

Improving Max-Sum through Decimation to Solve Cyclic Distributed Constraint Optimization Problems

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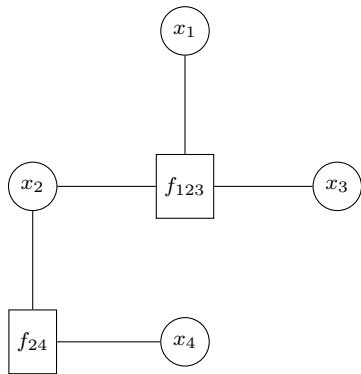
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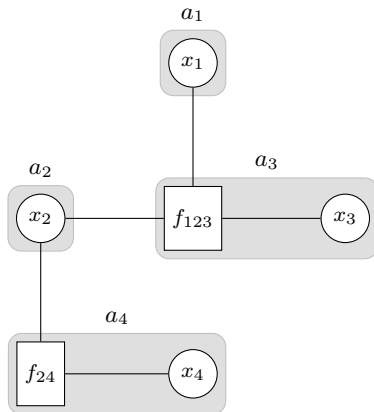
What problems are we dealing with?

Problems represented as factor graphs



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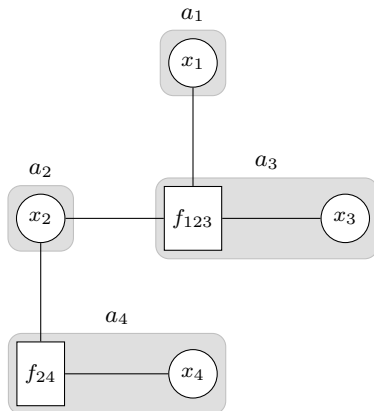
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Distributed Constraint Optimization Problems (DCOPs)

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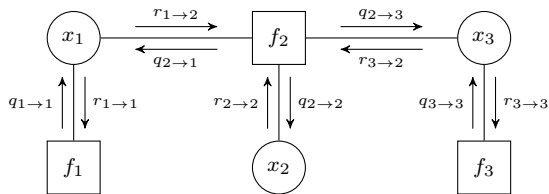


Distributed Constraint Optimization Problems (DCOPs)

One possible and often efficient solution method to find $\max_{\mathcal{X}} \sum_{m=1}^M f_m(\mathcal{X}_m)$: Max-Sum [FARINELLI et al., 2008]

What's Max-Sum?

Belief-Propagation-based message passing algorithm



Each variable/factor sends messages:

$$q_{n \rightarrow m}(x_n) = \alpha_{nm} + \sum_{m' \in \mathcal{V}(n) \setminus m} r_{m' \rightarrow n}(x_n) \quad (1)$$

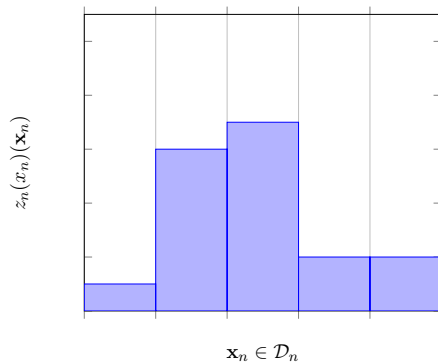
$$r_{m \rightarrow n}(x_n) = \max_{\mathcal{X}_m \setminus n} \left(f_m(\mathcal{X}_m) \sum_{n' \in \mathcal{F}(m) \setminus n} q_{n' \rightarrow m}(x_{n'}) \right) \quad (2)$$

and computes a marginal function:

$$z_n(x_n) = \max_{\mathcal{X}_m \setminus n} \sum_{m=1}^M f_m(\mathcal{X}_m) \quad (3)$$

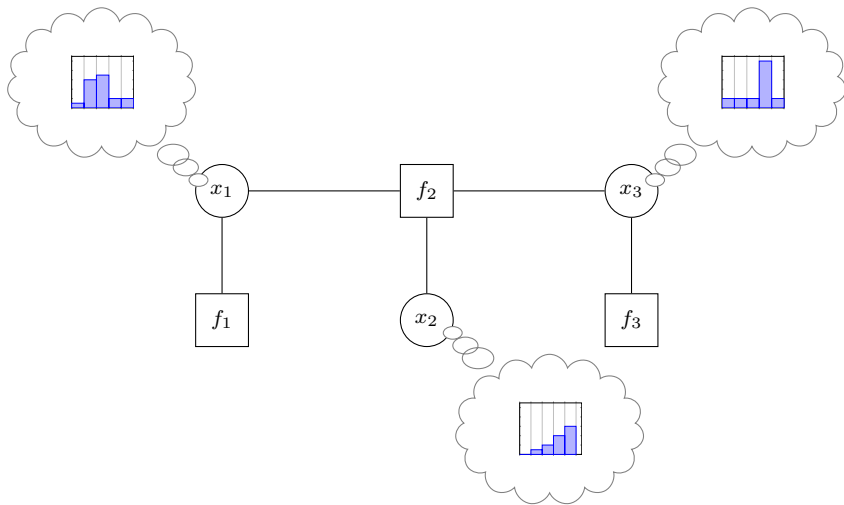
What's Max-Sum? (cont.)

In the end, each variable acquires belief about its influence on the overall objective \rightarrow decoding to get the solution ($\operatorname{argmax} z_n(x_n)$)



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What's the problem with Max-Sum (MS)?

- On tree-shaped FGs: MS proven to converge to optimal solutions
- In more general **cyclic** settings:
 - ▶ May converge to non optimal solutions
 - ▶ May not converge at all

Here, convergence means the marginal functions do not change for a while...

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Several approaches to handle loops in MS

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- Max-Sum_AD_VP [ZIVAN et al., 2017]

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But let's also have a look at...

- **Decimation** [MONTANARI et al., 2007], coming from statistical physics to solve k -satisfiability loopy problems

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Simple principle= alternating belief-propagation (BP) and assignment of values to some variables depending on their marginal value, until all variables have been assigned a value

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Example (implementing [MONTANARI et al., 2007])

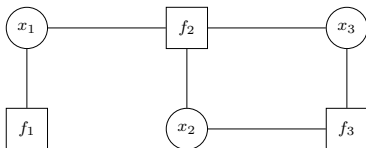
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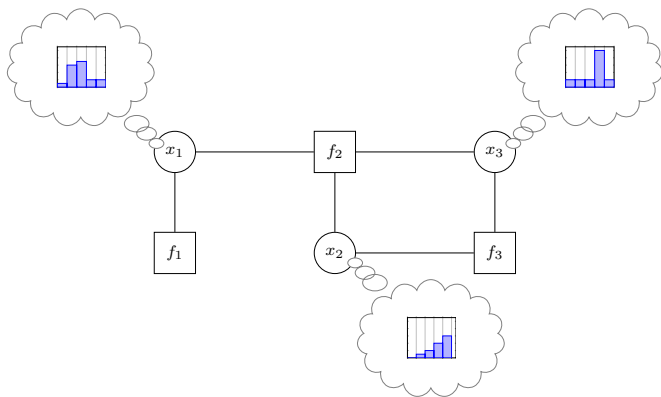


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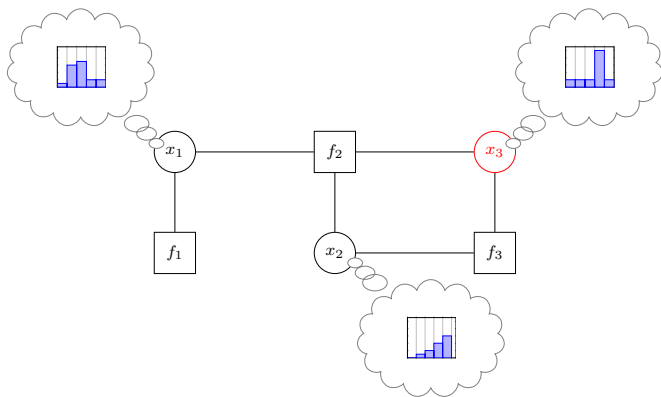


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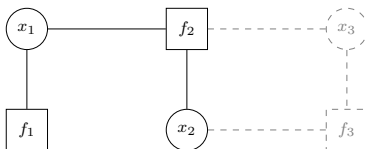


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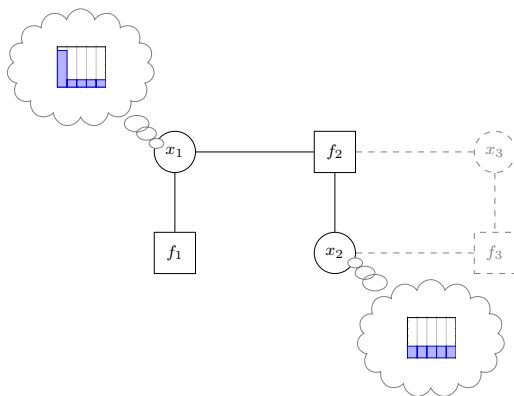


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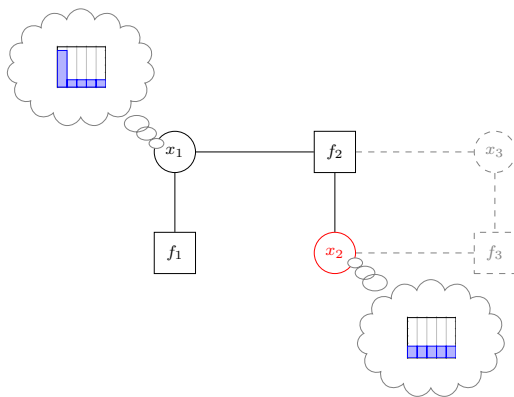


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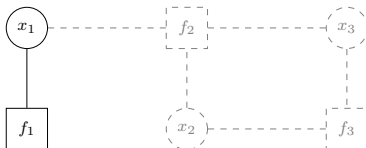


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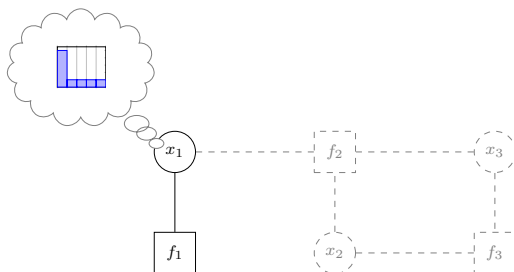


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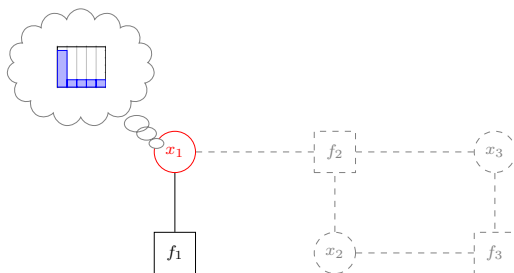


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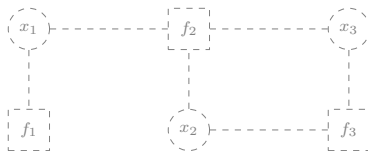


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Let's generalize and try to use decimation in Max-Sum

To install decimation in a BP-based solution method, we need to identify

1. when decimation should be triggered
 - ▶ each time step, each n time steps, once a loop is detected, ...
2. the subset of variables to decimate
 - ▶ one variable randomly, one variable with some properties, several variables, ...
3. the values to assign to decimated variable(s)
 - ▶ sampling on marginal values, most determined value, ...

We call a decimation policy any combination of (1), (2) and (3)

Our idea here is to apply different decimation policies to Max-Sum

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→ A generic decimation framework for Max-Sum, a.k.a **DECIMAXSUM**

DECIMAXSUM as an algorithm

Data: A factor graph $FG = \langle \mathcal{X}, \mathcal{C}, E \rangle$, a decimation policy $\pi = \langle \Theta, \Phi, \Upsilon, \Lambda \rangle$

Result: A feasible assignment \mathcal{X}^*

initialize BP messages

$\mathcal{U} \leftarrow \emptyset$

while $\mathcal{U} \neq \mathcal{X}$ **do**

run BP until decimation triggers, i.e. $\Theta(FG^t) = 1$

choose variables to decimate, $\mathcal{X}' = \{x_i \in \Phi(FG^t) \mid \Upsilon(x_i, FG^t)\}$

for $x_i \in \mathcal{X}'$ **do**

$x_i \leftarrow \Lambda(x_i, FG^t)$

$\mathcal{U} \leftarrow \mathcal{U} \cup \{x_i\}$

simplify FG^t

// remove variables, slice factors

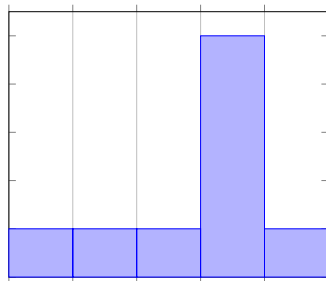
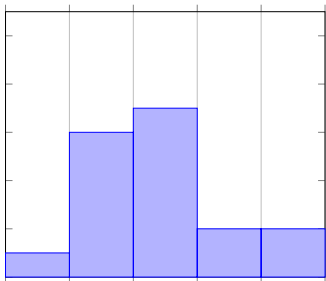
return \mathcal{X}^* by decoding \mathcal{U}

Implementing [MONTANARI et al., 2007] in DECIMAXSUM

1. decimate once BP converges (or halt after some time limit)
2. choose on random variable within the whole set of non decimated variables
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Implementing [Mooij, 2010] in DECIMAXSUM

1. decimate once BP converges (or halt after some time limit)
2. choose the most determined variable, i.e. the lowest entropy H on marginal values, within the whole set of non decimated variables

$$H(z_k(x_k)) = - \sum_{d \in \mathcal{D}_k} z_k(x_k)(d) \log(z_k(x_k)(d))$$

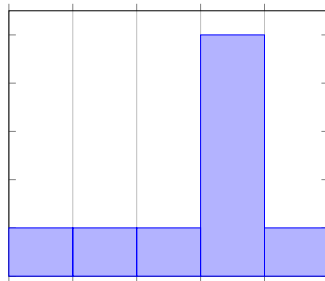
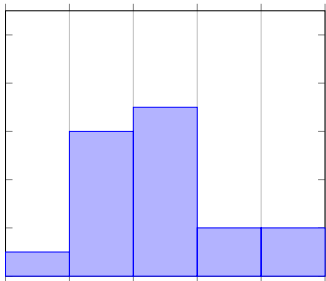
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And many more combinations...

- DECIMAXSUM (2-periodic, min-entropy, deterministic)
- DECIMAXSUM (3-periodic, min-entropy, deterministic)
- DECIMAXSUM (4-periodic, min-entropy, deterministic)
- DECIMAXSUM (5-periodic, min-entropy, deterministic)
- DECIMAXSUM (10-periodic, min-entropy, deterministic)
- DECIMAXSUM (20-periodic, min-entropy, deterministic)
- DECIMAXSUM (100-periodic, min-entropy, deterministic)

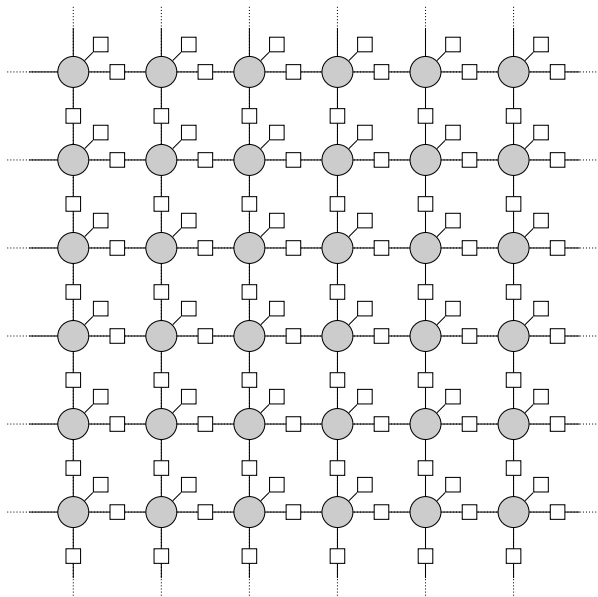
- DECIMAXSUM (10-periodic, random, sampling)
- DECIMAXSUM (100-periodic, random, sampling)

- DECIMAXSUM (periodic, min-entropy, deterministic)

- DECIMAXSUM (convergence, min-entropy, deterministic)

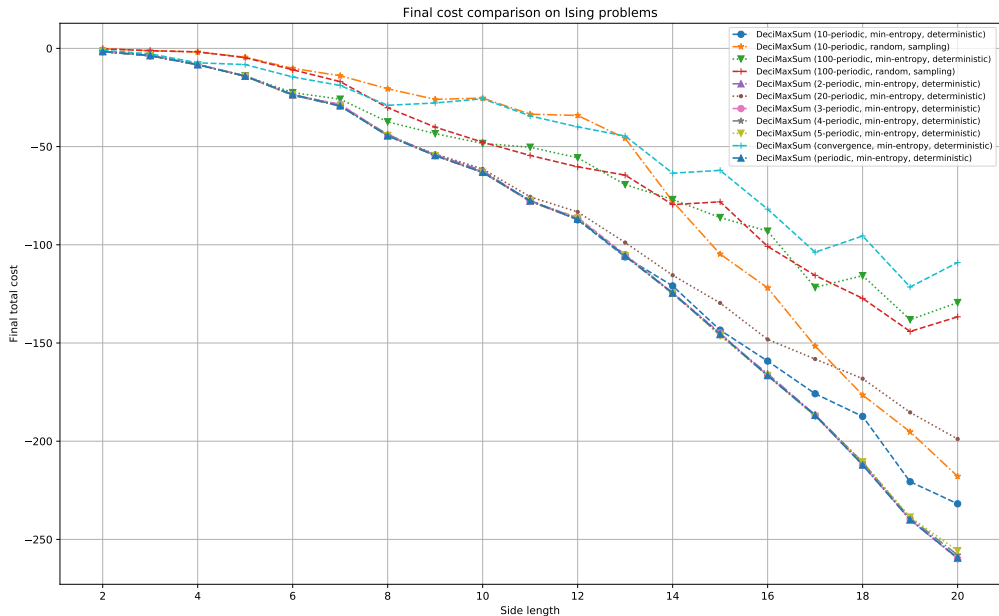
- MaxSum
- Montanari-Decimation
- Mooij-Decimation
- ...

Benchmarking on a very cyclic problem: the Ising model

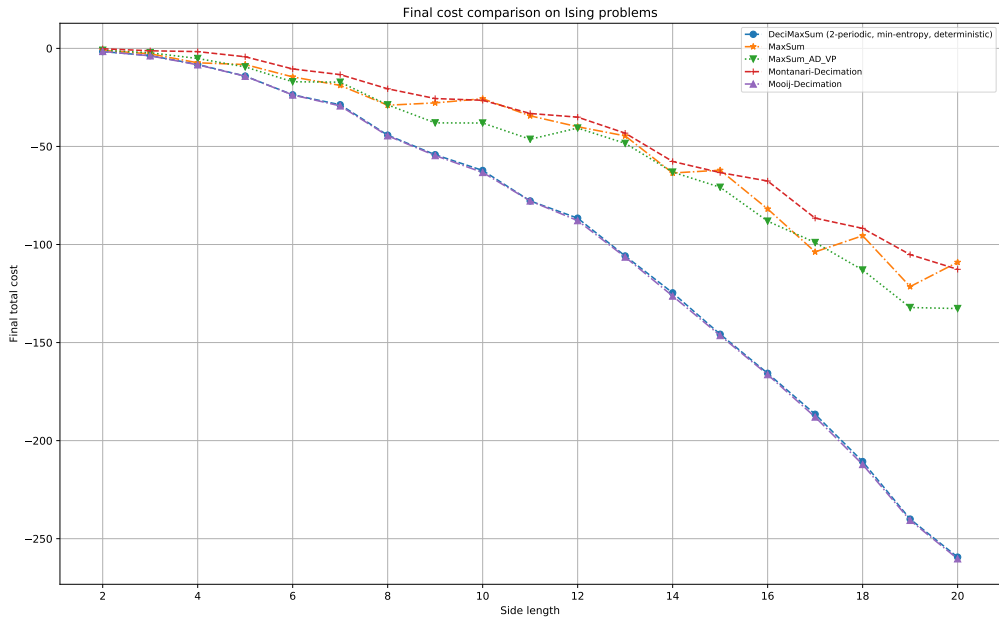


- toroidal grid structure
- boolean variables x_i 's
- unary costs r_i 's
- binary constraints r_{ij} 's

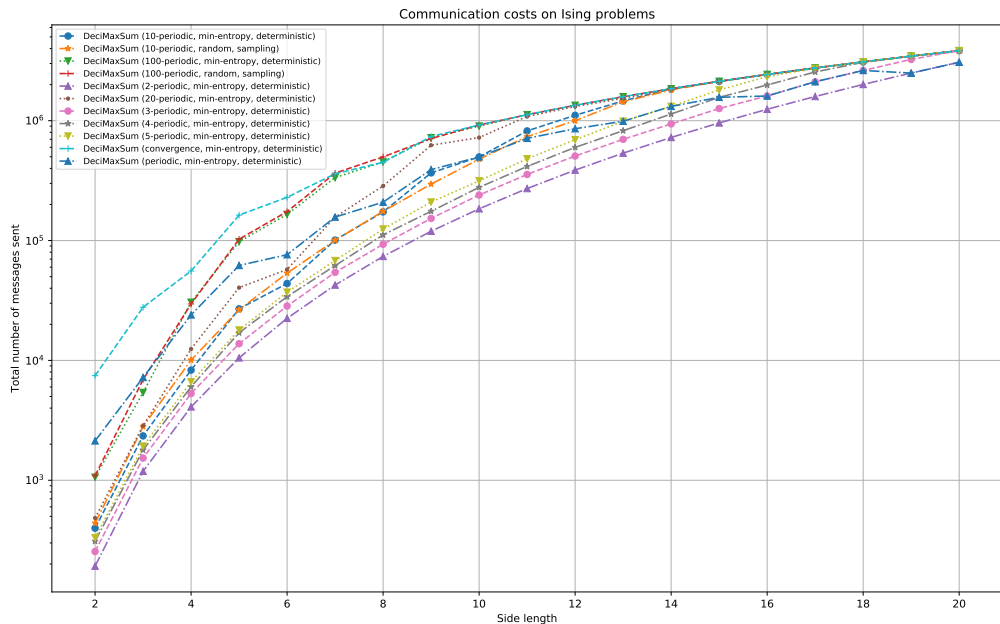
Quality of solutions



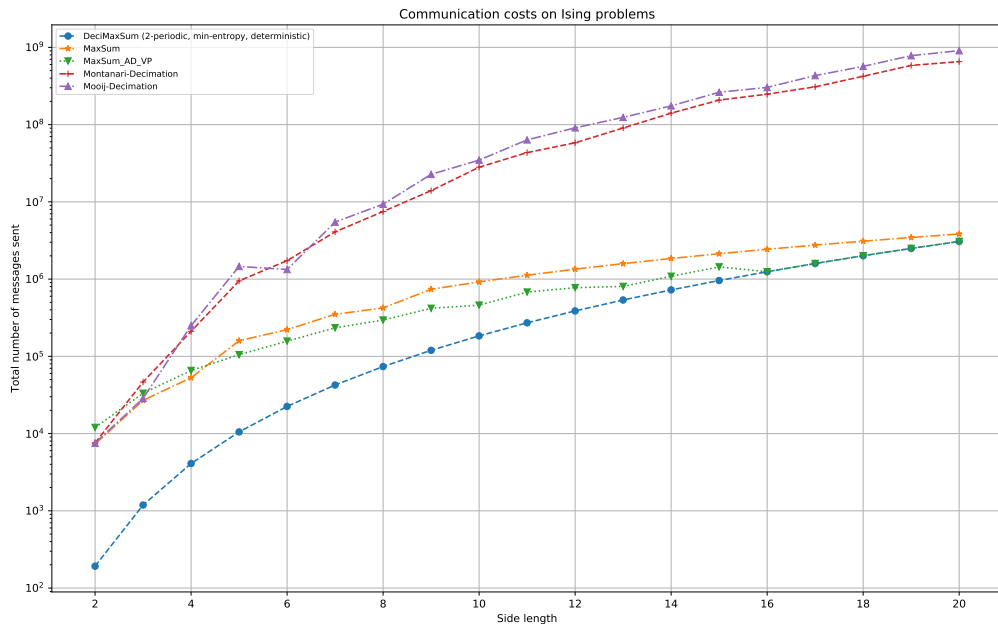
Quality of solutions (cont.)



Communication load



Communication load (cont.)



Conclusions

To sum up

- We have proposed a generic framework to integrate decimation mechanism into MaxSum/BP algorithms
- On very cyclic problems (Ising model), fast decimation based on marginal function entropy and deterministic value assignment showed very good quality solutions, with many less messages
- Decimation \equiv decoding at runtime?

Many ways to go

- Many more policies are possible
 - ▶ ex: decimation once a loop is detected
 - ▶ ex: alternating deterministic and non deterministic value assignment
- How does decimation behave on less cyclic but less regular problems?
- How does decimation behave on non boolean settings?

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