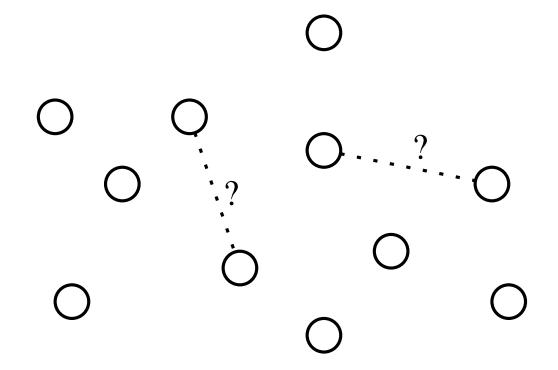
## Linear Programming in Bounded Tree-width Markov Networks

Percy Liang Nati Srebro U. Toronto

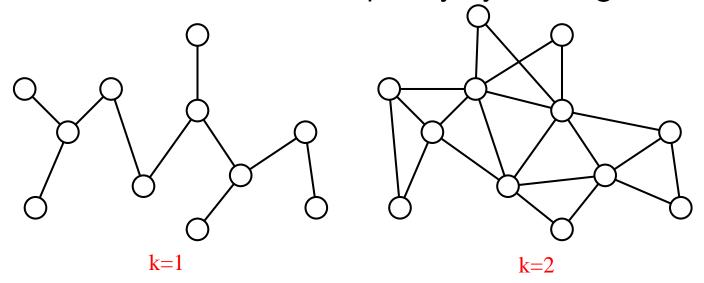
#### Motivation: Multivariate density estimation

Goal: to model the dependencies between a set of random variables



#### **Hypertrees**

Use Markov networks. Control complexity by limiting tree-width k.



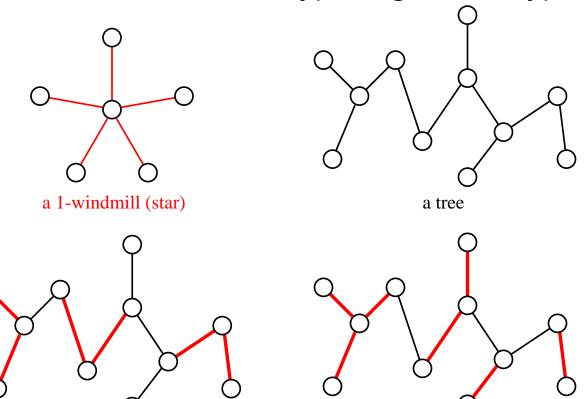
Weight of a hyperedge (clique) quantifies the importance of modeling the dependencies between the variables in the hyperedge. The maximum hypertree problem:

Input: weights of all candidate k-hyperedges

Output: a maximum weight k-hypertree

#### 1-windmill farms

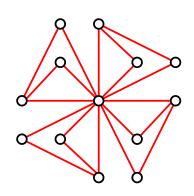
A windmill farm is a subset of the hyperedges of a hypertree.



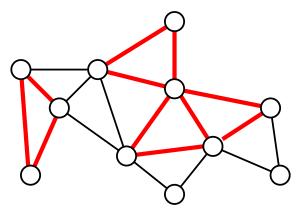
a 1-windmill farm in the tree

a 1-windmill farm in the tree

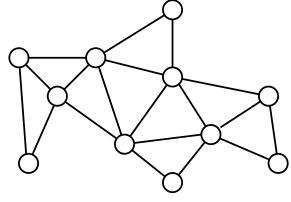
#### 2-windmill farms



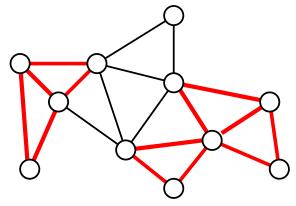
a 2-windmill



a 2-windmill farm in a 2-hypertree



a 2-hypertree



a 2-windmill farm in a 2-hypertree

#### Using windmills to approximate hypertrees

- A linear programming relaxation finds a windmill farm with weight  $\frac{1}{8^k k!}$  of the maximum windmill farm
- The maximum windmill farm captures at least  $\frac{1}{(k+1)!}$  of the weight of a hypertree
- Conclusion: The LP-based algorithm can find a hypertree with weight  $\frac{1}{8^k k! (k+1)!}$  of the optimal hypertree

 $C_k$  = the fraction of the weight of a k-hypertree that can be captured by a maximum weight k-windmill farm

Question: What is  $C_k$ ?

Approach: find the "worst" hypertrees for which the weight of the maximum windmill farm is minimized

Assume all weights are non-negative and weight of the hypertree w(T)=1.

1. Given a weighted hypertree (T, w), find the maximum weight windmill farm F.

$$C_k(T, w) = \max_{F \subset T} w(F)$$

Assume all weights are non-negative and weight of the hypertree w(T)=1.

- 1. Given a weighted hypertree (T, w), find the maximum weight windmill farm F.
- $C_k(T, w) = \max_{F \subset T} w(F)$
- 2. Given an unweighted hypertree structure T, find the "worst" weights w.

$$C_k(T) = \min_{w} \max_{F \subset T} w(F)$$

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3. Find the "worst" weighted hypertree  $C_k = \inf_T \min_w \max_{F \subset T} w(F)$ (T,w).

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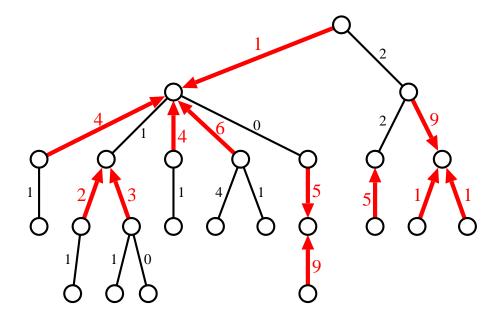
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Plan: solve problems 1, 2, and 3 for trees and then for hypertrees.

## **Problem 1:** $C_{k=1}(T, w) = \max_{F \subset T} w(F)$

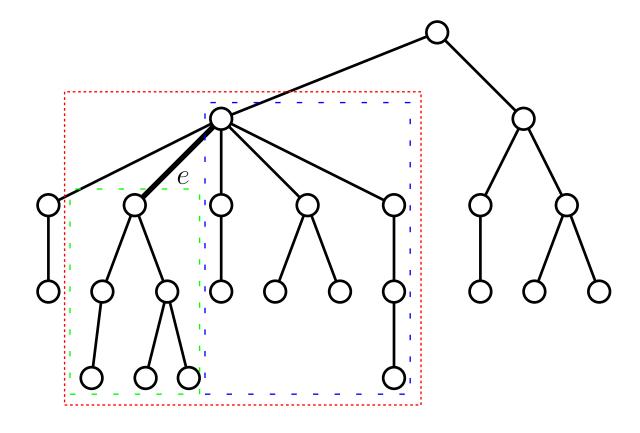
Goal: find the maximum weight windmill farm in a weighted tree.



$$w(F) = 1 + 4 + 4 + 6 + 2 + 3 + 5 + 9 + 9 + 5 + 1 + 1 = 50$$

**Problem 1:** 
$$C_{k=1}(T, w) = \max_{F \subset T} w(F)$$

Solve using dynamic programming:

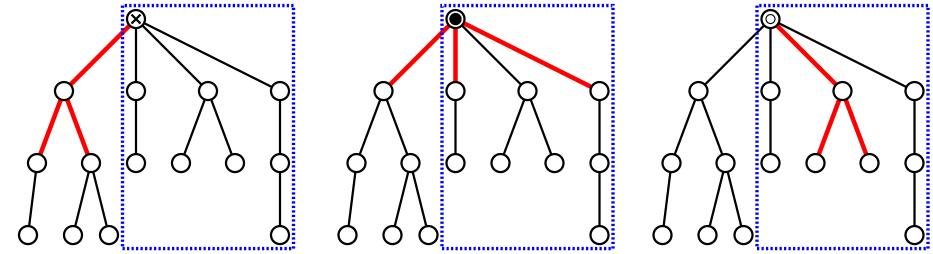


**Problem 1:** 
$$C_{k=1}(T, w) = \max_{F \subset T} w(F)$$

Find the maximum weight windmill farm given the state of the root vertex.

3 vertex states:

- o free
- regular
- × blocked

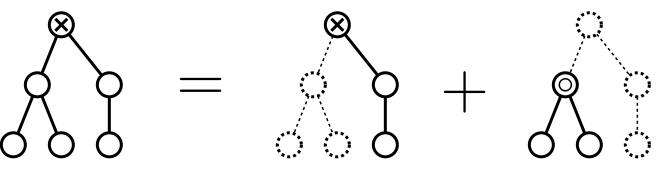


 $f_{v,i,s} = \text{maximum weight of a 1-windmill farm in subtree } (v,i)$  with vertex v in state s

## **Problem 1:** $C_{k=1}(T, w) = \max_{F \subset T} w(F)$

3 vertex states:

- o free
- regular
- × blocked



$$f_{v,i,\times} = f_{v,i+1,\times} + f_{c_i,1,\circ}$$

**Problem 1:** 
$$C_{k=1}(T, w) = \max_{F \in T} w(F)$$

3 vertex states:

- o free
- regular
- × blocked

$$f_{v,i,ullet} = \max \{ f_{v,i+1,ullet} + f_{c_i,1,\circ}, \ f_{v,i+1,ullet} + f_{c_i,1, imes} + w_{v,c_i} \}$$

### Problem 1: $C_{k=1}(T, w) = \max_{F \subset T} w(F)$

3 vertex states:

- o free
- regular
- × blocked

$$\begin{split} f_{v,i,\circ} &= \max \{ \ f_{v,i,\bullet}, \\ f_{v,i+1,\circ} + f_{c_i,1,\circ}, \\ f_{v,i+1,\times} + f_{c_i,1,\bullet} + w_{v,c_i} \ \} \end{split}$$

## **Problem 1:** $C_{k=1}(T, w) = \max_{F \subset T} w(F)$

Compute all dynamic programming states  $f_{v,i,s}$  in O(|V|) time:

$$f_{v,i,\times} = f_{v,i+1,\times} + f_{c_i,1,\circ}$$

$$f_{v,i,\bullet} = \max\{ f_{v,i+1,\bullet} + f_{c_i,1,\circ},$$

$$f_{v,i+1,\bullet} + f_{c_i,1,\times} + w_{v,c_i} \}$$

$$f_{v,i,\circ} = \max\{ f_{v,i,\bullet},$$

$$f_{v,i+1,\circ} + f_{c_i,1,\circ},$$

$$f_{v,i+1,\times} + f_{c_i,1,\bullet} + w_{v,c_i} \}$$

Problem 2: 
$$C_{k=1}(T) = \min_{w} \max_{F \subset T} w(F)$$

Preliminary step: convert the dynamic program into an equivalent linear program.

```
\begin{array}{ll} \text{Compute } f_{\mathsf{root}(T),1,\circ} \\ f_{v,i,\times} &= f_{v,i+1,\times} + f_{c_i,1,\circ} \\ f_{v,i,\bullet} &= \max\{ \ f_{v,i+1,\bullet} + f_{c_i,1,\circ}, \\ f_{v,i+1,\bullet} + f_{c_i,1,\times} + w_{v,c_i} \ \} \\ f_{v,i,\circ} &= \max\{ \ f_{v,i,\bullet}, \\ f_{v,i+1,\circ} + f_{c_i,1,\circ}, \\ f_{v,i+1,\times} + f_{c_i,1,\bullet} + w_{v,c_i} \ \} \end{array}
```

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$$\max_{F \subset T} w(F) = \min_{Af \ge Bw} f_{\mathsf{root}(T),1,\circ}$$

Problem 2: 
$$C_{k=1}(T) = \min_{w} \max_{F \subset T} w(F)$$

$$\max_{F \subset T} w(F) =$$

$$\min_{f:Af\geq Bw} f_{\mathsf{root}(T),1,\circ}$$

Problem 2: 
$$C_{k=1}(T) = \min_{w} \max_{F \subset T} w(F)$$

$$\min_{w \geq 0; \sum_{i=1}^{w} w_i = 1} \max_{F \subset T} w(F) = \min_{w \geq 0; \sum_{i=1}^{w} w_i = 1} \min_{f: Af \geq Bw} f_{\mathsf{root}(T), 1, \circ}$$

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#### A single linear program:

$$\min_{\substack{w,f\\w\geq 0; \sum w_i=1; Af\geq Bw}} f_{\mathsf{root}(T),1,\circ}$$

Problem 3: 
$$C_{k=1} = \inf_{T} \min_{w} \max_{F \subset T} w(F)$$

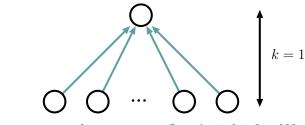
- Observation: A weighted tree with a weight 0 edge is equivalent to a weighted tree without the edge
- Construct a family of tree structures  $\{T_{b,h} \mid b,h=1,2,3,\dots\}$  (branching factor b, height h) that contains each tree structure

$$\bullet \ C_{k=1} = \lim_{b,h \to \infty} C_{k=1}(T_{b,h})$$

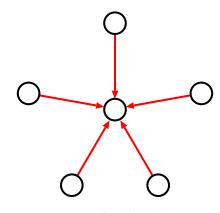
We solve the linear program and get  $C_{k=1}=rac{1}{2}$ 

#### k-windmill farms (definition)

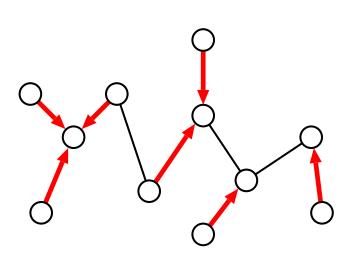
Hyperedges of windmill = root-to-leaf paths in representing tree k=1



representing tree of a 1-windmill



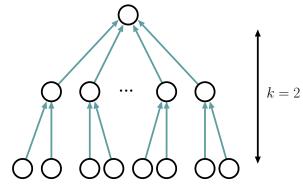
1-windmill



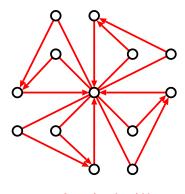
1-windmill farm in a tree

### k-windmill farms (definition)

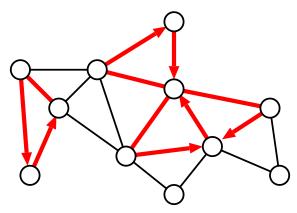
#### k = 2



representing tree of a 2-windmill



2-windmill

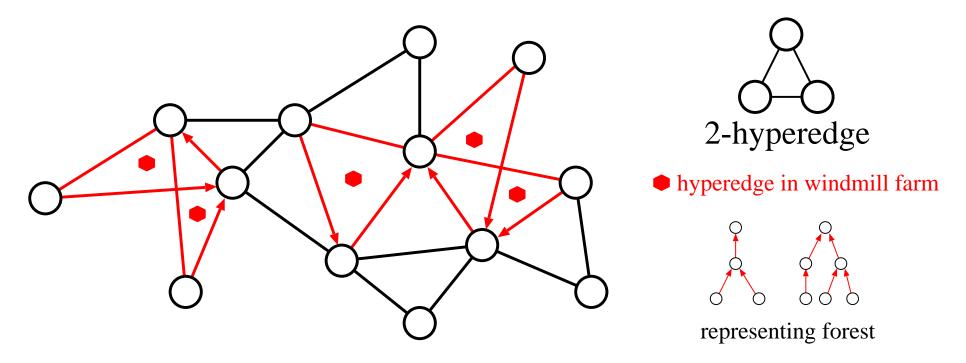


2-windmill farm in a hypertree

## Problem 1: $C_k(T, w) = \max_{F \subset T} w(F)$

Analyze the windmill coverge for hypertrees.

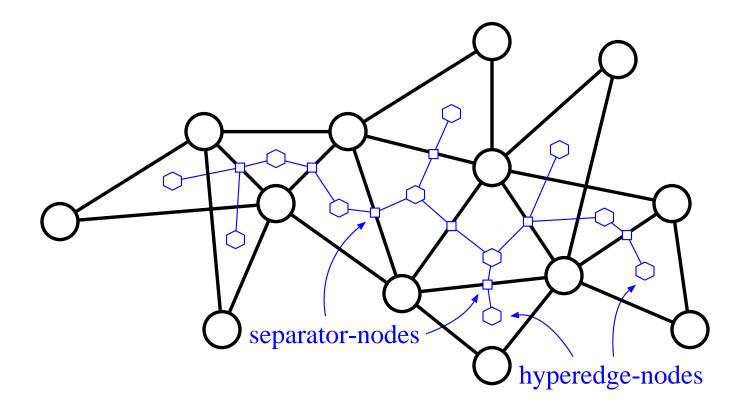
$$k = 2$$



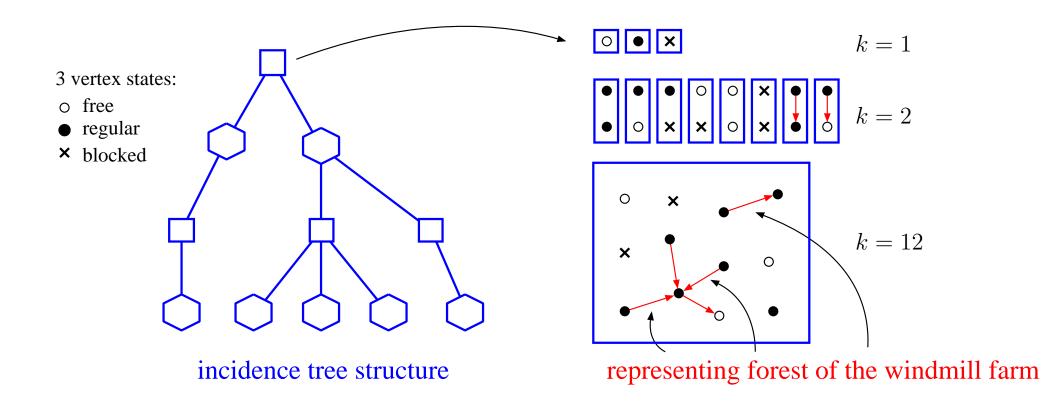
How do we decompose a hypertree?

Problem 1: 
$$C_k(T,w) = \max_{F \subset T} w(F)$$
 Incidence tree structure: represents how the hypertree is connected

Incidence tree structure: represents how the hypertree is connected k=2



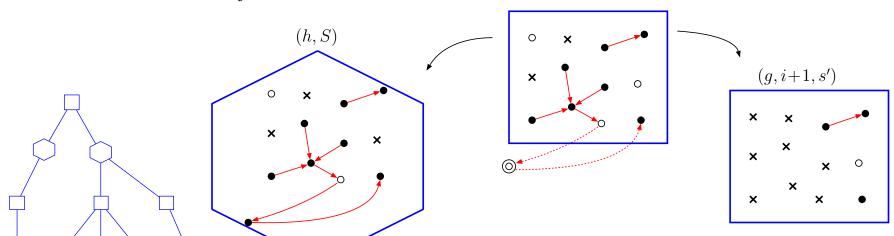
## Problem 1: $C_k(T, w) = \max_{F \subset T} w(F)$



# Problem 1: $C_k(T,w) = \max_{F \subset T} w(F)$ Dynamic programming states: $f_{g,i,s}$ , $f_{h,S}$

$$f_{g,i,s} = \max_{s \to S} \{ f_{g,i+1,s'} + f_{h,S} + w(h)[[S \text{ is a path}]] \}$$

$$f_{h,S} = \sum_{i} f_{g_i,1,\operatorname{restrict}(S,g_i)}$$



(g,i,s)

## Problem 2: $C_k(T) = \min_{w} \max_{F \subset T} w(F)$

Apply the duality technique from before.

$$\min_{w \geq 0; \sum w_i = 1} \max_{F \subset T} w(F) = \min_{w \geq 0; \sum w_i = 1} \min_{s, f : Af \geq Bw} f_{\mathsf{root}(T), 1, s}$$

A single linear program:

$$\min_{\substack{w,f\\w\geq 0;\sum w_i=1;Af\geq Bw}}f_{\mathsf{root}(T),1,\circ}$$

## Problem 3: $C_k = \inf_T \min_w \max_{F \subset T} w(F)$

Construct a family of hypertrees  $\{T_{k,b,h}\}$  such that:

- Each hypertree is contained in some  $T_{k,b,h}$  (branching factor b, height h)
- $ullet C_k = \lim_{b,h o \infty} C_k(T_{k,b,h})$

## Problem 3: $C_k = \inf \min \max_{F \subset T} w(F)$ $T_{k=2,b,h}$ b = 1 b = 2 b = 3 ...

$$T_{k=2,b,h}$$

$$b=1$$

$$b = 2$$

$$b = 3$$
 ...

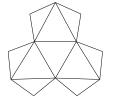
$$h = 1$$

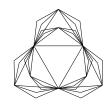


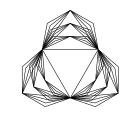




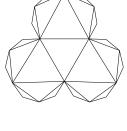
$$h=2$$



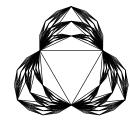




$$h = 3$$







Problem 3: 
$$C_k = \inf_T \min_w \max_{F \subset T} w(F)$$
 $T_{k=2,b,h}$   $b=1$   $b=2$   $0.5$   $0.5$   $0.5$   $0.5$   $0.5$   $0.308$   $0.$ 

#### Achieving a tighter upper bound

- Use weights obtained from the LP solution to construct a sequence of weighted hypertrees  $\{(T_{k,h}, w_{k,h})\}$
- Compute  $\lim_{h\to\infty} C_k(T_{k,h},w_{k,h})$  (involves solving Problem 1)

 $w_{k,h}$ : weight of a hyperedge is  $2^{-\text{height of hyperedge}}$ 

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$$k=2$$

$$T_{k=2,h=1} \qquad T_{k=2,h=2} \qquad T_{k=2,h=3} \qquad T_{k=2,h=4} \qquad \cdots$$
0.5 0.353 0.308 0.286 \cdots
2/4 6/17 16/52 40/140 \cdots \frac{2h+2}{9h-1} \rightarrow \frac{2}{9}

#### Achieving a tighter upper bound

 $C_k = \min_{T, w} C_k(T, w) = \min_{T} \min_{w} \max_{F \subset T} w(F)$ 

| $oxed{k}$      | $\leq C_k$     | $C_k$ | $\lim_{h\to\infty} \frac{C_k(T_{k,h},w_{k,h})\geq C_k}{C_k}$ | $\geq C_k$     |
|----------------|----------------|-------|--|----------------|
|                | Windmill Cover |       |  | Previous upper |
|                | Theorem        |       |  | bound          |
| 1              | 0.5            | 0.5   | 0.5  | 0.5            |
| 2              | 0.166666       | ?     | 0.222222   | 0.33333        |
| 3              | 0.041666       | ?     | 0.0953932  | 0.25           |
| 4              | 0.008333       | ?     | 0.0515625  | 0.2            |
| 5              | 0.001389       | ?     | 0.0258048  | 0.16666        |
| 6              | 0.000198       | ?     | 0.0123157  | 0.14286        |
| $\overline{k}$ | 1/(k+1)!       | ?     | $<1/2^k$ ?   | 1/(k+1)        |

#### **Conclusions**

- Motivation: using windmill farms to approximate the maximum likelihood Markov network
- We described an algorithmic technique for providing bounds on the windmill farm coverage

#### **Conclusions**

- Motivation: using windmill farms to approximate the maximum likelihood Markov network
- We described an algorithmic technique for providing bounds on the windmill farm coverage
- The exact windmill coverage  $C_k$  is open for k>1
- Future work: apply the duality technique to other problems (shortest path, minimum cut)