

AAAI-18 Tutorial on:

# MULTI-AGENT DISTRIBUTED CONSTRAINED OPTIMIZATION



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# SCHEDULE

- 11:20am: Preliminaries
- 11:40am: DCOP Algorithms
- 12:20pm: DCOP Extensions
- 12:30pm: Applications
- 12:50pm: Challenges and Open Questions
- 1:00pm: Done! Lunch? :)

# LIL' BIT OF SHAMELESS PROMOTION :)

- Tutorial materials are based on our recent JAIR survey paper:

Ferdinando Fioretto, Enrico Pontelli, and William Yeoh.

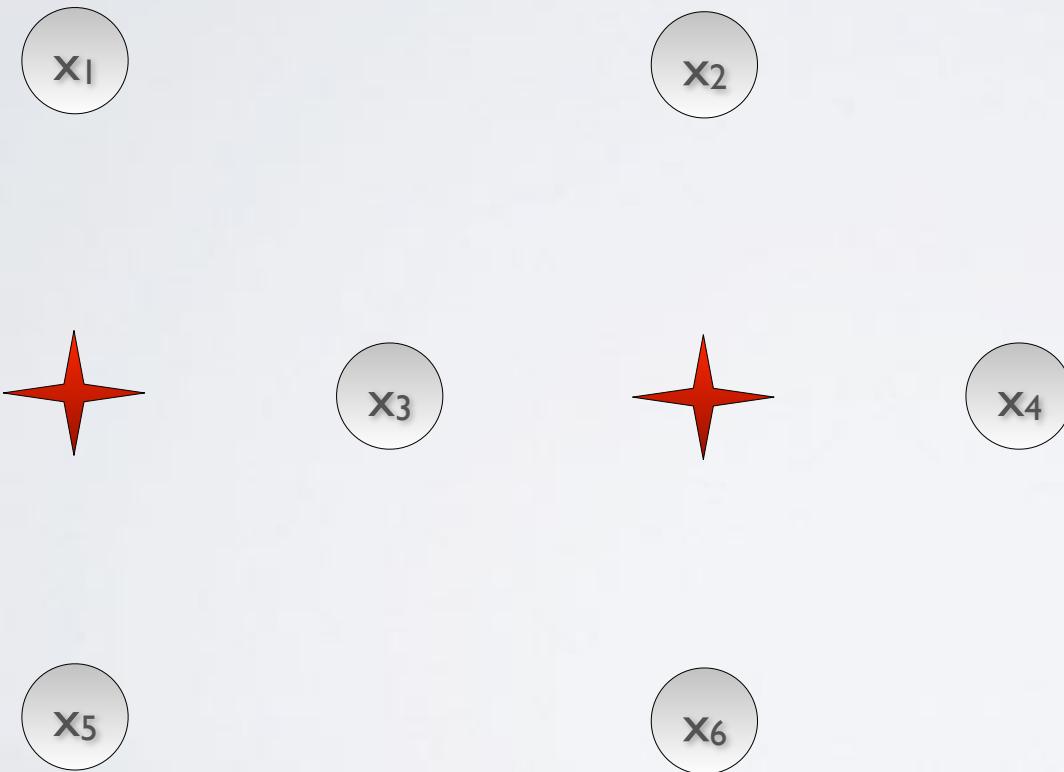
*Distributed Constraint Optimization Problems and Applications: A Survey.*  
Journal of Artificial Intelligence Research (JAIR), to appear, 2018.

- Includes more models, algorithms, and applications.
- Also available on arXiv.

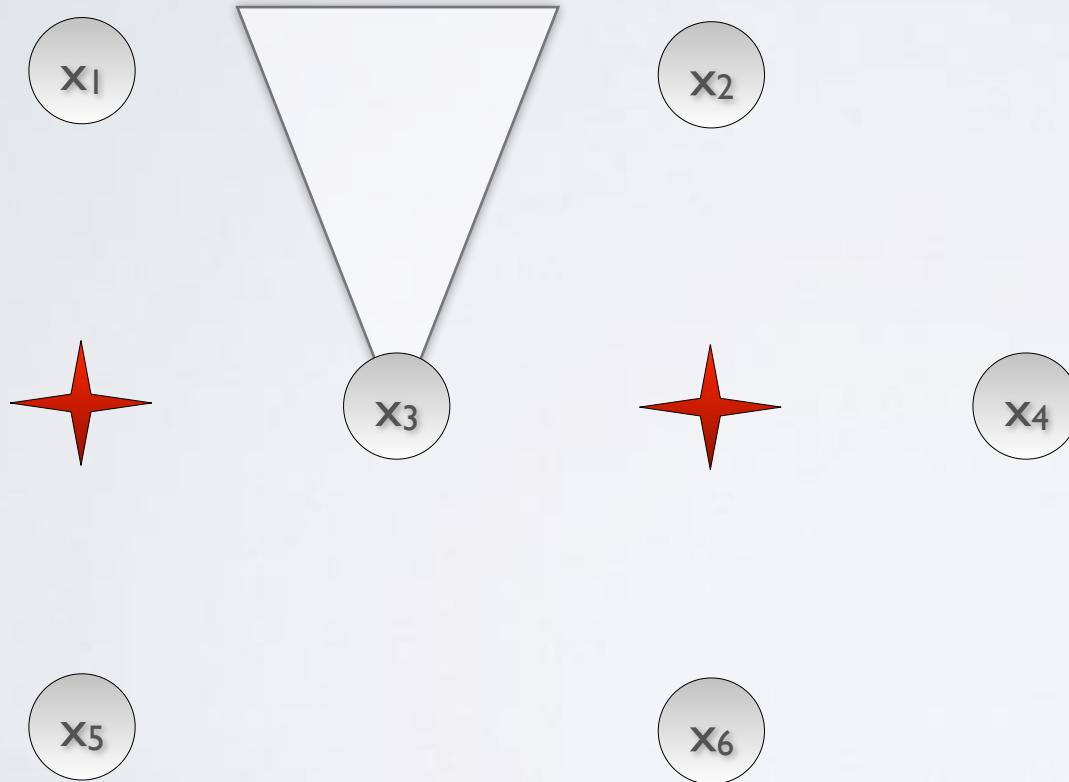
# PRELIMINARIES

AAAI-18 Tutorial on  
Multi-Agent Distributed Constrained Optimization

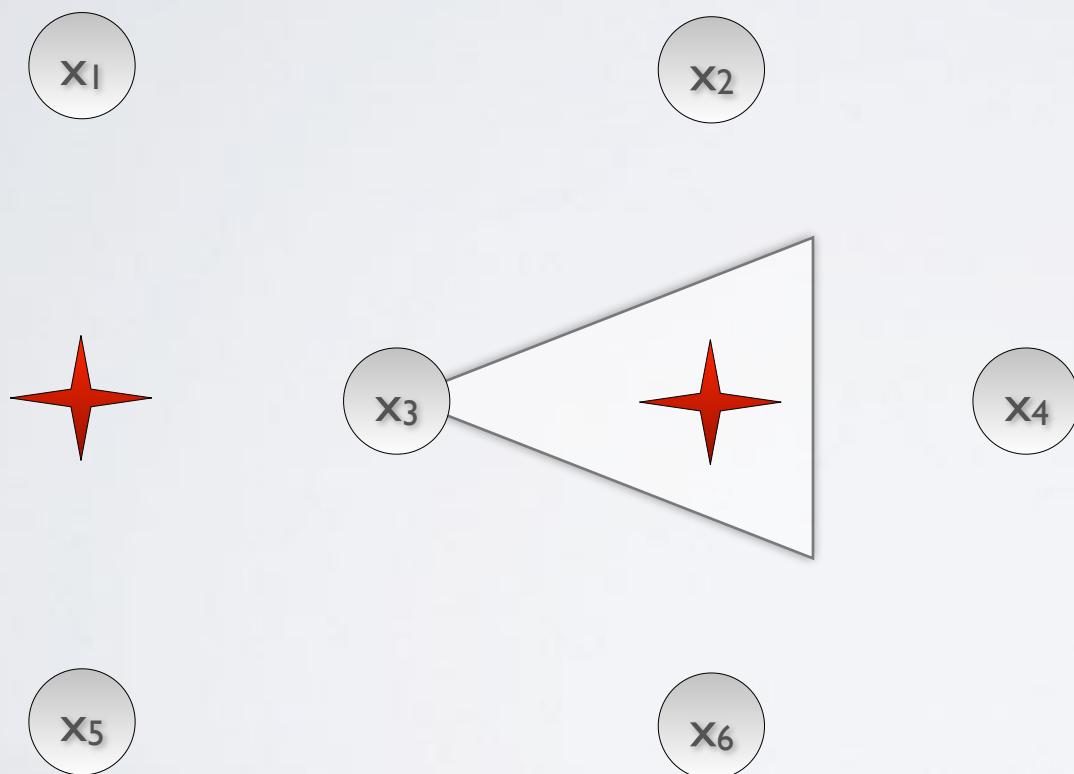
# MOTIVATING DOMAIN: SENSOR NETWORK



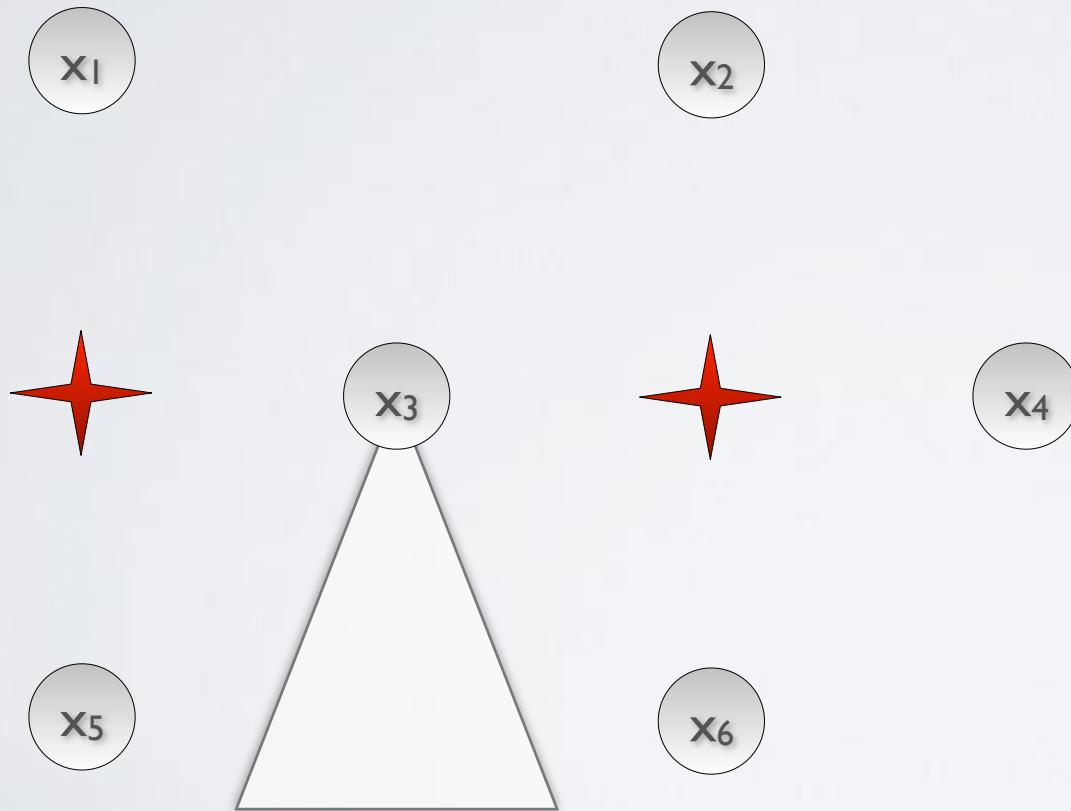
# MOTIVATING DOMAIN: SENSOR NETWORK



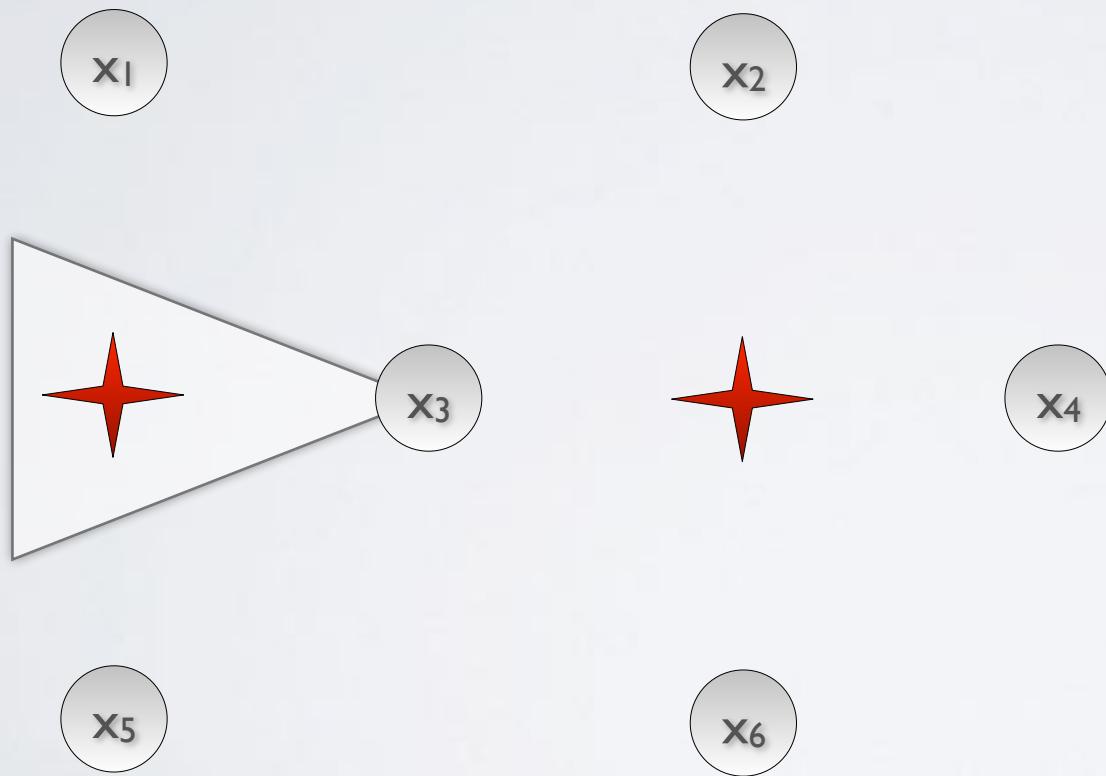
# MOTIVATING DOMAIN: SENSOR NETWORK



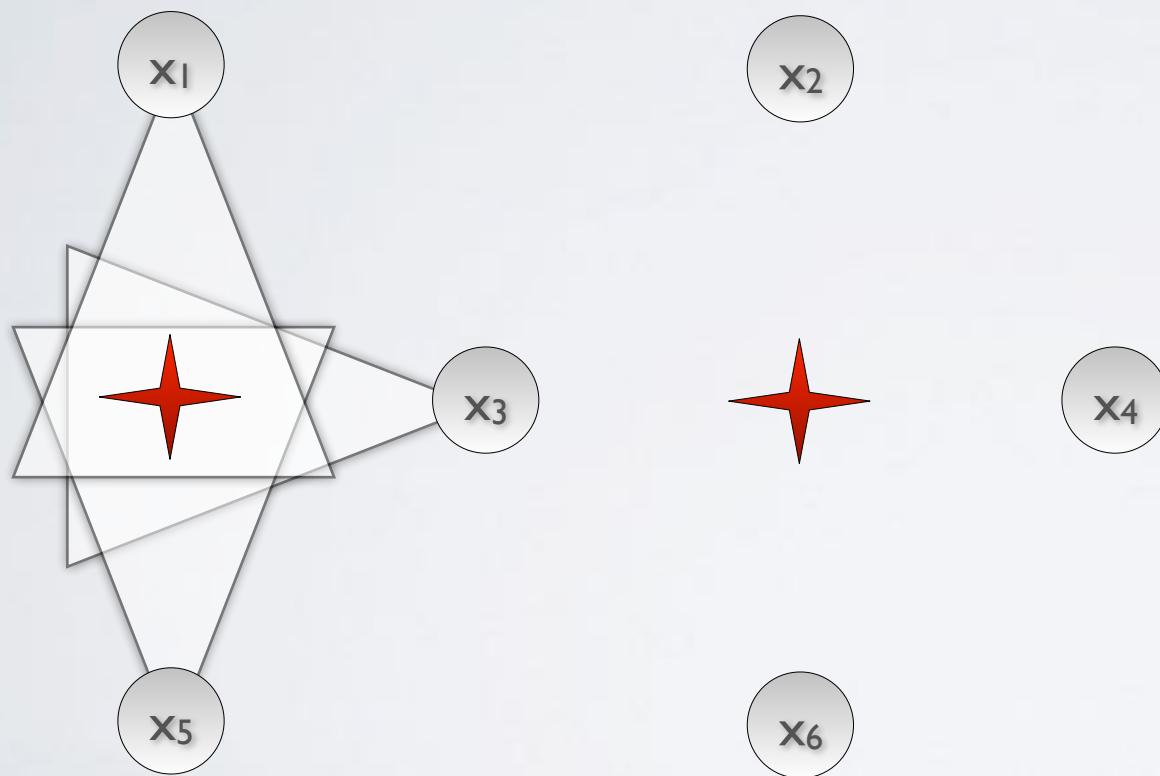
# MOTIVATING DOMAIN: SENSOR NETWORK



# MOTIVATING DOMAIN: SENSOR NETWORK



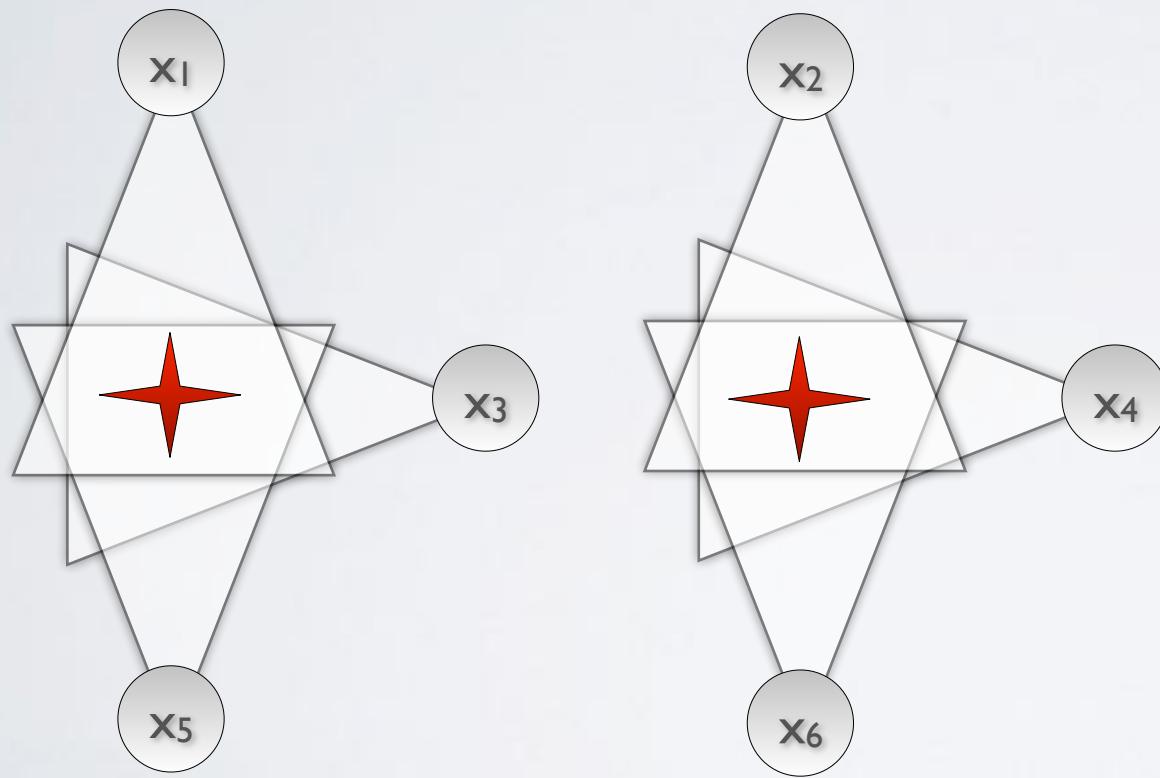
# MOTIVATING DOMAIN: SENSOR NETWORK



$x_1$	$x_3$	$x_5$	Sat?
N	N	N	X
N	N	E	X
...			X
S	E	W	✓
...			X
W	W	W	X

Model the problem as a  
CSP

# MOTIVATING DOMAIN: SENSOR NETWORK



$x_1$	$x_3$	$x_5$	Sat?
N	N	N	X
N	N	E	X
...			X
S	E	W	✓
...			X
W	W	W	X

Model the problem as a  
CSP

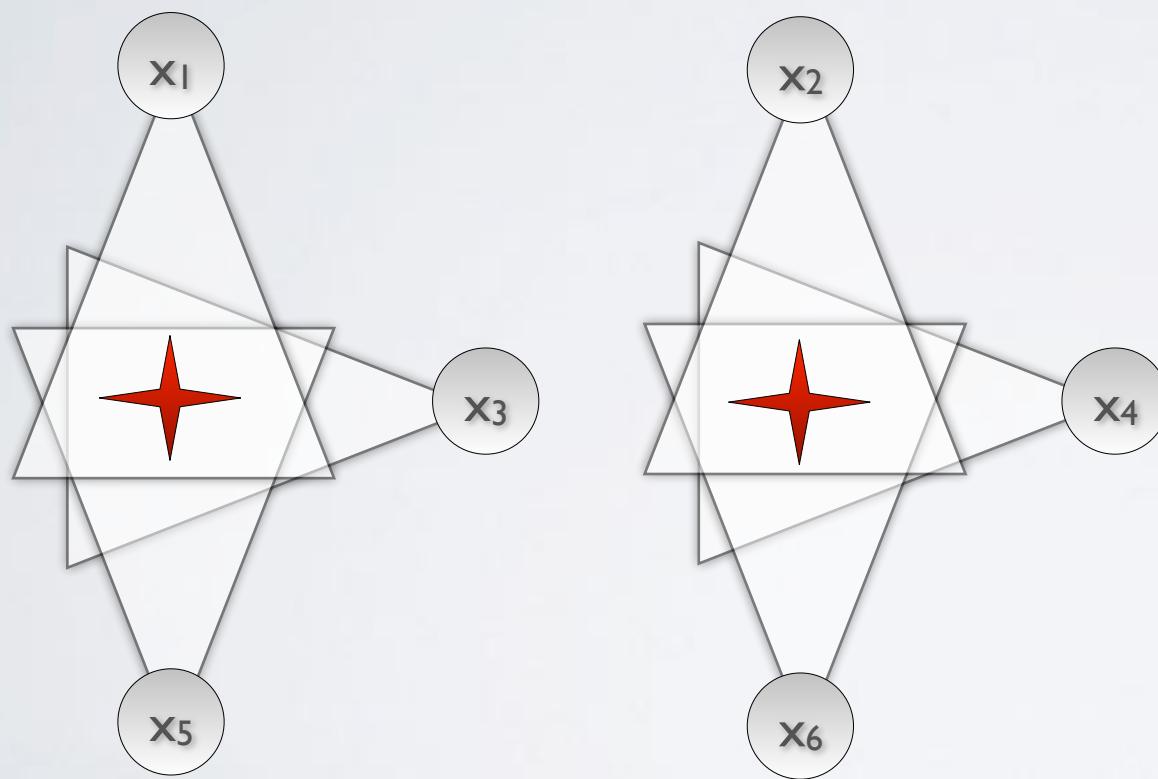
# CSP

## CONSTRAINT SATISFACTION

- Variables  $X = \{x_1, \dots, x_n\}$
- Domains  $D = \{D_1, \dots, D_n\}$
- Constraints  $C = \{c_1, \dots, c_m\}$   
where a constraint  $c_i \subseteq D_{i_1} \times D_{i_2} \times \dots \times D_{i_n}$   
denotes the possible valid joint assignments for the  
variables  $x_{i_1}, x_{i_2}, \dots, x_{i_n}$  it involves
- **GOAL:** Find an assignment to all variables that **satisfies**  
**all the constraints**

# CSP

## CONSTRAINT SATISFACTION

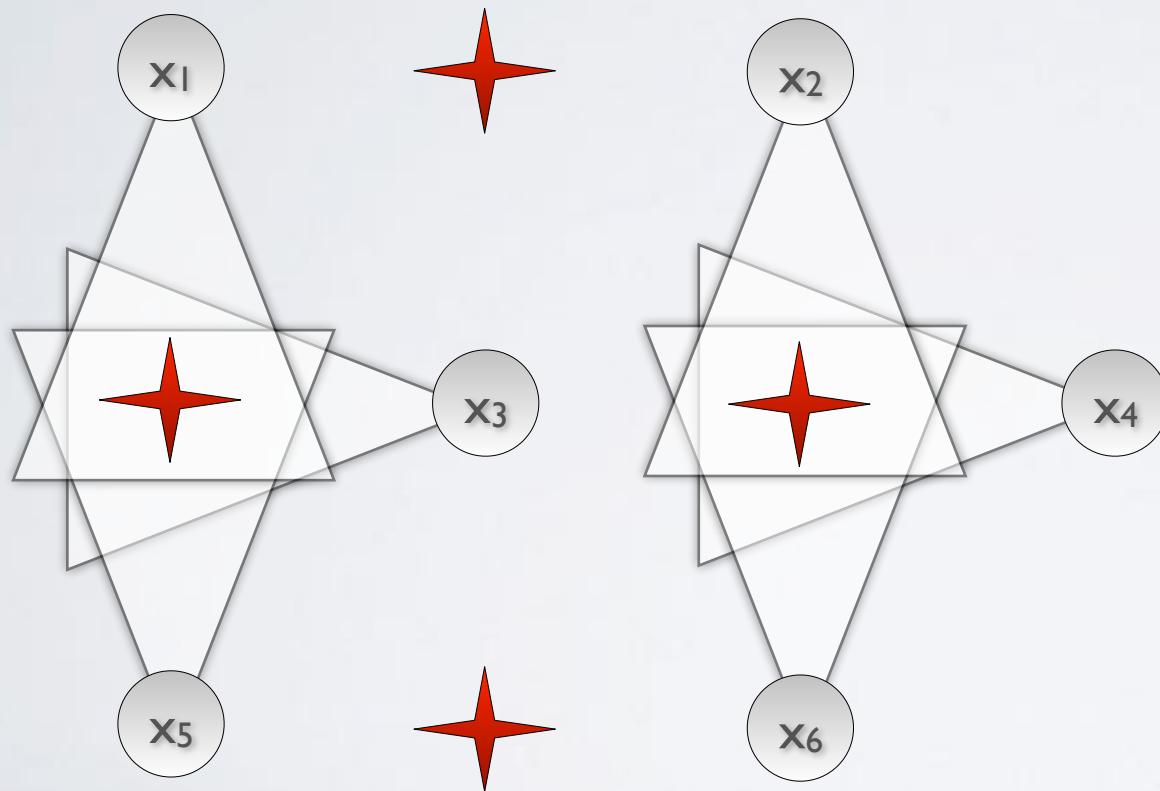


$x_1$	$x_3$	$x_5$	Sat?
N	N	N	X
N	N	E	X
...			X
S	E	W	✓
...			X
W	W	W	X

Model the problem as a  
CSP

# MAX-CSP

## MAX CONSTRAINT SATISFACTION



<b>x<sub>1</sub></b>	<b>x<sub>3</sub></b>	<b>x<sub>5</sub></b>	<b>Sat?</b>
N	N	N	X
N	N	E	X
...			X
<b>S</b>	<b>E</b>	<b>W</b>	<b>✓</b>
...			X
W	W	W	X

Model the problem as a  
Max-CSP

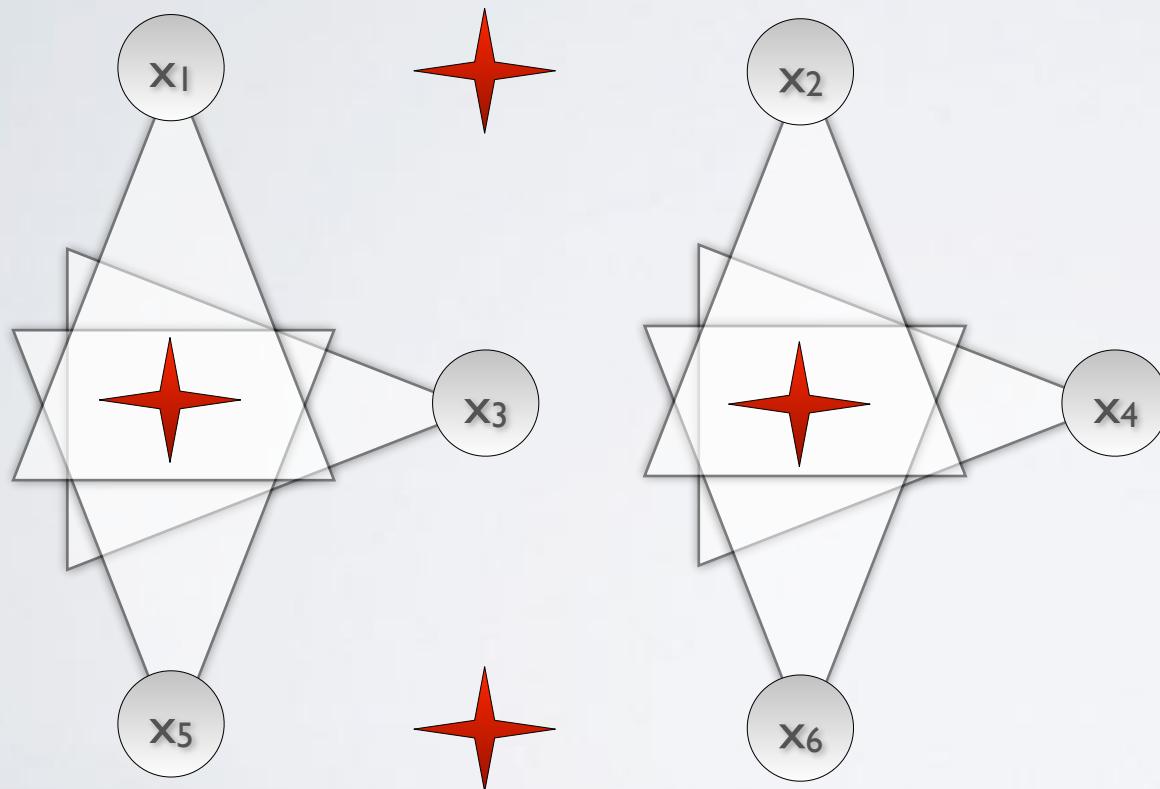
# MAX-CSP

## MAX CONSTRAINT SATISFACTION

- Variables  $X = \{x_1, \dots, x_n\}$
- Domains  $D = \{D_1, \dots, D_n\}$
- Constraints  $C = \{c_1, \dots, c_m\}$   
where a constraint  $c_i \subseteq D_{i_1} \times D_{i_2} \times \dots \times D_{i_n}$   
denotes the possible valid joint assignments for the  
variables  $x_{i_1}, x_{i_2}, \dots, x_{i_n}$  it involves
- **GOAL:** Find an assignment to all variables that **satisfies**  
**a maximum number of constraints**

# MAX-CSP

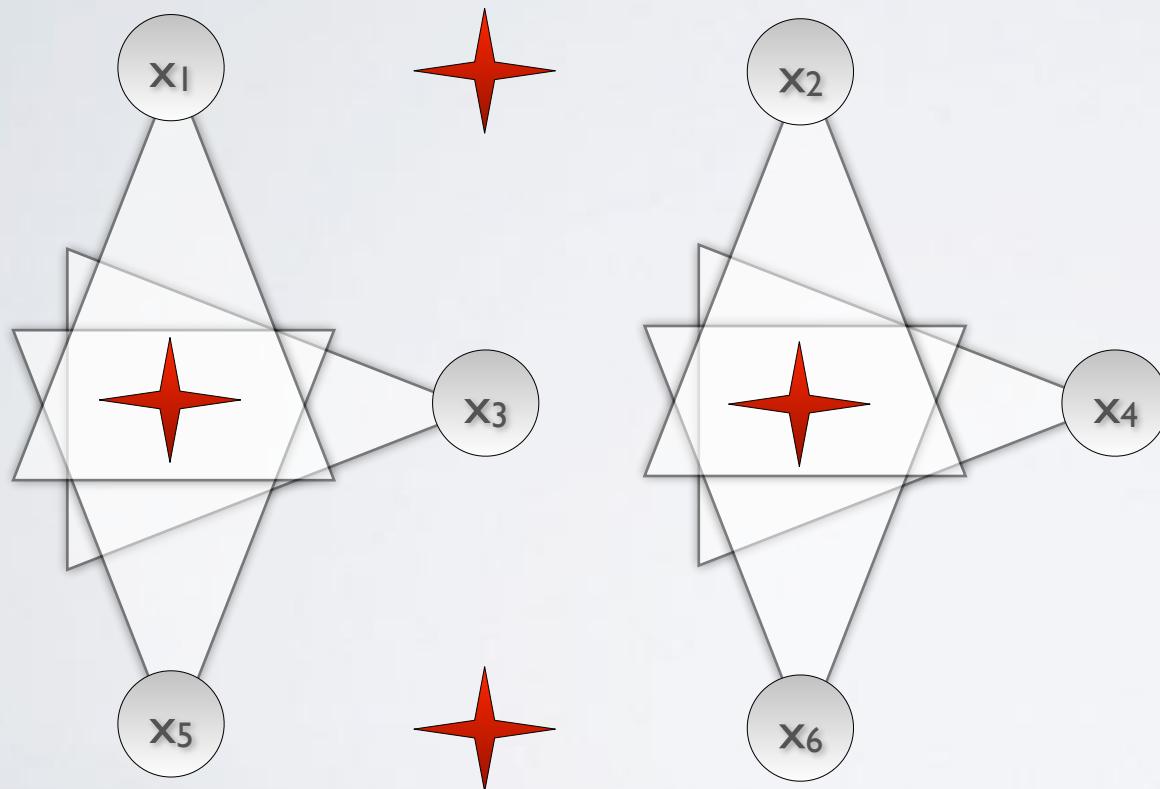
## MAX CONSTRAINT SATISFACTION



<b>x<sub>1</sub></b>	<b>x<sub>3</sub></b>	<b>x<sub>5</sub></b>	<b>Sat?</b>
N	N	N	X
N	N	E	X
...			X
<b>S</b>	<b>E</b>	<b>W</b>	<b>✓</b>
...			X
W	W	W	X

Model the problem as a  
Max-CSP

# WCSP (COP) CONSTRAINT OPTIMIZATION



<b>X<sub>1</sub></b>	<b>X<sub>3</sub></b>	<b>X<sub>5</sub></b>	<b>Cost</b>
N	N	N	$\infty$
N	N	E	$\infty$
...			$\infty$
S	E	W	10
...			$\infty$
W	W	W	$\infty$

Model the problem as a  
COP

# WCSP (COP)

## CONSTRAINT OPTIMIZATION

- Variables  $X = \{x_1, \dots, x_n\}$
- Domains  $D = \{D_1, \dots, D_n\}$
- Constraints  $C = \{c_1, \dots, c_m\}$   
where a constraint  $c_i : D_{i_1} \times \dots \times D_{i_n} \rightarrow \mathbb{R}_+ \cup \{\infty\}$   
expresses the degree of constraint violation
- **GOAL:** Find an assignment that minimizes the sum of  
the costs of all the constraints

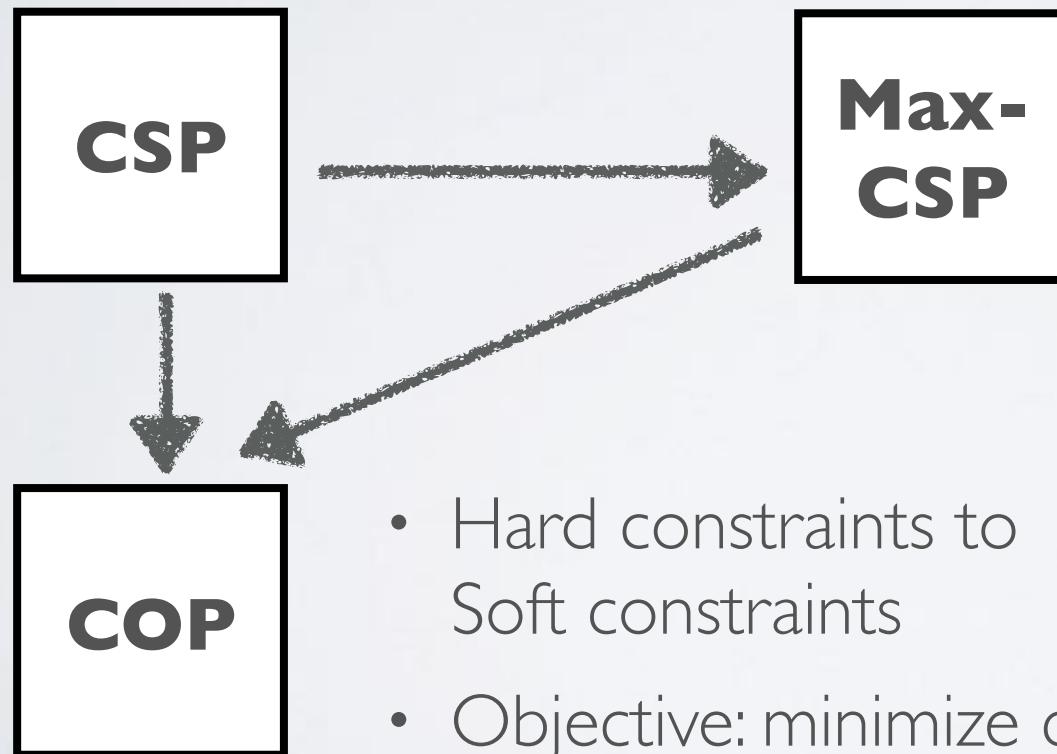
# WCSP (COP) CONSTRAINT OPTIMIZATION



- Objective: maximize #constraints satisfied

# WCSP (COP)

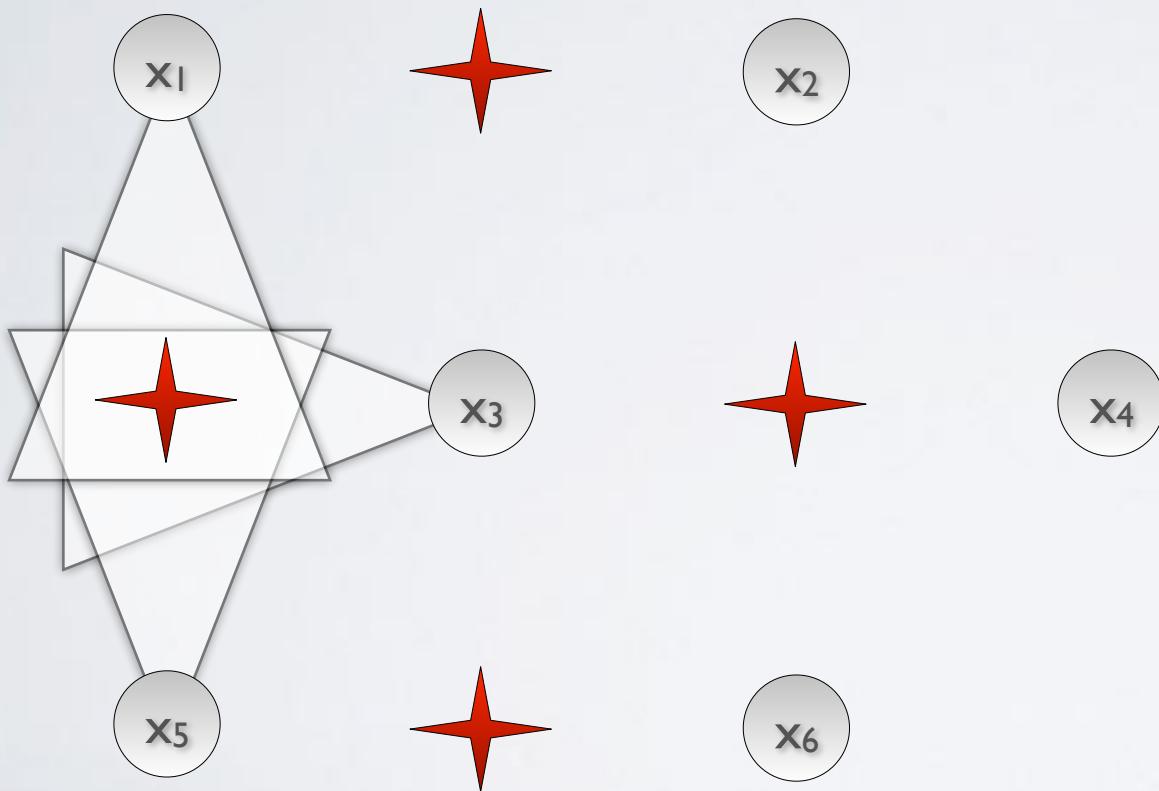
## CONSTRAINT OPTIMIZATION



- Objective: maximize #constraints satisfied

- Hard constraints to Soft constraints
- Objective: minimize cost

# WCSP (COP) CONSTRAINT OPTIMIZATION

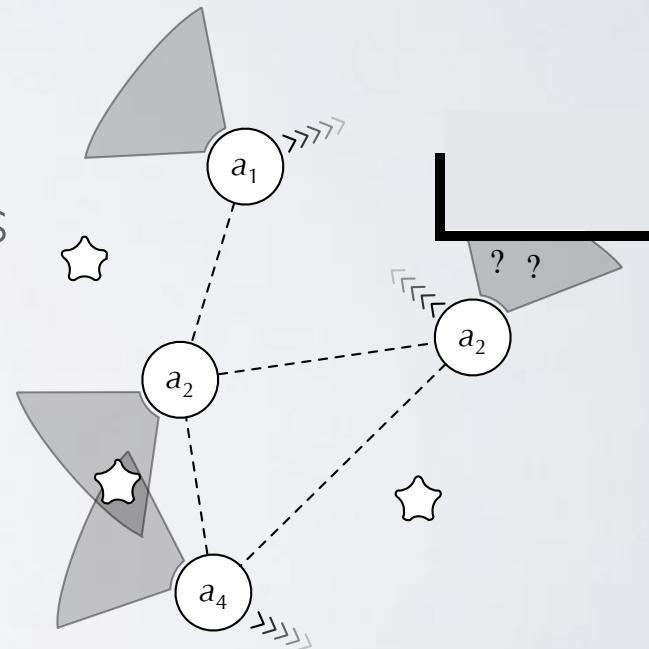


Imagine that each sensor is an autonomous agent.

*How should this problem be modeled and solved in a decentralized manner?*

# MULTI-AGENT SYSTEMS

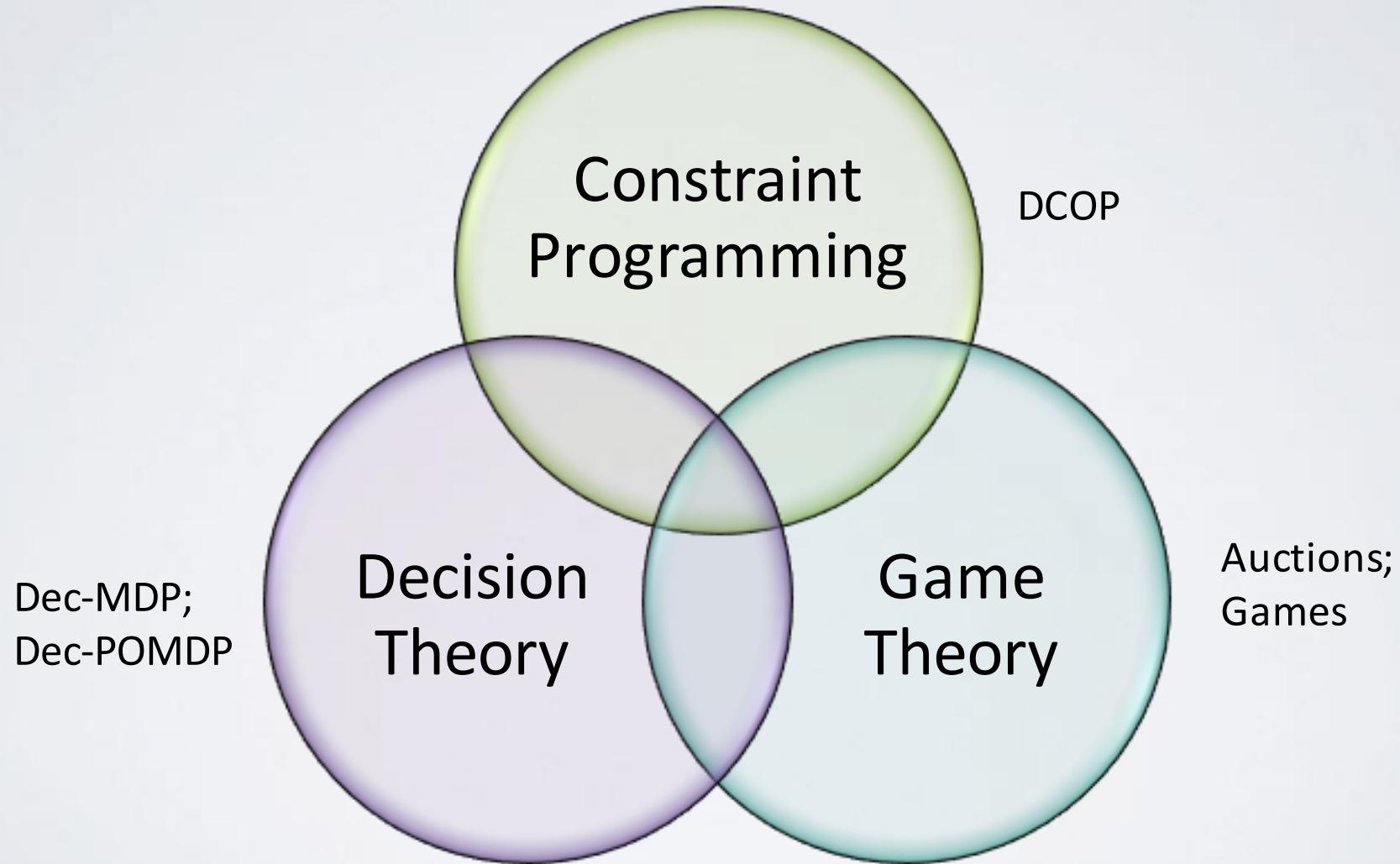
- **Agent:** An entity that behaves autonomously in the pursuit of goals
- **Multi-agent system:** A system of multiple interacting agents
- An agent is:
  - Autonomous: Is of full control of itself
  - Interactive: May communicate with other agents
  - Reactive: Responds to changes in the environment or requests by other agents
  - Proactive: Takes initiatives to achieve its goals



# MULTI-AGENT SYSTEMS

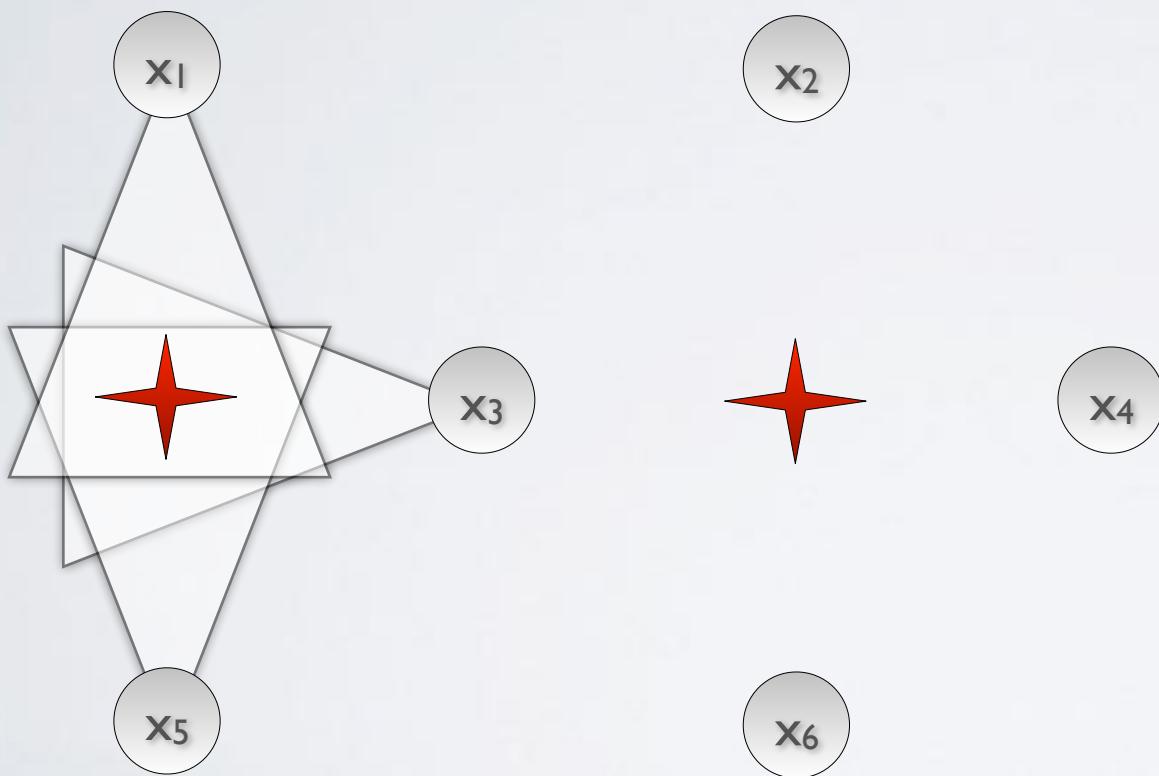
	<b>Element</b>	<b>Characterization</b>
<b>Agent</b>	behavior	deterministic / stochastic
	knowledge	total / partial
	teamwork	cooperative / competitive
<b>Environment</b>	behavior	deterministic / stochastic
	evolution	static / dynamic

# MULTI-AGENT SYSTEMS



# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION

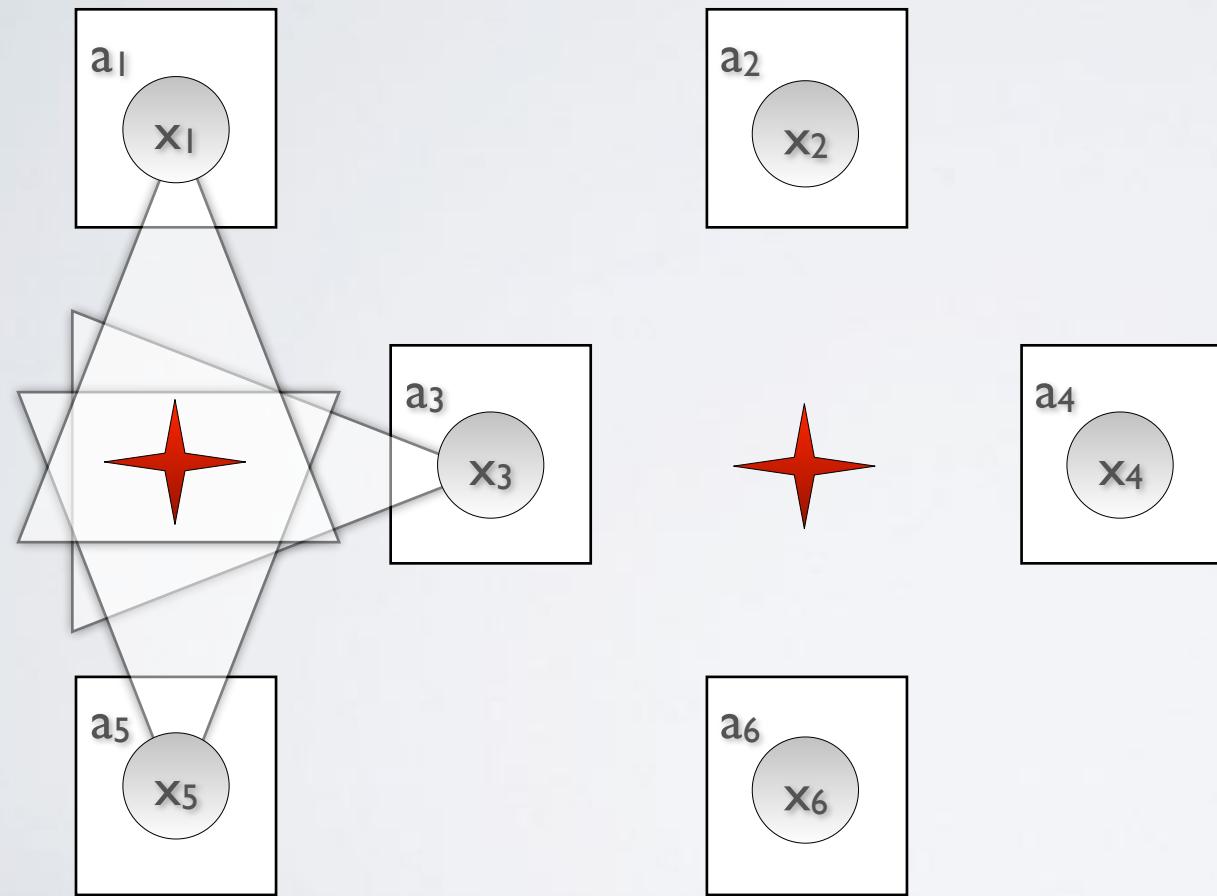


Imagine that each sensor is an autonomous agent.

*How should this problem be modeled and solved in a decentralized manner?*

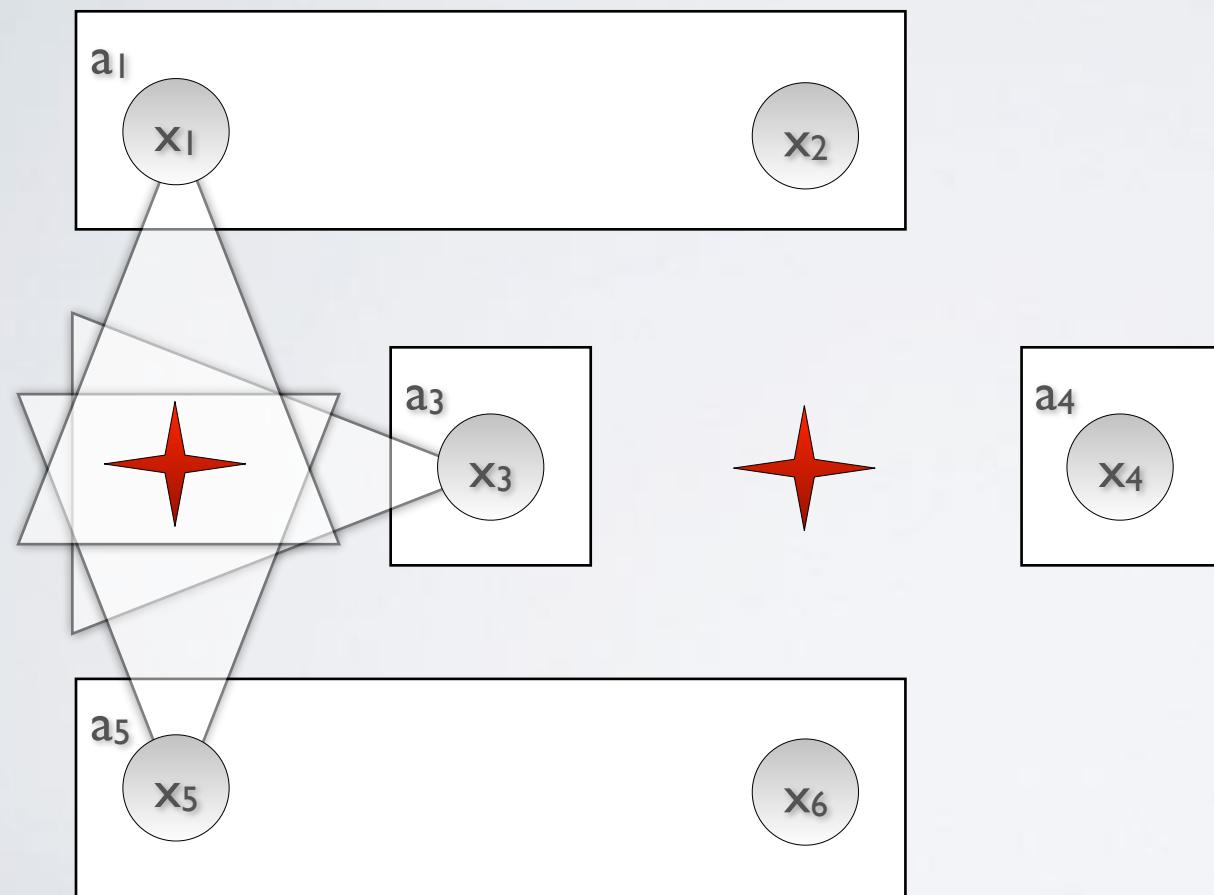
# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION



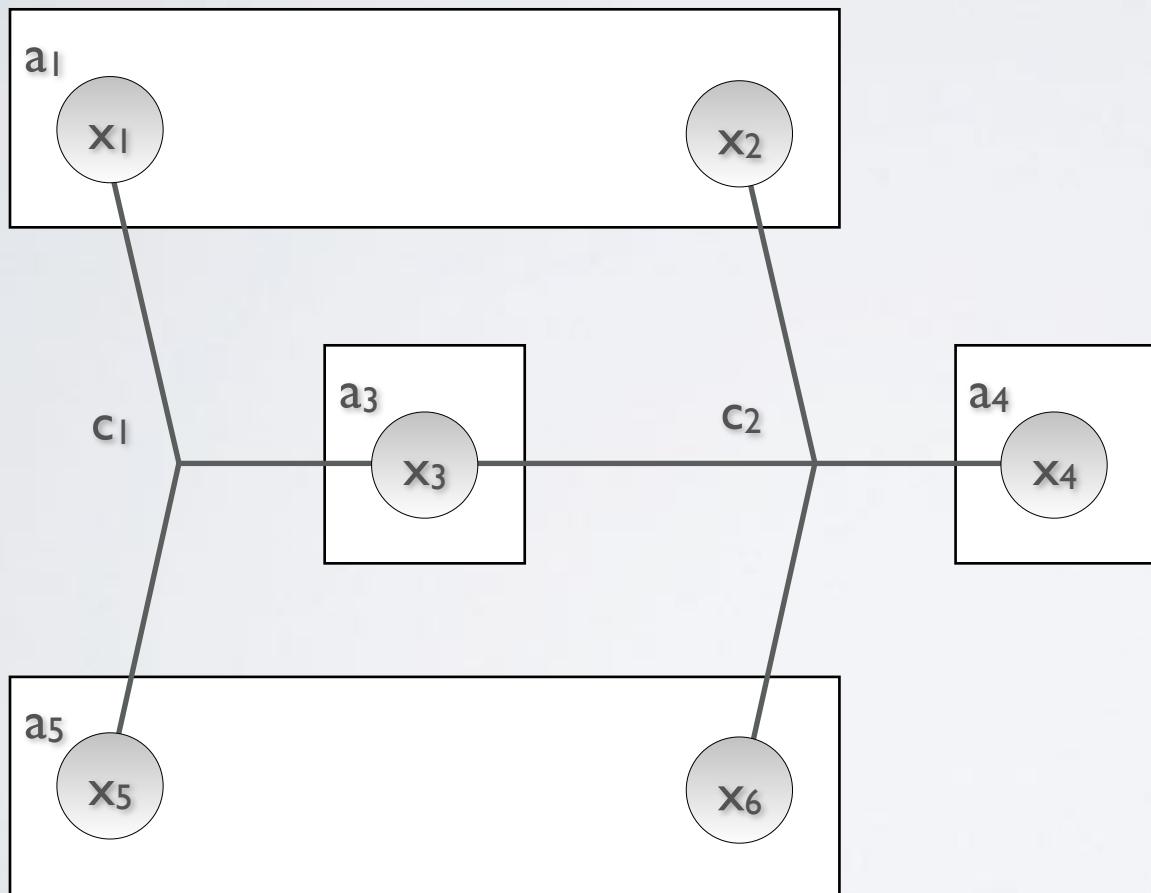
# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION



# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION



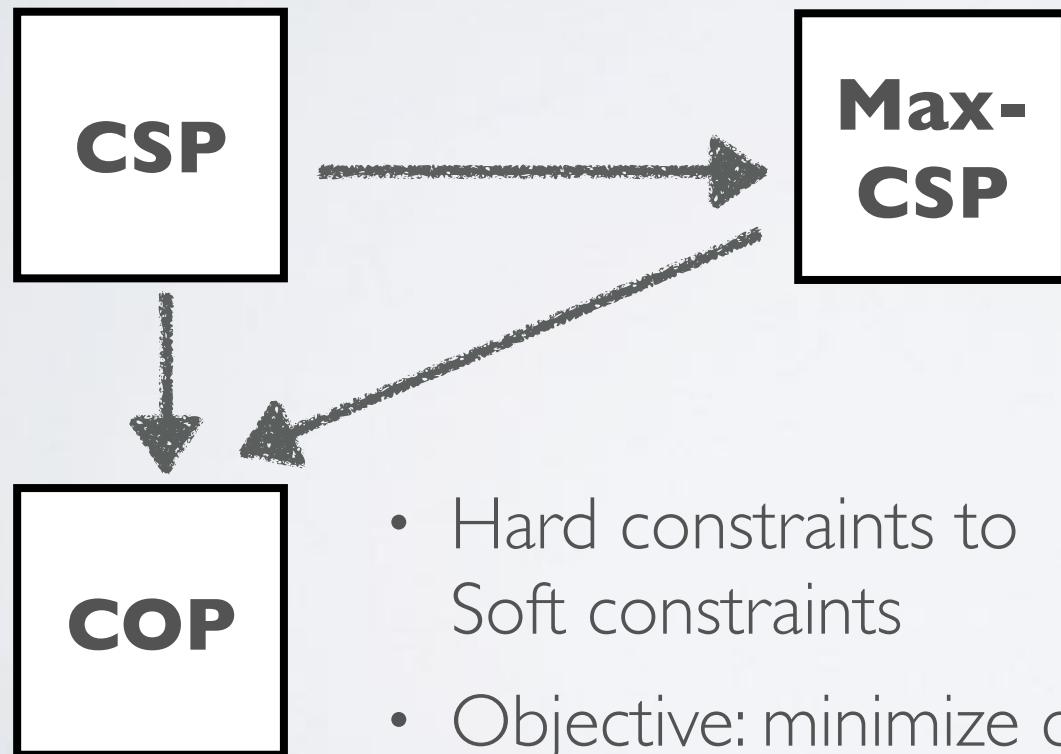
# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION

- Agents  $A = \{a_i, \dots, a_n\}$
- Variables  $X = \{x_1, \dots, x_n\}$
- Domains  $D = \{D_1, \dots, D_n\}$
- Constraints  $C = \{c_1, \dots, c_m\}$
- Mapping of variables to agents
- **GOAL:** Find an assignment that minimizes the sum of the costs of all the constraints

# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION

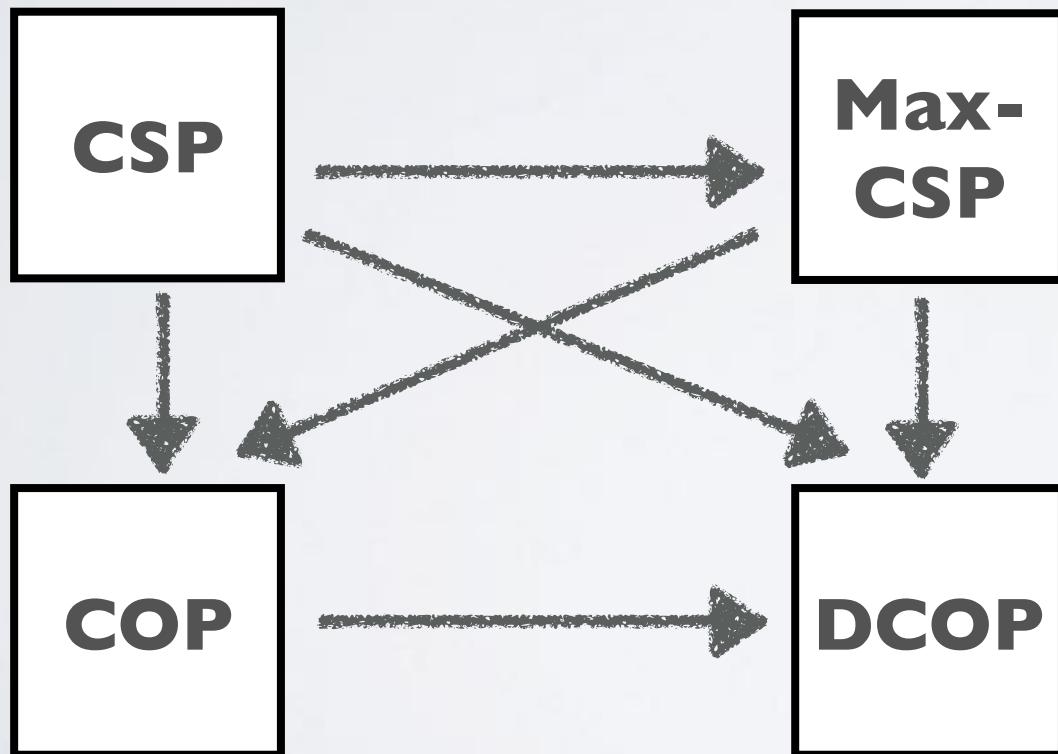


- Objective: maximize #constraints satisfied

- Hard constraints to Soft constraints
- Objective: minimize cost

# DCOP

## DISTRIBUTED CONSTRAINT OPTIMIZATION



- Variables are controlled by agents
- Communication model
- Local agents' knowledge

# DCOP

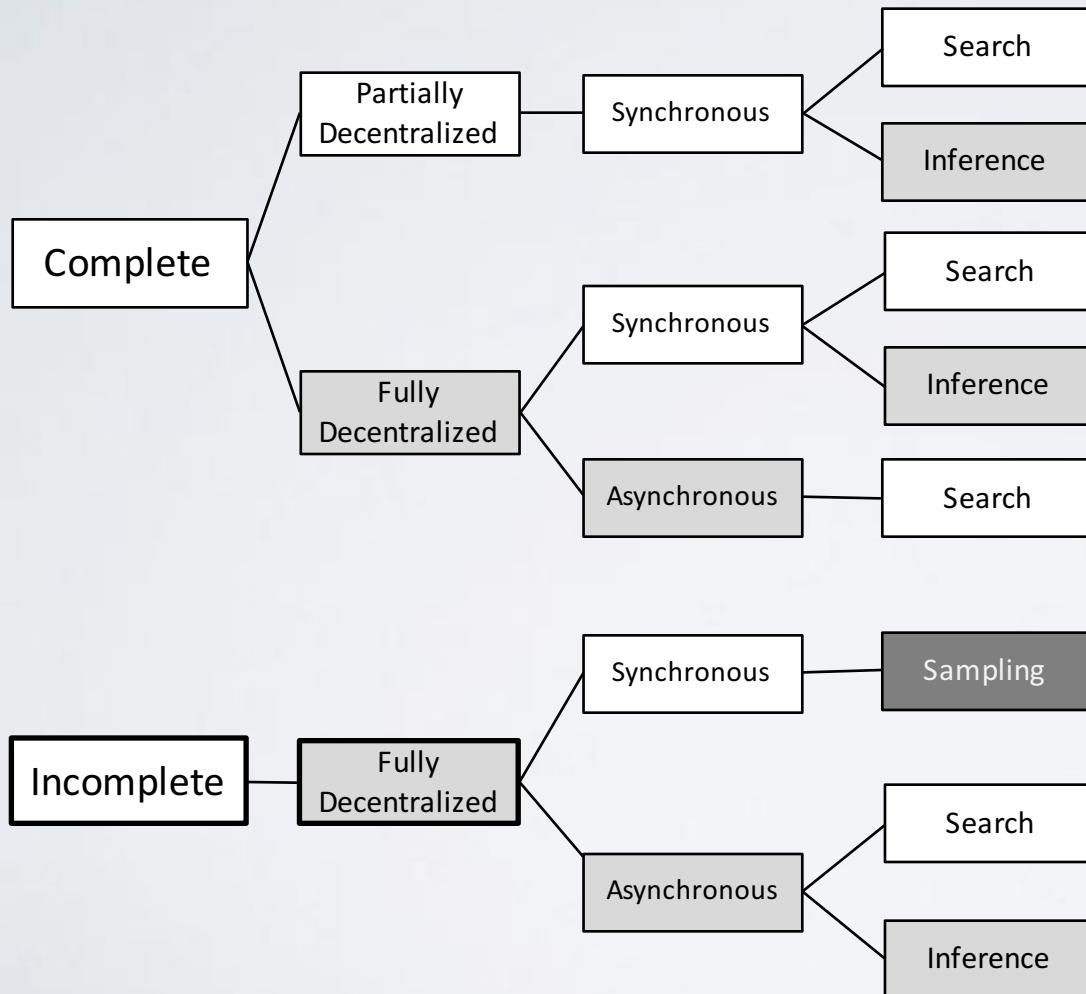
## DISTRIBUTED CONSTRAINT OPTIMIZATION

- Why distributed models?
  - Natural mapping for multi-agent systems
  - Potentially **faster** by exploiting parallelism
  - Potentially more **robust**: no single point of failure, no single network bottleneck
  - Maintains more **private information**
  - ...

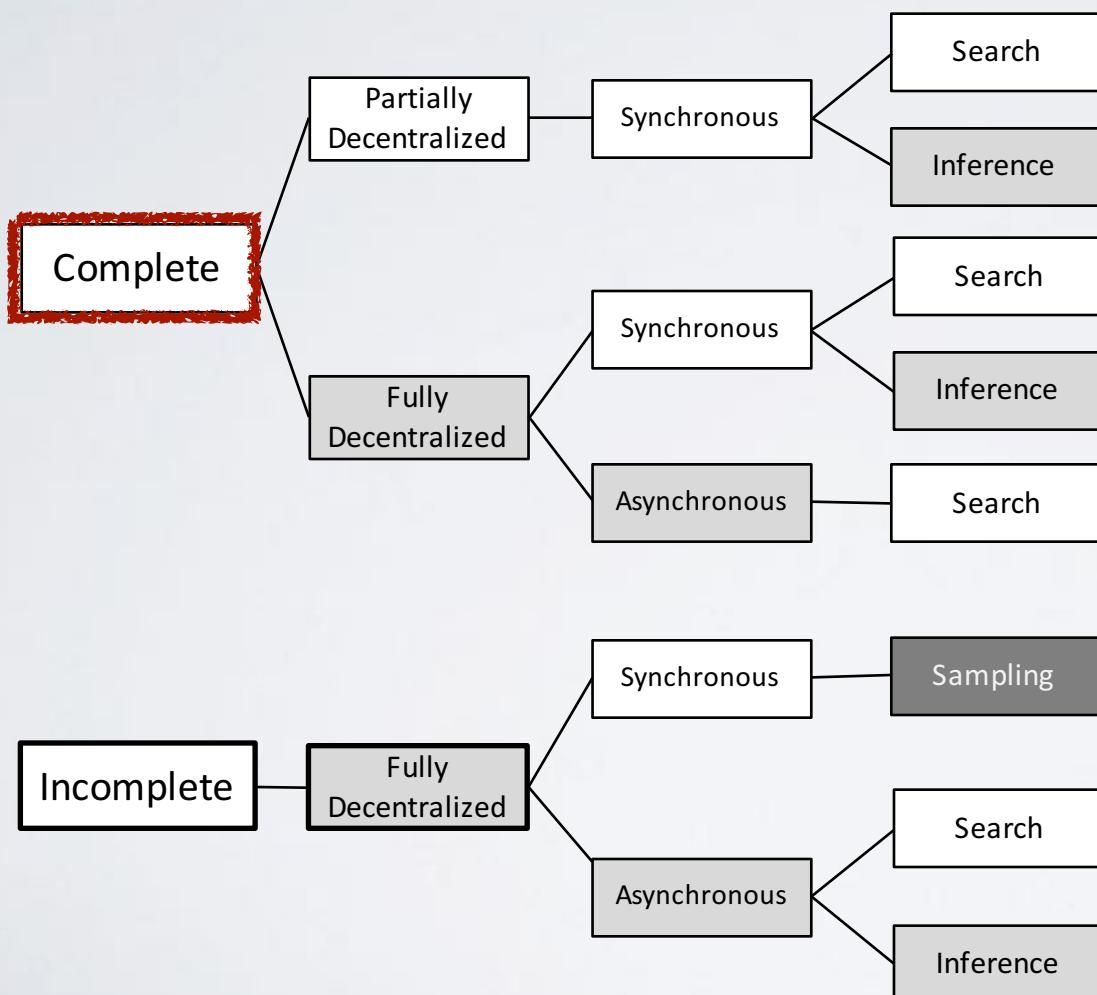
# DCOP ALGORITHMS

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# DCOP ALGORITHMS

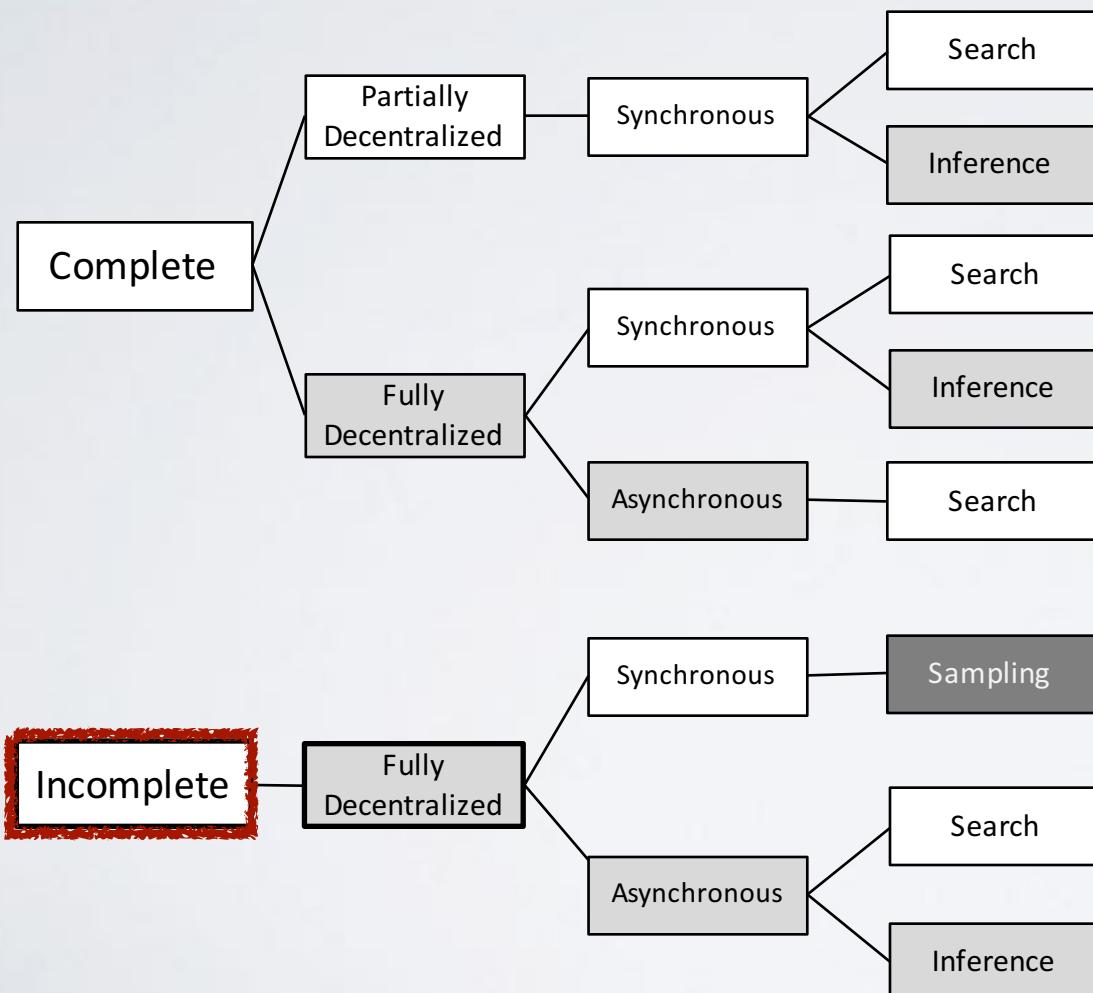


# DCOP ALGORITHMS



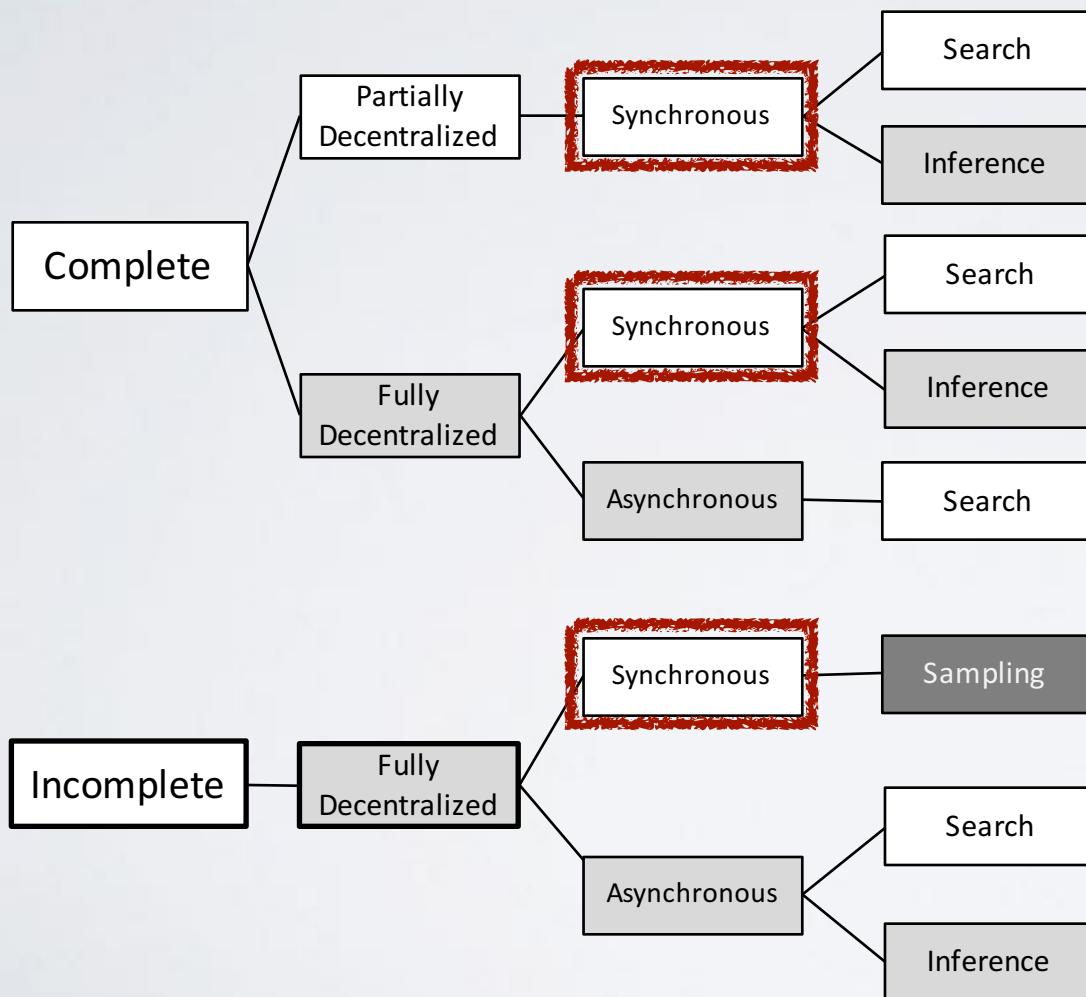
- Important Metrics:
  - Agent complexity
  - Network loads
  - Message size

# DCOP ALGORITHMS



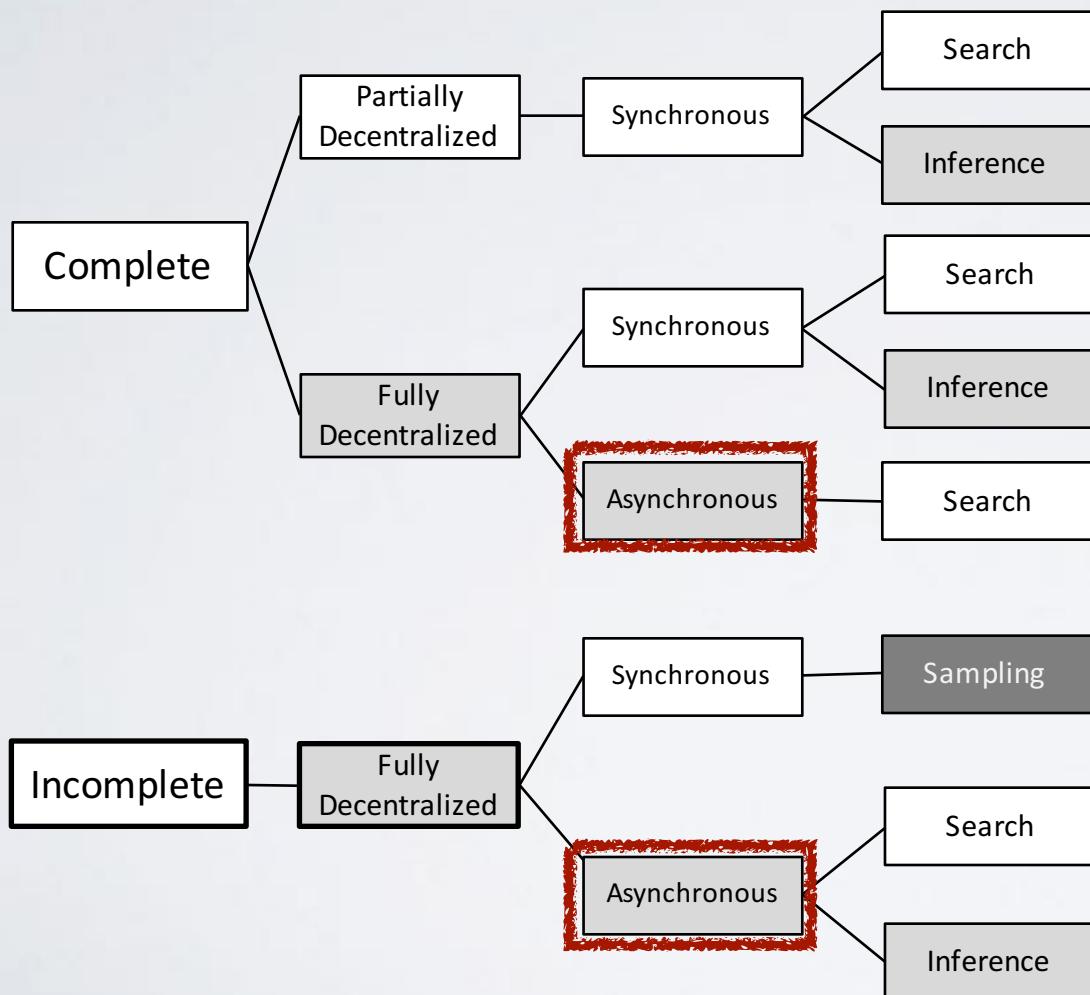
- Important Metrics:
  - Agent complexity
  - Network loads
  - Message size
- Anytime
- Quality guarantees
- Execution time vs. solution quality

# DCOP ALGORITHMS



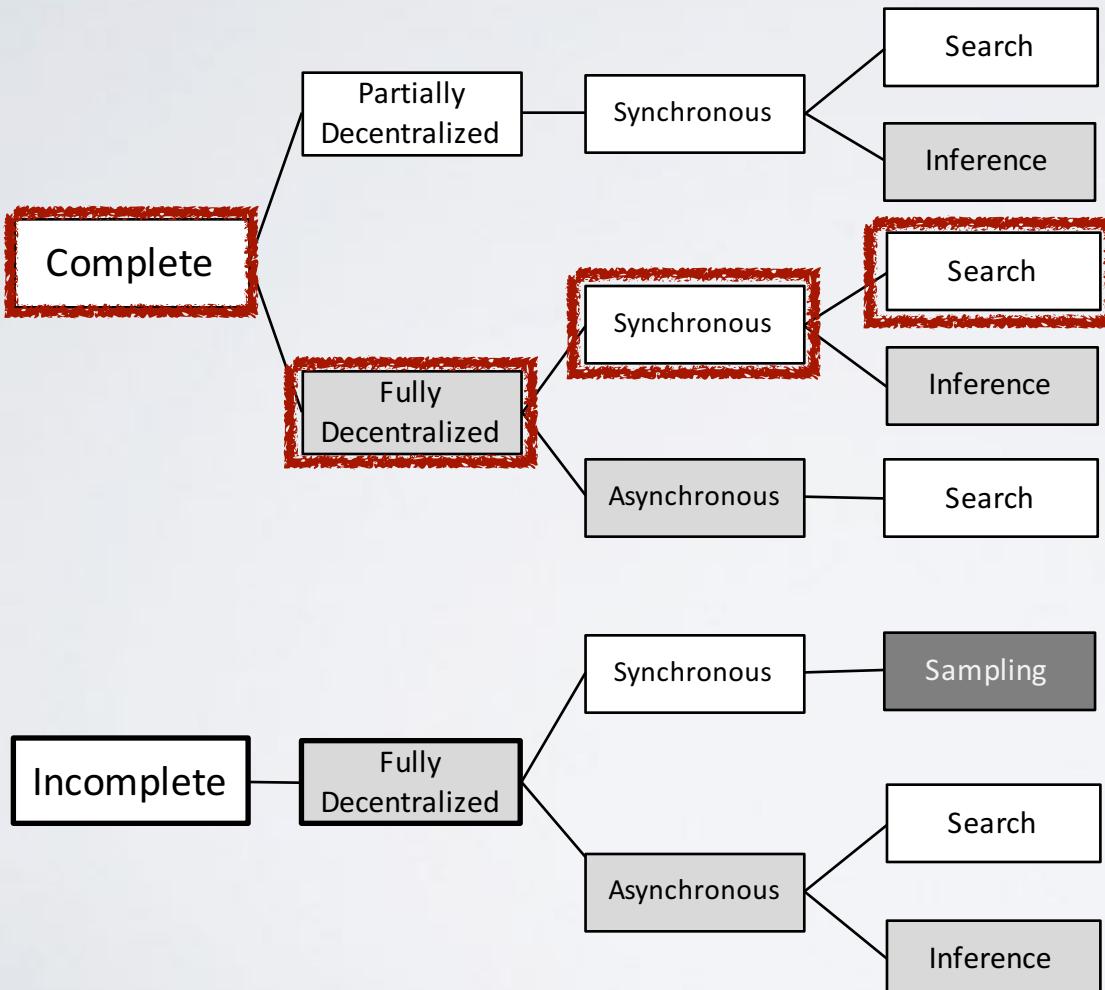
- Systematic process, divided in steps.
- Each agent waits for particular messages before acting
- Consistent view of the search process
- Typically, increases idle-time

# DCOP ALGORITHMS



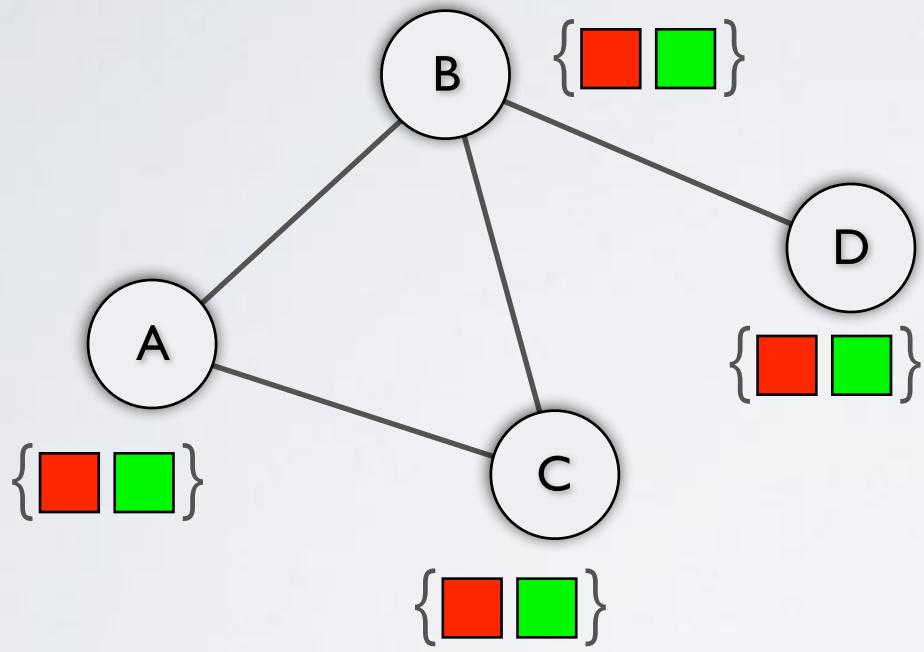
- Decision based on agents' local state
- Agents' actions do not depend on sequence of received messages
- Minimizes idle-time
- No guarantees on validity of local views

# DCOP ALGORITHMS



Synchronous Branch and Bound (SBB)

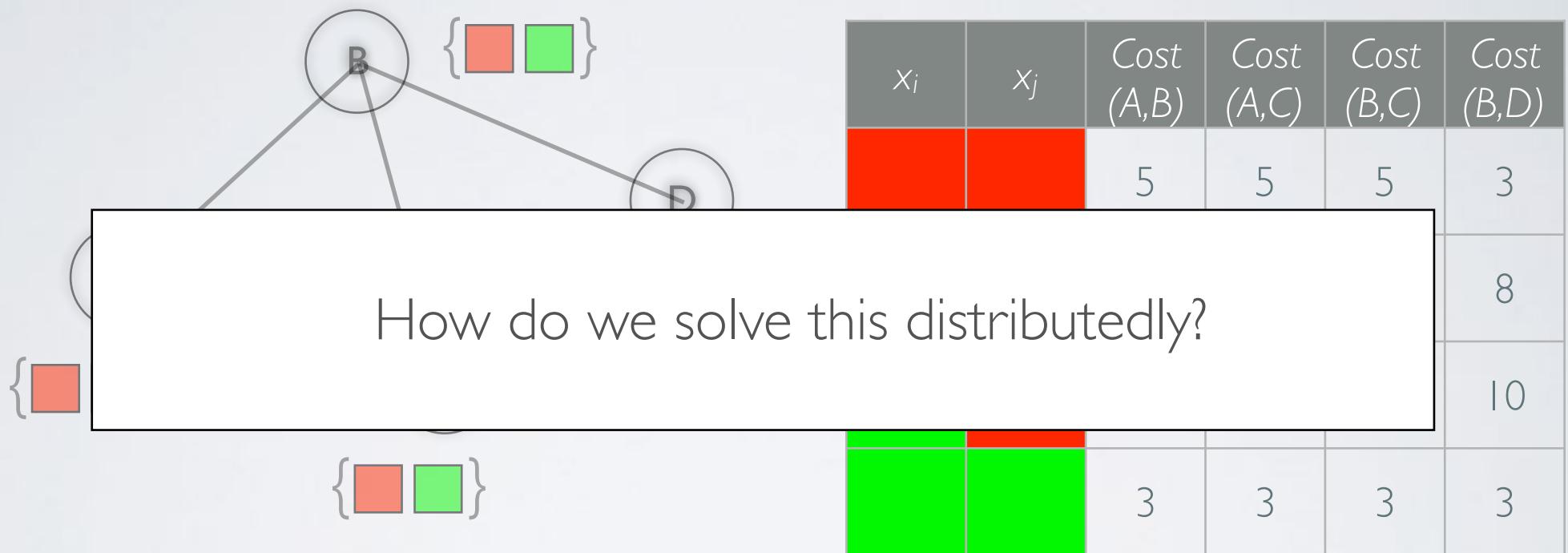
# SBB



$x_i$	$x_j$	Cost (A,B)	Cost (A,C)	Cost (B,C)	Cost (B,D)
Red	Red	5	5	5	3
Red	Green	8	10	4	8
Green	Red	20	20	3	10
Green	Green	3	3	3	3

Katsutoshi Hirayama, Makoto Yokoo: Distributed Partial Constraint Satisfaction Problem. CP 1997: 222-236

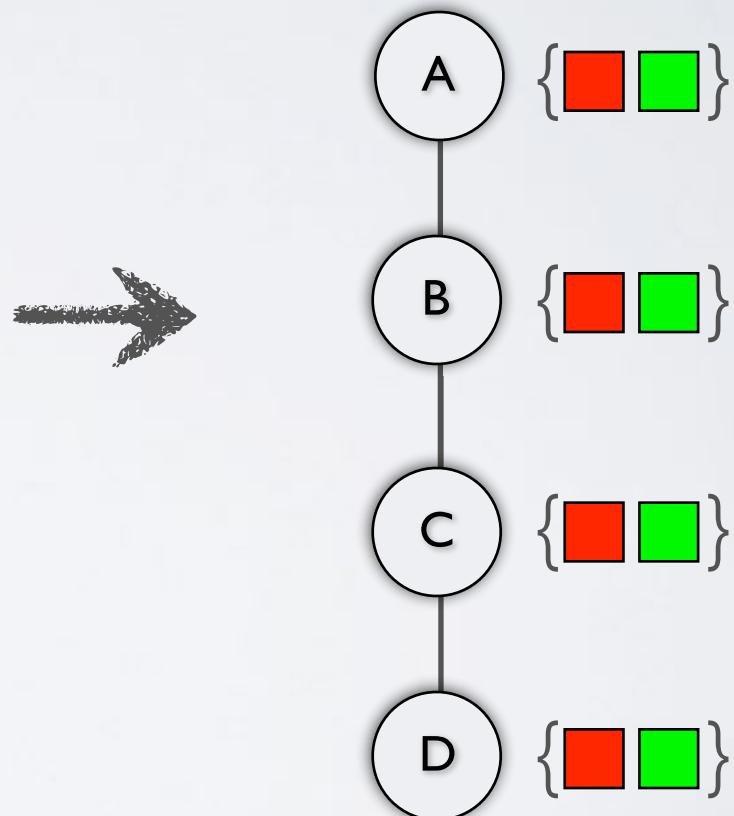
# SBB



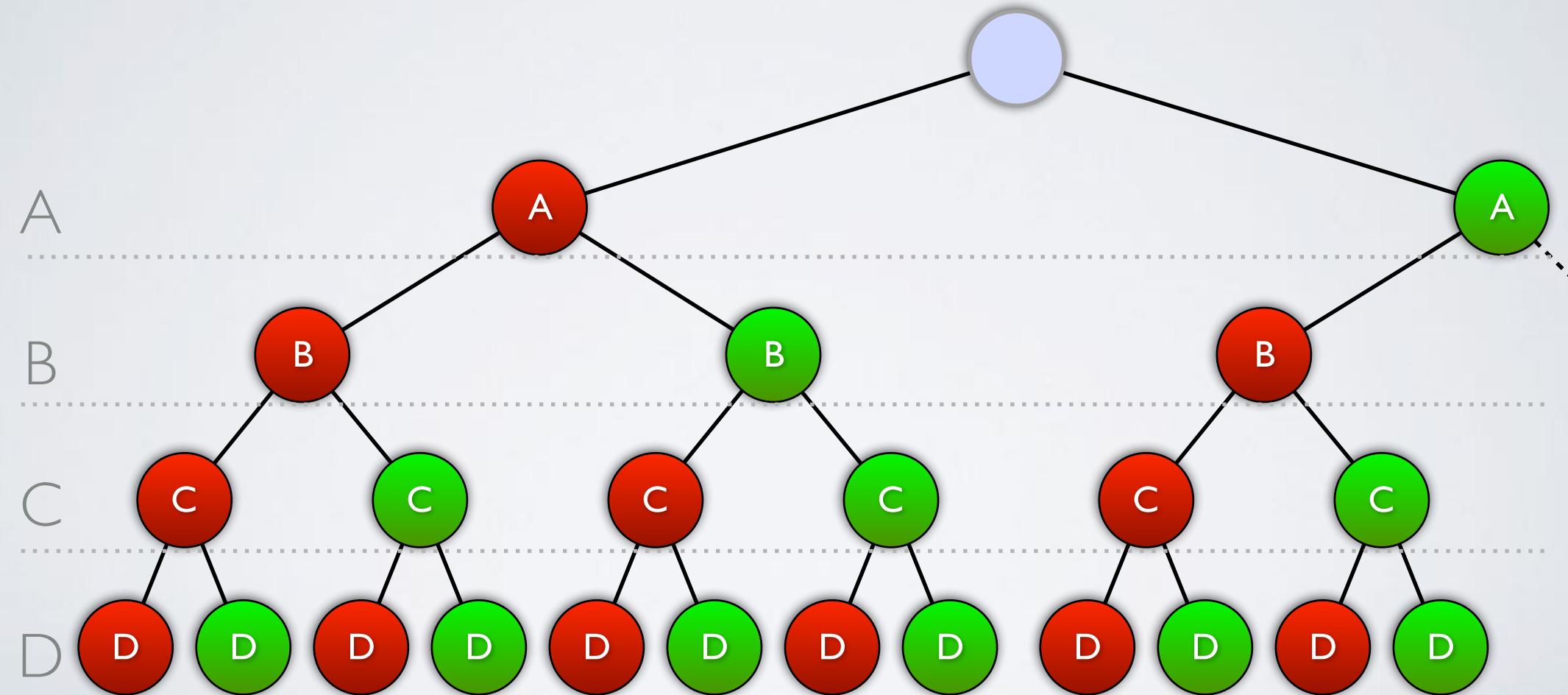
# SBB

- Agents operate on a complete ordering
- Agents exchange CPA messages containing partial assignments.
- When a solution is found a LB is broadcasted to all agents.
- The LB is used for branch pruning.

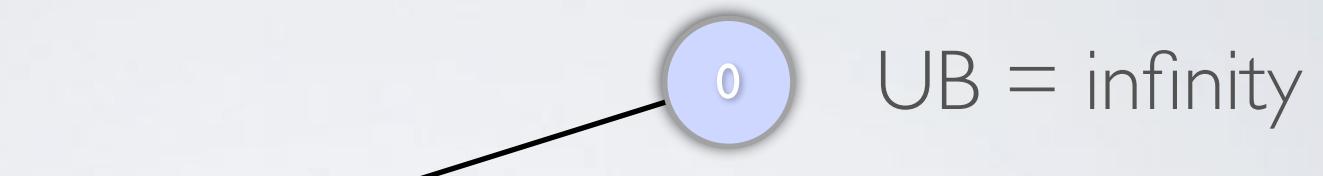
Complete Ordering



# SBB



# SBB



A

B

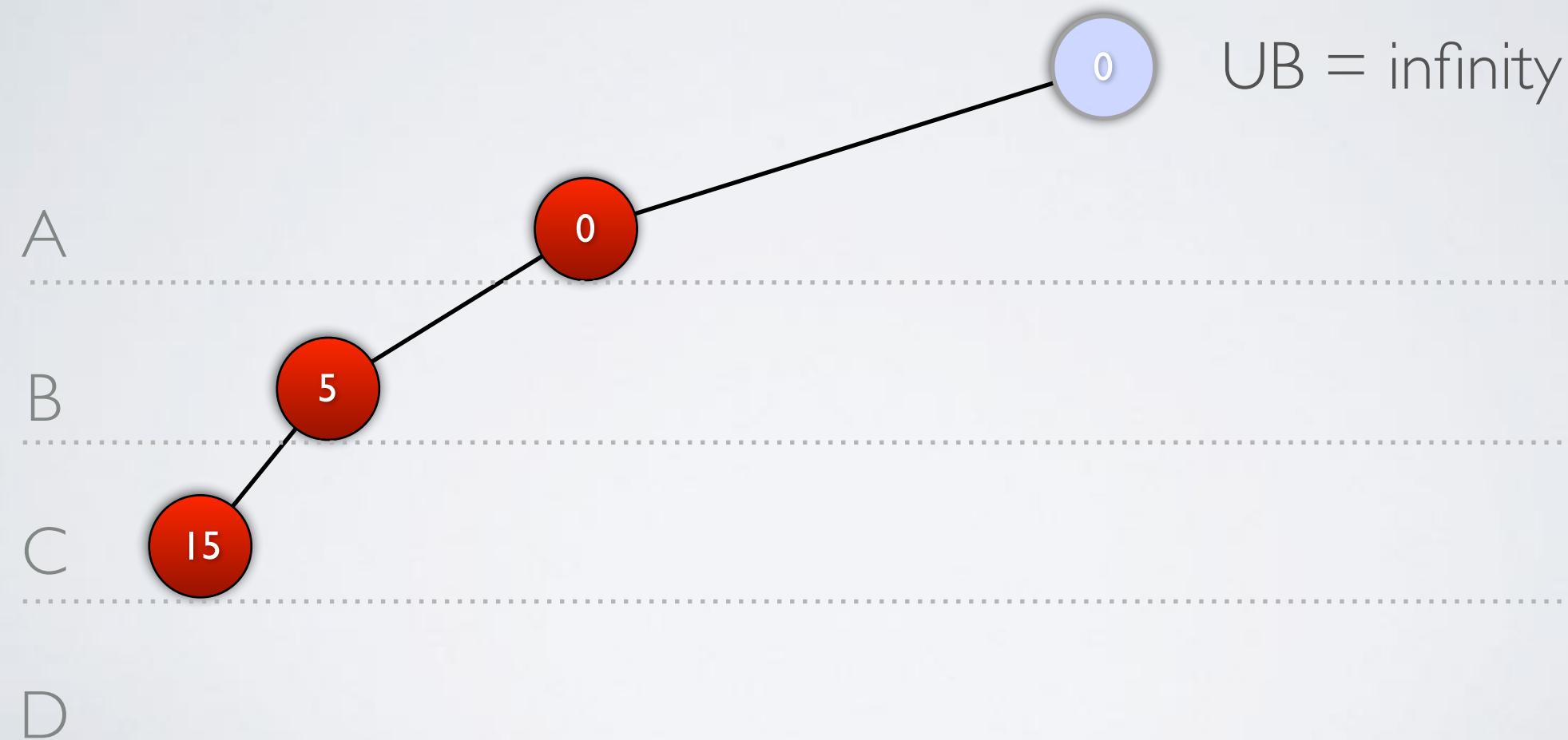
C

D

# SBB



# SBB



# SBB

UB = 18

A

B

C

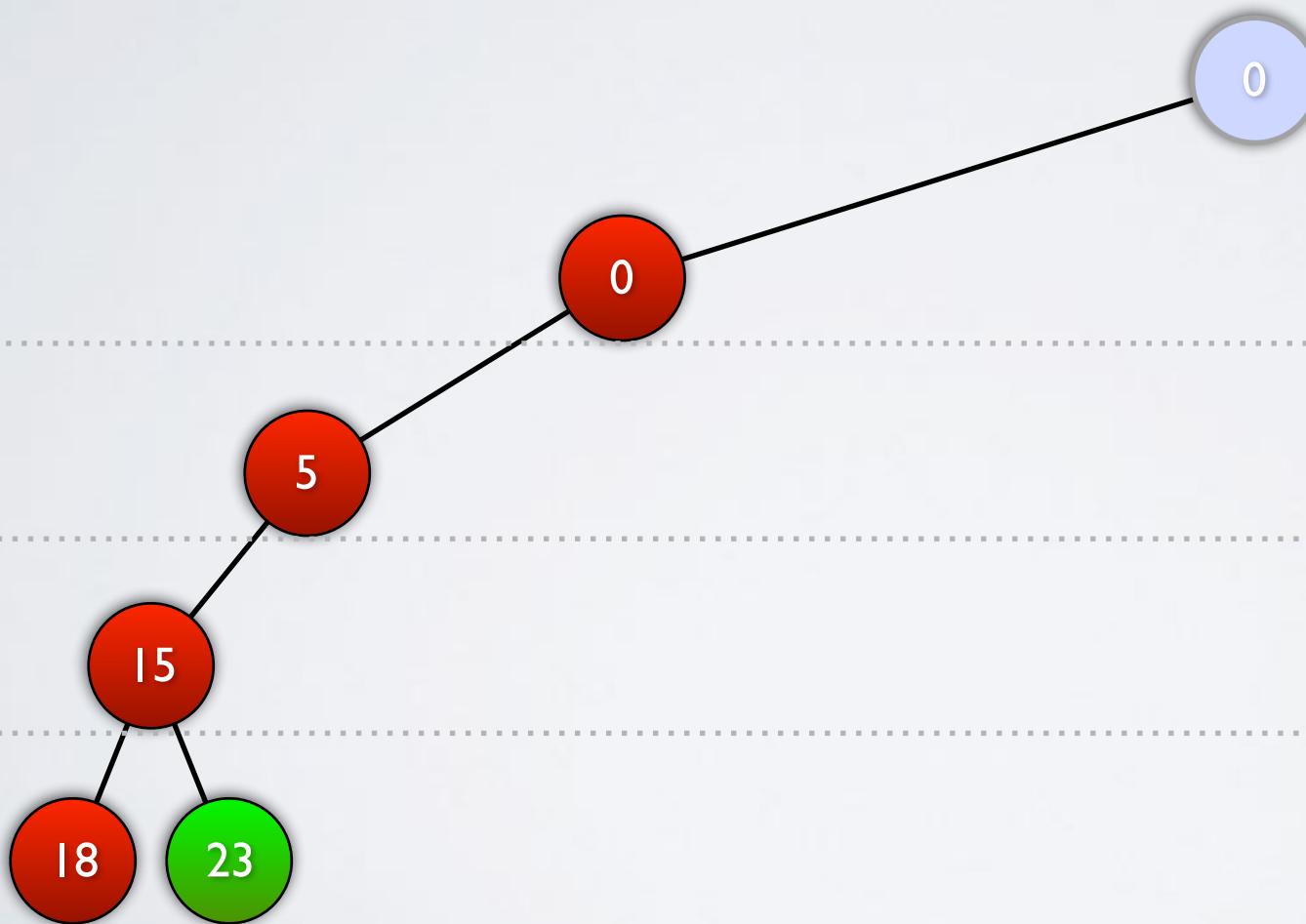
D



# SBB

UB = 18

A  
B  
C  
D



# SBB

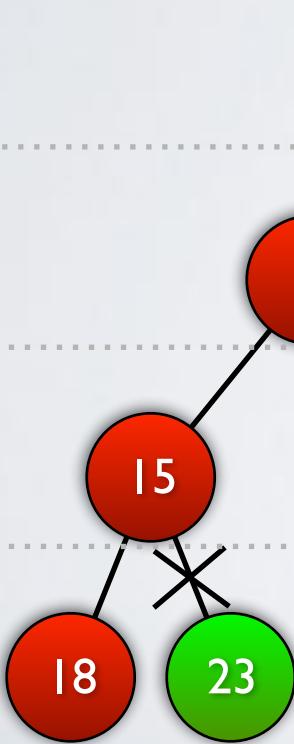
UB = 18

A

B

C

D



# SBB

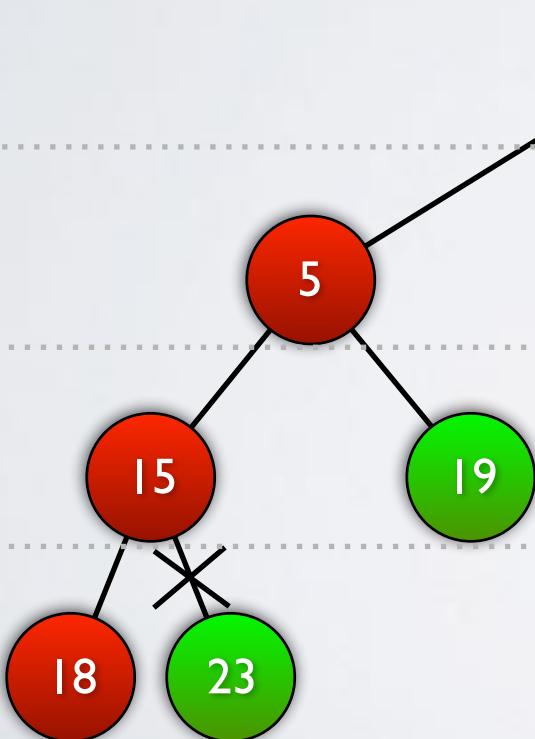
UB = 18

A

B

C

D



# SBB

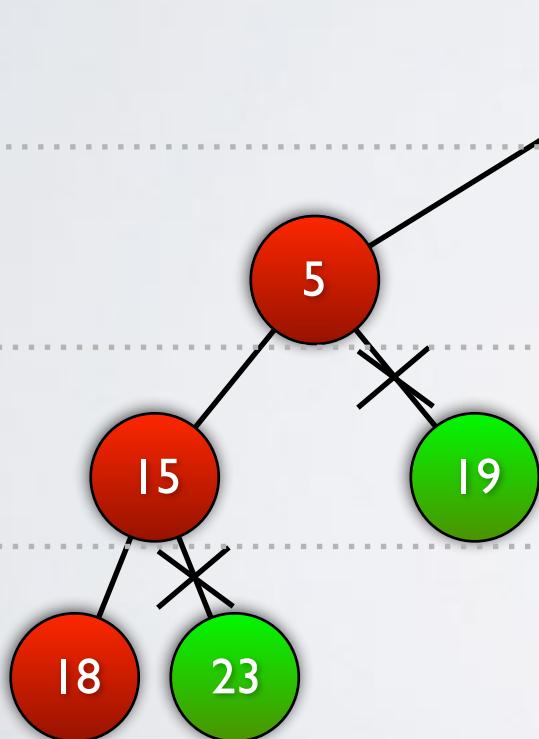
UB = 18

A

B

C

D



# SBB

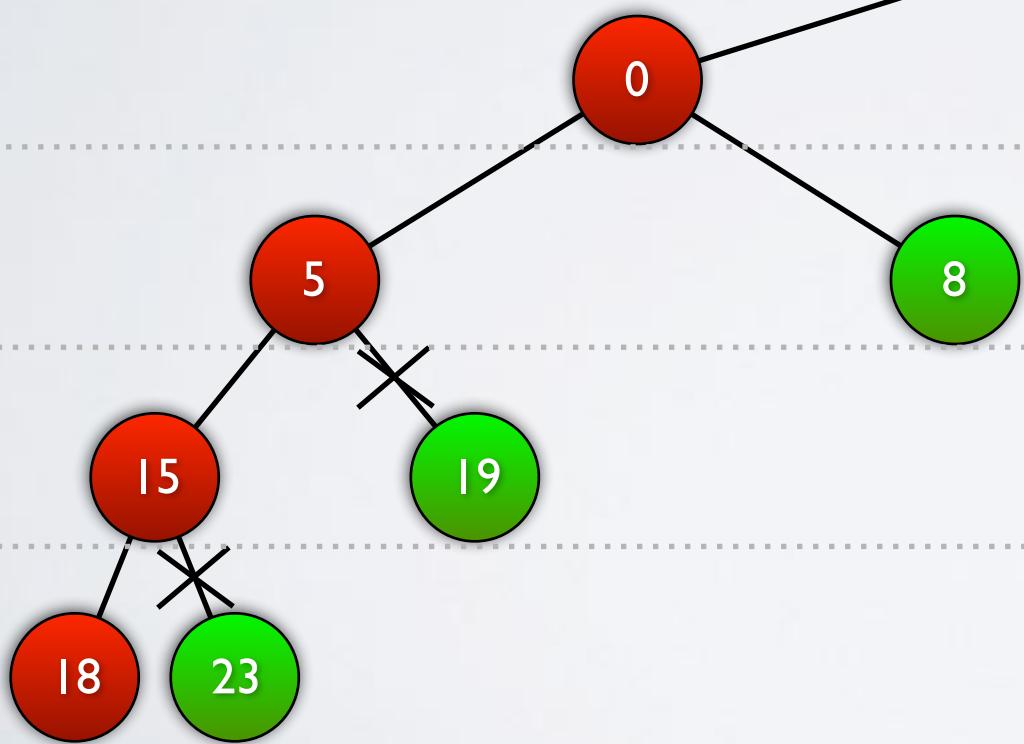
UB = 18

A

B

C

D



# SBB

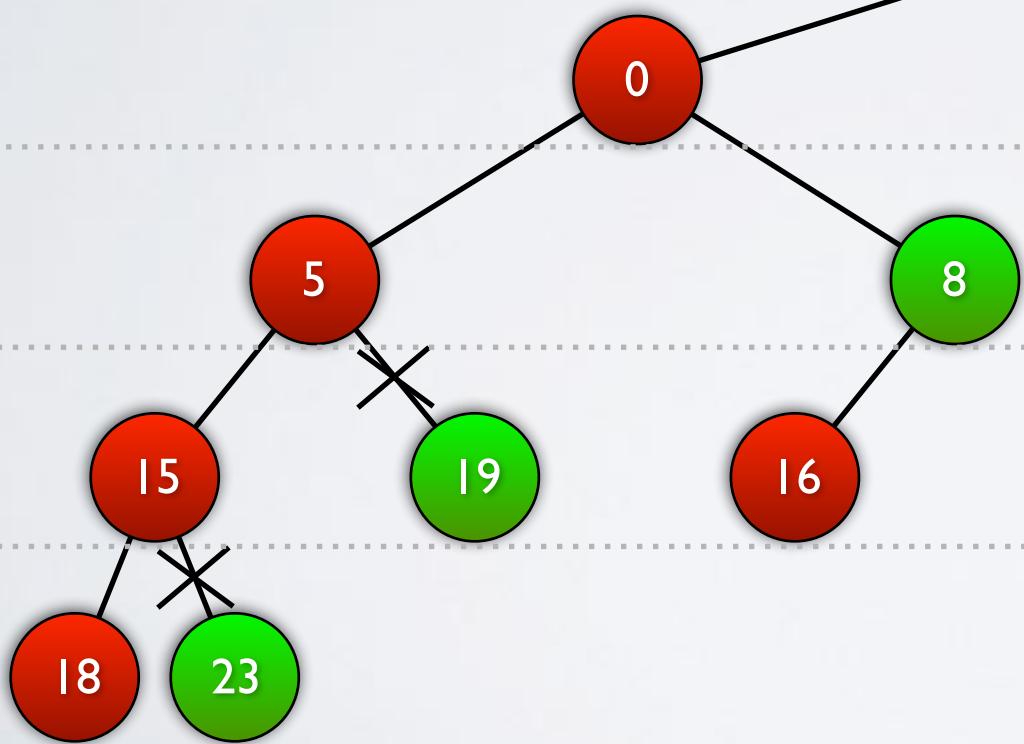
UB = 18

A

B

C

D



# SBB

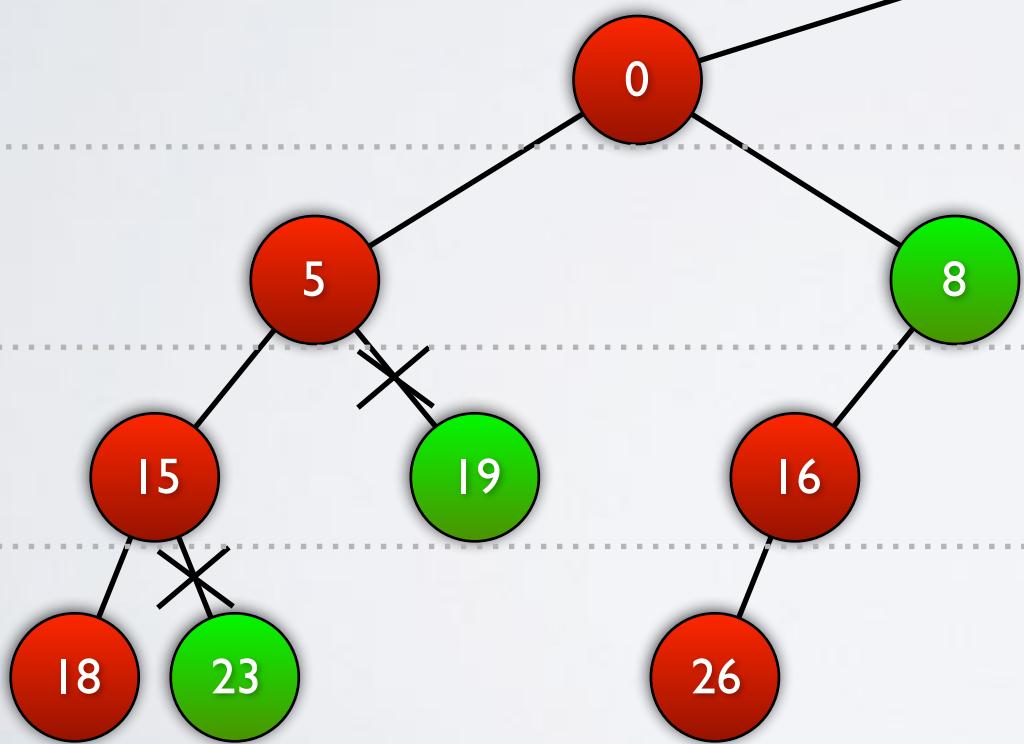
UB = 18

A

B

C

D



# SBB

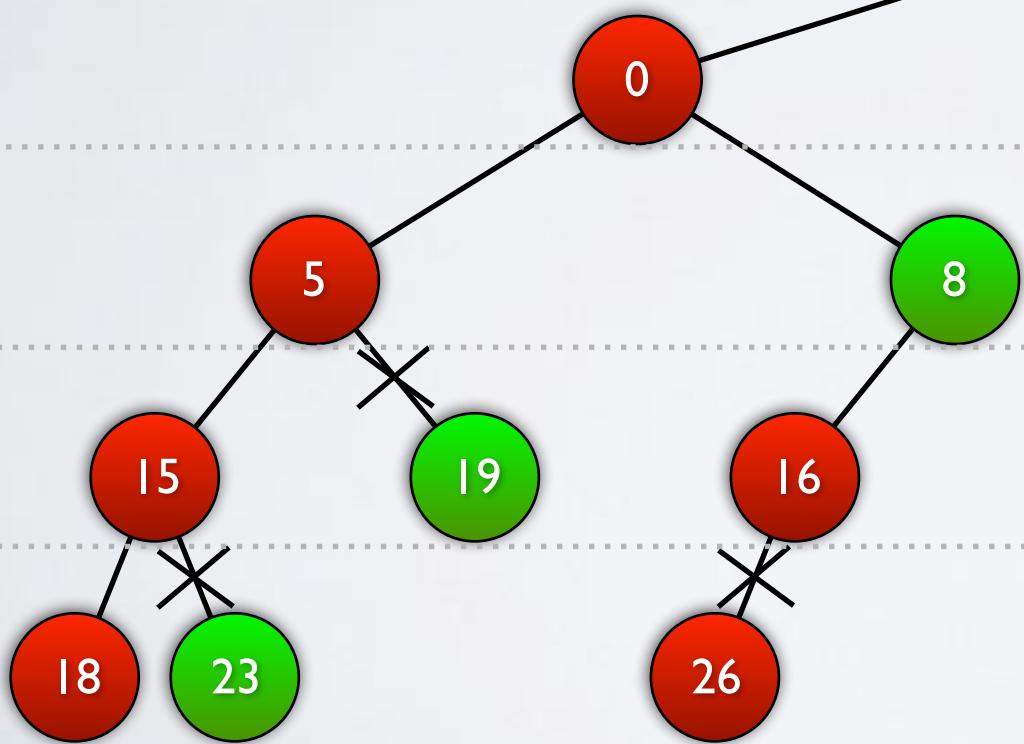
UB = 18

A

B

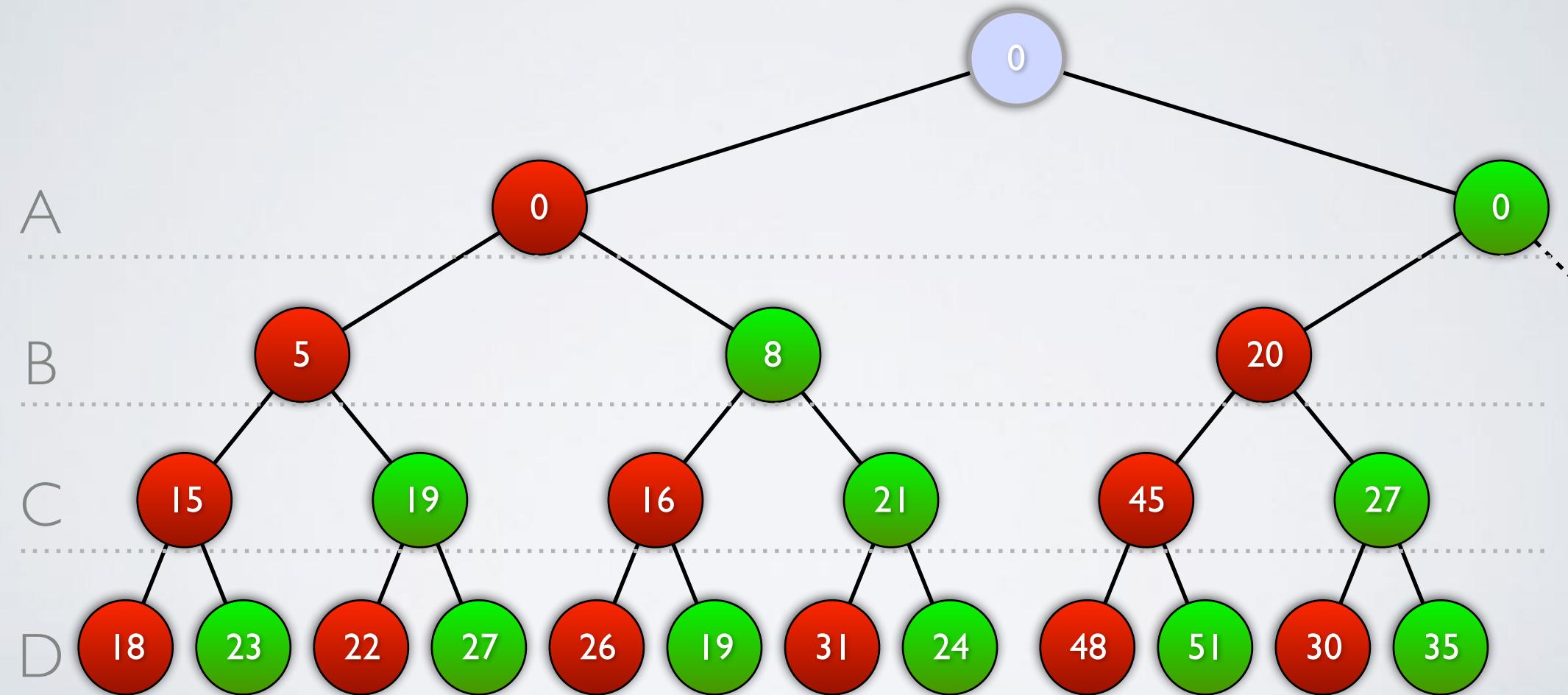
C

D



# SBB

A  
B  
C  
D



# SBB

	SBB
Correct the solution it finds is optimal	Yes
Complete it terminates	Yes
Message Complexity max size of a message	$O(d)$
Network Load max number of messages	$O(b^d)$
Runtime max number of cycles	$O(b^d)$

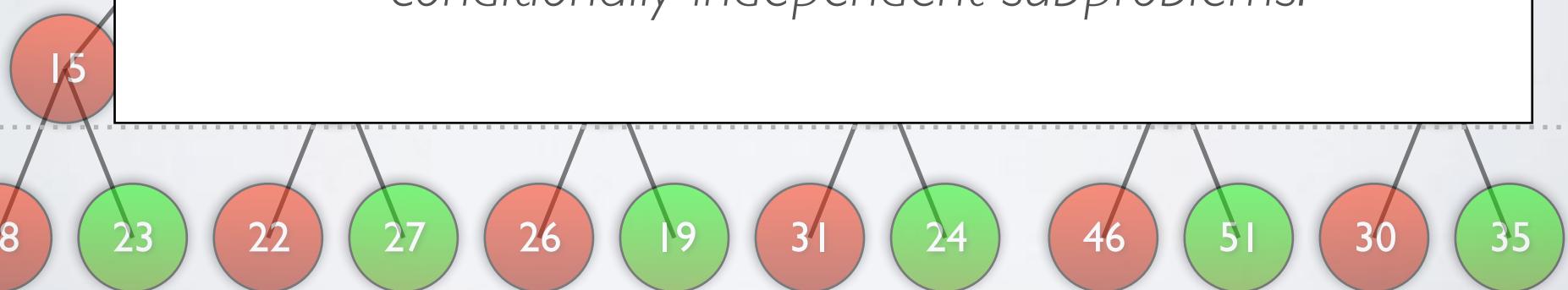
branching factor =  $b$   
num variables =  $d$

# SBB

A  
B  
C  
D

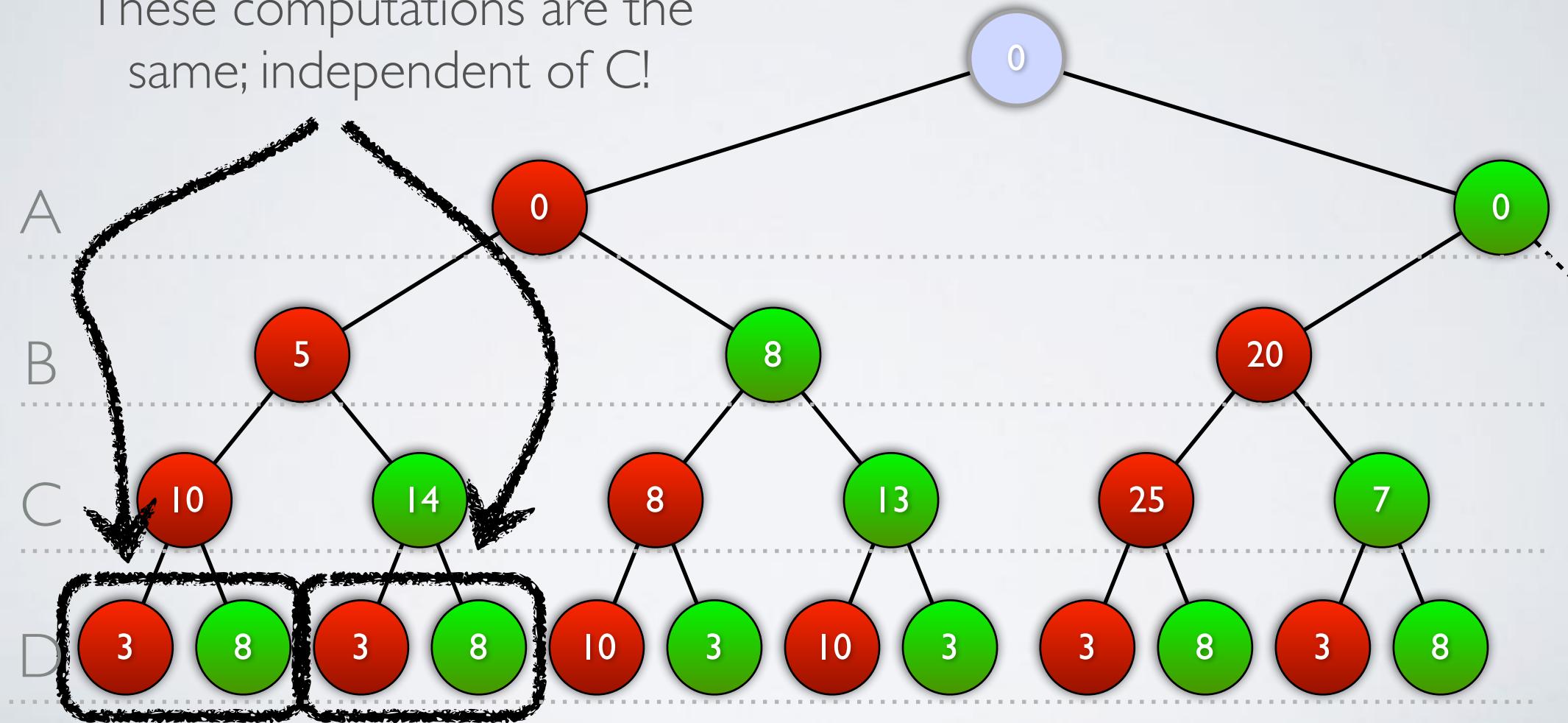
Can we speed this up by parallelizing some computations?

*Hint: Are there independent or conditionally independent subproblems?*

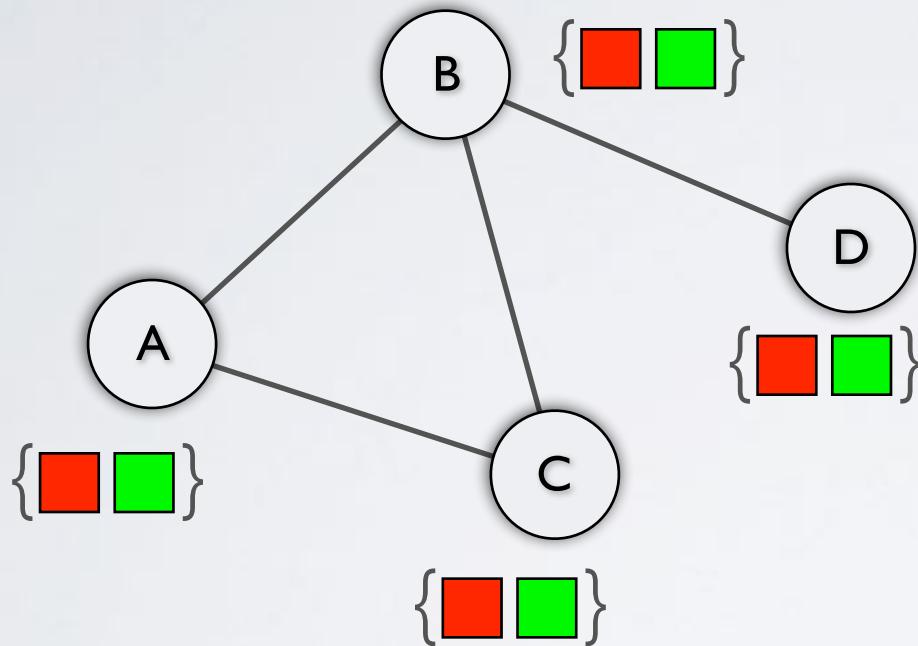


# SBB

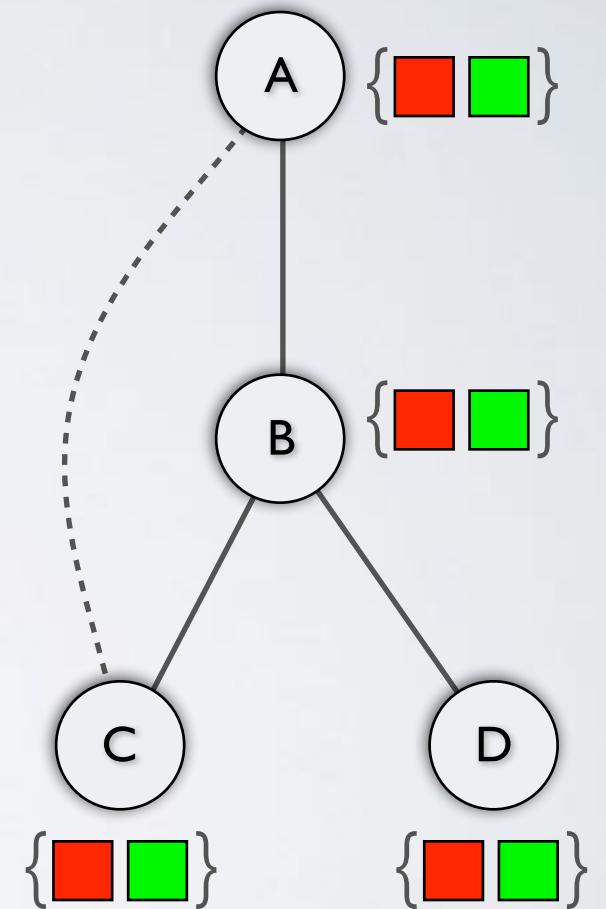
These computations are the same; independent of C!



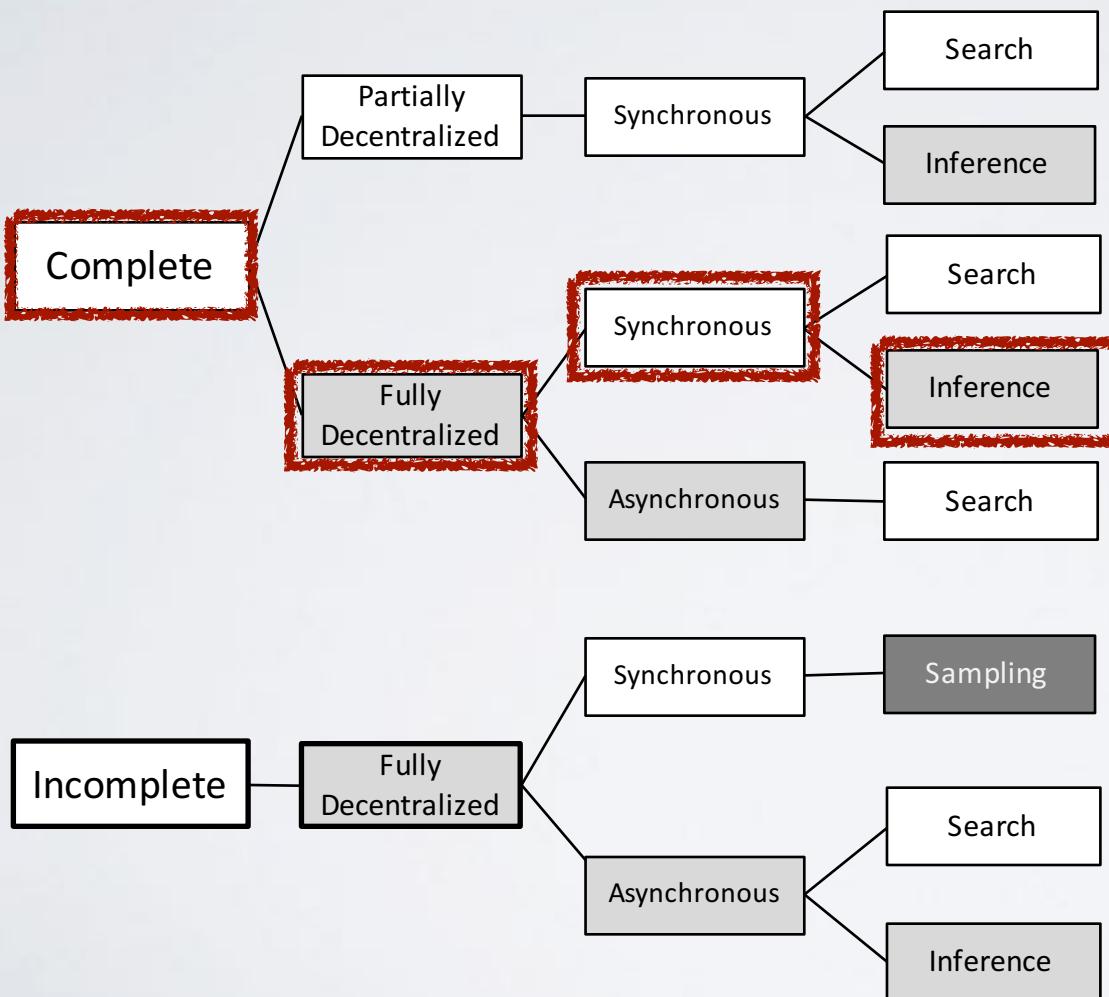
# PSEUDO-TREE



Definition: A *spanning tree of the constraint graph such that no two nodes in sibling subtrees share a constraint in the constraint graph*



# DCOP ALGORITHMS

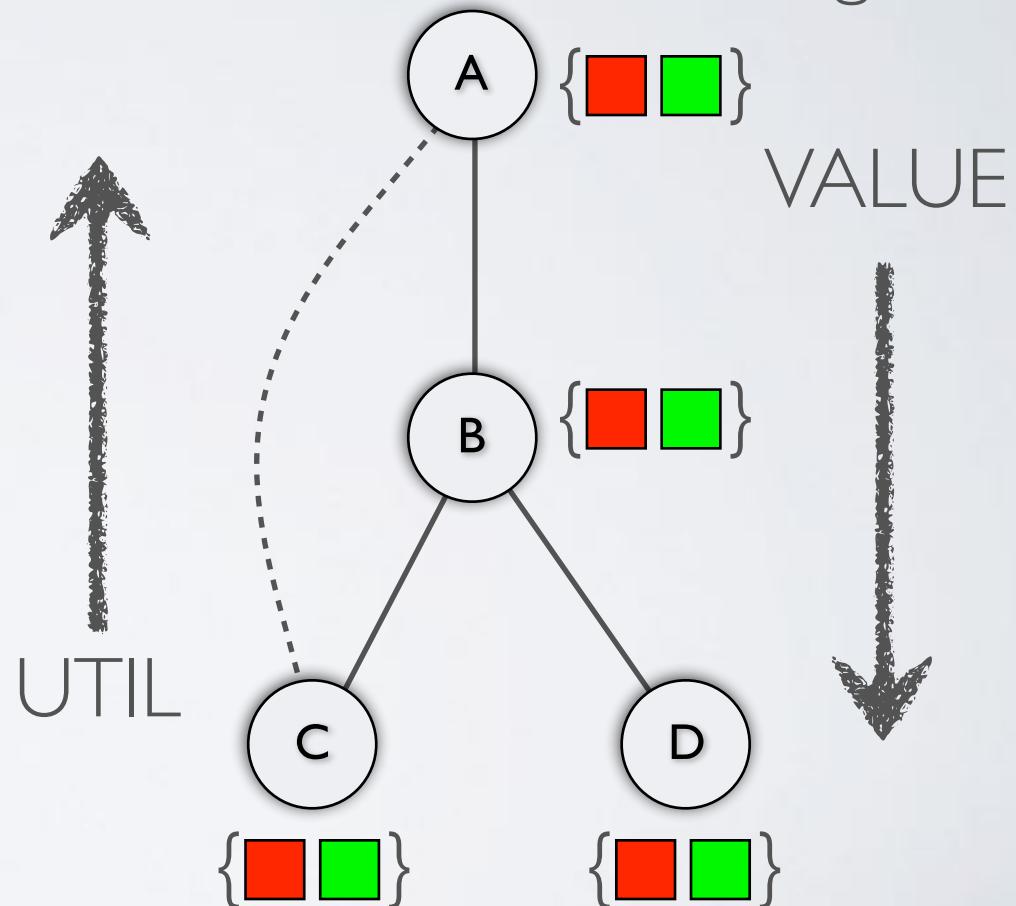


Distributed Pseudotree  
Optimization Procedure  
(DPOP)

# DPOP

- Extension of the Bucket Elimination (BE)
- Agents operate on a pseudo-tree ordering
- UTIL phase: Leaves to root
- VALUE phase: Root to leaves

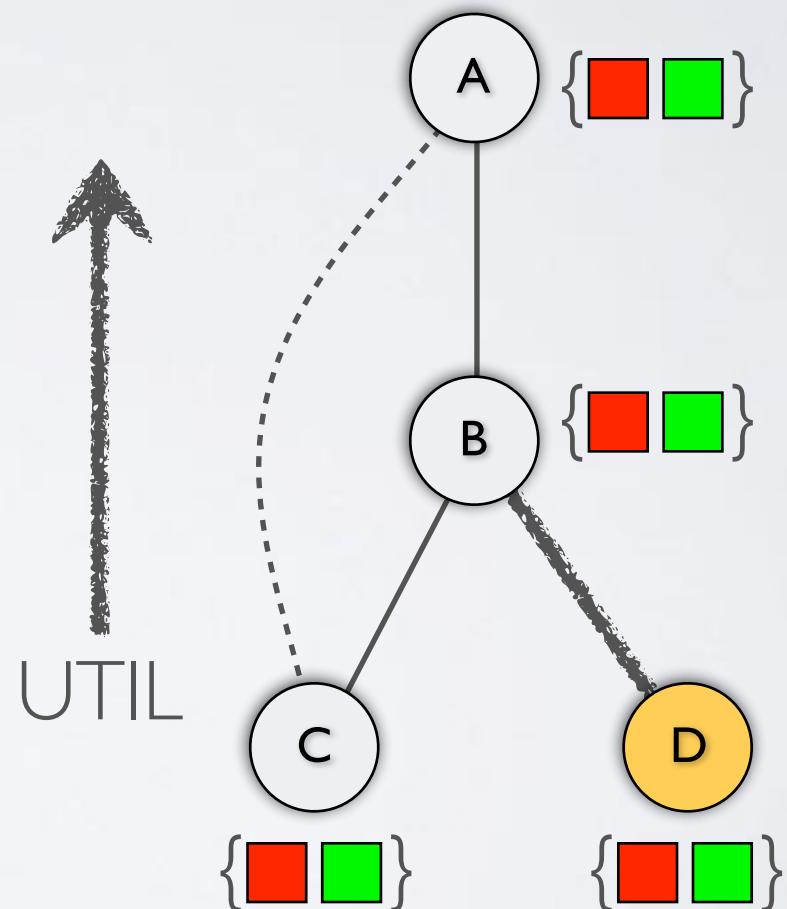
Pseudo-tree Ordering



# DPOP

B	D	(B,D)
r	r	3
r	g	8
g	r	10
g	g	3

Pseudo-tree Ordering



# DPOP

B	D	(B,D)
r	r	3
r	g	8
g	r	10
g	g	3

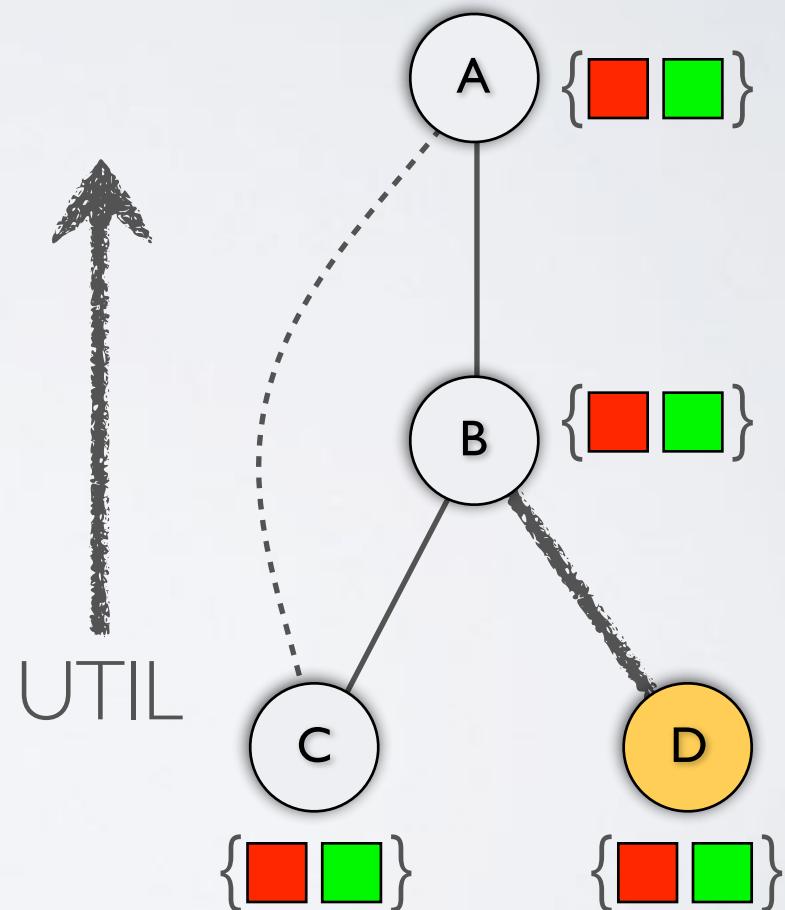
$$\min\{3, 8\} = 3$$

$$\min\{10, 3\} = 3$$

MSG to B

B	cost
r	3
g	3

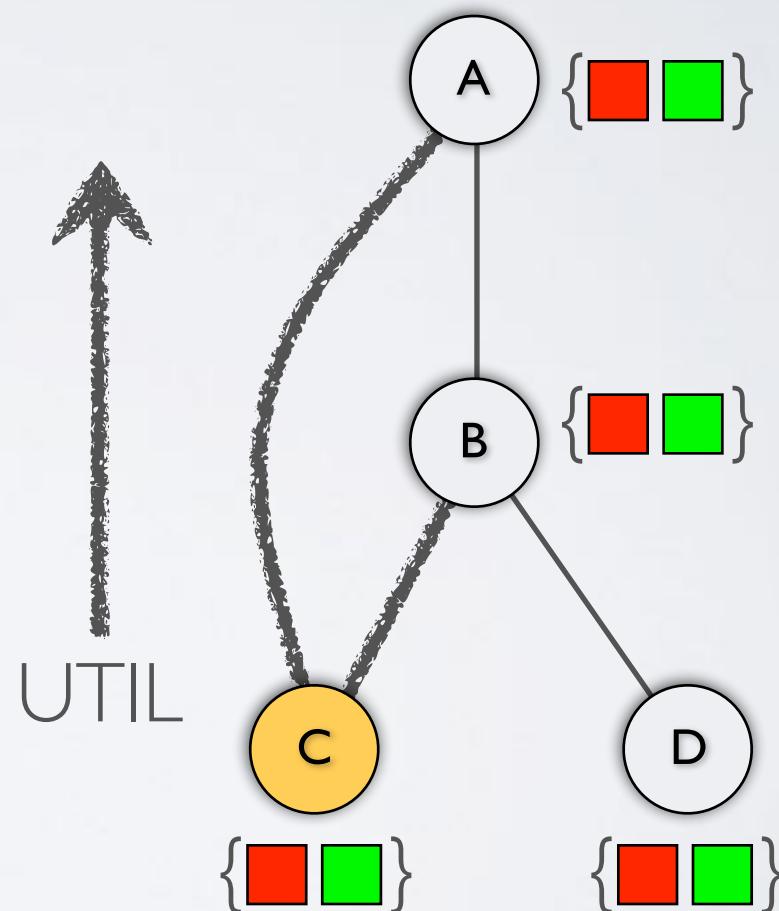
Pseudo-tree Ordering



# DPOP

A	B	C	(B,C)	(A,C)	
r	r	r	5	5	10
r	r	g	4	8	12
r	g	r	3	5	8
r	g	g	3	8	11
g	r	r	5	10	15
g	r	g	4	3	7
g	g	r	3	10	13
g	g	g	3	3	6

Pseudo-tree Ordering



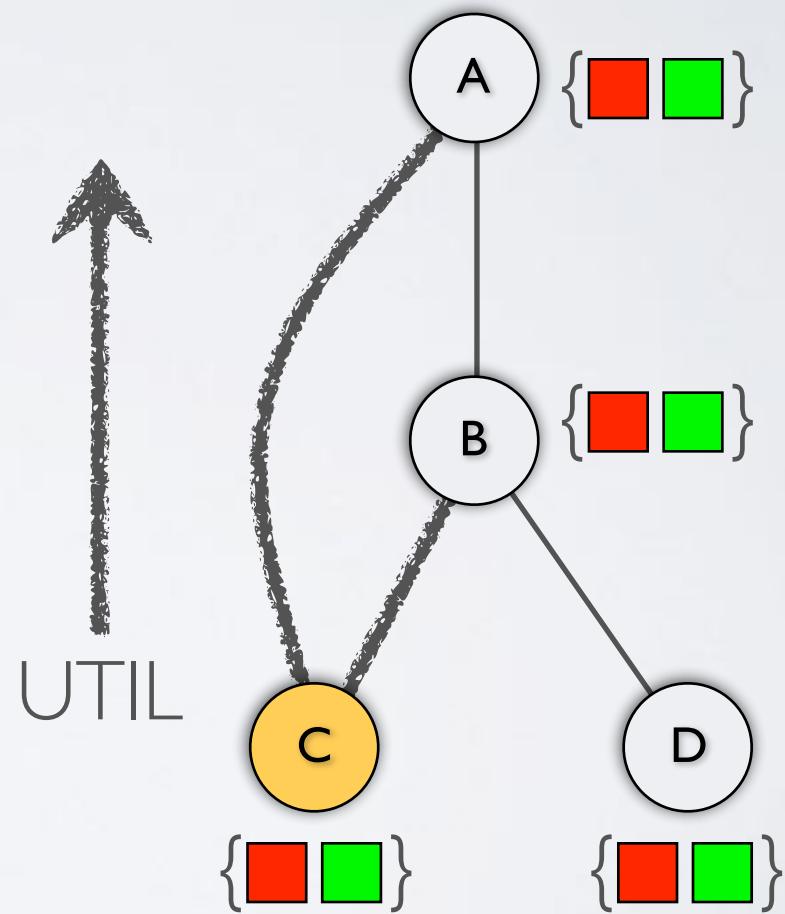
# DPOP

A	B	C	(B,C)	(A,C)	
r	r	r	5	5	10
r	r	g	4	8	12
r	g	r	3	5	8
r	g	g	3	8	11
g	r	r	5	10	15
g	r	g	4	3	7
g	g	r	3	10	13
g	g	g	3	3	6

MSG to B

A	B	
r	r	10
r	g	8
g	r	7
g	g	6

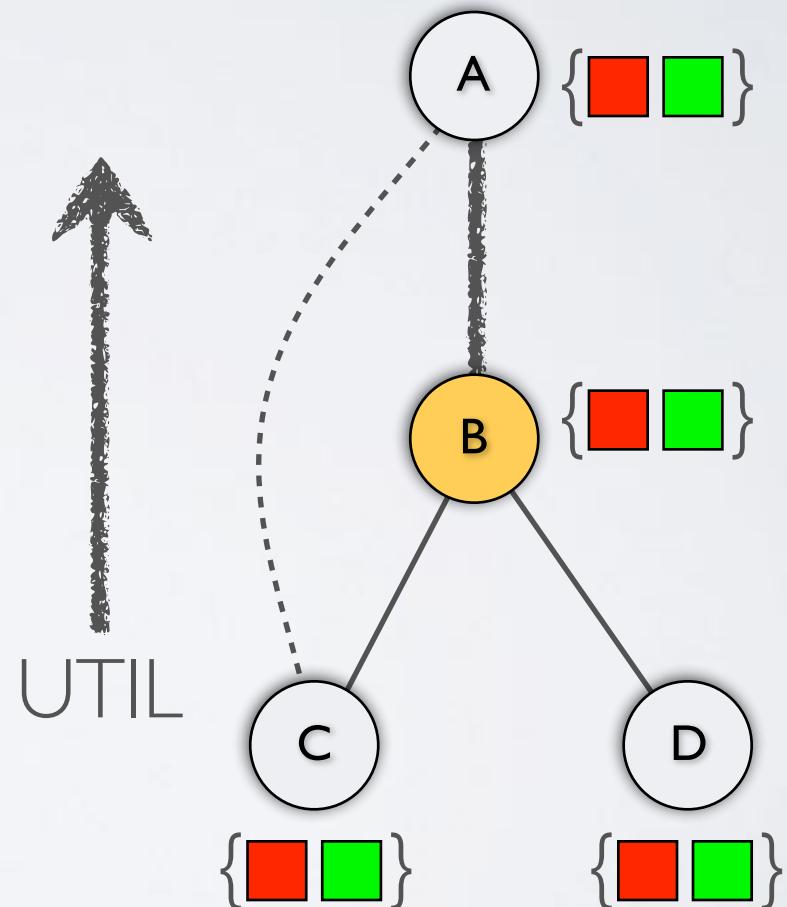
## Pseudo-tree Ordering



# DPOP

A	B	(A,B)	Util C	Util D	
r	r	5	10	3	18
r	g	8	8	3	19
g	r	20	7	3	30
g	g	3	6	3	12

Pseudo-tree Ordering



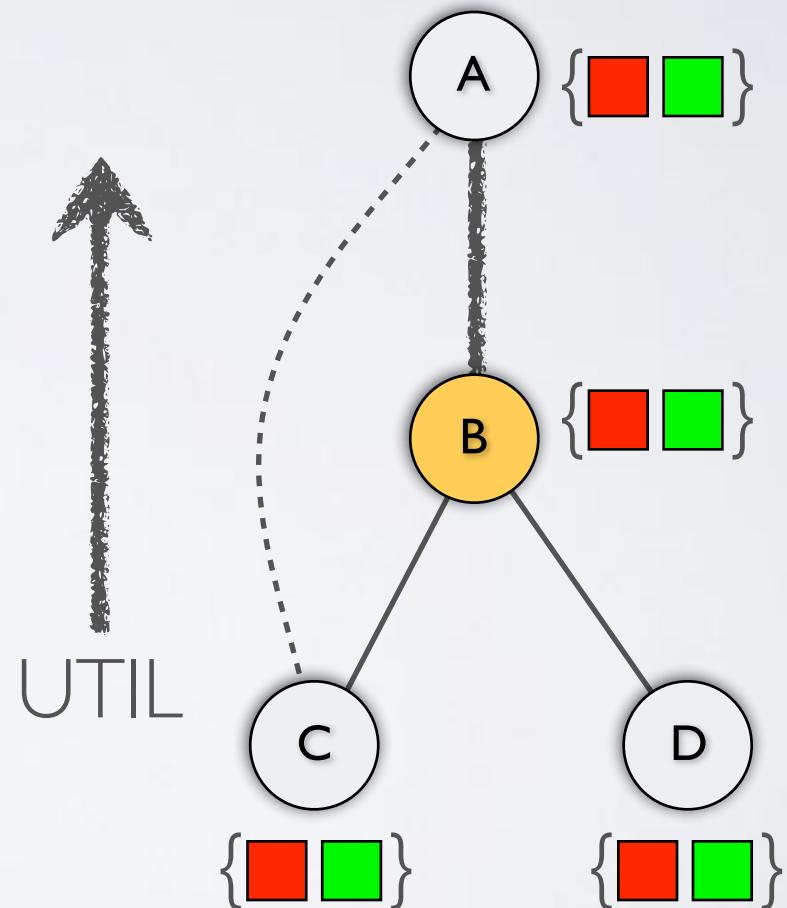
# DPOP

A	B	(A,B)	Util C	Util D	
r	r	5	10	3	18
r	g	8	8	3	19
g	r	20	7	3	30
g	g	3	6	3	12

MSG to A

A	cost
r	18
g	12

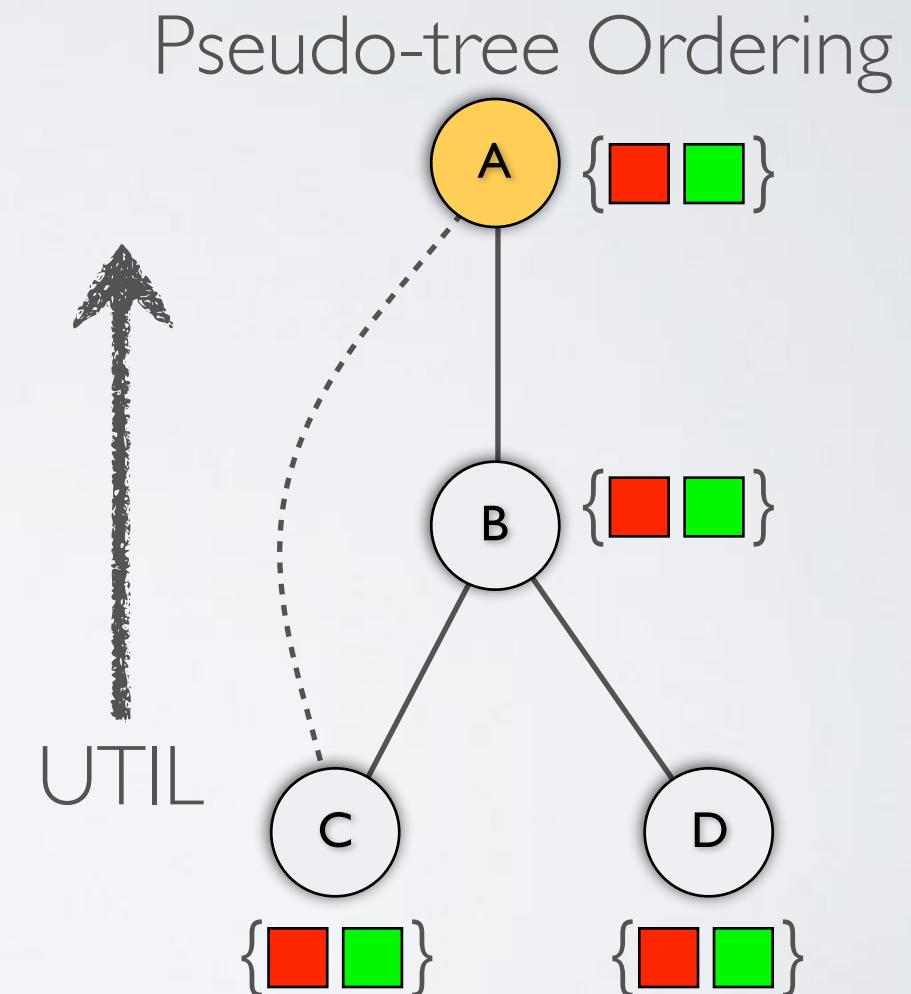
Pseudo-tree Ordering



# DPOP

A	cost
r	18
g	12

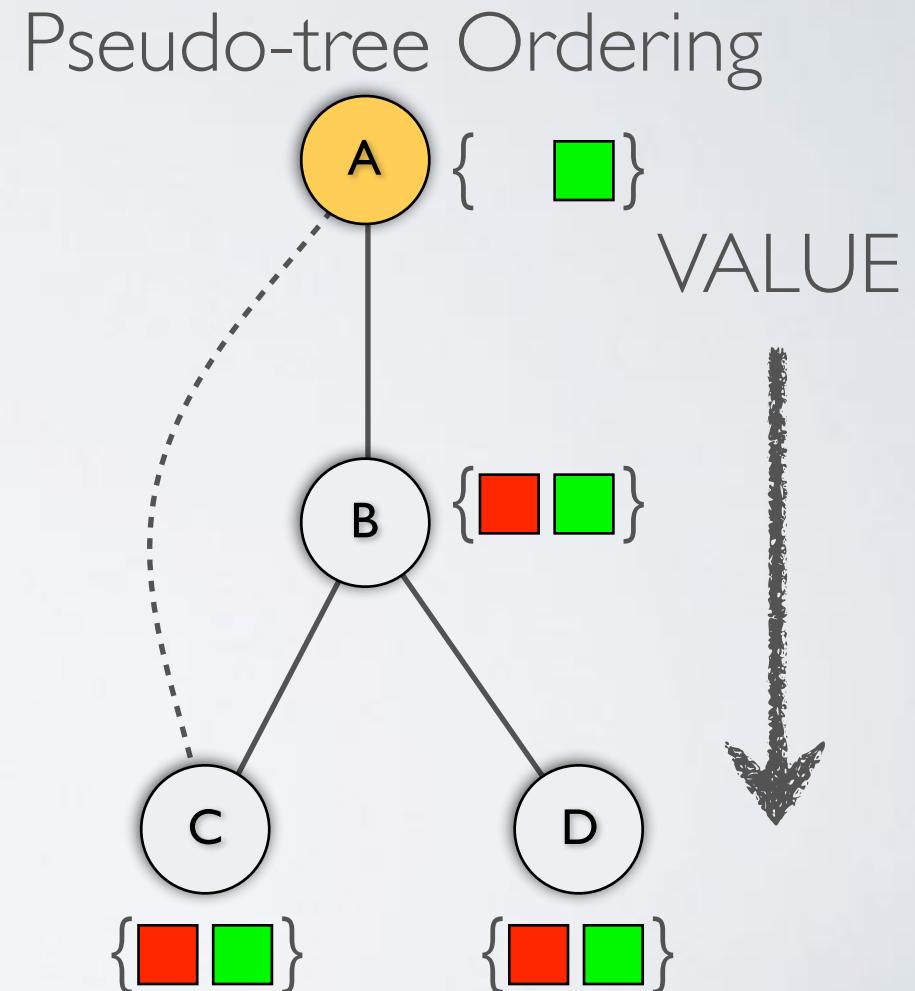
optimal cost = 12



# DPOP

A	cost
r	18
<b>g</b>	12

- Select value for A = 'g'
- Send MSG A = 'g' to agents B and C



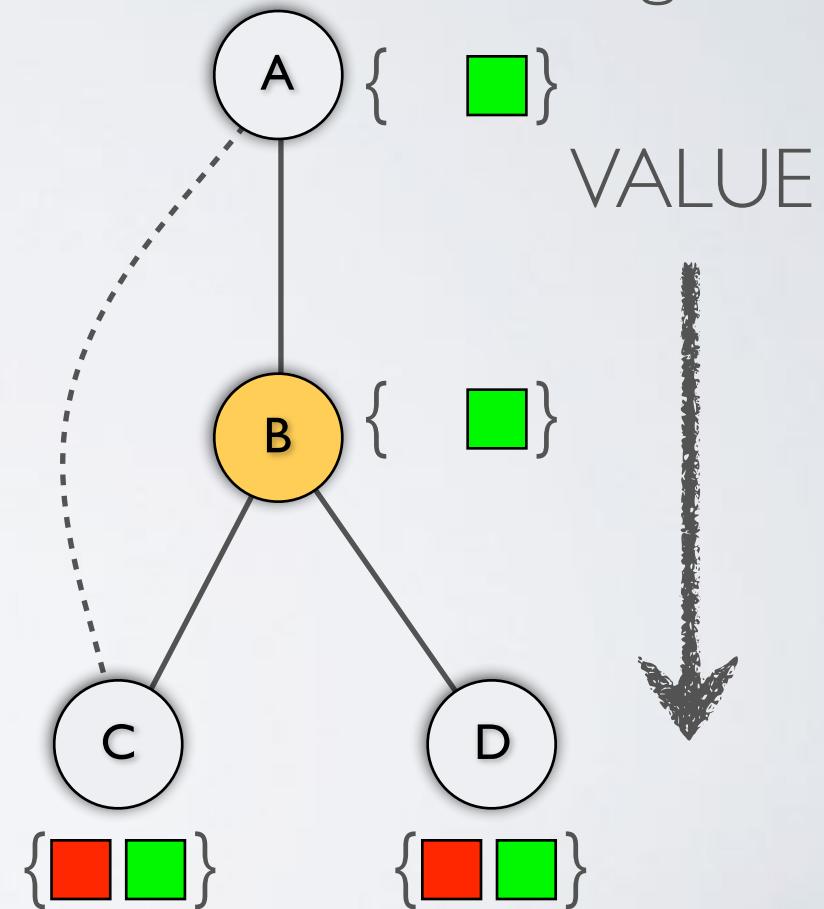
# DPOP



A	B	(A,B)	Util C	Util D	
r	r	5	10	3	18
r	g	8	8	3	19
g	r	20	7	3	30
g	g	3	6	3	12

- Select value for B = 'g'
- Send MSG B = 'g' to agents C and D

Pseudo-tree Ordering

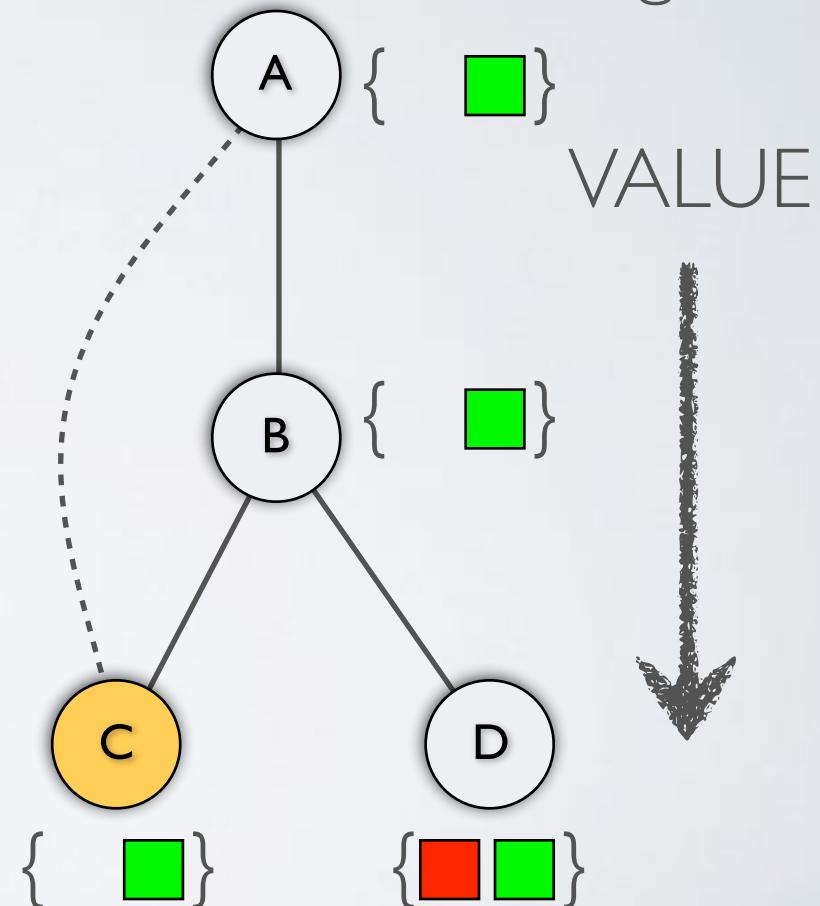


# DPOP



A	B	C	(B,C)	(A,C)	
r	r	r	5	5	10
r	r	g	4	8	12
r	g	r	3	5	8
r	g	g	3	8	11
g	r	r	5	10	15
g	r	g	4	3	7
g	g	r	3	10	13
g	g	g	3	3	6

Pseudo-tree Ordering



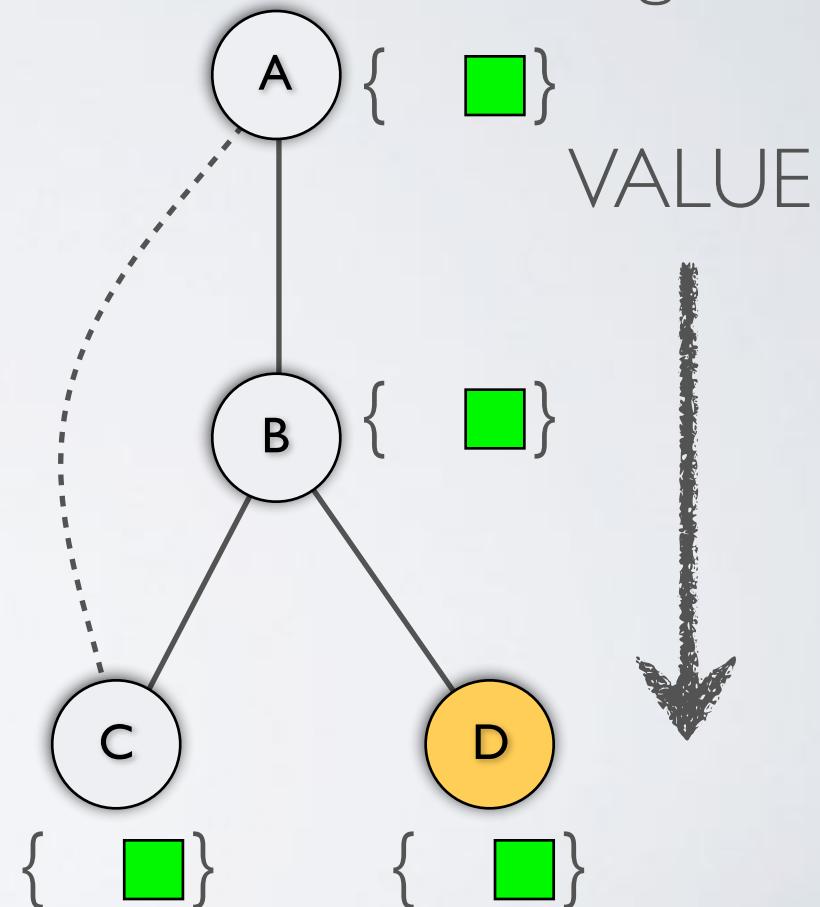
- Select value for C = 'g'

# DPOP



B	D	(B,D)
r	r	3
r	g	8
g	r	10
g	g	3

Pseudo-tree Ordering



- Select value for D = 'g'

# DPOP

	SBB	DPOP
Correct the solution it finds is optimal	Yes	Yes
Complete it terminates	Yes	Yes
Message Complexity max size of a message	$O(d)$	$O(b^d)$
Network Load max number of messages	$O(b^d)$	$O(d)$
Runtime max number of cycles	$O(b^d)$	$O(b^d)$

branching factor =  $b$   
num variables =  $d$

# CRITICAL OVERVIEW

Search Algorithms

Inference Algorithms

increasing memory

polynomial

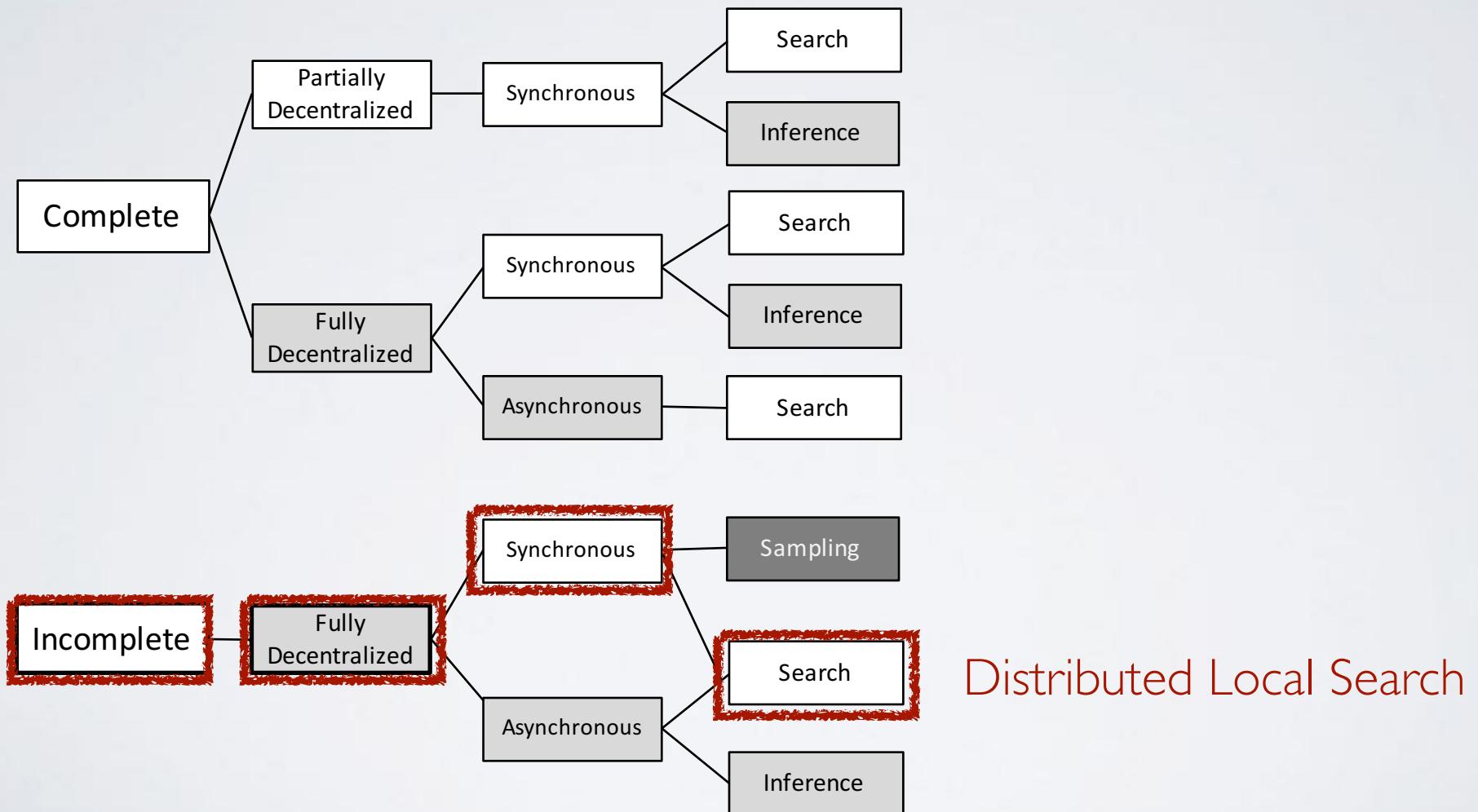
exponential

decreasing network load

exponential

polynomial

# DCOP ALGORITHMS



# LOCAL SEARCH ALGORITHMS

- DSA: Distributed Stochastic Algorithm
- MGM: Maximum Gain Messages Algorithm
- Every agent individually decides whether to change its value or not
- Decision involves
  - knowing neighbors' values
  - calculation of utility gain by changing values
  - probabilities

Weixiong Zhang, Guandong Wang, Zhao Xing, Lars Wittenburg: Distributed stochastic search and distributed breakout: properties, comparison and applications to constraint optimization problems in sensor networks. Artif. Intell. 161(1-2): 55-87 (2005)

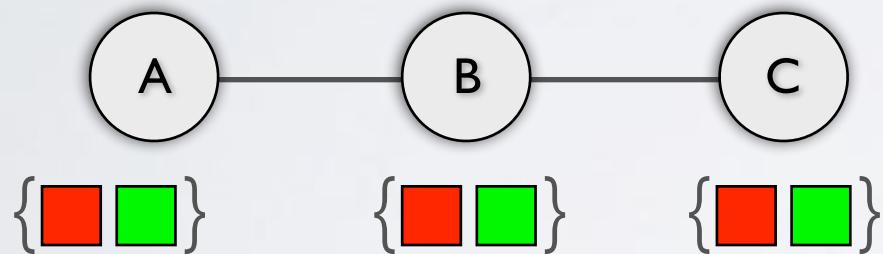
Rajiv Maheswaran, Jonathan Pearce, Milind Tambe: Distributed Algorithms for DCOP: A Graphical-Game-Based Approach. ISCA PDCS 2004: 432-439

# DSA ALGORITHM

- All agents execute the following
  - Randomly choose a value
  - while (termination is not met)
    - if (a new value is assigned)
      - send the new value to neighbors
    - collect neighbors' new values if any
    - select and assign the next value based on assignment rule

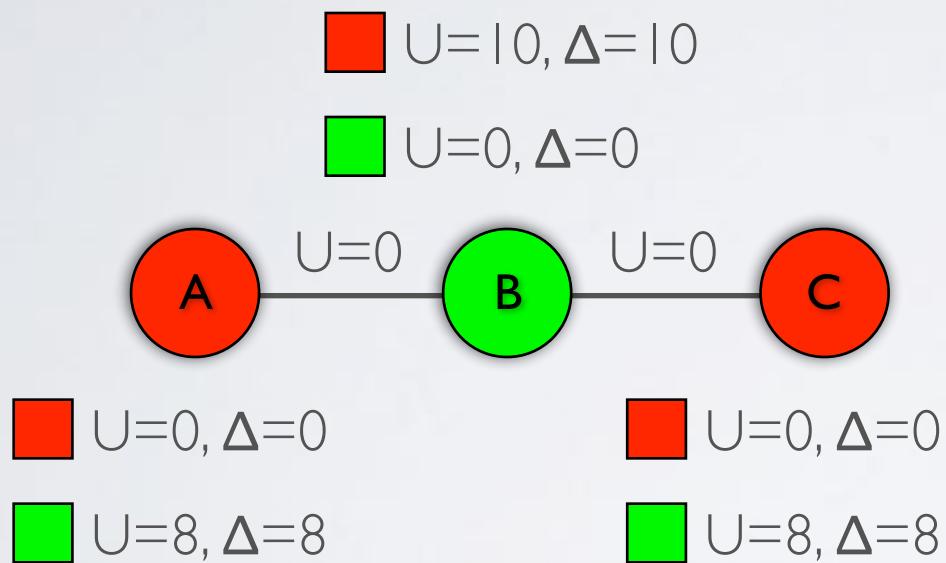
Weixiong Zhang, Guandong Wang, Zhao Xing, Lars Wittenburg: Distributed stochastic search and distributed breakout: properties, comparison and applications to constraint optimization problems in sensor networks. Artif. Intell. 161(1-2): 55-87 (2005)

# DSA ALGORITHM



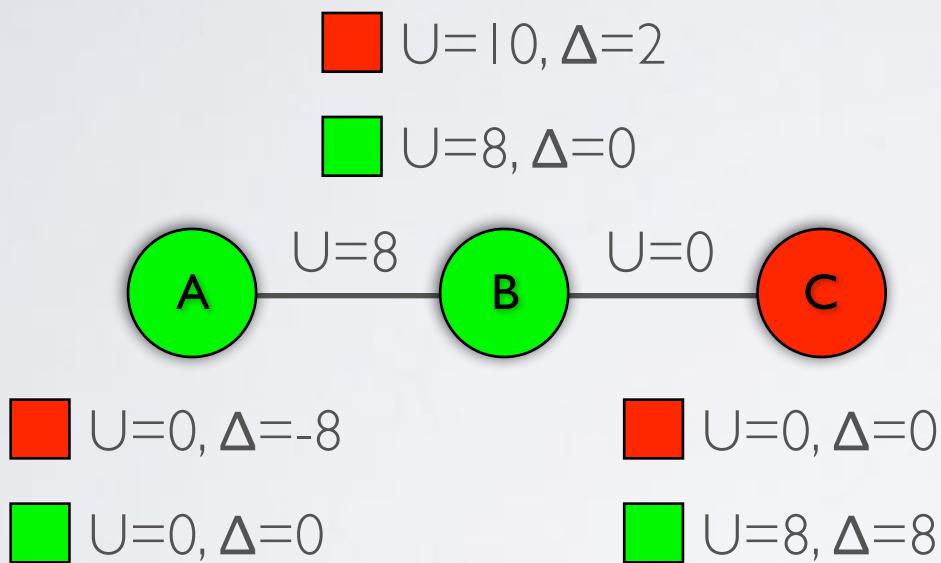
$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
Red	Red	5	5
Red	Green	0	0
Green	Red	0	0
Green	Green	8	8

# DSA ALGORITHM



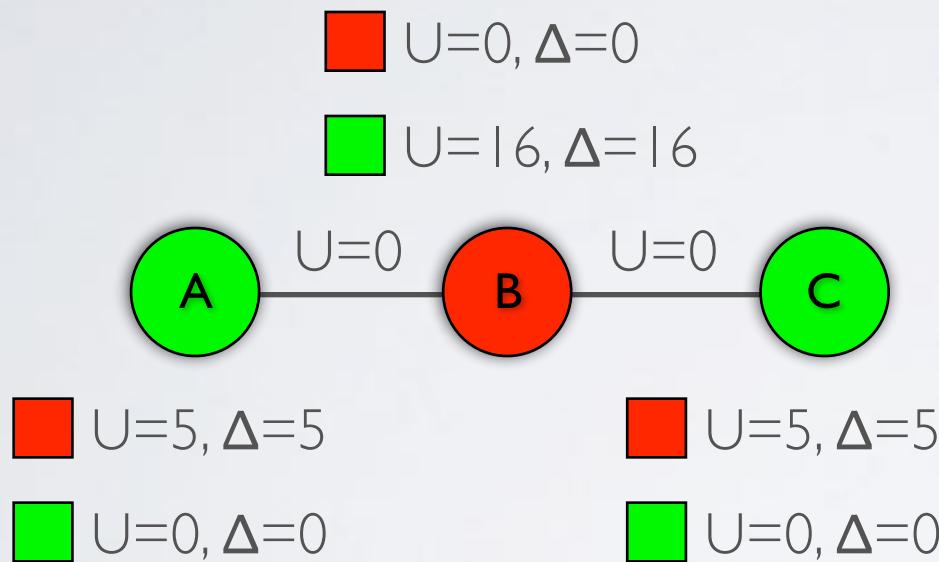
$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
Red	Red	5	5
Red	Green	0	0
Green	Red	0	0
Green	Green	8	8

# DSA ALGORITHM



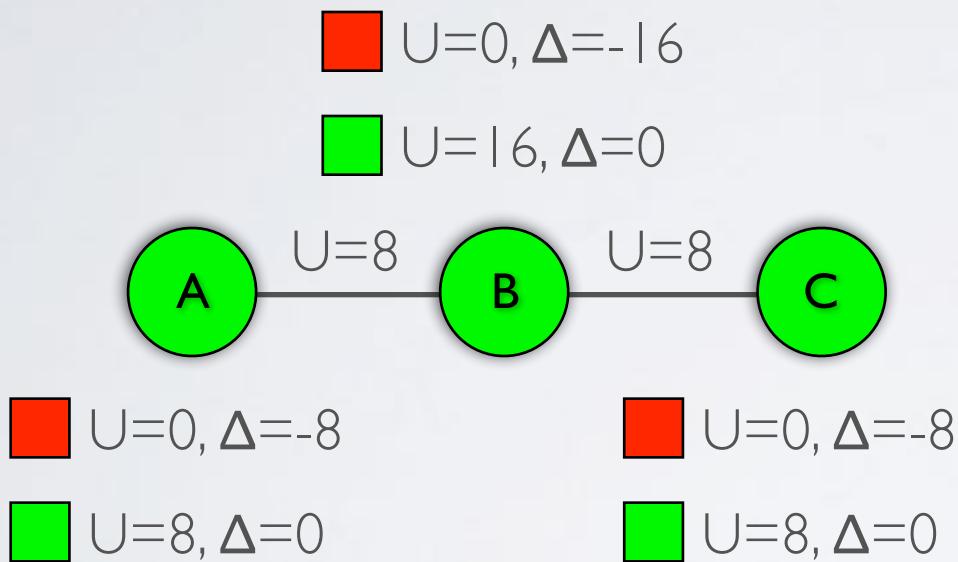
$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
Red	Red	5	5
Red	Green	0	0
Green	Red	0	0
Green	Green	8	8

# DSA ALGORITHM



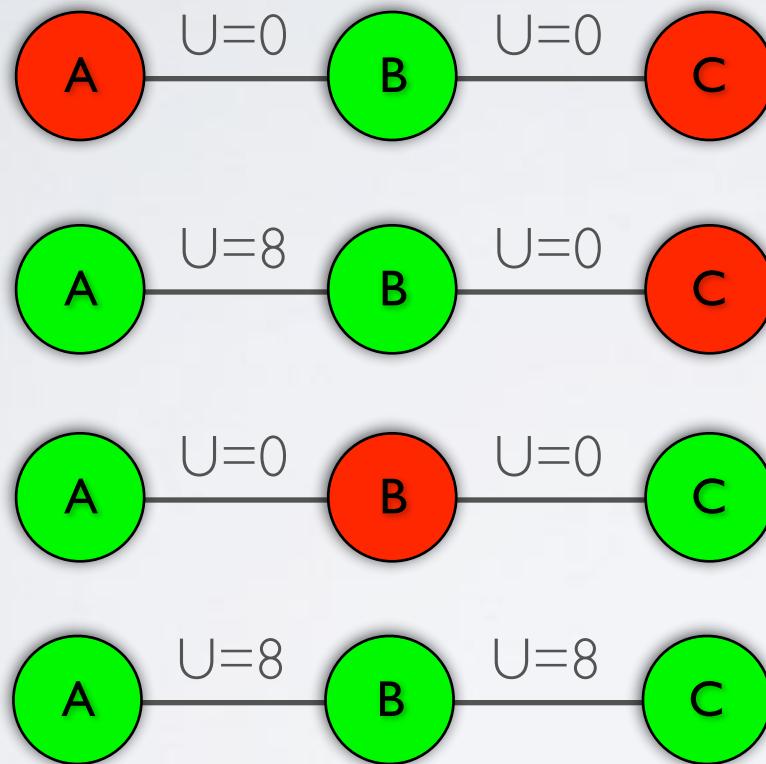
$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
<span style="color:red;">█</span>	<span style="color:red;">█</span>	5	5
<span style="color:red;">█</span>	<span style="color:green;">█</span>	0	0
<span style="color:green;">█</span>	<span style="color:red;">█</span>	0	0
<span style="color:green;">█</span>	<span style="color:green;">█</span>	8	8

# DSA ALGORITHM



$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
Red	Red	5	5
Red	Green	0	0
Green	Red	0	0
Green	Green	8	8

# DSA ALGORITHM



$x_i$	$x_j$	Utility (A,B)	Utility (B,C)
red	red	5	5
red	green	0	0
green	red	0	0
green	green	8	8

One possible execution trace

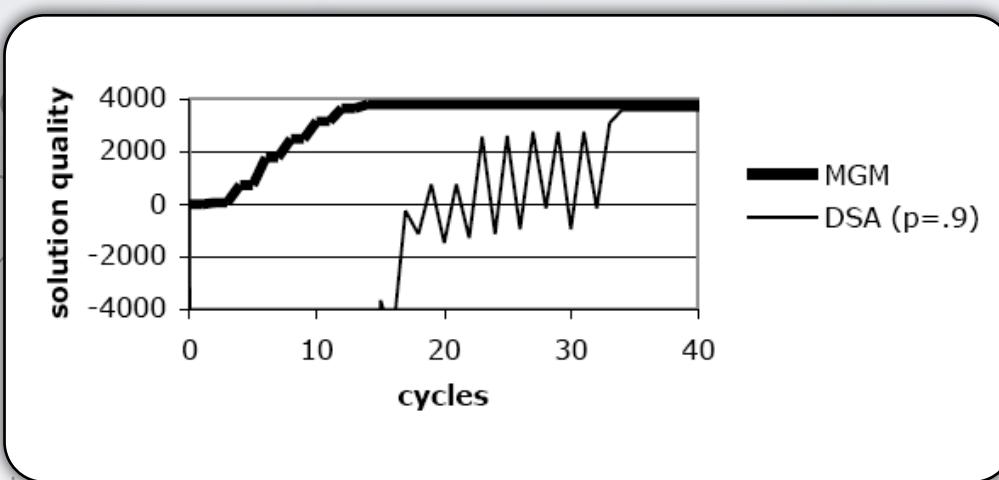
# MGM ALGORITHM

- All agents execute the following
  - Randomly choose a value
  - while (termination is not met)
    - if (a new value is assigned)
      - send the new value to neighbors
    - collect neighbors' new values if any
    - *calculate gain and send it to neighbors*
    - *collect neighbors' gains*
    - *if (it has the highest gain among all neighbors)*
      - *change value to the value that maximizes gain*

Rajiv Maheswaran, Jonathan Pearce, Milind Tambe: Distributed Algorithms for DCOP: A Graphical-Game-Based Approach. ISCA PDCS 2004: 432-439

# MGM ALGORITHM

- All agents execute the following:
  - Randomly choose a neighbor
  - while (termination condition not met)
    - if (a new value is received from a neighbor)
      - send the value to all neighbors
    - collect neighbors' new values if any



*Great if you need an anytime algorithm*

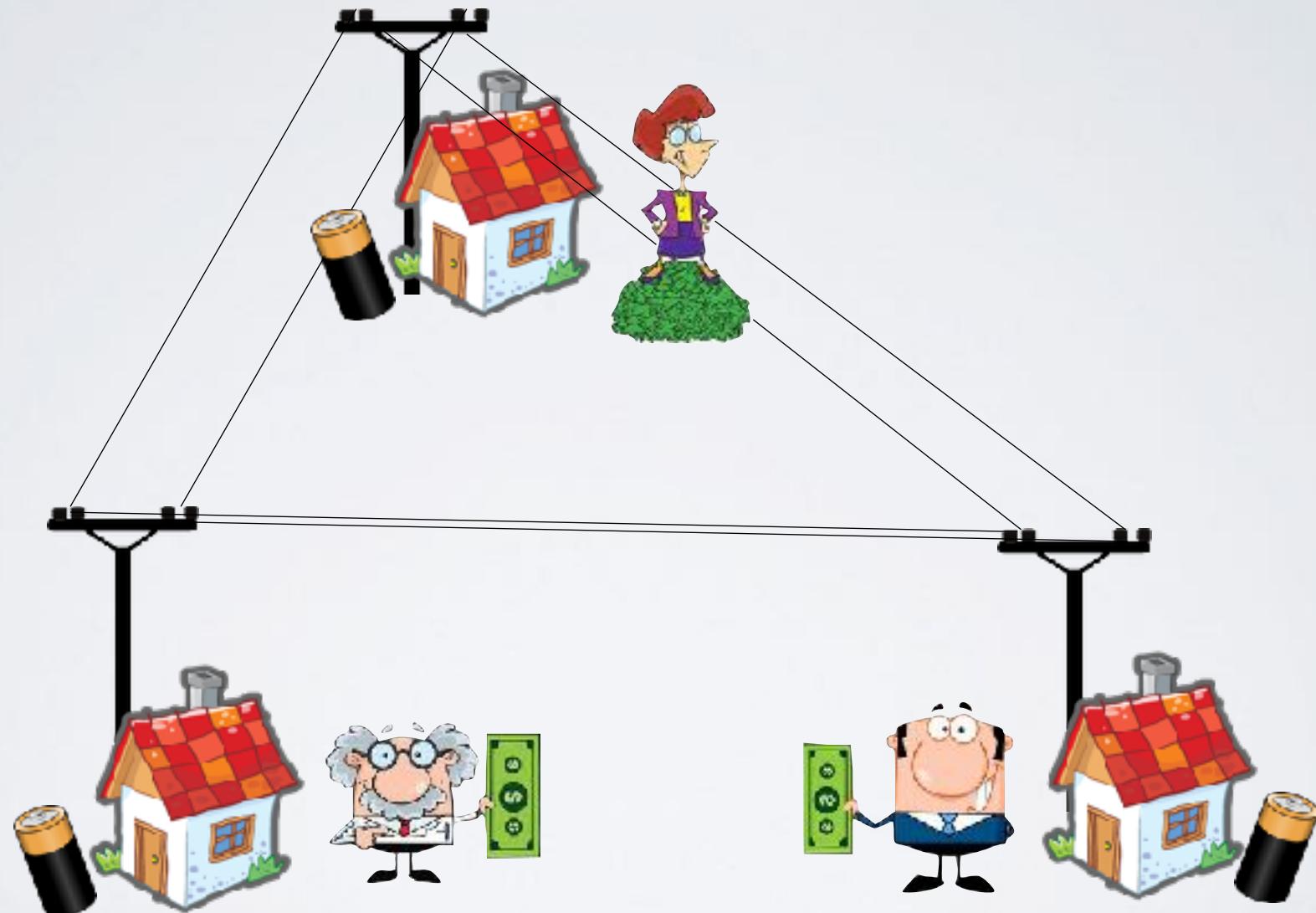
- *collect neighbors' gains*
- *if (it has the highest gain among all neighbors)*
  - *change value to the value that maximizes gain*

Rajiv Maheswaran, Jonathan Pearce, Milind Tambe: Distributed Algorithms for DCOP: A Graphical-Game-Based Approach. ISCA PDCS 2004: 432-439

# DCOP EXTENSIONS

AAAI-18 Tutorial on  
Multi-Agent Distributed Constrained Optimization

# PROSUMER ENERGY TRADING

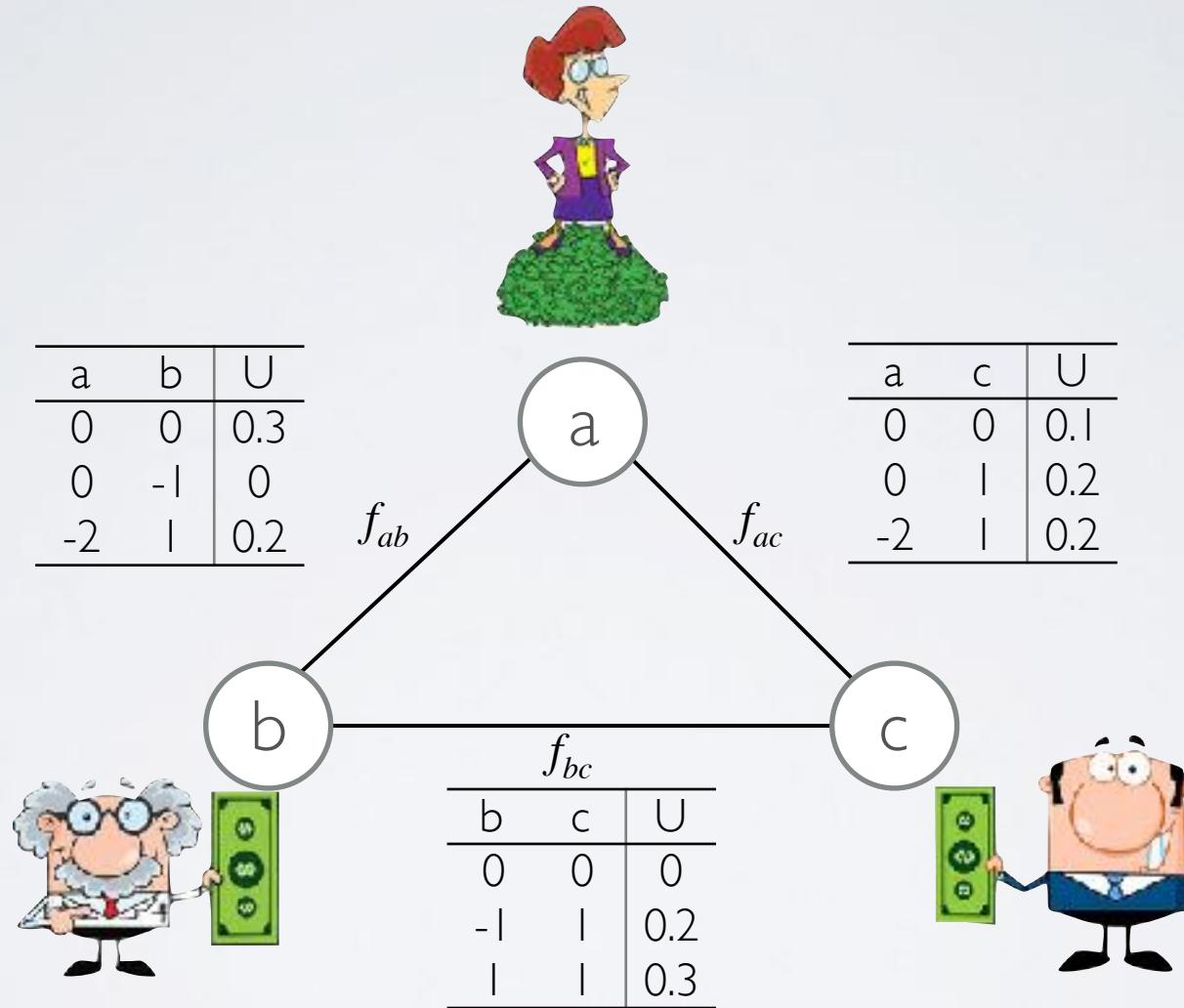


Designing a Marketplace for the Trading and Distribution of Energy in the Smart Grid. AAMAS 2015: 1285-1293

# PROSUMER ENERGY TRADING

- Prosumers: capable of both generating and consuming resources
- Each prosumer can sell or buy a given amount of power to another prosumer
- Line capacity and flow constraints are required to be satisfied
- Each offer has a desired utility
- Goal: Find a buy/selling assignment that maximizes the actors' rewards and is feasible with the operating power constraints

# PROSUMER ENERGY TRADING

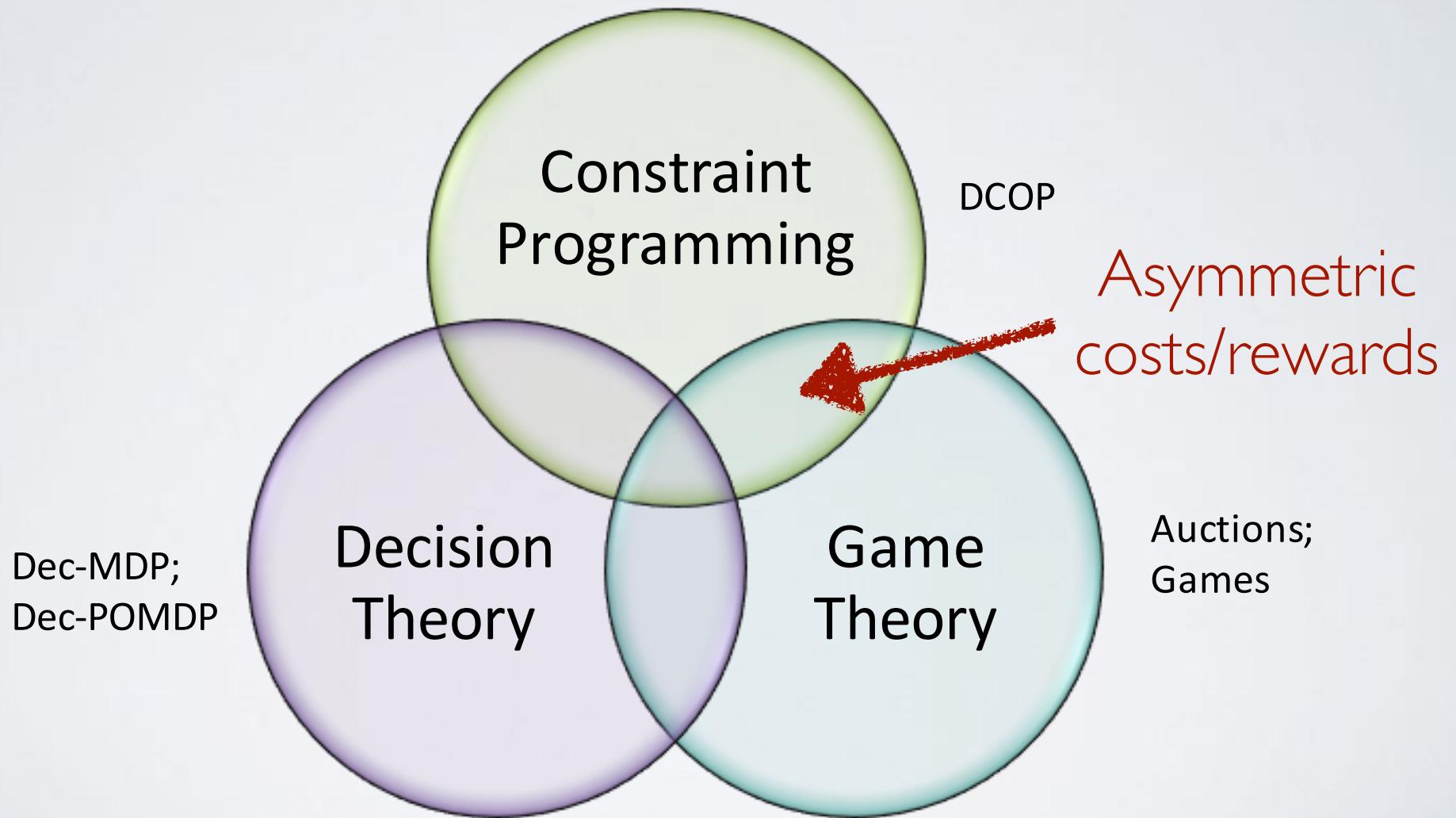


Designing a Marketplace for the Trading and Distribution of Energy in the Smart Grid. AAMAS 2015: 1285-1293

# PROSUMER ENERGY TRADING

- What if Alice cannot disclose the costs associated her action?
- What if we want to describe the scenario in which
  - Bob desires to gain 0.2 for selling 1 KW of power to Carl
  - Carl desires to gain 0.1 for buying 1 KW of power from Bob?

# ASYMMETRIC DCOP



# ASYMMETRIC DCOP

- Asymmetric DCOPs are DCOPs where:
- A joint assignment may produce different costs for the agents participating in a constraint

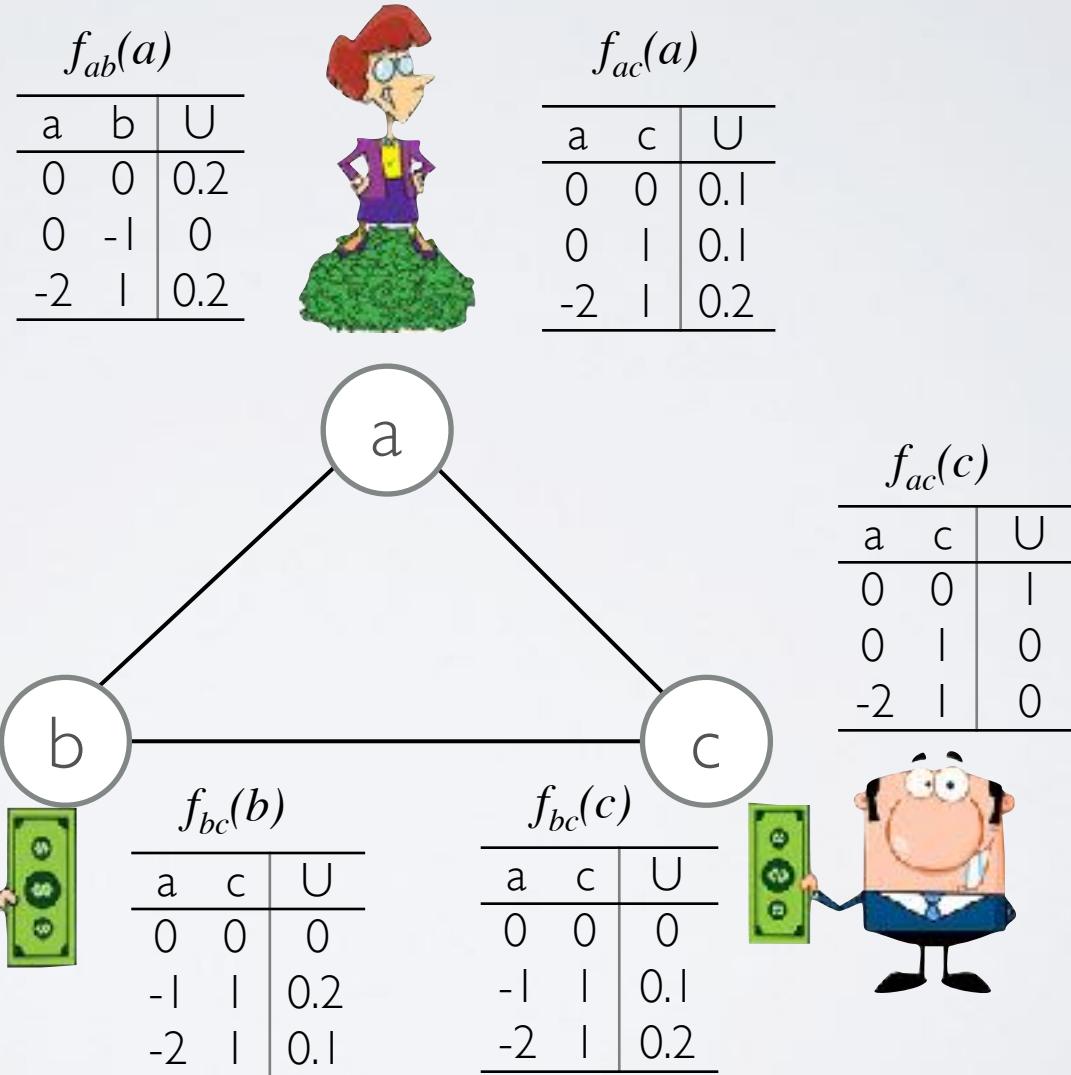
A	B	Cost
r	g	3
r	g	2
g	r	10
g	g	0

# ASYMMETRIC DCOP

- Asymmetric DCOPs are DCOPs where:
- A joint assignment may produce different costs for the agents participating in a constraint

A	B	Cost A	Cost B
r	g	2	1
r	g	0	2
g	r	3	7
g	g	0	0

# PROSUMER ENERGY TRADING



# ASYMMETRIC DCOP

- Why asymmetric DCOPs?
- ...

# ASYMMETRIC DCOP

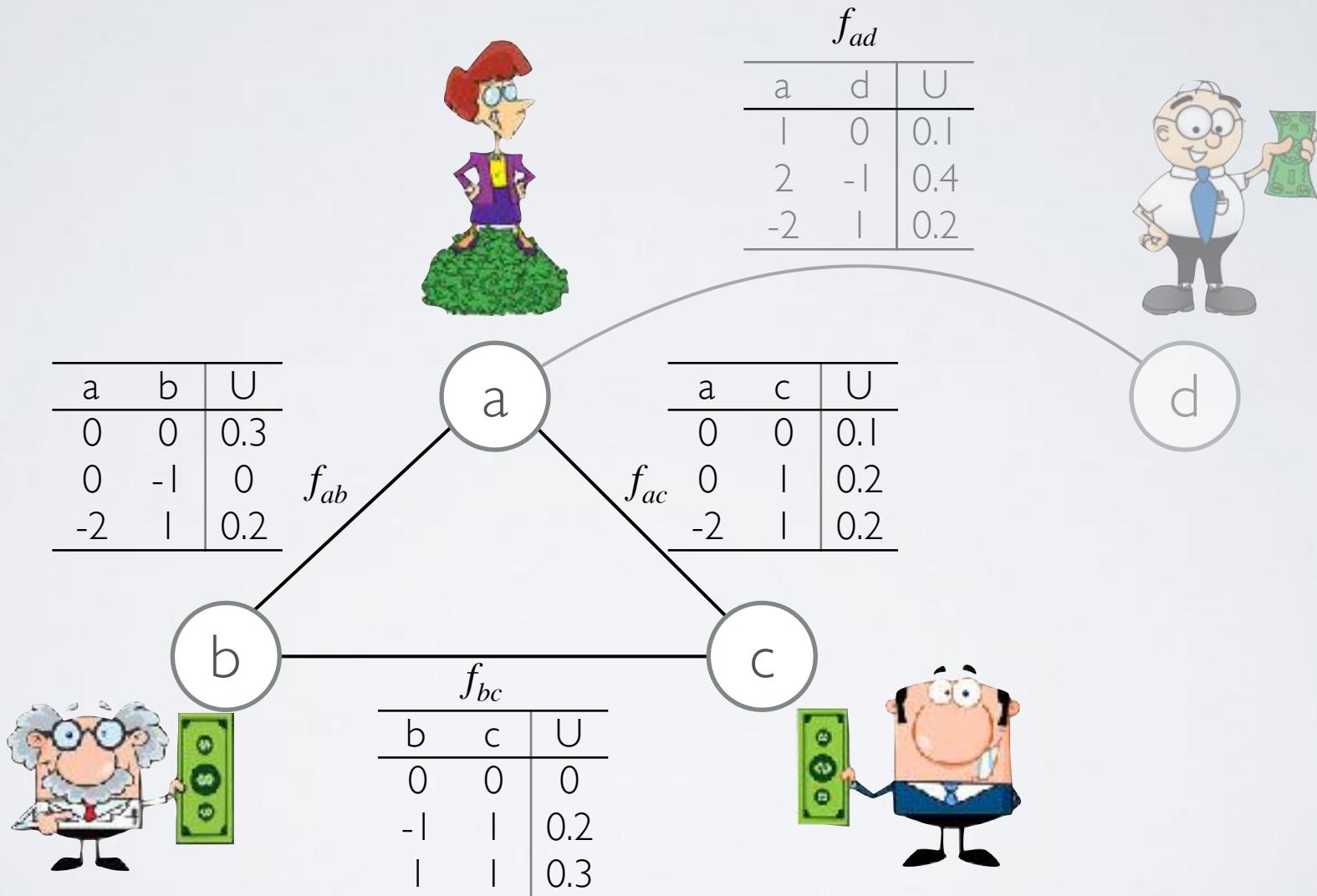
- Why asymmetric DCOPs?
  - Models richer forms of cooperation
  - Privacy: Agents do not need to reveal the costs associated to their action
  - Resource allocation problems:
    - Different costs for using the same resource
    - Different preferences

# PROSUMER ENERGY TRADING

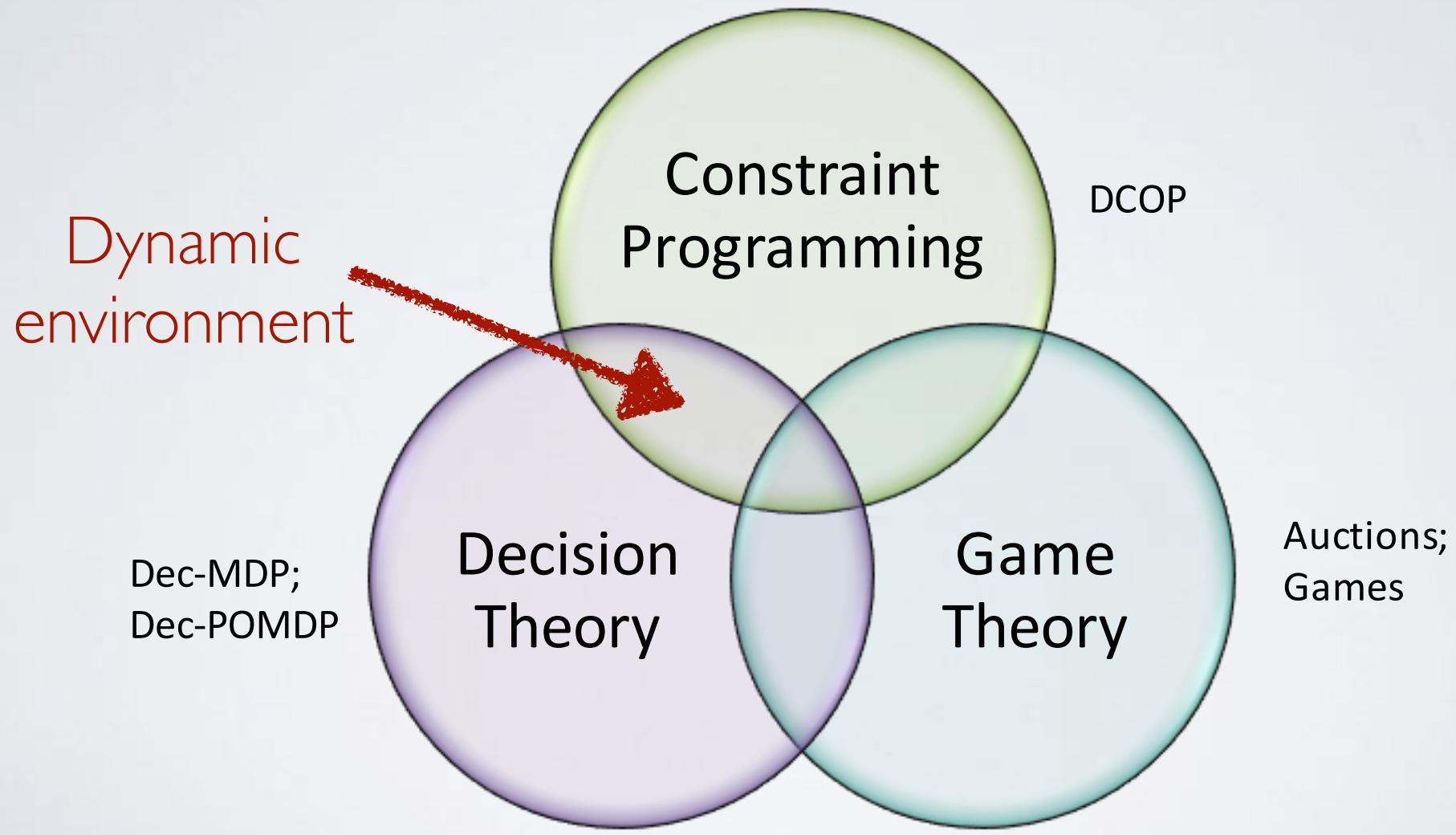
- What if a new prosumer would like to join the market?
- What if a prosumer would like to modify her preferences?



# PROSUMER ENERGY TRADING

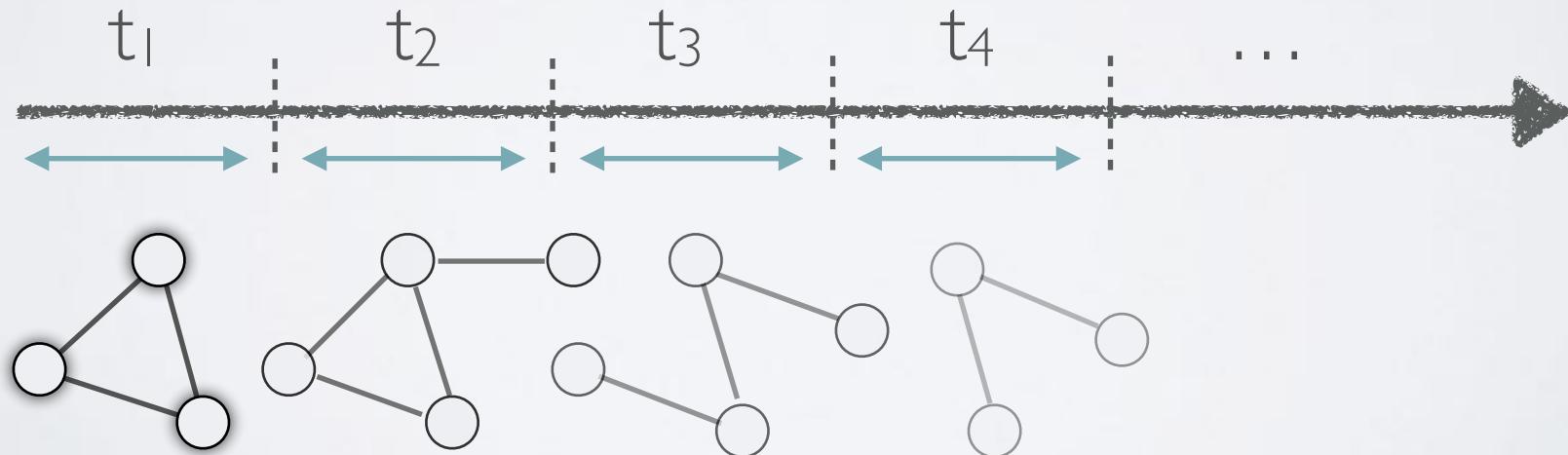


# DYNAMIC DCOP



# DYNAMIC DCOP

- A Dynamic DCOP is sequence  $P_1, P_2, \dots, P_k$  of  $k$  DCOPs
- The agent knowledge about the environment is confined within each time step
- Each DCOP is solved sequentially



# DYNAMIC DCOP

- Why dynamic DCOPs?
- ...

# DYNAMIC DCOP

- Why dynamic DCOPs?
  - MAS commonly exhibit dynamic environments
  - The capture scenarios with:
    - Moving agents, change of constraints, change of preferences
    - Additional information become available during problem solving
  - Application domains: Sensor networks, cloud computing, smart home automation, ...

# APPLICATIONS

AAAI-18 Tutorial on  
Multi-Agent Distributed Constrained Optimization

# DCOP APPLICATIONS

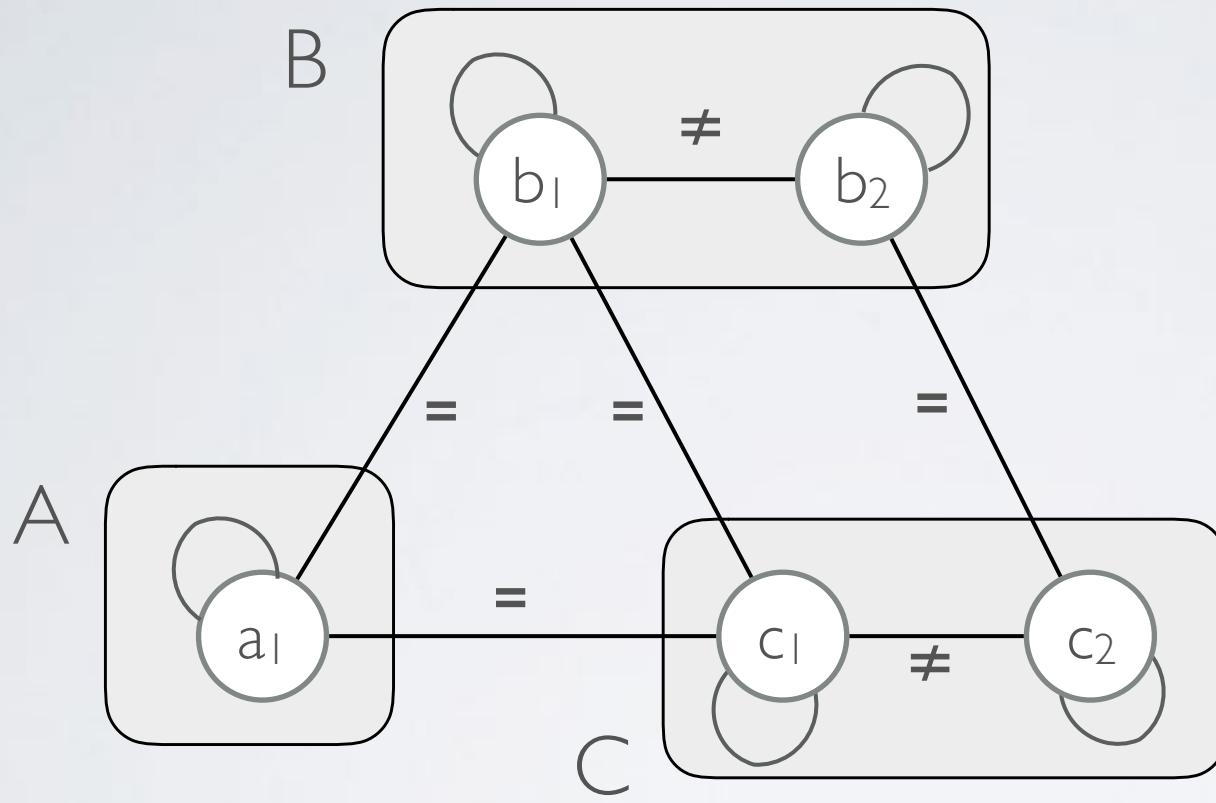
- Scheduling Problems
  - Taking DCOP to the Real World: Efficient Complete Solutions for Distributed Multi-Event Scheduling. AAMAS 2004
- Radio Frequency Allocation Problems
  - Improving DPOP with Branch Consistency for Solving Distributed Constraint Optimization Problems. CP 2014
- Sensor Networks
  - Preprocessing techniques for accelerating the DCOP algorithm ADOPT. AAMAS 2005
- Home Automation
  - A Multiagent System Approach to Scheduling Devices in Smart Homes. AAMAS 2017, IJCAI 2016
- Traffic Light Synchronization
  - Evaluating the performance of DCOP algorithms in a real world, dynamic problem. AAMAS 2008
- Disaster Evacuation
  - Disaster Evacuation Support. AAAI 2007; JAIR 2017
- Combinatorial Auction Winner Determination
  - H-DPOP: Using Hard Constraints for Search Space Pruning in DCOP. AAAI 2008

# MEETING SCHEDULING

- Meeting 1: Alice, Bob, Carl
- Meeting 2: Bob, Carl
- ...
- Alice is only free in the mornings from 9am-noon
- Bob prefers to not meet during lunch (noon-1pm)
- Carl does not wake up until 11am and loves late evening meetings
- ...

Rajiv T. Maheswaran, Milind Tambe, Emma Bowring, Jonathan P. Pearce, Pradeep Varakantham: Taking DCOP to the Real World: Efficient Complete Solutions for Distributed Multi-Event Scheduling. AAMAS 2004: 310-317

# MEETING SCHEDULING



- Values: time slots to hold the meetings
- All agents participating in a meeting must meet at the same time
- All meetings of an agent must occur at different times

# TRAFFIC FLOW CONTROL

- Given a set of traffic lights in adjacent intersections
- How coordinate them to create green waves?



de Oliveira, D., Bazzan, A. L., & Lesser, V.. Using cooperative mediation to coordinate traffic lights: a case study. AAMAS 2005: 371-378  
Junges, R., & Bazzan, A. L. Evaluating the performance of DCOP algorithms in a real world, dynamic problem. AAMAS 2008: 463-470

# TRAFFIC FLOW CONTROL

- Agents: Each traffic light
- Values: Flow traffic direction



de Oliveira, D., Bazzan, A. L., & Lesser, V.. Using cooperative mediation to coordinate traffic lights: a case study. AAMAS 2005: 371-378  
Junges, R., & Bazzan, A. L. Evaluating the performance of DCOP algorithms in a real world, dynamic problem. AAMAS 2008: 463-470

# TRAFFIC FLOW CONTROL

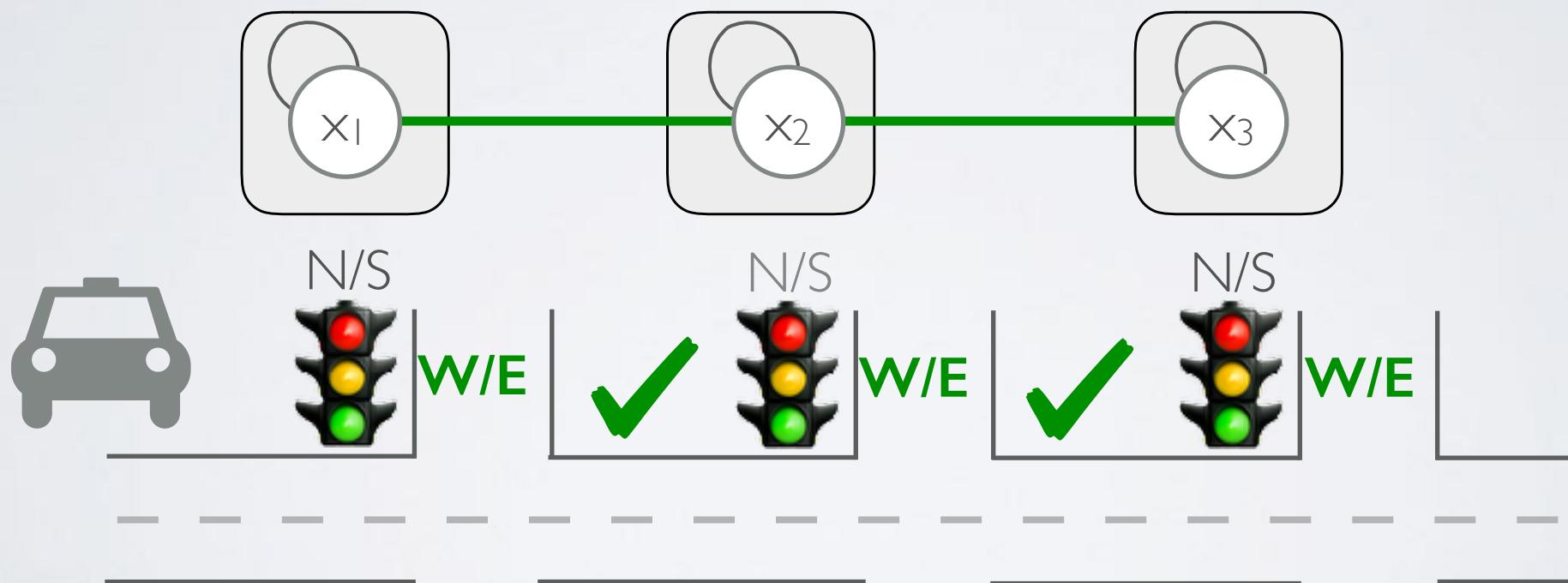
- Agents: Each traffic light
- Values: Flow traffic direction
- Conflict if 2 neighboring signals choose different directions



de Oliveira, D., Bazzan, A. L., & Lesser, V.. Using cooperative mediation to coordinate traffic lights: a case study. AAMAS 2005: 371-378  
Junges, R., & Bazzan, A. L. Evaluating the performance of DCOP algorithms in a real world, dynamic problem. AAMAS 2008: 463-470

# TRAFFIC FLOW CONTROL

- Cost functions model the number of incoming vehicles
- Maximize the traffic flow



de Oliveira, D., Bazzan, A. L., & Lesser, V.. Using cooperative mediation to coordinate traffic lights: a case study. AAMAS 2005: 371-378  
Junges, R., & Bazzan, A. L. Evaluating the performance of DCOP algorithms in a real world, dynamic problem. AAMAS 2008: 463-470

# SMART DEVICES



Innovative  
**SAMSUNG SmartFridge**

Say goodbye to food gone bad.

The SmartFridge makes it easy to keep track of what food you have and when it gets old.

You can add food to the list by:

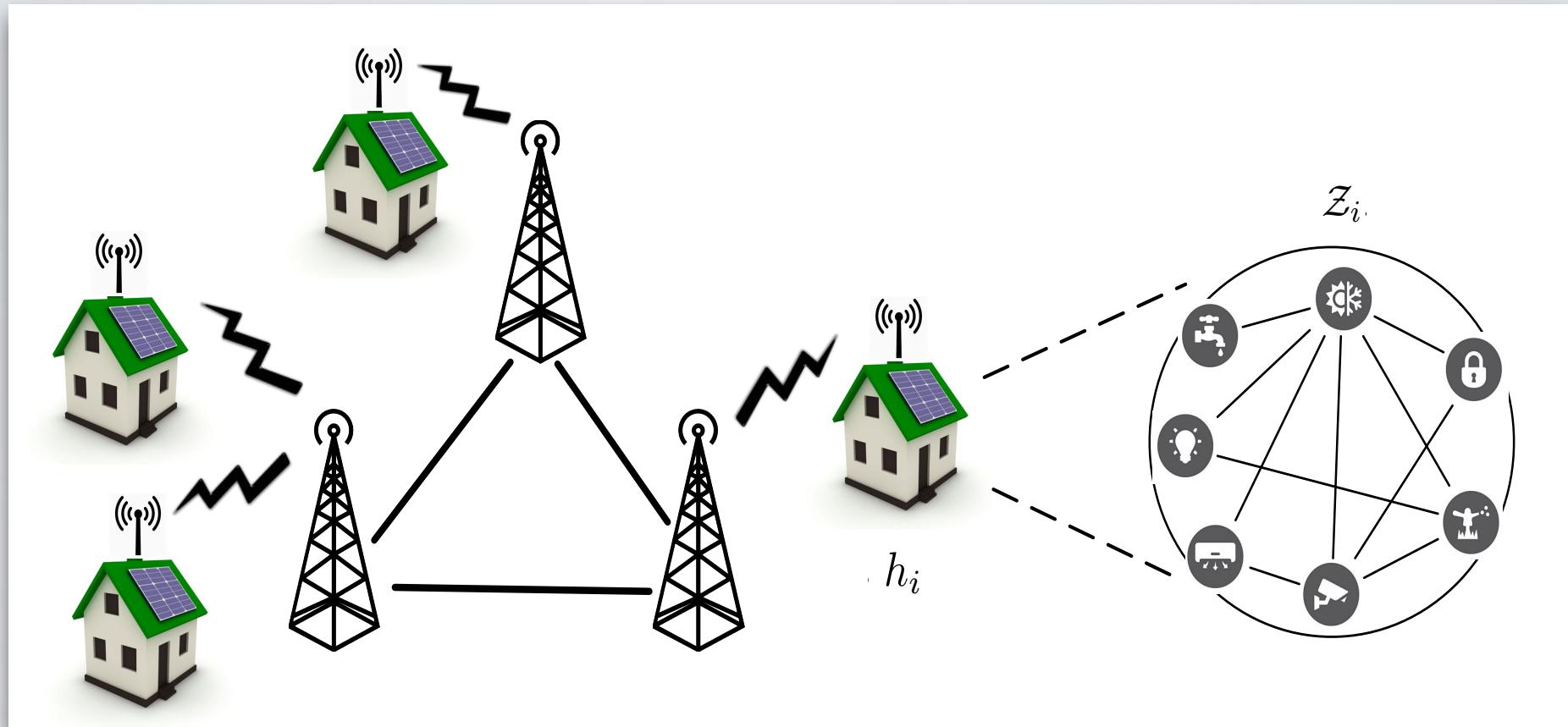
- Scanning it via the scanner.
- Typing it in.
- Clipping it via the magnet menu.

A Samsung SmartFridge is shown with its door open. On the left door, there is a built-in scanner and a small digital display showing some information. The main body of the refrigerator has a sleek, metallic finish. The interior is visible through the glass door.

# HOME ASSISTANTS

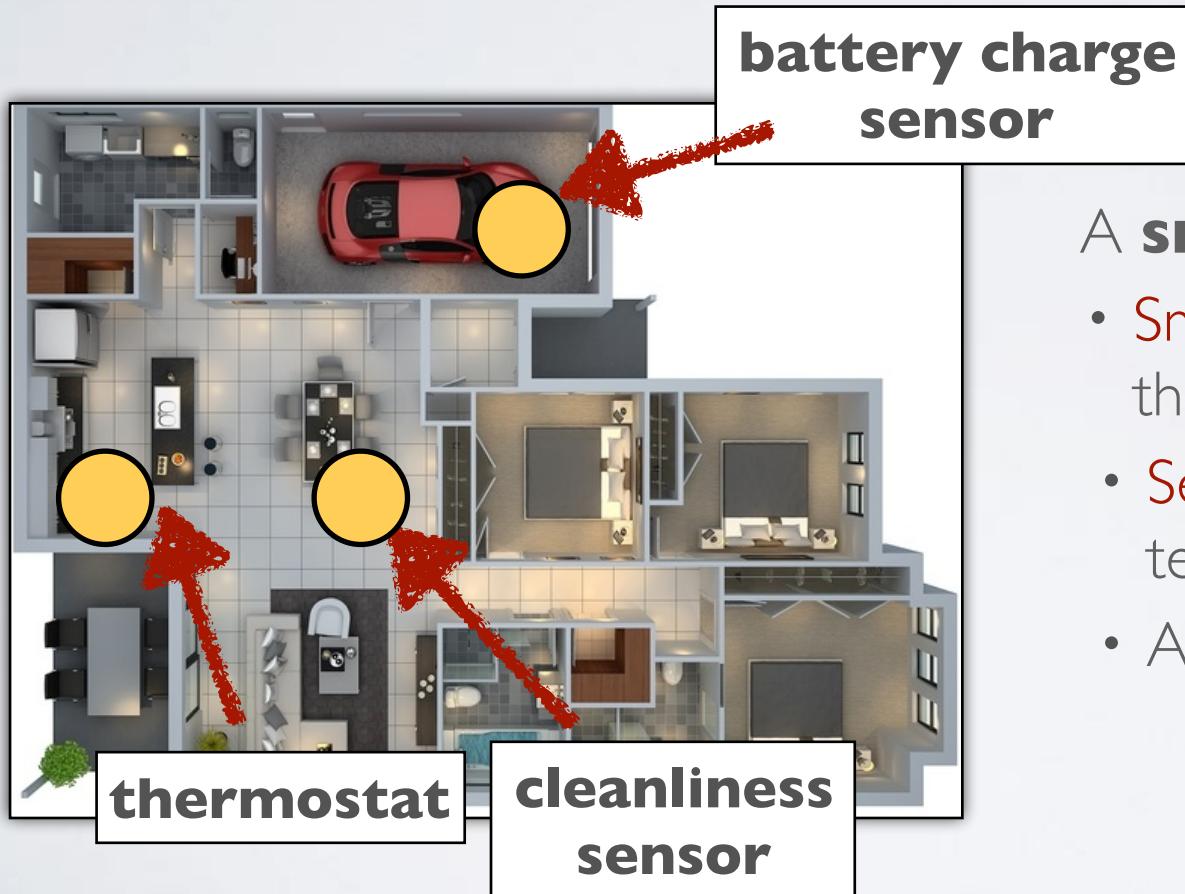


# SMART HOMES DEVICE SCHEDULING



Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "A Multiagent System Approach to Scheduling Devices in Smart Homes". AAMAS, 2017.

# SMART HOMES DEVICE SCHEDULING



A **smart home** has:

- Smart devices (roomba, HVAC) that it can control
- Sensors (cleanliness, temperature)
- A set of locations

Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "A Multiagent System Approach to Scheduling Devices in Smart Homes". AAMAS, 2017.

# SMART HOMES DEVICE SCHEDULING



## Smart device:

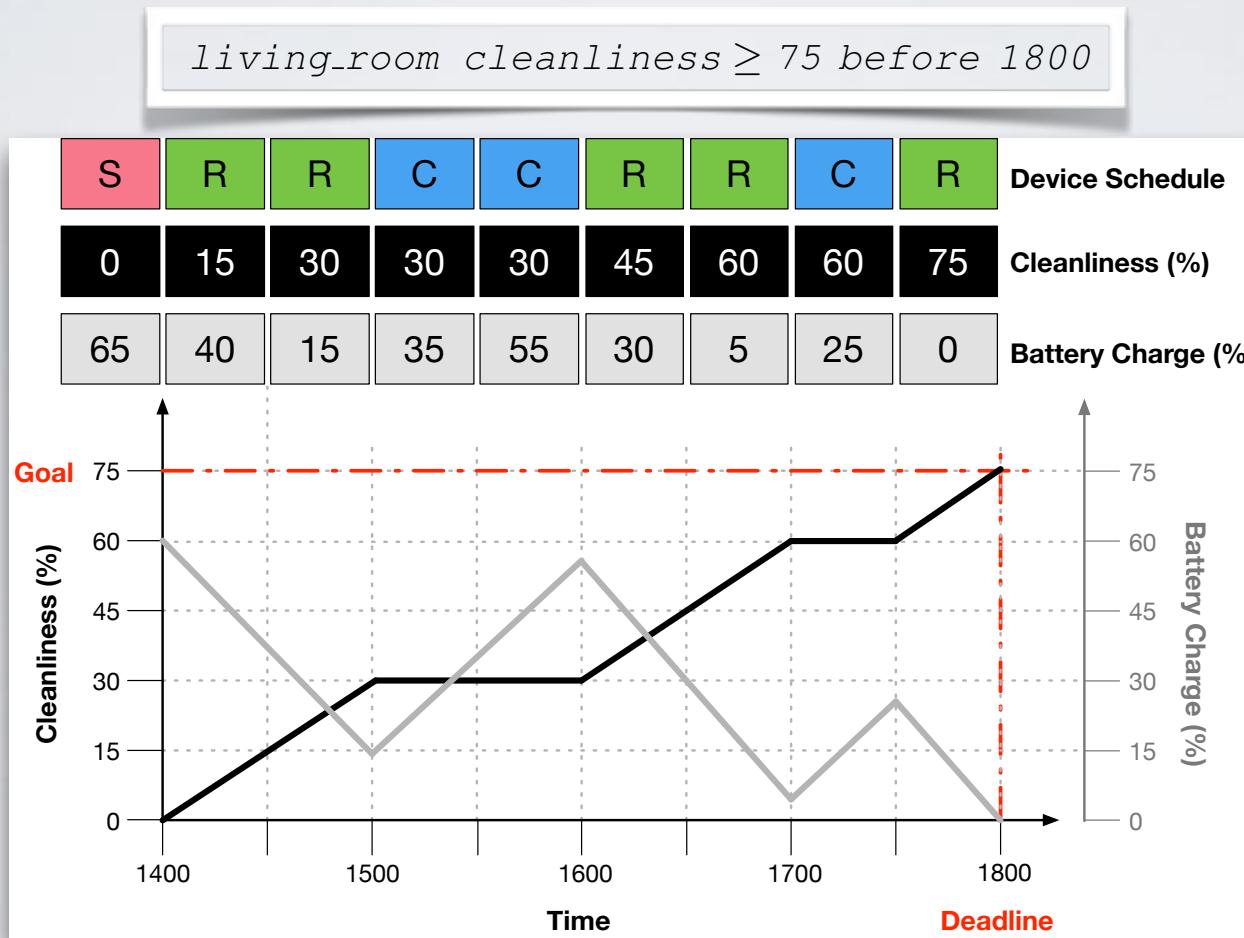
- A set of **actions** it can perform (clean, charge)
- Power consumption associated to each action.

## Scheduling Rules:

*living\_room cleanliness ≥ 75 before 1800*

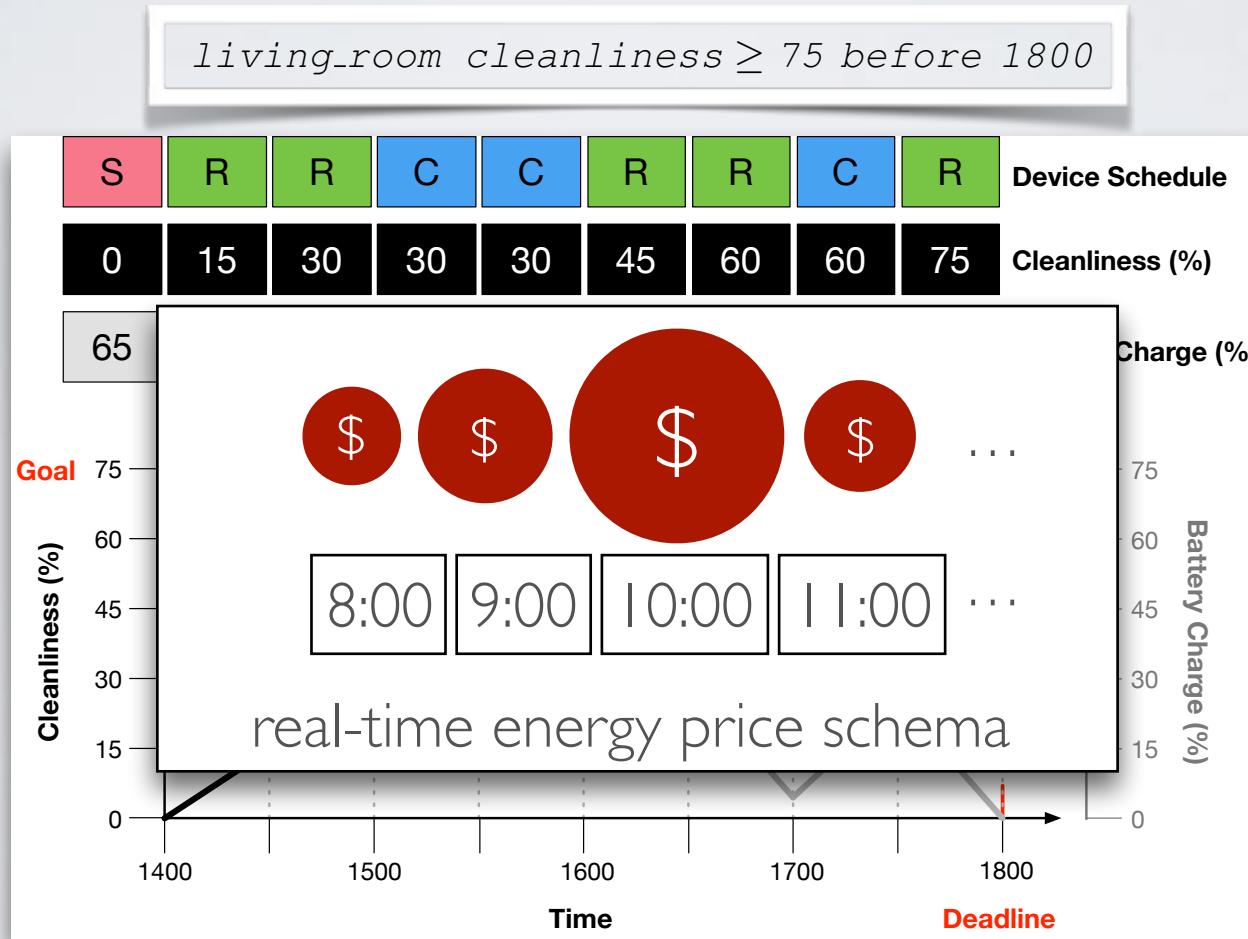
Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "A Multiagent System Approach to Scheduling Devices in Smart Homes". AAMAS, 2017.

# SMART HOMES DEVICE SCHEDULING



Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "A Multiagent System Approach to Scheduling Devices in Smart Homes". AAMAS, 2017.

# SMART HOMES DEVICE SCHEDULING



Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "A Multiagent System Approach to Scheduling Devices in Smart Homes". AAMAS, 2017.

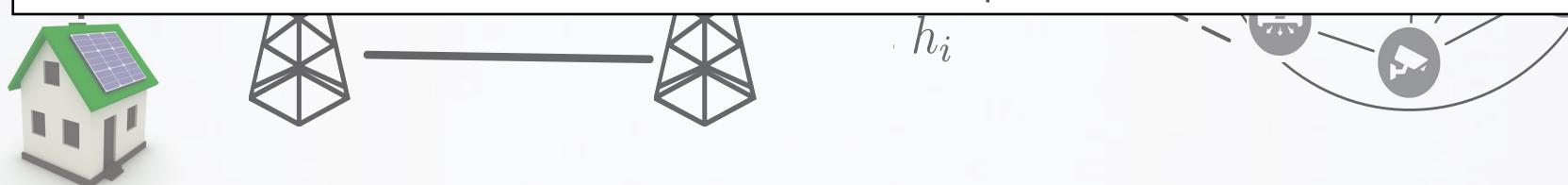
# SMART HOMES DEVICE SCHEDULING

()

**How to schedule smart devices to satisfy the user preferences while**

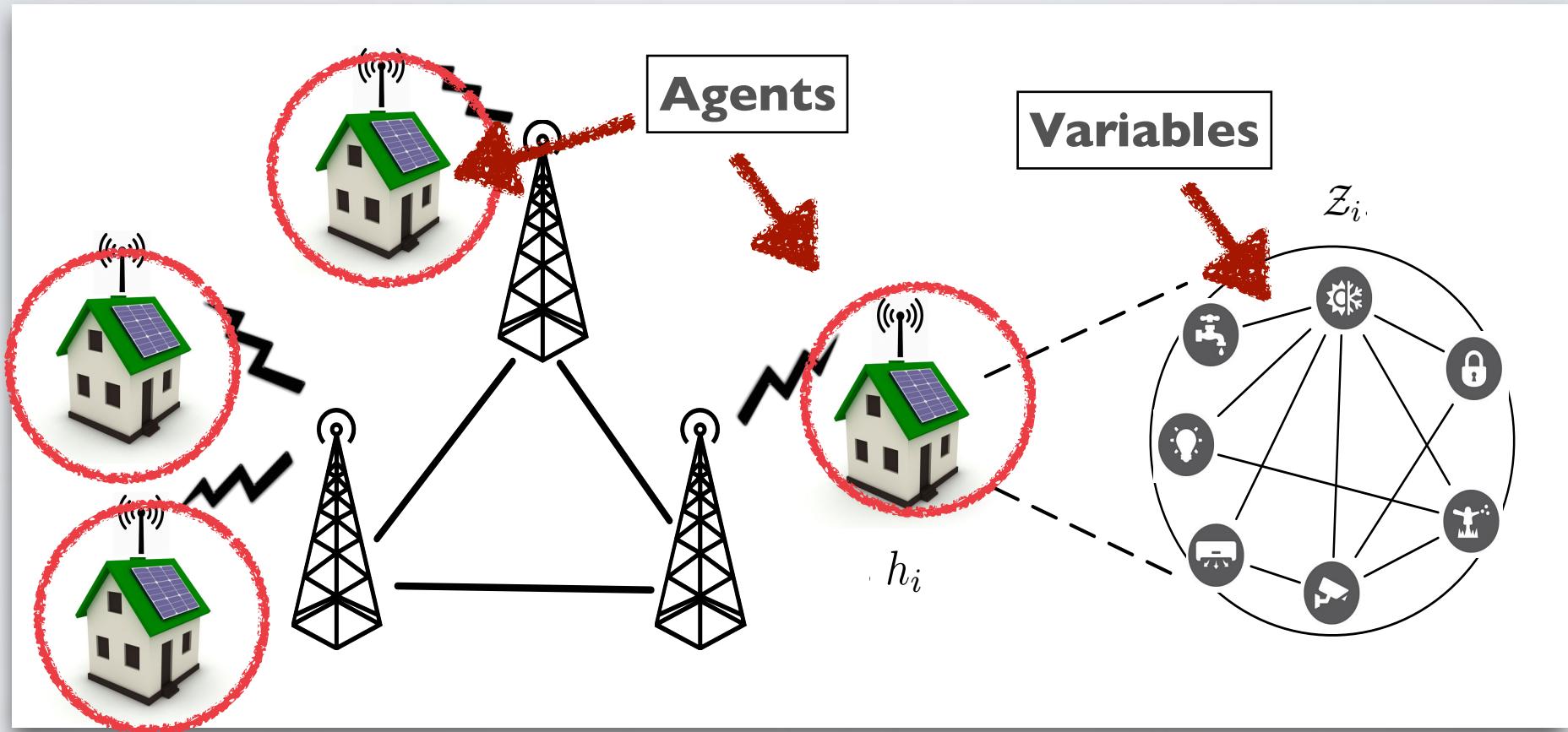
- 1) minimizing energy costs and**
- 2) reducing peaks in load demand?**

Assumptions: Each home have communication and controllable load capabilities.



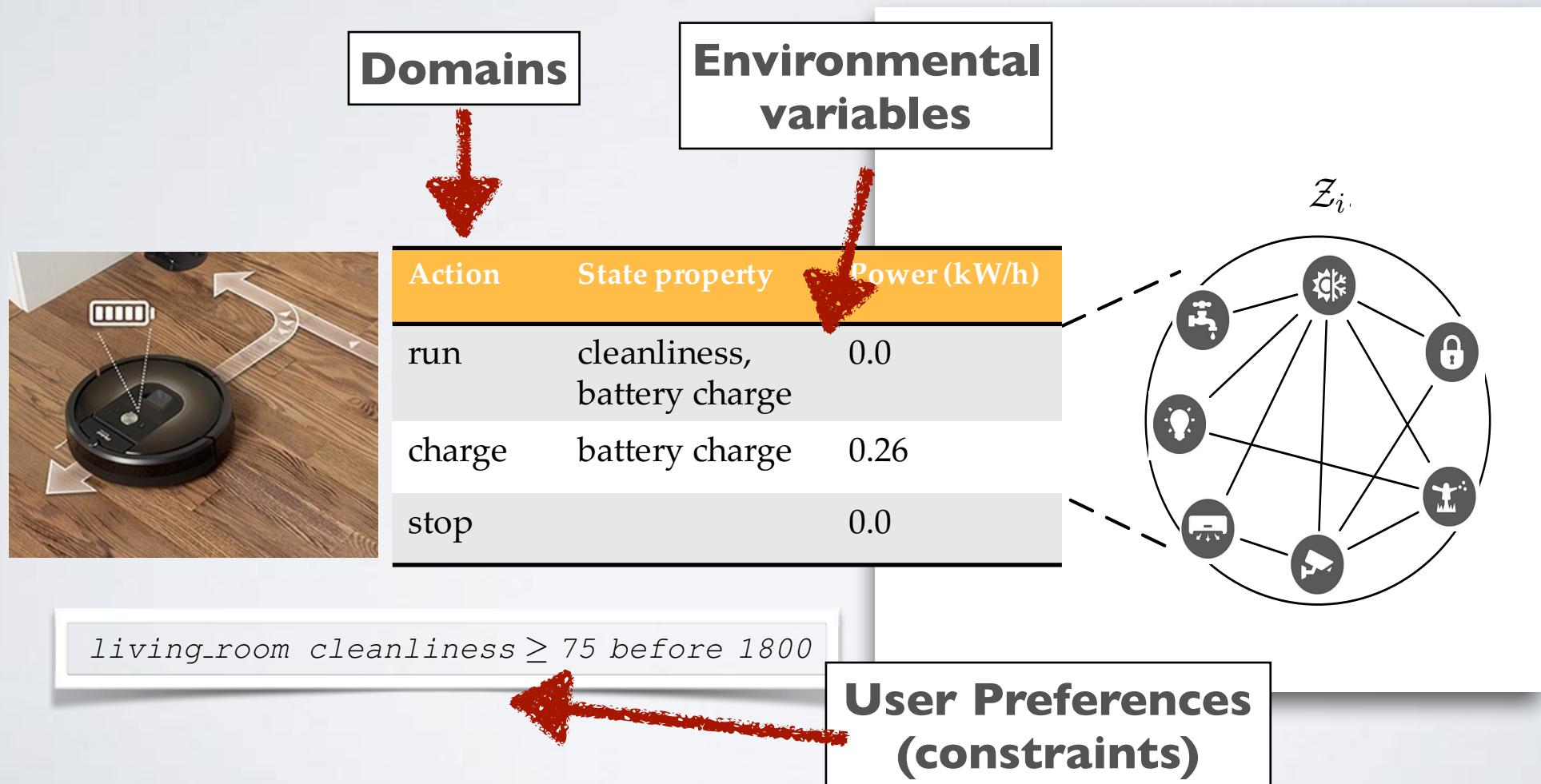
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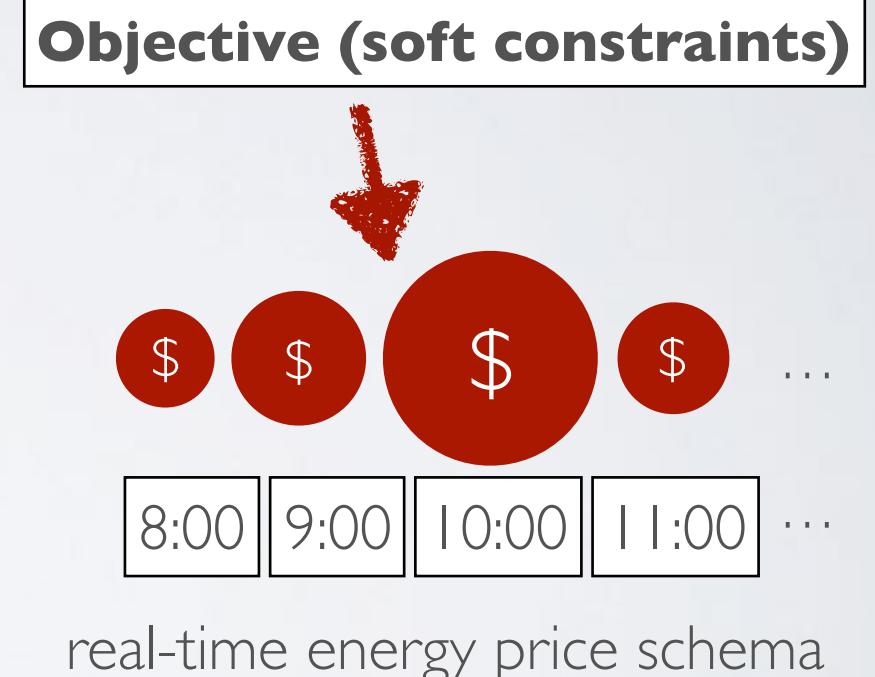
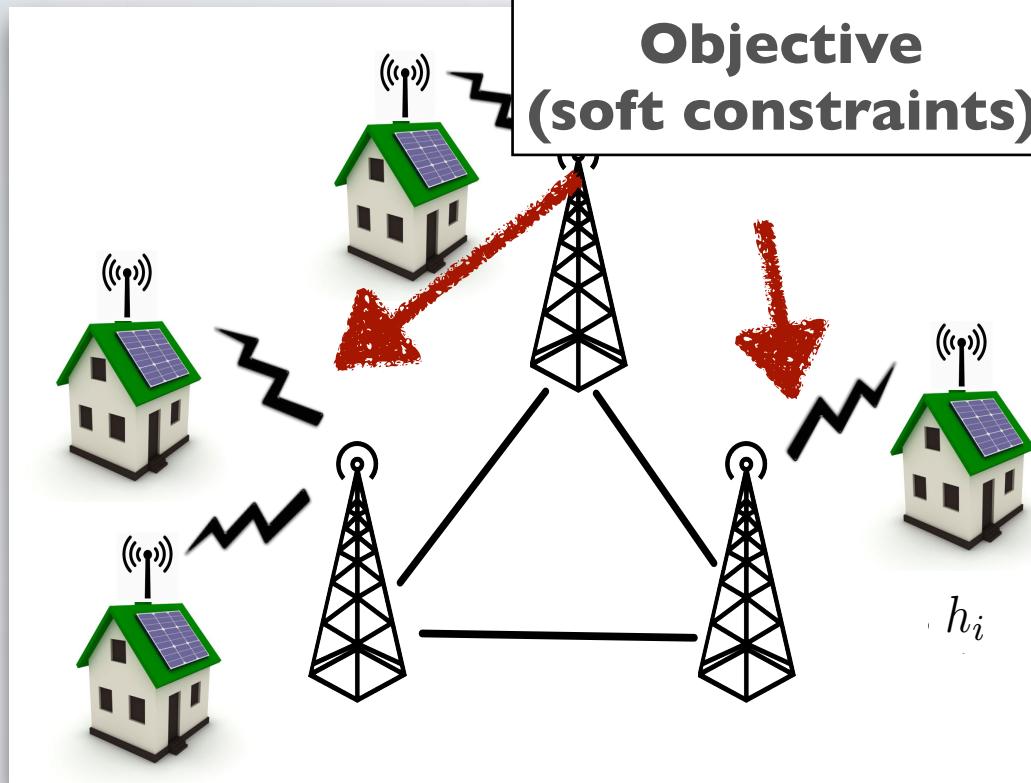


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# SMART HOMES DEVICE SCHEDULING



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# CHALLENGES AND OPEN QUESTIONS

AAAI-18 Tutorial on  
Multi-Agent Distributed Constrained Optimization

# MAS DECISION MAKING

- Decentralized decision making difficult due to:
  - Large number of interacting entities

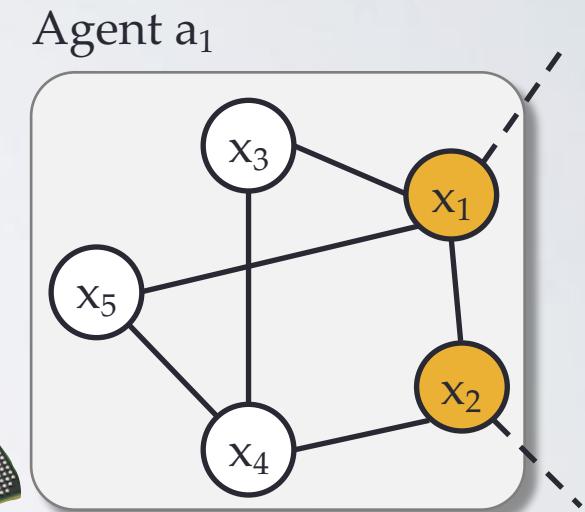
# MAS DECISION MAKING

- Decentralized decision making difficult due to:
  - Large number of interacting entities
  - Can we use **decomposition techniques** to reduce the amount of interactions?
  - Can we create **hierarchical models** to increase parallelism and efficiency?

- Bistaffa, Farinelli, Bombieri. "Optimising memory management for belief propagation in junction trees using GPGPUs", ICPADS 2014
- Ferdinando Fioretto, William Yeoh, Enrico Pontelli. "Multi-Variable Agent Decomposition for DCOPs". In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI), 2016.
- Ferdinando Fioretto, Hong Xu, Sven Koenig, TK Satish Kumar. "Constraint Composite Graph-Based Lifted Message Passing for Distributed Constraint Optimization Problems". In International Symposium on Artificial Intelligence and Mathematics (ISAIM), 2018.
- Ferdinando Fioretto, Enrico Pontelli, William Yeoh, Rina Dechter. "Accelerating Exact and Approximate Inference for (Distributed) Discrete Optimization with GPUs". In Constraints, 2018.

# MAS DECISION MAKING

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# DYNAMIC ENVIRONMENT

- Interaction in a dynamic environment is required to be robust to several changes

- R. Mailler; H. Zheng, and A. Ridgway. 2017. Dynamic, distributed constraint solving and thermodynamic theory. *Auton Agent Multi-Agent Syst* (2017).
- Zhang, C., & Lesser,V. (2013). Coordinating multi-agent reinforcement learning with limited communication. In Proceedings of the International Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 1101–1108.

# DYNAMIC ENVIRONMENT

- Interaction in a dynamic environment is required to be robust to several changes
  - How do agents respond to dynamic changes?
  - Can we study adaptive algorithms so that the MAS interaction is resilient and adaptive to changes in the communication layer, the underlying constraint graph, etc.?

- R. Mailler; H. Zheng, and A. Ridgway. 2017. Dynamic, distributed constraint solving and thermodynamic theory. *Auton Agent Multi-Agent Syst* (2017).
- Zhang, C., & Lesser,V. (2013). Coordinating multi-agent reinforcement learning with limited communication. In Proceedings of the International Conference on Autonomous Agents and Multiagent Systems (AAMAS), pp. 1101–1108.

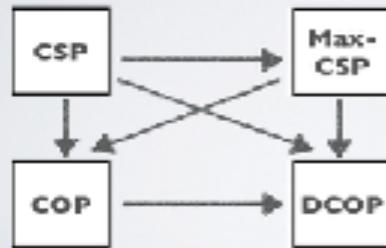
# AGENT PREFERENCES

- How to model, learn, and update agent preferences?

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- How to model, learn, and update agent preferences?
  - Agent's preferences are assumed to be available. This is not always feasible. How to efficiently elicit agents' preferences?
  - When full elicitation is not possible, how to adaptively learn the preference of an agent?
- Atena M.Tabakhi,Tiep Le, Ferdinando Fioretto, and William Yeoh. "Preference Elicitation for DCOPs." In Proceedings of the International Conference on Principles and Practice of Constraint Programming (CP), pages 278-296, 2017

# Preliminaries



- + Variables are controlled by agents
- + Communication is local
- + Local agents' knowledge

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# DCOP Algorithms



## Important Metrics:

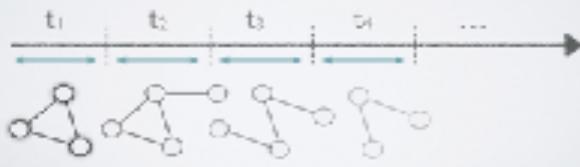
- Agent complexity
- Network loads
- Message size

- Anytime
- Quality guarantees
- Execution time vs. solution quality

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# DCOP Extensions

- A Dynamic DCOP is a sequence  $P_1, P_2, \dots, P_k$  of  $k$  DCOPs
- The agent's knowledge about the environment is confined within each time step
- Each DCOP is solved sequentially

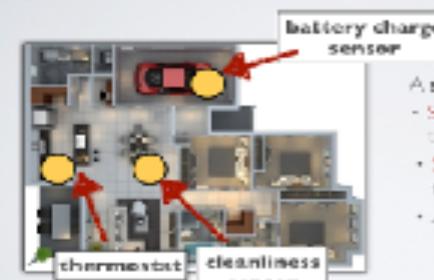


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# DCOP Applications



## A smart home use

- Smart devices (e.g., lights, HVAC)
- Sensors (humidity, temperature)
- A set of locations

Antonios Vassilicos, Ioannis Psarros, "A Multiagent System Approach to Solving DCOPs in Smart Homes", IJCAI-10

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# THANK YOU!

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