## A Generic Approach to Accelerating Belief Propagation based Incomplete Algorithms for DCOPs via A Branch-and-Bound Technique



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#### **Outline**

- Background
  - Distributed Constraint Optimization Problems (DCOPs)
  - Max-sum
- Proposed Method
  - Motivation
  - Function Decomposing and State Pruning (FDSP)
- Experimental Evaluation



## **Distributed Constraint Optimization Problems** (DCOPs)

■ DCOPs are a fundamental framework for Multi-agent Systems in which agents need to coordinate their decisions to optimize a global objective

#### Applications

- Task scheduling
- Power networks
- Sensor networks

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#### **Formal Definition of DCOPs**

#### **■** Notations:

- Agents:  $A = \{a_1, a_2, ..., a_h\}$
- lacktriangle Variables:  $X = \{x_1, x_2, ..., x_q\}$
- Domains:  $D = \{D_1, D_2, ..., D_q\}$
- Constraints:  $F = \{F_1, F_2, ..., F_r\}$

#### Note:

Each constraint is a n-ary function:  $F_k : \mathbf{x_k} \to \mathbb{R}^+, \ \mathbf{x_k} \subseteq X \ and \ n = |\mathbf{x_k}|$ 

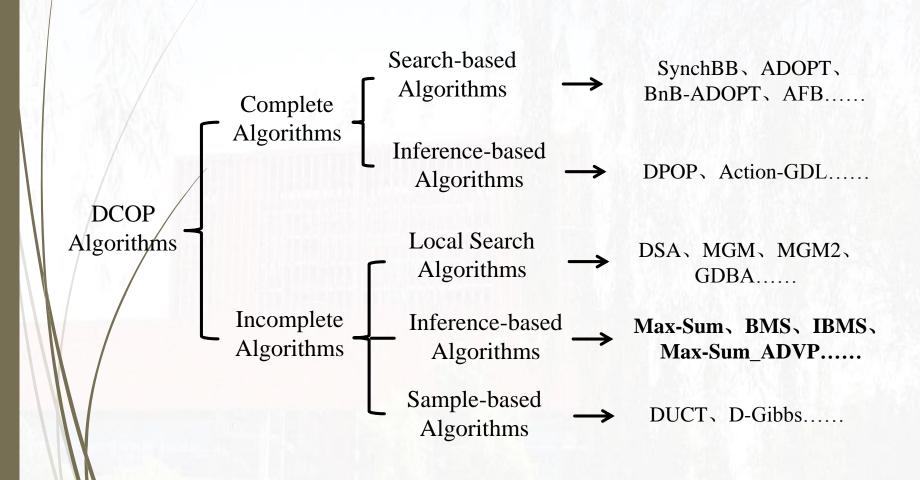
#### **■** Goal:

Find an assignment  $X^*$  to maximize the total utility:

$$X^* = rg \max_{X} \sum_{F_k(\mathbf{x_k}) \in F, \mathbf{x_k} \subseteq X} F_k(\mathbf{x_k})$$

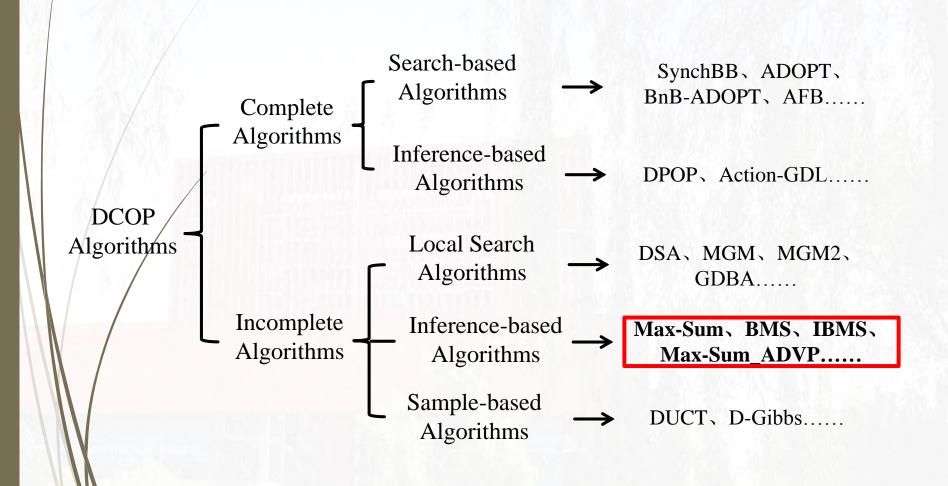


#### **Taxonomy of Algorithms for DCOPs**





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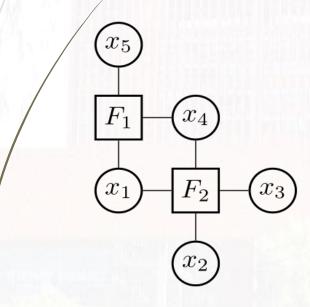


#### Max-Sum Algorithm (belief propagation approach)

#### Factor Graph

- Variable-nodes: variables  $X = \{x_1, x_2, ..., x_q\}$
- Function-nodes: **constraint functions**  $F = \{F_1, F_2, ..., F_r\}$

#### Example



A factor graph

 $F_1$  and  $F_2$  are two function-nodes

 $x_1, x_2, x_3, x_4$  and  $x_5$  are variable-nodes

 $F_1(\mathbf{x_1})$  is a 3-ary constraint

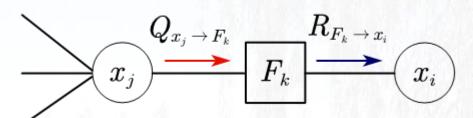
$$\mathbf{x_1} = \{x_1, x_4, x_5\}$$

 $F_2(\mathbf{x_2})$  is a 4-ary constraint

$$\mathbf{x_2} = \{x_1, x_2, x_3, x_4\}$$



#### **Max-Sum Algorithm**



Messages from variable-nodes: accumulating and forwarding utilities

$$igg/ Q_{x_i 
ightarrow F_k}(x_i) = lpha_{ik} + \sum_{F_j \in N_i \,ackslash \, F_k} R_{F_j 
ightarrow \, x_i}(x_i) \qquad (1)$$

Messages from function-nodes: maximizing utilities upon received utilities and local functions

$$R_{F_k o x_i}(x_i) = \max_{\mathbf{x_k}} \left( F_k(\mathbf{x_k}) + \sum_{x_j \in \mathbf{x_k}} Q_{x_j o F_k}(x_j) 
ight)$$
 (2)

Decision-making strategy for variable-nodes: selecting a value to maximize the total utility:

$$x_i^* = rgmax \sum_{x_i} R_{F_k \, 
ightarrow \, x_i}(x_i) \hspace{0.5cm} (3)$$



#### Motivation

- **Problem:** the *scalability* of Max-sum and its variants
- **Reason:** the *complexity*  $O(d^n)$  of computing message with Eq. (2) (d: domain size, n: arity)
- Existing methods
  - Branch and bound: BnB-MS and BnB-FMS
    - ? Exchange a number of messages in the preprocessing phase
    - ? Lack of generalization
  - Sorting: G-FBP, GDP
    - ? Require *prohibitively expensive sorting* in the preprocessing phase
    - ? G-FBP may lead to a complete traverse to all possible combinations
    - ? GDP cannot prune the search space dynamically
- Our goal: a generic, fast and easy-to-use approach



## **Function Decomposing and State Pruning (FDSP)**

- **Idea:** using the learned experience from the combinations explored to dynamically prune the search space
- Scheme
  - **►** Function Decomposing (FD) in the preprocessing phase
    - Computing *function estimations* to provide upper bounds for the local function by means of *Dynamic Programming*
  - **■** State Pruning (SP)
    - ➤ Pruning the search space by means of *Branch and Bound* in terms of the optimal upper bound from *function estimations* and *the received query message estimations*



#### **Function Decomposing (FD)**

■ The function estimation of  $F_k(\mathbf{x_k})$ :

$$egin{aligned} FunEst_{\mathbf{x_{k,i}}}(PA|\frac{\mathbf{x_{k,i}}}{\mathbf{x_{k,1}}}) &= \max_{z = \{\mathbf{x_{k,j}}|j > i\}} F_k(PA|\frac{\mathbf{x_{k,i}}}{\mathbf{x_{k,1}}}, z) \\ PA|\frac{\mathbf{x_{k,i}}}{\mathbf{x_{k,1}}} & ext{is a partial assignment and } \{\mathbf{x_{k,w}} \in \mathbf{x_k} | 1 \leq w \leq i\} \end{aligned}$$

- Two types of function estimations:
  - uninformed function estimation for tight upper bounds

$$\mathit{FunEst}_{\mathbf{x}_{\mathtt{k},\mathtt{i}}} = egin{cases} F_k(\mathbf{x_k}) & i = n \ \max_{\mathbf{x}_{\mathtt{k},\mathtt{i}+1}} FunEst_{\mathbf{x}_{\mathtt{k},\mathtt{i}+1}} & otherwise \end{cases}$$

informed function estimation for tighter upper bounds

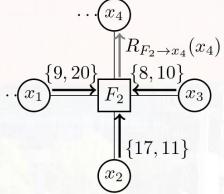
$$FunEst_{\mathbf{x_{k,i}}}^{\,\mathbf{x_{k,j}}\,=\,v_{k,j}} = egin{cases} FunEst_{\mathbf{x_{k,j}}}(v_{k,j}) & i=j-1 \ \max_{\mathbf{x_{k,i+1}}} FunEst_{\mathbf{x_{k,i+1}}}^{\,\mathbf{x_{k,j}}\,=\,v_{k,j}} & otherwise \end{cases}$$



■ The uninformed function estimations for variable  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$ 

$x_2$ R	$x_3$	$x_4$	$F_2$
D			
1/	R	R	4
R	R	G	13
R	G	R	26
R	G	G	5
G	R	R	1
G	R	G	5
G	G	R	2
G	G	G	4
R	R	R	10
R	R	G	7
R	G	R	6
R	G	G	9
G	R	R	11
G	R	G	8
G	G	R	12
G	G	G	1
	R R G G G R R R R G G	R G R G R G G G G R R R R R R G R G R G	R G R R G R R G G G R R R R R R R R G R G G R R G G R R G G R R R G G R R R G G R R R G G R R R G G R R R

(a) utility matrix of  $F_2$ 



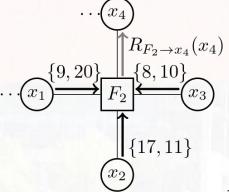
(b) messages exchange for  $F_2$ 



■ The uninformed function estimations for variable  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$ 

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

(a) utility matrix of  $F_2$ 



(b) messages exchange for  $F_2$ 

Step1:	$FunEst_{x_4}$	$=F_2$
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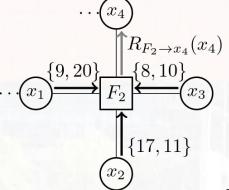
$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1



■ The uninformed function estimations for variable  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$ 

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

(a) utility matrix of  $F_2$ 



(b) messages exchange for  $F_2$ 

Step1:  $FunEst_{x_4} = F_2$ 

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

Step2:  $FunEst_{x_3} = \max_{x_4} FunEst_{x_4}$ 

$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	13
R	R	G	26
R	G	R	5
R	G	G	4
G	R	R	10
G	R	G	9
G	G	R	11
G	G	G	12



Step1:  $FunEst_{x_4} = F_2$ 

■ The uninformed function estimations for variable  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$ 

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

(a) utility matrix of  $F_2$ 

			50 4	
$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12

Step2:  $FunEst_{x_3} = \max_{x_4} FunEst_{x_4}$ 

$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	13
R	R	G	26
R	G	R	5
R	G	G	4
G	R	R	10
G	R	G	9
G	G	R	11
G	G	G	12

Step3:  $FunEst_{x_2} = \max_{x_2} FunEst_{x_3}$ 

$\cdots (x_4)$
$\{9, 20\} \qquad \{8, 10\} $
$\begin{array}{cccccccccccccccccccccccccccccccccccc$
$\begin{pmatrix} x_2 \end{pmatrix}$

(b) messages	exchange f	for $F_2$
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$x_3$		
$x_1$	$x_2$	$F_2$
R	R	26
R	G	5
G	R	10
G	G	12



The uninformed function estimations for variable  $x_1$ ,  $x_2$ ,  $x_3$ , and  $x_4$ 

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

(a) utility matrix of  $F_2$ 

Step1:	$FunEst_{x_4}$	$=F_2$
--------	----------------	--------

$x_1$	$x_2$	$x_3$	$x_4$	$F_2$
R	R	R	R	4
R	R	R	G	13
R	R	G	R	26
R	R	G	G	5
R	G	R	R	1
R	G	R	G	5
R	G	G	R	2
R	G	G	G	4
G	R	R	R	10
G	R	R	G	7
G	R	G	R	6
G	R	G	G	9
G	G	R	R	11
G	G	R	G	8
G	G	G	R	12
G	G	G	G	1

Step2:  $FunEst_{x_3} = \max FunEst_{x_4}$ 

			88 2W 8
$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	13
R	R	G	26
R	G	R	5
R	G	G	4
G	R	R	10
G	R	G	9
G	G	R	11
G	G	G	12

Step3:  $FunEst_{x_2} = \max_{x_3} FunEst_{x_3}$  Step4:  $FunEst_{x_1} = \max_{x_2} FunEst_{x_2}$ 

$\cdots (x_4)$	
$ ightharpoons R_{F_2  o x_4}$	$x_4$
$\{9,20\}$ $\{8,10\}$	
$x_1$	3)
$\boxed{\{17,11\}}$	
$(x_2)$	

(b) messages exchange for $F_2$			
(S) Hisborges chieffelings for - Z	<b>(b)</b>	messages exchange for	$\cdot F_2$

$x_1$	$x_2$	$F_2$
R	R	26
R	G	5
G	R	10
G	G	12

$x_1$	$F_2$
R	26
G	12





**Step1:** 
$$FunEst_{x_3}^{x_4=R} = FunEst_{x_4}(x_4=R)$$

$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	4
R	R	G	26
R	G	R	1
R	G	G	2
G	R	R	10
G	R	G	6
G	G	R	11
G	G	G	12



**Step1:** 
$$FunEst_{x_3}^{x_4=R} = FunEst_{x_4}(x_4=R)$$

$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	4
R	R	G	26
R	G	R	1
R	G	G	2
G	R	R	10
G	R	G	6
G	G	R	11
G	G	G	12

Step2: 
$$FunEst_{x_2}^{x_4=R} = \max_{x_3} FunEst_{x_3}^{x_4=R}$$

$x_1$	$x_2$	$F_2$		
R	R	26		
R	G	2		
G	R	10		
G	G	12		



**Step1:** 
$$FunEst_{x_3}^{x_4=R} = FunEst_{x_4}(x_4=R)$$

$x_1$	$x_2$	$x_3$	$F_2$
R	R	R	4
R	R	G	26
R	G	R	1
R	G	G	2
G	R	R	10
G	R	G	6
G	G	R	11
G	G	G	12

Step2: 
$$FunEst_{x_2}^{x_4=R} = \max_{x_3} FunEst_{x_3}^{x_4=R}$$

$x_1$	$x_2$	$F_2$
R	R	26
R	G	2
G	R	10
G	G	12

Step3: 
$$FunEst_{x_1}^{x_4=R} = \max_{x_2} FunEst_{x_2}^{x_4=R}$$

$x_1$	$F_2$
R	26
G	12



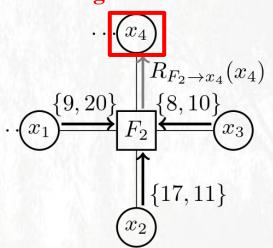
■ The received query message estimation:

$$MsgEst_{\mathbf{x_{k,i}}} = egin{cases} \sum_{j>i \wedge j 
eq t} \max\left(\mathcal{M}_{\mathbf{x_{k,i}}}
ight) & i = n-1 \ MsgEst_{\mathbf{x_{k,i+1}}} + \max\left(\mathcal{M}_{\mathbf{x_{k,i+1}}}
ight) & otherwise \end{cases}$$

Example

$$MsgEst_{x_3} = 0 \ MsgEst_{x_2} = MsgEst_{x_3} + \max \mathcal{M}_{x_3} = 10 \ MsgEst_{x_1} = MsgEst_{x_2} + \max \mathcal{M}_{x_2} = 10 + 17 = 27$$

#### Target variable



The upper bound  $ub_{\mathbf{x}_{k,i}}$  for a partial assignment  $Assign \begin{vmatrix} \mathbf{x}_{k,i} \\ \mathbf{x}_{k,1} \end{vmatrix}$  is

$$ub_{\mathbf{x_{k,i}}} = egin{cases} msgUtil_{\mathbf{x_{k,i}}} + MsgEst_{\mathbf{x_{k,i}}} + FunEst_{\mathbf{x_{k,i}}}ig(Assignig|_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}}}ig) & i > t \ msgUtil_{\mathbf{x_{k,i}}} + MsgEst_{\mathbf{x_{k,i}}} + FunEst_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}} = v_{k,t}}ig(Assignig|_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}}}ig) & i < t \end{cases}$$

Here,

$$extit{msgUtil}_{\mathbf{x_{k,i}}} = \sum_{1 \leqslant w \leqslant i} \mathcal{M}_{\mathbf{x_{k,w}}}\left(v_{k,w}
ight)$$

Discard the search space corresponding to the partial assignment when  $ub_{\mathbf{x}_{k,l}} \leq lb$ .

The upper bound  $ub_{\mathbf{x}_{k,i}}$  for a partial assignment  $Assign \begin{vmatrix} \mathbf{x}_{k,i} \\ \mathbf{x}_{k,1} \end{vmatrix}$  is

$$ub_{\mathbf{x_{k,i}}} = egin{cases} msgUtil_{\mathbf{x_{k,i}}} + MsgEst_{\mathbf{x_{k,i}}} \\ msgUtil_{\mathbf{x_{k,i}}} + MsgEst_{\mathbf{x_{k,i}}} \\ + FunEst_{\mathbf{x_{k,i}}} (Assignig|_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}}}) & i > t \\ + FunEst_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}}} - v_{k,t} (Assignig|_{\mathbf{x_{k,i}}}^{\mathbf{x_{k,i}}}) & i < t \\ & Message \\ & estimation \end{cases}$$

Here,

$$\mathit{msgUtil}_{\mathbf{x_{k,i}}} = \sum_{1 \leqslant w \leqslant i} \mathcal{M}_{\mathbf{x_{k,w}}}\left(v_{k,w}
ight)$$

Discard the search space corresponding to the partial assignment when  $ub_{\mathbf{x}_{k,i}} \leq lb$ .

■ The upper bound  $ub_{\mathbf{x}_{k,i}}$  for a partial assignment  $Assign \begin{vmatrix} \mathbf{x}_{k,i} \\ \mathbf{x}_{k,1} \end{vmatrix}$  is

$$ub_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} = egin{cases} msgUtil_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} + MsgEst_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} + FunEst_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} \left( Assignig|_{\mathbf{x}_{\mathbf{k},\mathbf{i}}}^{\mathbf{x}_{\mathbf{k},\mathbf{i}}} 
ight) i > t \ msgUtil_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} + MsgEst_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} + FunEst_{\mathbf{x}_{\mathbf{k},\mathbf{i}}}^{\mathbf{x}_{\mathbf{k},\mathbf{i}}} = v_{k,t} \left( Assignig|_{\mathbf{x}_{\mathbf{k},\mathbf{i}}}^{\mathbf{x}_{\mathbf{k},\mathbf{i}}} 
ight) i < t \ Here, \ msgUtil_{\mathbf{x}_{\mathbf{k},\mathbf{i}}} = \sum_{1 \leq w \leq i} \mathcal{M}_{\mathbf{x}_{\mathbf{k},\mathbf{w}}} \left( v_{k,w} 
ight)$$

Discard the search space corresponding to the partial assignment when  $ub_{\mathbf{x}_{k,i}} \leq lb$ .





$$\{\emptyset,\emptyset,\emptyset,R\}$$



$$\{\emptyset,\emptyset\,,\emptyset\,,R\}$$
  $[-\infty,62]$ 



$$\{\emptyset,\emptyset\,,\emptyset\,,R\}$$
  $[-\infty,62]$   $\{R,\emptyset\,,\emptyset\,,R\}$ 



$$\{\emptyset,\emptyset\,,\emptyset\,,R\}$$
  $[-\infty,62]$   $\{R,\emptyset\,,\emptyset\,,R\}$   $[-\infty,62]$   $[2]$ 



$$\{\emptyset,\emptyset\,,\emptyset\,,R\}$$
  $[-\infty,62]$   $\{R,\emptyset\,,\emptyset\,,R\}$   $[-\infty,62]$   $\{R,R,\emptyset\,,R\}$ 



$$\{\emptyset,\emptyset,\emptyset,R\}$$
 $[-\infty,62]$ 
 $\{R,\emptyset,\emptyset,R\}$ 
 $[-\infty,62]$ 
 $\{R,R,\emptyset,R\}$ 
 $[-\infty,38]$ 
 $[3]$ 



$$\{\emptyset,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$\{R,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$\{R,R,\emptyset,R\}$$

$$[-\infty,38]$$

$$\{R,R,R,R\}$$



$$\{\emptyset,\emptyset,\emptyset,R\}$$
 $[-\infty,62]$ 
 $\{R,\emptyset,\emptyset,R\}$ 
 $[-\infty,62]$ 
 $\{R,R,\emptyset,R\}$ 
 $[-\infty,38]$ 
 $\{R,R,R,R\}$ 



$$\{\emptyset,\emptyset,\emptyset,R\}$$
 $[-\infty,62]$ 
 $\{R,\emptyset,\emptyset,R\}$ 
 $[-\infty,62]$ 
 $\{R,R,\emptyset,R\}$ 
 $[-\infty,38]$ 
 $\{R,R,R,R\}$ 
 $\{R,R,G,R\}$ 



$$\{\emptyset,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$\{R,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$[62,32]$$

$$\{R,R,\emptyset,R\}$$

$$[-\infty,38]$$

$$[38,62]$$

$$\{R,R,R,R\}$$

$$\{R,R,G,R\}$$



$$\{\emptyset,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$\{R,\emptyset,\emptyset,R\}$$

$$[-\infty,62]$$

$$\{R,R,\emptyset,R\}$$

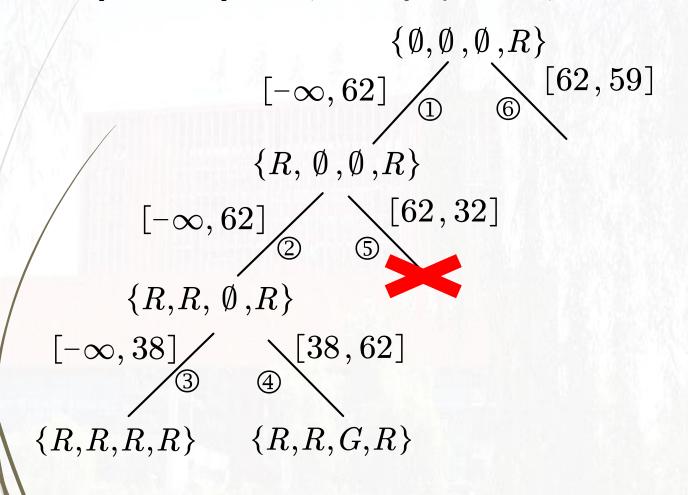
$$\{R,R,R,R\}$$

$$[38,62]$$

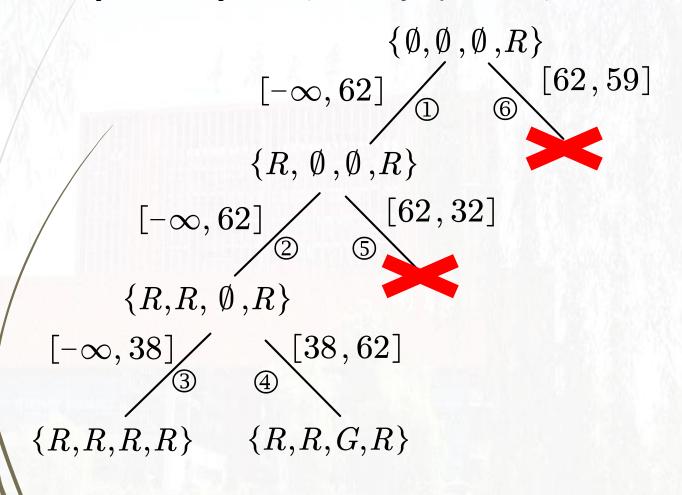
$$\{R,R,R,R,R\}$$

$$\{R,R,G,R\}$$











## **Experimental Evaluation**

#### Evaluation criteria

- Percentage of search space pruned
- **■** Runtime

#### Experimental configuration

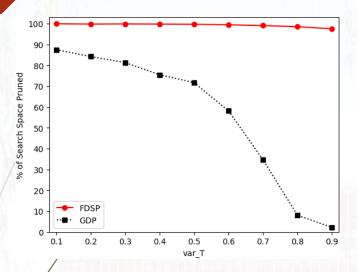
- Complexity of n-ary DCOPs
  - Function-nodes number
  - Average/Maximal arity
  - Domain Size
  - *Variable tightness (var\_T)*

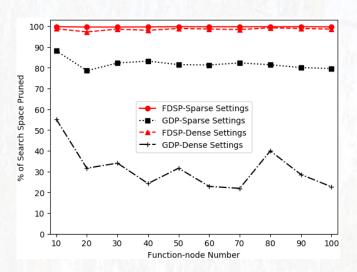
$$var\_T = 1 - \frac{number of variable - nodes}{total number of arities}$$

- Random DCOPs
  - Function-nodes number: 100
  - *Maximal arity*: [2,7]
  - *Cost Range*: [1,100]
  - *Domain Size*: [2,10]
  - $var\_T \in [0.1,0.5]$  (sparse)  $var\_T \in (0.5,0.9]$  (dense)



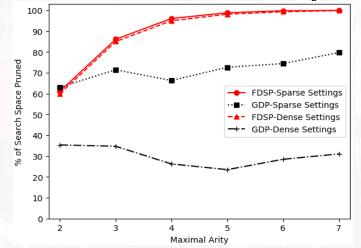
#### **Experimental Results (Percentage of search space pruned)**





Performance comparison on different var\_T

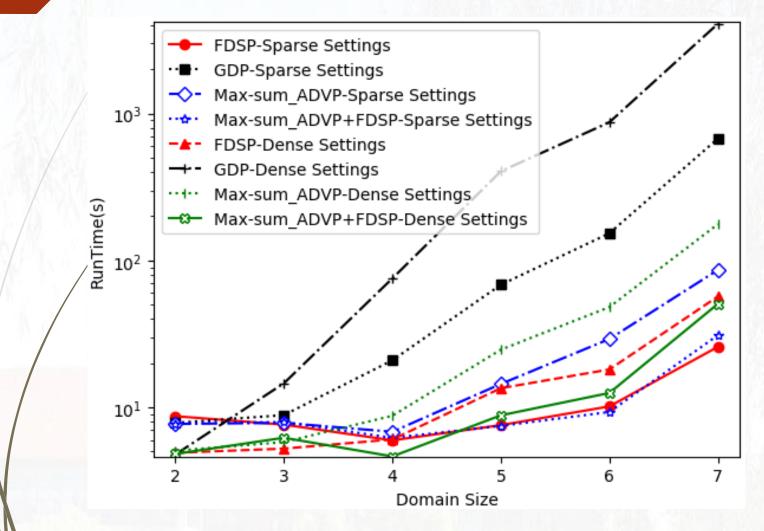
Performance comparison on different function-node numbers



Performance comparison on different maximal arities



#### **Experimental Results (Runtime)**



Runtime on different domain sizes



#### **Conclusion**

- Propose a generic, fast and easy-to-use method, named FDSP
  - ► Function decomposing (FD) with *Dynamic Programming* to effectively compute the function estimations
  - State pruning (SP) based on *branch and bound* to reduce the séarch space
- Theoretically prove that FDSP provides monotonically nonincreasing bounds and never prunes the assignment with the maximum utility
- ► *Empirical* evaluation shows that FDSP can reduce at least 97% of the search space and effectively accelerate Max-Sum and its variants



# Thank you