Supplementary Material: Survey Propagation beyond Constraint Satisfaction Problems

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Abstract

This is the supplementary material for the paper titled “Survey Propagation beyond Constraint Satisfaction Problems”.

1 EXPERIMENTS

Here are the full results for the experiments described in the main paper “Survey Propagation beyond Constraint Satisfaction Problems”. Figures fig. 1 through fig. 5 show results for different graph types: *fig. 1)* 10 variable, fully connected; *fig. 2)* 40 variable, bipartite with 20 variables blocks; *fig. 3)* 100 variable 3-regular; *fig. 4)* 100 variable, 10x10 periodic grid; *fig. 5)* 1000 variable, 10x100 non-periodic grid.

Recalling the setup, we test on three types of pairwise couplings for each graph: attractive (1st column in each figure), mixed (2nd column), and repulsive (3rd column). All couplings are sampled from a uniform distribution. Attractive couplings are sampled in the range $[0, \beta]$, mixed from the range $[-\beta, \beta]$, and repulsive from the range $[-\beta, 0]$ where β ranges from 0 to 2. Local fields θ_i are always sampled uniformly in the range $[-0.05, 0.05]$. For each graph and coupling type, we run three versions of SP: SP with 11 bins, 101 bins, and 1001 bins. BP messages are initialized to be uniform while SP messages are initialized randomly. All message passing algorithms do parallel message updates and run for a maximum 1000 iterations or until convergence, whichever comes first. Gibbs sampling is run for 100,000 iterations where a sample was recorded after each 100 iterations. We repeat the experiments for 10 trials, each on a new instance, at each β value.

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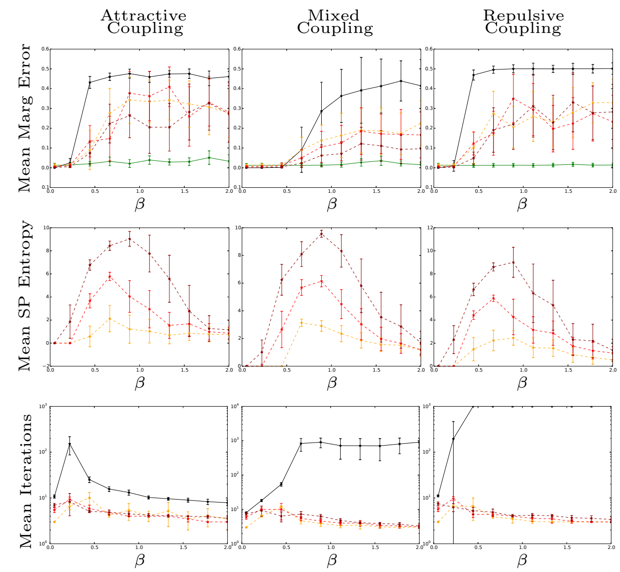

Figure 1: Results for 10 variable fully connected graph

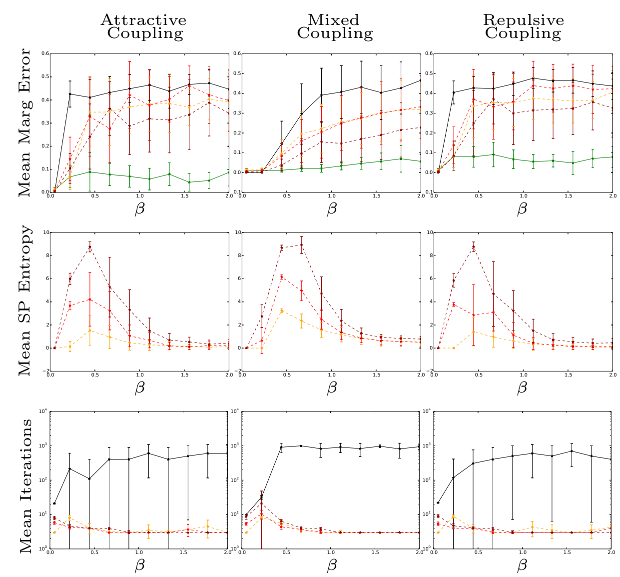

Figure 2: Results for 40 variable bipartite graph

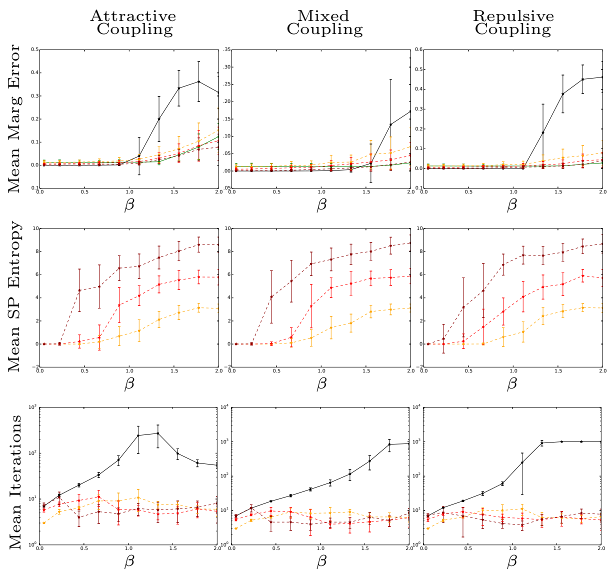

Figure 3: Results for 100 variable 3-regular graph

The curve colour scheme is as follows. Green: Gibbs sampling, black: BP, dashed orange: SP 11 bins, dashed red: SP 101 bins, and dashed dark red: SP 1001 bins.

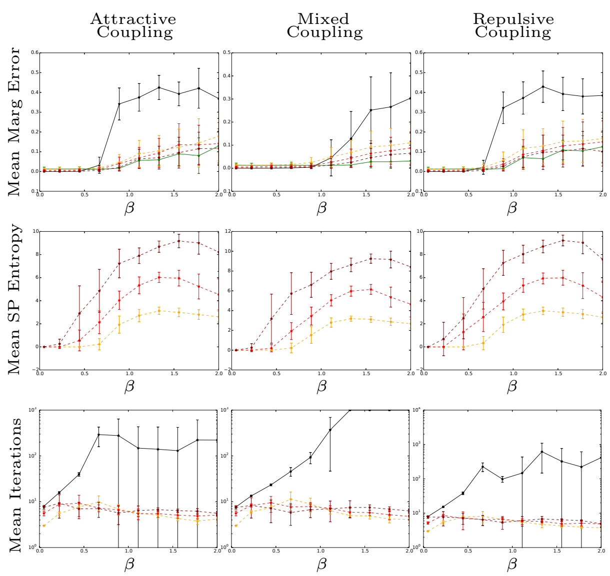

Figure 4: Results for 10x10 grid (periodic)

We limit the size of the graphs so that the exact marginals can be obtained using the junction tree algorithm (Lauritzen and Spiegelhalter, 1988). However, as the complexity analysis suggests, our approximation scheme can easily scale up to millions of variables. At each value of β, each row of each figure shows: *1st)* the mean absolute error of the marginal for all methods; *2nd)* the mean SP marginal entropy for the SP algorithms; *3rd)* the number of iterations. The libDAI library (Mooij, 2010) is used for BP, Gibbs sampling,

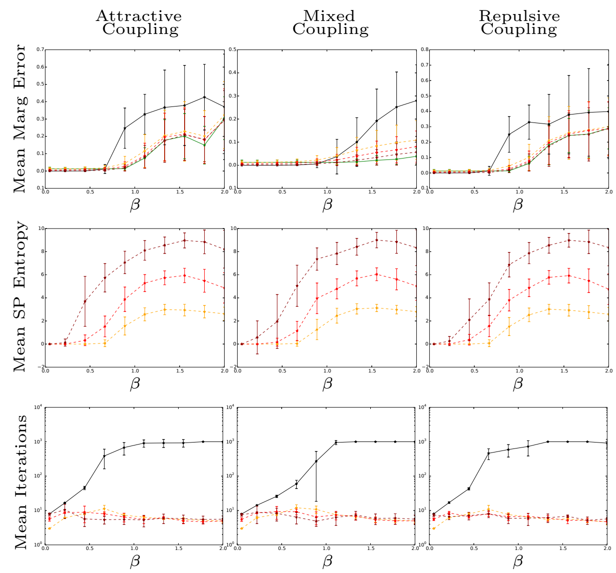

Figure 5: Results for 10x100 grid (non-periodic)

and the junction tree method. The analysis of these results can be found in the main paper.

References

Steffen L Lauritzen and David J Spiegelhalter. Local computations with probabilities on graphical structures and their application to expert systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 157–224, 1988.

Joris M. Mooij. libDAI: A free and open source C++ library for discrete approximate inference in graphical models. *Journal of Machine Learning Research*, 11:2169–2173, 2010.