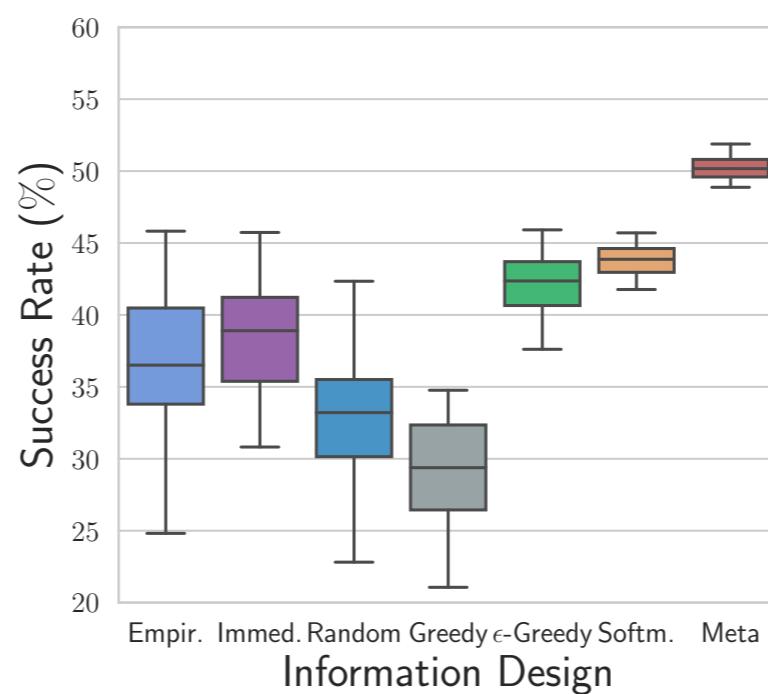
- Meta group performed consistently the best among all the groups in terms of both actual and expected revenue.
- Meta group had the highest project success rate.
- Meta group required the most computational time.



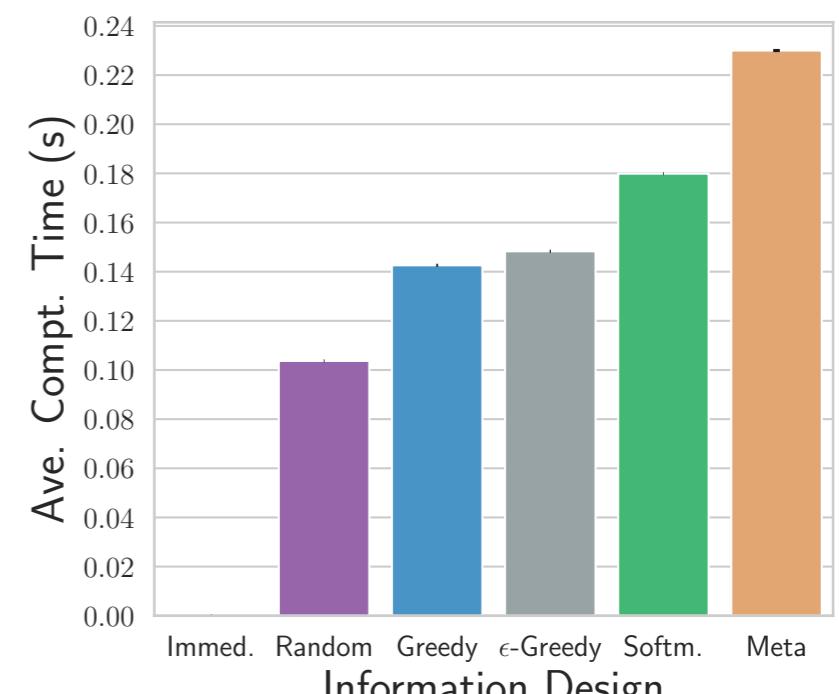
**(a) Overall revenue ( $t = 1440$ )**



**(b) Expected revenue over time**



**(c) Project success rate (%)**



**(d) Computation time**

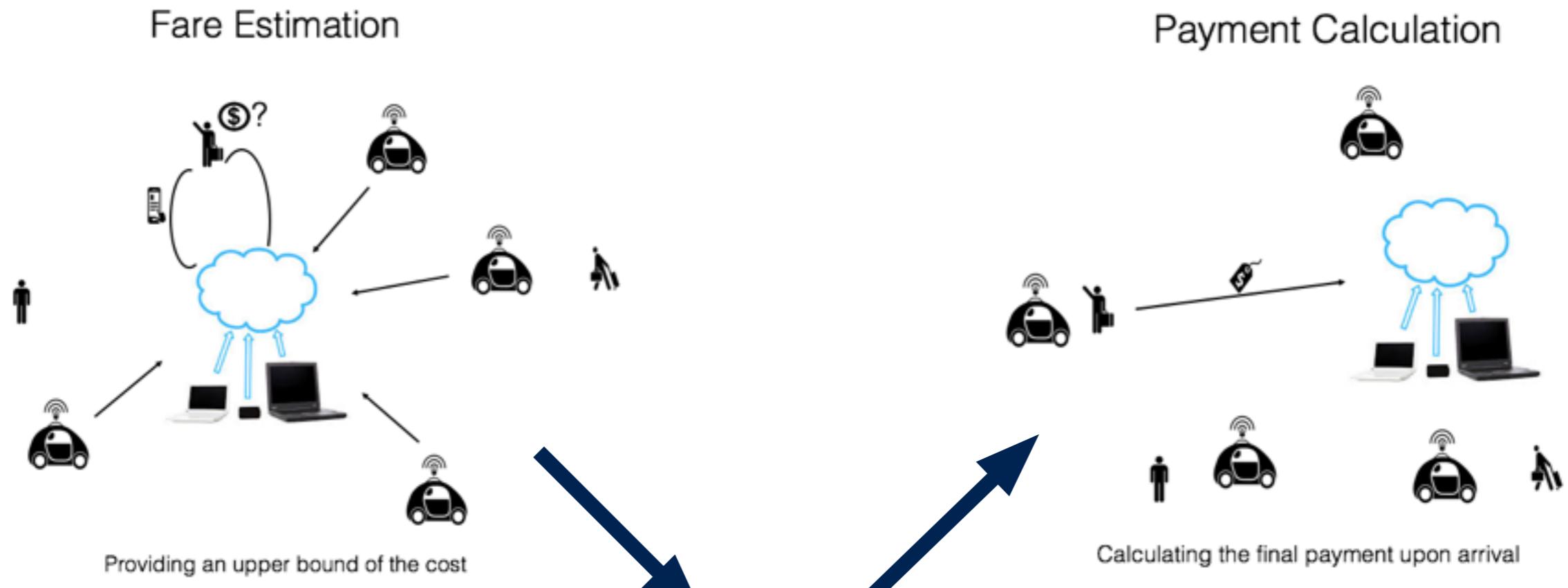
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# Autonomous Mobility-on-Demand Systems



# An Online Post-Price Mechanism for Autonomous Ridesharing Systems



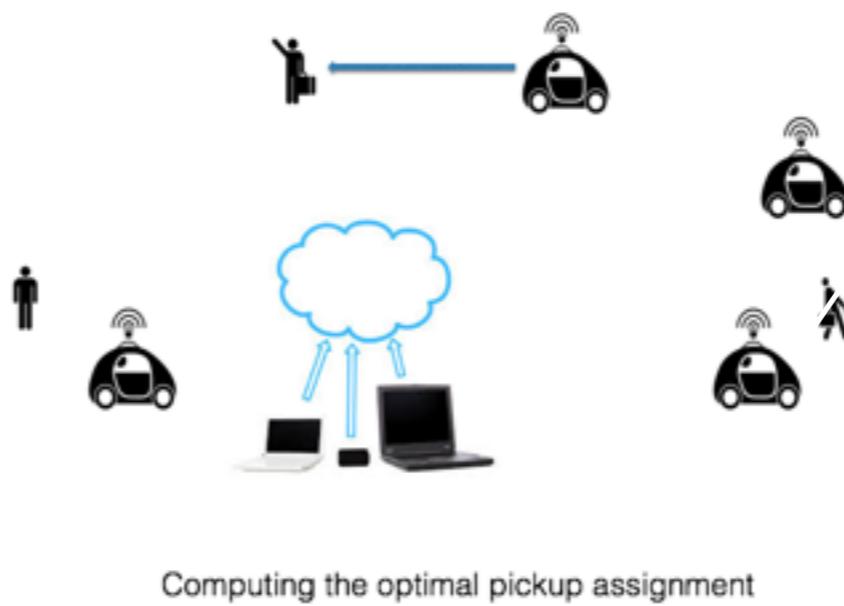
## Objective:

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

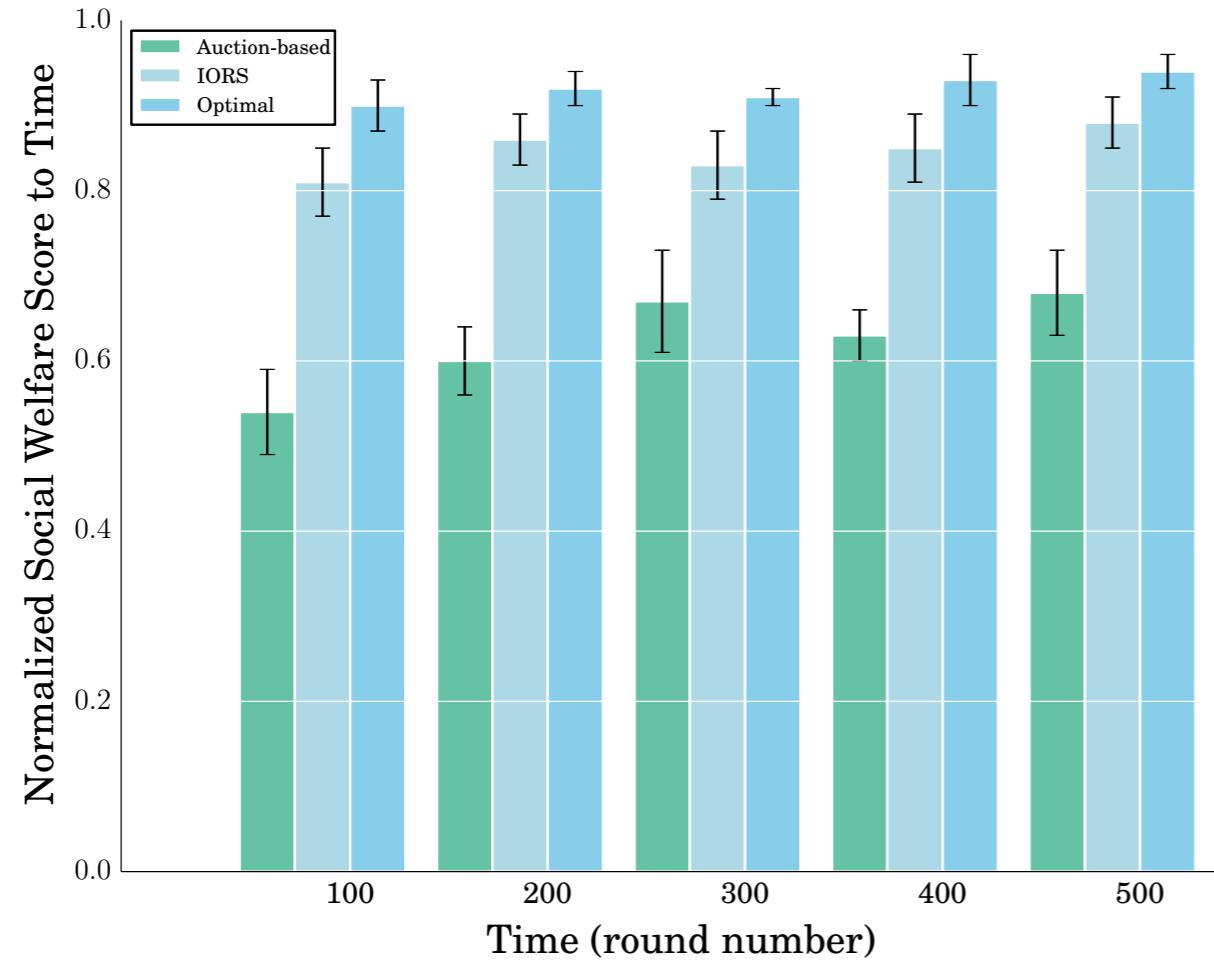
**Method:** Integrated Online RideSharing (IORS) mechanism

## Properties:

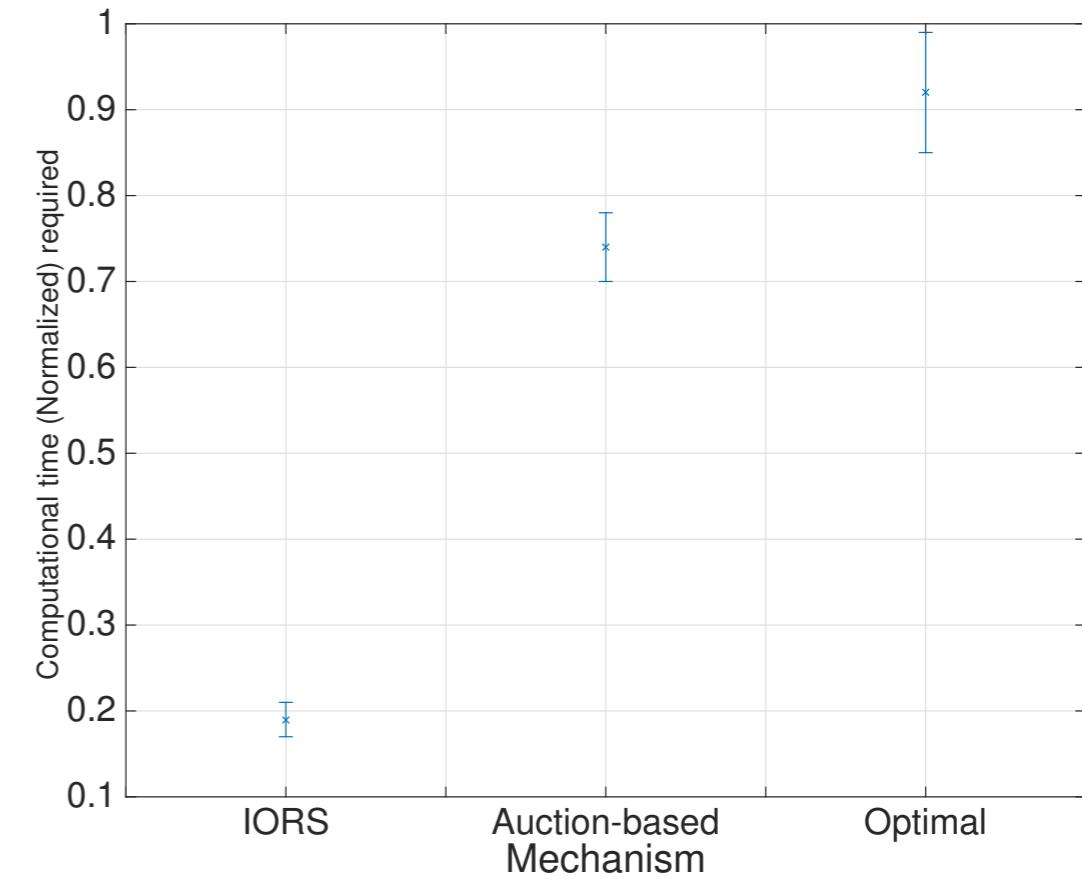
- Ex-post incentive compatibility
- Individual rationality
- Budget constraint



# IORS is Competitive



Social welfare scores to time.



Computational time.

**Benchmarks:** Optimal offline, Auction-based (101 X101 grid city)

## 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

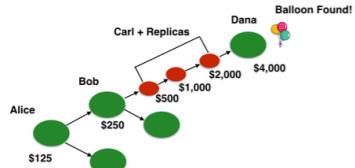
**Results:** outperforms immediate disclosure

**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



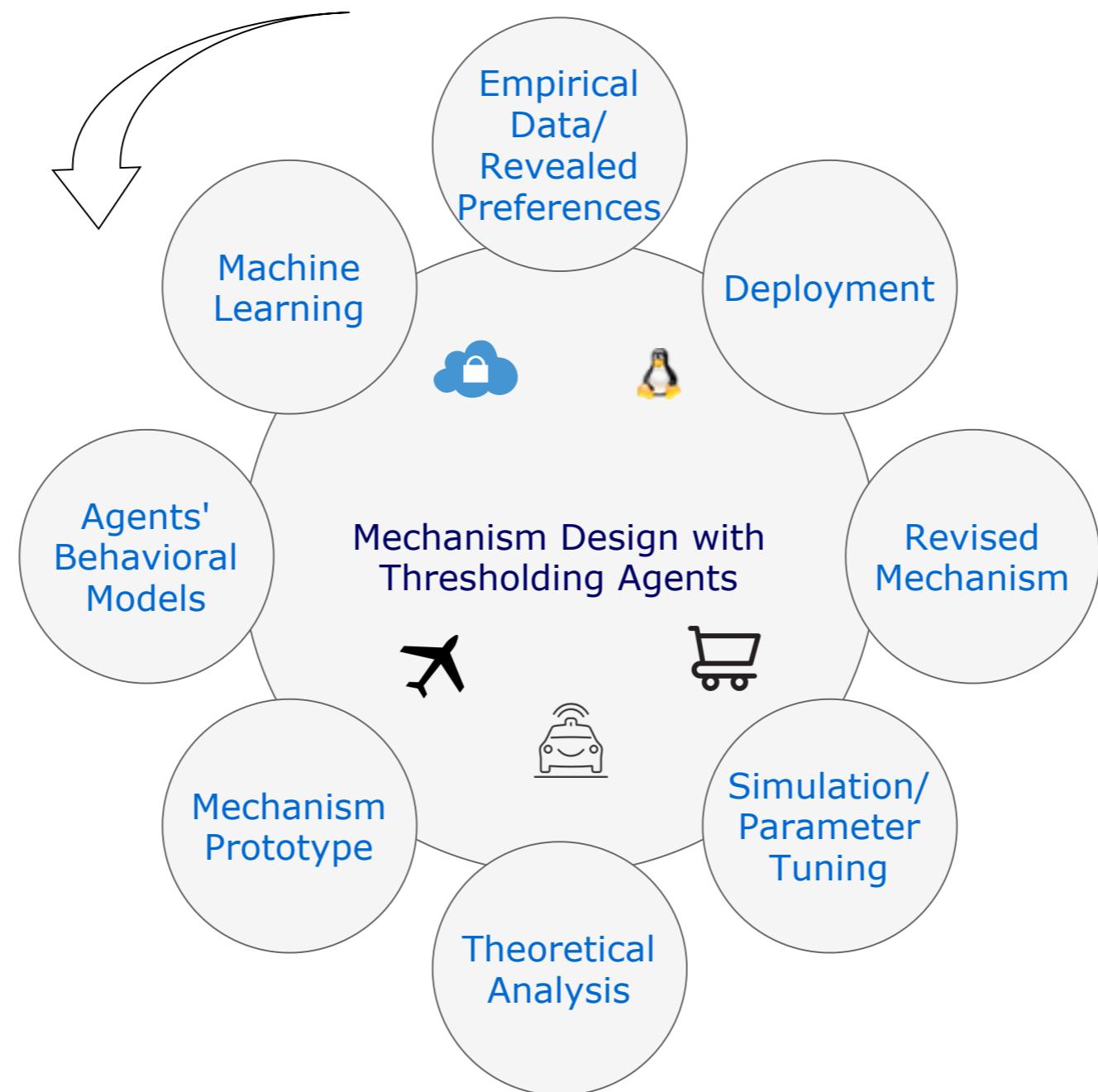
Shen, Crandall, Yan, Lopes AAMAS'18

## Ridesharing



Shen, Lopes, Crandall IJCAI'16

# Future Directions



# Publications

## Published Papers

- W. Shen**, R. Achar, C. V. Lopes: A Simulation Analysis of Large Contests with Thresholding Agents. In Proc. of the 51st Winter Simulation Conference (*WinterSim 2019*). To appear.
- 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*).
- K. Yan, **W. Shen**, H. Lu, and Q. Jin: Emerging Privacy Issues and Solutions in Cyber-Enabled Sharing Services. *IEEE Access*, 7 (2019), pp. 26031-26059.
- 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*).
- K. Yan, Z. Ji, **W. Shen**: Online Fault Detection Methods for Chillers Combining Extended Kalman Filter and Recursive One-class SVM. *Neurocomputing*, 229 (2017), pp 205-212.
- 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*).

## Working Manuscripts

- W. Shen**, K. Yan, C. V. Lopes: Manipulation-Resistant Mechanism Design for Strategic Network Diffusion.
- W. Shen**, C. V. Lopes: Counteracting Free Riding in Utility Sharing with Sequential Contests.

# Acknowledgments

- Advisor: Prof. Cristina Lopes
- Committee: Prof. Amelia Regan, Prof. David Redmiles
- Collaborators
- Labmates and friends at UCI
- Family

Thank You!

Q & A