

Improved Bounded Max Sum for Distributed Constraint Optimization

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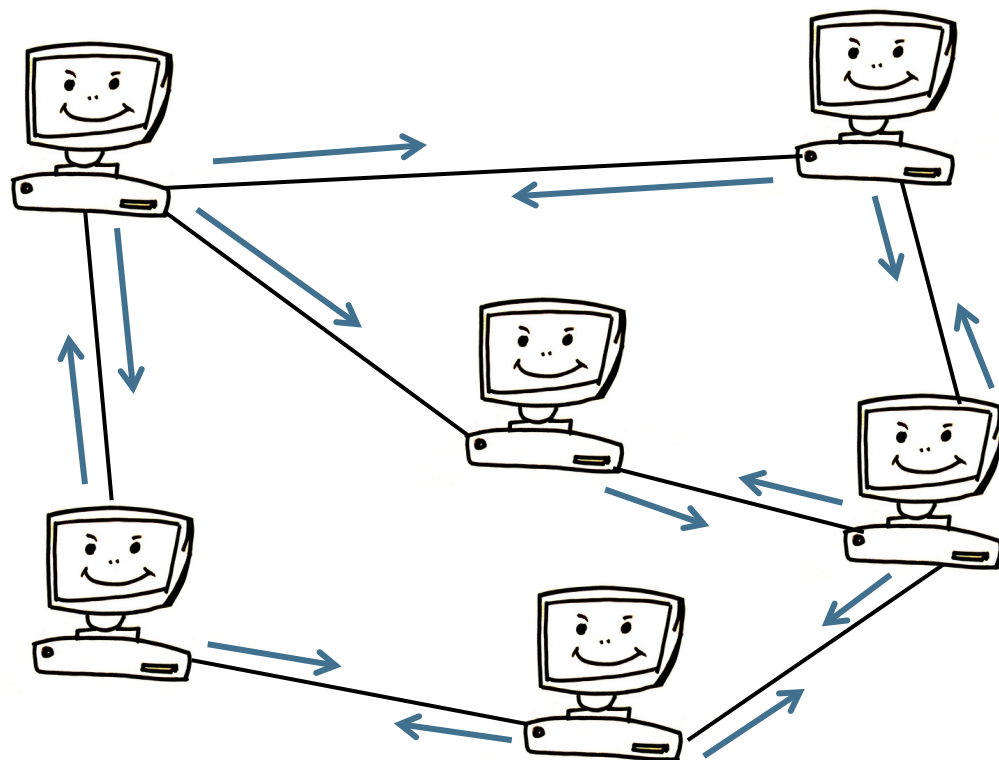
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Introduction



Context:

- Low-power devices
- Very fast response

We cannot find the optimal solution, but just a good solution

Approximation ratio (AR):

$$AR = UB / LB$$

Bad approximation ratio:

1. Bad solution (LB)
2. Bad UB

Contribution

We propose an improved version of Bounded Max-Sum:

1. It improves the approximation ratio
2. It improves the approximate solution

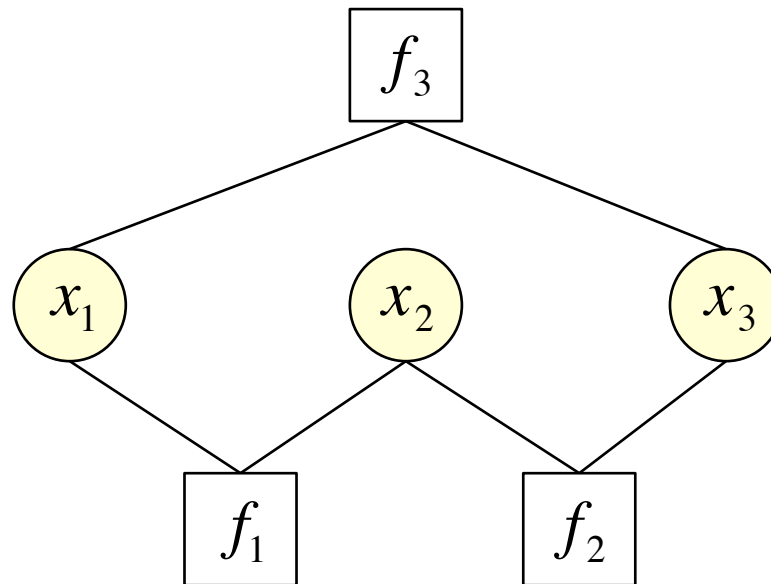
DCOP

- $X = \{x_1, \dots, x_n\}$: a set of variables
- $D = \{D_1, \dots, D_n\}$: a set of domain values
- $F = \{f_1, \dots, f_e\}$: a set of cost functions
- $A = \{a_1, \dots, a_r\}$: a set of agents
- $\beta : F \rightarrow A$: a mapping between cost functions to agents

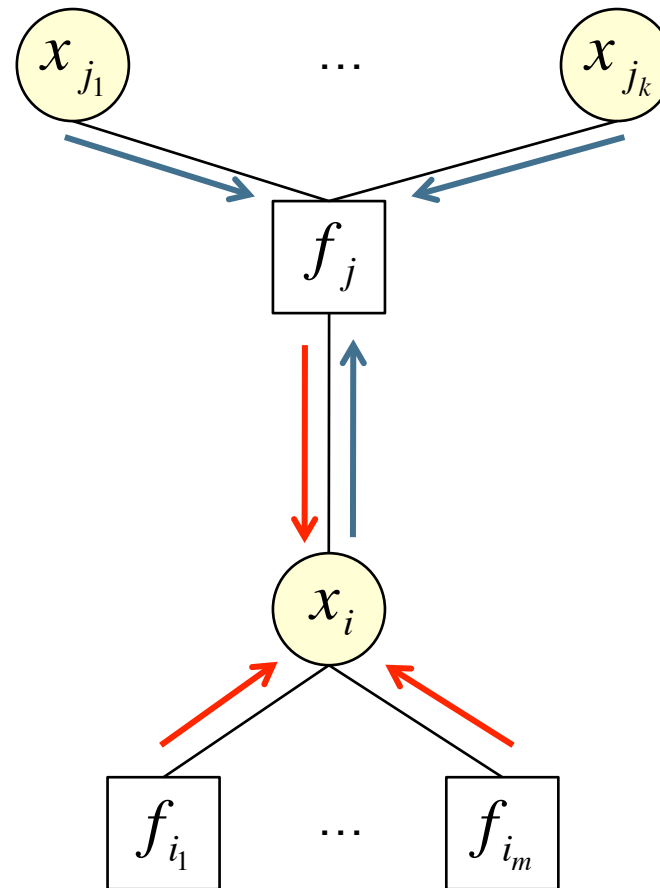
- Objective function:
$$F(X) = \sum_{f \in F} f(X)$$
- Task:
$$x^* = \arg \max_X F(X)$$
- Approximation ratio:
$$F(x) \leq F(x^*) \leq \rho F(x)$$

Factor Graph

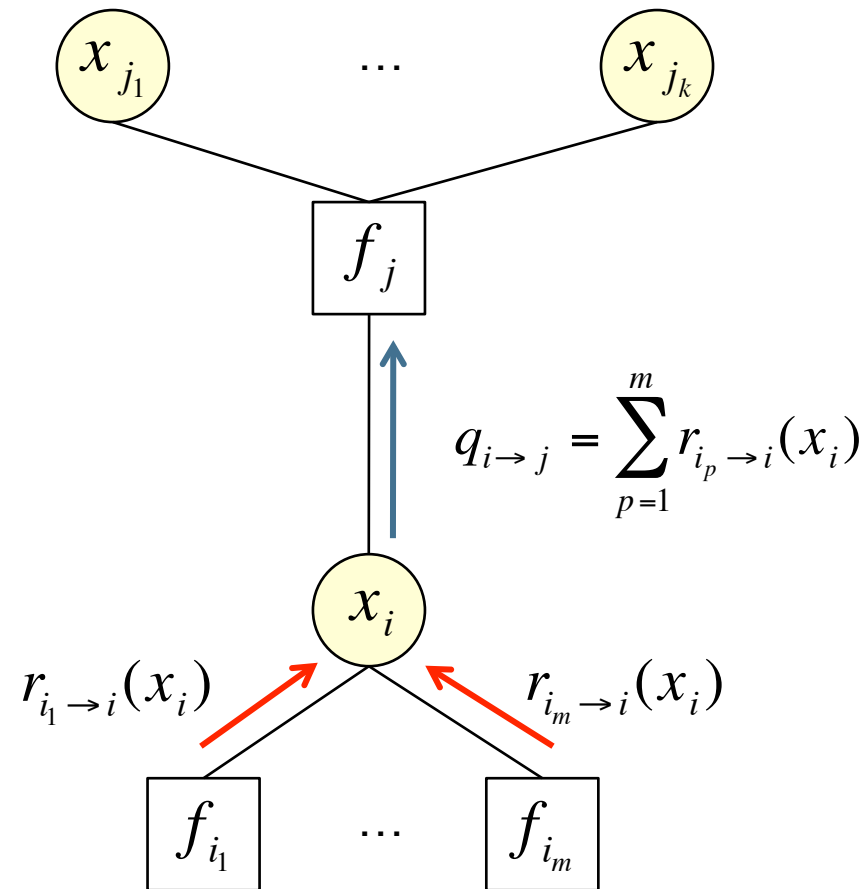
$$\{ f_1(x_1, x_2), f_2(x_2, x_3), f_3(x_1, x_3) \}$$



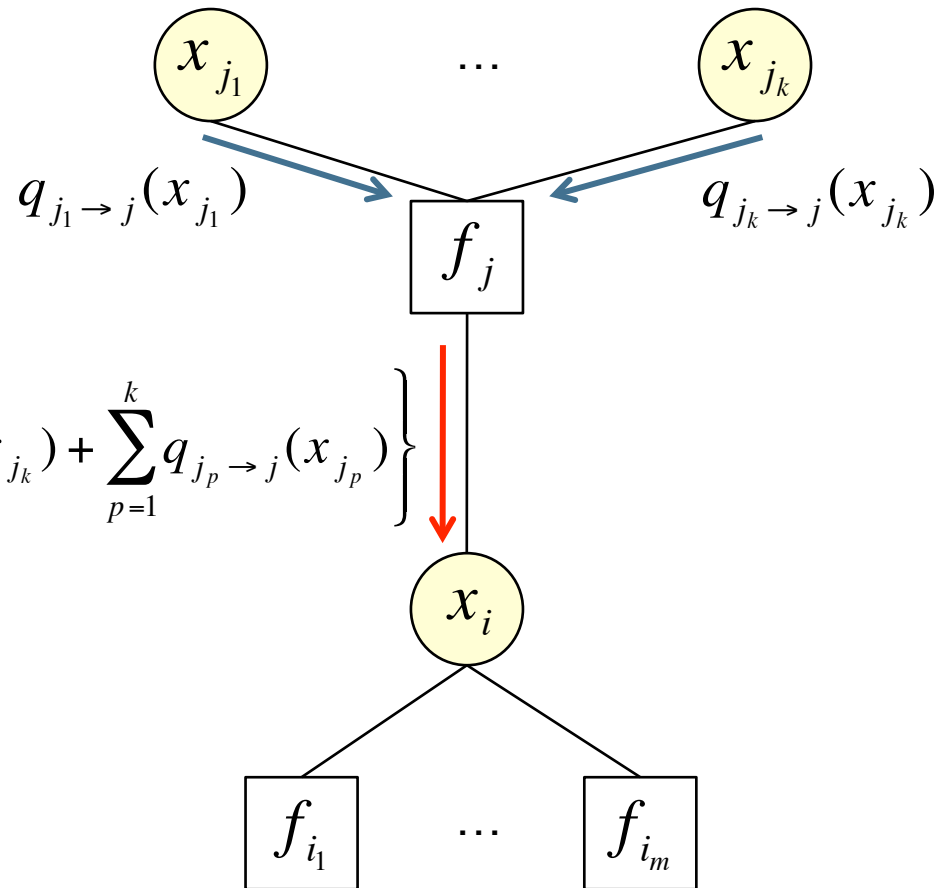
Max-Sum



Max-Sum



Max-Sum



$$r_{j \rightarrow i}(x_i) = \max_{x_{j_1}, \dots, x_{j_k}} \left\{ f_j(x_i, x_{j_1}, \dots, x_{j_k}) + \sum_{p=1}^k q_{j_p \rightarrow j}(x_{j_p}) \right\}$$

Max eliminates variables from the problem

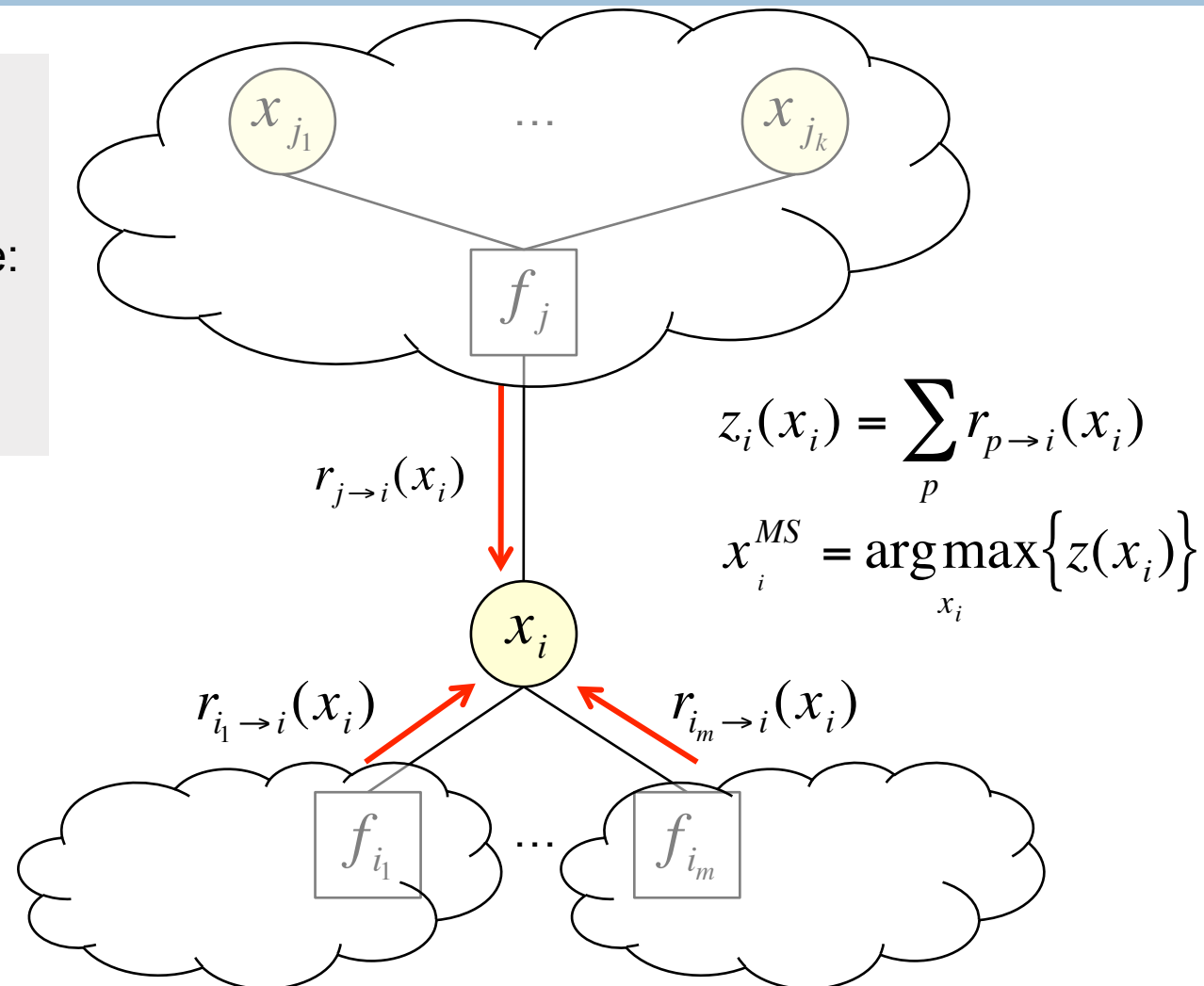
Max-Sum

Always:

$$F(x^{MS}) \leq F(x^*)$$

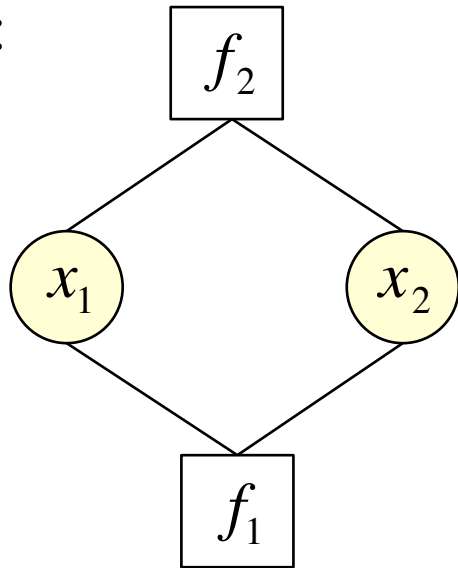
If the factor graph is a tree:

$$F(x^{MS}) = F(x^*)$$



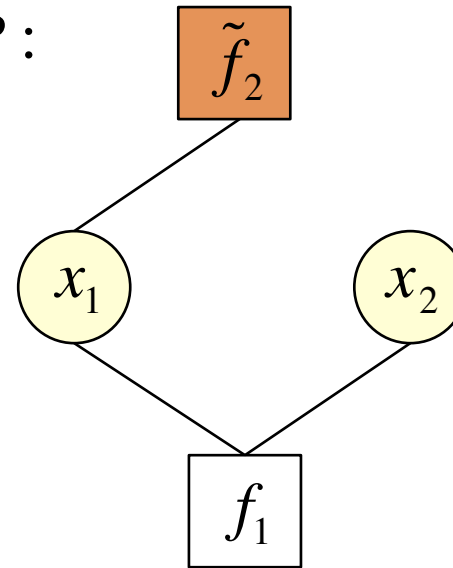
Bounded Max-Sum (BMS)

P :



1. Remove cycles:

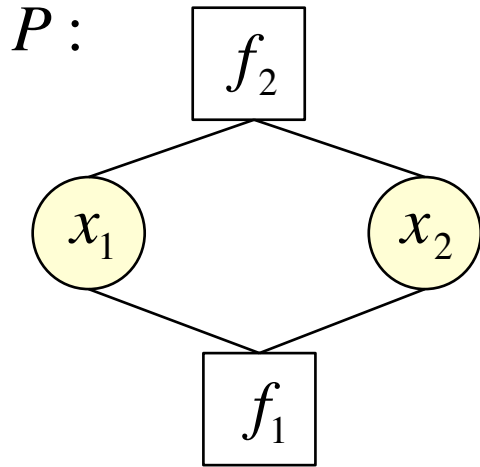
\tilde{P} :



2. Solve \tilde{P} using Max-Sum

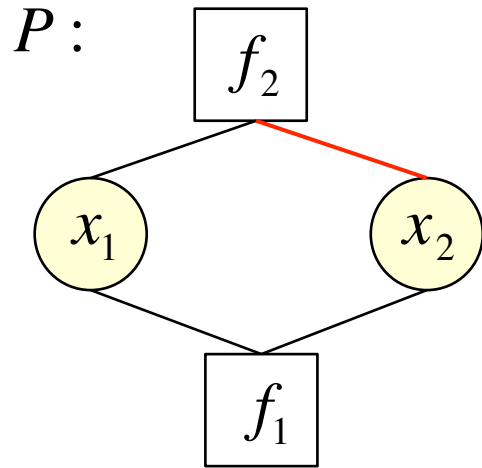
3. Bound the optimum solution

BMS: remove cycles

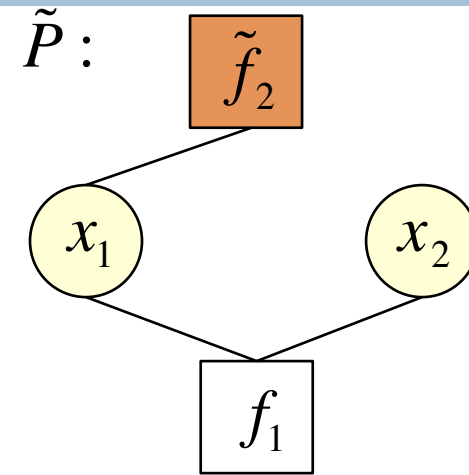


1. Select an edge to remove
2. Remove selected edge

BMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10

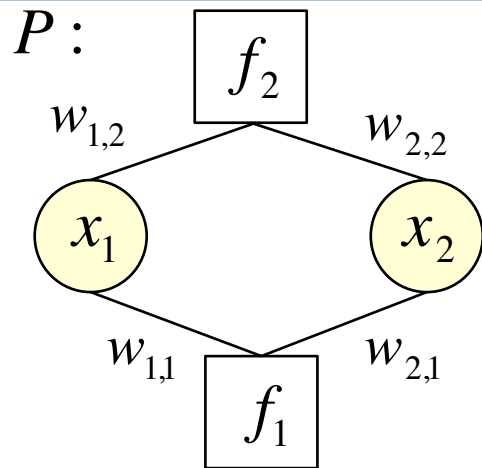


1. Select an edge to remove

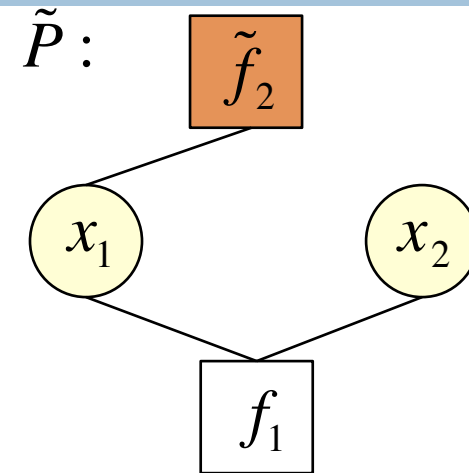
2. Remove selected edge

$$\min_{x_2} \left\{ \begin{array}{|c|c|c|} \hline x_1 & x_2 & f_2(x_1, x_2) \\ \hline a & a & 10 \\ \hline a & b & 10 \\ \hline b & a & 0 \\ \hline b & b & 10 \\ \hline \end{array} \right\} = \begin{array}{|c|c|} \hline x_1 & \tilde{f}_2(x_1) \\ \hline a & 10 \\ \hline b & 0 \\ \hline \end{array}$$

BMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10



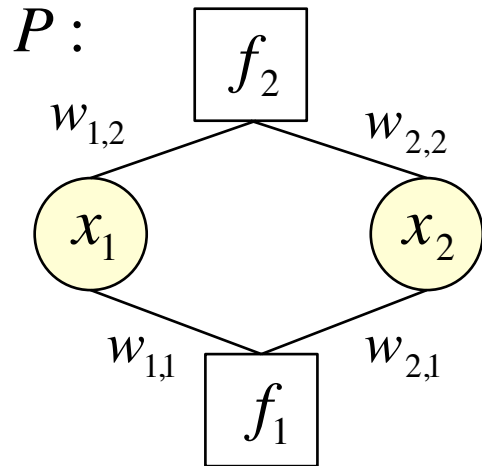
1. Select an edge to remove

2. Remove selected edge

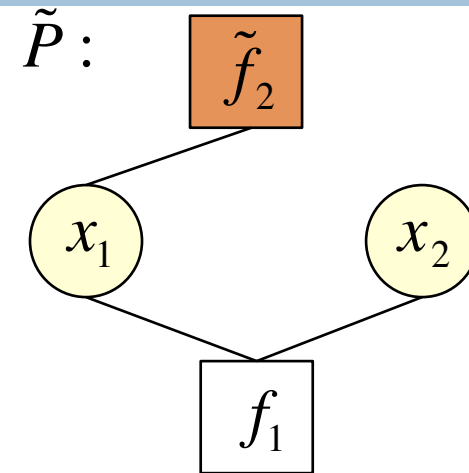
Maximum cost lost by removing that edge

$$w_{2,2} = \max_{x_1} \left\{ \max_{x_2} \left[\begin{array}{|c|c|c|} \hline x_1 & x_2 & f_2(x_1, x_2) \\ \hline a & a & 10 \\ \hline a & b & 10 \\ \hline b & a & 0 \\ \hline b & b & 10 \\ \hline \end{array} \right] - \min_{x_2} \left[\begin{array}{|c|c|c|} \hline x_1 & x_2 & f_2(x_1, x_2) \\ \hline a & a & 10 \\ \hline a & b & 10 \\ \hline b & a & 0 \\ \hline b & b & 10 \\ \hline \end{array} \right] \right\}$$

BMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10



1. Select an edge to remove

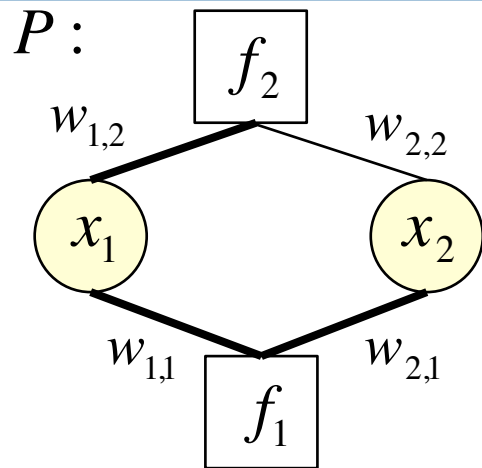
2. Remove selected edge

Maximum cost lost by removing that edge

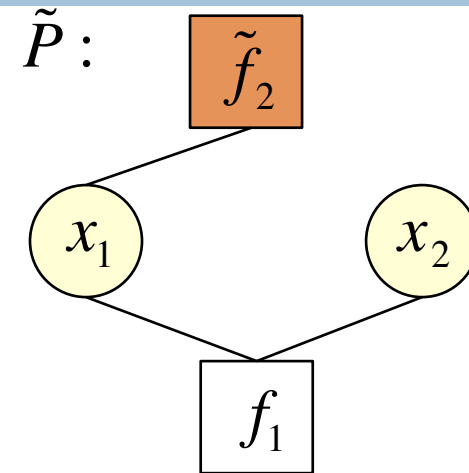
x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10

$$= \begin{array}{|c|c|} \hline x_1 & \tilde{f}_2(x_1) \\ \hline a & 10 \\ \hline b & 0 \\ \hline \end{array} + w_{2,2}$$

BMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10



1. Select an edge to remove

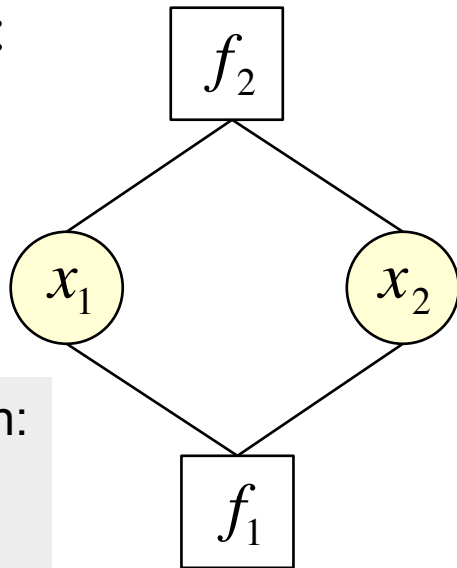
2. Remove selected edge

Maximum cost lost by removing that edge

- Compute a maximum spanning tree
- Eliminate edges not in the spanning tree

BMS: bound the solution

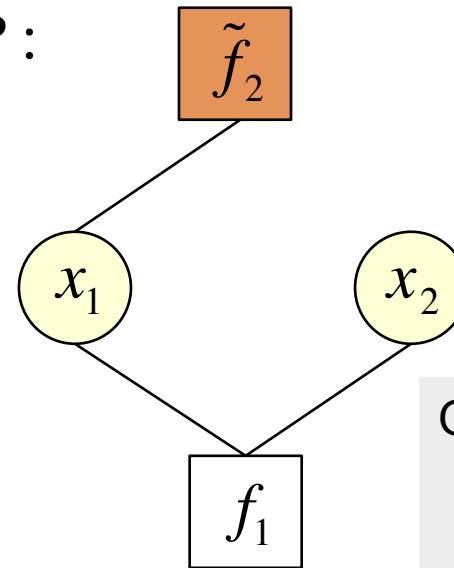
$P:$



Optimal solution:

x^*

$\tilde{P}:$



Optimal solution:

x^{BMS}

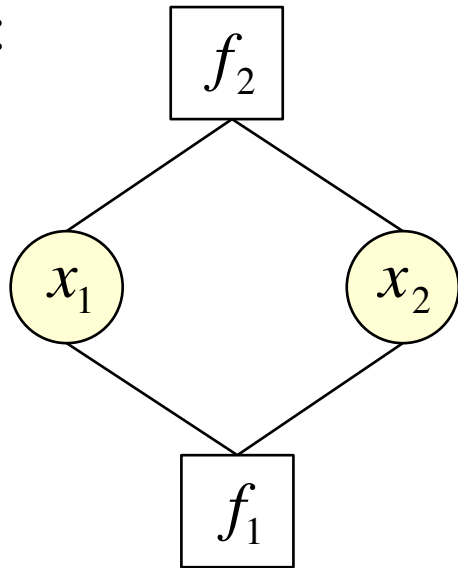
$$F(x^{BMS}) \leq F(x^*) \leq \tilde{F}(x^{BMS}) + W$$

$$F(x^{BMS}) \leq F(x^*) \leq \frac{\tilde{F}(x^{BMS}) + W}{F(x^{BMS})} F(x^{BMS})$$

$\tilde{\rho}$

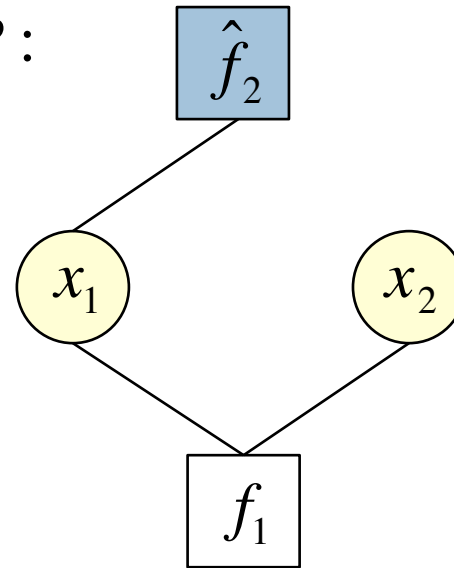
Weak Improved Bounded Max-Sum (wIBMS)

P :



1. Remove cycles:

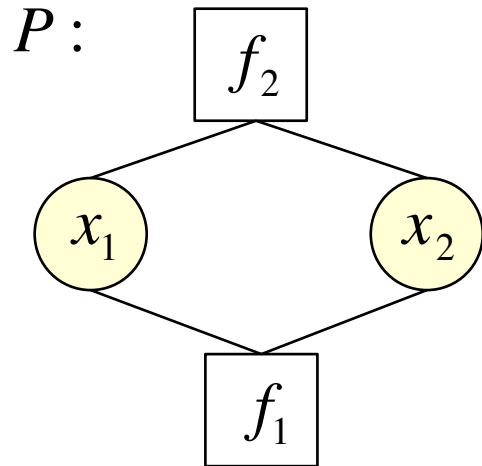
\hat{P} :



2. Solve using Max-Sum

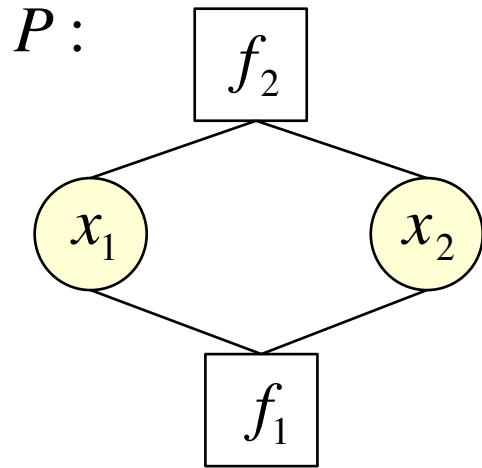
3. Bound the optimum solution

wBMS: remove cycles



1. Select an edge to remove
2. Remove selected edge

wBMS: remove cycles

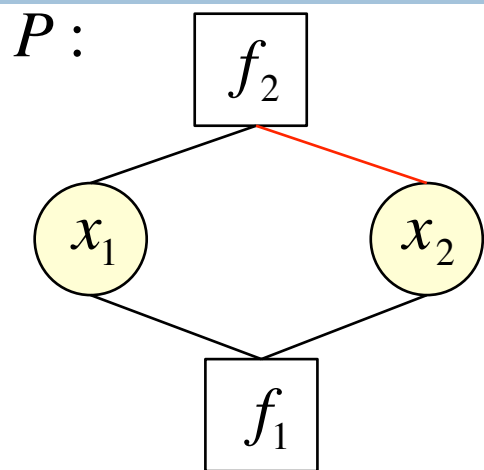


1. Select an edge to remove

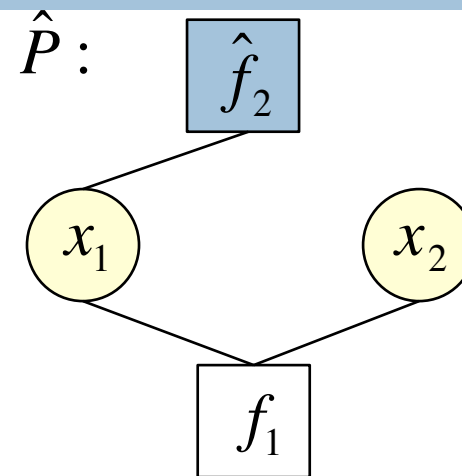
2. Remove selected edge

Same procedure as BMS

wBMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10

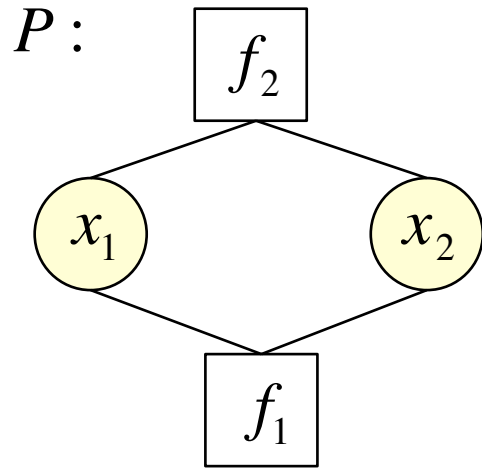


1. Select an edge to remove

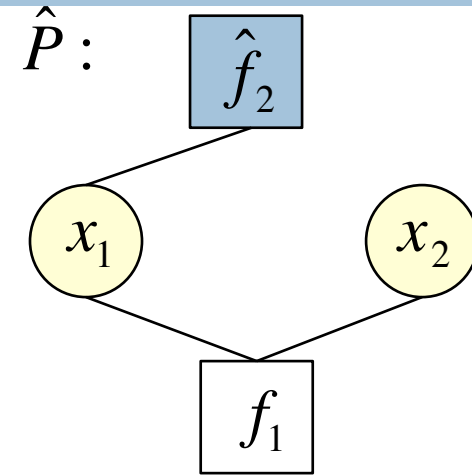
2. Remove selected edge

$$\max_{x_2} \left\{ \begin{array}{|c|c|c|} \hline x_1 & x_2 & f_2(x_1, x_2) \\ \hline a & a & 10 \\ \hline a & b & 10 \\ \hline b & a & 0 \\ \hline b & b & 10 \\ \hline \end{array} \right\} = \begin{array}{|c|c|} \hline x_1 & \hat{f}_2(x_1) \\ \hline a & 10 \\ \hline b & 10 \\ \hline \end{array}$$

wBMS: remove cycles



x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10



1. Select an edge to remove

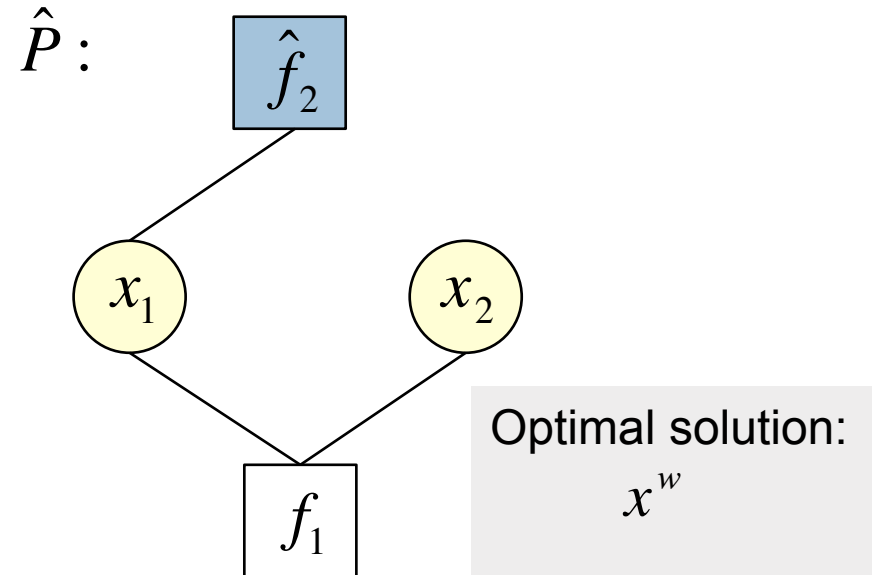
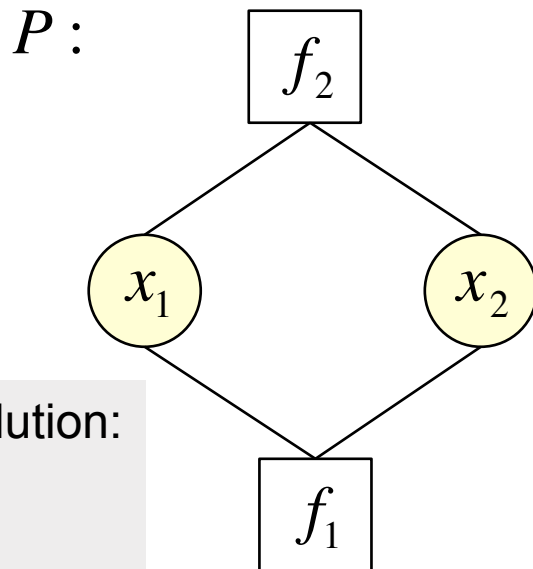
2. Remove selected edge

x_1	x_2	$f_2(x_1, x_2)$
a	a	10
a	b	10
b	a	0
b	b	10

\cong

x_1	$\hat{f}_2(x_1)$
a	10
b	10

wIBMS: bound the solution

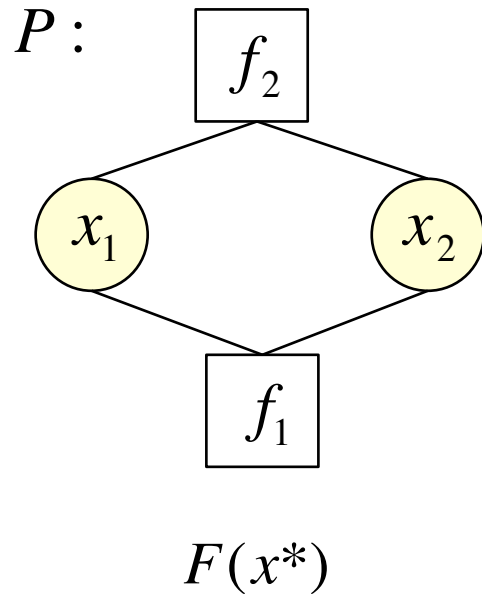


$$F(x^w) \leq F(x^*) \leq \hat{F}(x^w)$$

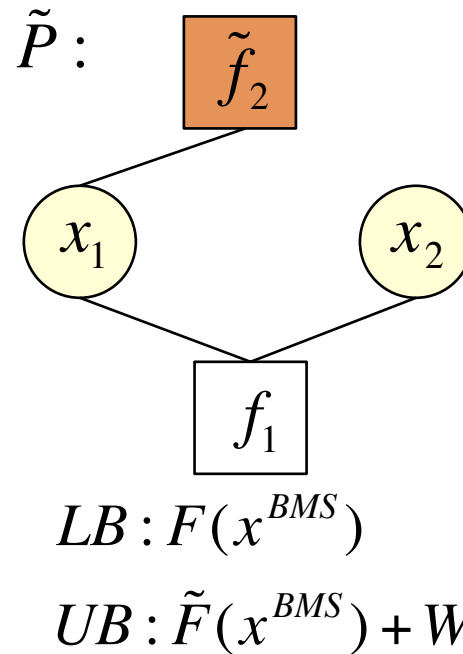
$$F(x^w) \leq F(x^*) \leq \underbrace{\frac{\hat{F}(x^w)}{F(x^w)}}_{\hat{\rho}} F(x^w)$$

Relation BMS, wIBMS and IBMS

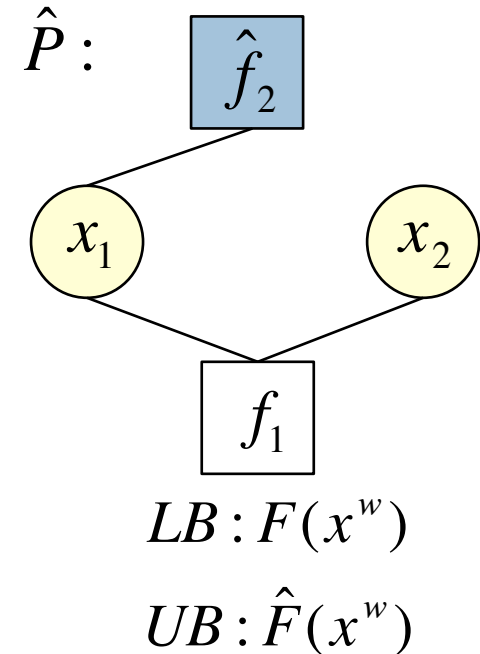
Original



BMS



weak IBMS



$$UB^{wIBMS} \leq UB^{BMS}$$

$$LB^{wIBMS} \leq LB^{BMS}$$



IBMS

$$\rho = \frac{UB^{wIBMS}}{\max\{LB^{BMS}, LB^{wIBMS}\}} \leq \tilde{\rho}$$

$$\leq \hat{\rho}$$

Experiments



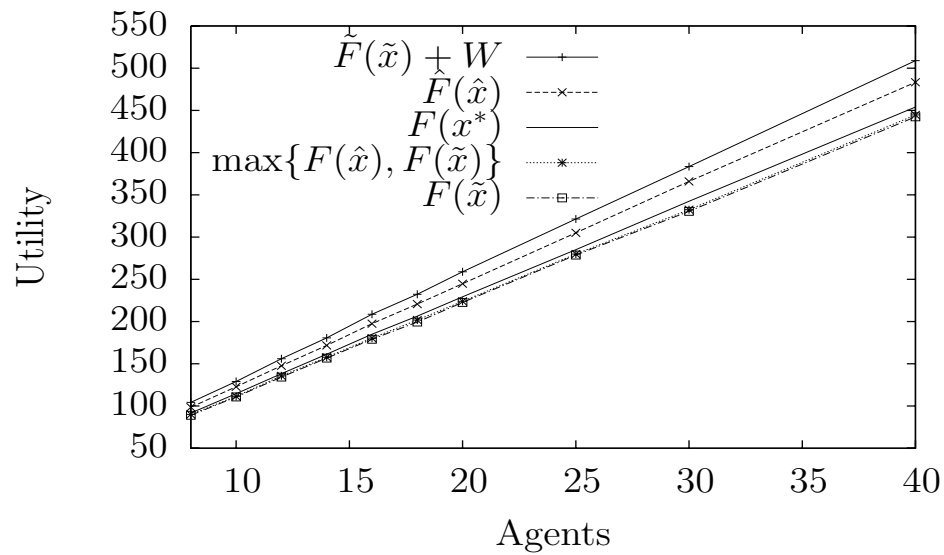
- Evaluate the improvement of:
 - ▣ the upper bound of IBMS.
 - ▣ the approximation ratio of IBMS.

- Graph coloring problems from the ADOPT repository:
 - ▣ Two different cost distributions:
 - gamma ($\alpha = 2, \beta = 3$)
 - uniform
 - ▣ Number of variables: $[8, \dots, 40]$
 - ▣ Mean values over 25 repetitions

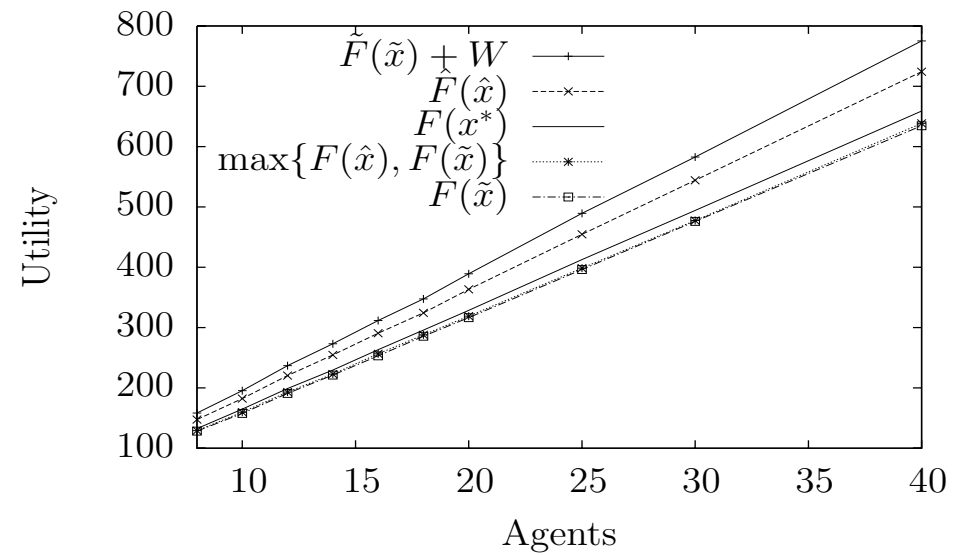
Upper and Lower Bounds



GAMMA, link density = 2



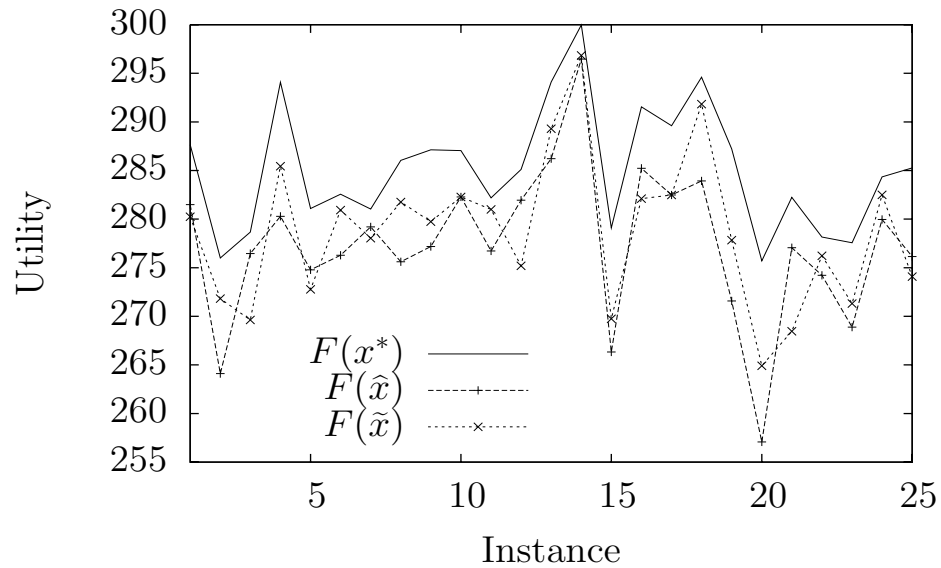
GAMMA, link density = 3



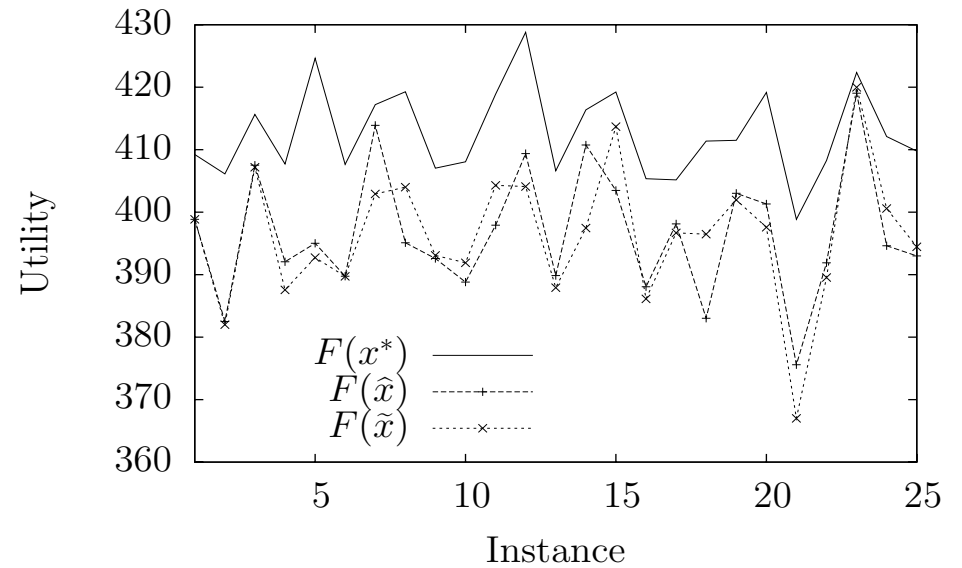
Detail on the Lower Bounds



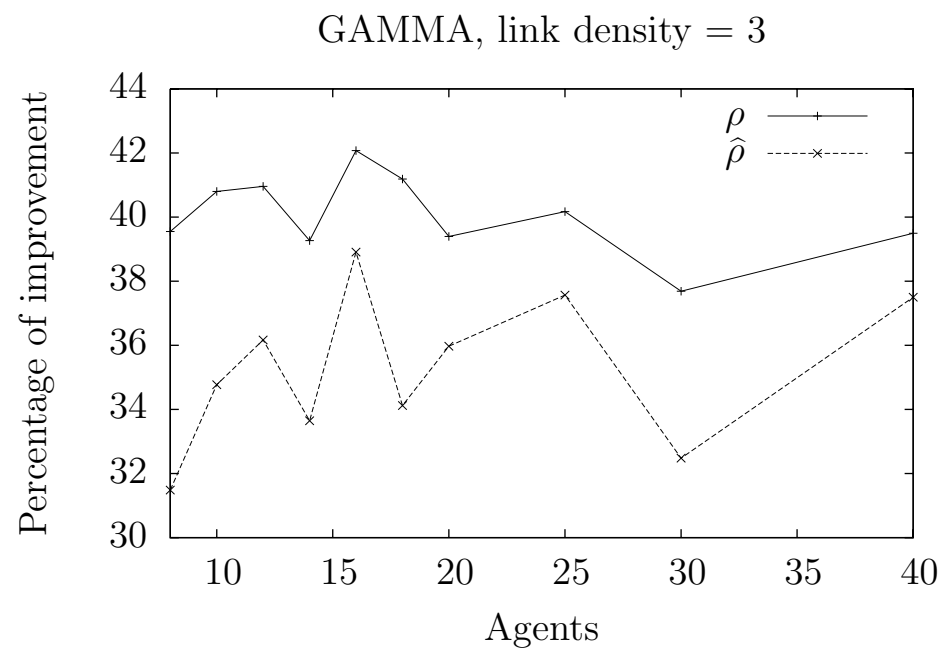
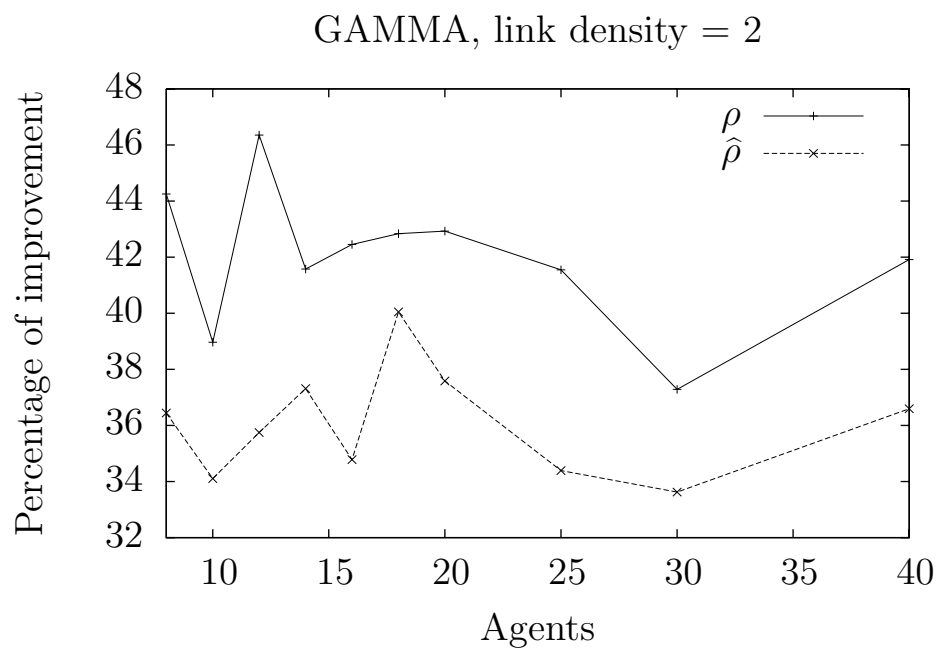
GAMMA, link density = 2, agents = 25



GAMMA, link density = 3, agents = 25



Approximation ratios wrt BMS



Conclusions



- We introduced IBMS:
 - proved its superiority wrt BMS
 - at the only cost of doubling its communication requirements
- We also introduced weak IBMS:
 - proved its better UB wrt BMS
 - maintain the communication requirements
- Future work: study other relaxation behaviour.

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