Proactive Dynamic DCOPs

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Content

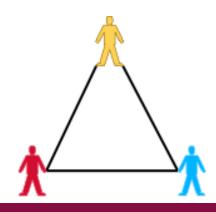
- Distributed Constraint Optimization Problem
- Proactive Dynamic DCOPs
- Algorithms
- Experimental results
- Conclusions



Distributed Meeting Scheduling Problem

Person A	Person B	Utility
8:00	8:00	0
8:00	9:00	invalid
16:00	16:00	0

Person A	Utility
8:00	2
9:00	5
16:00	10



Person A	Person C	Utility
8:00	8:00	0
8:00	9:00	invalid
16:00	16:00	0

Person B	Person C	Utility
8:00	8:00	0
8:00	9:00	invalid
16:00	16:00	0



•
$$A = \{a_1, a_2, ..., a_n\}$$

•
$$X = \{x_1, x_2, ..., x_m\}$$

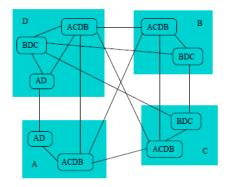
•
$$D = \{D_1, D_2, ..., D_m\}$$

•
$$F = \{f_1, f_2, ..., f_l\}$$

•
$$F(\sigma) = \sum f_i$$

•
$$\sigma_{max} = argmax F(\sigma)$$

Person A	Utility
8:00	2
9:00	5
16:00	10





•
$$A = \{a_1, a_2, ..., a_n\}$$

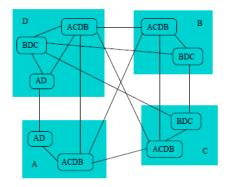
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Person A	Utility
8:00	2
9:00	5
16:00	10



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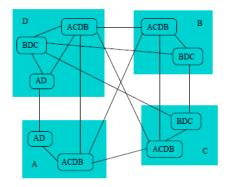
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$$F(\sigma) = \sum f_i$$

•
$$\sigma_{\text{max}} = \text{argmax } F(\sigma)$$

Person A	Utility
8:00	2
9:00	5
16:00	10





DCOP is a tuple <A, X, D, F, $\alpha>$

•
$$A = \{a_1, a_2, ..., a_n\}$$

•
$$X = \{x_1, x_2, ..., x_m\}$$

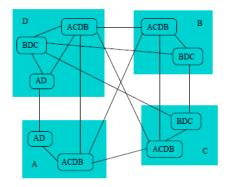
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$$D = \{D_1, D_2, ..., D_m\}$$

•
$$F = \{f_1, f_2, ..., f_l\}$$

•
$$F(\sigma) = \sum f_i$$

• $\sigma_{\text{max}} = \text{argmax } F(\sigma)$

Person A	Utility
8:00	2
9:00	5
16:00	10





•
$$A = \{a_1, a_2, ..., a_n\}$$

•
$$X = \{x_1, x_2, ..., x_m\}$$

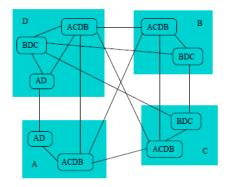
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$$D = \{D_1, D_2, ..., D_m\}$$

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$$F = \{f_1, f_2, ..., f_l\}$$

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$$F(\sigma) = \sum f_i$$

•
$$\sigma_{max} = argmax F(\sigma)$$

Person A	Utility
8:00	2
9:00	5
16:00	10



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Proactive Dynamic DCOPs

- Random variables
 - Initial distribution
 - Transition function



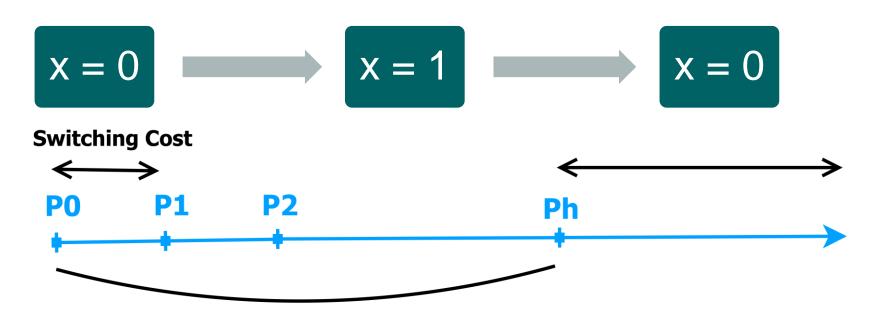
Person A	Raining	Utility
8:00	8:00	2
8:00	9:00	9
16:00	16:00	10

Week	0	Rai	ning			We	ek 1	Raining
		8:00)		→			10:00
P =	0 0).9 .15 .25	0.07 0.8 0.2	75 } 5	0.0 0.0 0)25 05 .5		



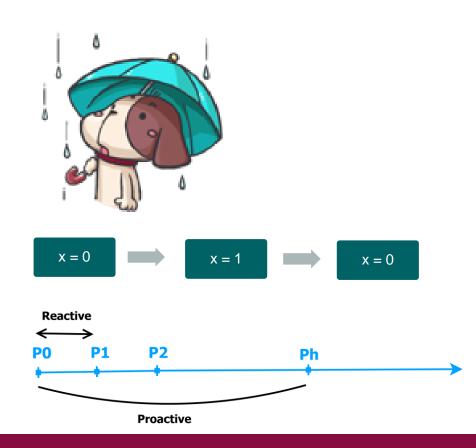
Proactive Dynamic DCOPs

Switching cost



Proactive Dynamic DCOPs (cont.)

- $Y = \{y_1, y_2, ..., y_m\}$
 - $-\Omega$: event space
 - p⁰: initial distribution
 - T: transition function
- c: switching cost
- h: horizon
- Discounted utility





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Algorithms

- Preprocessing
 - Eliminate random variables
 - Calculate discounted and expected utility
- Exact algorithm
- Approximation algorithm

Preprocessing

Constraint without random variables

x1	x2	
0	0	a
0	1	b
1	0	C
1	1	d

x1	x2	ts = k
0	0	δ ^k a
0	1	$\delta^k b$
1	0	δ ^k C
1	1	$\delta^k d$

x 1	x2	ts = h
0	0	δ ^h * 1/(1-δ) * a
0	1	δ ^h * 1/(1-δ) * b
1	0	δ ^h * 1/(1-δ) * c
1	1	δ ^h * 1/(1-δ) * d

Preprocessing (cont.)

Constraint with random variables

X	у	
0	0	a
0	1	b
1	0	С
1	1	d

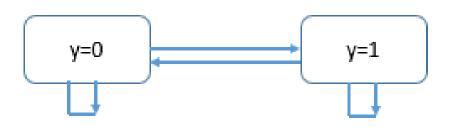
x	ts = k
0	δ^k [a*prob(y=0) + b*prob(y=1)]
1	δ^{k} [c*prob(y=0) + d*prob(y=1)]

Preprocessing (cont.)

Constraint with random variables

X	у	
0	0	а
0	1	b
1	0	C
1	1	d

X	у	ts = h
0	0	u(0,0)
0	1	u(0,1)
1	0	u(1,0)
1	1	u(1,1)



$$u(0,0) | \delta^{h*} v + \delta[u(0,0)*prob(y=0|y=0) + u(0,1)*prob(y=1|y=0)]$$

$$u(0,1)$$
 $\delta^h * x + \delta[u(0,1)*prob(y=1|y=1) + u(0,0)*prob(y=0|y=1)]$

Preprocessing (cont.)

Constraint with random variables

X	у	ts = h
0	0	u(0,0)
0	1	u(0,1)
1	0	u(1,0)
1	1	u(1,1)

X	ts = h
0	u(0,0)*prob(y=0) + u(0,1)*prob(y=1)
1	u(1,0)*prob(y=0) + u(1,1)*prob(y=1)

Regular DCOP at every time step

Exact algorithm

- Collapse h+1 DCOPs into a single DCOP
- Use any off-the-shelf exact DCOP algorithm
- Optimal solution



Exact algorithm (cont.)

t=0	x1	x2	Utility
	0	0	u11
	0	1	u12
	1	0	u13
	1	1	u14

t=1	x1	x2	Utility
	0	0	u21
	0	1	u22
	1	0	u23
	1	1	u24

t=2	x1	x2	Utility
	0	0	u31
	0	1	u32
	1	0	u33
	1	1	u34

Collapsed table	x1	x2	Aggregated utility
	0,0,0	0,0,0	u11 + u21 + u31
	0,0,0	0,0,1	u11 + u21 + u32
	1,1,1	1,1,1	u14 + u24 + u34

Approximation algorithm

- Each variable picks a sequence of initial assignments for every time step
- Use any local search approach
- Initial assignments
 - Random
 - Heuristic-based



Approximation algorithm (cont.)

- Initial random assignments
- Heuristic based
 - Solve each DCOP optimally
 - Reuse information at every time step



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Experimental setup

Decision variable: 12

Random variables: 3

Domain size: 3

• Horizon: 3

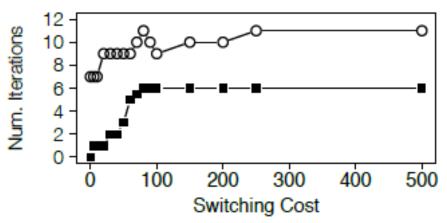
Constraint density: 0.5

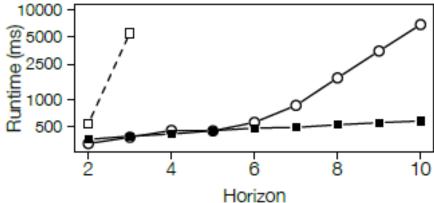
Real distributed system, actual runtime



Experimental results

--E- C-DPOP - LS-RAND - LS-SDPOP





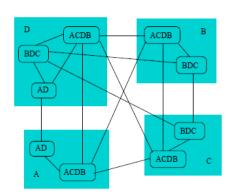
Experimental results (cont.)

$ \mathbf{A} $	C-DPOP		LS-SDPOP			LS-RAND	
	time (ms)	ρ	time (ms)		ρ	time (ms)	ρ
2	223	1.001	197	(207)	1.003	203	1.019
4	489	1.000	255	(307)	1.009	273	1.037
6	5547	1.000	382	(456)	1.011	385	1.045
8			739	(838)	1.001	556	1.034
12	_		4821	(7091)	1.003	1092	1.031
16	_		264897	(595245)	1.033	2203	1.015



Result for DisMSP

- 4 starting times, 2 locations
- 1 meeting per week



$ \mathbf{A} $	C-DPOP		LS-SD	POP	LS-RAND	
	time (ms)	% SAT	time (ms)	% SAT	time (ms)	% SAT
2	509	100	262	100	271	100
4	4786	100	367	100	399	100
6			2651	96	718	93
8			71726	96	3249	86
10					9723	86
12					15370	86

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Conclusions

- DCOP can model static problems
- Proactive Dynamic DCOP:
 - Prior information on changes of random variables
 - Initial distribution, transition function
 - Switching cost
- Exact algorithm and approximation algorithms

Thank you





