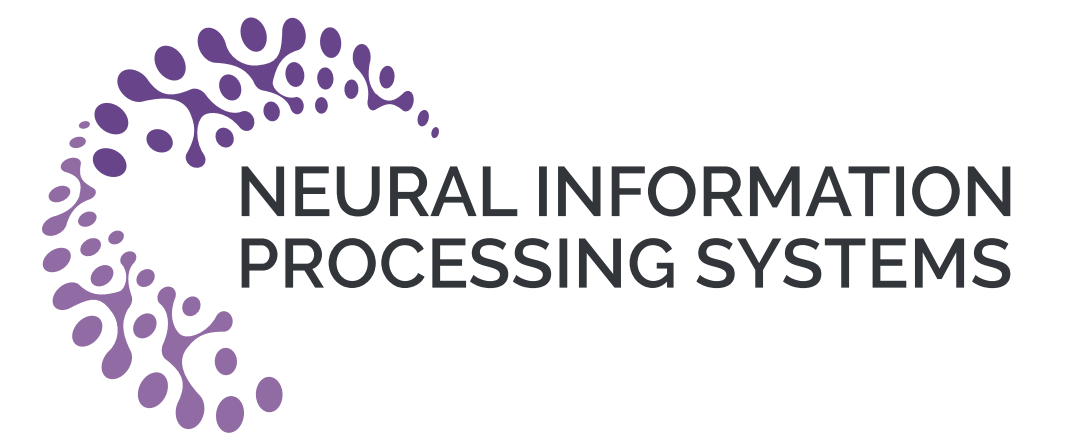




# Probabilistic Circuits for Variational Inference in Discrete Graphical Models

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## Variational Inference

$$\log Z \geq \mathbb{E}_{\mathbf{x} \sim q}[\log p(\mathbf{x}) - \log q(\mathbf{x})]$$

Any choice of  $q$  gives a lower bound

### Choice of $q$

Analytic optimization:

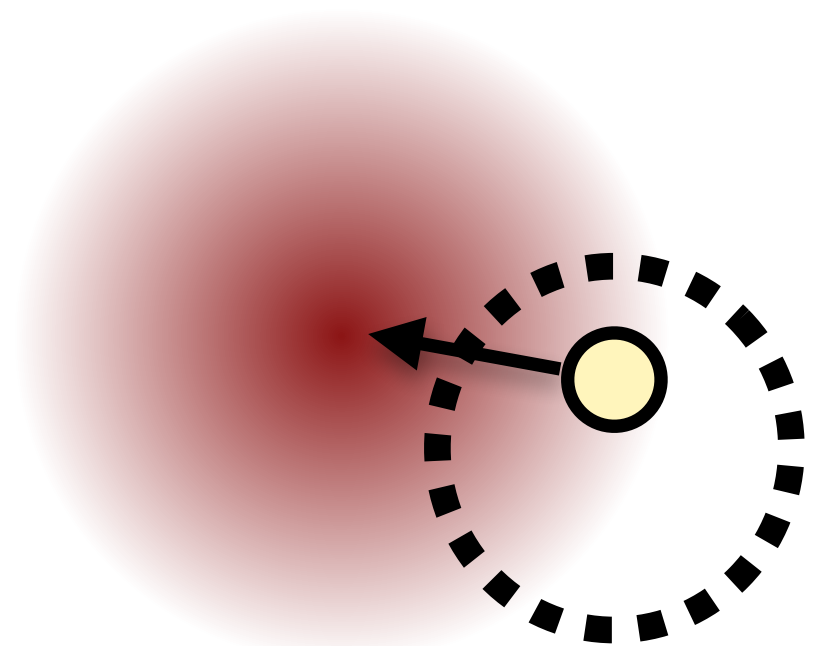
- mean field / structured mean field

Stochastic optimization:

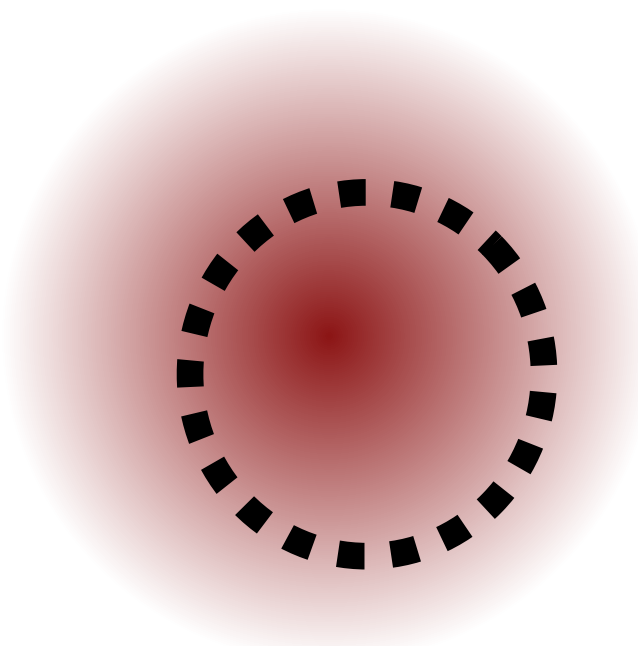
- neural networks
- more expressive, but requires *sampling*

✓ continuous ✗ discrete [Zhang 2017]

### Continuous Settings



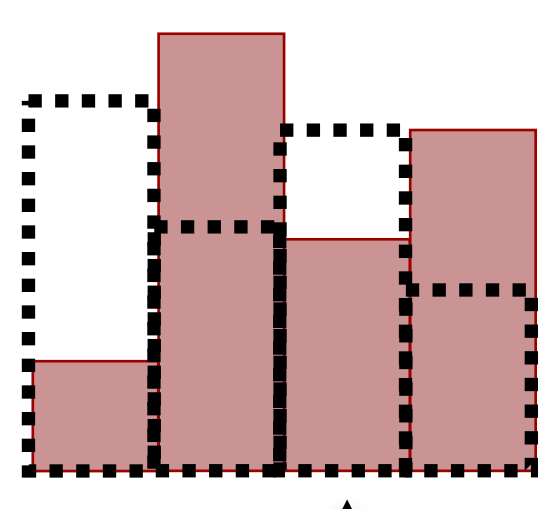
draw a sample



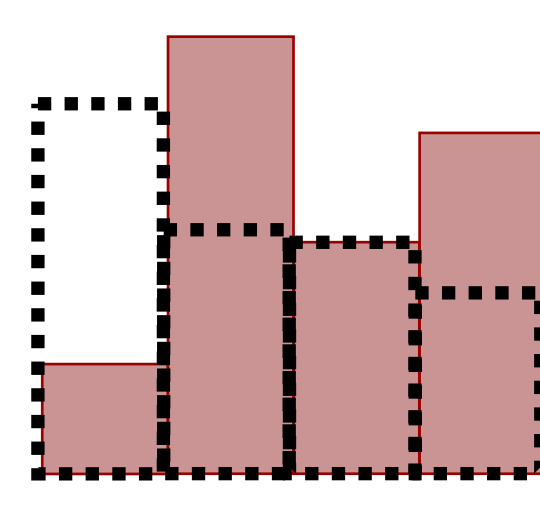
follow gradients

Sampling works well  
Reparameterization trick: low variance  
✓

### Discrete Settings



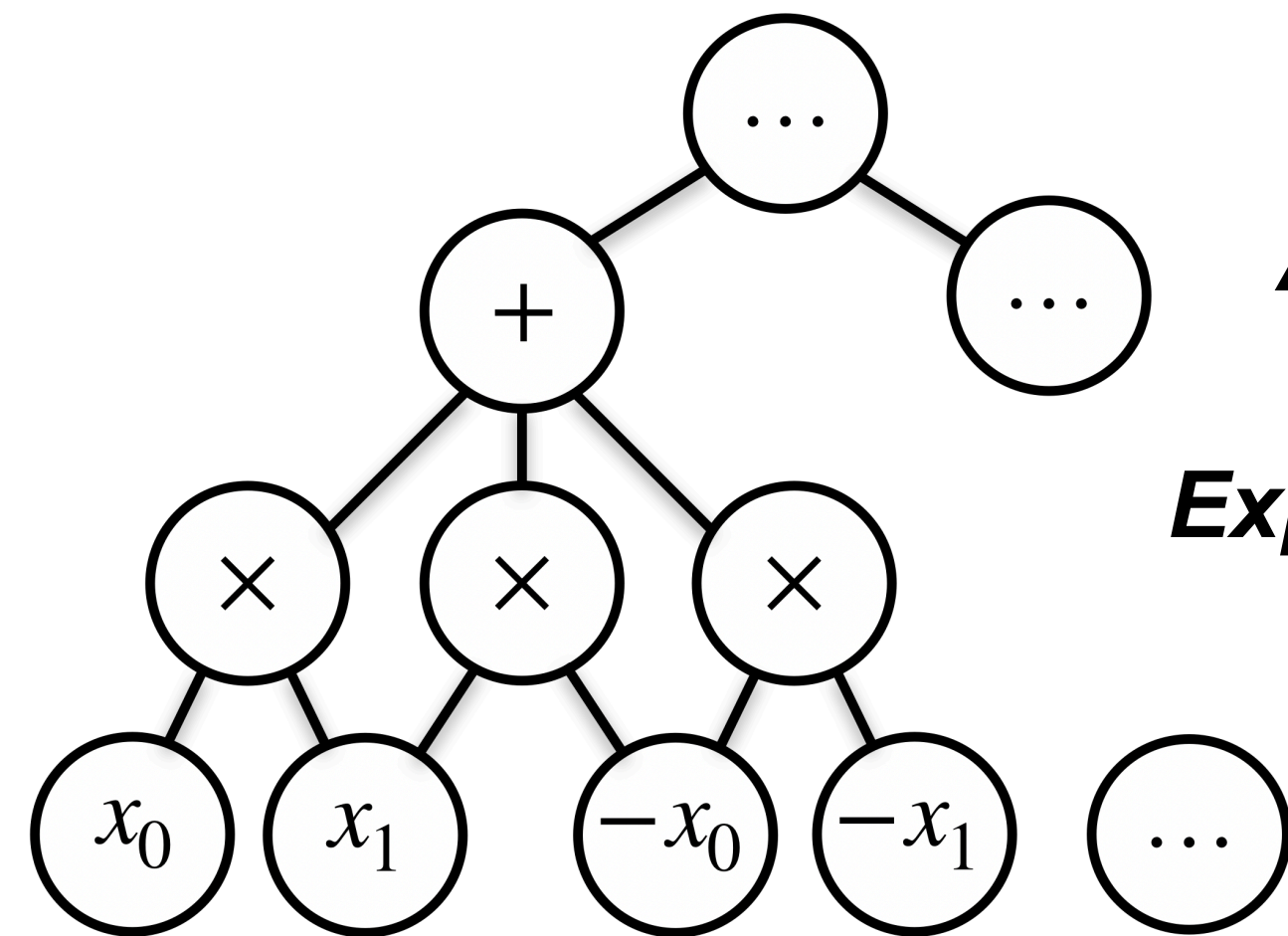
draw a sample



follow gradients

No info "around" the sample  
Large variance in high dimensions  
✗

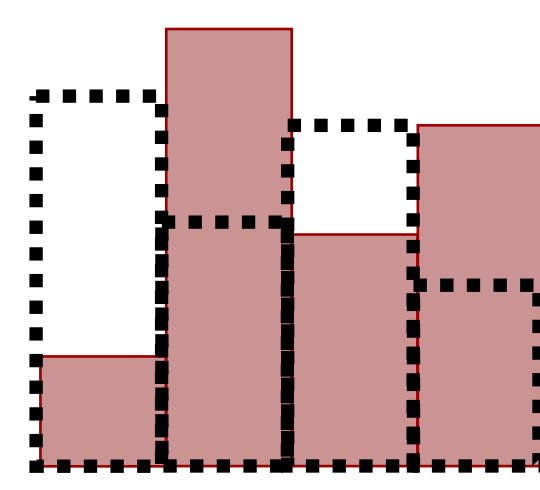
## Sum Product Networks



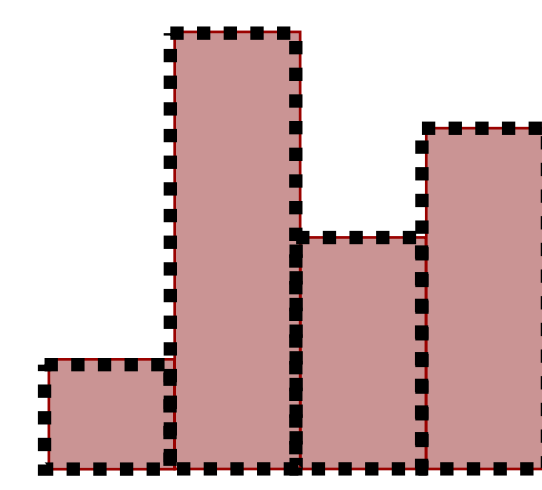
Avoids sampling

Expressive distribution

✓ discrete settings



exact gradients "everywhere"



follow gradients "everywhere"

### Sum Node

Selectivity / Determinism:

$$-\mathbb{E}_{\mathbf{x} \sim g_i}[\log g_i(\mathbf{x})] = -\sum_{j \in \text{ch}(i)} \alpha_{ij} \log \alpha_{ij} + \alpha_{ij} \mathbb{E}_{\mathbf{x} \sim g_j}[\log g_j(\mathbf{x})]$$

*entropy of sum* *sum of (constant terms + entropy)*

### Product Node

Children are independent

Computes the expectation analytically:

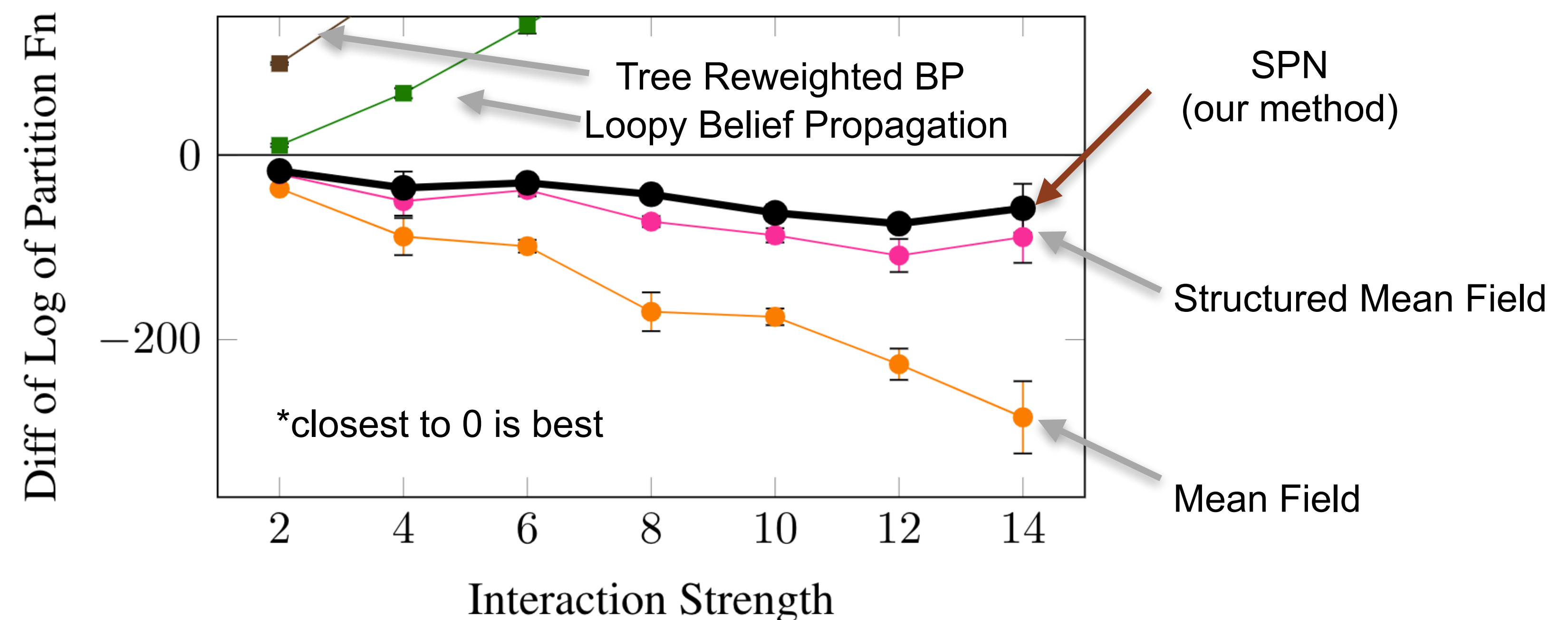
$$\log Z \geq \mathbb{E}_{\mathbf{x} \sim q}[\log p(\mathbf{x}) - \log q(\mathbf{x})]$$

Computation cost:  $O(tm)$   $O(m)$  ← previously  $O(m^2)$  [Lowd 2010]

$t$ : size of discrete model,  $m$ : size of SPN

expressed in log-polynomial form

## Experiments



Paper / Code

