Probabilistic Graphical Models

Loopy BP and Bethe Free Energy

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Learning objective

- loopy belief propagation
- its variational derivation: Bethe approximation

So far...

- exact inference:
  - variable elimination
  - equivalent to belief propagation (BP) in a clique tree

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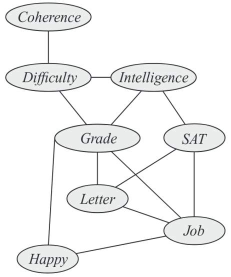
This lecture...

- what if the exact inference is too expensive? (i.e., the tree-width is large)
  - continue to use BP: **loopy BP**
  - why is this a good idea?
    - answer using variational interpretation

Recap: BP in clique trees

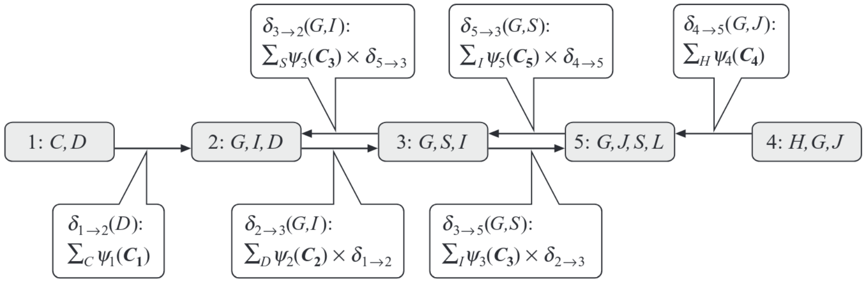


sum-product **BP** message update:

$$\delta_{i \to j}(S_{i,j}) = \sum_{C_i - S_{i,j}} \psi_i(C_i) \prod_{k \in Nb_i - j} \delta_{k \to i}(S_{i,k})$$

sepset   cluster/clique

- from leaves towards the root
- back to leaves



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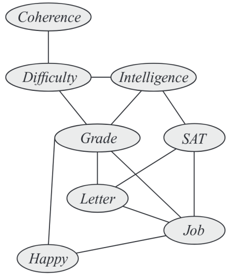

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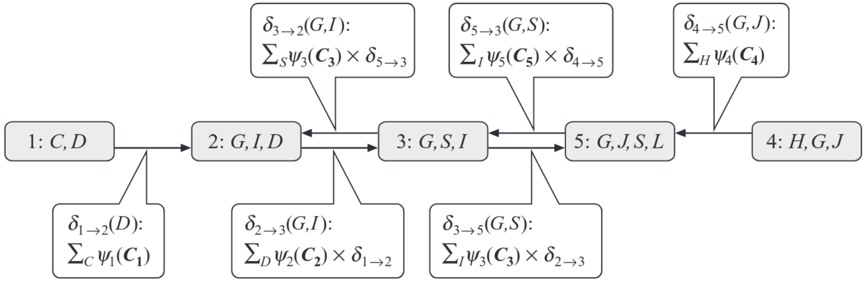
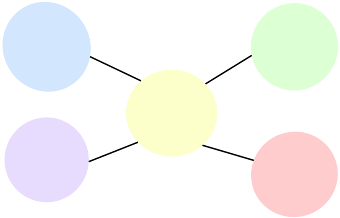


marginal (belief) for each cluster:

$$p_i(C_i) \propto \beta_i(C_i) = \psi_i(C_i) \prod_{k \in Nb_i} \delta_{k\to i}(S_{i,k})$$

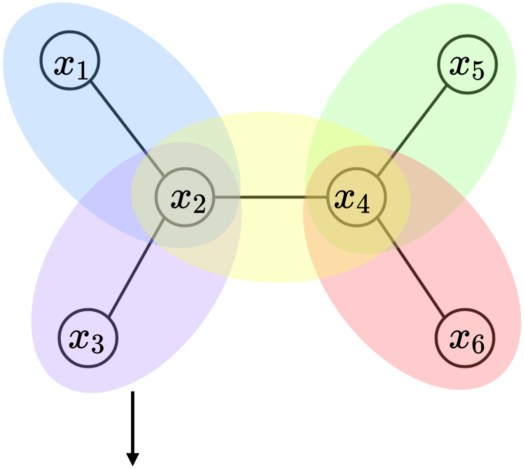
Clique-tree for tree structures

- pairwise potentials $\phi_{i,j}(x_i, x_j)$
- tree width = 1



one possible clique-tree

what are the sepsets?



one cluster per factor

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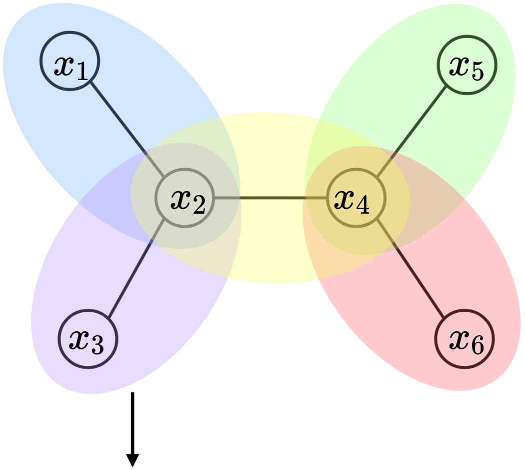

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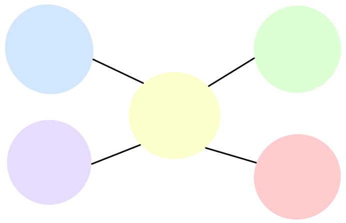

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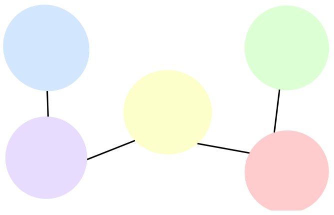


a different valid clique-tree

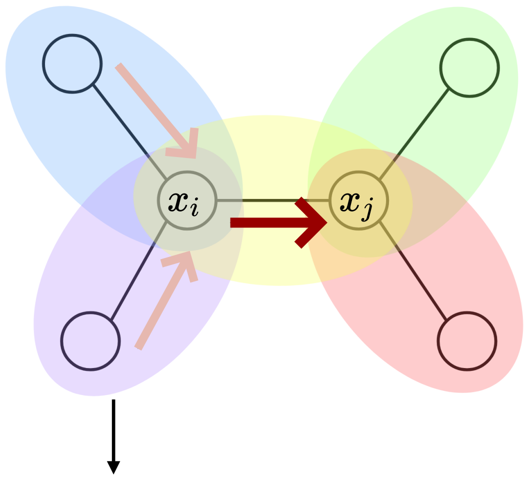
check for *running intersection property*

BP for tree structures

- pairwise potentials $\phi_{i,j}(x_i, x_j)$
- message update

$$\delta_{i\to j}(x_j) = \sum_{x_i} \phi_{i,j}(x_i, x_j) \prod_{k \in Nb_i - j} \delta_{k\to i}(x_i)$$

- *from leaves towards **a** root*
- *back to leaves*



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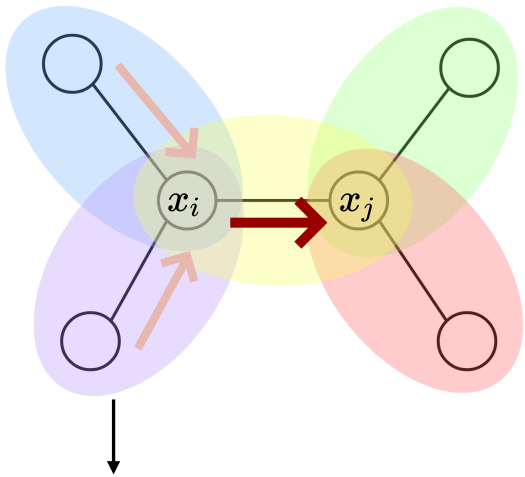


one cluster per factor

- marginal (belief) for each cluster

$$p_i(x_i) \propto \prod_{k\in Nb_i} \delta_{k\to i}(x_i)$$

$$p_{i,j}(x_i, x_j) \propto \phi_{i,j}(x_i, x_j) \prod_{k\in Nb_i - j} \delta_{k\to i}(x_i) \prod_{k\in Nb_j - i} \delta_{k\to j}(x_j)$$

BP for tree structures: reparametrization

graphical model represents

$$* \quad p(\mathbf{x}) = \frac{1}{z} \prod_{i,j \in \mathcal{E}} \phi_{i,j}(x_i, x_j)$$

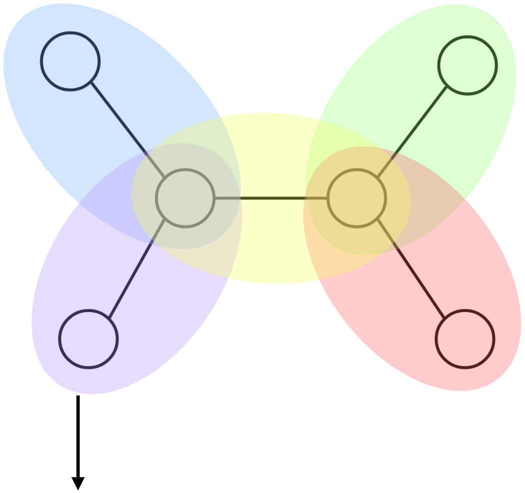
write it in terms of marginals

$$p(\mathbf{x}) = \frac{\prod_{i,j \in \mathcal{E}} p_{i,j}(x_i, x_j)}{\prod_i p_i^{|Nb_i|-1}}$$

why is this correct?

the denominator is adjusting for double-counts

substitute the marginals using BP messages to get (*)



one cluster per factor

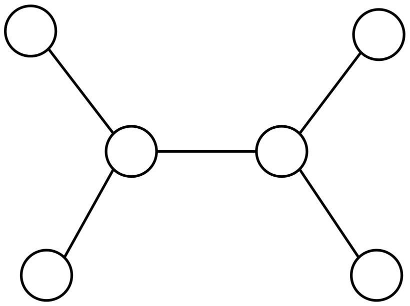
Variational interpretation

BP as I-projection

$$\arg\min_q D(q||p)$$

$$p(x) = \frac{1}{Z} \prod_k \phi_{i,j}(x_i, x_j)$$

$$q(x) = \frac{\prod_{i,j \in \mathcal{E}} q_{i,j}(x_i, x_j)}{\prod_i q_i(x_i)^{|Nb_i|-1}}$$



write q in terms of marginals of interest

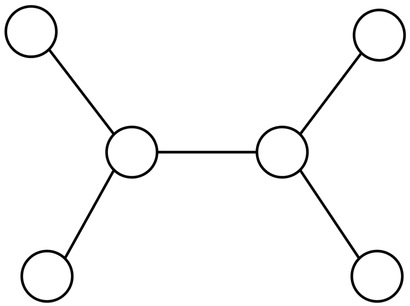
minimization gives us the marginals $q_{i,j}, q_i$

Variational free energy

$$D(q\|p) = \sum_{\mathbf{x}} q(\mathbf{x})(\ln q(x) - \ln p(x))$$

$q(\mathbf{x})(\ln q(x)$ → $-H(q)$

$\ln p(x)$ → $\mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)] - \ln(Z)$



$$= -H(q) - \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)] + \ln Z$$

ignore: does not depend on q

I-projection is equivalent to $\arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)]$

variational free energy

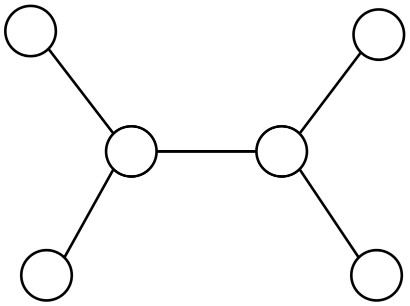
free energy is a lower-bound on $\ln Z$

Simplifying the free energy

$\arg\min_q D(q||p)$

$p(x) = \frac{1}{Z} \prod_k \phi_{i,j}(x_i, x_j)$

$q(x) = \frac{\prod_{i,j \in \mathcal{E}} q_{i,j}(x_i, x_j)}{\prod_i q_i(x_i)^{|Nb_i|-1}}$



$\equiv \arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)]$

so far did not use the **decomposed form of q**

both entropy and energy involve summation over exponentially many terms

Simplifying the free energy

$$\arg\min_q D(q||p)$$

$$p(x) = \frac{1}{Z}\prod_k \phi_{i,j}(x_i, x_j)$$

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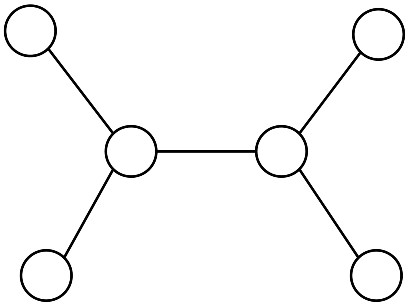

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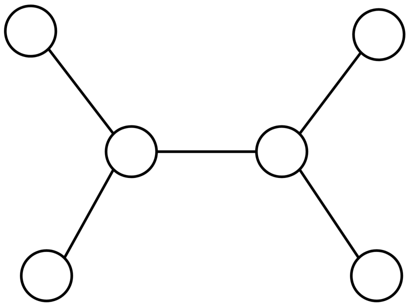

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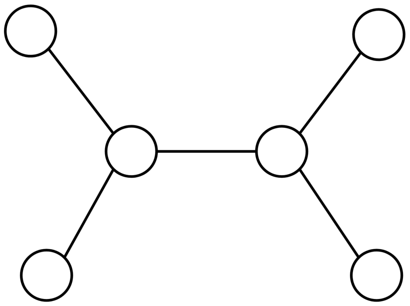

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$$\sum_{i,j\in\mathcal{E}} \sum_{x_{i,j}} q_{i,j}(x_i, x_j) \ln \phi_{i,j}(x_i, x_j)$$

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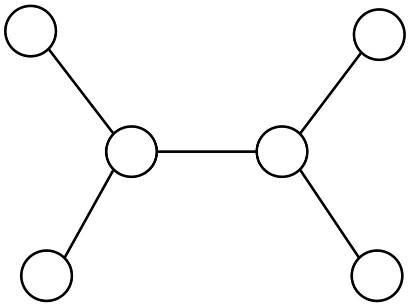

$$\equiv \arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln\phi_{i,j}(x_i, x_j)]$$

$$\sum_{i,j\in\mathcal{E}}\sum_{x_{i,j}} q_{i,j}(x_i, x_j)\ln\phi_{i,j}(x_i, x_j)$$

$$\sum_{i,j\in\mathcal{E}} H(q_{i,j}) - \sum_i(|Nb_i| - 1)H(q_i)$$ follows from the decomposition of q

Variational interpretation: marginal constraints

$$\arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)]$$

$$\sum_{i,j\in\mathcal{E}} \sum_{x_{i,j}} q_{i,j}(x_i, x_j) \ln \phi_{i,j}(x_i, x_j)$$

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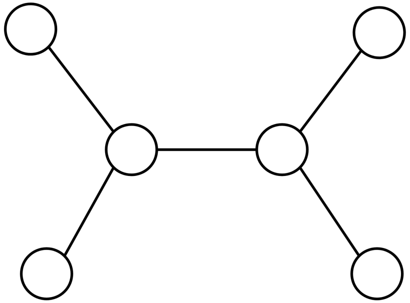

marginals $q_{i,j}, q_i$ should be "valid"

a real distribution with these marginals should exist

marginal polytope

$$\sum_{x_i} q_{i,j}(x_i, x_j) = q_j(x_j) \quad \forall i, j \in \mathcal{E}, x_j$$

for tree graphical models this **local** consistency is enough

Variational derivation of BP

$$\arg\max_{\{q\}} \sum_{i,j\in\mathcal{E}} H(q_{i,j}) - \sum_i (|Nb_i| - 1) H(q_i) + \sum_{i,j\in\mathcal{E}} \sum_{x_{i,j}} q_{i,j}(x_i, x_j) \ln \phi_{i,j}(x_i, x_j)$$

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$$\sum_{x_i} q_{i,j}(x_i, x_j) = q_j(x_j) \quad \forall i, j \in \mathcal{E}, x_j$$

$$q_{i,j}(x_i, x_j) \geq 0 \quad \forall i, j \in \mathcal{E}, x_i, x_j$$

$$\sum_{x_i} q_i(x_i) = 1 \quad \forall i$$

locally consistent
marginal distributions

Variational derivation of BP

$$\arg\max_{\{q\}} \sum_{i,j\in\mathcal{E}} H(q_{i,j}) - \sum_i (|Nb_i| - 1) H(q_i) + \sum_{i,j\in\mathcal{E}} \sum_{x_{i,j}} q_{i,j}(x_i, x_j) \ln \phi_{i,j}(x_i, x_j)$$

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locally consistent marginal distributions

BP update is derived as "fixed-points" of the Lagrangian

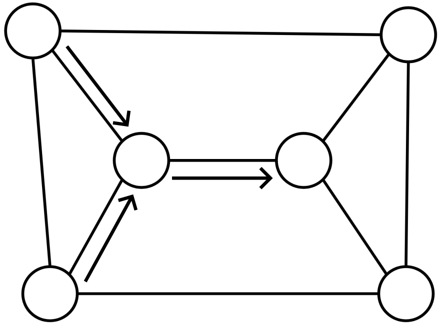
- BP **messages** are the (exponential form of the) **Lagrange multipliers**

What happens if there are loops?

We can still apply BP update:

$$\delta_{i\to j}(x_j) \propto \sum_{x_i} \phi_{i,j}(x_i, x_j) \prod_{k\in Nb_i - j} \delta_{k\to i}(x_k)$$

proportional to
normalize the message for numerical stability



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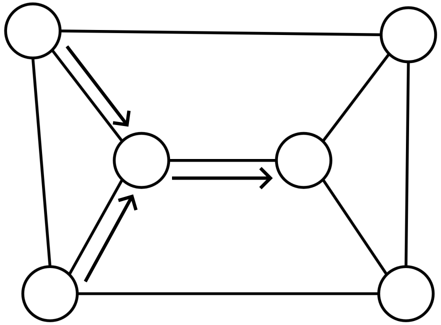

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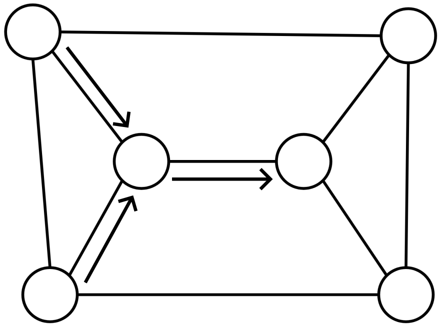

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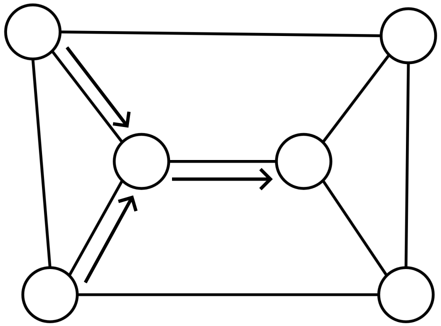


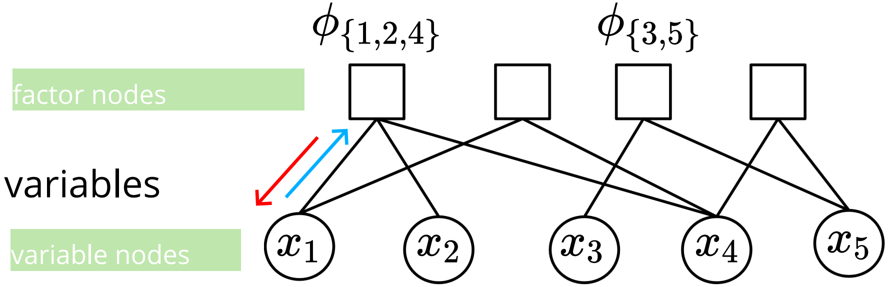
- update the messages **synchronously** or **sequentially**
- may not **converge** *(oscillating behavior)*
- even when convergent only gives an **approximation:**

$\hat{p}(x_i) \propto \prod_{k\in Nb_i} \delta_{k\to i}(x_i)$ is not (proportional to) the exact marginal $p(x_i)$

Loopy BP on factor graphs

$$p(\mathbf{x}) = \frac{1}{Z} \prod_I \phi_I(x_I)$$

$I \subseteq \{1, \ldots, N\}$ is a subset of variables



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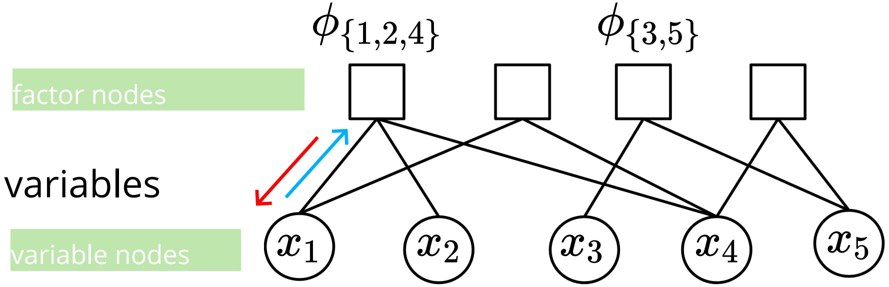

variable-to-factor message: $\delta_{i \to I}(x_i) \propto \prod_{J | i \in J, J \neq I} \delta_{J \to i}(x_i)$

Loopy BP on **factor graphs**

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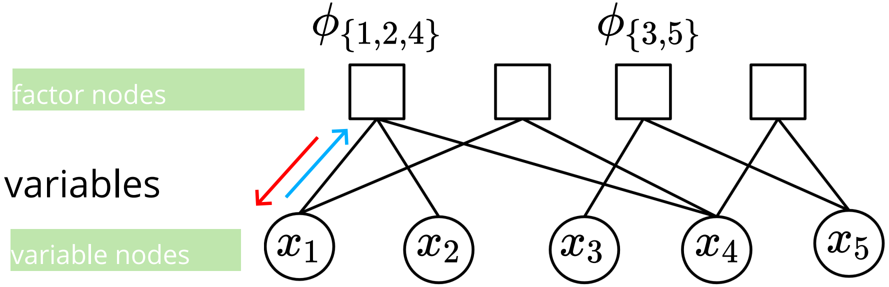

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factor-to-variable message: $\delta_{I \to i}(x_i) \propto \sum_{x_{I-i}} \phi_I(x_I) \prod_{j \in I-i} \delta_{j \to I}(x_i)$

Loopy BP on factor graphs

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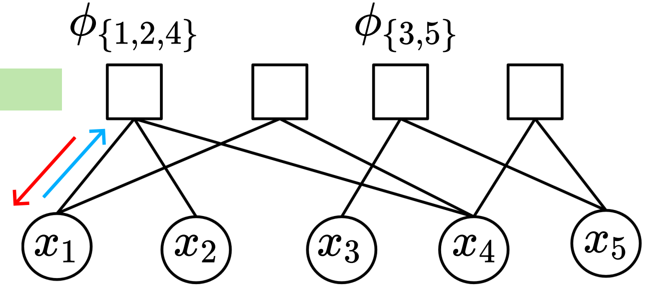

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after convergence: $\hat{p}(x_i) \propto \prod_{J | i \in J} \delta_{J \to i}(x_i)$

(Loopy) BP has found many applications

Machine Learning:

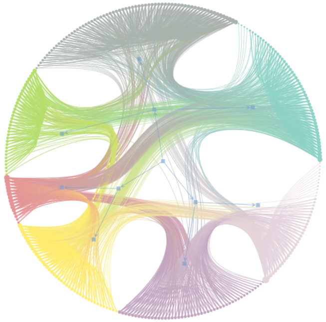
- clustering
- tensor factorization

www.jianxiongxiao.com

Vision:

- inpainting &denoising
- stereo matching

https://graph-tool.skewed.de

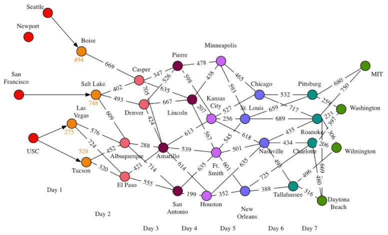


Social network analysis:

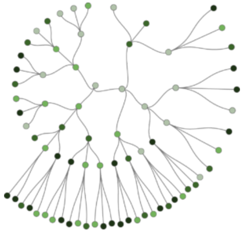
- stochastic block modelling

NLP and bioinformatics:

- Viterbi algorithm



Combinatorial optimization:



Application: LDPC coding using BP

low-density parity check

$x_1, \ldots, x_n$ are sent through a noisy channel

$y_1, \ldots, y_n$ are observerd

$$p(y_i = 1 \mid x_i = 1) = p(y_i = 0 \mid x_i = 0) = 1 - \epsilon$$

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the message satisfies parity constraints:

$$\phi_{stu}(x_s, x_t, x_u) = \begin{cases} 1 & \text{if } x_s \oplus x_t \oplus x_u = 1 \\ 0 & \text{otherwise} \end{cases}$$

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joint dist. over unobserved message:

$$p(x \mid y) = \prod_{s,t,u} \phi(x_s, x_t, x_u) \prod_{i=1}^{n} (1-\epsilon)\mathbb{I}(x_i = y_i) + \epsilon \mathbb{I}(x_i \neq y_i)$$

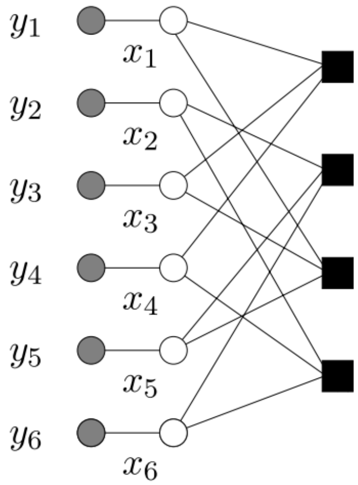

image: wainwright&jordan

Application: LDPC coding using BP

low-density parity check

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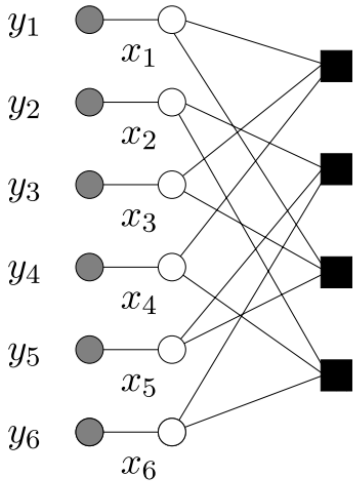

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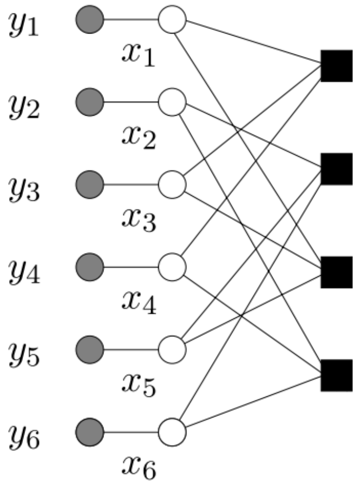

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  - using **loopy BP**

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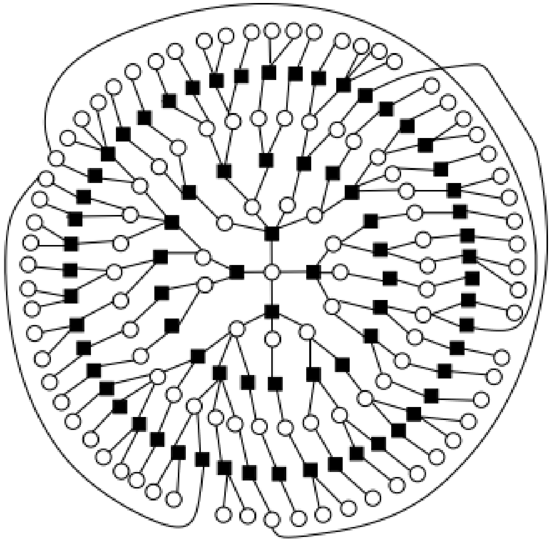

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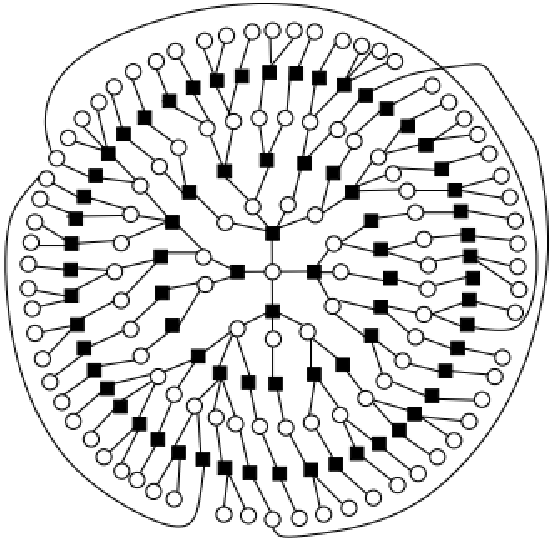

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Loops and variational interepretation

$$\arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)]$$

$$\sum_{i,j \in \mathcal{E}} \sum_{x_{i,j}} q_{i,j}(x_i, x_j) \ln \phi_{i,j}(x_i, x_j)$$

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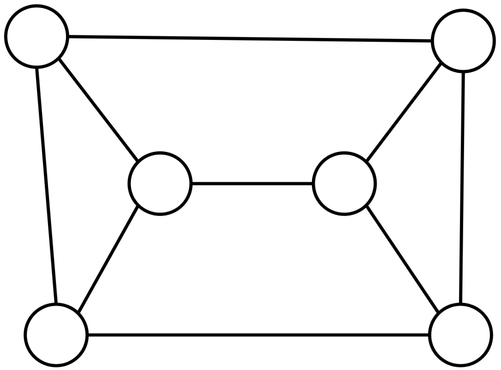

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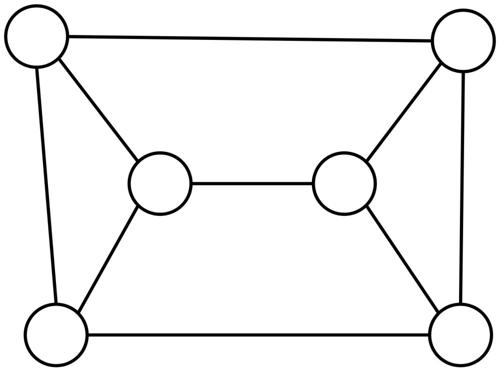

the entropy term is not exact anymore

- called **Bethe approximation** to the entropy
- generally not convex anymore *(multiple fixed points)*

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- locally consistent $q_{i,j}, q_i$ may not be marginals for any joint dist.

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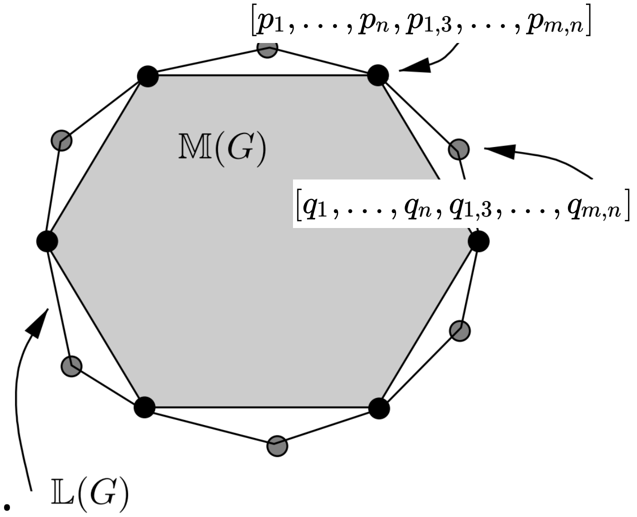

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Variations on BP

$$\arg\max_q H(q) + \mathbb{E}_q[\sum_{i,j} \ln \phi_{i,j}(x_i, x_j)]$$

- the entropy term is not exact anymore:
  - improved entropy approximations (e.g., region-based, convex)
- local consistency constraints are inadequate
  - tighter constraints (e.g., marginal consistency of larger clusters)

Variations on BP: cluster-graph

cluster-graph generalizes clique-tree

- clusters are not necessarily max-cliques
- running intersection property
- family-preserving property
- $S_{i,j} \subseteq C_i \cap C_j$

↓ instead of = in clique-tree

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instead of = in clique-tree

similar reparametrization:

$$p(\mathbf{x}) \propto \frac{\prod_i \hat{p}(C_i)}{\prod_{i,j} \hat{p}(S_{i,j})}$$

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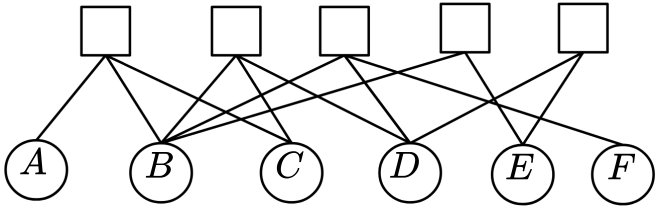

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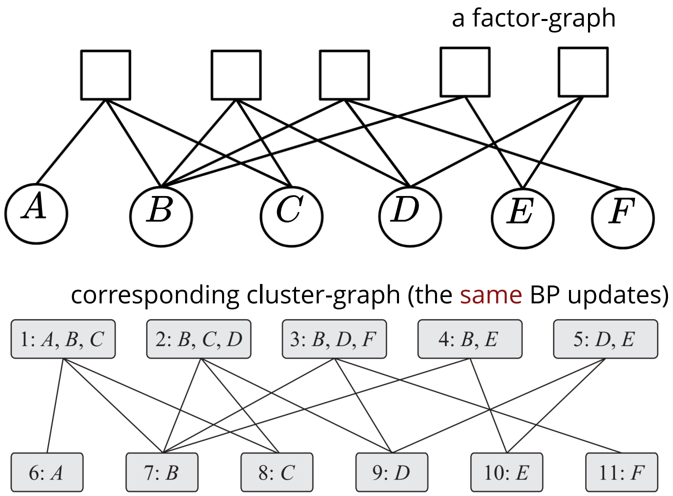

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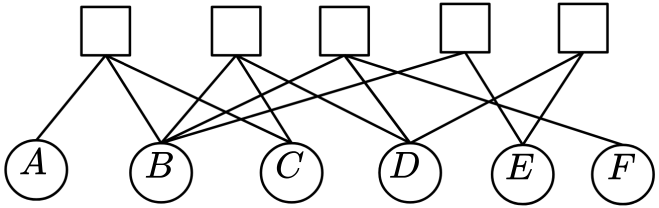
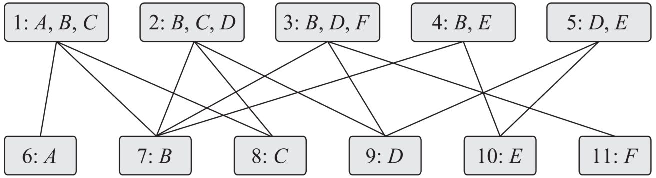
a factor-graph



corresponding cluster-graph (the same BP updates)



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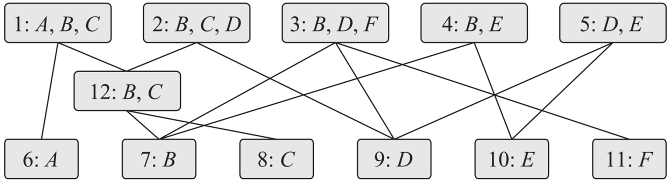
improved cluster-graph (better entropy approximation + marginal constraint)



BP in practice

11 x 11 Ising grid

- works well when:
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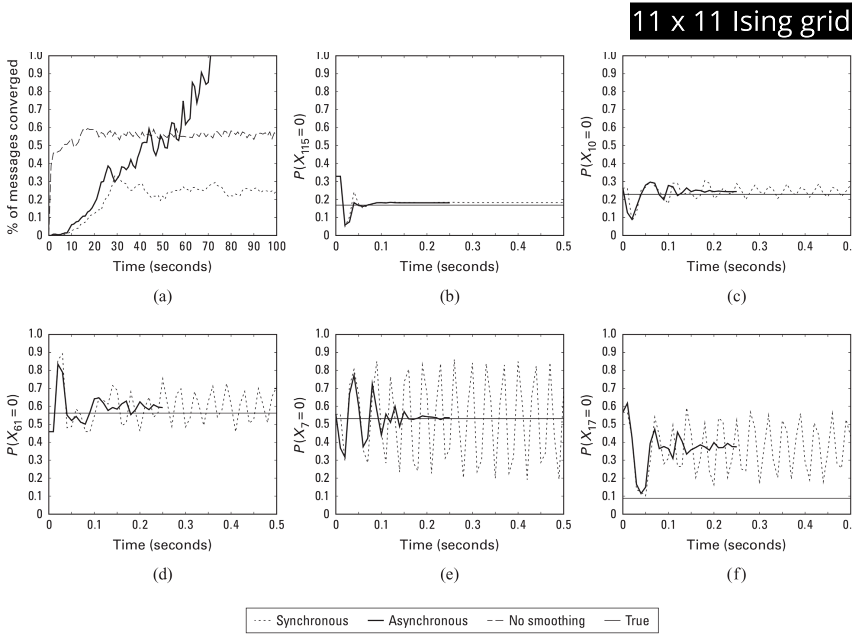

- sequential update works better than parallel update

- improved convergence by damping (smoothing) the update

$$\delta_{i\to I}^{(t+1)}(x_i) \propto (1-\alpha)\delta_{i\to I}^{(t)}(x_i) + \alpha \prod_{J|i\in J, J\neq I} \delta_{J\to i}^{(t)}(x_i)$$

Summary

belief propagation: efficient deterministic inference

- exact in clique-tree = variable elimination
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- works well in (cluster) graphs with loops (large tree-width)

bonus slides

Loopy BP on factor graphs: complexity

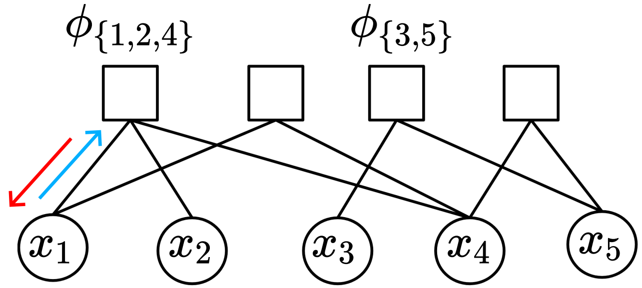
variable-to-factor message:

- from each var to all neighbors

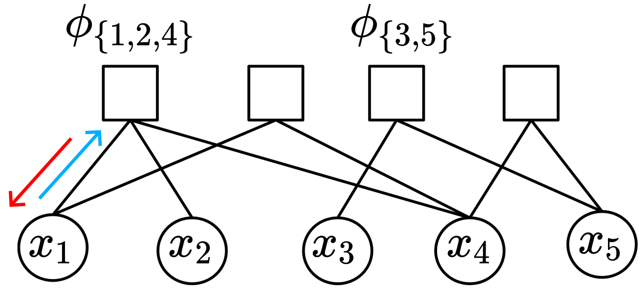
$\delta_{i \to I}(x_i) \propto \prod_{J | i \in J, J \neq I} \delta_{J \to i}(x_i)$

$n d \Delta_{max}^2$

- n: number of vars
- d: domain size (2 for binary)
- Δ_{max}: max neighbours



Loopy BP on factor graphs: complexity



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$|\text{Scope}_{\max}|$: vars in a factor

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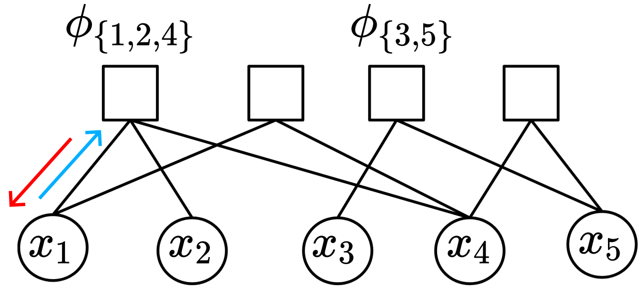

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