

today: M3-net : M vs. L polytopes

marginal polytope (M) formulation:

$$\langle \alpha, s \rangle = \sum_{\tilde{y} \in \mathcal{Y}} \alpha(\tilde{y}) \left(\sum_C s_C(\tilde{y}_C) \right)$$

$$= \sum_{C \in \mathcal{C}} \sum_{\tilde{y}_C \in \mathcal{Y}_C} s_C(\tilde{y}_C) \left[\sum_{\substack{\tilde{y} \in \mathcal{Y} \\ \tilde{y}_C = \tilde{y}_C}} \alpha(\tilde{y}) \right]$$

$\triangleq \mu_C(\tilde{y}_C)$

"clique marginal variables"

$$\mu = (\mu_C)_{C \in \mathcal{C}} \quad \mu_C \in \Delta_{|\mathcal{Y}_C|}$$

$$\mu = A_M \alpha$$

A_M marginalization linear operator

$$\max_{\alpha \in \Delta_{|\mathcal{Y}|}} \langle \alpha, s \rangle = \max_{\mu \in A_M \Delta_{|\mathcal{Y}|}} \sum_{C \in \mathcal{C}} \sum_{\tilde{y}_C \in \mathcal{Y}_C} s_C(\tilde{y}_C) \underbrace{\mu_C(\tilde{y}_C)}_{\langle \mu_C, s_C \rangle}$$

$$M \triangleq A_M \Delta$$

"... .."

$$M \triangleq \{ (\mu_C)_{C \in \mathcal{C}} : \exists \alpha \in \Delta_{|\mathcal{Y}|} \text{ s.t. } \mu_C(\tilde{y}_C) = \sum \alpha(\tilde{y}) \forall C \}$$

$$M \triangleq \Delta_{\text{m}} \Delta$$

"marginal polytope"

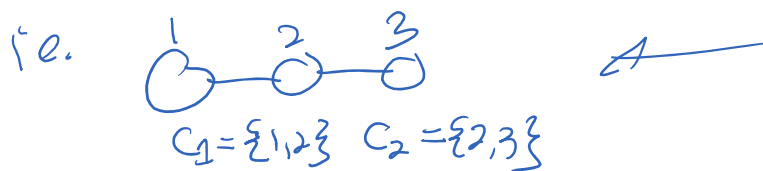
$$M \triangleq \left\{ (\mu_c)_{c \in \mathcal{C}} : \exists \alpha \in \Delta_{\mathcal{X}} \text{ s.t. } \mu_c(y_c) = \sum_{\substack{y \in \mathcal{X} \\ y_c = y_c}} \alpha(y) \forall c \right\}$$

$$M \subseteq \sum_{c \in \mathcal{C}} \Delta_{\mathcal{X}_c}$$

also: $M \subseteq L \triangleq \left\{ (\mu_c)_{c \in \mathcal{C}} : \mu_c \in \Delta_{\mathcal{X}_c} \text{ and } \mu_c \text{'s are "locally consistent"} \right\}$

"local consistency polytope"

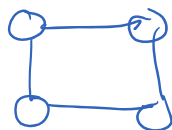
ie. $\forall c, c' \in \mathcal{C}$



$$\forall S \subseteq C \cap C' \\ \forall y_S, \sum_{\substack{y_{C'} \in \mathcal{X}_{C'} \\ \text{s.t. } y_S = y_S}} \mu_c(y_{C'}) = \sum_{\substack{y_{C'} \in \mathcal{X}_{C'} \\ \text{s.t. } y_S = y_S}} \mu_{c'}(y_{C'}) \\ = \mu_S(y_S)$$

⊗ L can be seen as a relaxation of M

if G is not triangulated, then we can have $M \neq L$



⊗ key property: if G is triangulated then $M = L$?? ⊗ ⊗

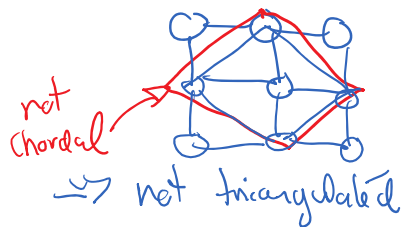
implication here $\max \sum \langle s_c + l_c, \mu_c \rangle = \max \sum \langle s_c + l_c, \mu_c \rangle$ [assuming ...]

implication here $\max_{\mu \in M} \sum_C \langle s_c + l_c, \mu_c \rangle = \max_{\mu \in L} \sum_C \underbrace{\langle s_c + l_c, \mu_c \rangle}_{g(w, z)}$

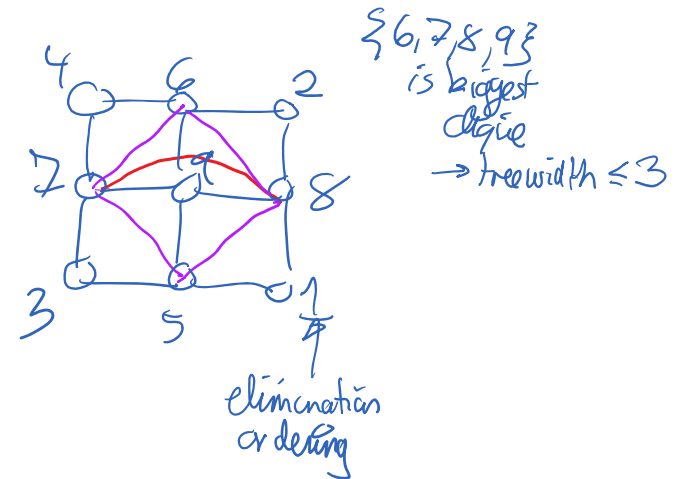
[assuming $l(y, y') \leq l_c(y, y')$]

aside: triangulated graph review:

Δ -graph $\rightarrow$ iff it has no cycle of size 4 and more which is not chordal

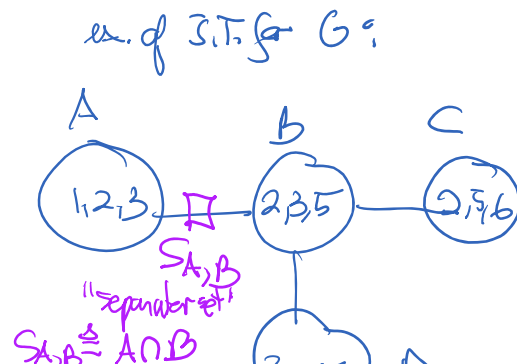
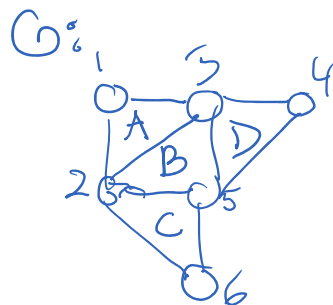


(*) you can triangulate a graph by running variable elimination



(*) if G is triangulated $\Rightarrow$ can construct a junction tree

$\hookrightarrow$ clique tree is tree on the maximal cliques of G with the running intersection property i.e. every $C \in \mathcal{C}$ is a node of the J.T.

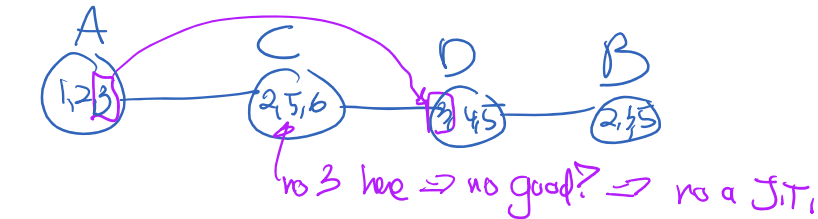
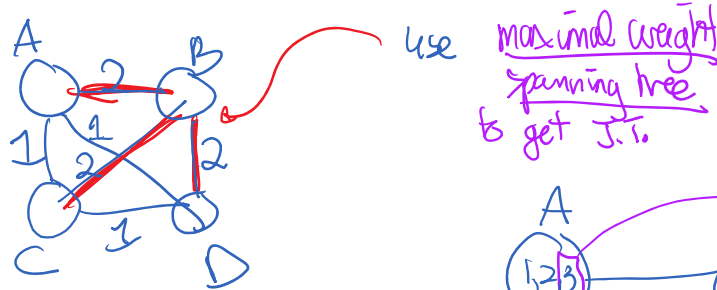


$\hookrightarrow$ if $v \in C_1 \cap C_2$ then v belongs to all cliques along the unique path from C_1 to C_2 in J.T.

ub

$$S_{A,B} \triangleq A \cap B = \{2,3\} \quad (3,4,5) \quad D$$

* to build a J.T.; first build weighted complete graph on cliques where weight on edges is $|C_i \cap C_j|$



15h28

$M = L$ for Δ -graphs

$M \subseteq L$

$$L \subseteq M: \alpha(y) = \frac{\prod_{C \in \mathcal{C}} \mu_C(y_C)}{\prod_{S \in \mathcal{S}} \mu_S(y_S)}$$

maximal cliques

separator sets from a J.T.

this is generalization
that
for tree UGM $p(x) = \prod_i p(x_i; z_i) \prod_i p(z_i)$

Suppose $\mu \in L$; then we show μ is valid marginal from some joint α

we'll show that α is a valid joint

$$\text{i.e. } \mu = A_{\mu} \alpha$$

where $\mathcal{C}$ are maximal cliques

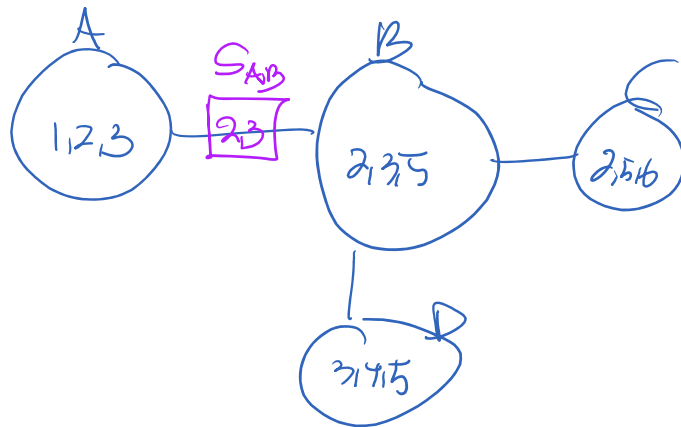
and $\mathcal{S}$ are separators from a J.T.

let's say want to show

that
for tree UGM $p(x) = \prod_{i,j \in E} \frac{p(x_i, x_j)}{p(x_i)p(x_j)} \prod_{i \in V} p(x_i)$

let's say want to show

$$\mu_B(y_B) = \sum_{y: y_B = y_B} \alpha(y)$$



$$\sum_{y: y_B = y_B} \left(\frac{\prod_{C \in \mathcal{C}} \mu_C(y_C)}{\prod_S \mu_S(y_S)} \right)$$

$$\frac{\sum_{y_A} \mu_A(y_A)}{\mu_{S_{A,B}}(y_{S_{A,B}})} \frac{\sum_{\text{rest}} \prod_{C \in \mathcal{C}} \mu_C(y_C)}{\prod_{\substack{C \in \mathcal{C} \\ C \not\supset A}} \mu_C(y_C)} = \frac{\prod_{S \neq S_{A,B}} \mu_S(y_S)}{\prod_{S \neq S_{A,B}} \mu_S(y_S)}$$

there is no y_i here, since $y_i \notin S_{A,B}$ crucially using run. intersect property

now, $\sum_{y_A} \mu_A(y_A) = \mu_{\{2,3\}}(y_{\{2,3\}})$ [by local consistency]
 $= \mu_{S_{A,B}}(y_{S_{A,B}})$

keep plucking the leaves until you are left with $\mu_B(y_B)$

⊛ why do we care to have shown $M=L$ for Δ -graph?

→ because describing L is simple i.e. $\text{Poly}(\max_C |\mathcal{C}_C|)$ # of constraints

vs. M which needs exponential # " " in worst case

[intuition: triangulating a general graph yields big cliques C_{max} and thus $|S_{C_{max}}|$ is exponential in $|C_{max}|$]

one way to see source of exp. # of constraints

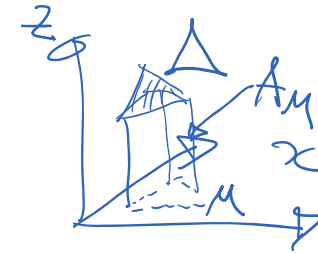
is Fourier-Motzkin elimination
(to project polytopes on lower dim. space)

$$a_i^T x \leq z \text{ for } i \in I$$

$$a_j^T x \geq z \text{ for } j \in J$$

↳ for z feasible to exist

$$\Rightarrow a_i^T x \leq a_j^T x \quad \forall (i,j) \in I \times J$$



to get back to M^z_{net} :

$$\max_{y \in S} S(y) = \max_{\alpha \in \Delta[S]} \langle \alpha, S \rangle = \max_{\mu \in M} \sum_c \langle \mu_c, S_c \rangle \stackrel{\text{when } M \subseteq L \text{ (i.e. } \Delta\text{-graph)}}{=} \max_{\mu \in L} \sum_c \langle \mu_c, S_c \rangle$$

all the vertices have
integer component
(i.e. $\{0,1\}$)

$$\text{i.e. } \mu^* = \arg \max_{\mu \in L} \sum_c \langle \mu_c, S_c \rangle$$

$$\text{will have } \mu_c^*(\cdot) = S_{y_c^*}(\cdot)$$

note: could use
junction algorithm
[max form]
(generalization of
vertex)

to solve this LP
(much more efficient
than interior point method)
on L

overall, suppose that $Q_i(y)$ decomposes also on L

$$\{ \dots \} \quad g(w, z)$$

$$\max_{\tilde{y} \in \tilde{S}_i} \tilde{Q}_i(\tilde{y}) - w^T \psi_i(\tilde{y}) = \max_{\mu \in L_i} Q_i + (C_i + F^T w)^T \mu - w^T F_i \mu^{(i)} s$$

(integer)
marginal from
ground truth $y^{(i)}$

last class: A) dualize this LP and plug it in structured SVM obj.
to get a small "complicated" QP

use Mosek, Cplex, etc. to solve to $1e-16$ accuracy
using IPM e.g.

B) saddle pt. formulation $\min_w \max_{\mu \in L_i} \mathcal{L}(w, \mu)$

extragradient $\rightarrow$ would require projection on L_i (local consistency polytope)
which is more expensive than LP

[to check: can you use message passing for that?]

C) later: saddle pt. FW alg. which only requires LMOs
"linear minimization oracles"
on L_i
instead of projection

next class: Lagrangian dual of SVM struct