

Inference! On GMS → Efficient Algorithm

Inference problems given a MRF $G = (V, E)$, $P(x) = \prod_{c \in \mathcal{C}} f_c(x_c)$

- (1) Calculate $P(x_i)$ ^{marginals}
- (2) Calculate $\operatorname{argmax}_x P(x)$
Or $\operatorname{argmax}_{x_2} P(x_2 | x_3)$
- (3) Calculate Z
(normalization term / partition fn)
- (4) Sample from $P(x)$

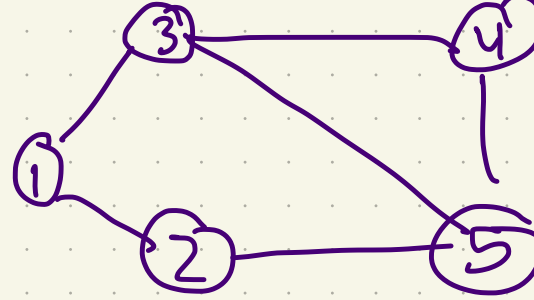
Brute Force — baby's first "algorithm" for marginals

- (1) Enumerate all values x_i could take ($|X|$)
- (2) Sum over all other $n-1$ variables ($|X|^{n-1}$)

complexity: $O(|X|^n)$.

$$P(X_1 = x_1) = \sum_{x_2 \dots x_n} P(x_1, x_2, \dots, x_n)$$

Elimination Algorithm



$$P(X) = \frac{1}{Z} f_{12}(x_1, x_2) f_{13}(x_1, x_3) f_{25}(x_2, x_5) f_{345}(x_3, x_4, x_5)$$

Goal: Compute $P(x_1)$ (Brute force $O(|X|^5)$)

$$P(x_1) \propto \sum_{x_2, x_3, x_4, x_5} f_{12}(x_1, x_2) f_{13}(x_1, x_3) f_{25}(x_2, x_5) f_{345}(x_3, x_4, x_5)$$

Eliminate variables in order (5, 4, 3, 2)

(5) $\propto \sum_{x_2, x_3, x_4} f_{12}(x_1, x_2) f_{13}(x_1, x_3)$

num $\rightarrow |X| \cdot |X| \cdot |X|$
 x_5 $\rightarrow$ summing x_2, x_3, x_4

$\propto \sum_{x_2, x_3} f_{12}(x_1, x_2) f_{13}(x_1, x_3) \sum_{x_4} m_5(x_2, x_3, x_4)$

$|X| \cdot |X|^2$

$m_4(x_2, x_3)$

$$\alpha \sum_{x_2} f_{12}(x_1, x_2) \underbrace{\sum_{x_3} f_{13}(x_1, x_3) \cdot m_4(x_2, x_3)}_{m_3(x_1, x_2)} \quad |X| \cdot |X|^2$$

$$\alpha \underbrace{\sum_{x_2} f_{12}(x_1, x_2) m_3(x_1, x_2)}_{m_2(x_1)} \quad |X| \cdot |X|$$

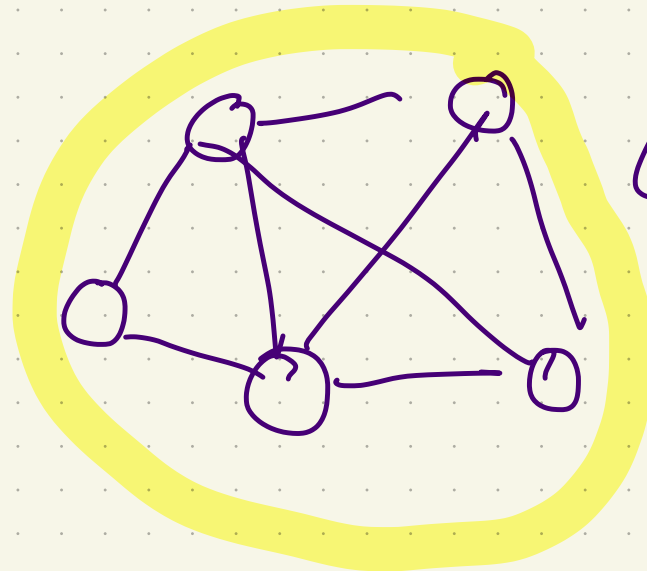
Total CC = $O(|X|^4)$
 To compute $P(x_1 = x_1) \quad \forall x_1 \in X$

Def A reconstituted graph $G' = (V, \tilde{E})$ of $G = (V, E)$ and a variable elimination ordering $P = (p_1, \dots, p_n) = \sigma_1 \dots \sigma_n$

Remove p_1 and let $E_1 = \{ (i, j) \text{ where } i \neq j \text{ were neighbors of } \sigma_1 \text{ in } G \}$

$\vdots$
 p_n

$$\tilde{E} = E \cup E_1 \cup \dots \cup E_n$$



$$G' = (V, E_{n-1})$$

Def The tree-width of a graph

$\min_{\text{all ordering}} \{ \text{max size of a clique in } G' = (V, \tilde{E}) \text{ the reconstituted graph} \}$

$E \cup E_1$
Has a clique of size 4 $\Rightarrow |X| = 4$

Elimination Alg for MAP $\operatorname{argmax}_x P(x) = x^*$

Q: Can we use our marginal alg?

(No! but sort of :)) $\operatorname{argmax}_{x_1} P_1(x_1) \stackrel{?}{=} x_1^*$ marginal dist over x_1

$$\operatorname{argmax}_{x_1} \sum_{x_2, \dots, x_n} P(x_1, x_2, \dots, x_n) \neq \operatorname{argmax}_{x_1} \max_{x_2, \dots, x_n} P(x_1, x_2, \dots, x_n)$$

Ordering (5, 4, 3, 2, 1)

$$\operatorname{argmax}_{x_1, \dots, x_5} P(x_1, \dots, x_5) \propto \operatorname{argmax}_{x_1, \dots, x_5} f_{12} f_{13} f_{25} f_{345}$$

$$\operatorname{argmax}_{x_1, \dots, x_4} f_{12} f_{13} \max_{x_5} f_{25} f_{345} \xrightarrow{M_5^*(x_2, x_3, x_4)} \boxed{X_5^*(x_2, x_3, x_4)}$$

$$\alpha \operatorname{argmax}_{x_1, x_2, x_3} f_{12} f_{13} \max_{x_4} m_5^*(x_2, x_3, x_4) \quad \begin{matrix} m_4^*(x_2, x_3) \\ x_4^*(x_2, x_3) \end{matrix}$$

$$\alpha \operatorname{argmax}_{x_1, x_2} f_{12} \max_{x_3} f_{13} m_4^*(x_2, x_3) \quad \begin{matrix} m_3^*(x_1, x_2) \\ x_3^*(x_1, x_2) \end{matrix}$$

$$\alpha \operatorname{argmax}_{x_1} \max_{x_2} f_{12} m_3^*(x_1, x_2) \quad \begin{matrix} m_2^*(x_1) \\ x_2^*(x_1) \end{matrix}$$

$$m_2 = \left[\begin{matrix} \in \{0,1\}^n \\ \rightarrow i \end{matrix} \right] \quad \text{"Probability of the most probable } x_2 \dots x_n \mid x_1 = x_i$$

$$P(x_1, \dots, x_n) = P(x_2, \dots, x_n \mid x_1) \cdot P(x_1)$$

CC : again $O(|X|^4)$

Our first formal measure of graph complexity
which directly captures CC of inference

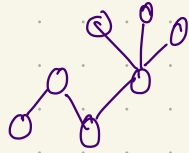
Small
Simple
'not dense'



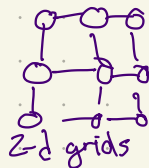
$E = \emptyset$
 $W = 1$
 $(n |X|)$
 $r\text{-deg } 0$



Chain
2
 $O(|X|^2)$
2



tree
2
 $O(|X|^2)$
 $\lceil n \rceil$



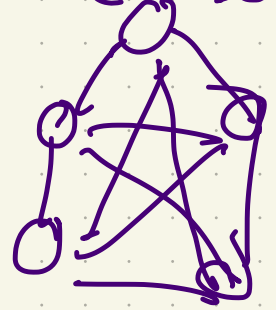
2-d grids
 $\sqrt{n}$
 $O(|X|^{\sqrt{n}})$
4

3-d grid
 $n^{2/3}$
 $O(|X|^{n^{2/3}})$
6

Erdős-
Rényi
Graph
(random)
 $p = \frac{c}{n}$

$W = n$
 $O(|X|^n)$
max degree
 c

large
complex
'dense'



1
0
max