

### UC SANTA BARBARA

## Information *as* Control: The Role of Communication in Distributed Systems

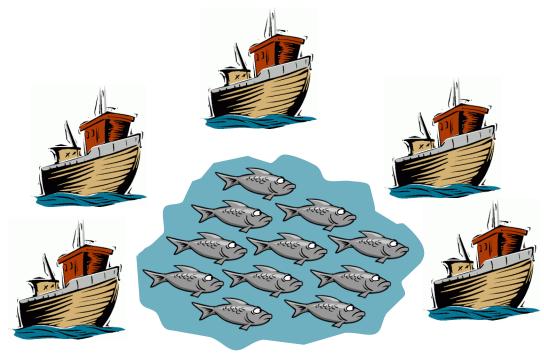
Bryce L. Ferguson

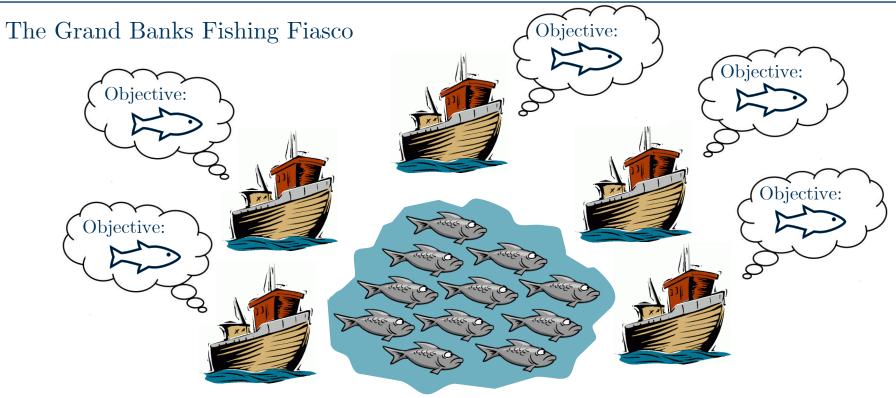
For the ECE Department at UC Santa Cruz

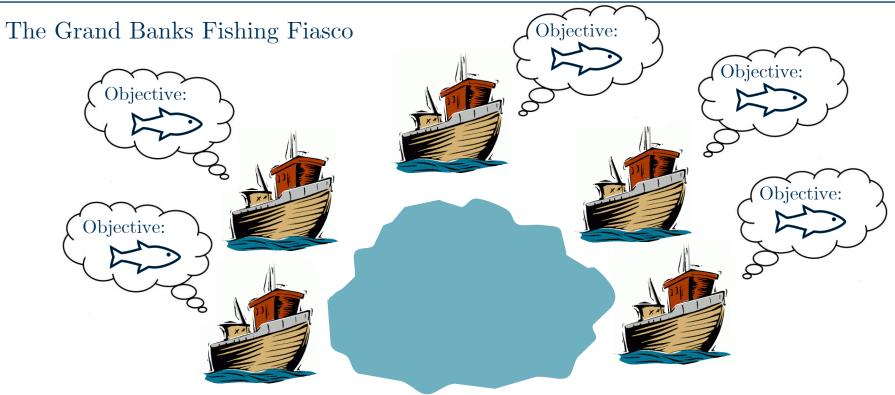
May  $15^{\text{th}}$ , 2023

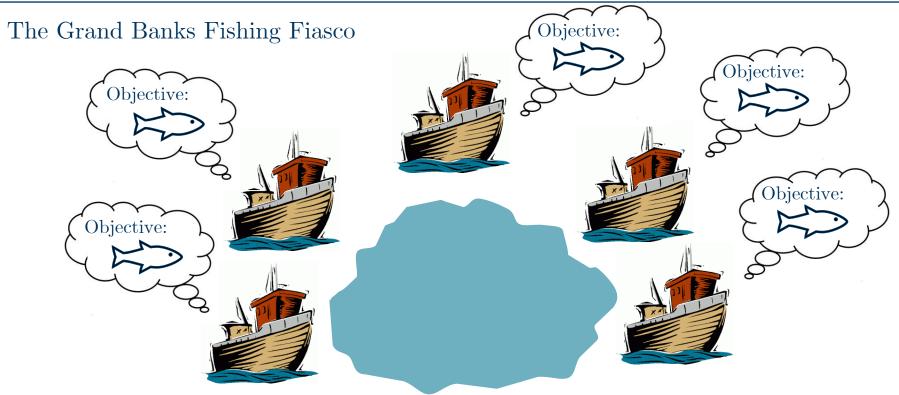
Supported by NSF, ONR, AFOSR, and ARL

The Grand Banks Fishing Fiasco









Local Decision Making (catch many fish) • Sub-optimal Global Behavior (fish population disappears)

#### The Grand Banks Fishing Fiasc

### Environment

THE BALTIMORE SUN

Climate change and the "tragedy of the commons"

By Dylan Selterman Baltimore Sun + Jan

Deforestation in Brazilian Amazon hits tragic record in 2022

PUBLISHED WED, JUL 13 2022-9:36 AM EDT

### Traffic/Congestion

The New York Times

Data Driving New Approaches to Transportation Analyzing digital streams of information from electric scooters and motor-assisted bicycles is helping solve travel congestion issues.

By Norman Mayersol Feb. 5, 2020 Uber exemplifies the Tragedy of the Commons FINANCIAL TIMES

This article is part of From Tad Borek, San Francisco, CA, US — Wednesday's most read letter

Five seconds after a operated databank is

operated databank is noting the location. In

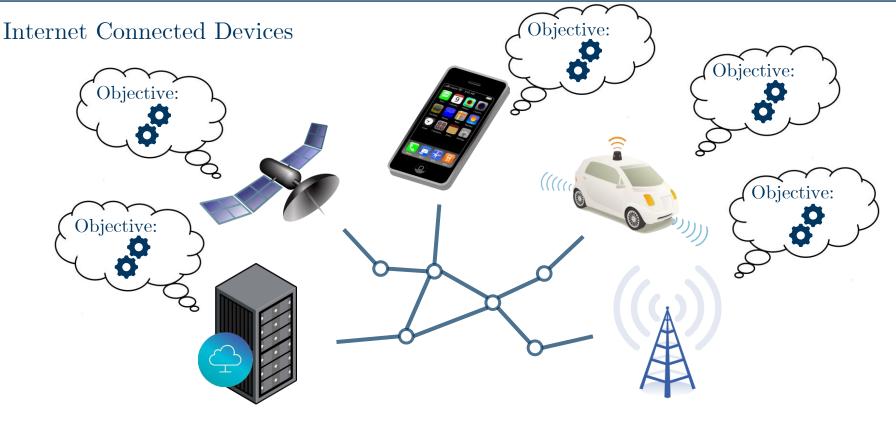
### Finance/Business



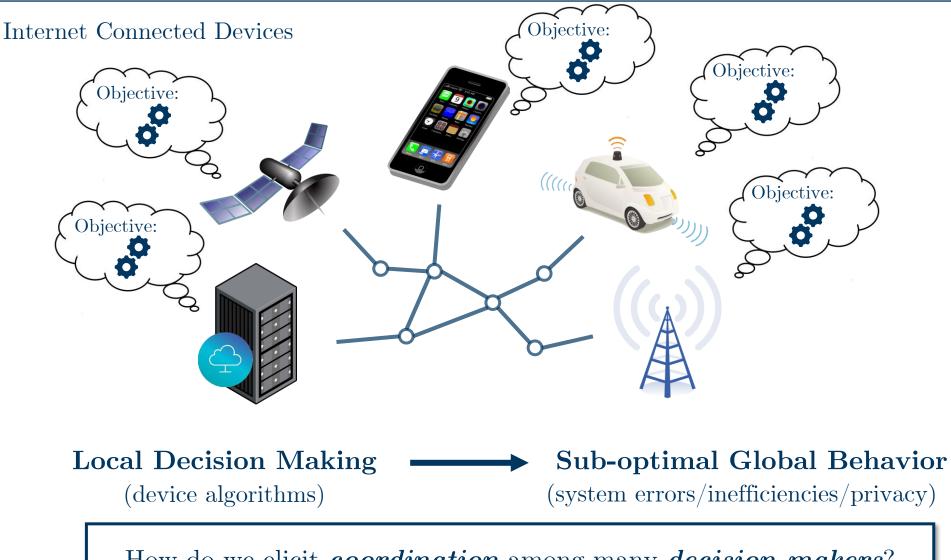
Matthew Erskine Contributor ③

### **Cloud Computing Services**

Chat	GPT is at capacity right now; yes, it
	is really annoying
Just like any oth	VentureBeat
-	3 ways data teams can avoid a tragedy of the
Lately, the "ChatGPT is outstanding chatbot.	cloud commons
"ChatGPT is at capacit when the chatbot server when the chatbot serve	Clinton Ford, Unravel Data

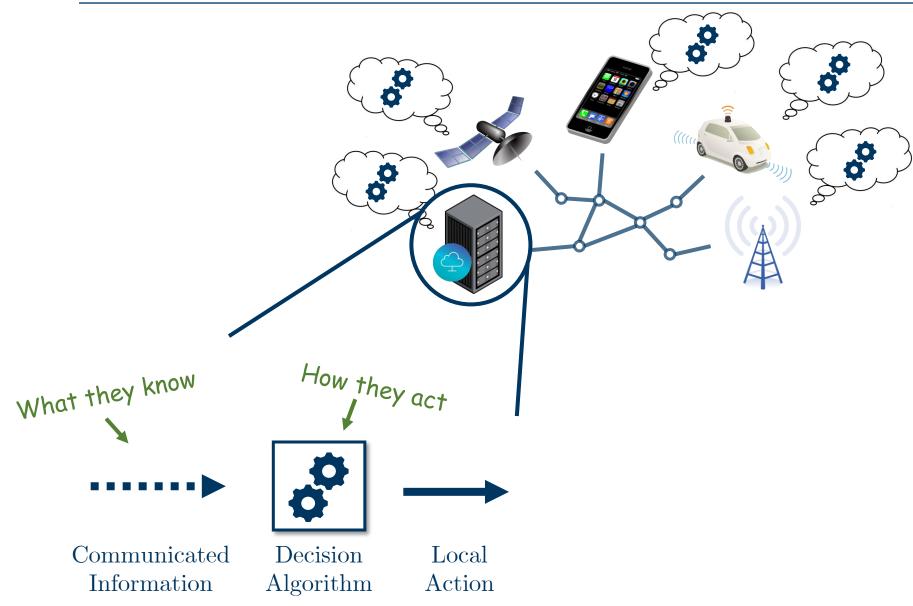


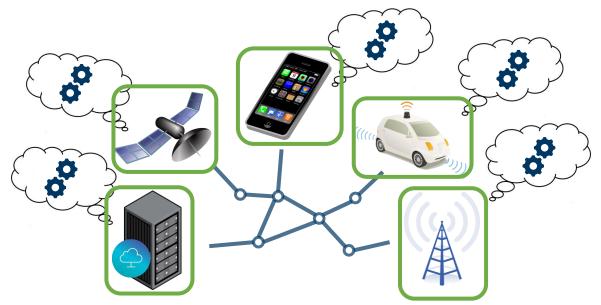
Local Decision Making (device algorithms)  Sub-optimal Global Behavior (system errors/inefficiencies/privacy)



How do we elicit *coordination* among many *decision-makers*?

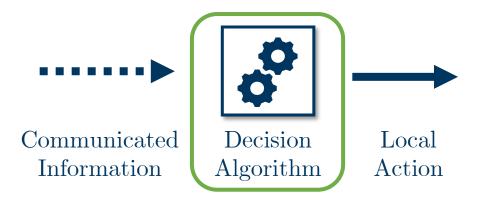


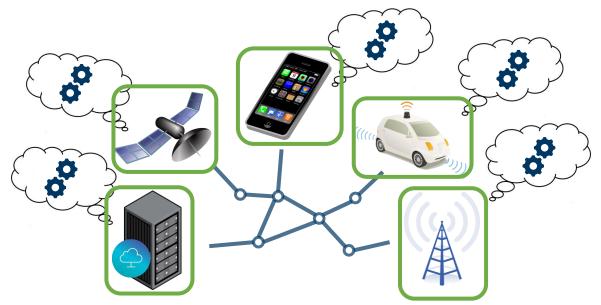




#### **Objective Design**

- Design local decision algorithm
- Utilize limited information





#### **Objective Design**

- Design local decision algorithm
- Utilize limited information



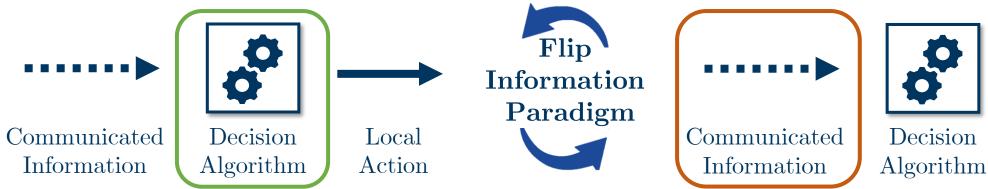


#### **Objective Design**

- Design local decision algorithm
- Utilize limited information ۲

#### Information Design

- Design communication structure
- Alter inputs to existing decision algorithms ٠





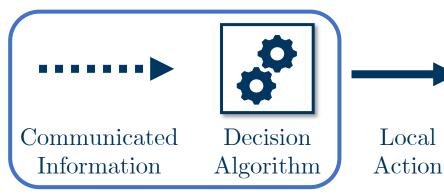


Local Action



#### **Intelligent Information System Design**

- Design communication and local algorithms together
- Improved performance at the cost of increased complexity



Information Sharing

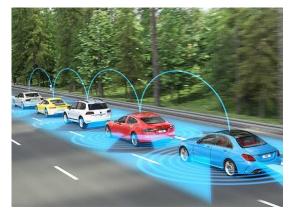
Collaboratively exchange information

Information Provisioning

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



Vehicle Platooning

### Information Provisioning

Strategically send out information

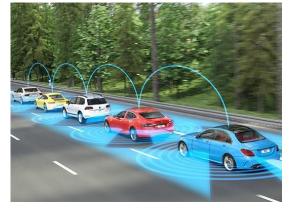


Traffic Signaling

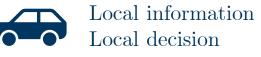
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Collaboratively exchange information

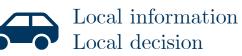
E.g., Autonomous Driving



Vehicle Platooning







Information Provisioning Strategically send out information



Traffic Signaling

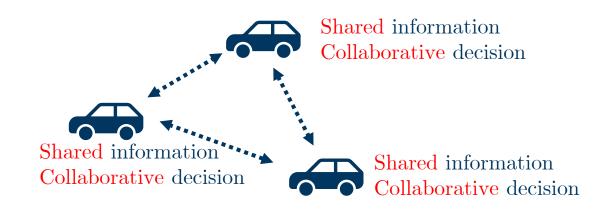
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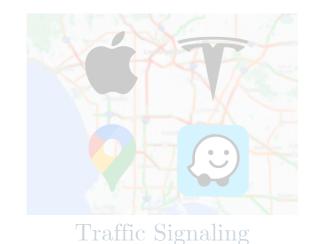
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Vehicle Platooning



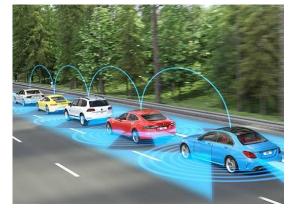
Information Provisioning Strategically send out information



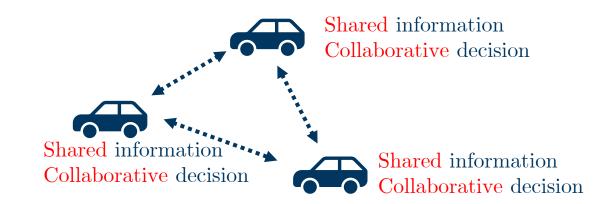
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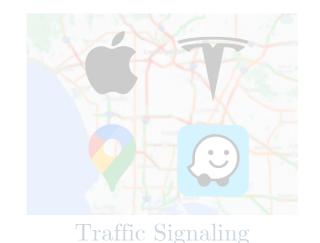
E.g., Autonomous Driving



Vehicle Platooning



Information Provisioning Strategically send out information



#### What information is shared?

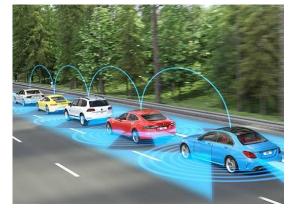
How is information used?

Network Coordination [Jackson & Watts '02] Collaborative Control [Fong et. al. '03] Coalition Formation [Ray & Vohra '15]

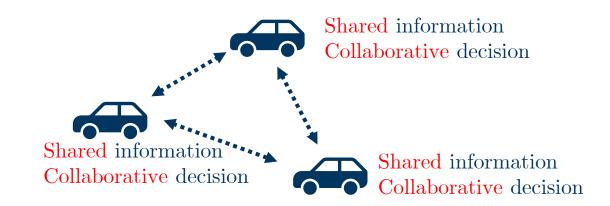
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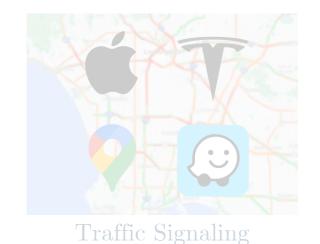
E.g., Autonomous Driving



Vehicle Platooning



Information Provisioning Strategically send out information



What information is shared?

How is information used?

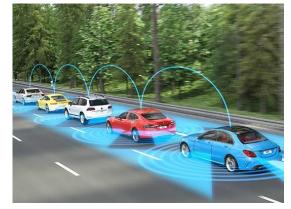
Network Coordination [Jackson & Watts '02] Collaborative Control [Fong et. al. '03] Coalition Formation [Ray & Vohra '15]

Focus on convergence to equilibrium behavior

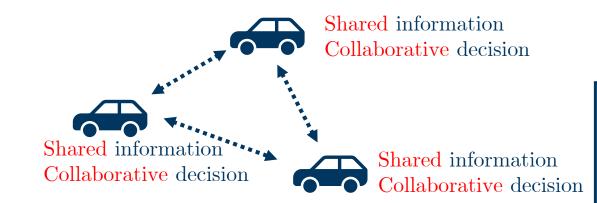
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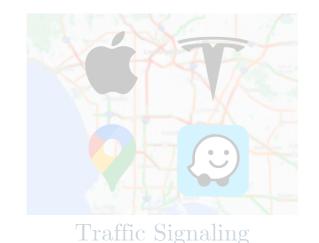
E.g., Autonomous Driving



Vehicle Platooning



Information Provisioning Strategically send out information



What information is shared?

How is information used?

#### My work:

Quantify the benefit of collaborative information sharing to system performance

Information Sharing Collaboratively exchange information



Vehicle Platooning

### Information Provisioning

Strategically send out information



Traffic Signaling





Information Sharing Collaboratively exchange information



Vehicle Platooning

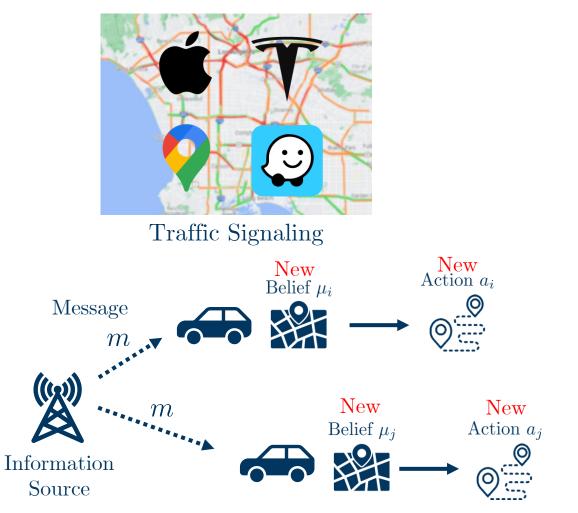
Social Systems:

- Matching Markets [Ostrovsky et. al. '10]
- Social Media [Romero et. al. '11]
- Elections [Alonso et. al. '16]

Bayesian Persuasion: (more general framework)

- Public [Kamenica & Gentzkow '11]
- Private [Arieli & Babichenko '19]

### Information Provisioning



Information Sharing Collaboratively exchange information



Vehicle Platooning

Social Systems:

- Matching Markets [Ostrovsky et. al. '10]
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Bayesian Persuasion: (more general framework)

- Public [Kamenica & Gentzkow '11]
- Private [Arieli & Babichenko '19]

Identify scenarios where revealing info helps / hurts

### Information Provisioning



Information Sharing Collaboratively exchange information



Vehicle Platooning

#### My work:

Quantify how information provisioning affects *algorithmic guarantees* of distributed systems

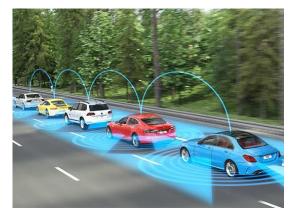
### Information Provisioning



### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



Vehicle Platooning

### Information Provisioning

Strategically send out information

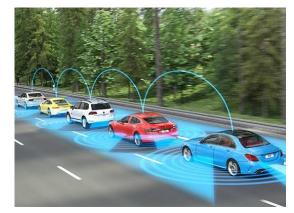


Traffic Signaling

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



Vehicle Platooning

### Information Provisioning

Strategically send out information



Traffic Signaling

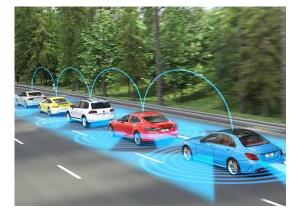


Cloud computing

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



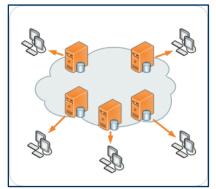
Vehicle Platooning

### Information Provisioning

Strategically send out information



Traffic Signaling



Cloud computing

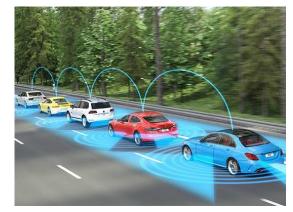


Supply-chain

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



Vehicle Platooning

### Information Provisioning

Strategically send out information



Traffic Signaling



Cloud computing





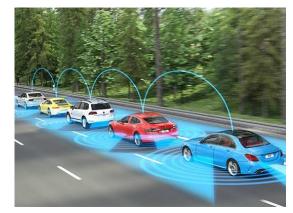


Power Grids

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



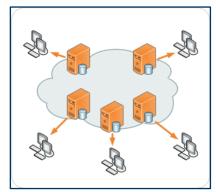
Vehicle Platooning

### Information Provisioning

Strategically send out information



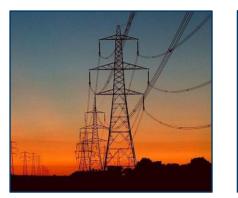
Traffic Signaling



Cloud computing



Supply-chain



Power Grids

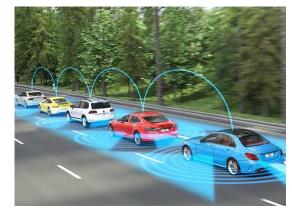


Fleet Robotics

### Information Sharing

Collaboratively exchange information

E.g., Autonomous Driving



Vehicle Platooning

### Information Provisioning

Strategically send out information



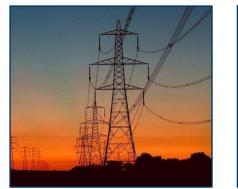
#### Traffic Signaling



Cloud computing



Supply-chain



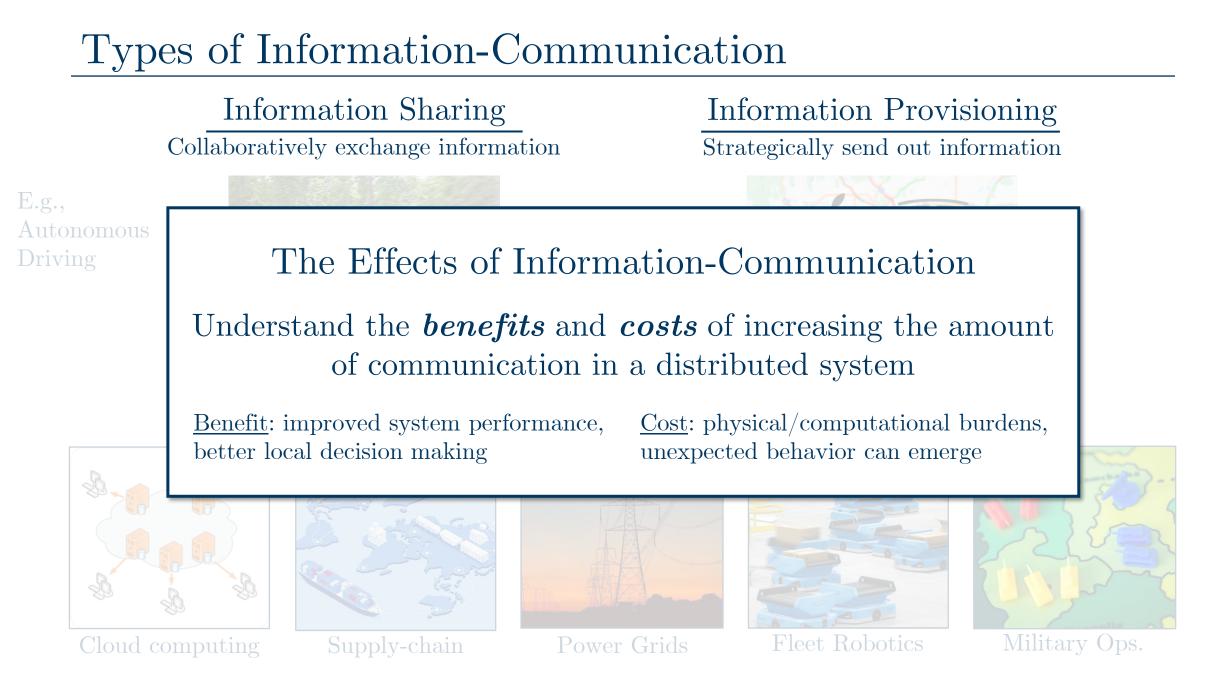
Power Grids



Fleet Robotics



Military Ops.



## Unreliable Communicators

Unreliable Information Sharing Collaboratively exchange information

E.g., Autonomous Driving



### Unreliable Information Provisioning

Strategically send out information



Simon Weckert

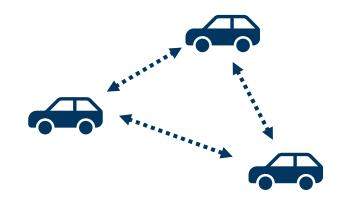
My work:

What are the effects of *unreliable communicators* and what can we do to mitigate them?

### Outline

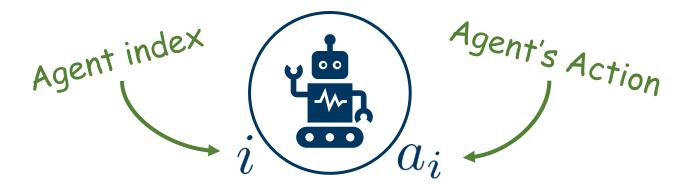
- I. Information Sharing
- II. Information Provisioning
- III. Unreliable Communicators
- IV. Conclusion and Directions

# I. Information Sharing



Communication Design in Engineered System

### Engineered Agent



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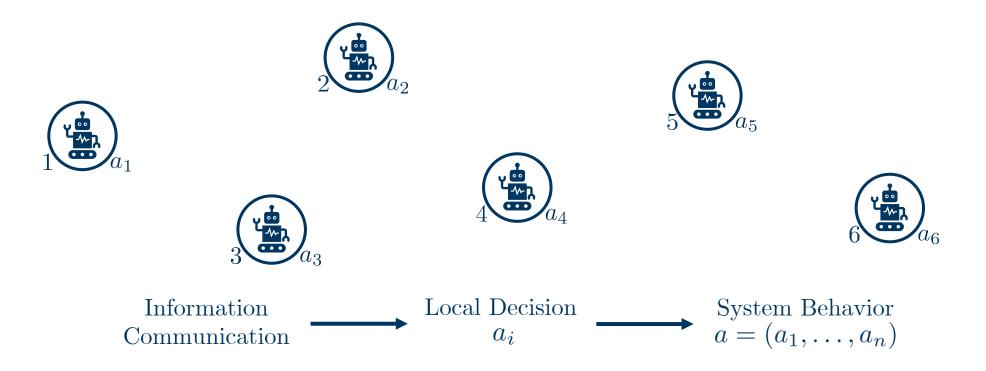


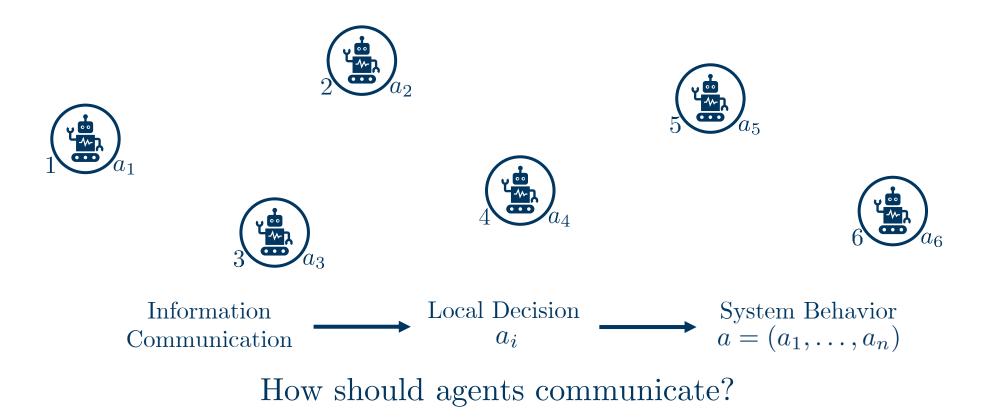


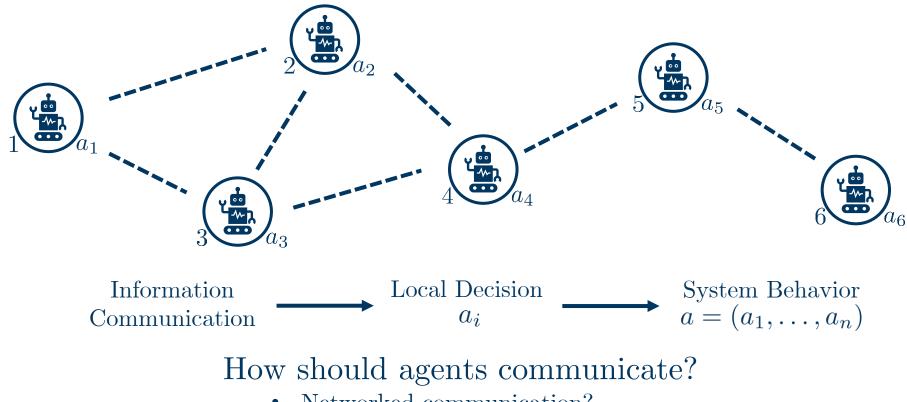




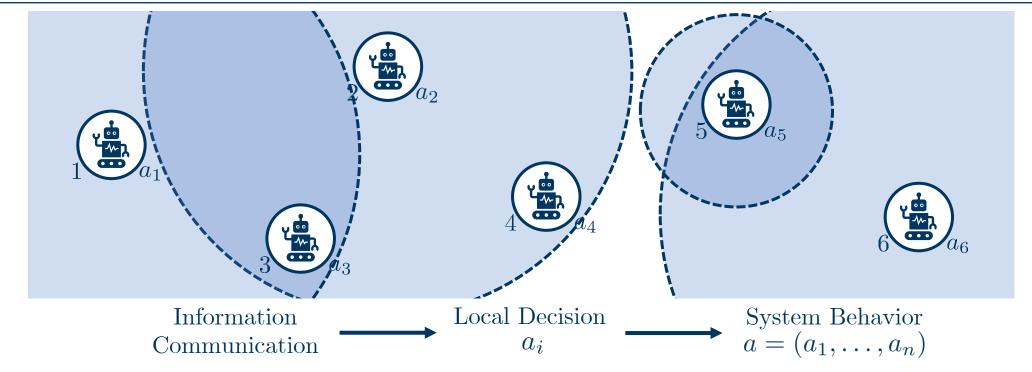






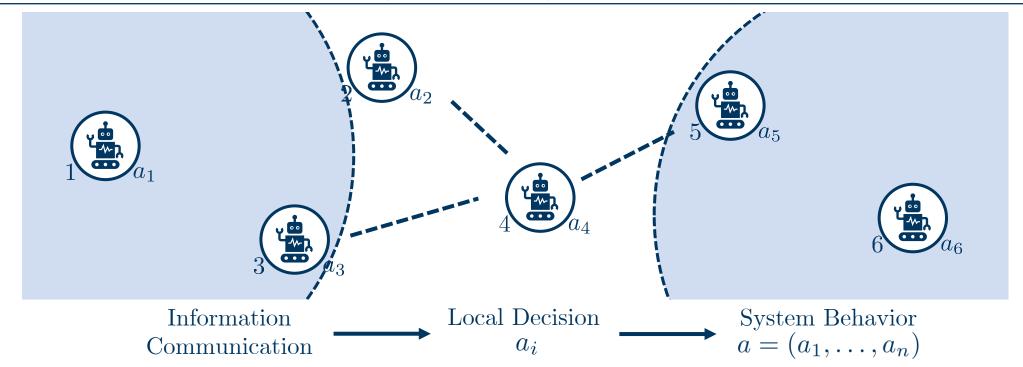


Networked communication? 



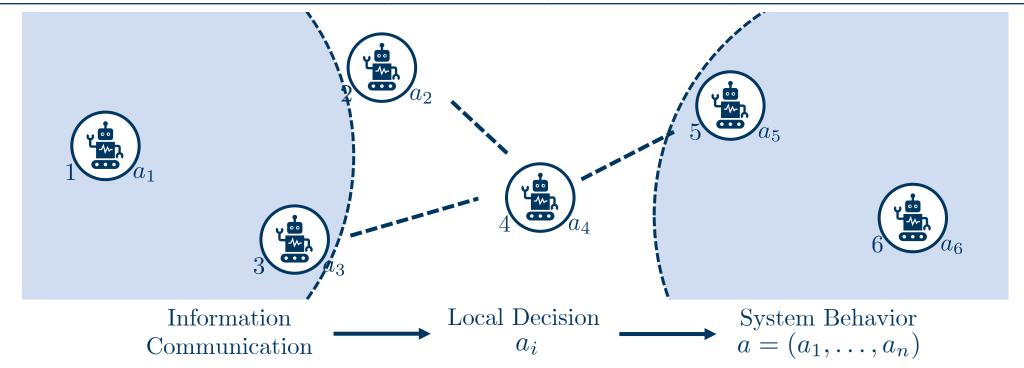
How should agents communicate?

- Networked communication?
- Spatially Local communication?



How should agents communicate?

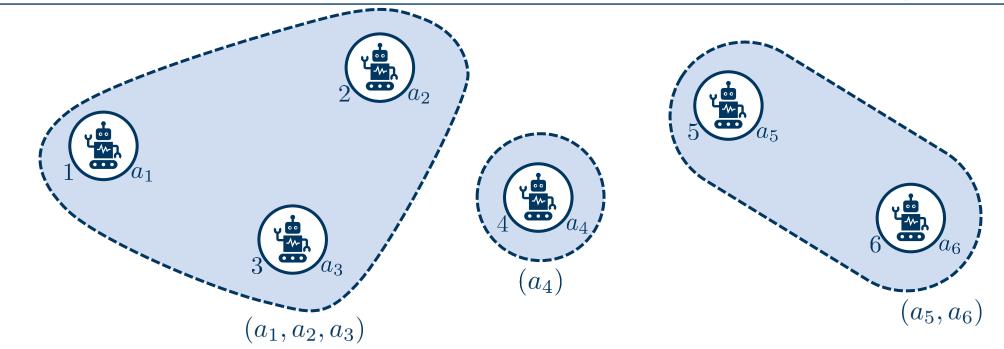
- Networked communication?
- Spatially Local communication?
- Pairwise communication?
- Etc.



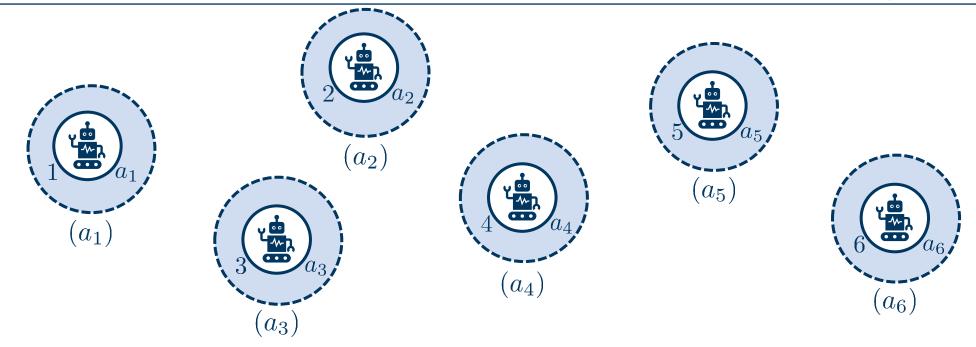
How should agents communicate?

- Networked communication?
- Spatially Local communication?
- Pairwise communication?
- Etc.

### How does communication affect decision-making?

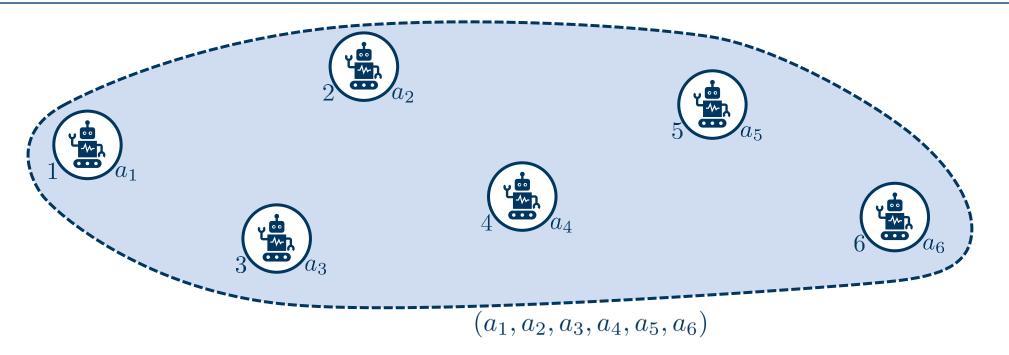


<u>Collaborative Multi-Agent System</u>: Defined groups of agents can communicate and collaborate in making their decision.



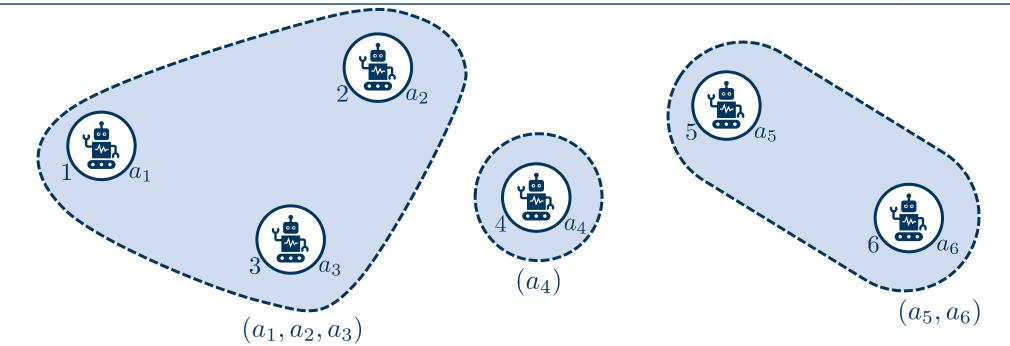
<u>Collaborative Multi-Agent System</u>: Defined groups of agents can communicate and collaborate in making their decision.

Distributed Decision-making (Bad performance / low complexity)



### <u>Collaborative Multi-Agent System</u>: Defined groups of agents can communicate and collaborate in making their decision.

Distributed Decision-making (Bad performance / low complexity) Centralized Decision-making (Best performance / high complexity)



<u>Collaborative Multi-Agent System</u>: Defined groups of agents can communicate and collaborate in making their decision.

Distributed Decision-making (Bad performance / low complexity)

Partially Collaborative

Decision-making

Study the *benefits* and *costs* of collaborative multi-agent systems

Centralized Decision-making

(Best performance / high complexity)

Distributed Decision-Making in Engineered Systems

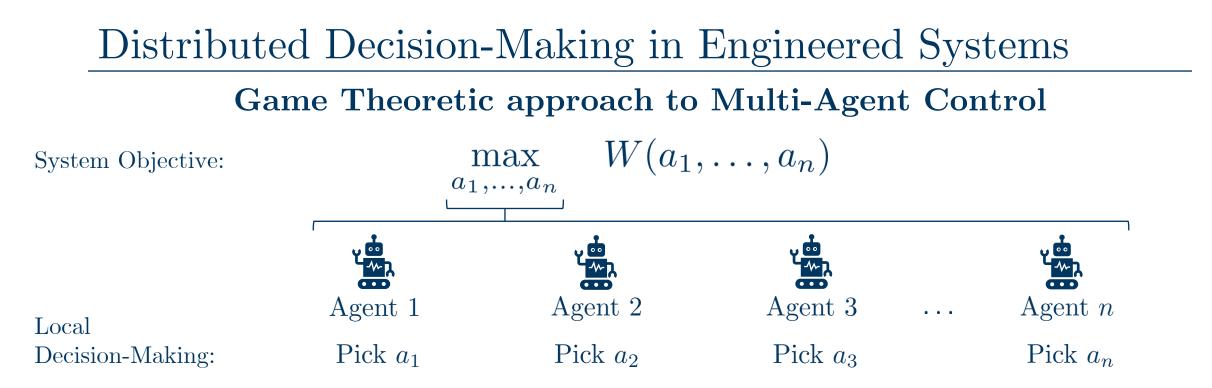
Game Theoretic approach to Multi-Agent Control

## Distributed Decision-Making in Engineered Systems

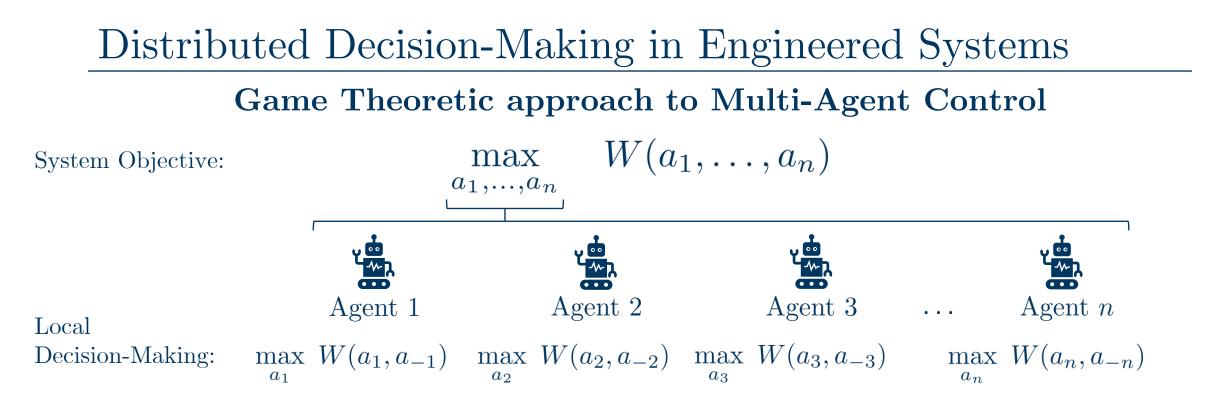
### Game Theoretic approach to Multi-Agent Control

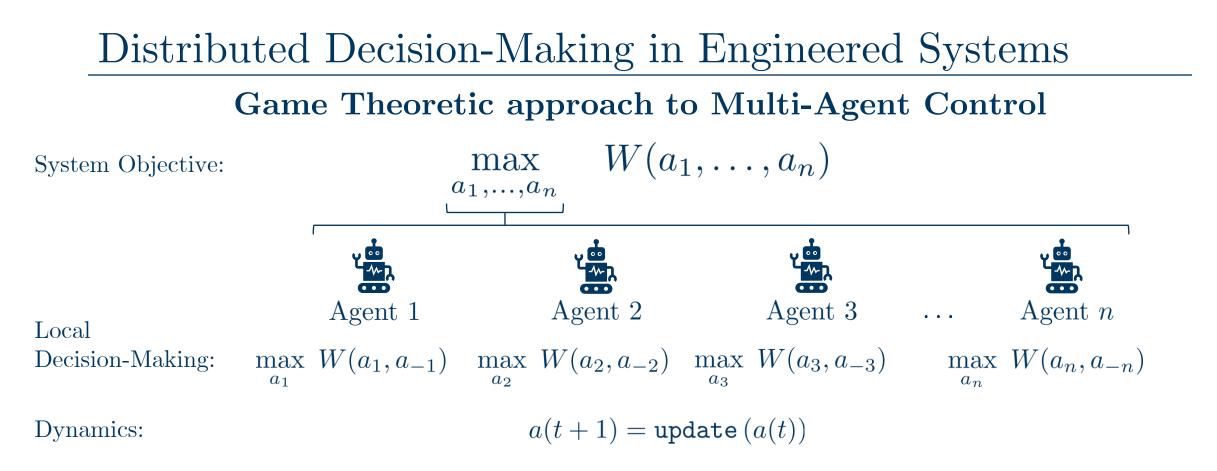
System Objective:

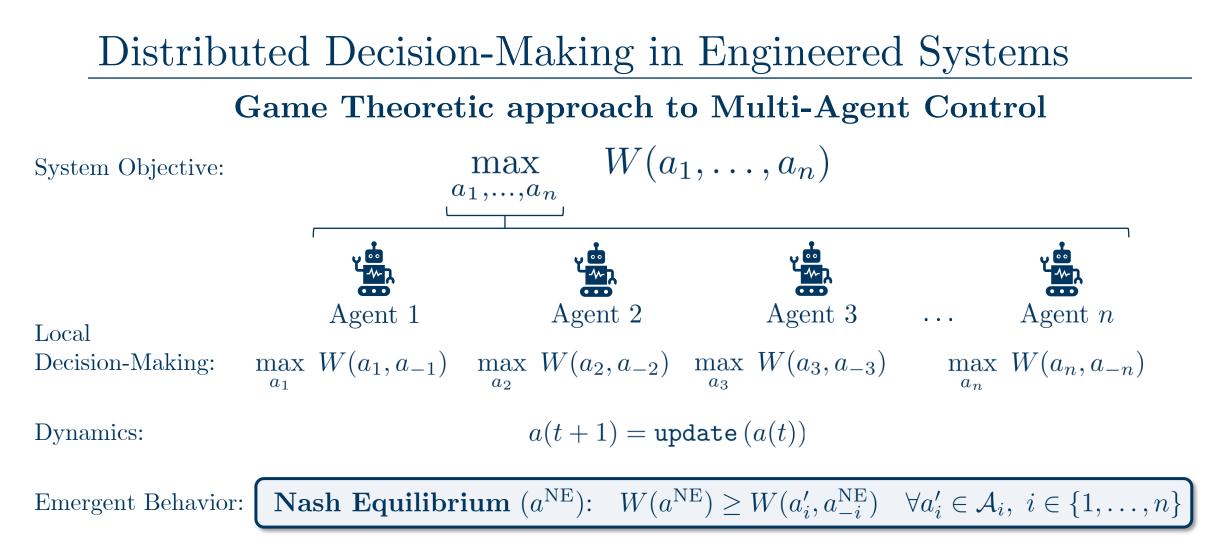
 $\max_{a_1,\ldots,a_n} \quad W(a_1,\ldots,a_n)$ 

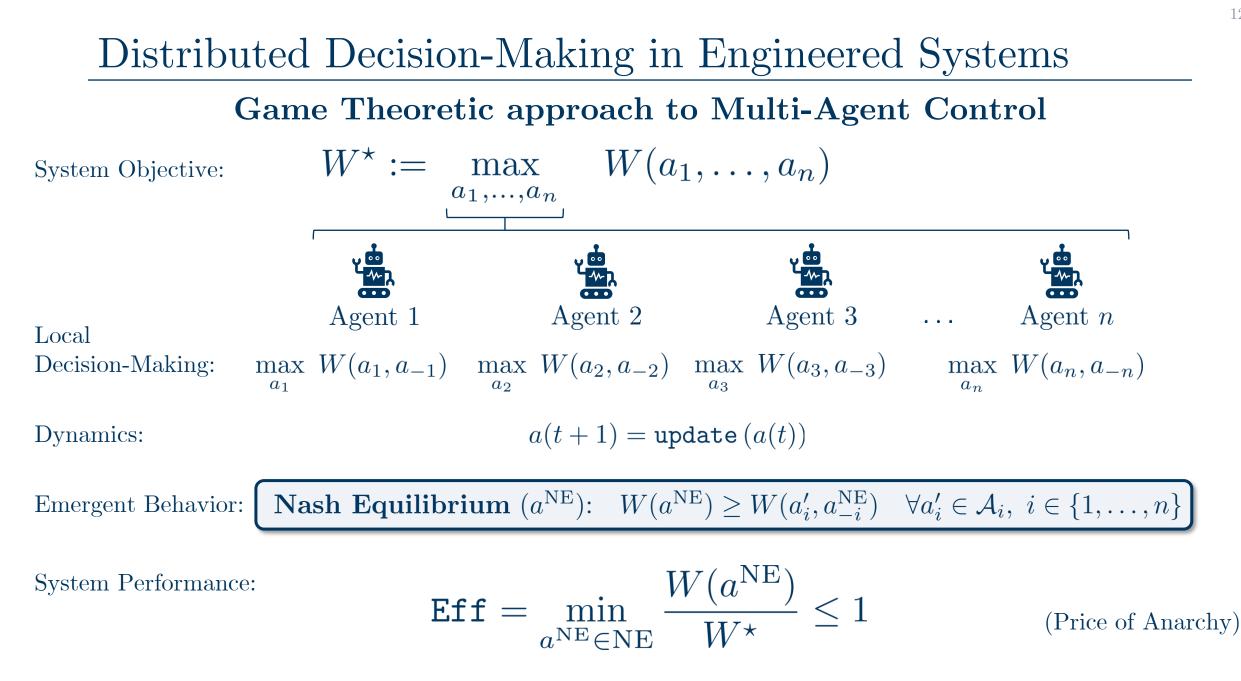


#### 









# Focus of Existing Research

### Dynamics Reaching Nash Equilibria

#### Convergence Rate

- Uncoupled dynamics do not lead to Nash equilibrium. American Economic Review. Hart S, Mas-Colell A. 2003
- The complexity of computing a Nash equilibrium. SIAM Journal on Computing, Daskalakis C, Goldberg PW, Papadimitriou CH. 2009.

#### Asynchrony

- Nash equilibrium seeking in noncooperative games. IEEE Transactions on Automatic Control. Frihauf P, Krstic M, Basar T. 2011.
- Learning efficient Nash equilibria in distributed systems. Games and Economic behavior. Pradelski BS, Young HP. 2012.

#### Noise and Perturbations

- Learning with Bandit Feedback in Potential Games. Advances in Neural Information Processing Systems. Heliou A, Cohen J, Mertikopoulos P. 2017.
- Learning in Games: Robustness of Fast Convergence. Advances in Neural Information Processing Systems. Foster D, Li Z, Lykouris T, Sridharan K, Tardos E. 2016.

### Performance Efficiency of Nash Equilibria

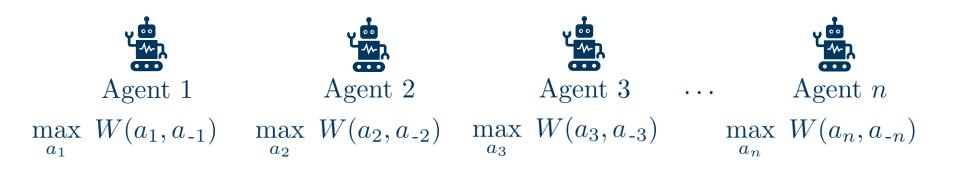
#### Quantify the Price of Anarchy

- *Worst-case equilibria.* Computer science review. Koutsoupias E, Papadimitriou C. 2009.
- Nash equilibria in competitive societies, with applications to facility location, traffic routing and auctions. Symposium on Foundations of CS. Vetta A. 2002
- The price of anarchy of finite congestion games. In Proceedings of the thirtyseventh annual ACM symposium on Theory of computing. Christodoulou G, Koutsoupias E. 2005.
- Intrinsic robustness of the price of anarchy. Journal of the ACM (JACM). Roughgarden T. 2015.

#### Optimize the Price of Anarchy

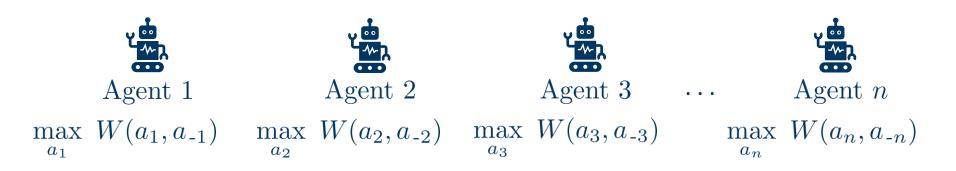
- Covering games: Approximation through non-cooperation. In International Workshop on Internet and Network Economics. Gairing M. 2009.
- A unifying tool for bounding the quality of non-cooperative solutions in weighted congestion games. Theory of Computing Systems. Bilò V. 2018.
- Utility design for distributed resource allocation—part I: Characterizing and optimizing the exact price of anarchy. IEEE Transactions on Automatic Control. Paccagnan D, Chandan R, Marden JR. 2019.

Challenge existing *informational* and *communication* assumptions of Nash equilibria and associated efficiency guarantees

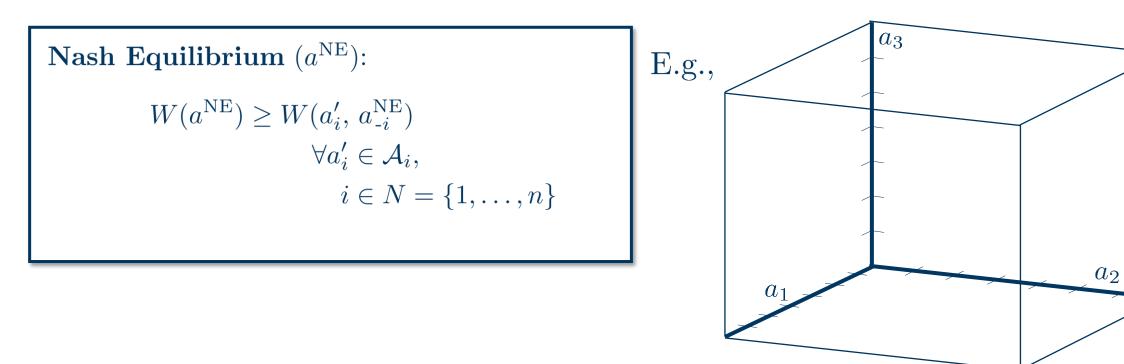


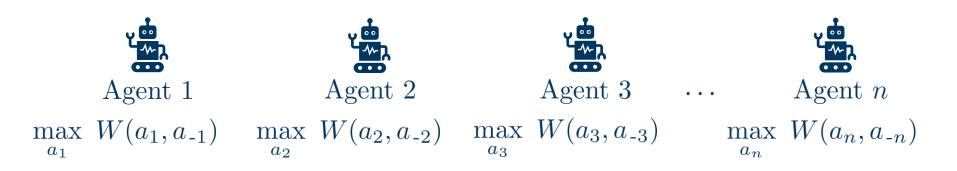
No communication: unilateral deviations

Nash Equilibrium  $(a^{NE})$ :  $W(a^{NE}) \ge W(a'_i, a^{NE}_{-i})$   $\forall a'_i \in \mathcal{A}_i,$  $i \in N = \{1, \dots, n\}$ 

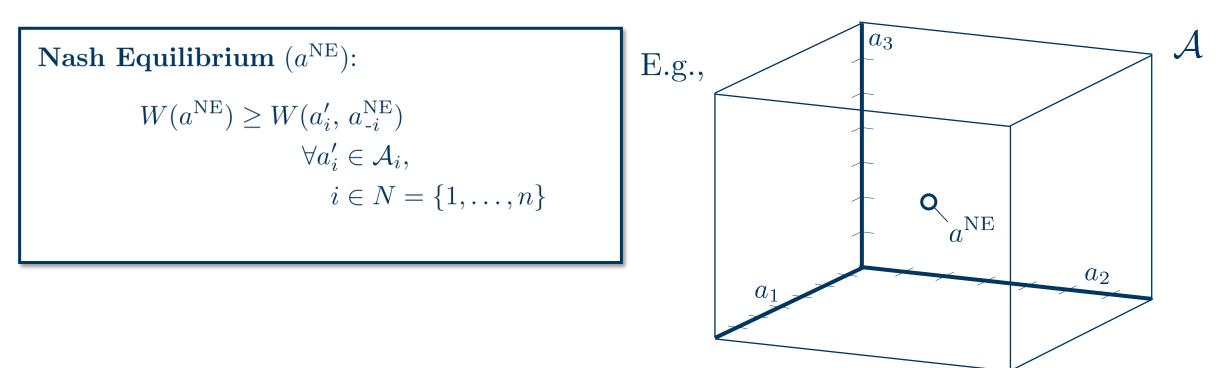


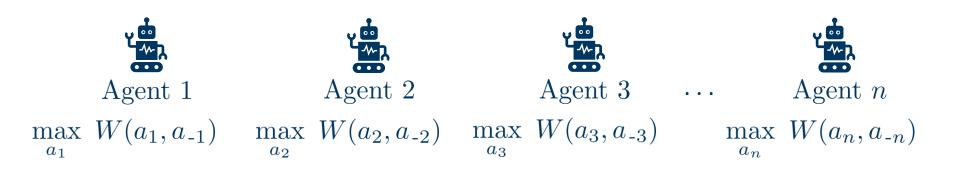
No communication: unilateral deviations



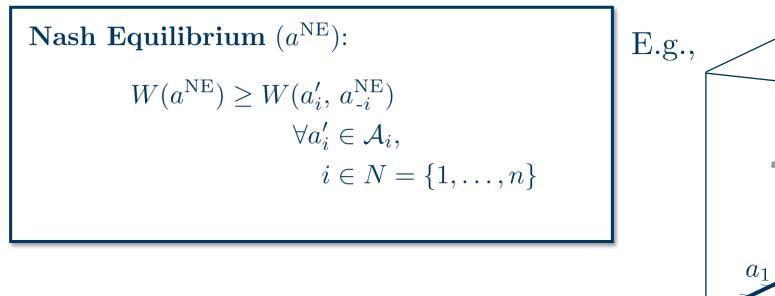


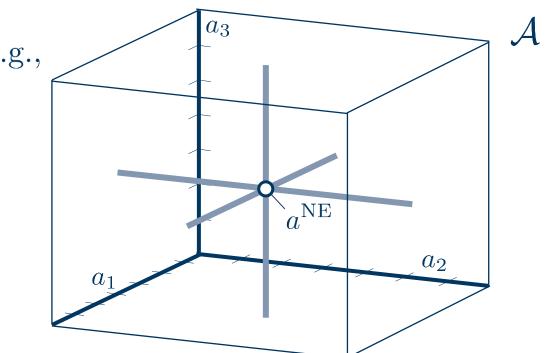
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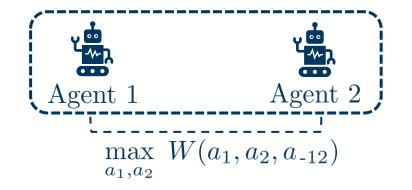




No communication: unilateral deviations



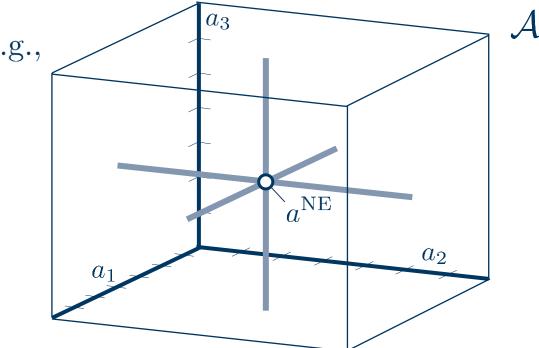


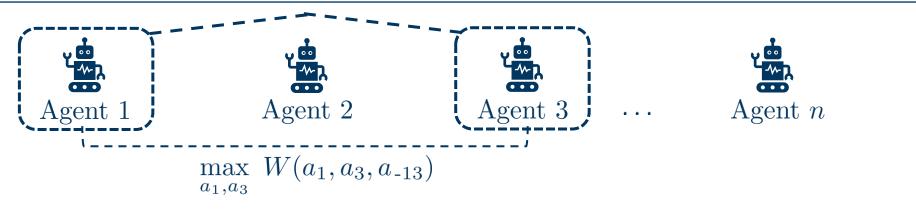


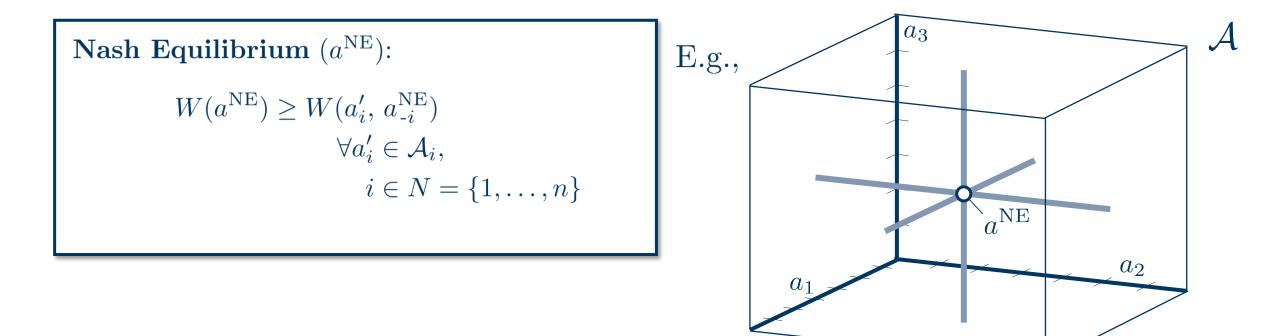


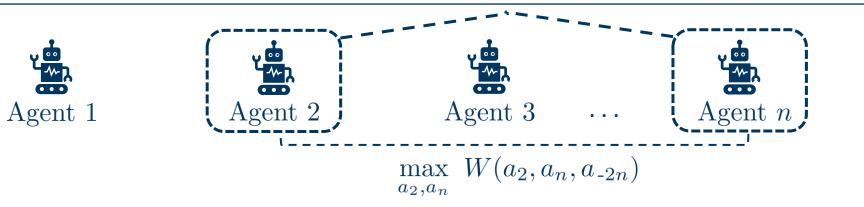


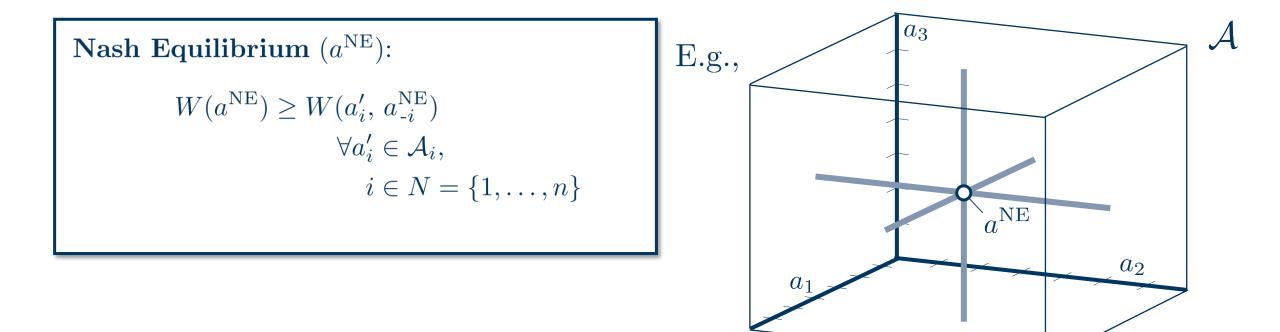
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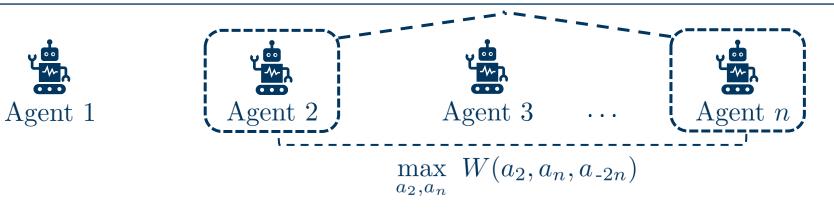




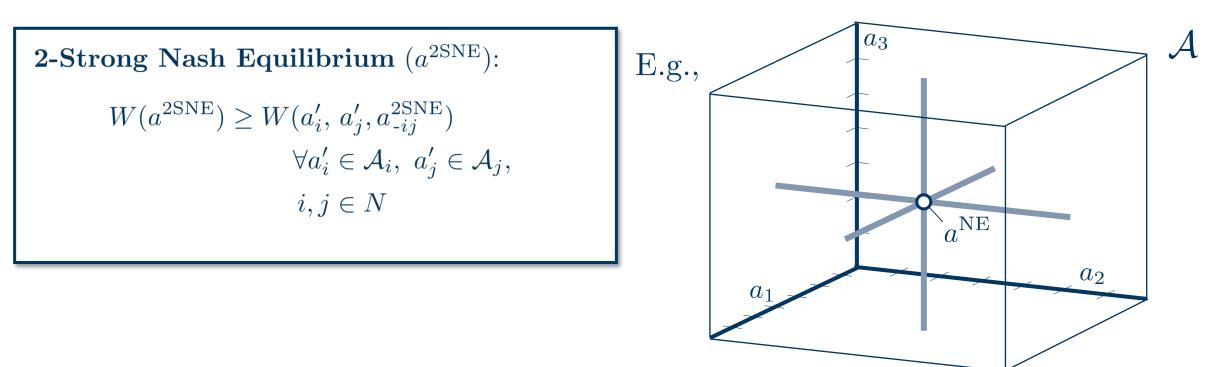


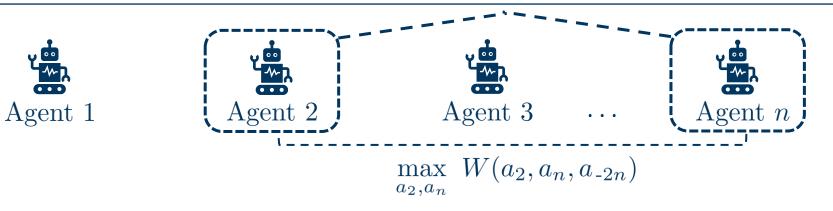




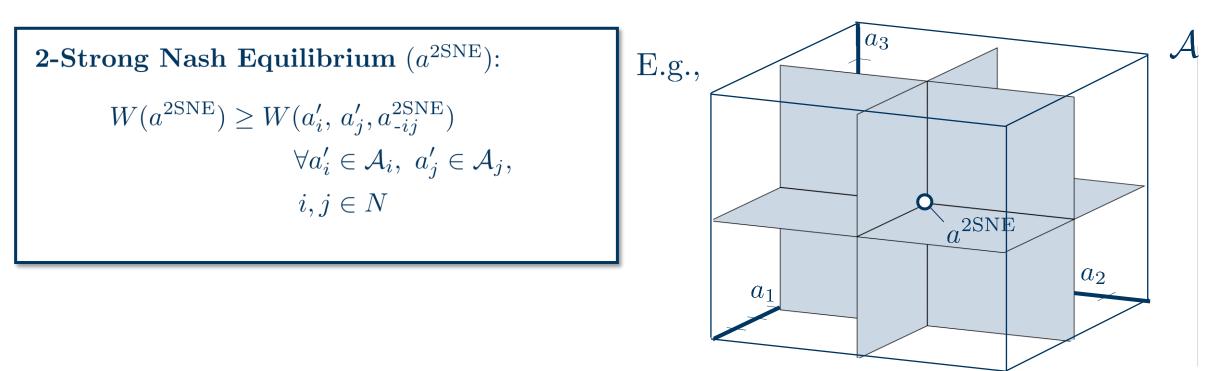


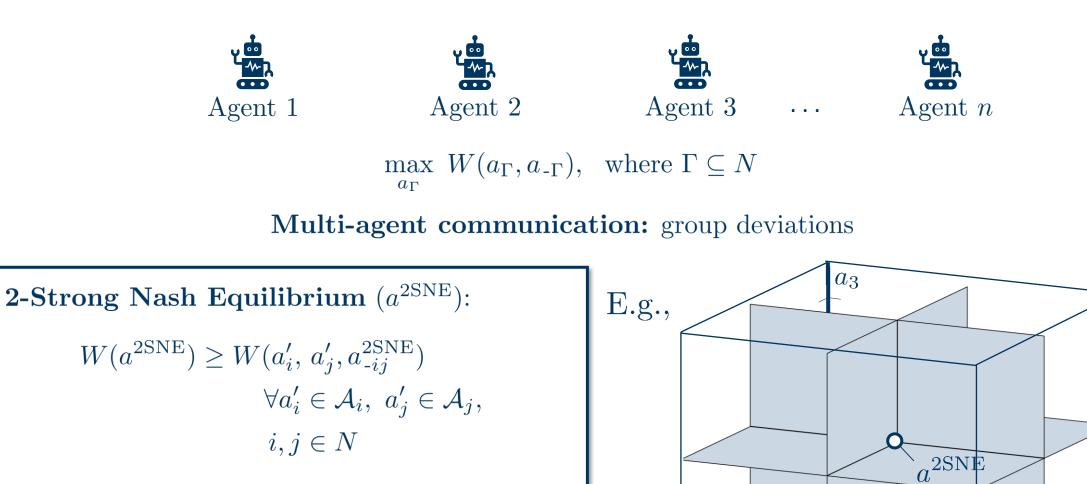
Pair-wise communication: bilateral deviations





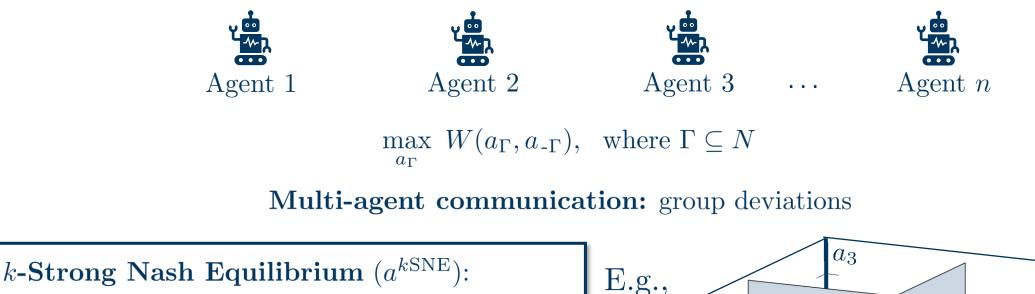
Pair-wise communication: bilateral deviations





 $a_1$ 

 $a_2$ 



$$W(a^{k\text{SNE}}) \ge W(a'_{\Gamma}, a^{k\text{SNE}}_{-\Gamma})$$
  

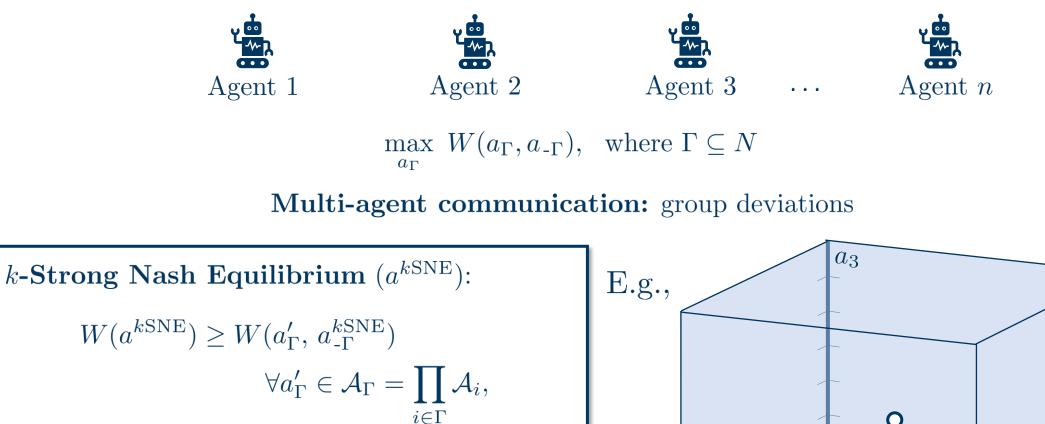
$$\forall a'_{\Gamma} \in \mathcal{A}_{\Gamma} = \prod_{i \in \Gamma} \mathcal{A}_{i},$$
  

$$\Gamma \in \{Z \subseteq N : |Z| \le k\}$$
  
E.g.,  

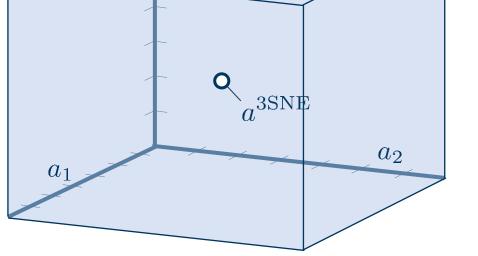
$$E.g.,$$
  

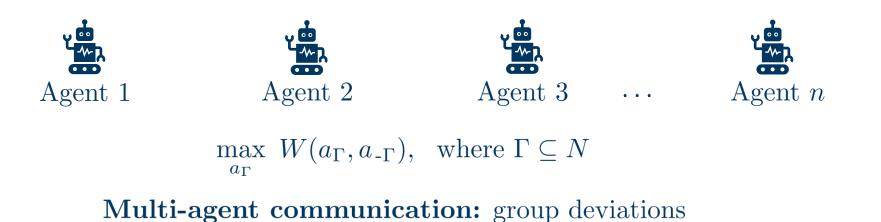
$$a_{2\text{SNE}}$$
  

$$a_{1}$$



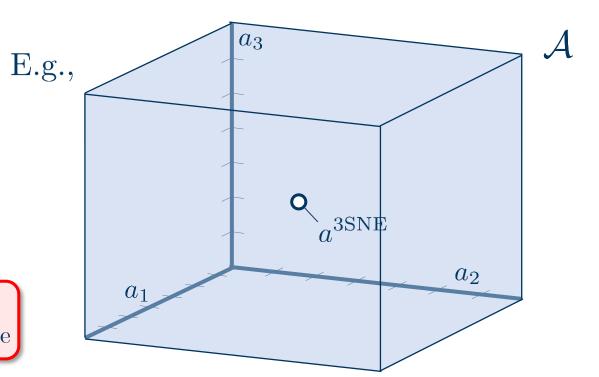
$$\Gamma \in \{Z \subseteq N : |Z| \le k\}$$





 $k\text{-Strong Nash Equilibrium } (a^{k\text{SNE}}):$  $W(a^{k\text{SNE}}) \ge W(a'_{\Gamma}, a^{k\text{SNE}}_{-\Gamma})$  $\forall a'_{\Gamma} \in \mathcal{A}_{\Gamma} = \prod_{i \in \Gamma} \mathcal{A}_{i},$  $\Gamma \in \{Z \subseteq N : |Z| \le k\}$ 

Use communication to *improve efficiency* and bridge gap between *centralized* and *decentralized* performance



## k – Strong Nash Equilibria

In General:

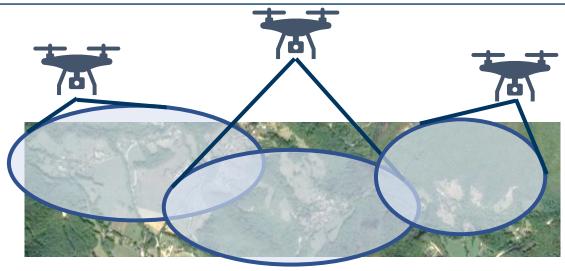
- Typically discussed in cooperative/cost-sharing games
- Need not exist (in general games)
- No guarantee of efficiency improvement (when such an equilibrium exists)

### In Our Work:

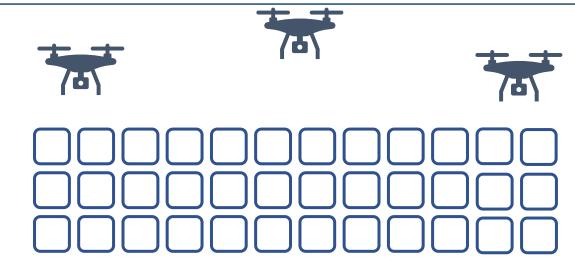
- Group of players collaborate to improve global (common interest) objective
- Existence guaranteed
- Optimal solution is a k-SNE
- Finite convergence time

Focus: 1. How does *efficiency* improve with communication (k)?
2. What additional *complexity* is incurred?

### Resource Allocation Problems



### Resource Allocation Problems



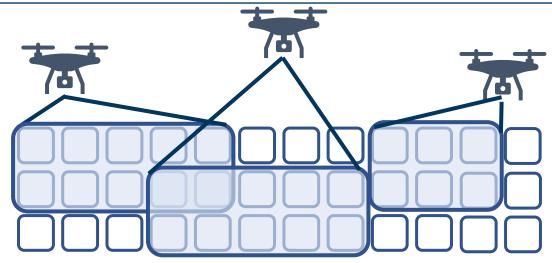
Resources:

Agents:

 $i \in N = \{1, \dots, n\}$ 

 $r \in \mathcal{R} = \{1, \dots, R\}$ 

## Resource Allocation Problems

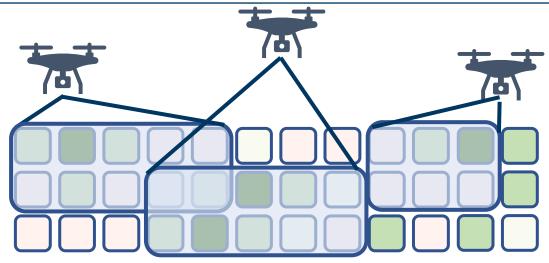


Resources:

Agents:

 $r \in \mathcal{R} = \{1, \dots, R\}$  $i \in N = \{1, \dots, n\}$ 

Actions:  $a_i \subset \mathcal{R}, \quad \mathcal{A}_i \subseteq 2^{\mathcal{R}}$ 



Resources:

 $r \in \mathcal{R} = \{1, \dots, R\}$ 

 $i \in N = \{1, \ldots, n\}$ 

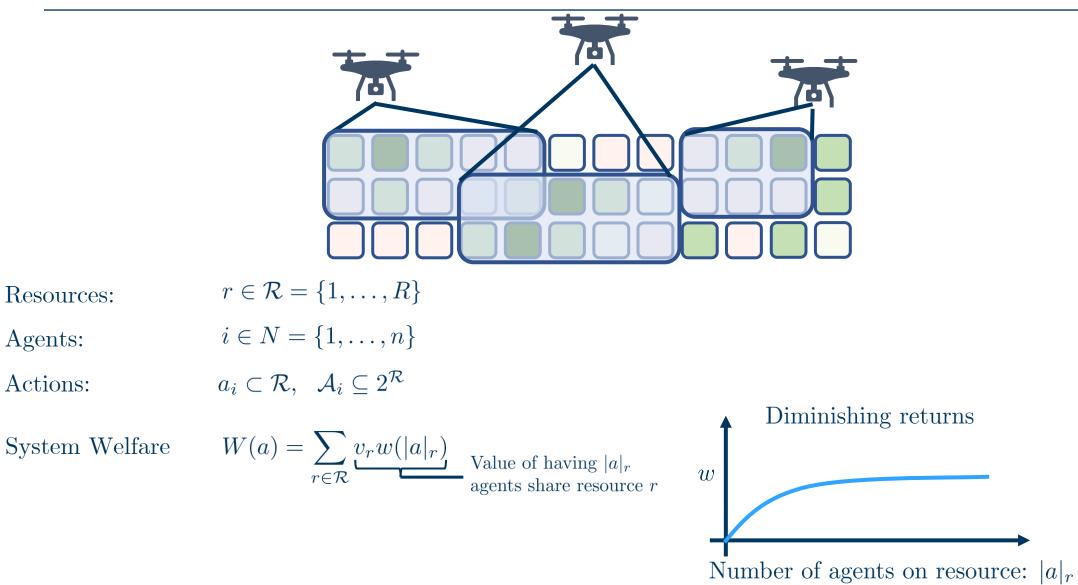
Agents:

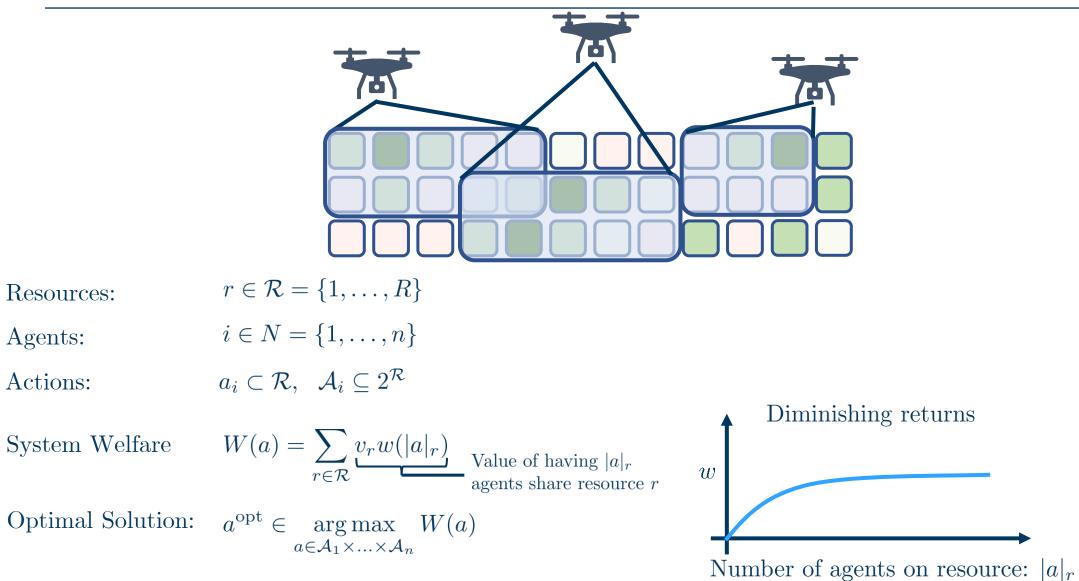
Actions:

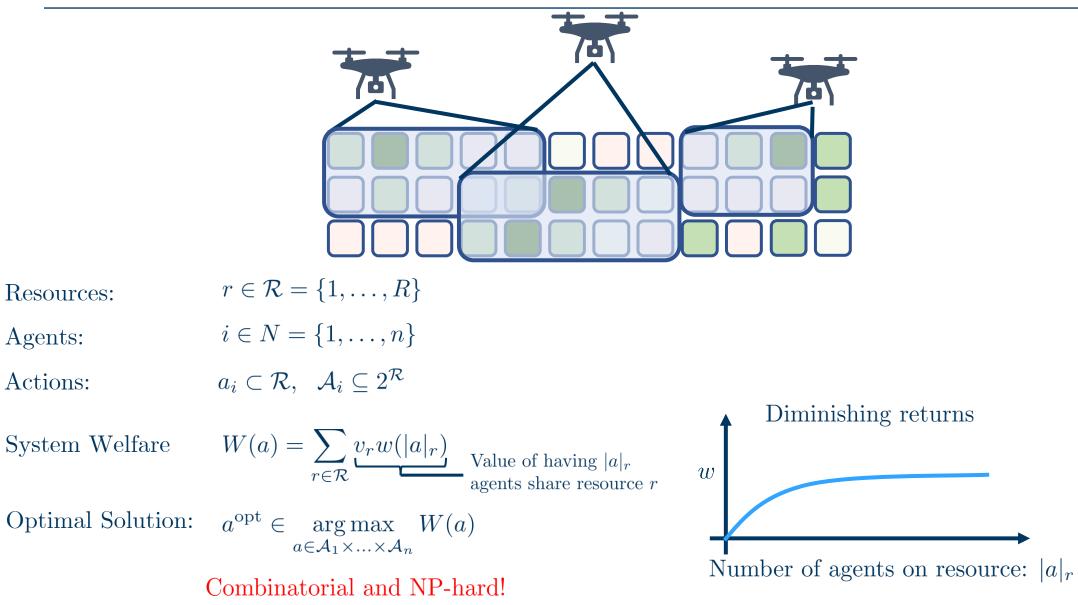
 $a_i \subset \mathcal{R}, \quad \mathcal{A}_i \subseteq 2^{\mathcal{R}}$ 

System Welfare

$$W(a) = \sum_{r \in \mathcal{R}} v_r w(|a|_r)$$



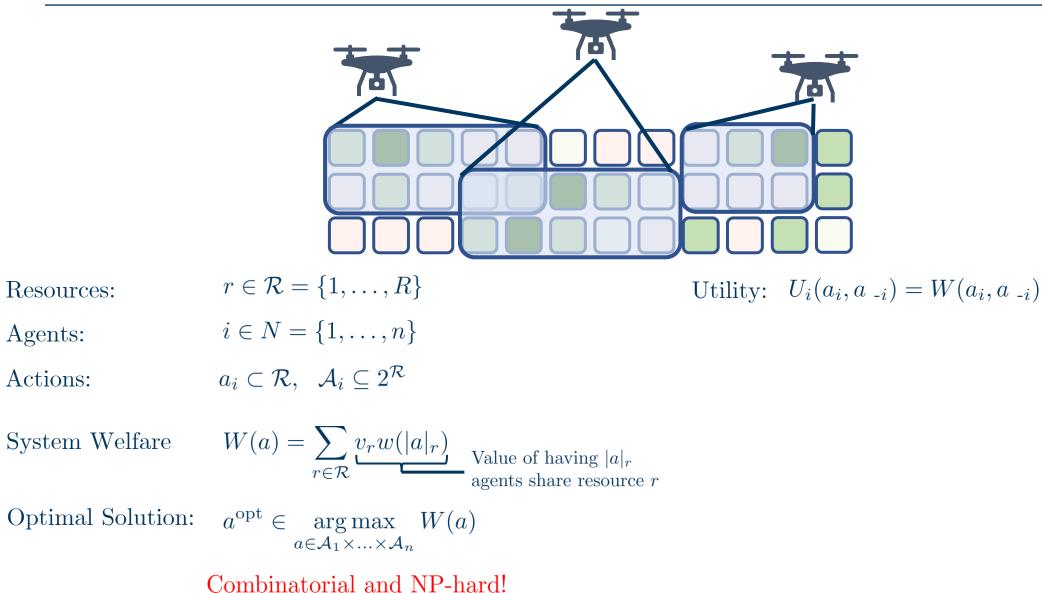


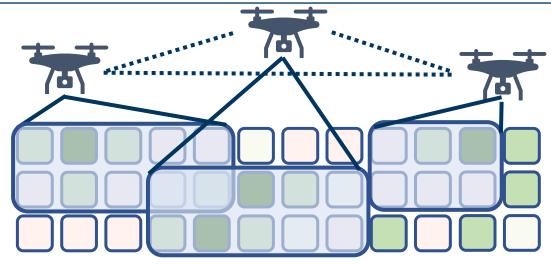


Resources:

Agents:

Actions:





 $|a|_r$ 

Resources:

Agents:

Actions:

 $i \in N = \{1, \dots, n\}$  $a_i \subset \mathcal{R}, \quad \mathcal{A}_i \subset 2^{\mathcal{R}}$ 

 $r \in \mathcal{R} = \{1, \dots, R\}$ 

System Welfare

$$W(a) = \sum_{r \in \mathcal{R}} \underbrace{v_r w(|a|_r)}_{\text{Maine of having } |a|_r}$$
 Value of having  $|a|_r$  agents share resource  $r$ 

Optimal Solution:

$$a^{\text{opt}} \in \underset{a \in \mathcal{A}_1 \times \ldots \times \mathcal{A}_n}{\operatorname{arg\,max}} W(a)$$

Combinatorial and NP-hard!

Utility:  $U_{\Gamma}(a_{\Gamma}, a_{-\Gamma}) = W(a_{\Gamma}, a_{-\Gamma}), \ \Gamma \subseteq N$ 

Emergent System Behavior:

k-Strong Nash Equilibrium

Efficiency:

$$\mathtt{Eff}(k) = \min_{a^{k \text{SNE}} \in k \text{SNE}} \frac{W(a^{k \text{SNE}})}{W(a^{\text{opt}})}$$

Efficiency as a function of the level of communication between agents

How much does inter-agent communication *improve efficiency*?

Theorem 1.1: [BLF, Paccagnan, Pradeslki, Marden CDC23\*] For a resource allocation problem  $(\mathcal{R}, N, \mathcal{A}, \{v_r\}_{r \in \mathcal{R}}, w)$ , a kSNE approximates the optimal solution with

 $\mathsf{Eff}(k) \ge P^{\star}(n, w, k),$ 

where  $P^{\star}(n, w, k)$  is the solution to a linear program with k+1 decision variables and  $\mathcal{O}(kn^3)$  constraints. Further, this bound is tight.

$$P^{\star}(n, w, k) = \max_{\theta \in \mathbb{R}_{\geq 0}^{|\mathcal{I}|}} \sum_{e, x, o} w(o+x)\theta(e, x, o)$$
s.t. 
$$\sum_{e, x, o} \left( \frac{n!}{(n-\zeta)!} w(e+x) - \sum_{\substack{0 \leq \alpha \leq \zeta \\ 0 \leq \beta \leq \alpha}} \binom{\zeta}{\alpha} \binom{\zeta - \alpha}{\beta} e^{\underline{\alpha}} o^{\underline{\beta}}(n-e-o)^{\underline{\zeta}-\underline{\alpha}-\underline{\beta}} w(e+x+\beta-\alpha) \right) \theta(e, x, o) \geq 0$$

$$\forall \zeta \in \{1, \dots, k\}$$

$$\sum_{e, x, o} w(e+x)\theta(e, x, o) = 1$$

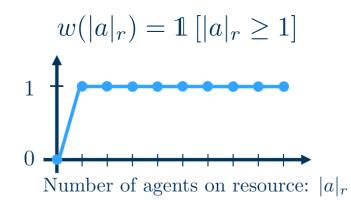
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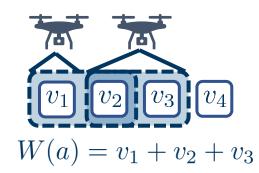
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$$\mathrm{Eff}(k) \ge P^{\star}(n, w, k)$$

Example: Covering Problems





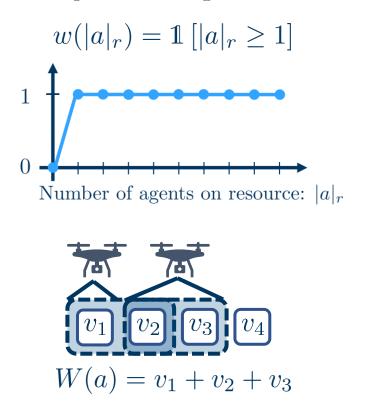
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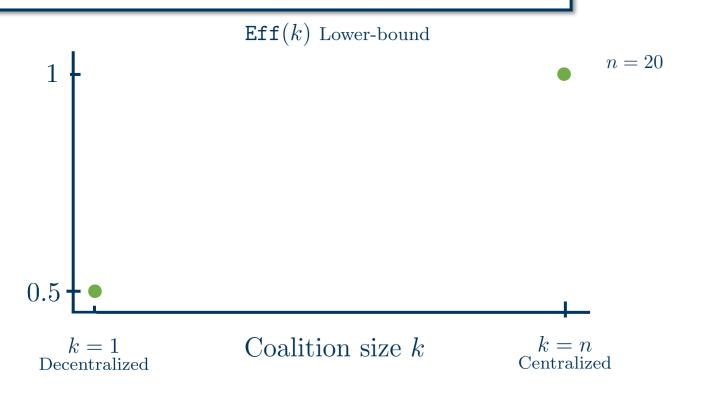
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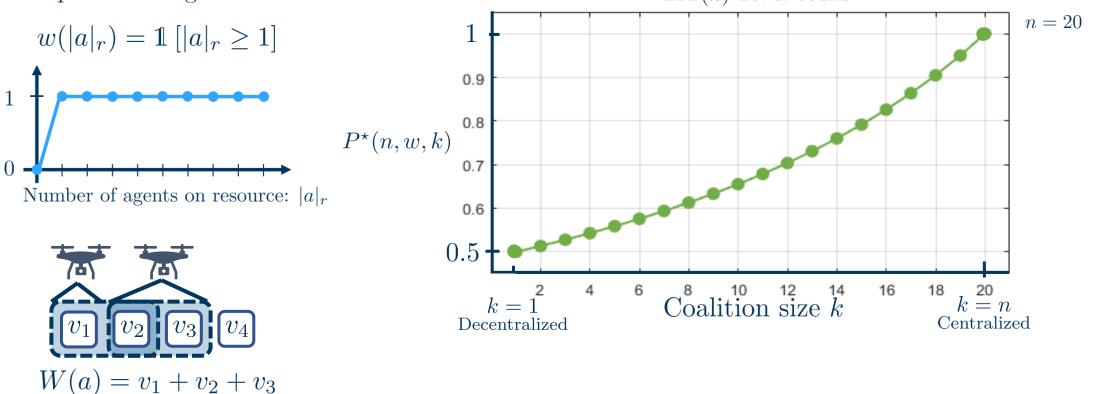
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Example: Covering Problems

Eff(k) Lower-bound



How much does inter-agent communication *improve efficiency*?

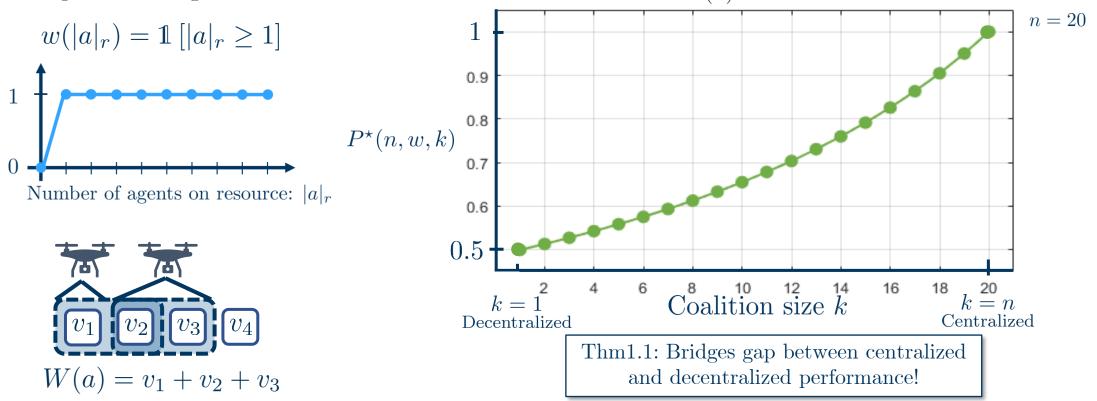
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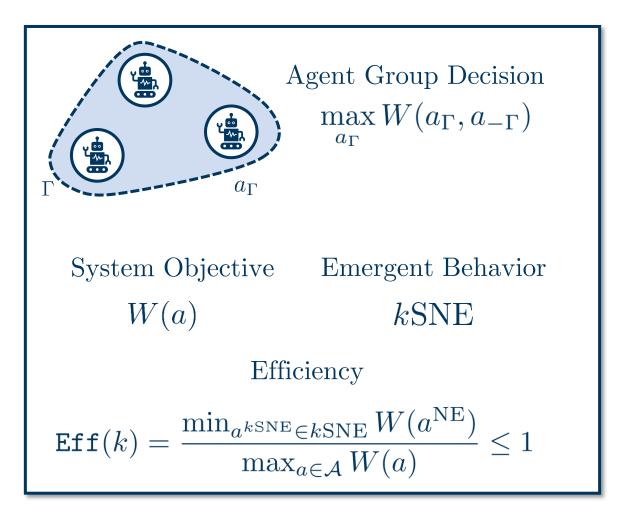
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Example: Covering Problems

Eff(k) Lower-bound

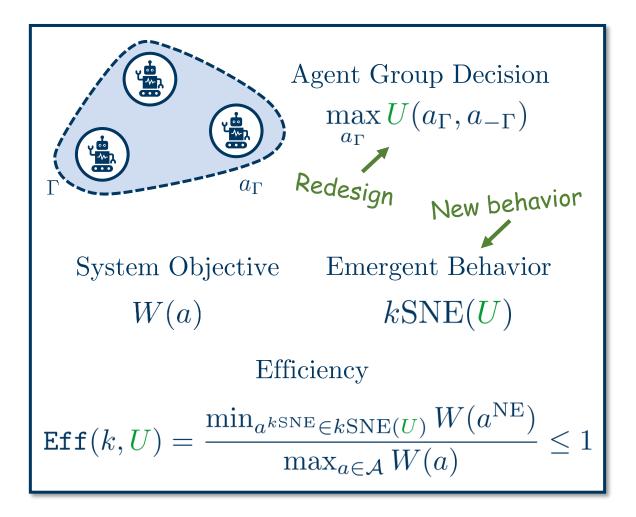


### Coalitional Utility Design



Design group objective to alter global behavior

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Design group objective to alter global behavior

# Coalitional Utility Design



#### How much does *designing utility* help?

$$\mathsf{Eff}(k, U) = \frac{\min_{a^k \in \mathcal{SNE}(U)} W(a^{NE})}{\max_{a \in \mathcal{A}} W(a)} \leq 1$$

Design group objective to alter global behavior

# Coalition Utility Design

Proposition 1.2: $[BLF, Paccagnan, Pradeslki, Marden CDC23^*]$ For a resource allocation problem  $(\mathcal{R}, N, \mathcal{A}, \{v_r\}_{r \in \mathcal{R}}, w)$ , under the optimalutility design, a kSNE approximates the optimal solution with

 $\mathrm{Eff}(k, U^{\star}) \ge Q^{\star}(n, w, k),$ 

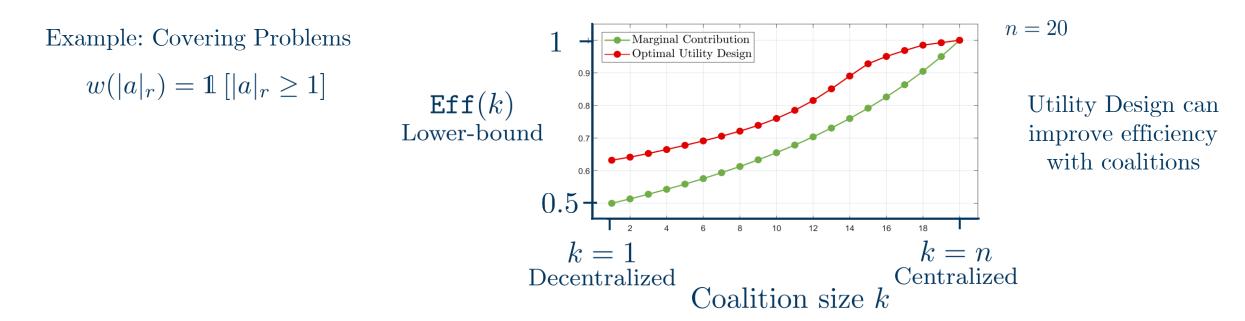
where  $Q^{\star}(n, w, k)$  is the solution to a linear program with nk + 1 decision variables and  $\mathcal{O}(kn^3)$  constraints.

# Coalition Utility Design

Proposition 1.2:[BLF, Paccagnan, Pradeslki, Marden CDC23\*]For a resource allocation problem  $(\mathcal{R}, N, \mathcal{A}, \{v_r\}_{r \in \mathcal{R}}, w)$ , under the optimalutility design, a kSNE approximates the optimal solution with

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# A Performance/Complexity Trade-off

Distributed Decision-making (Bad performance / low complexity)

Partially Collaborative Decision-making Centralized Decision-making (Best performance / high complexity)

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Distributed Decision-making (Bad performance / low complexity)

**Partially Collaborative** Decision-making Centralized Decision-making (Best performance / high complexity)

Increasing Communication
Improve Increase
Efficiency Complexity

# A Performance/Complexity Trade-off

Distributed Decision-making (Bad performance / low complexity)

**Partially Collaborative** Decision-making Centralized Decision-making (Best performance / high complexity)



We now have some understanding of performance, What happens to complexity? How does communication affect *convergence rate*?

n := number of players m := number of agent actions k := size of coalitions

Complexity of kSNE

How does communication affect *convergence rate*?

Nash Equilibrium

k-Strong Nash Equilibrium

Evaluating an equilibrium

 $\mathcal{O}(nm)$ 

 $\mathcal{O}\left(\frac{n!}{(n-k)!k!}m^k\right)$ 

n := number of players m := number of agent actions

k := size of coalitions

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How does communication affect *convergence rate*?

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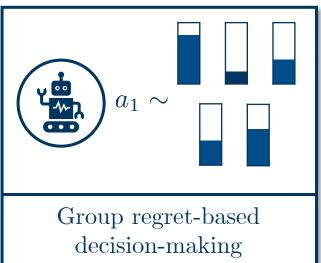
Complexity of kSNE How does communication affect *convergence rate*? k-Strong Nash Equilibrium Nash Equilibrium Evaluating an equilibrium  $\mathcal{O}\left(\frac{n!}{(n-k)!k!}m^k\right)$  $\mathcal{O}(nm)$ 7 As long or longer! Finding an equilibrium  $\mathcal{O}(m^n)$ 

> The relative value of faster convergence is context dependent! What techniques can we employ to *reduce complexity* with the *least sacrifice* to performance?

n := number of players m := number of agent actions k := size of coalitions

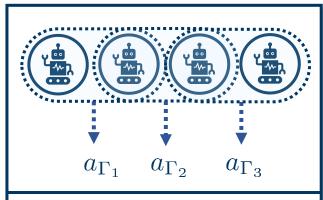
# Exploring the Trade-off

#### Non-Deterministic Algorithms



- Stochastic decision making to non-pure equilibrium concepts
- Coarse-correlated equilibria and smoothness

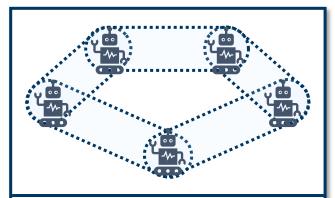
#### Non-Equilibrium Algorithms



- One-round walk & finite run time
- Each group revises their action finite times

 $\mathcal{O}\left(\frac{n!}{(n-k)!k!}m^k\right)$ 

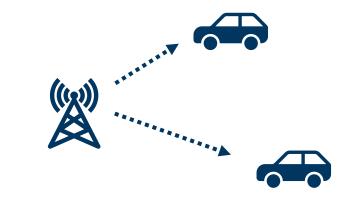
#### Weaker Communication Structures



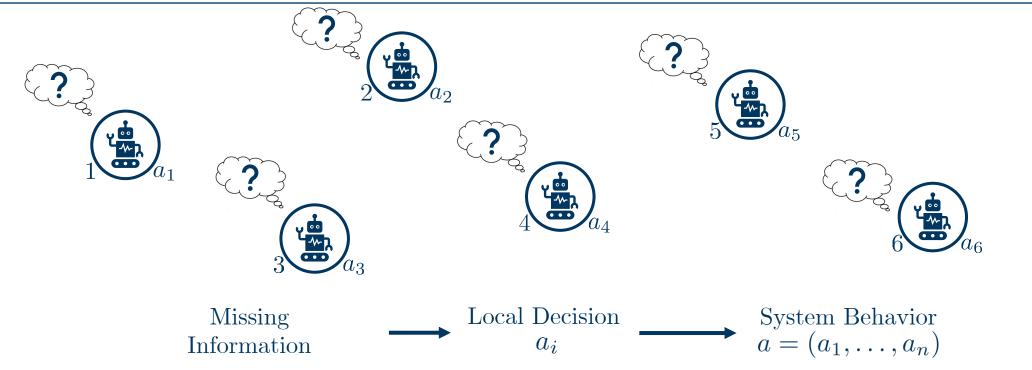
#### Not every subset communicates

- Lesser communication structure means worse performance guarantees
- Ideally, the reduction in complexity outweighs the loss in performance

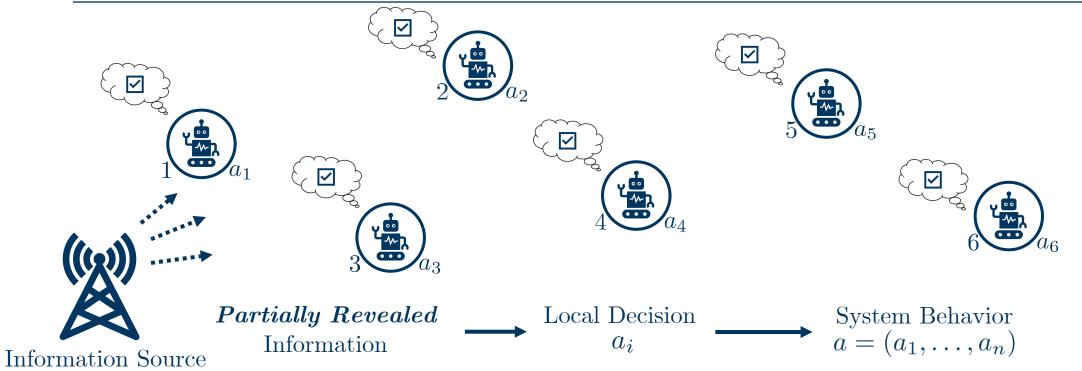
# II. Information Provisioning



### Information Provisioning



# Information Provisioning

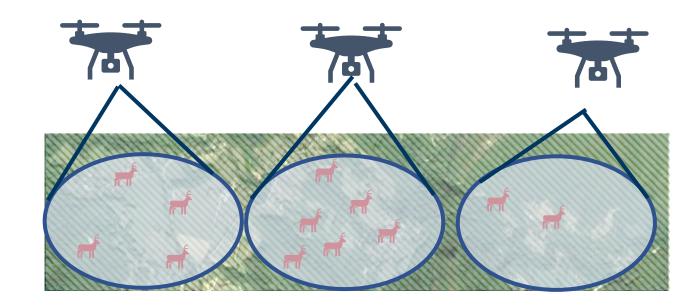


How does *revealing information* to local decision makers affect system performance?

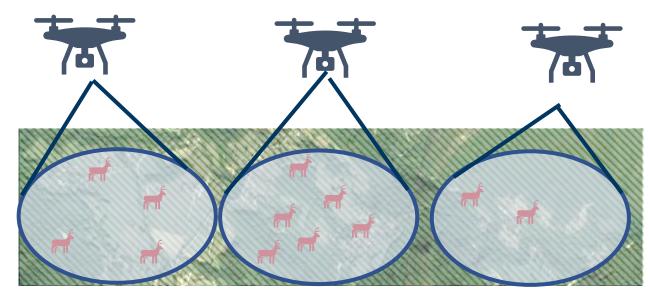




Uncertain Environment

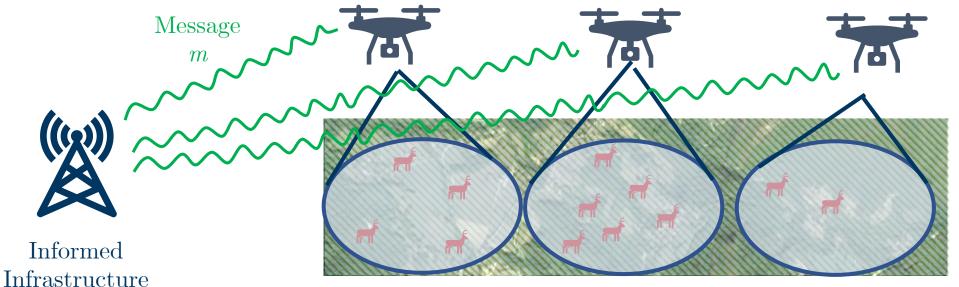


Uncertain Environment



Uncertain Environment

#### Number of deer detected: 172

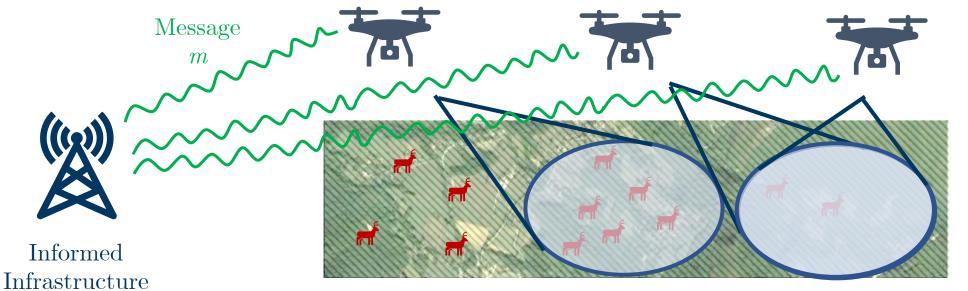


Uncertain Environment

### Number of deer detected: 172

Goal: surveil number of deer with a distributed drone team

Proposal: send **messages** to inform drones of areas with more deer throughout day

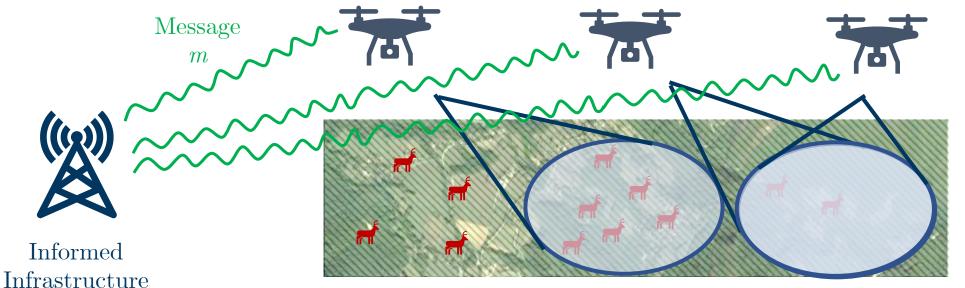


Uncertain Environment

### Number of deer detected: 172

Goal: surveil number of deer with a distributed drone team

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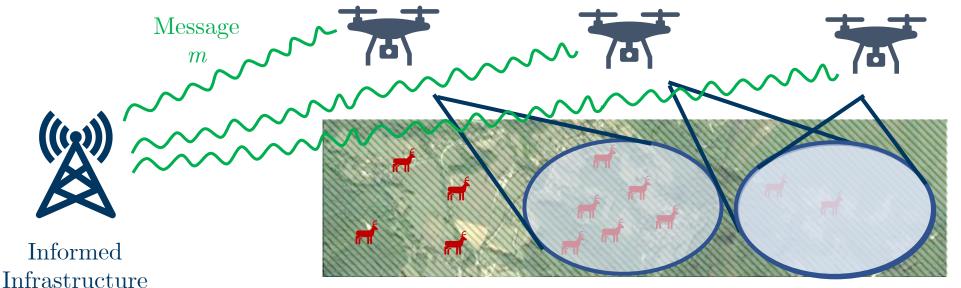


Uncertain Environment

Number of deer detected: 86

Goal: surveil number of deer with a distributed drone team

Proposal: send **messages** to inform drones of areas with more deer throughout day Result: far *fewer* deer were detected?



Uncertain Environment

### Number of deer detected: 86

Goal: surveil number of deer with a distributed drone team

Proposal: send **messages** to inform drones of areas with more deer throughout day Result: far *fewer* deer were detected?

Why did revealing information worsen system performance?

# Information Signaling



System state  $\alpha$  affects agent costs

.... Agent 3  $\dots$ Agent 2 Agent 1 Agent n $U_1(a; \boldsymbol{\alpha})$  $U_2(a; \boldsymbol{\alpha})$  $U_3(a; \boldsymbol{\alpha})$  $U_n(a; \boldsymbol{\alpha})$ System state  $\alpha$  affects agent costs Player knowledge: full information on state  $\alpha$ Nash Equilibrium  $(a^{NE}, \alpha)$ :  $U_i(a^{\text{NE}}; \boldsymbol{\alpha}) \leq U_i(a'_i, a^{\text{NE}}_{-i}; \boldsymbol{\alpha})$  $\forall a'_i \in \mathcal{A}_i,$  $i \in N = \{1, \dots, n\}$ 

Agent 1  $U_1(a; \boldsymbol{\alpha})$ 

Agent 2Agent 3 $U_2(a; \alpha)$  $U_3(a; \alpha)$ System state  $\alpha$  affects agent costs

Player knowledge: a prior belief

$$\mu_0(x) = \mathbb{P}[\alpha = x]$$

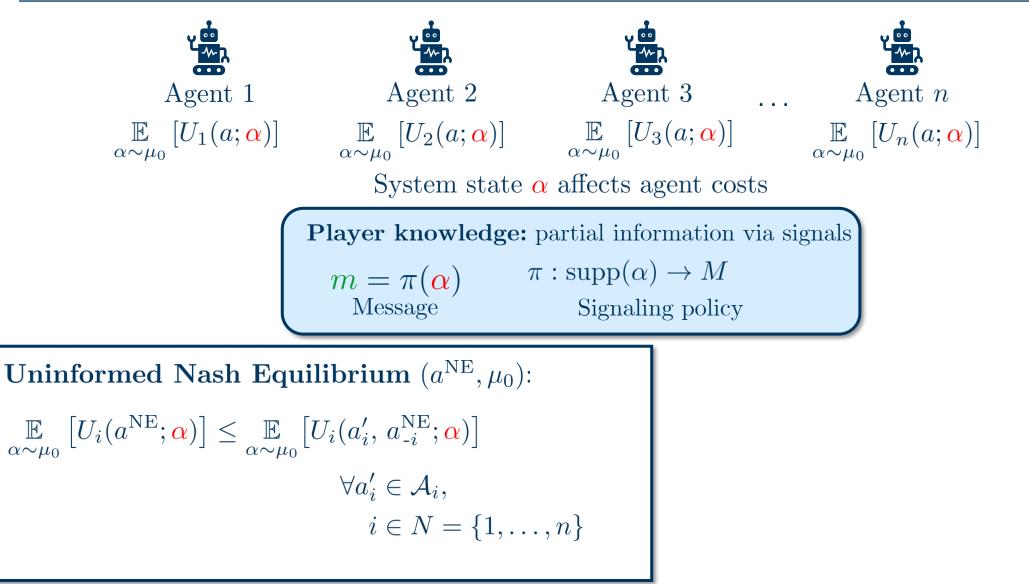
Nash Equilibrium  $(a^{NE}, \alpha)$ :

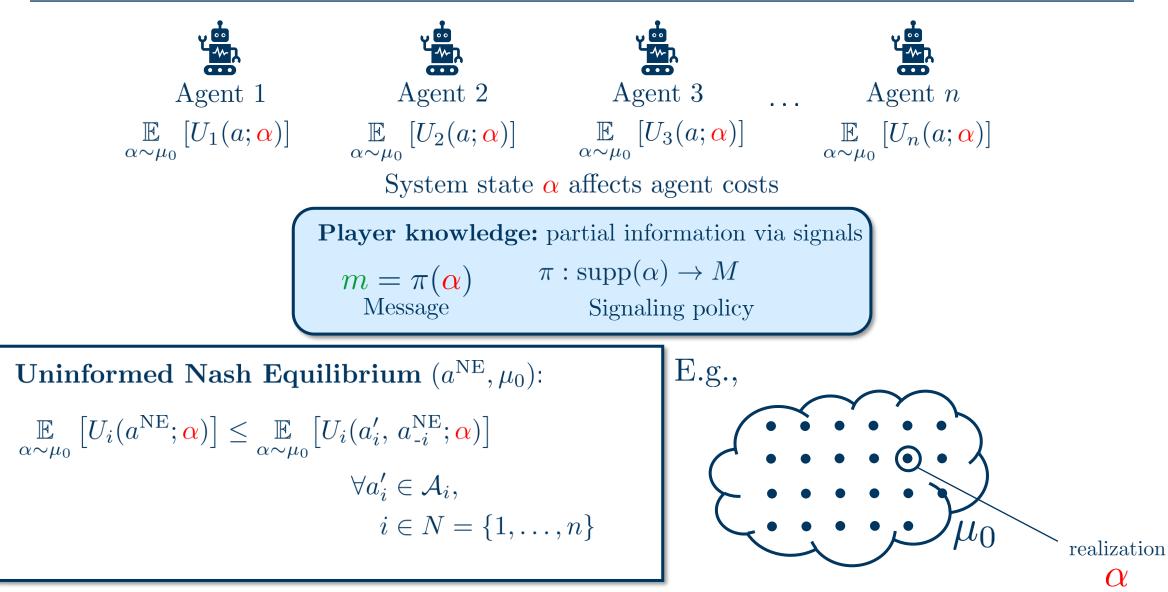
$$U_{i}(a^{\text{NE}}; \boldsymbol{\alpha}) \leq U_{i}(a'_{i}, a^{\text{NE}}_{-i}; \boldsymbol{\alpha})$$
$$\forall a'_{i} \in \mathcal{A}_{i},$$
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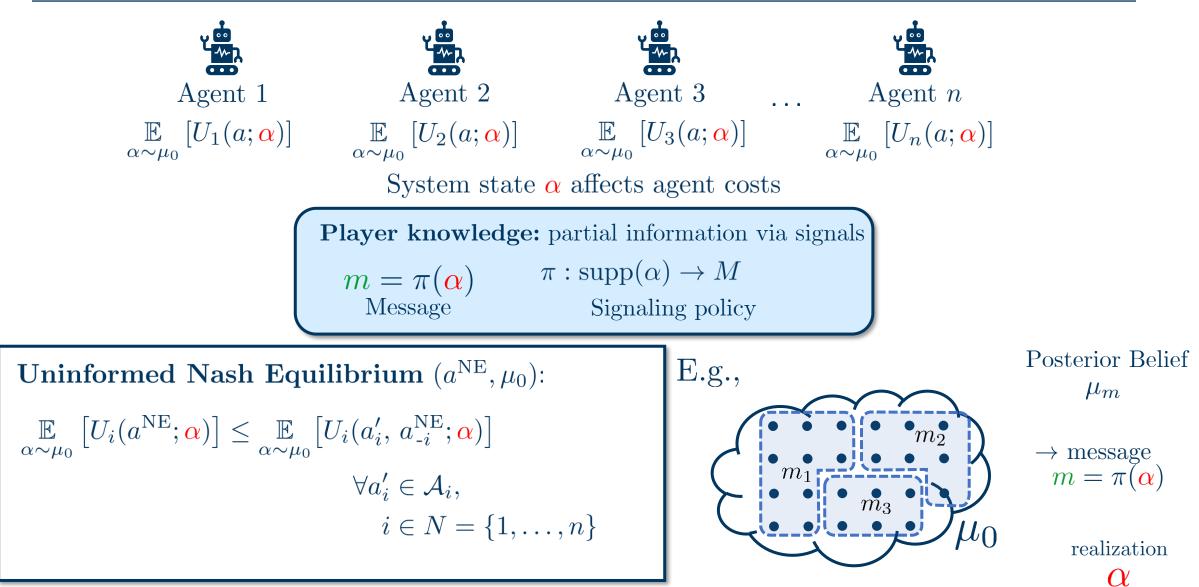
Agent n

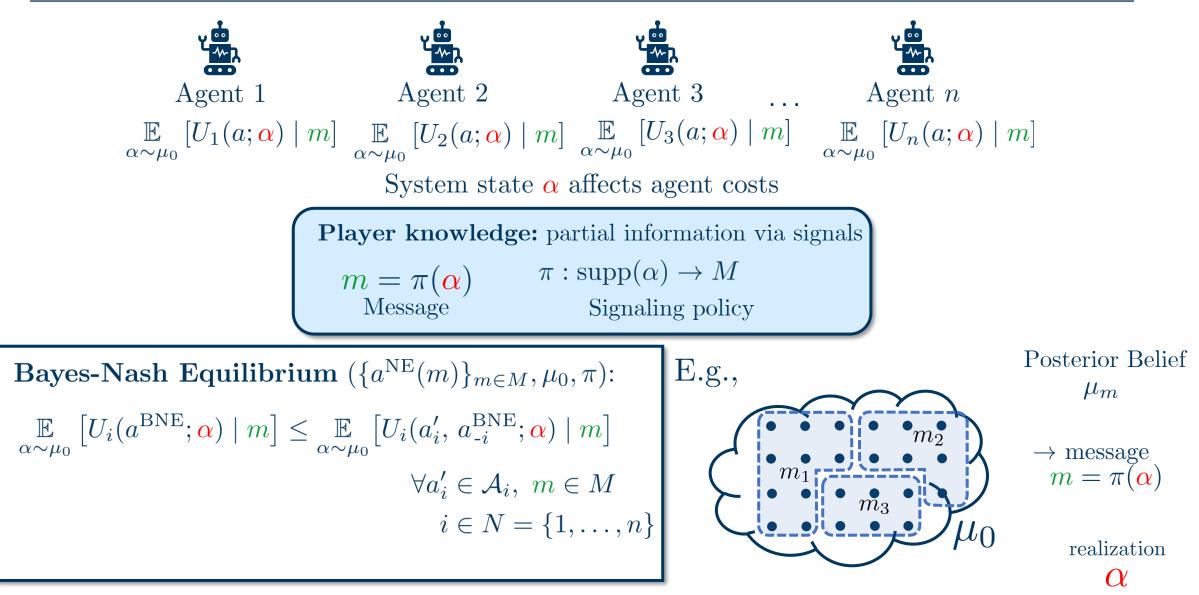
 $U_n(a; \boldsymbol{\alpha})$ 

Agent 2Agent 3 $\dots$ Agent nAgent 1  $\mathbb{E}_{\alpha \sim \mu_0} \left[ U_1(a; \boldsymbol{\alpha}) \right] \qquad \mathbb{E}_{\alpha \sim \mu_0} \left[ U_2(a; \boldsymbol{\alpha}) \right] \qquad \mathbb{E}_{\alpha \sim \mu_0} \left[ U_3(a; \boldsymbol{\alpha}) \right] \qquad \mathbb{E}_{\alpha \sim \mu_0} \left[ U_n(a; \boldsymbol{\alpha}) \right]$ System state  $\alpha$  affects agent costs Player knowledge: a prior belief  $\mu_0(x) = \mathbb{P}[\alpha = x]$ Uninformed Nash Equilibrium  $(a^{NE}, \mu_0)$ :  $\mathbb{E}_{\alpha \sim \mu_0} \left[ U_i(a^{\text{NE}}; \boldsymbol{\alpha}) \right] \leq \mathbb{E}_{\alpha \sim \mu_0} \left[ U_i(a'_i, a^{\text{NE}}_{-i}; \boldsymbol{\alpha}) \right]$  $\forall a'_i \in \mathcal{A}_i,$  $i \in N = \{1, \dots, n\}$ 









Informed System Performance:  $W(a^{BNE}(\pi))$ Uninformed System Performance:  $W(a^{NE}(\mu_0))$  Informed System Performance:  $W(a^{BNE}(\pi))$  = Uninformed System Performance:  $W(a^{NE}(\mu_0))$  =

$$\frac{\left(a^{\mathrm{DNE}}(\pi)\right)}{\left(a^{\mathrm{NE}}(\mu_{0})\right)} =: \operatorname{VoI}(\pi)$$
(value of informing)

Informed System Performance:  $\frac{W(a^{\text{BNE}}(\pi))}{W(a^{\text{NE}}(\mu_0))} =: \underset{\text{(value of informing)}}{\text{Vol}(\pi)}$ 

#### Multiple Equilibria $\rightarrow$ Multiple Perspectives

**Optimistic Perspective** 

$$\operatorname{VoI}^{+}(\pi) = \frac{\max_{a^{\mathrm{BNE}} \in \mathrm{BNE}(\pi)} \mathbb{E}\left[W\left(a^{\mathrm{BNE}}\right)\right]}{\max_{a^{\mathrm{NE}} \in \mathrm{NE}(\mu_{0})} \mathbb{E}\left[W\left(a^{\mathrm{NE}}\right)\right]}$$

Gain of **best-case** equilibrium performance

$$\underline{\text{Pessimistic Perspective}}$$
$$\text{VoI}^{-}(\pi) = \frac{\min_{a^{\text{BNE}} \in \text{BNE}(\pi)} \mathbb{E}\left[W\left(a^{\text{BNE}}\right)\right]}{\min_{a^{\text{NE}} \in \text{NE}(\mu_{0})} \mathbb{E}\left[W\left(a^{\text{NE}}\right)\right]}$$

Gain of worst-case equilibrium performance

Bounding the Value of Informing

 $\texttt{Torestore} \quad \texttt{Covering Problems} \quad w_r(|a|_r) = \alpha_r \mathbb{1} \left[ |a|_r \ge 1 \right] \quad \texttt{Torestore} \quad \texttt$ 

System Objective  $U(a; \boldsymbol{\alpha}) = W(a; \boldsymbol{\alpha}) = \sum_{r \in \mathcal{R}} \boldsymbol{\alpha}_r \mathbb{1} |a|_r > 0$ 

Thm 2.1 [BLF, D.Paccagnan, J.R.Marden LCSS\*] For a resource allocation game with the covering objective:

 $1 \le \operatorname{VoI}^+(\pi) \le |M|$ 

 $1/2 \le \mathrm{VoI}^-(\pi) \le 2|M|$ 

Bounding the Value of Informing

To Covering Problems  $w_r(|a|_r) = \alpha_r \mathbb{1}[|a|_r \ge 1]$ 

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Observations:

- Revealing information only helps best-case
- A richer message space leads to greater opportunities for improvement (|M|)
- Revealing information can *worsen worst-case*

Bounding the Value of Informing

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- A richer message space leads to greater opportunities for improvement (|M|)
- Revealing information can *worsen worst-case*

Optimal Pessimistic Utility Design  $U(a; \boldsymbol{\alpha}) = \sum_{r \in \mathcal{R}} \alpha_r (|a|_r - 1)! \frac{\frac{1}{(n-1)(n-1)!} + \sum_{i=|a|_r}^{n-1} \frac{1}{i!}}{\frac{1}{(n-1)(n-1)!} + \sum_{i=1}^{n-1} \frac{1}{i!}}$ 

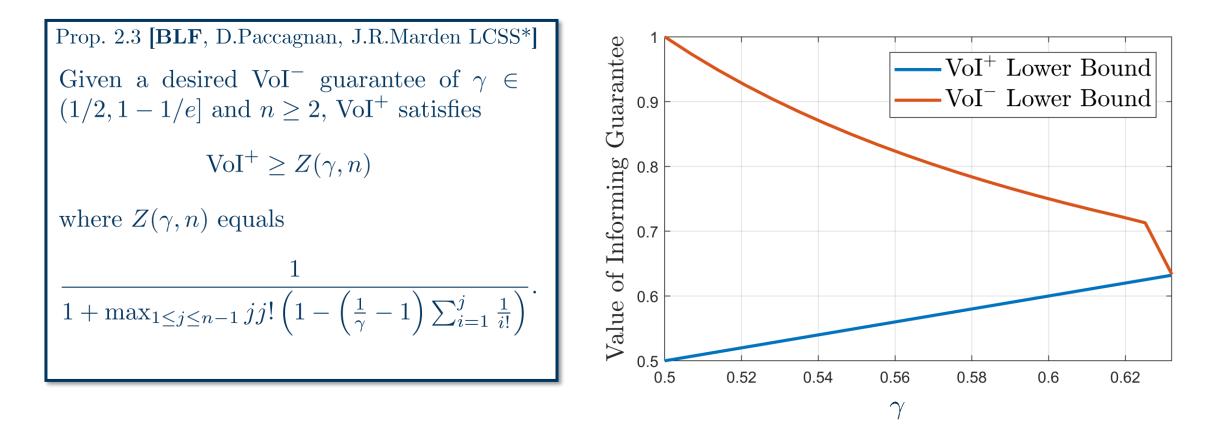
> Thm 2.2 [BLF, D.Paccagnan, J.R.Marden LCSS\*] For a resource allocation game with the covering objective and pessimistic design:

$$1 - \frac{1}{e} \le \text{VoI}^+(\pi) \le \left(1 - \frac{1}{e}\right)^{-1} |M|$$

$$1 - \frac{1}{e} \le \text{VoI}^{-}(\pi) \le \left(1 - \frac{1}{e}\right)^{-1} |M|$$

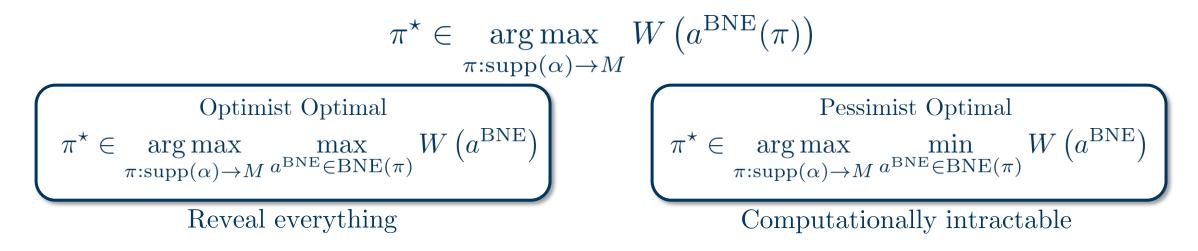
Observation:

• Improving worst-case guarantee has negative consequences on best-case guarantee



Designing utilities for better pessimistic guarantees worsens the optimistic guarantees

 $\pi^{\star} \in \underset{\pi:\operatorname{supp}(\alpha) \to M}{\operatorname{arg\,max}} W\left(a^{\operatorname{BNE}}(\pi)\right)$ 

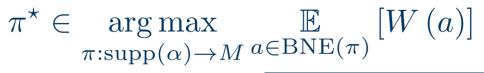


 $\pi^{\star} \in \underset{\pi:\operatorname{supp}(\alpha) \to M}{\operatorname{arg\,max}} \underset{a \in \operatorname{BNE}(\pi)}{\mathbb{E}} \left[ W\left(a\right) \right]$ 

Average Case Performance

Algorithm 1 Bandit Approach to Optimal Signals

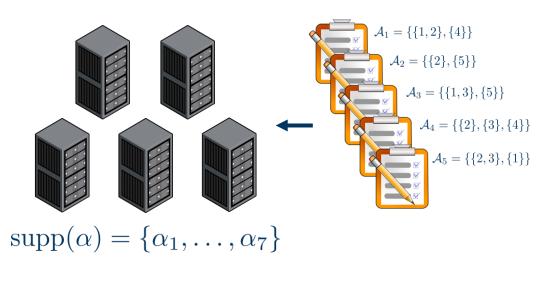
- 1: Pick signaling policy  $\pi$  via UCB
- 2: Sample State  $\alpha$  and initial allocation  $a_0$
- 3: Find BNE via Best-Response  $BR(a_0, \pi(\alpha))$
- 4: Record Equilibrium Reward



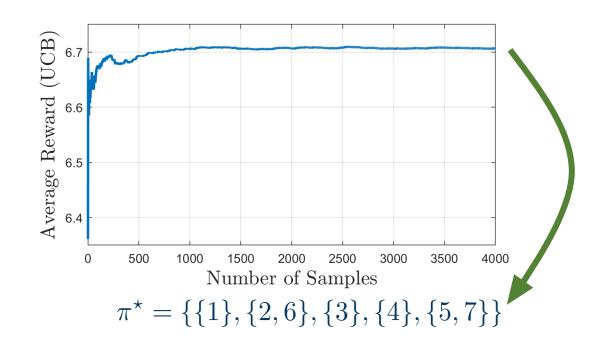
#### Average Case Performance

#### Algorithm 1 Bandit Approach to Optimal Signals

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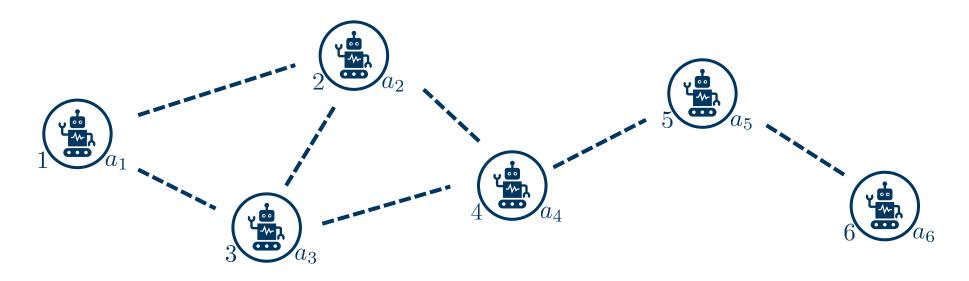


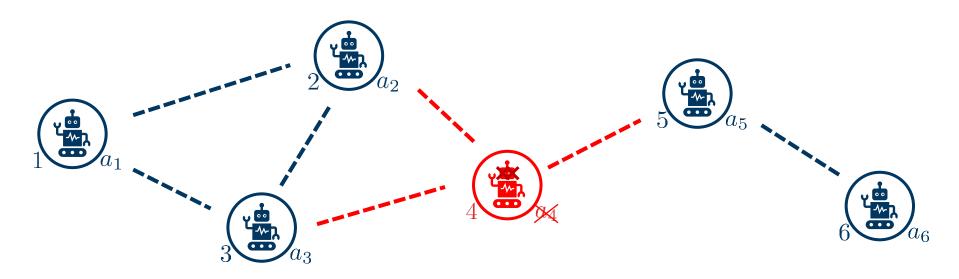
$$w_r(|a|_r) = \frac{\alpha_r}{|a|_r} \exp(-c|a|_r)$$



# III. Unreliable Communicators



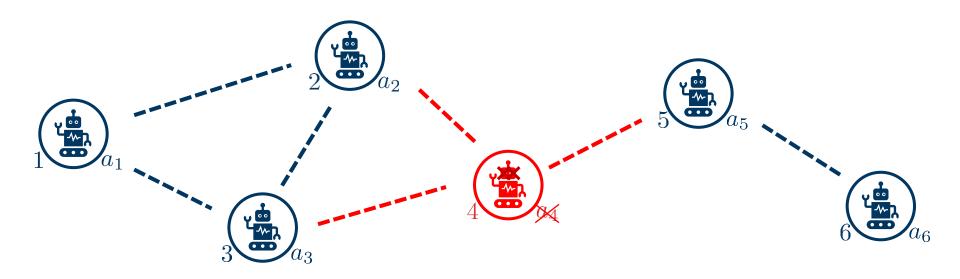




**Defective Agent**: Agent still communicates but does not contribute to the system objective



Nominal agents cannot determine which agents are defective. They must operate under the assumption some agents might be.

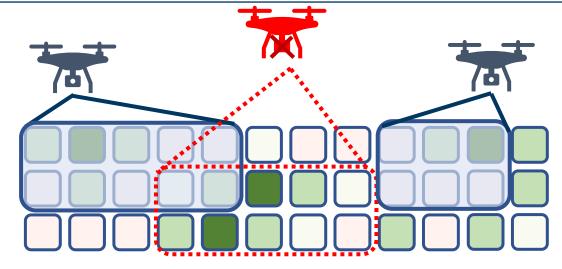


Defective Agent: Agent still communicates but does not contribute to the system objective



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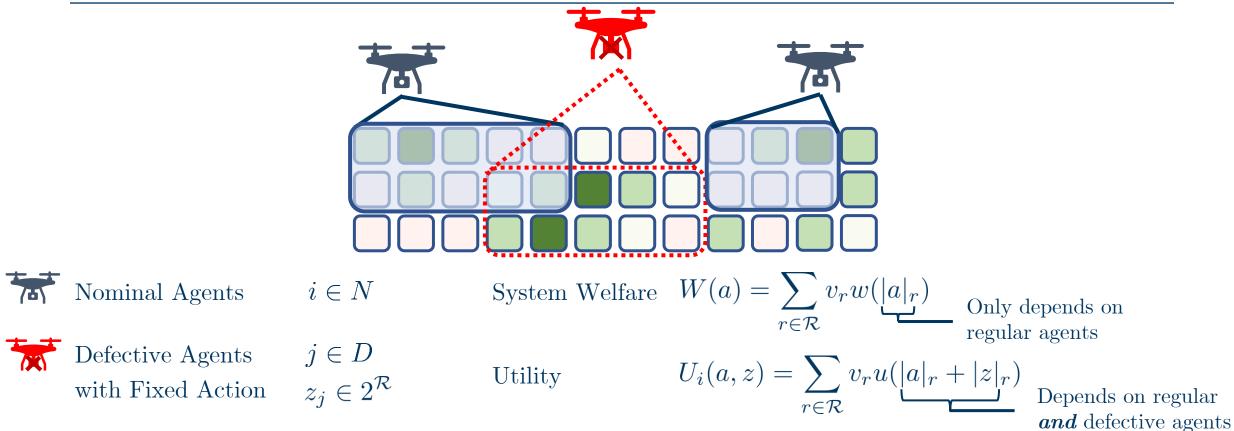
How should agents be designed when others may be defective?

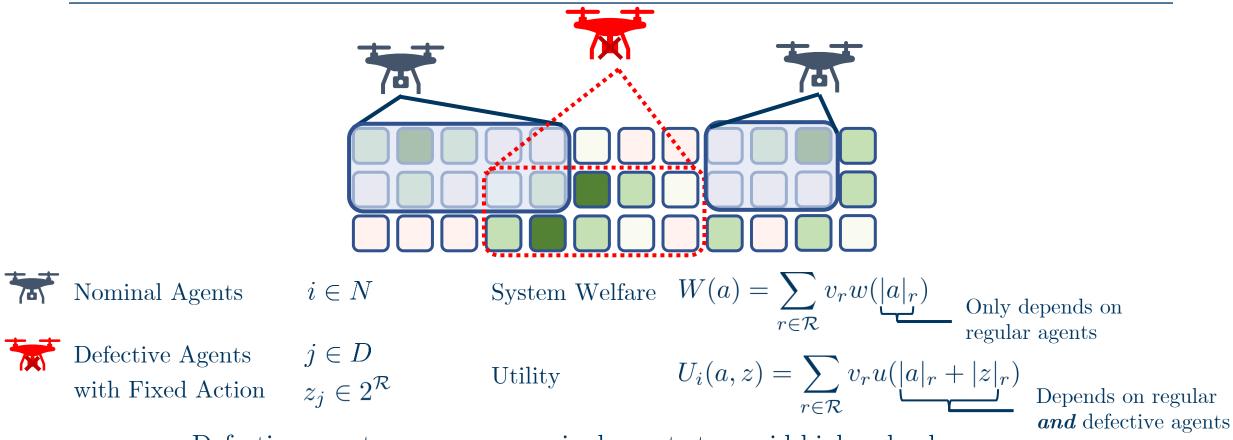






**D**efective Agents with Fixed Action  $j \in D$  $z_j \in 2^{\mathcal{R}}$ 





Defective agents can cause nominal agents to avoid high valued resources **Robust Design**: choose utility functions to promote more overlap

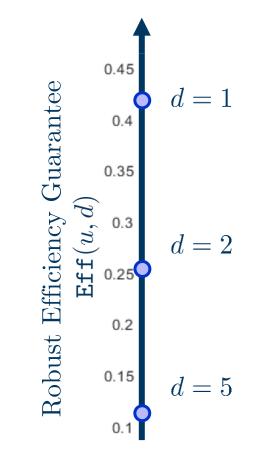
Proposition 1.3:[CDC21,DGAA]The optimal utility design and associated efficiency is<br/>the solution to a linear program.



#### Nominal/Robust Performance Trade-off

• Nominal Utility Rule

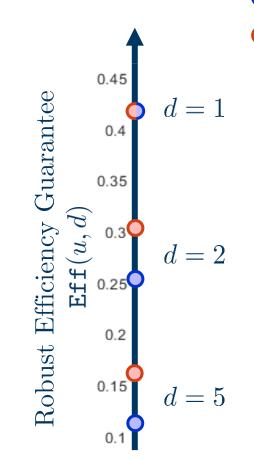
In the class of covering games,



d := # defective agents

#### Nominal/Robust Performance Trade-off

In the class of covering games,

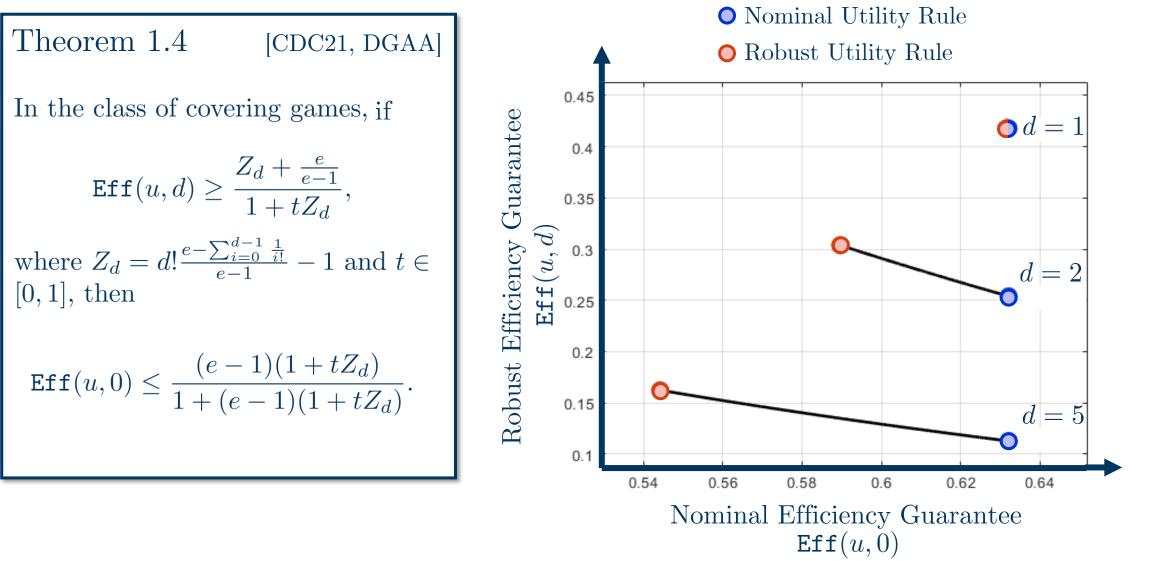


• Nominal Utility Rule

○ Robust Utility Rule

d := # defective agents

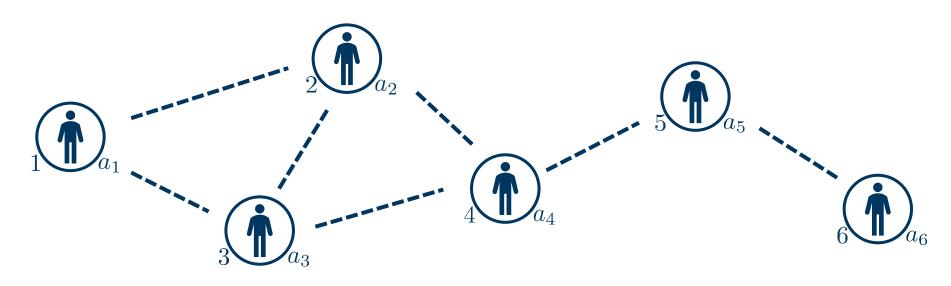
#### Nominal/Robust Performance Trade-off

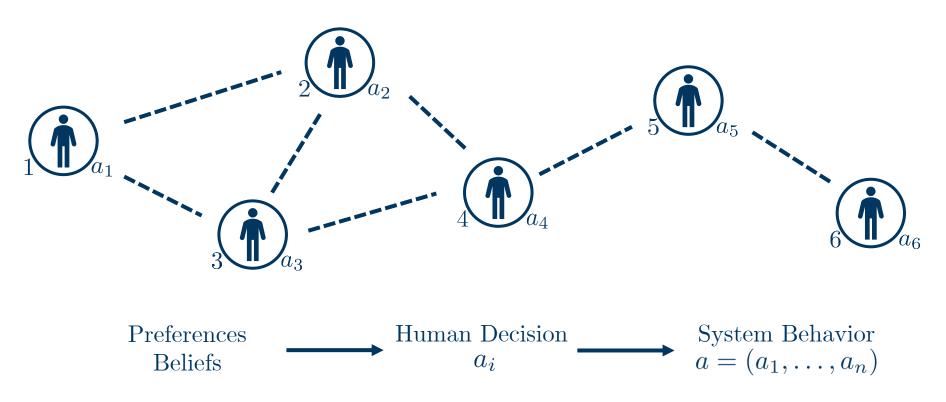


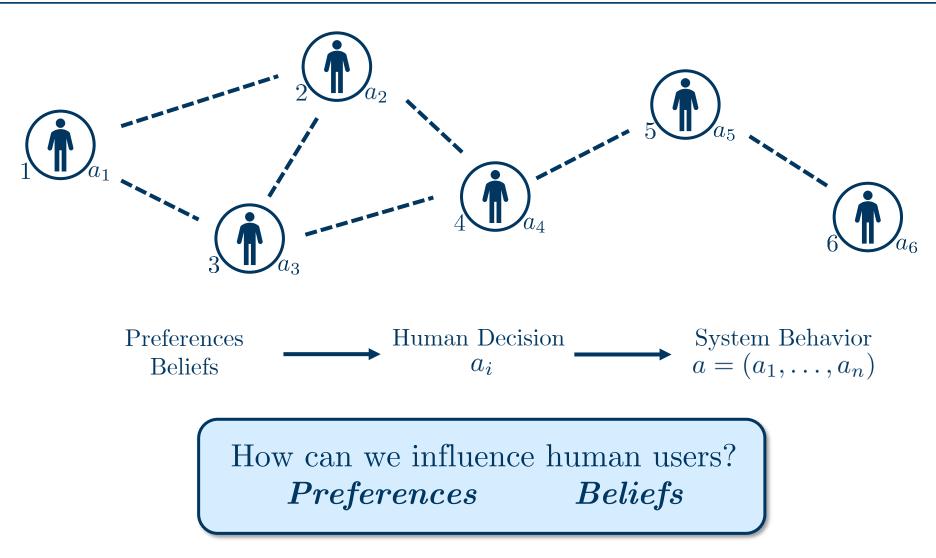
d := # defective agents

# IV. Directions & Conclusions

Human User Agent Human Action User index Can't design this directly!

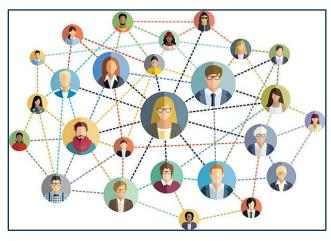






## Types of Information Communication (Social Systems)

#### Agent-to-Agent



Social Networks and Viral Marketing

#### Agent-to-Infrastructure



Recommender Systems and Advertising

#### Unreliable Communicators



Belief Propagation and Fake News

Design communication mechanisms to alter *users' beliefs* and actions to ultimately guide system behavior

#### Directions in Socio-Technical Systems



#### Intersection of *Engineered* and *Social* systems



Smart services human demand



Autonomous mobility services



Human-robot interaction



Automation with human oversight



Human language AI interfaces

## Conclusion

#### The Role of Communication in Distributed Systems

Share information to strategically alter system behavior

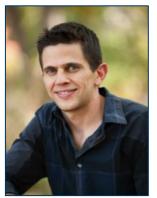
Benefits:	<ul><li>Increase coordination</li><li>Improve global objective</li><li>Robustness to sub-system failures</li></ul>
Costs:	<ul><li>Increased complexity</li><li>Unexpected behavior</li></ul>

Understanding benefits/costs can help us design distributed systems more intelligently



#### References

#### In Collaboration With:



Jason R. Marden UC Santa Barbara



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Bary S. R. Pradelski CNRS (University of Grenoble)

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#### UC SANTA BARBARA

#### Information *as* Control: The Role of Communication in Distributed Systems

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May  $15^{\text{th}}$ , 2023

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