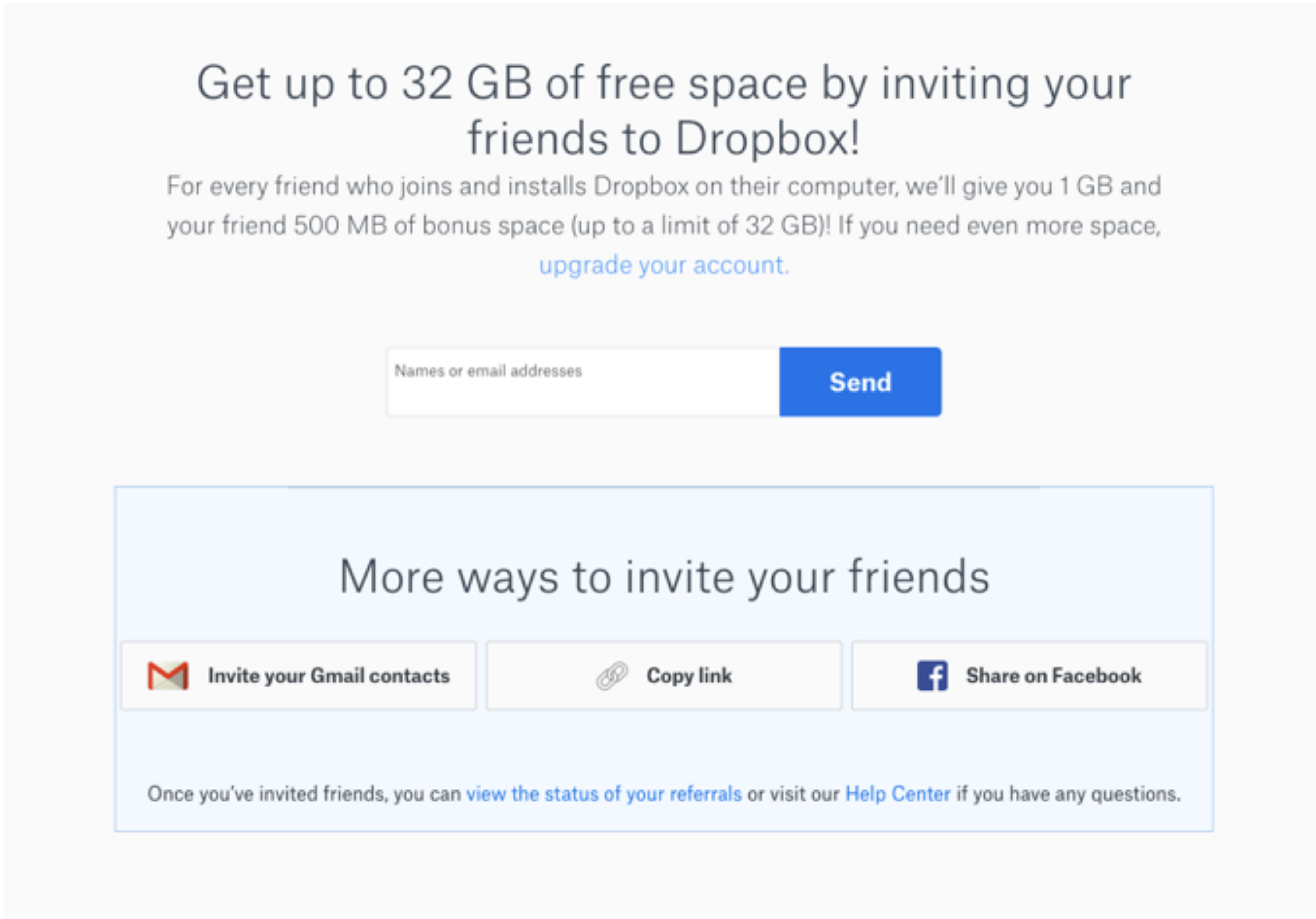
Beyond Nash Equilibrium: Mechanism Design with Thresholding Agents

Wen Shen
June 5, 2019

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

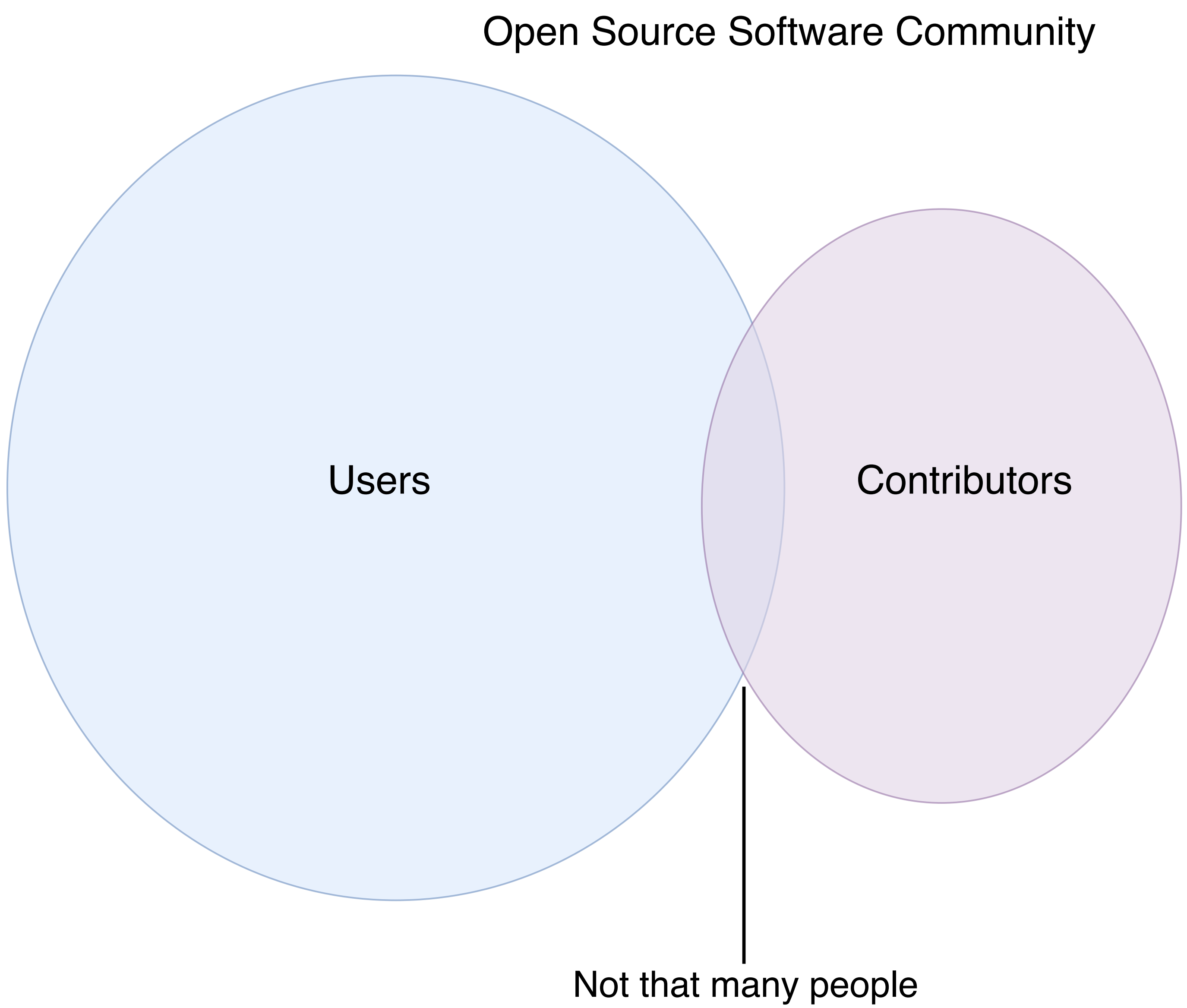
Motivating Example I



Credit: Dropbox

Dropbox VS Strategic Users

Motivating Example II



Stakeholder VS Users without Contributions

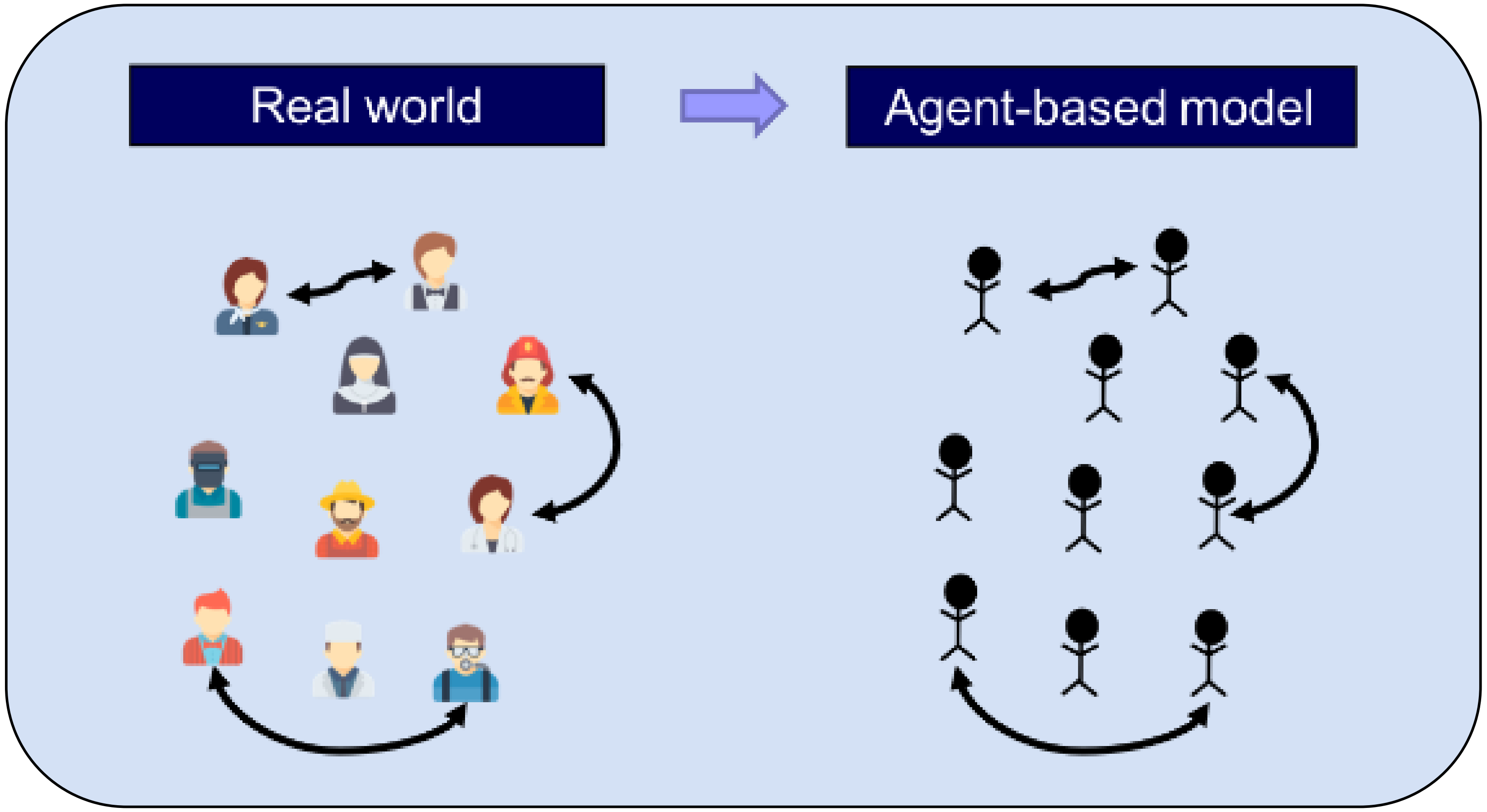
Motivating Example III

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

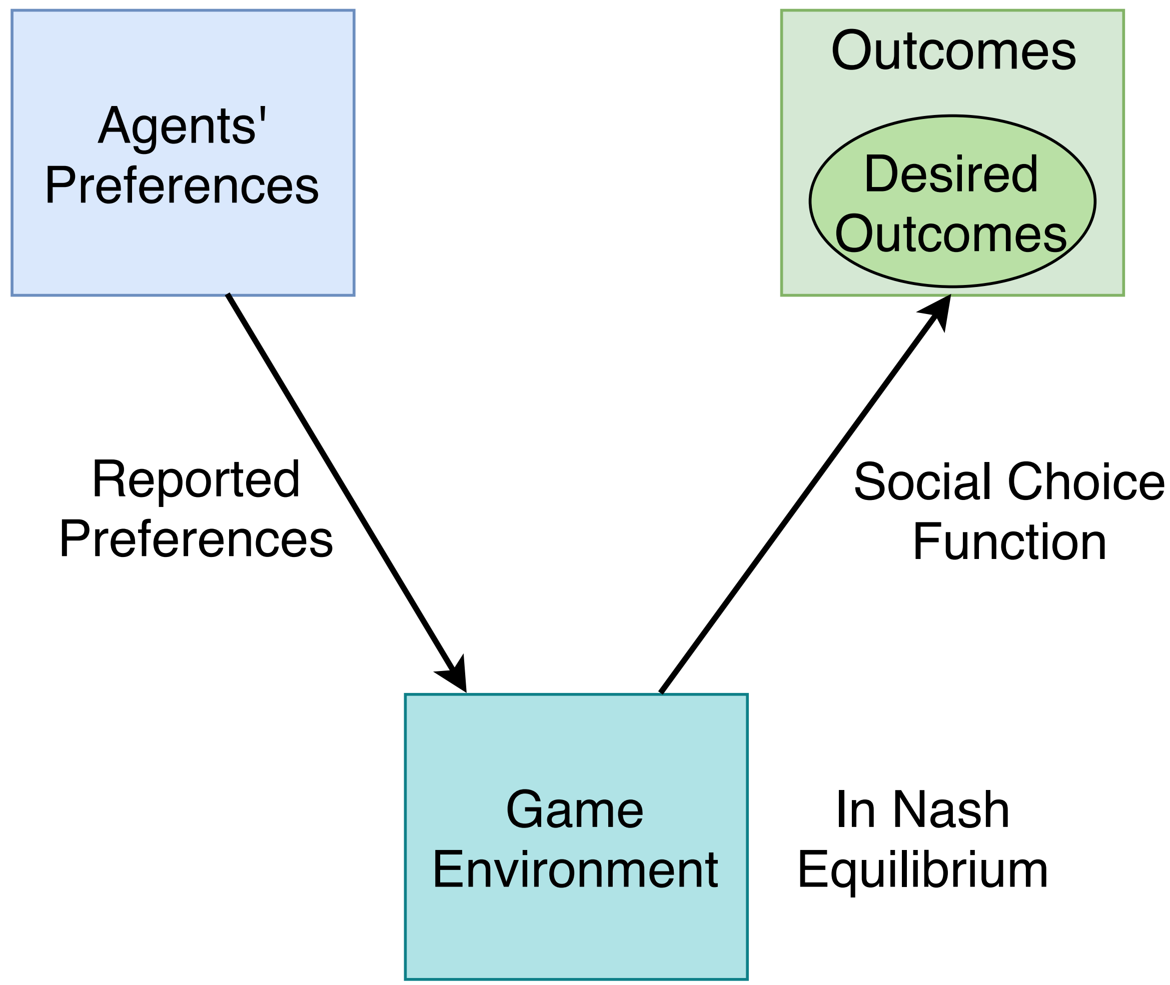
Game Theory

ROW → / COL ↓	Co-operate	Defect
Co-operate	(3, 3)	(0, 5)
Defect	(5, 0)	(1, 1)

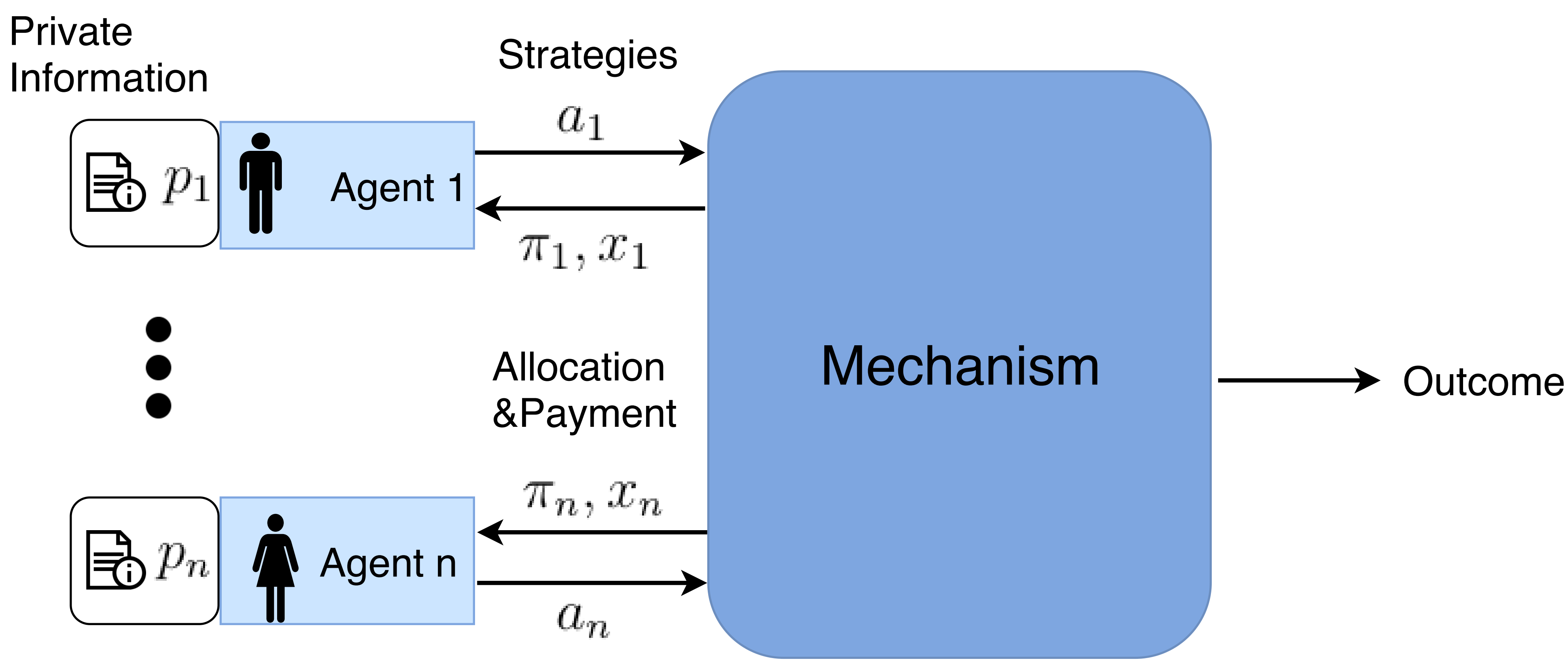
Preference to Move Based on Higher Payoff

Nash Equilibrium

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

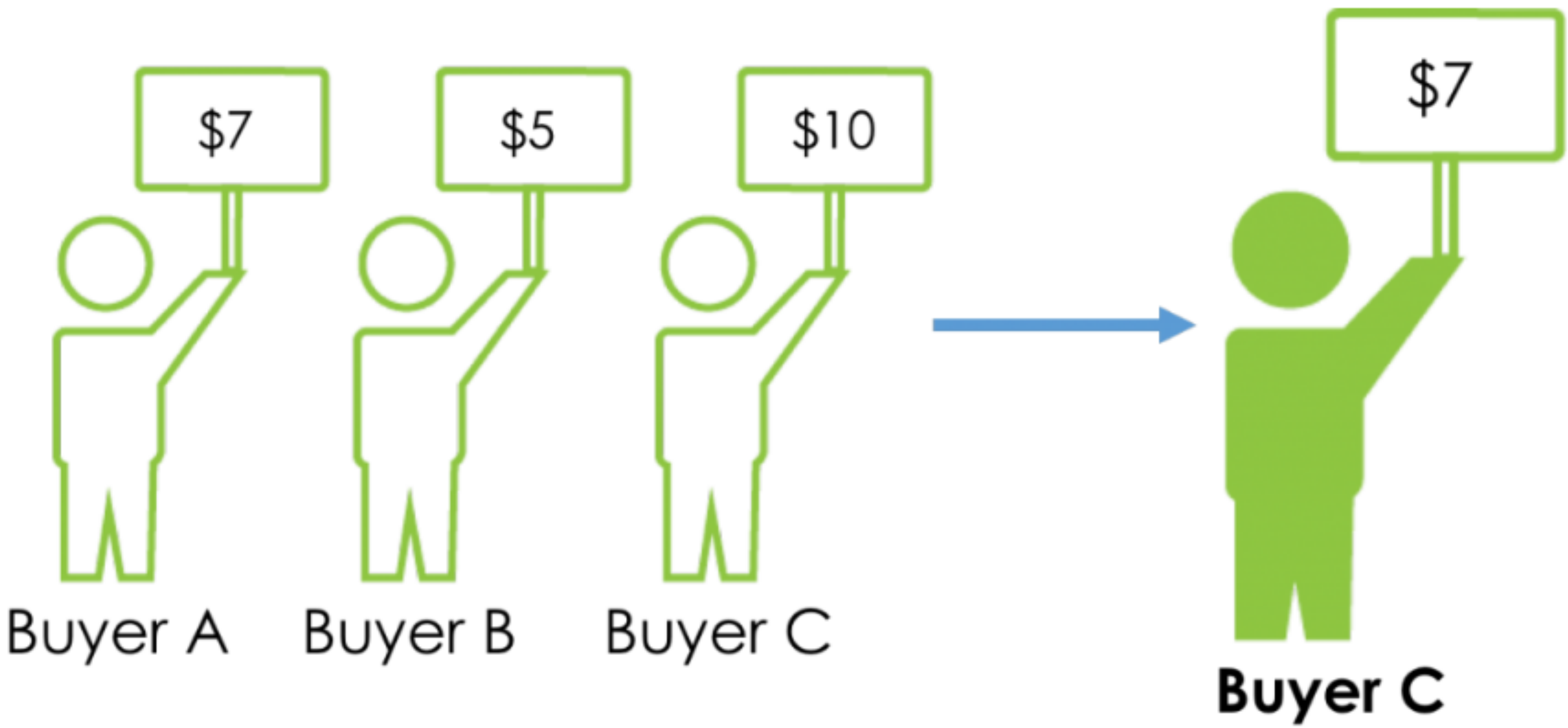
Credit: poparide

Mechanism Design for Revenue Optimization

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

Credit: The balance

Second Price Auction



Benefit: incentive compatible

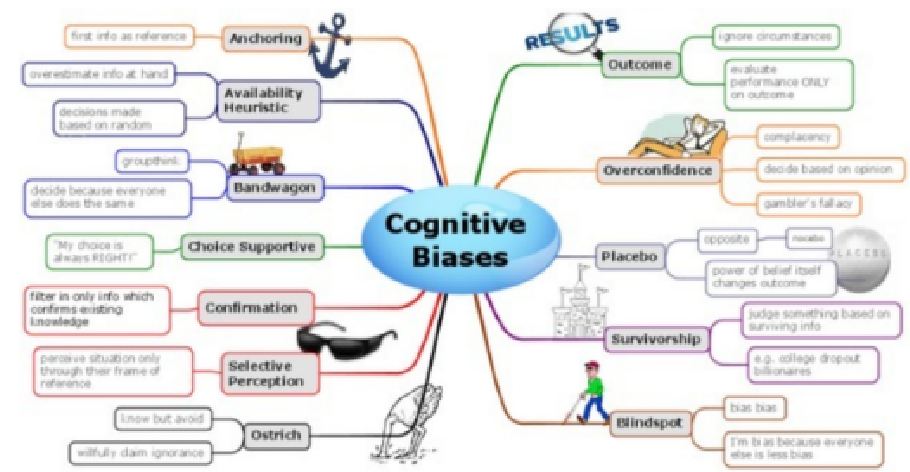
Challenges in Traditional Mechanism Design Theory

- **Full Rationality Assumption**

VS

- **Agents may make mistakes**
  - Cognitive limits
  - Incomplete/Imperfect information
  - Computation constraints (insufficient time to decide)

(Simon 55, Selten 90)



Cognitive Limits

Agents Make Mistakes

Incomplete/Imperfect Information

Time (Computation) Constraint

Challenges in Traditional Mechanism Design Theory

- **Direct Preference Revelation**

VS

- **Agents may be unwilling to report their preference directly**
  - Privacy
  - Uncertainty

Credit: Amazon

(Naor et al. 99, Huang et al. 15, Wu et al. 15)

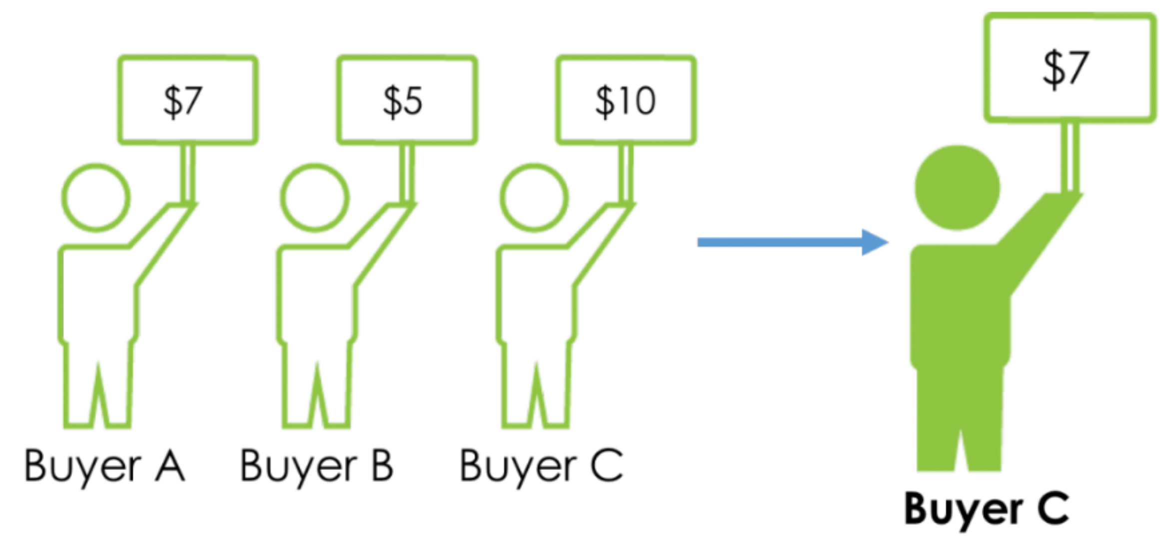
Challenges in Traditional Mechanism Design Theory

- **Vulnerability to Group Manipulations**

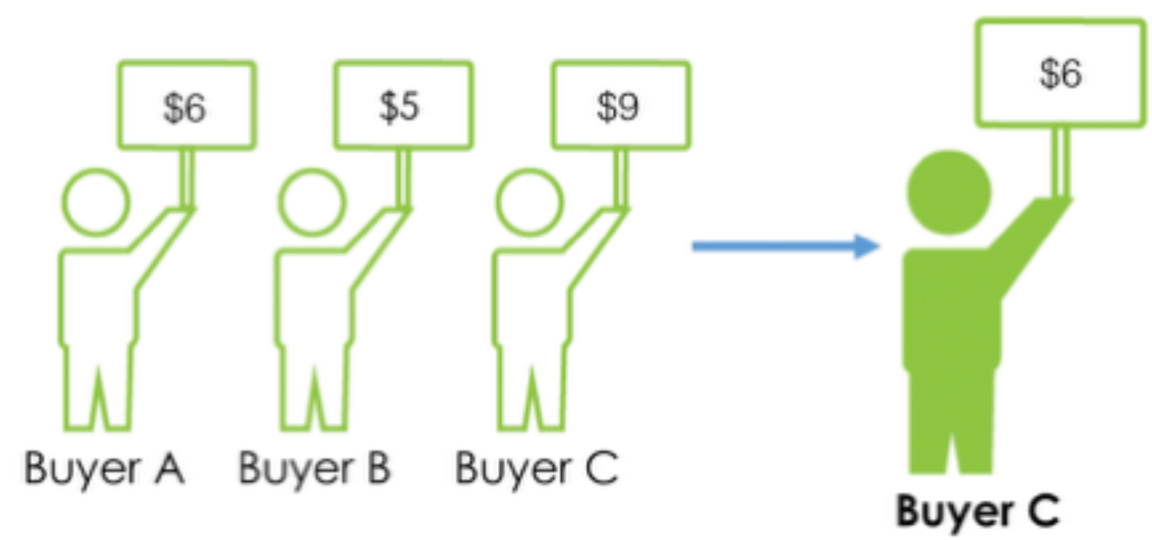
VS

- **Agents have incentives to conduct group manipulations**
    - Collusion
    - False-name attacks

(Wagman and Conitzer 08, Todo et al. 11, Drucker et al. 12, Mar 97, Che and Kim 09)



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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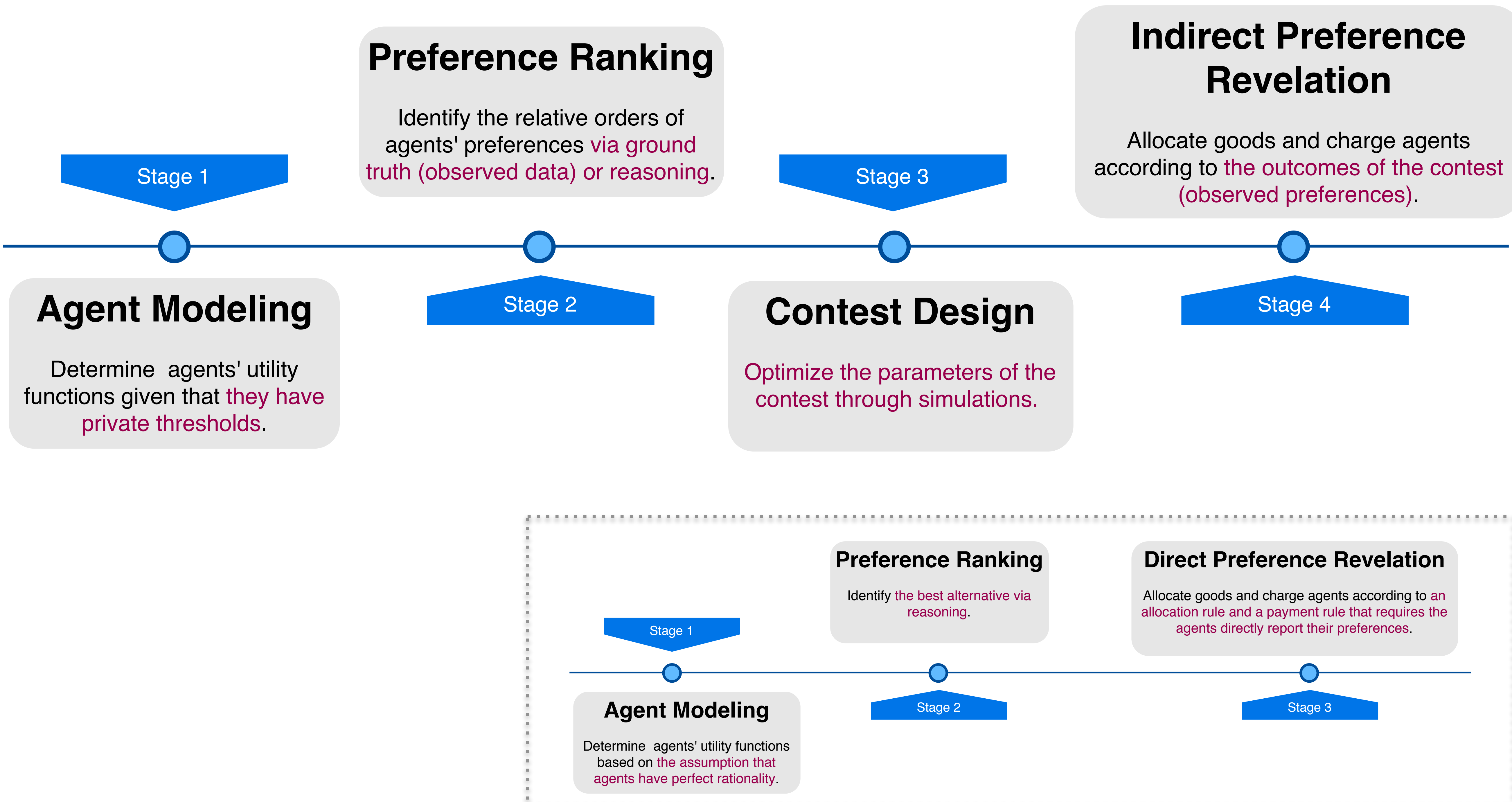
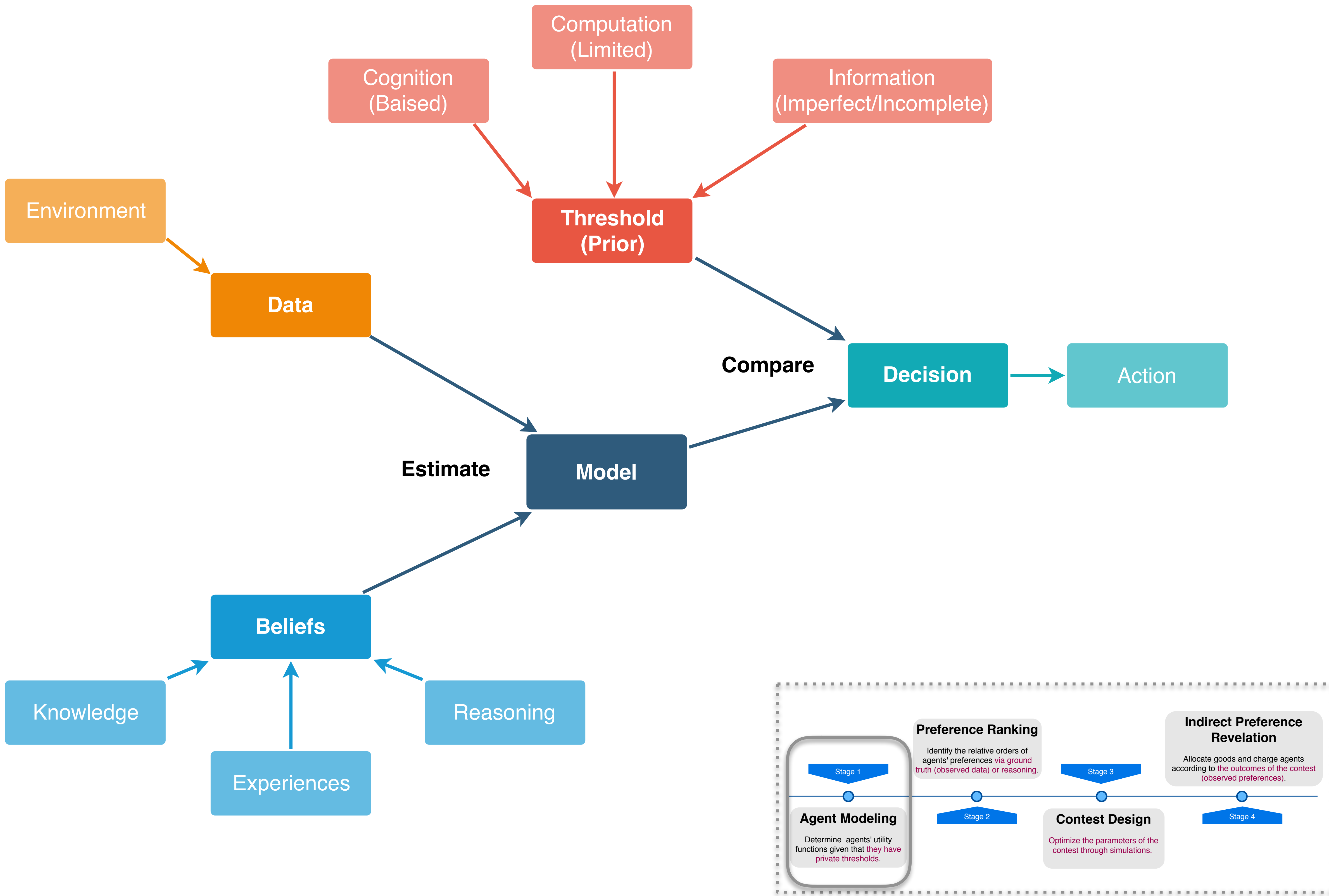
Mechanism Design with Thresholding Agents

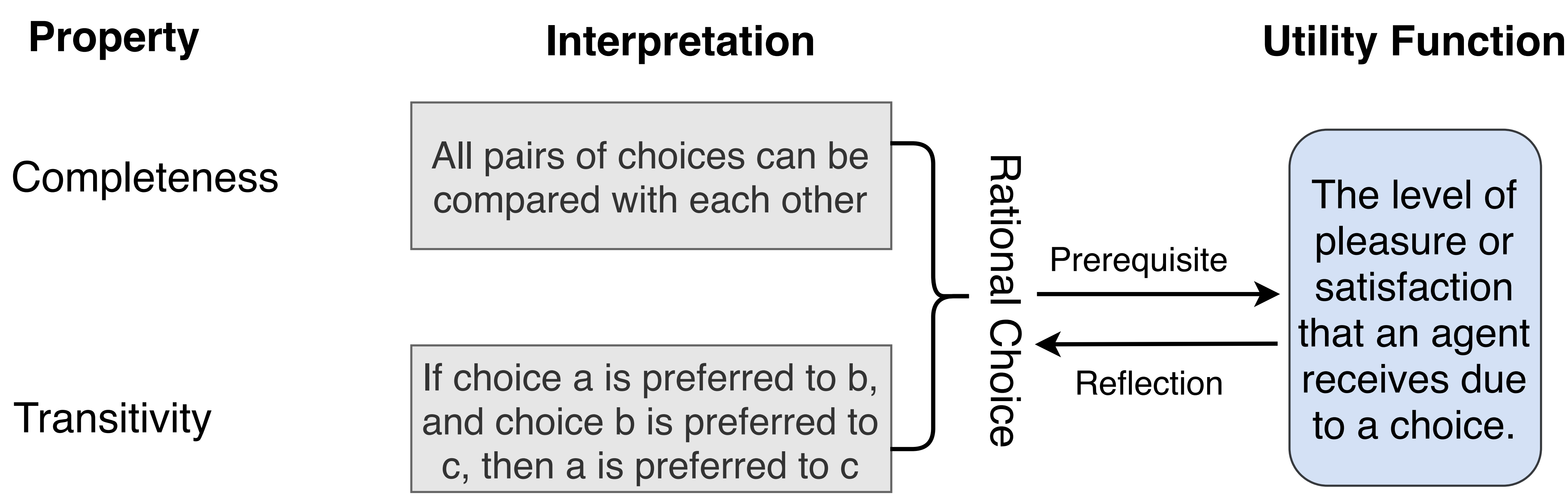


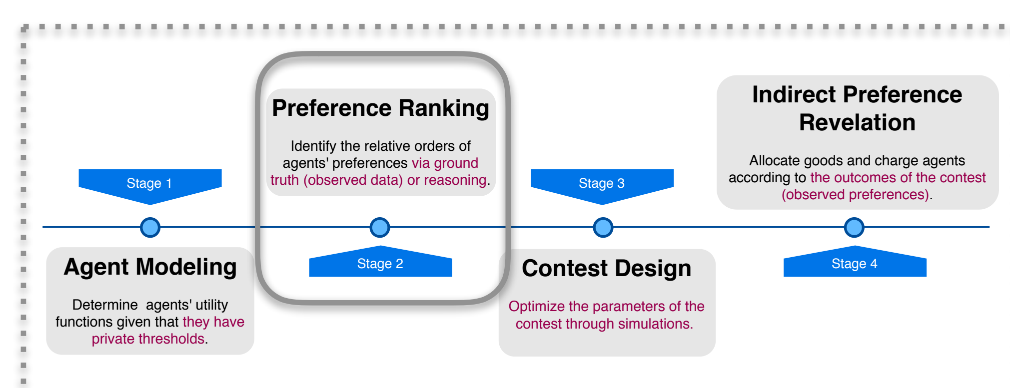
Agent Modeling



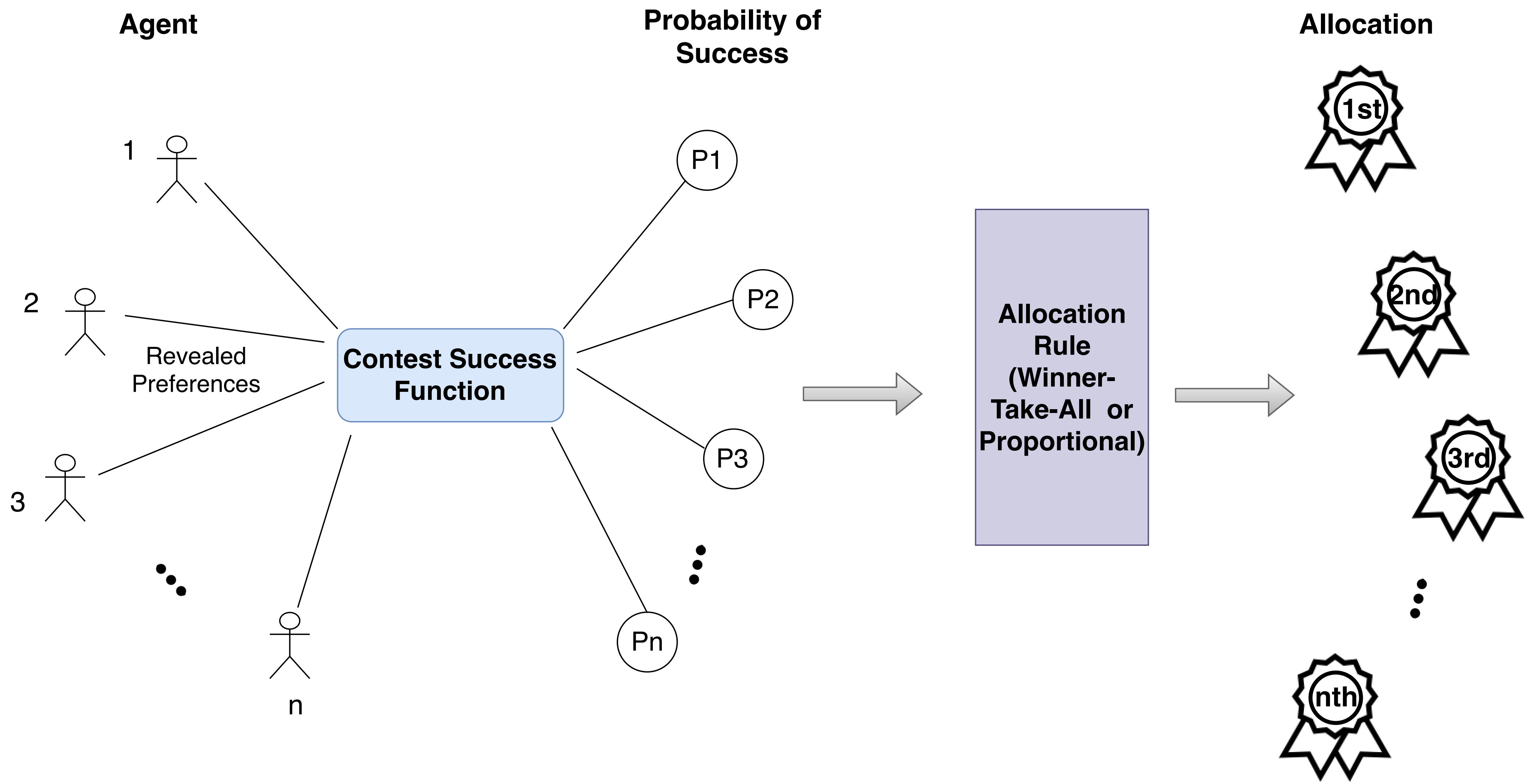
Preference Ranking

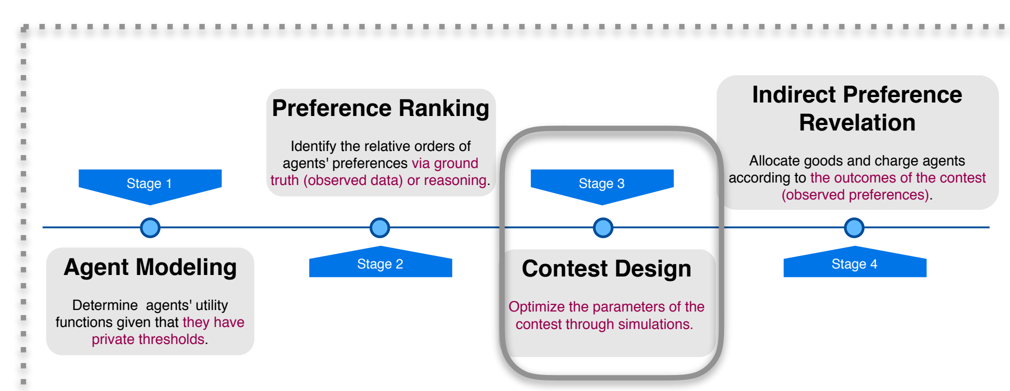
Identify the relative order of agents' preferences based on empirical data and/or reasoning





Contest Design



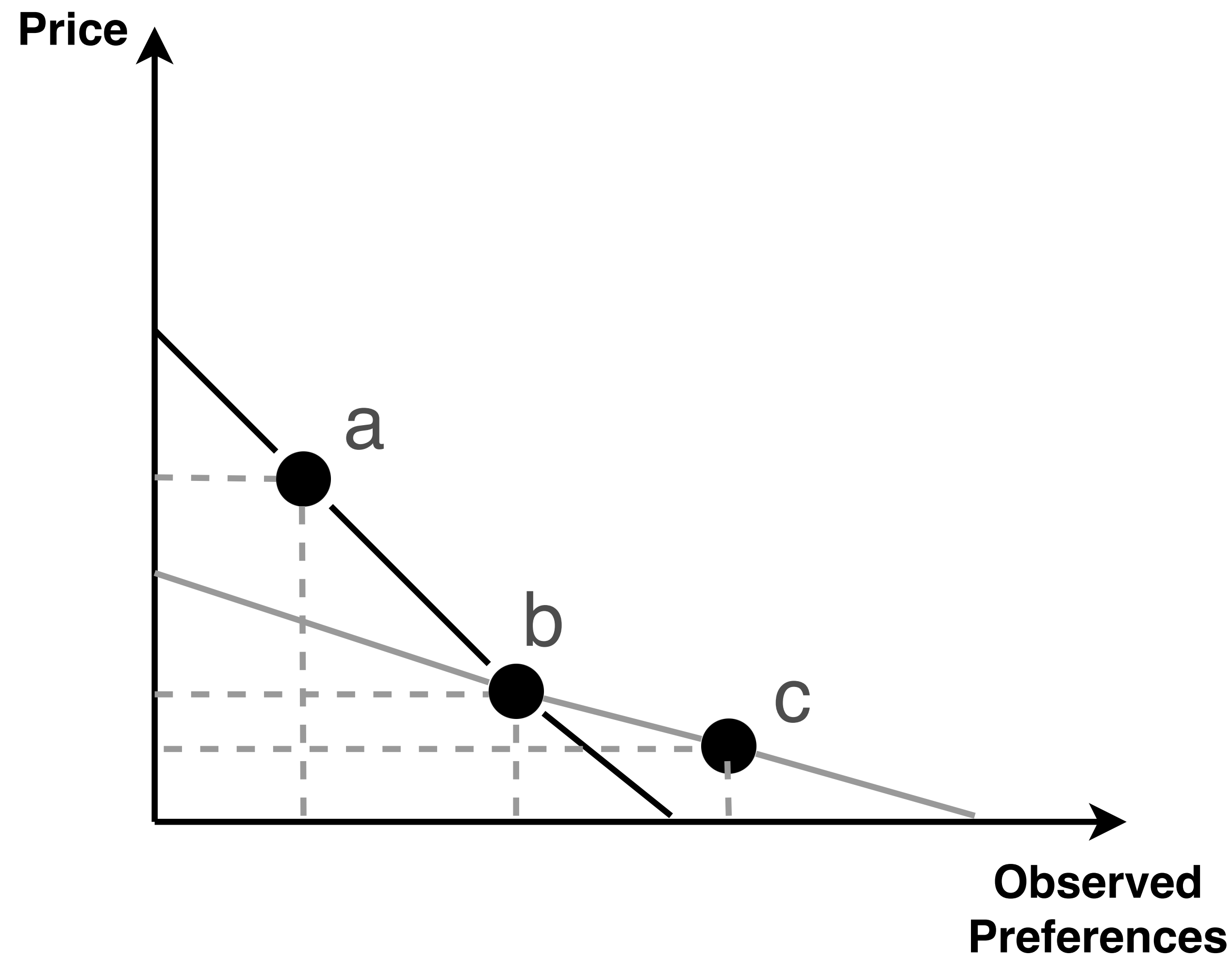


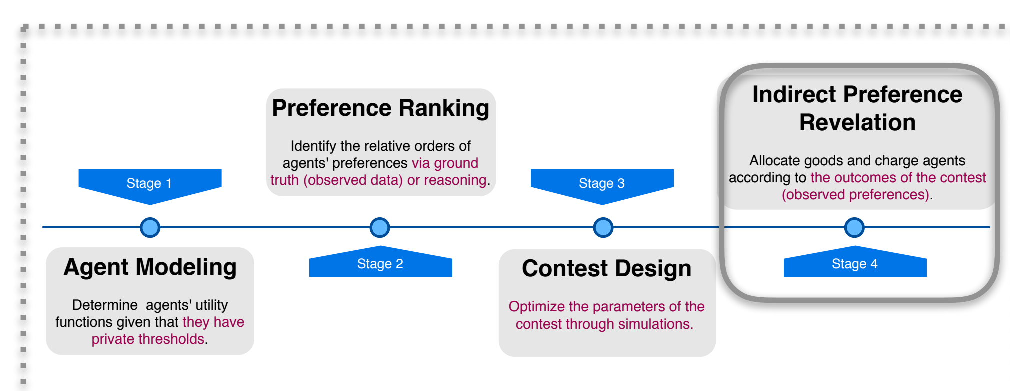
Indirect Preference Revelation

Method: Post-Price Mechanism

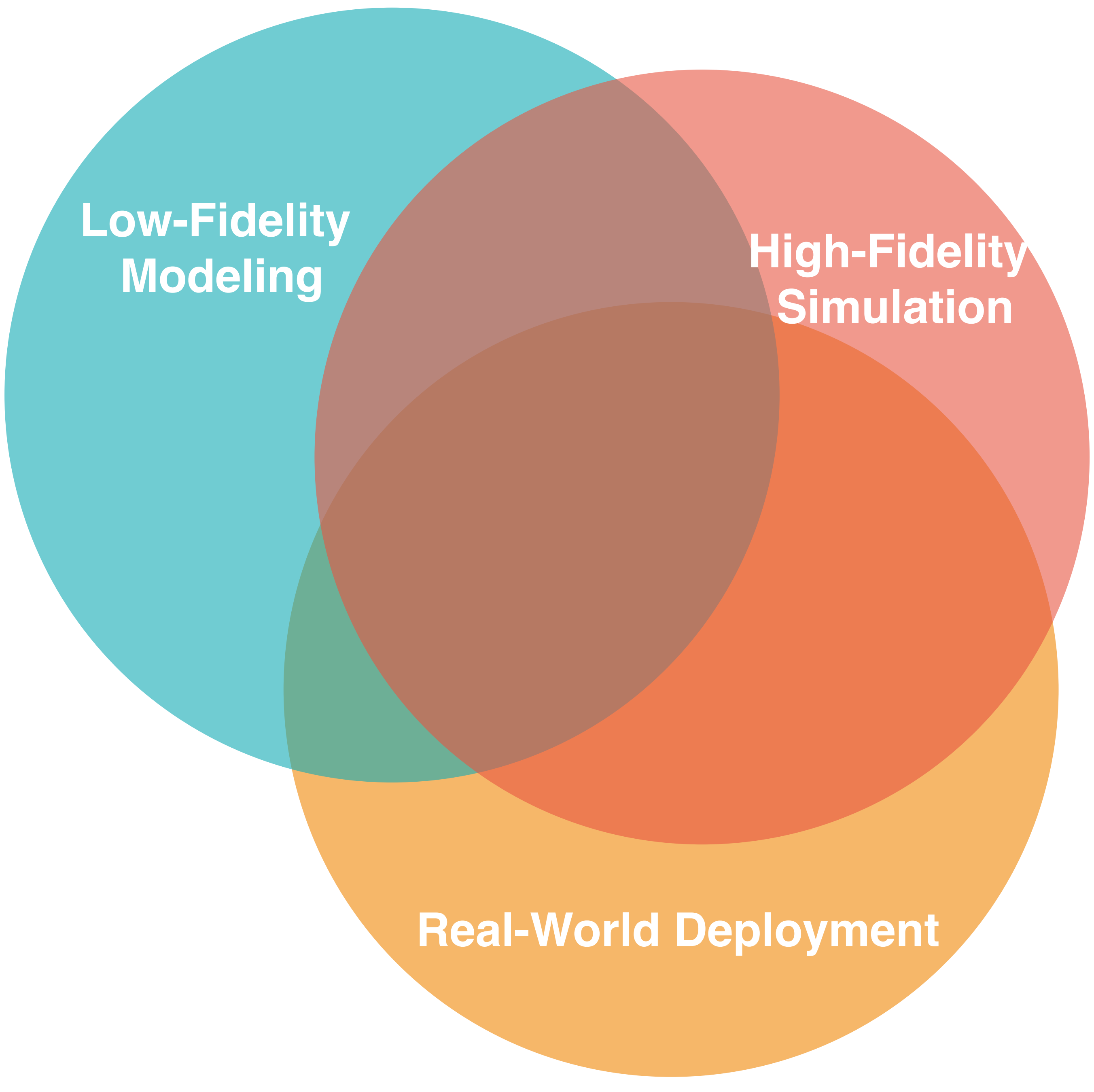
Benefit: allow the principal to learn agents’ preferences

- 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


Low-Fidelity
Modeling
High-Fidelity
Simulation
Real-World Deployment

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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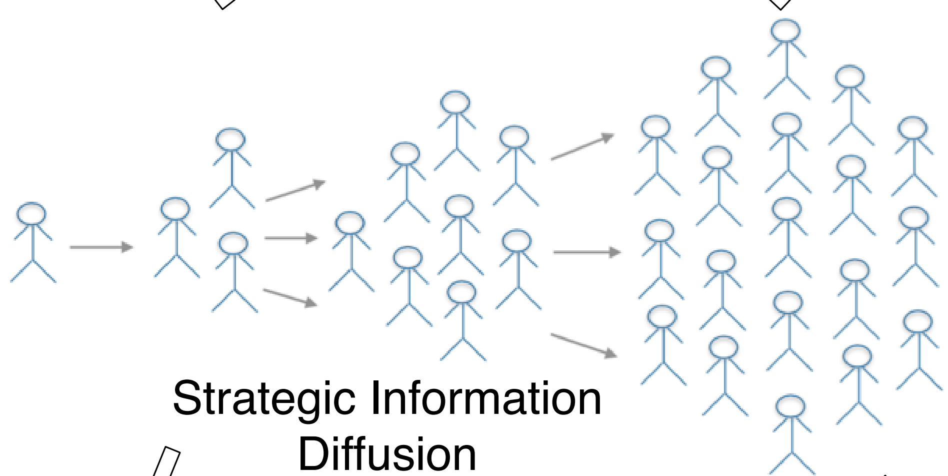
Strategic Diffusion in Social Networks

Marketing

Crowdsourcing

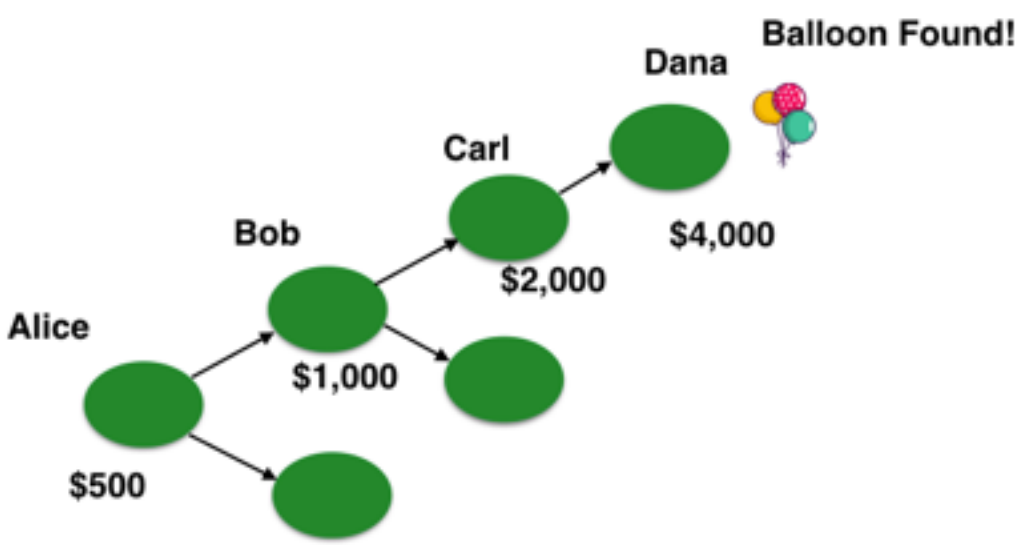


Strategic Information Diffusion

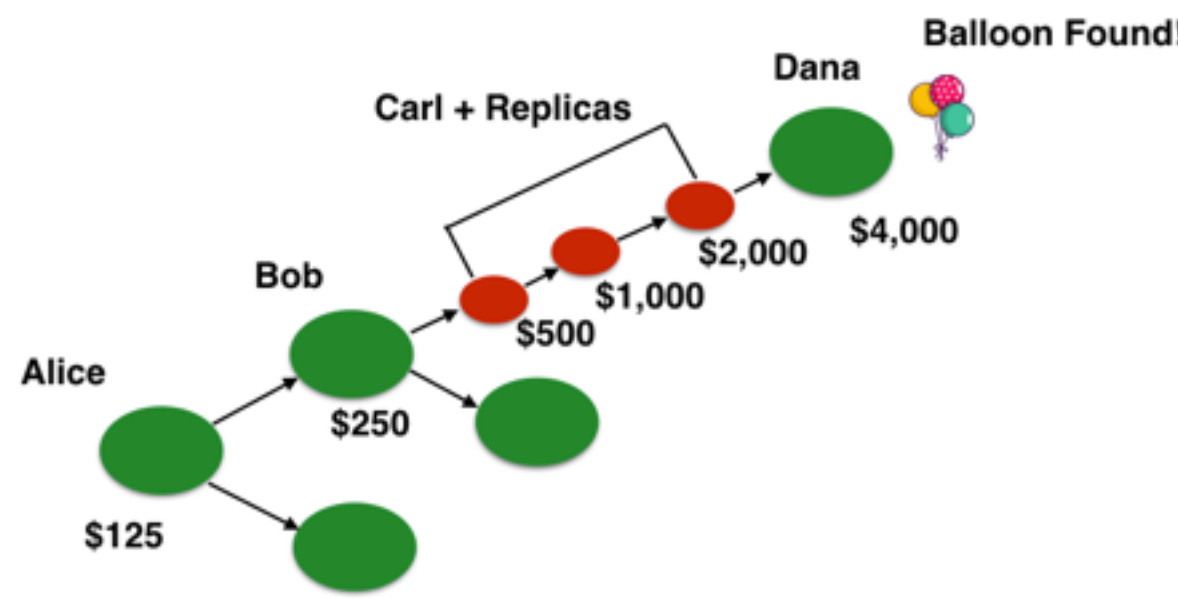
People Search

Propaganda

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**

the rewards that player v receives

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

player v's efforts

player v's utility

player v's cost coefficient (private)

- **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.

player v's virtual credits

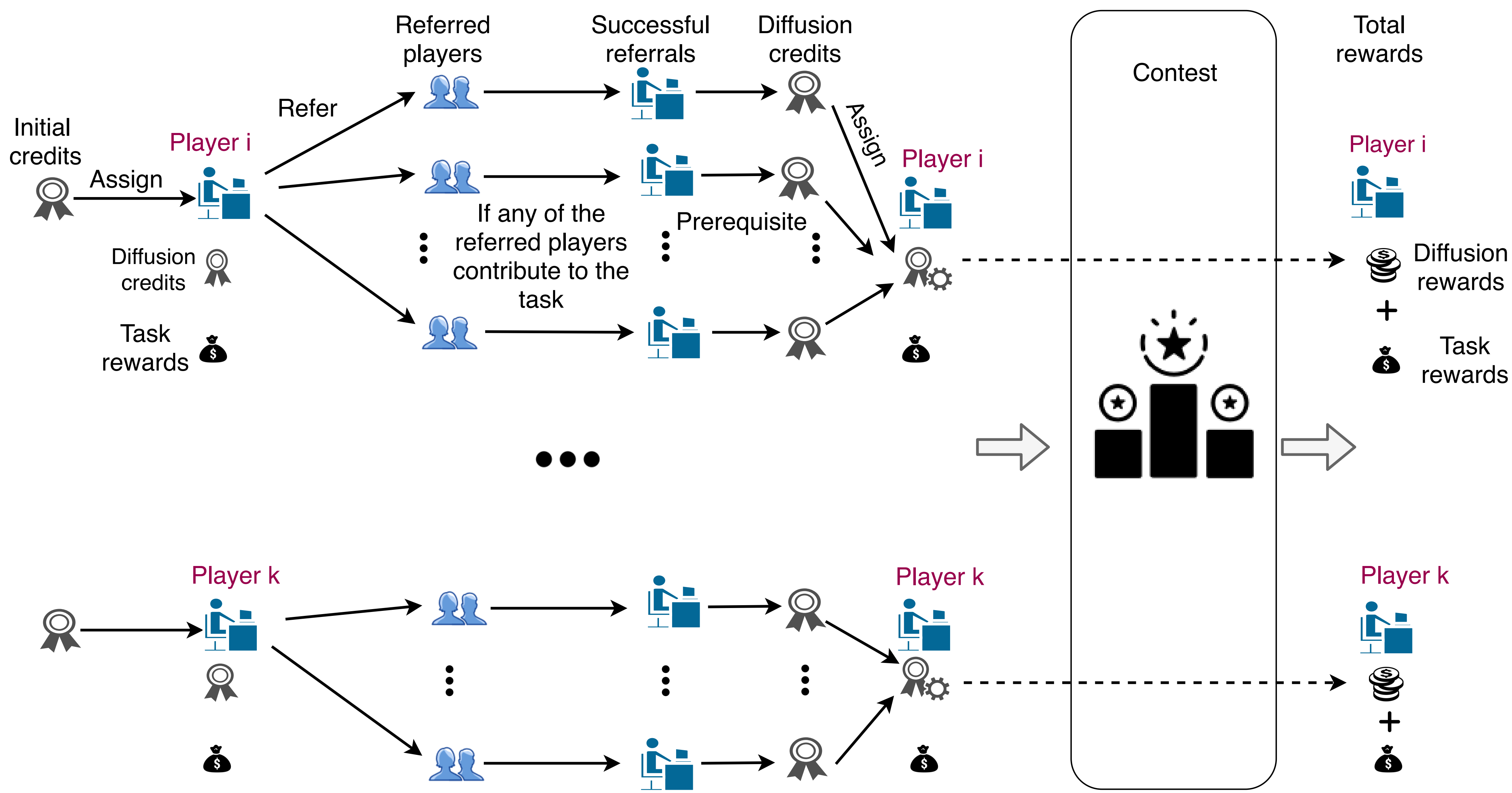
noise factor

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

player v's probability of winning

players in the same subgraph of player v

Multi-Winner Contests



(Shen, Feng, Lopes AAAI'19)

Experimental Settings

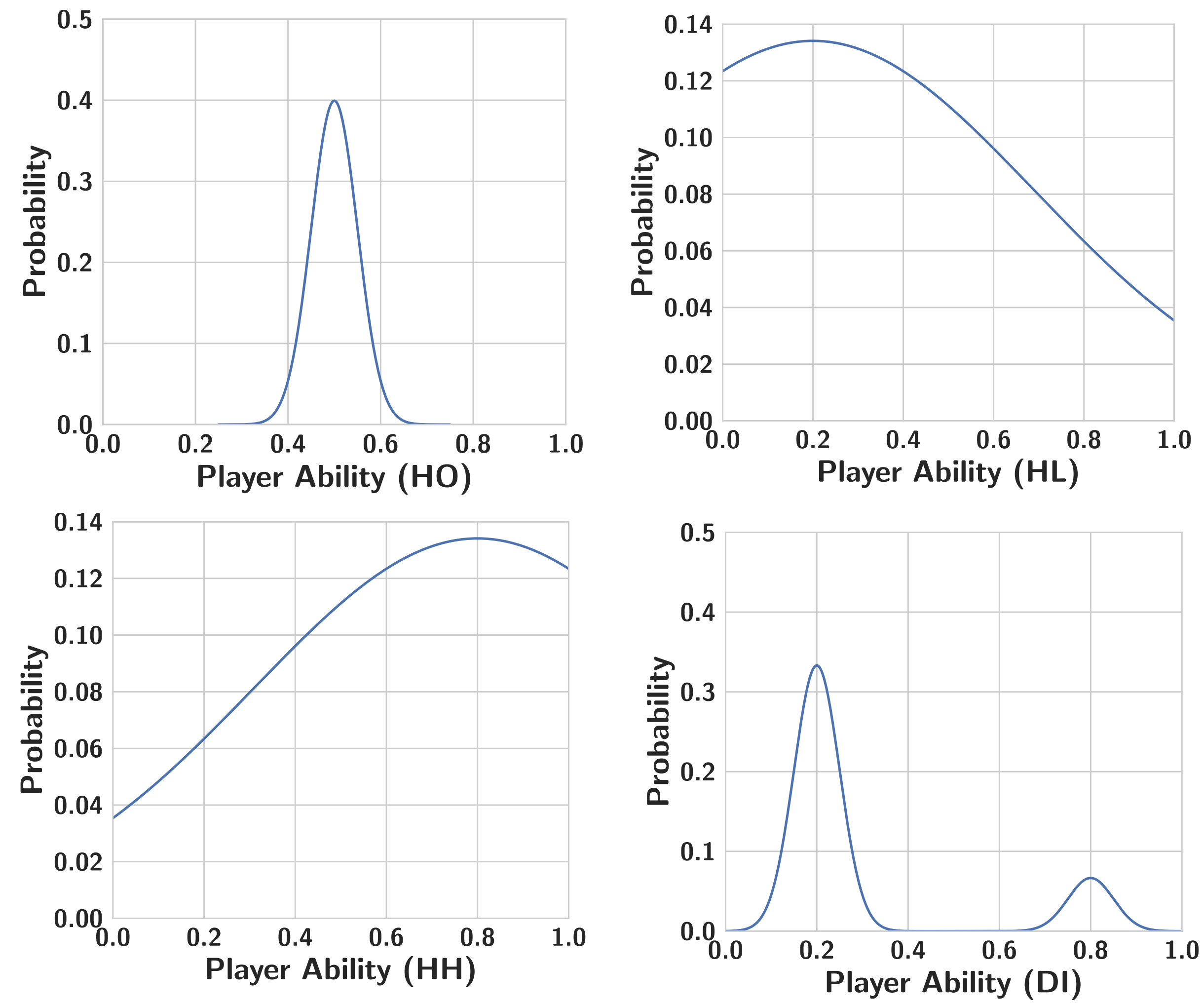
Dataset	#Nodes	#Edges	#Seeds	M.D.	A.D.
Twitter	323,185	2,148,717	1,715	8,822	52
Flickr	145,305	2,149,882	768	6,731	34
Flixster	95,969	484,865	502	3,109	27
Digg	17,817	128,587	107	1,375	20

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.



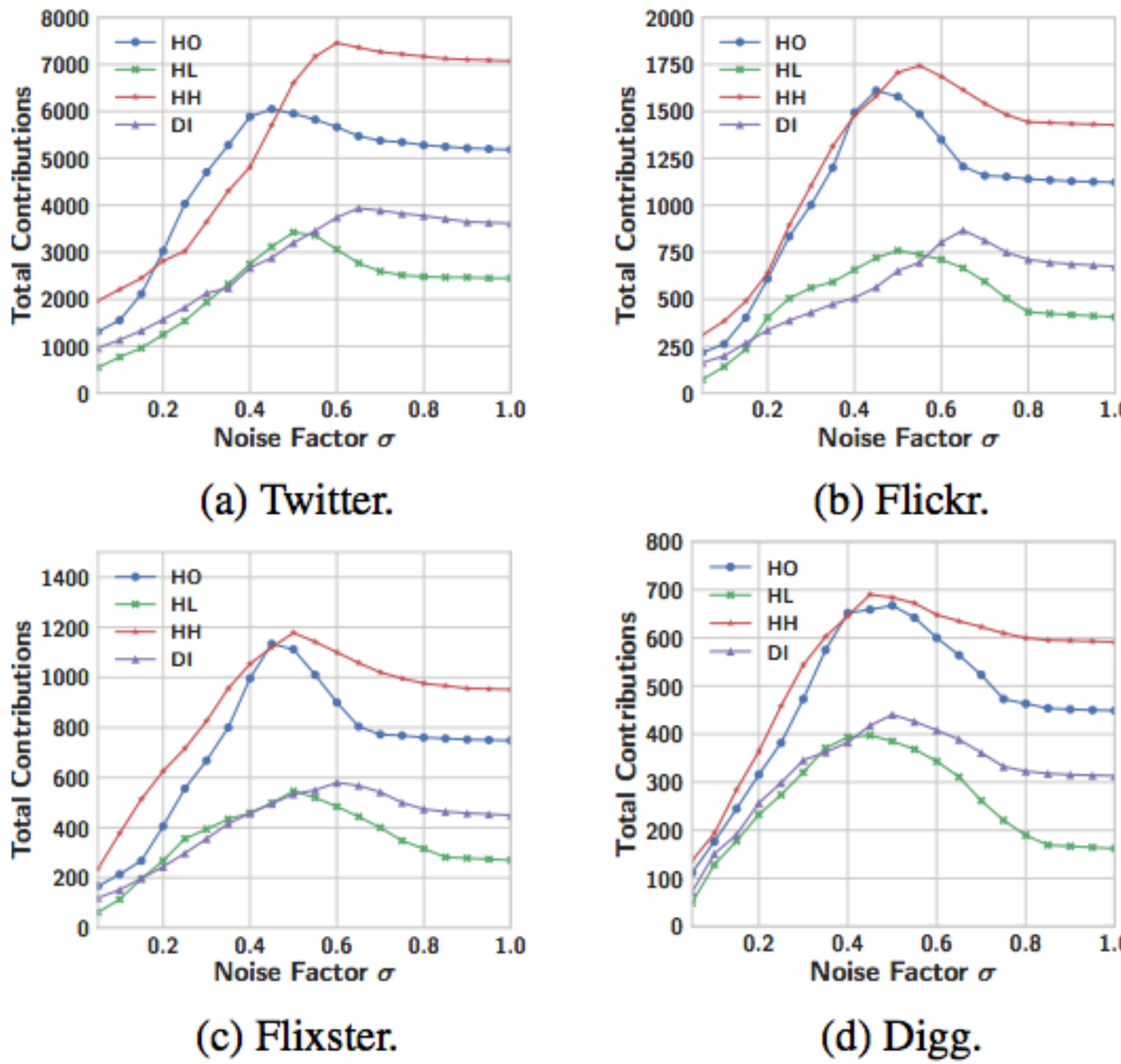
HO- homogeneous; HL- heterogeneously low;
HH -heterogeneously high; DI-distinctive

$$\delta_v = 1 - \rho_v$$

player v's
cost coefficient

player v's
ability

Total Contributions

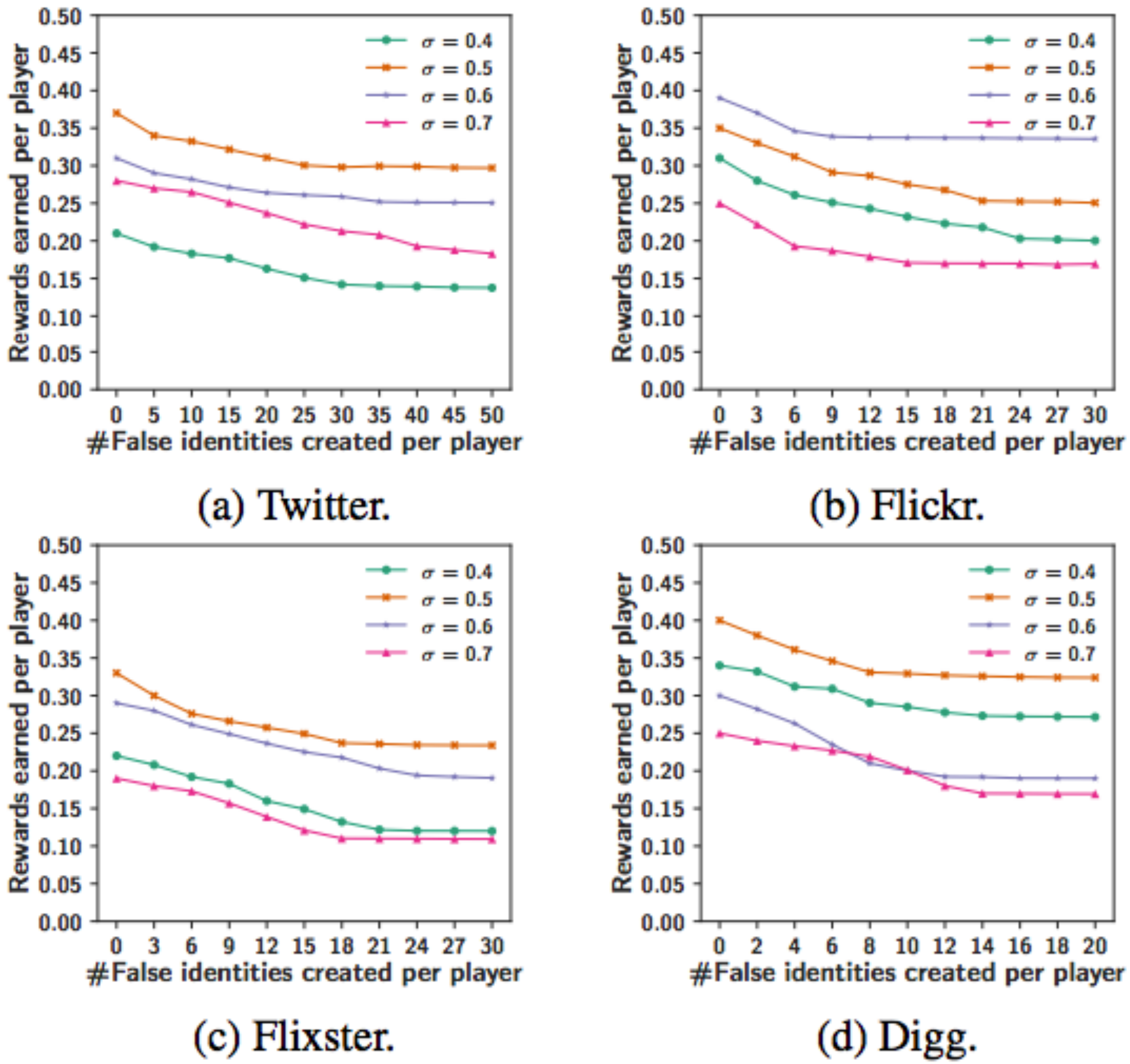


(a) Twitter. (b) Flickr.

(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:**
  - Countering collusion (Shen, Yan and Lopes, Working Paper 2019)
  - Countering free riding (Shen and Lopes, Working Paper 2019)

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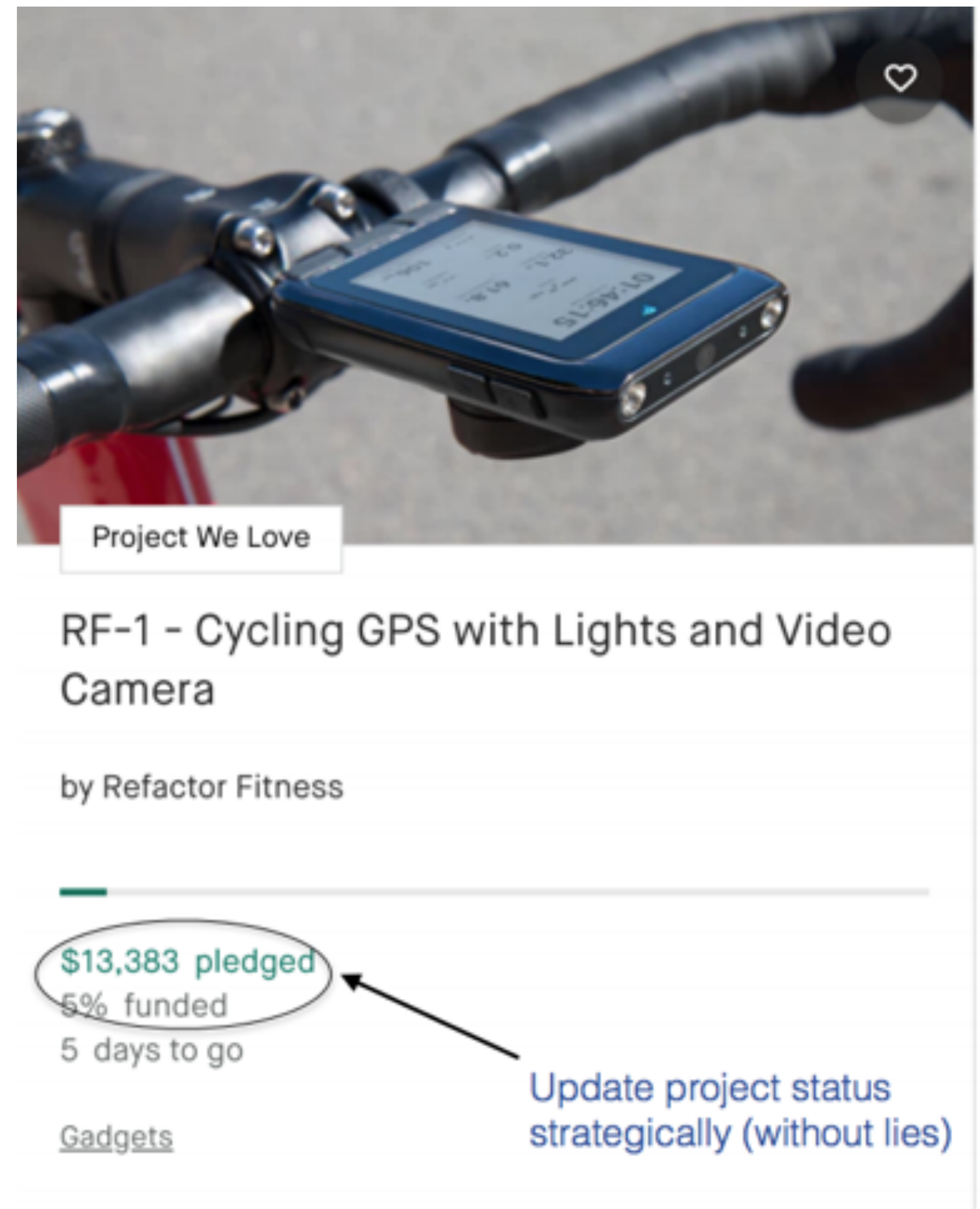
Information Design for Crowdfunding

- **Objective:** to solicit contributions from early backers to generate revenue

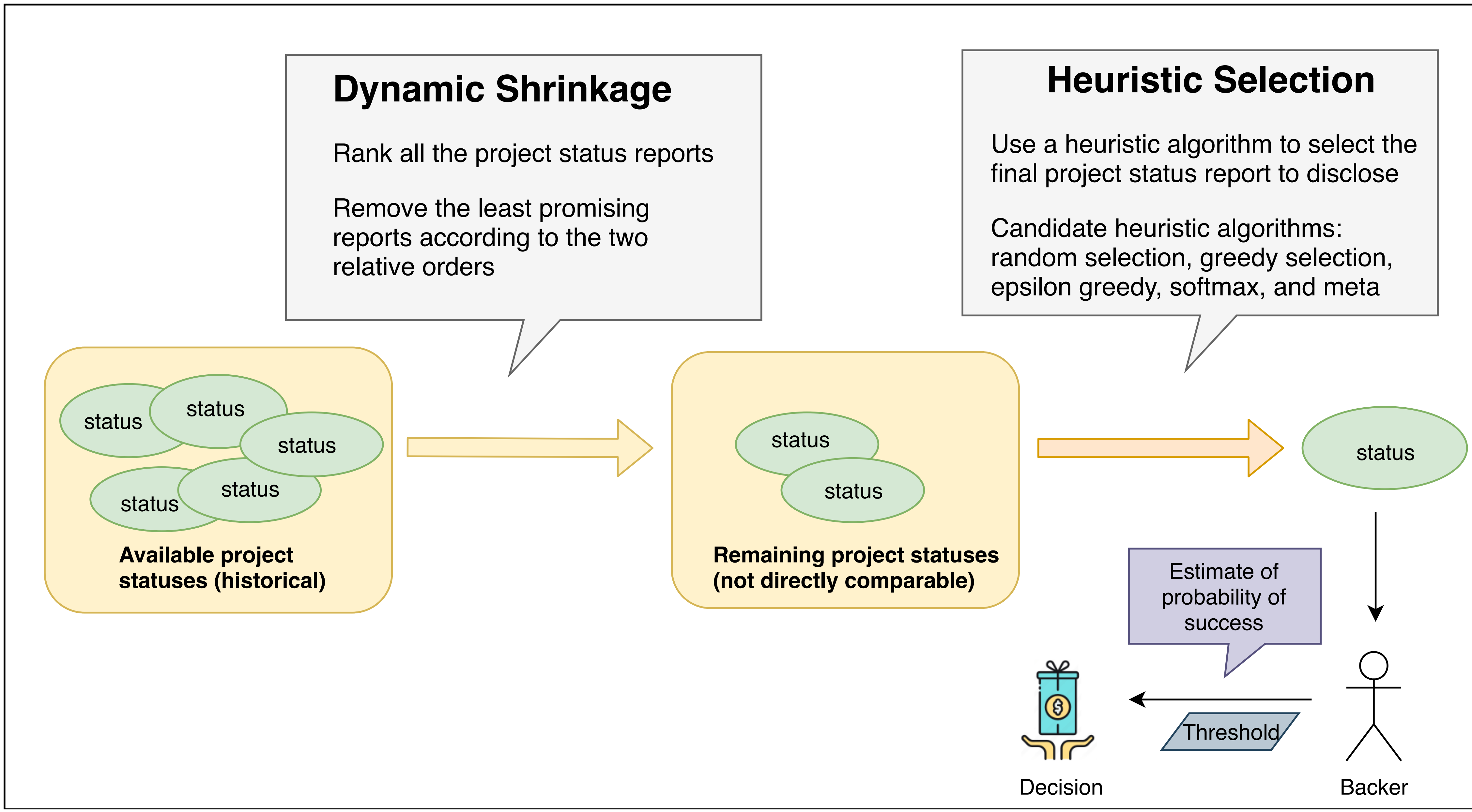
- **Intuition:** to influence agents' beliefs by designing information disclosure policies (i.e. information structures that determine which pieces of information are disclosed to whom for desirable outcomes)



Credit: Kickstarter

Dynamic Information Design

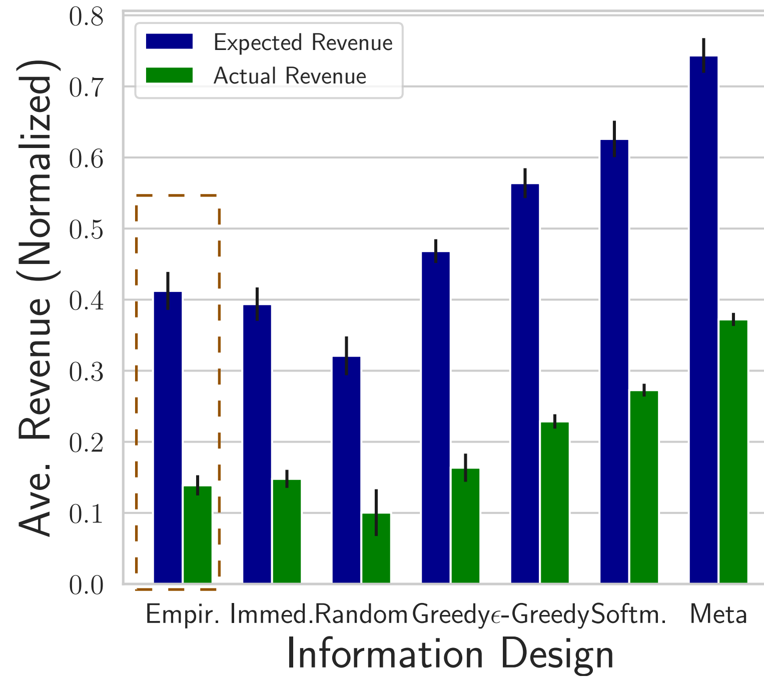
Dynamic Shrinkage with Heuristic Selection



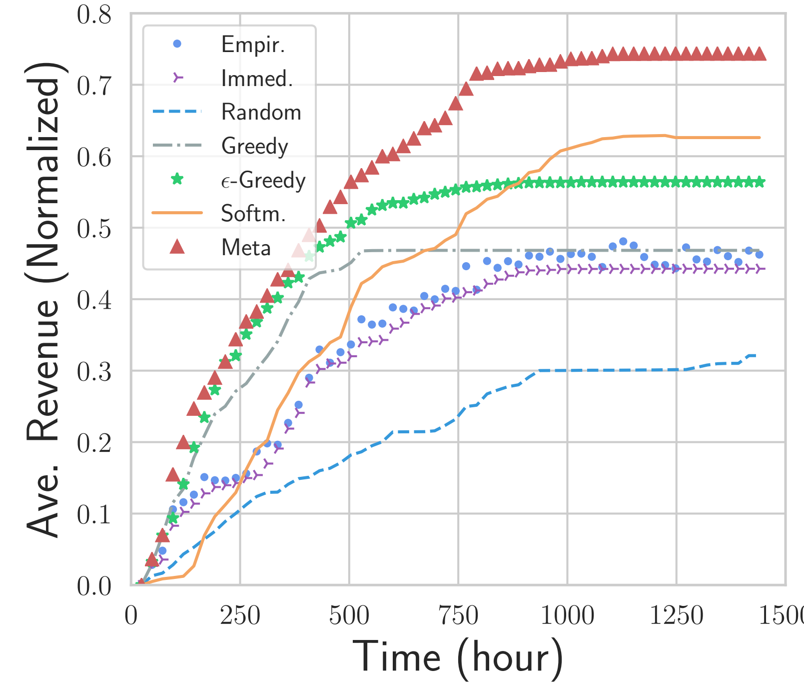
(Shen, Crandall, Yan, Lopes AAMAS'18)

Simulation Results

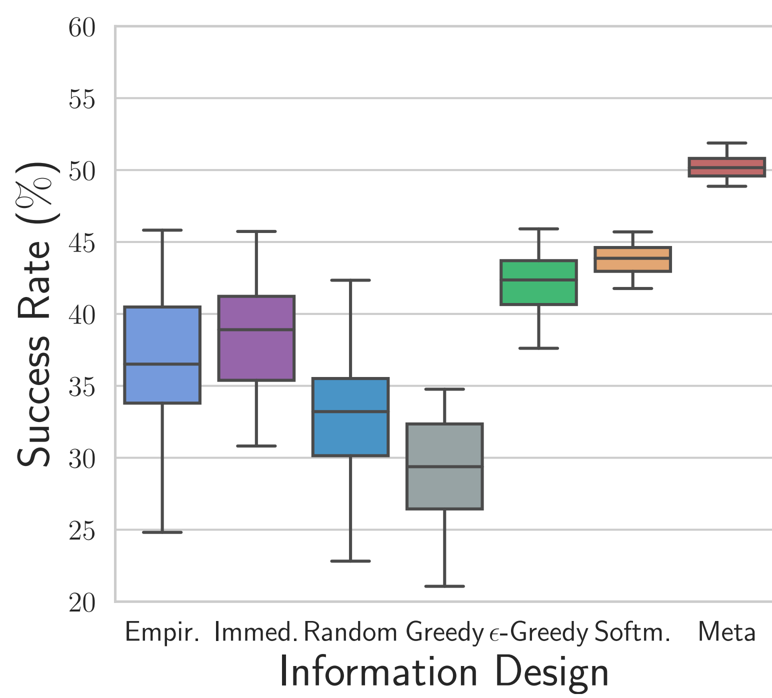
- **Observations**
  - Meta group performed consistently the best among all the groups in terms of both actual and expected revenue.
  - Meta group had the highest project success rate.
  - Meta group required the most computational time.
- **Indications**
  - Immediate disclosure is not always optimal in crowdfunding.
  - Dynamic information design is helpful



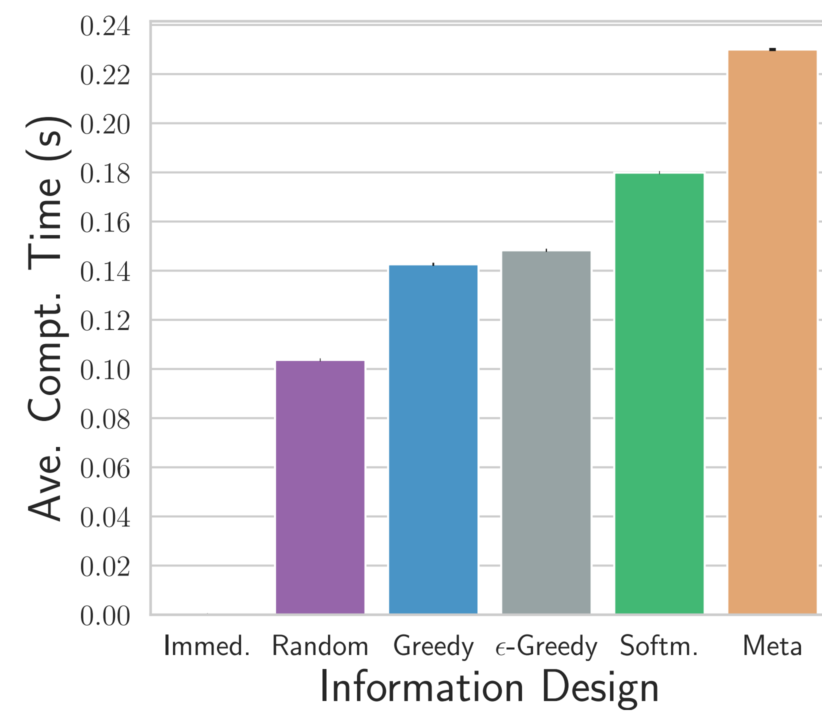
(a) Overall revenue (t = 1440)



(b) Expected revenue over time



(c) Project success rate (%)



(d) Computation time

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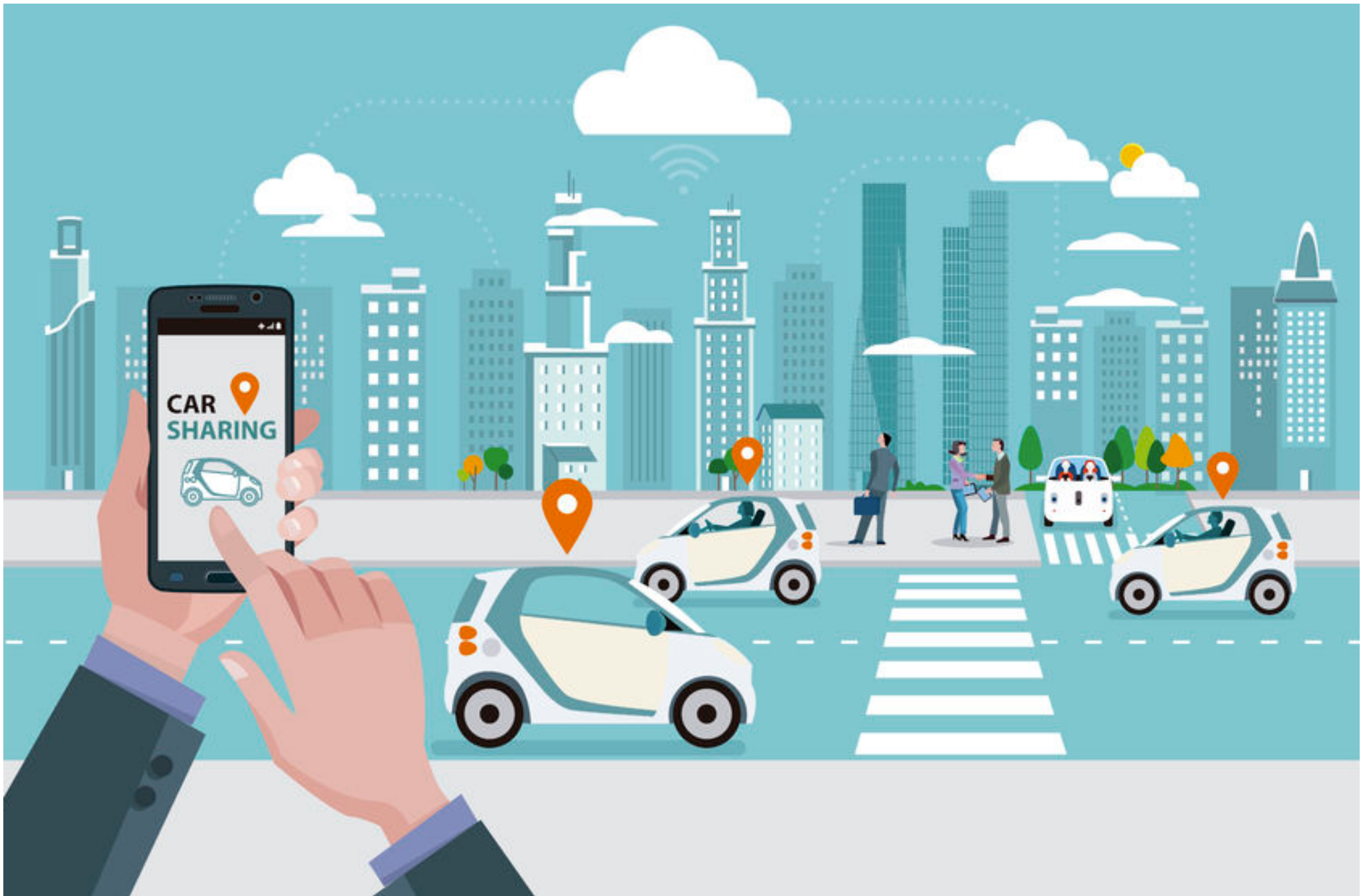
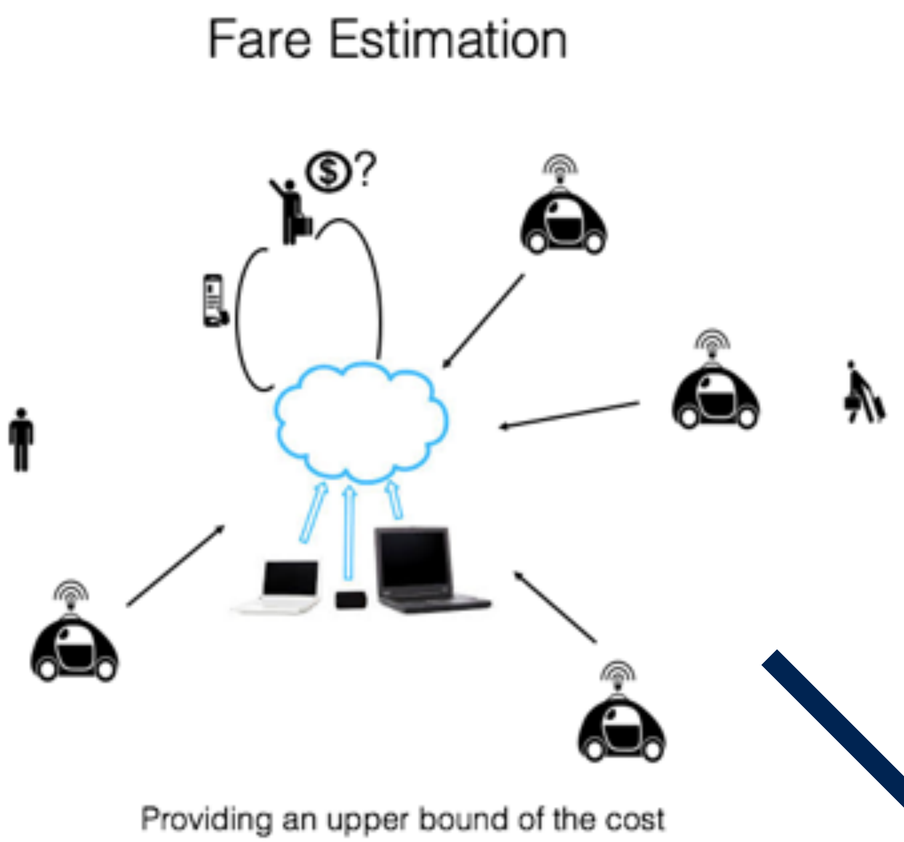
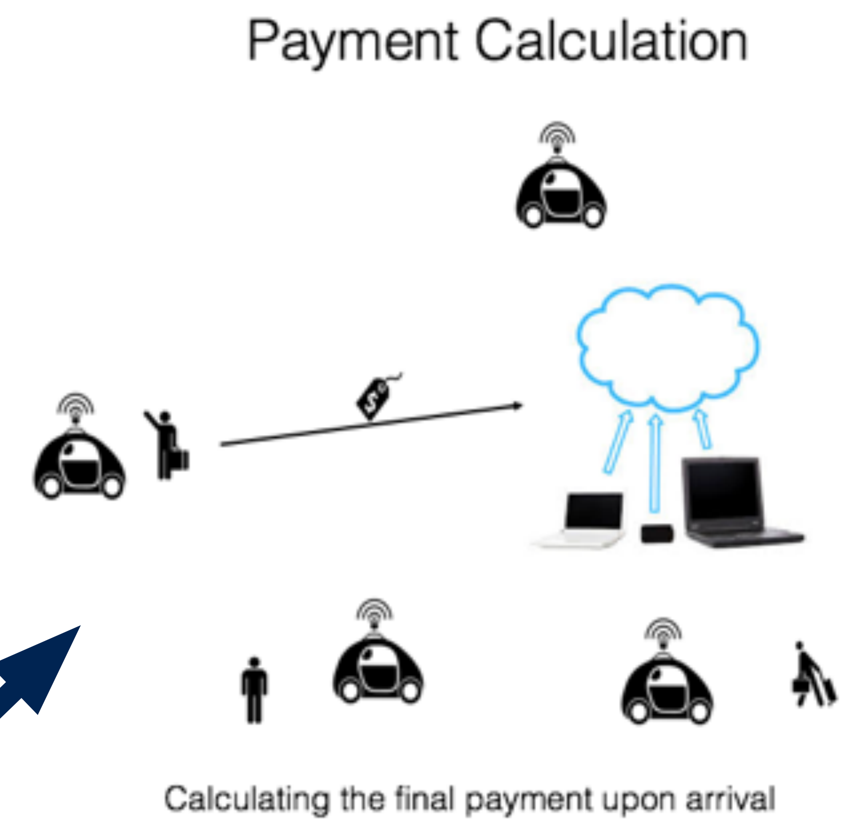
Autonomous Mobility-on-Demand Systems

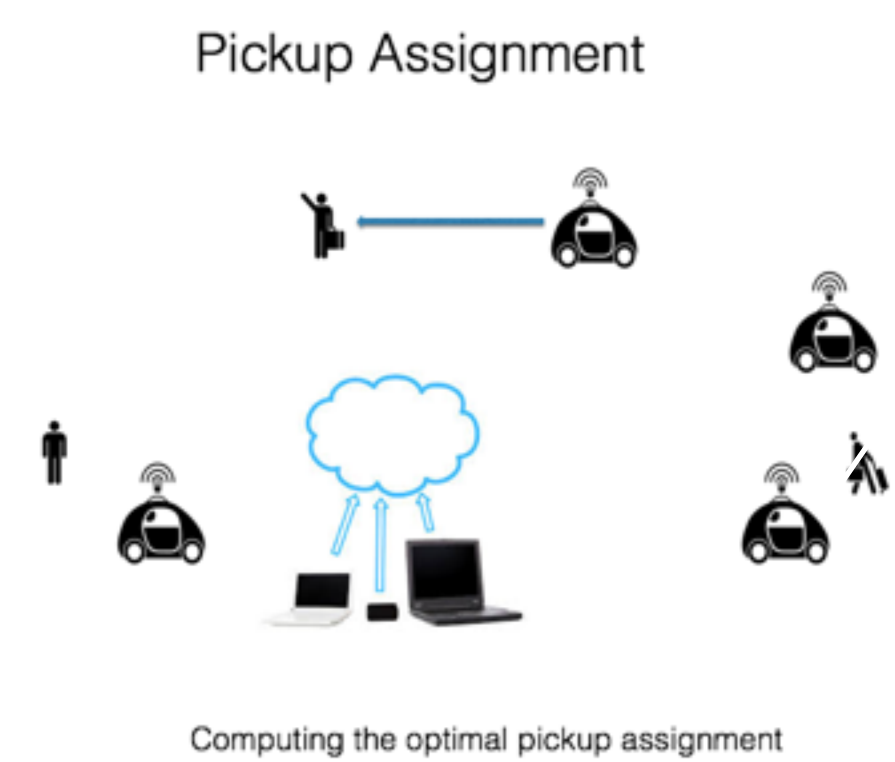


Credit: marketers media

An Online Post-Price Mechanism for Autonomous Ridesharing Systems







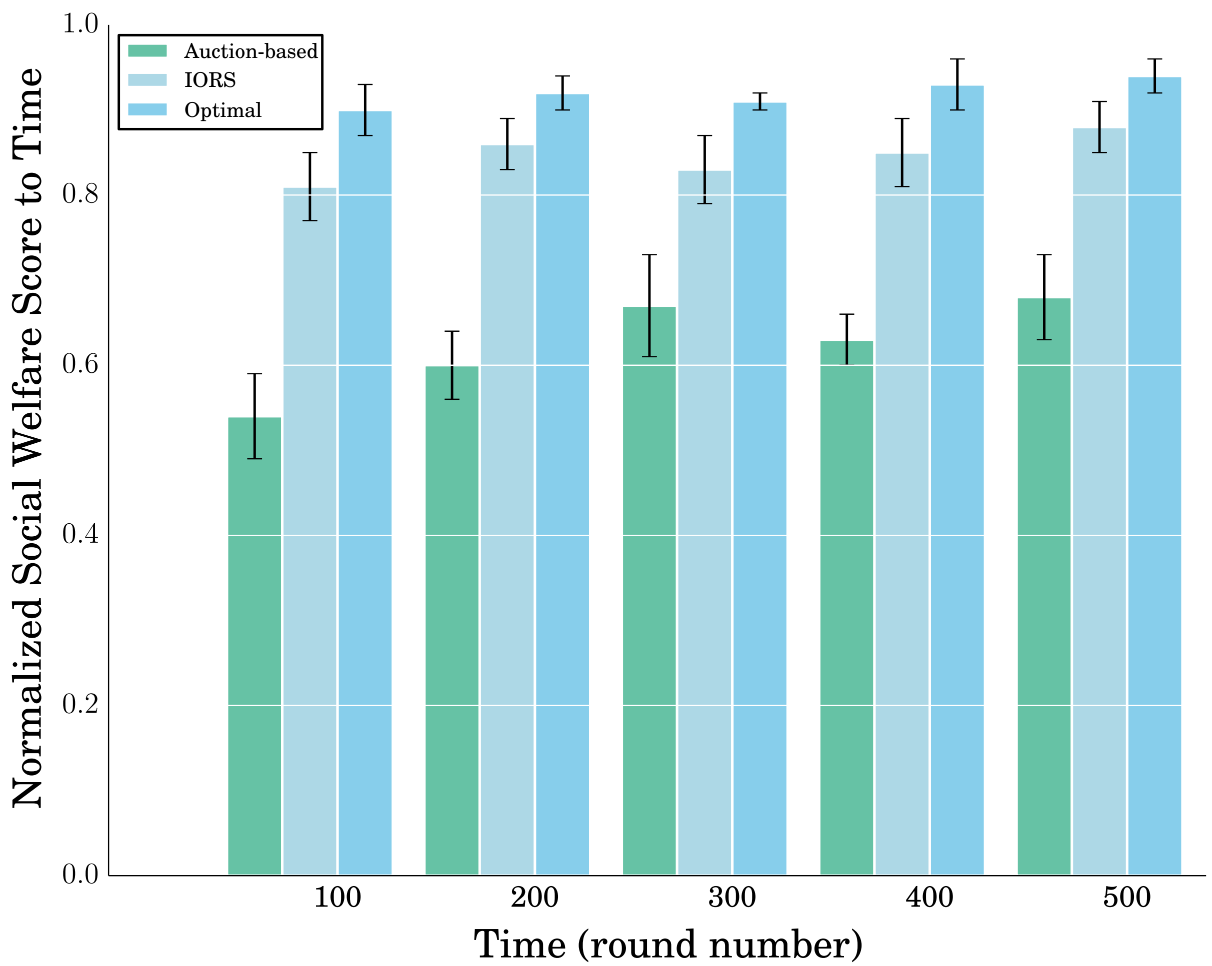
Objective:
To minimize the operational cost per unit demand (i.e. to maximize the serviced demand per unit cost).

Method: Integrated Online RideSharing (IORS) mechanism

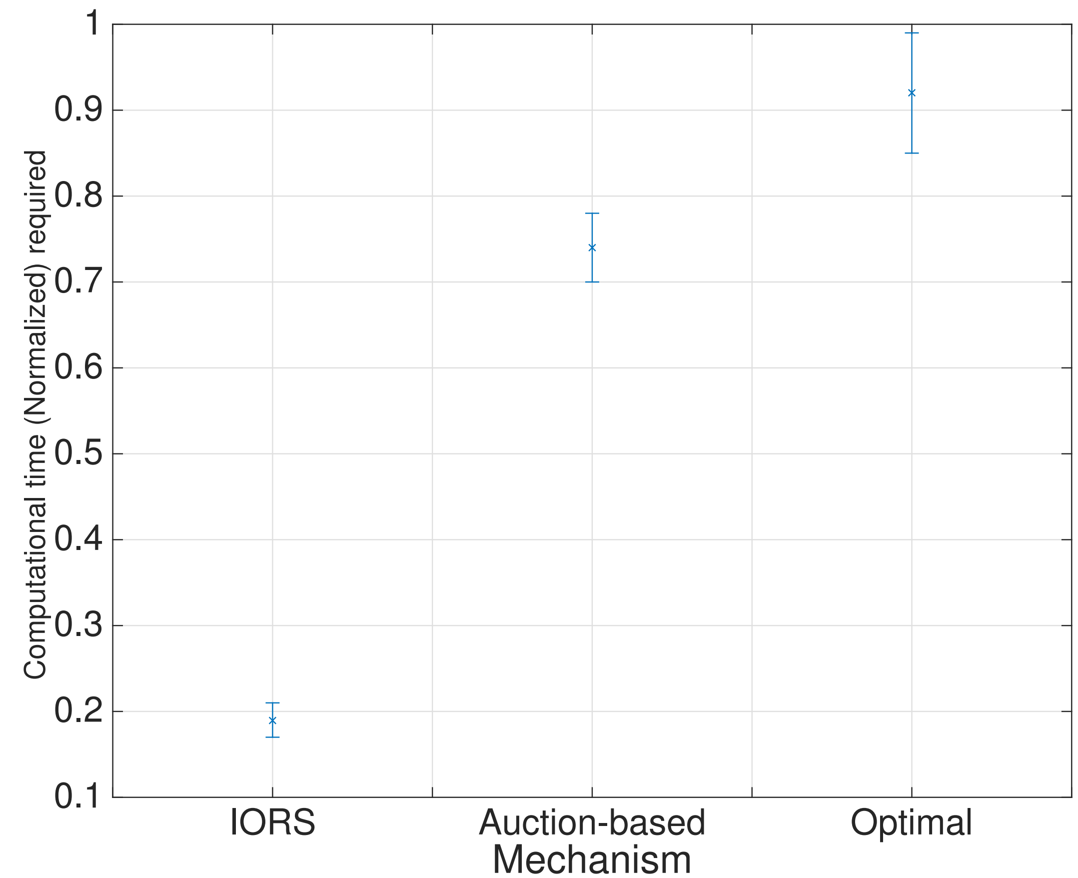
Properties:
-Ex-post incentive compatibility
-Individual rationality
-Budget constraint

(Shen, Lopes, Crandall IJCAI'16)

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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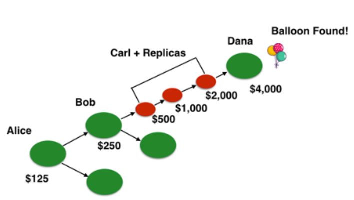
Mechanism Design with Thresholding Agents

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

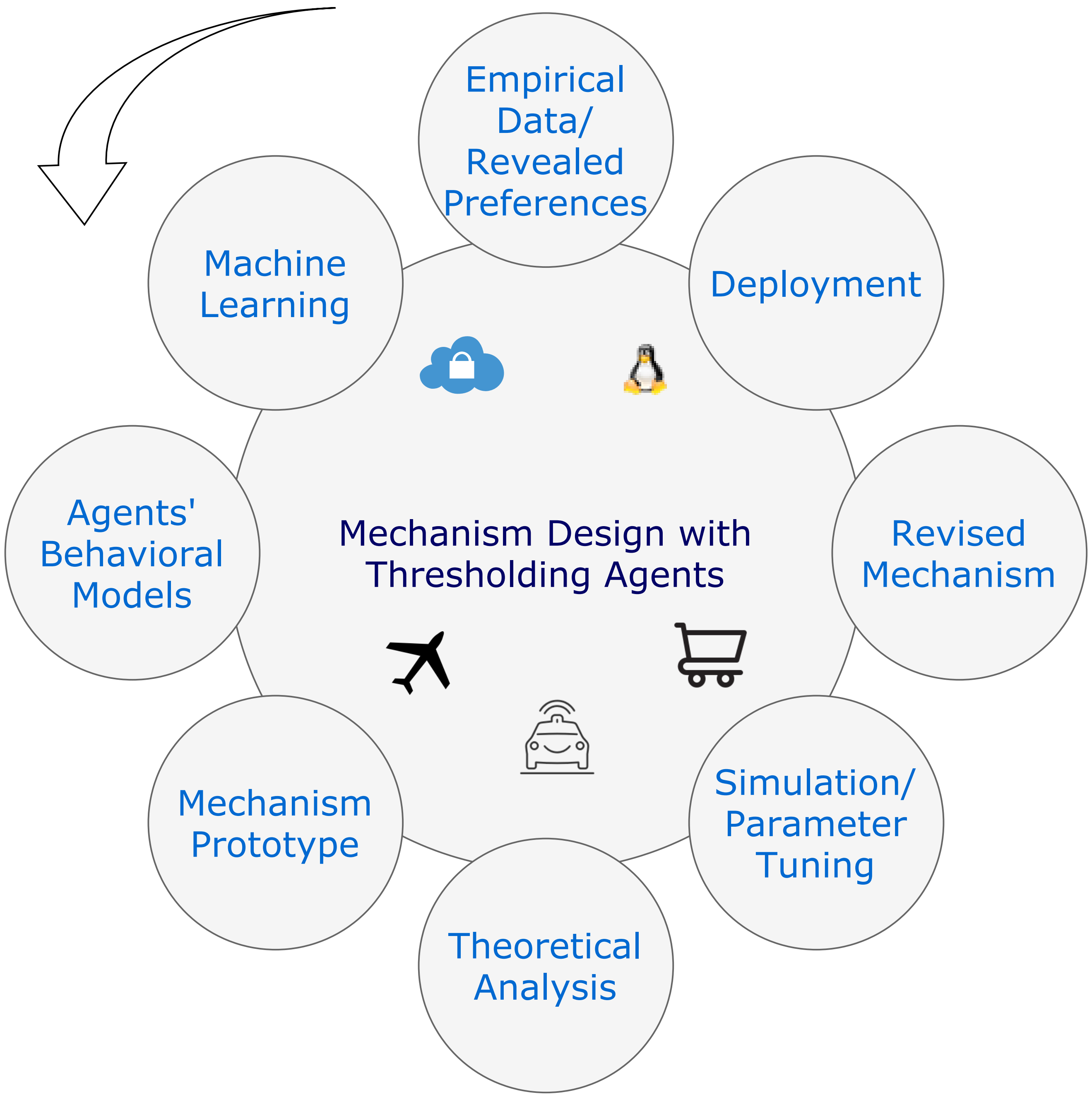
Crowdfunding

Shen, Crandall, Yan, Lopes AAMAS’18

Ridesharing

Shen, Lopes, Crandall IJCAI’16

Future Directions



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: Countering Free Riding in Utility Sharing with Sequential Contests.

Acknowledgments

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- Collaborators
- Labmates and friends at UCI
- Family

Thank You!

Q & A