

Recap. Inference Algorithms

Marginalization

Maximization

✓ Elimination Algs

Elimination Algs

Exact, any G ,

$\mathcal{O}(|\mathcal{X}|^{\text{TreeWidth}})$
ac best but
NP-hard to find
ordering

Sum-product
= Belief Propagation

Max-product

Approx, Pairwise MRF, $\mathcal{O}(|\mathcal{X}|^2)$

✓ Sum-product algorithm on factor graphs Max-product algorithm on factor graphs Approx, any G , $\mathcal{O}(|\mathcal{X}|^{\text{max-degree}})$

Today Elimination algorithm on Junction trees Elimination Algorithm on Junction trees Exact, Junction Trees, $\mathcal{O}(|\mathcal{X}|^{\text{TreeWidth}})$
NP-hard to find the best ordering.

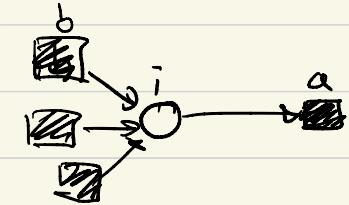
An exercise to derive Pairwise MRF BP, get 2 different looking updates.

BP for Factor Graphs

Repeat $t=1 \dots T$

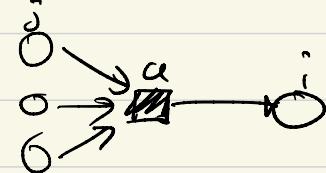
Update $M_{i \rightarrow a}$'s :

$$M_{i \rightarrow a}(x_i) = \prod_{b \in \text{dai}_i} \tilde{m}_{b \rightarrow i}(x_i)$$



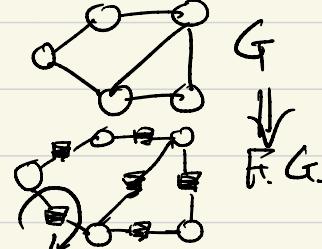
Update $\tilde{m}_{a \rightarrow i}$'s :

$$\tilde{m}_{a \rightarrow i}(x_i) = \sum_{j \in \text{dai}_i} f_{aj}(x_{ja}) \prod_{b \in \text{dai}_i} M_{b \rightarrow i}(x_b)$$



Let's apply it to Pairwise MRF:

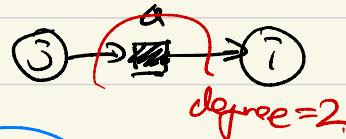
$$P(x) = \frac{1}{Z} \prod_{(i,j) \in E} f_{ij}(x_i, x_j)$$



Update: $M_{i \rightarrow a}(x_i) = \prod_{b \in \text{dai}_i} \tilde{m}_{b \rightarrow i}(x_i)$

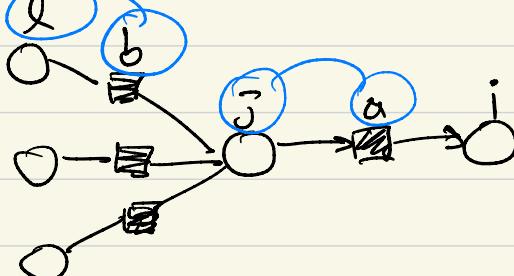
$$\tilde{m}_{a \rightarrow i}(x_i) = \sum_{x_j} f_{ij}(x_i, x_j) M_{j \rightarrow a}(x_j)$$

degree on factor node is 2



let's try to simplify by ① plug-in $M_{i \rightarrow a}$'s

$$\tilde{m}_{a \rightarrow i}(x_i) = \sum_{x_j} f_{ij}(x_i, x_j) \cdot \prod_{\substack{b \in \text{dai}_i \\ b \neq j}} \tilde{m}_{b \rightarrow i}(x_b) = \text{exactly BP for Pairwise MRF}$$



$$\tilde{m}_{b \rightarrow i}(x_b)$$

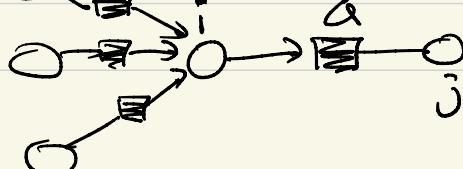
BP for Pairwise MRF

$$\tilde{m}_{i \rightarrow j}(x_j)$$

target

let's try to simplify by ② plug-in $\tilde{m}_{a \rightarrow i}$'s

$$M_{i \rightarrow j}(x_i) = \prod_{\substack{b \in \text{dai}_i \\ b \neq j}} \left\{ \sum_{x_k} f_{ki}(x_k, x_i) \cdot M_{k \rightarrow i}(x_k) \right\}$$



$$M_{i \rightarrow j}(x_i)$$

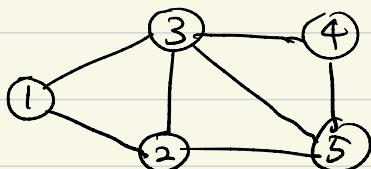
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any G can be turned into a Junction tree (or a loss)

- * Junction Tree Algorithm: Elimination algorithm exact on Junction Tree
 - * If G is chordal, we can easily find a Junction Tree (Special case of MRF) and solve inference exactly.

- * If G is not chordal, we add edges to make G chordal
↳ increases complexity.

$$\text{MRF: } P(X) = \frac{1}{Z} f_{123}(X_1, X_2, X_3) f_{235}(X_2, X_3, X_5) f_{345}(X_3, X_4, X_5)$$



Def. clique tree of MRF $G = (V, E)$.

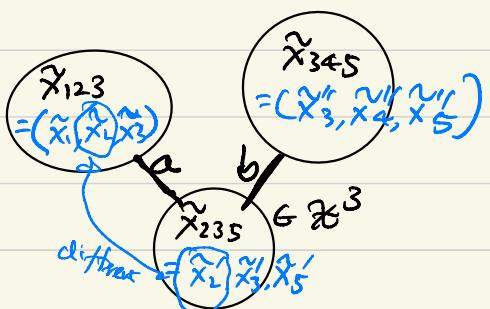
one example : Create a super-node for each clique $c \in C$

Clique Tree assign variable $\tilde{x}_c \in \tilde{X}^{(C)}$

each node has a local copy of global x_i 's

assign edges to form a tree.

Each edge ensures that the local copies are consistent.



Clique Tree Model $T = (\tilde{V}, \tilde{E})$ w.r.t $G = (V, E)$

$$\tilde{P}(\tilde{x}_{123}, \tilde{x}_{235}, \tilde{x}_{345}) = \frac{1}{Z} f_{123}(\tilde{x}_{123}) \cdot f_{235}(\tilde{x}_{235}) \cdot f_{345}(\tilde{x}_{345})$$

$\times \text{ fail } \tilde{x}_{123}, \tilde{x}_{235}$

$$\mathbb{I}(\tilde{x}_2 = \tilde{x}_2') \cdot \mathbb{I}(\tilde{x}_3 = \tilde{x}_3')$$

not the same

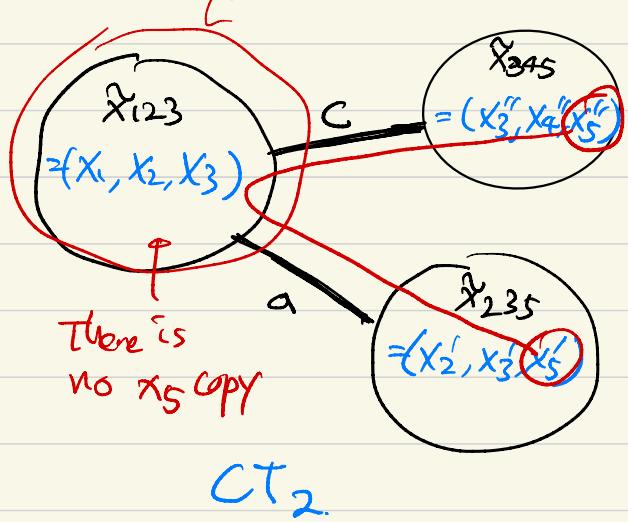
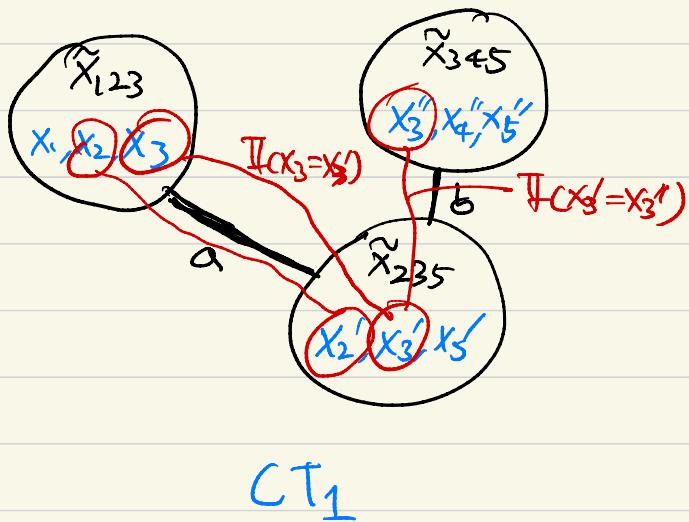
$$f_b(\tilde{x}_{235}, \tilde{x}_{345})$$

$$\mathbb{I}(\tilde{x}_3' = \tilde{x}_3'') \cdot \mathbb{I}(\tilde{x}_5' = \tilde{x}_5'')$$

$$= \frac{1}{Z}$$

$$\boxed{\tilde{f}_a(\tilde{x}_{123}, \tilde{x}_{235}) \cdot \tilde{f}_b(\tilde{x}_{235}, \tilde{x}_{345})}$$

example when Global consistency is not achievable (depending on the tree)



Claim:

If CT is globally consistent,

X_5 cannot be made consistent
for each variable i , remove all supernodes not containing local copy of X_i , and the resulting graph is still connected

then,

$$\tilde{P}_{CT}(\tilde{X}_{123}) = P_{MRF}(x_1, x_2, x_3)$$

\uparrow marginal

\uparrow marginal

Q. When is a clique tree of MRF globally consistent?
[existence] $G = (V, E)$

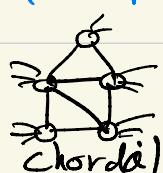
Def. Junction Tree Property.

a clique tree $T = (\tilde{V}, \tilde{E})$ from $G = (V, E)$ satisfy J.T.P
if all cliques contain i form a connected subtree in T .
 \uparrow supernodes

Def. T is a junction tree for G if all $i \in V$ has $J.T.P$

Q. [Existence] When does G have a Junction Tree?

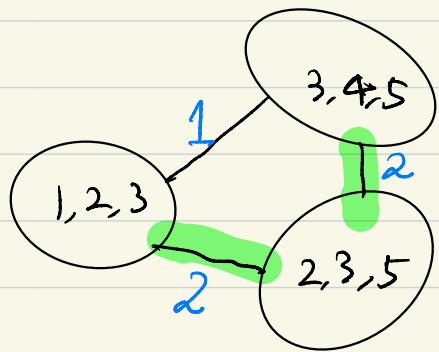
If G is chordal ($\hat{\cong}$ any loop ≥ 4 has a chord)



Q. [Construction] Given a chordal G , how do we find it? ①

Q. If the graph is not chordal, what do we do? ②

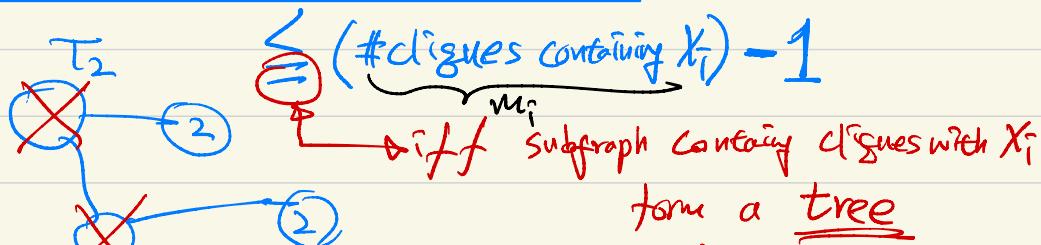
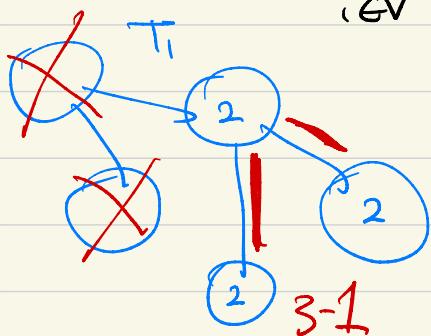
- ① Sketch of Algorithm: to find J.T for $G = (V, E)$, C set of \max_{cliques}
- create a complete graph on super nodes
 - assign weights to each edge as # variables shared b/w two cliques.
 - find the maximum weight spanning tree
 \cong a tree whose sum of edge weights is maximum
 by Kruskal's.



claim: [Correctness]

A clique tree T is a junction tree if and only if it is a max. spanning tree.

$$\begin{aligned} w[T] &= \sum_{\substack{\text{for any tree} \\ (C_l, C_r) \in T}} |C_l \cap C_r| \xrightarrow{\text{weight on edge } (C_l, C_r)} \\ &= \sum_{(C_l, C_r) \in T} \sum_{i \in V} I(x_i \in C_l \wedge x_i \in C_r) \\ &= \sum_{i \in V} \boxed{\sum_{(C_l, C_r) \in T} I(x_i \in C_l \wedge x_i \in C_r).} \end{aligned}$$



$$\leq \boxed{\sum_{i \in V} (m_i - 1)}$$

If T is a Junction Tree

② What if G is not chordal?

Sketch Algorithm.

make G chordal. (

- choose an elimination ordering, π
- find reconstituted graph. (which is chordal)
- Construct clique nodes complete max-weight spanning tree.

at best π , $O(|\pi|^{TreeWidth})$