Constraint Satisfaction Problems (CSPs)

CS 221 Section – 11/03/16

Agenda

- CSP Problem Modeling
- N-ary Constraints
- Elimination Example

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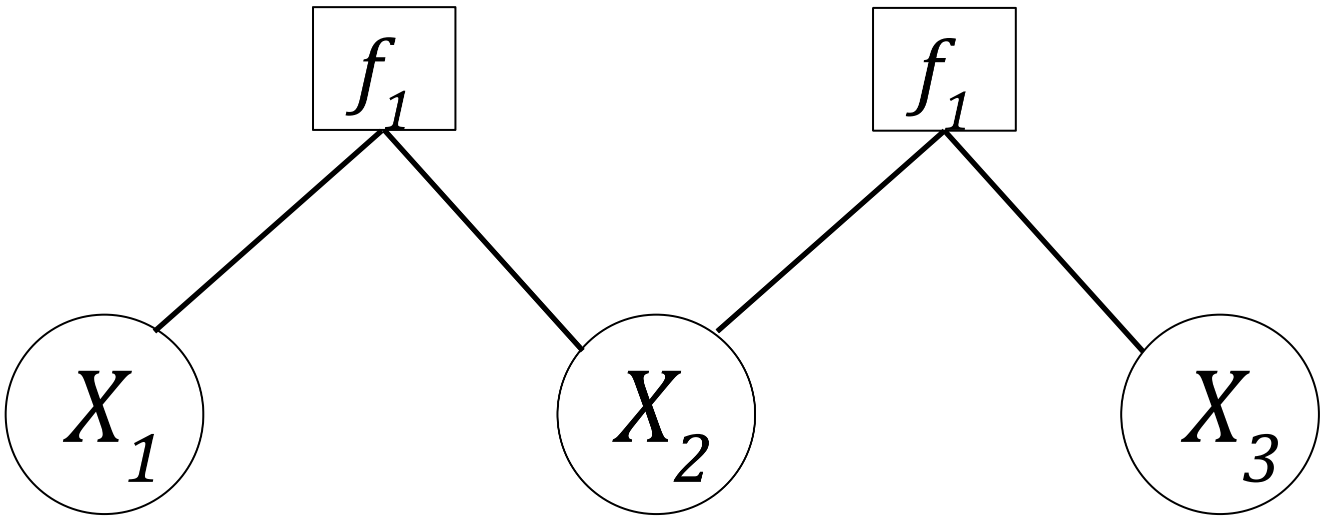
Definition: Factor Graph

Variables:

$$X = (X_1, \ldots, X_n), \text{ where } X_i \in Domain_i$$

Factors:

$$f_1, \ldots, f_m, \text{ with each } f_j(X) \geq 0$$



Definition: Constraint Satisfaction Problem (CSP)

A CSP is a factor graph where all factors are **constraints**:

for all $j = 1, \ldots, m$.

The constraint is satisfied iff $f_j(x) = 1$.

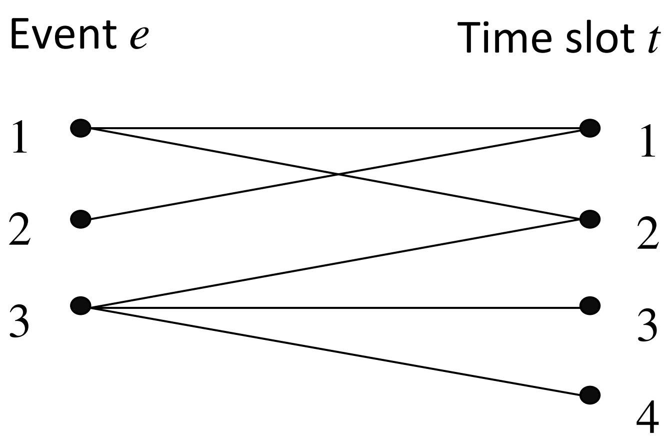
Definition: Consistent Assignments

An assignment x if $Weight(x) = 1$ (i.e., all constraints are satisfied.)

Event Scheduling

Setup:

- Have E events and T time slots
- Each event e must be put in **exactly one** time slot
- Each time slot t can have **at most one** event
- Event e only allowed at time slot e if (e, t) in A



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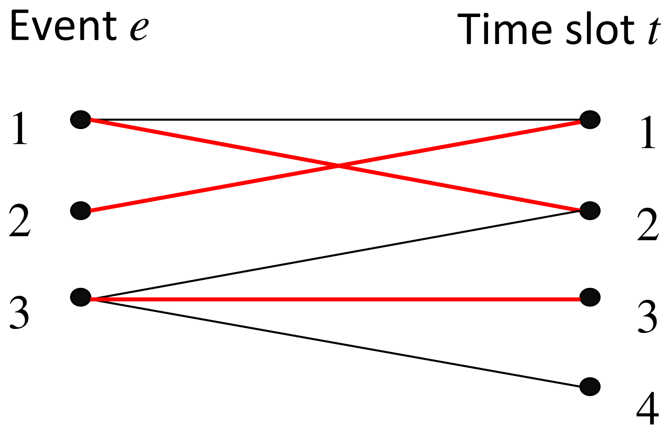
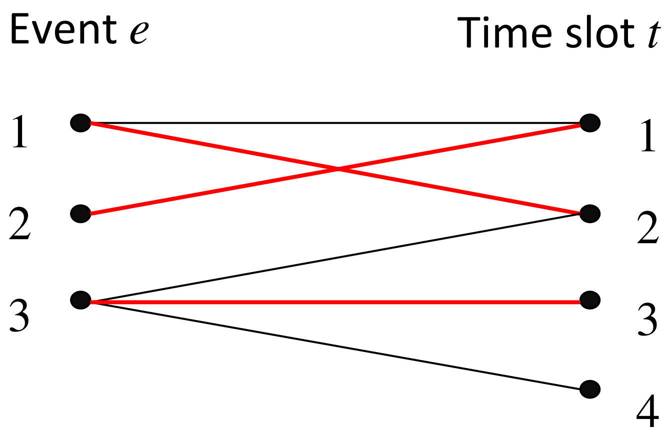


Event Scheduling

Formulation 1a:

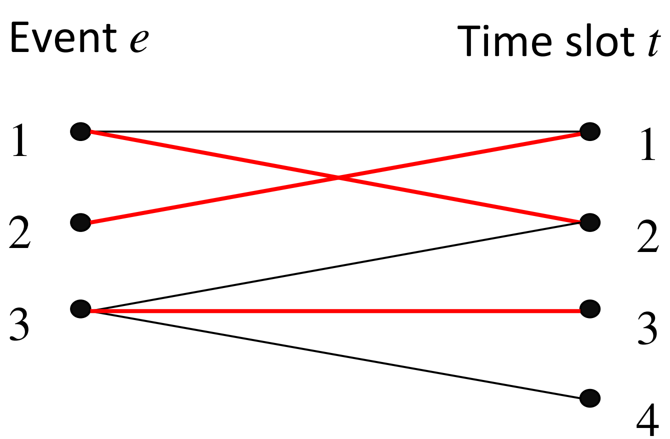
- Variables for each event e, $X_e \in \{1,\ldots,T\}$



Event Scheduling

Formulation 1a:

- Variables for each event e, $X_e \in \{1,\ldots,T\}$
- Constraints (only one event per time slot): for each pair of events $e \neq e'$, enforce $[X_e \neq X_{e'}]$



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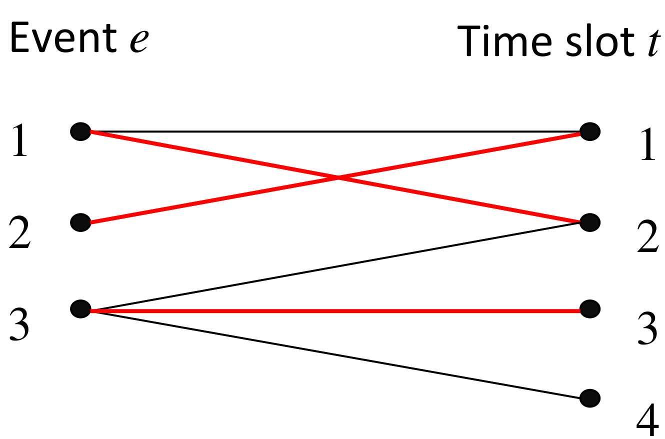

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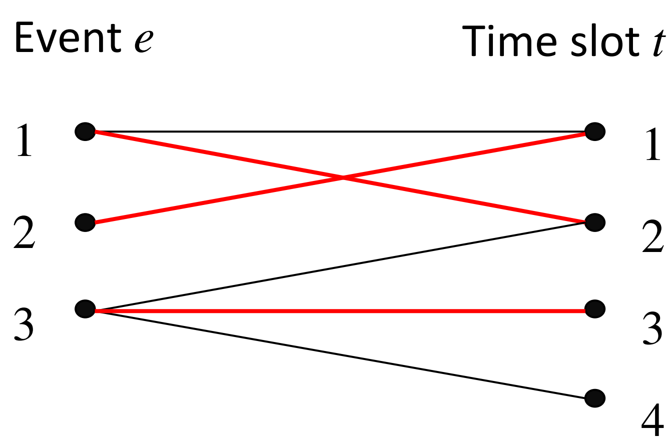

$\{X_1 : 1, X_2 : 1, X_3 : 3\}$

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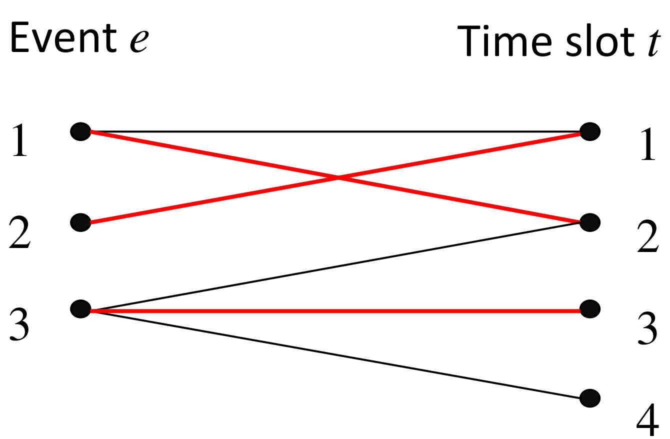

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Bad! $(X_1 = X_2)$

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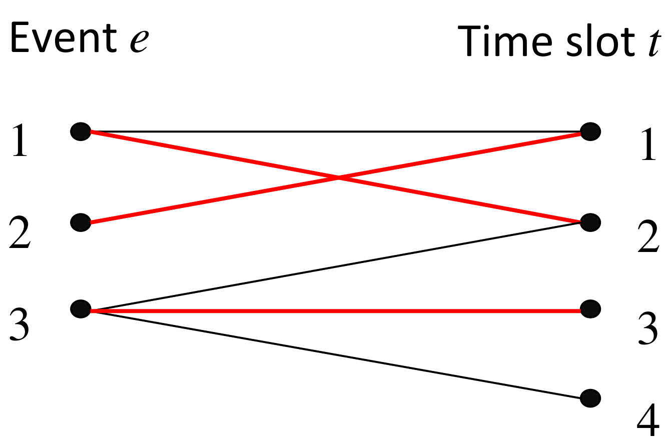

$\{X_1 : 1, X_2 : 1, X_3 : 3\}$

Bad! ($X_1 = X_2$)

$\{X_1 : 1, X_2 : 4, X_3 : 3\}$

Event Scheduling

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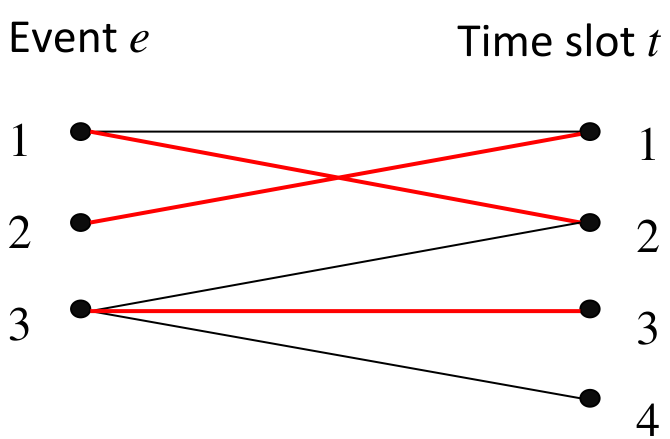

$\{X_1 : 1, X_2 : 1, X_3 : 3\}$

Bad! ($X_1 = X_2$)

$\{X_1 : 1, X_2 : 4, X_3 : 3\}$

Bad! ((2, 4) not in A)

Event Scheduling

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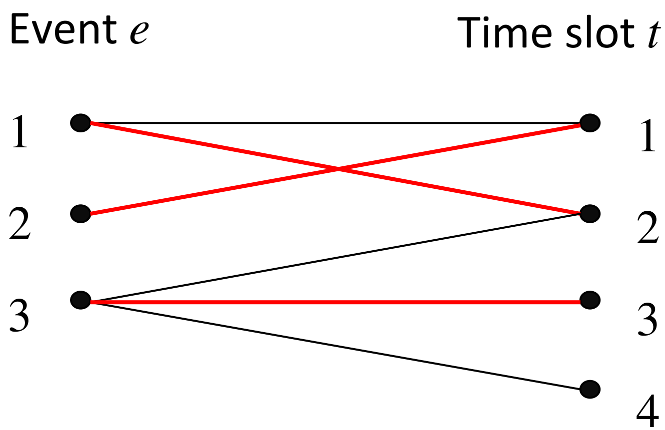
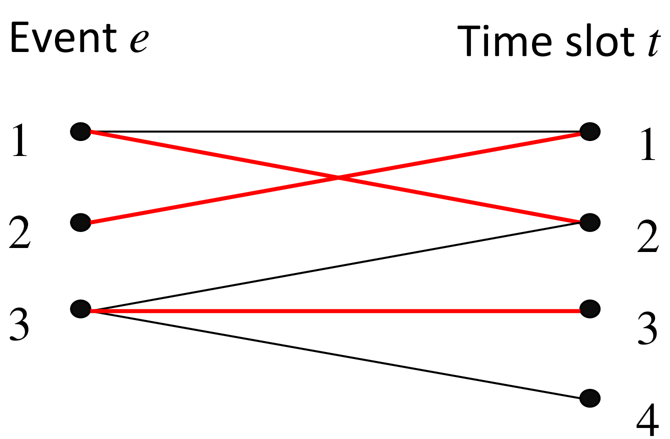


Event Scheduling

Formulation 1b:

- Variables for each event e, $X_1, \ldots, X_E$

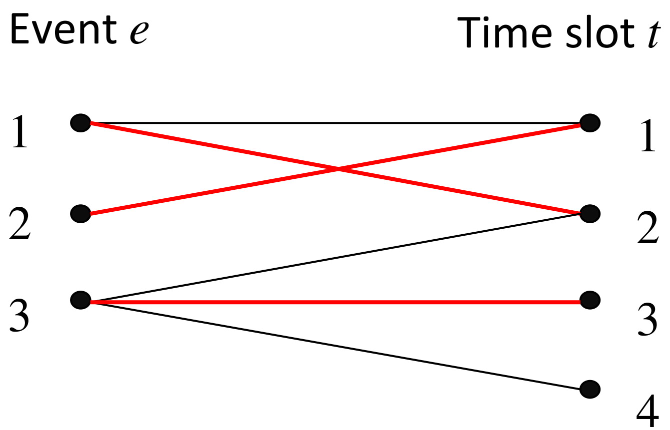


Event Scheduling

Formulation 1b:

- Variables for each event e, $X_1, \dots, X_E$

$$Domain_i = \{t : (i,t) \in A\}$$



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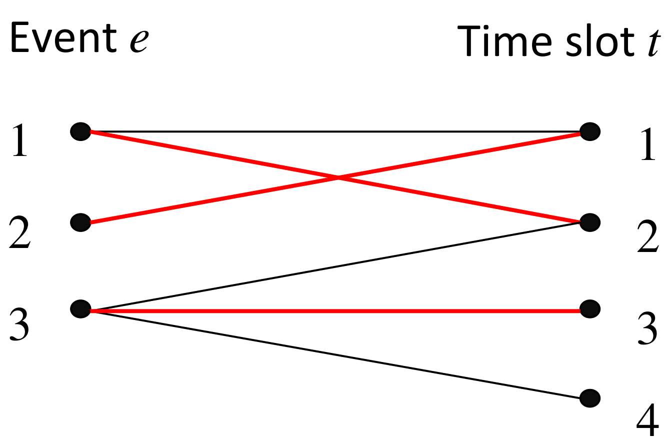
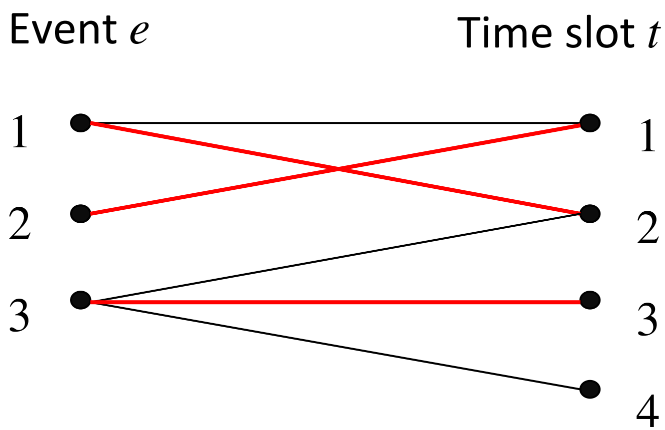


Event Scheduling

Formulation 2a:

- Variables for each time slot t: $Y_t \in \{1,\ldots,E\} \cup \{\varnothing\}$



Event Scheduling

Formulation 2a:

- Variables for each time slot t: $Y_t \in \{1,\ldots,E\} \cup \{\varnothing\}$
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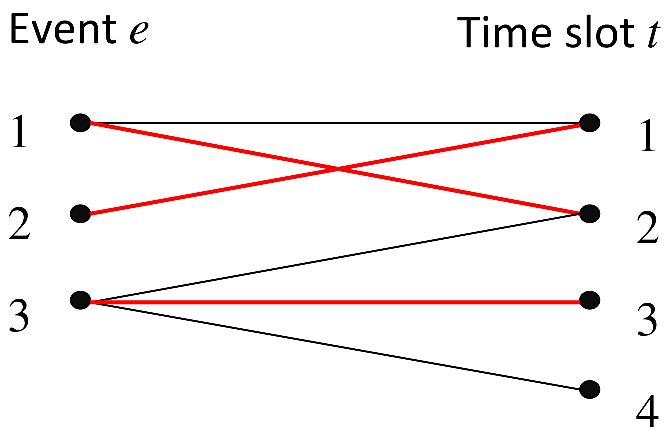

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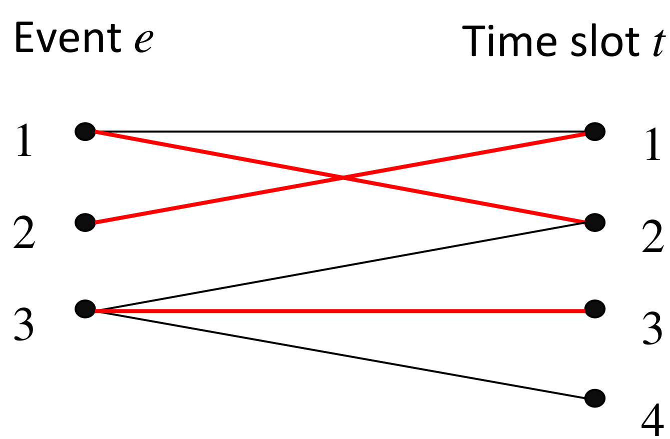

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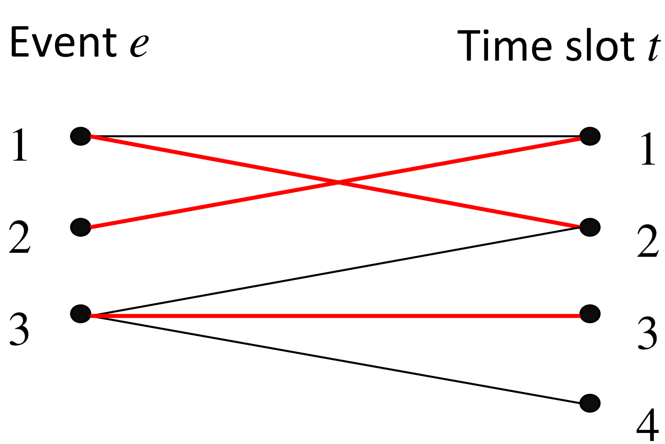

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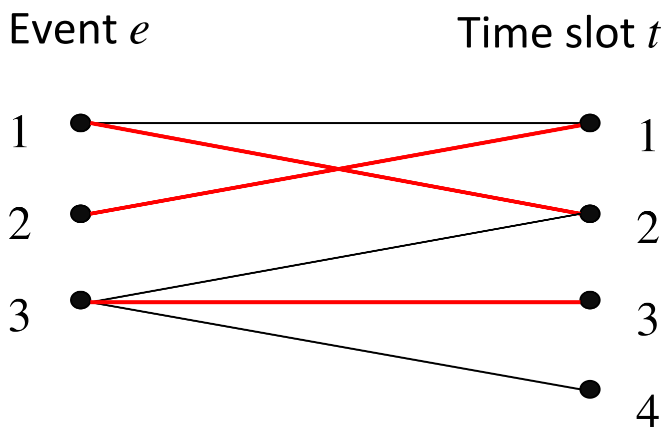

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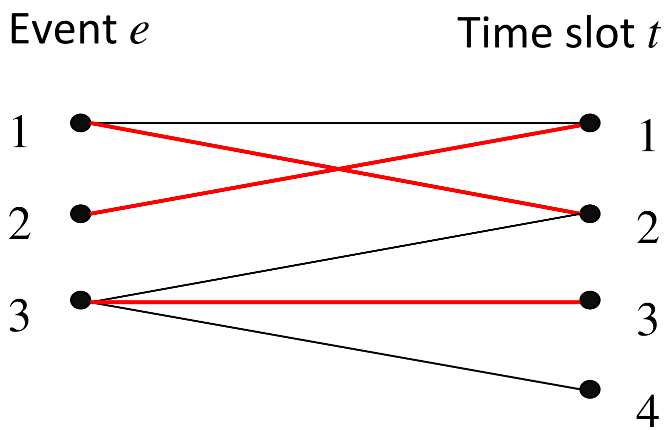
$$Domain_i = \{e : (e, i) \in A\} \cup \{\varnothing\}$$



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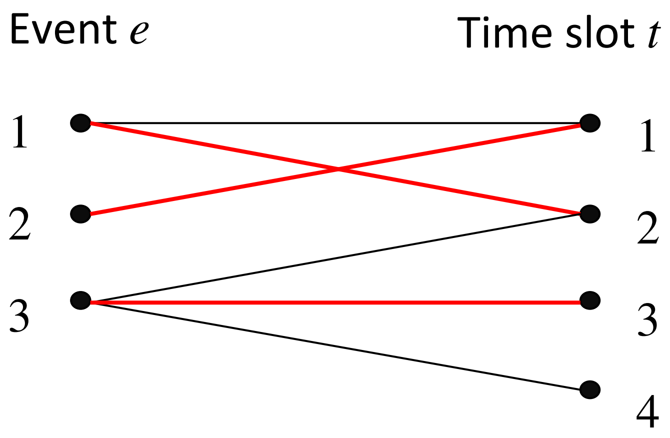
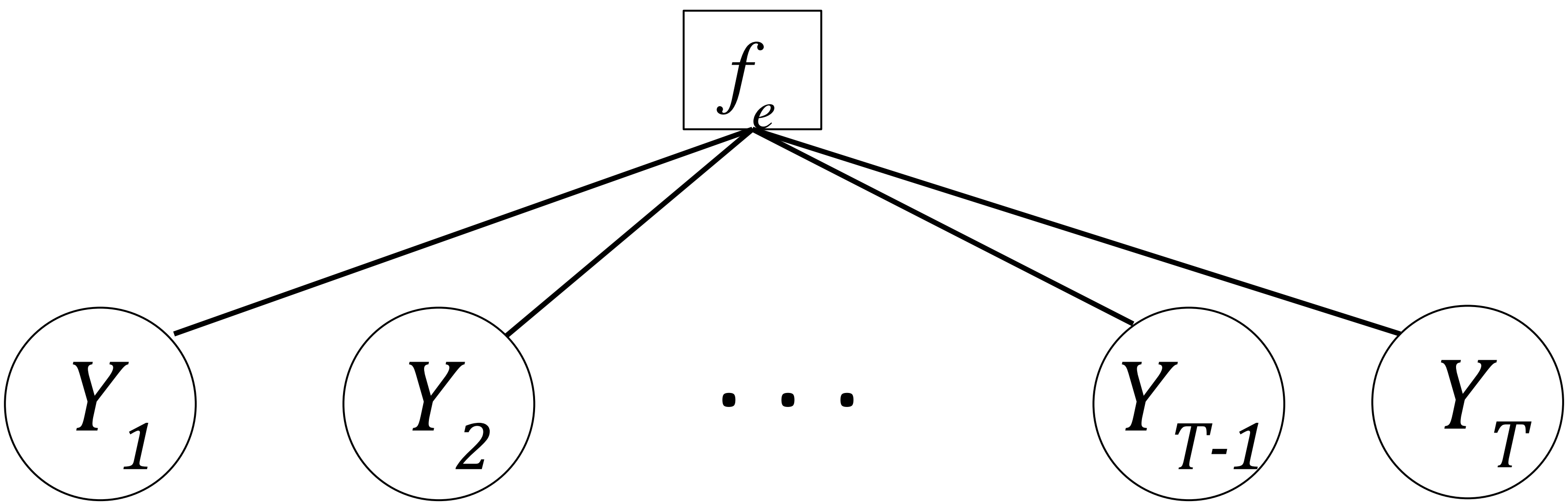


- Problem Modeling
- N-ary Constraints
- Elimination Example

N-ary Constraints

- From event scheduling:
  - Constraints (each event is scheduled exactly once): for each event e, enforce

$$[Y_t = e \text{ for exactly one } t]$$



N-ary Constraints

Key Idea: Auxiliary Variables

Auxiliary Variables hold intermediate computation.

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Factors:

Initialization: $[A_0 = 0]$

i	0	1	2	3	4
Y_i		3	1	2	1
A_i	0				

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Factors:

Initialization: $[A_0 = 0]$

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Initialization: $[A_0 = 0]$
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Final Output: $1[A_T = 1]$

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Still have factors with three variables…

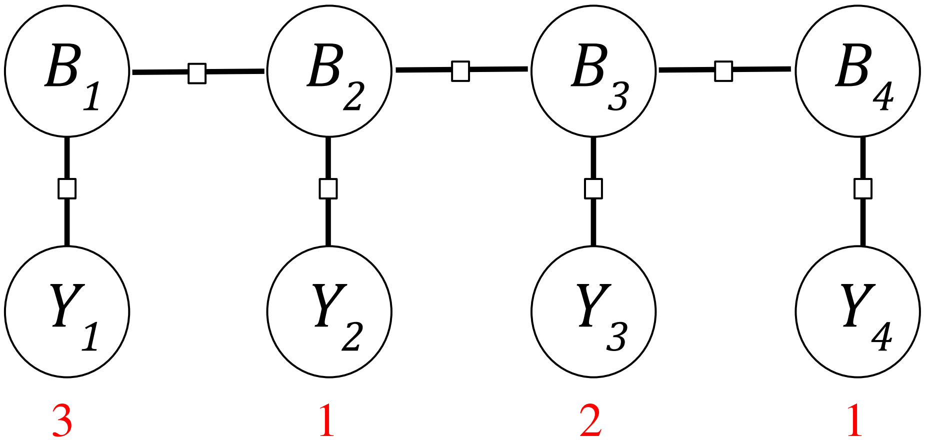
N-ary Constraints

Key idea: Combine $A_{i\text{-}1}$ and A_i into one variable B_i

N-ary Constraints

Key idea: Combine A_{i-1} and A_i into one variable B_i

$e = 1$



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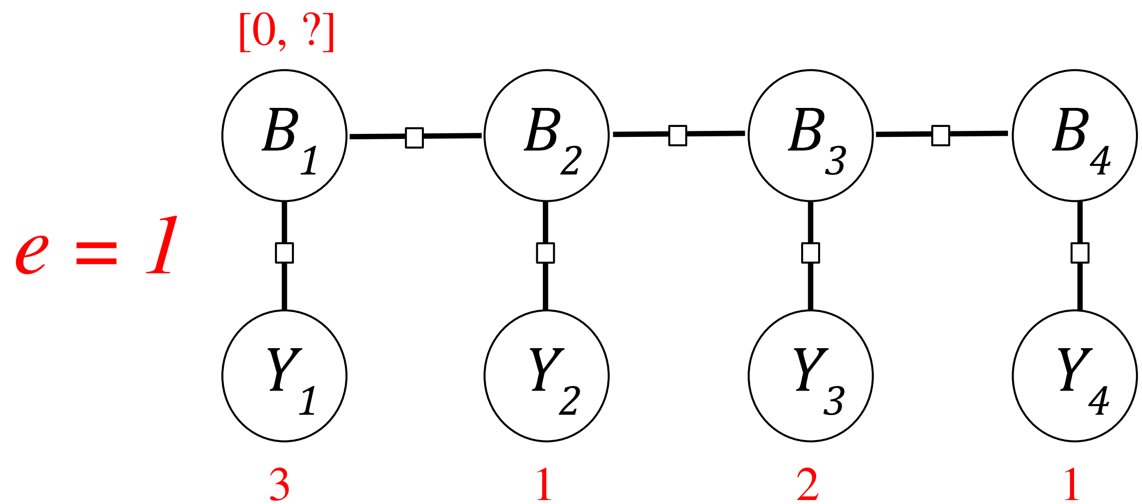

Factors:

Initialization: $[B_1[0] = 0]$

N-ary Constraints

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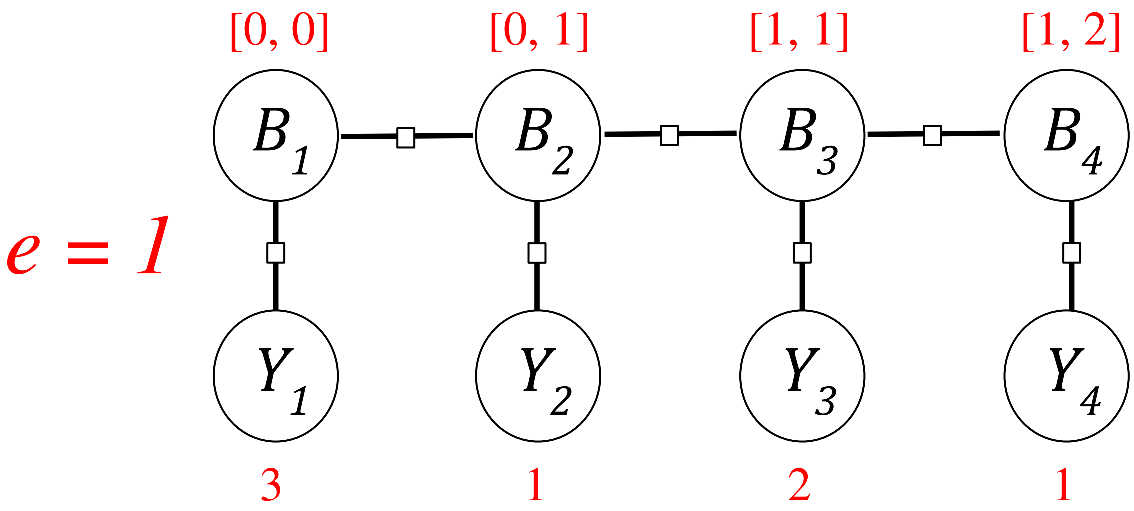

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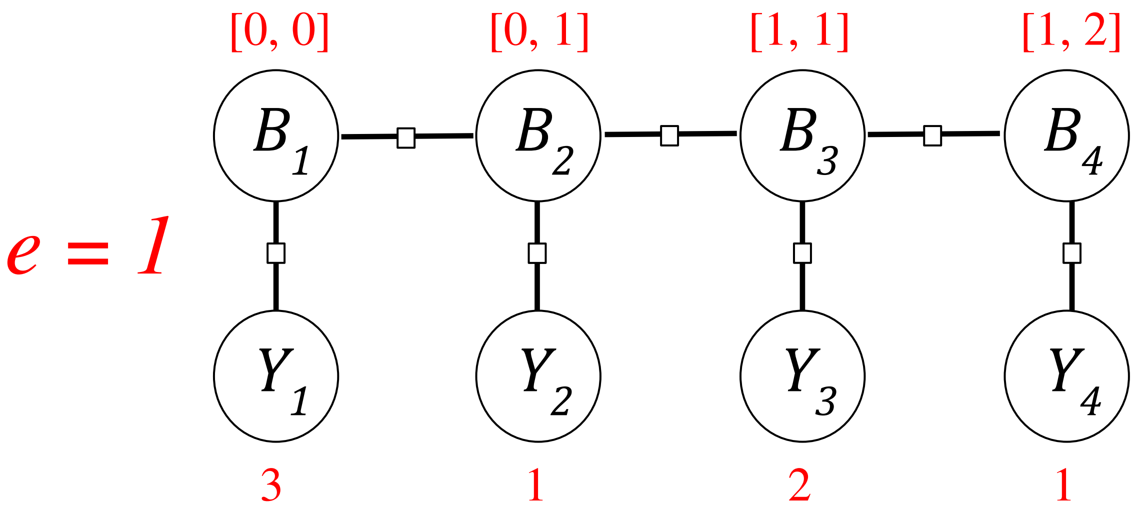

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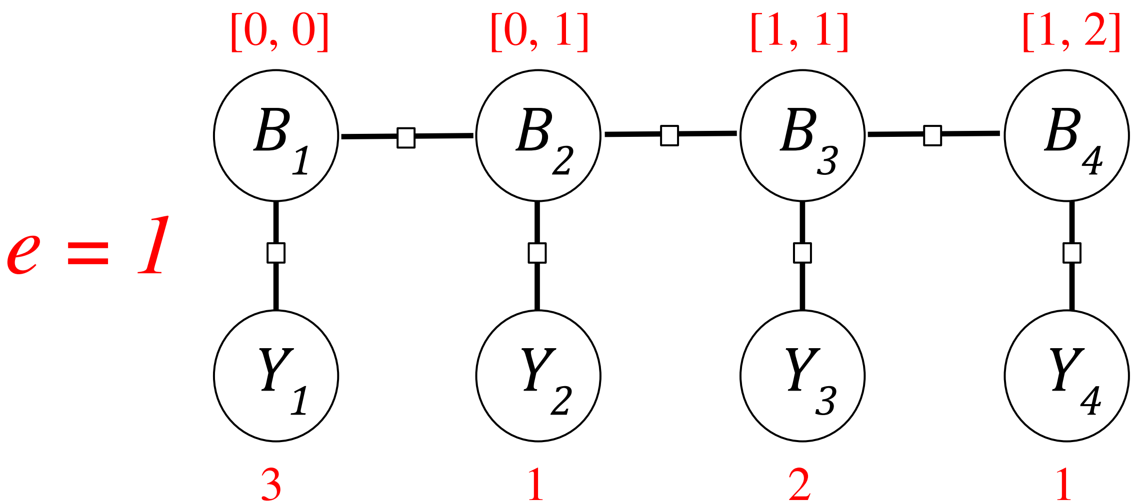

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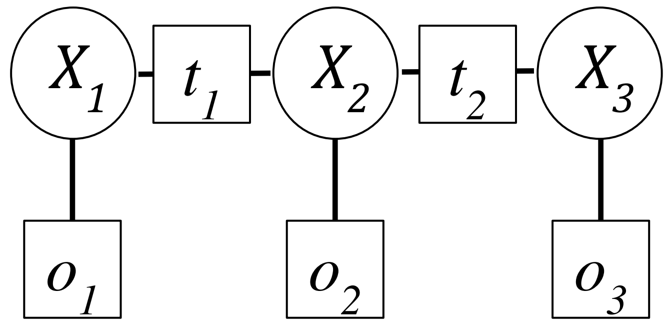
- Processing: $[B_i[1] = \min(B_i[0] + 1[Y_i = e], 2)]$
- Final Output: $1[B_T[1] = 1]$
- Consistency: $[B_{i-1}[1] = B_i[0]]$

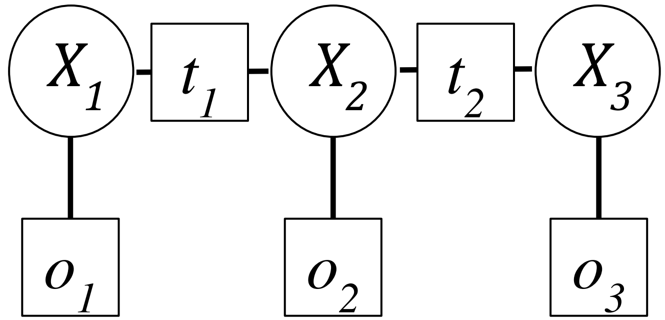
- Problem Modeling
- N-ary Constraints
- Elimination Example

Person Tracking Example



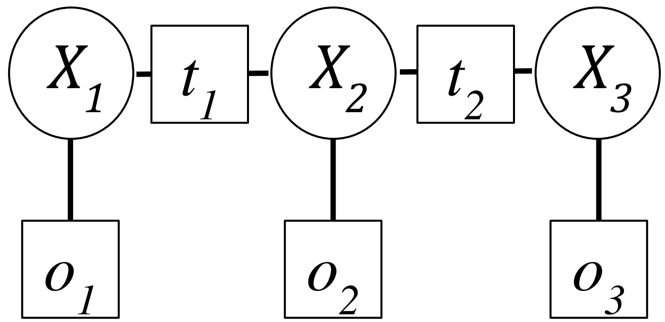
- Variables X_i: Location of object at position i

Person Tracking Example



- Variables X_i: Location of object at position i
- Transition Factors $t_i(x_i, x_{i+1})$: object positions can't change too much

Person Tracking Example



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- Observation Factors $o_i(x_i)$: noisy information compatible with position

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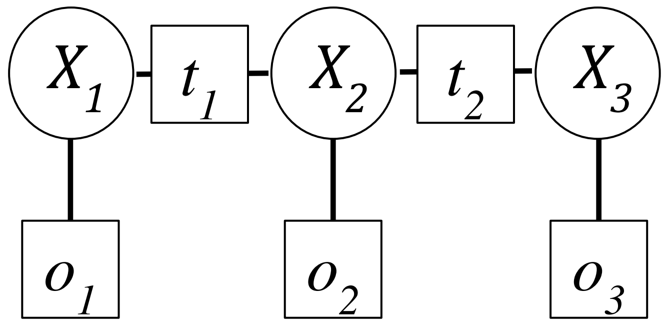

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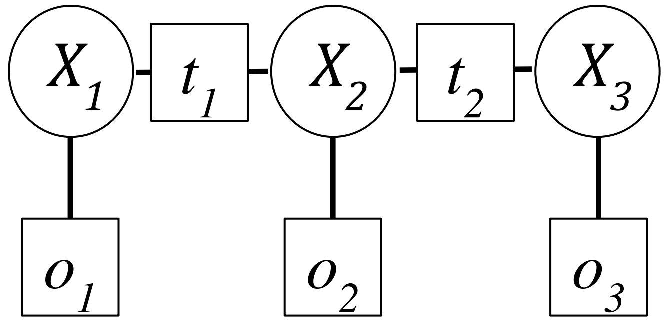
```
def t(x, y):
   if x == y: return 2
   if abs(x – y) == 1: return 1
   return 0
```

Person Tracking Example



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```
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  if x == y: return 2
  if abs(x — y) == 1: return 1
  return 0
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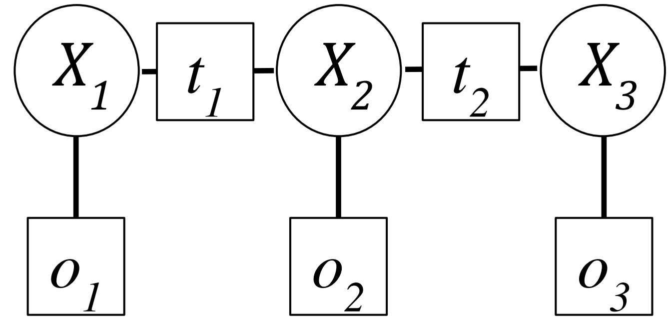
```
def o1(x): return t(x, 0)
def o2(x): return t(x, 2)
def o3(x): return t(x, 2)
```

Variable Elimination

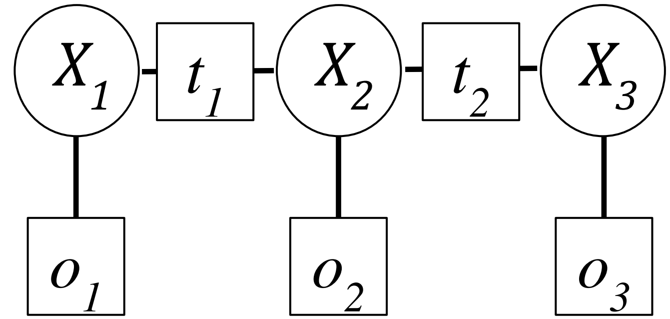
Definition: Elimination

- To **eliminate** a variable X_i, consider all factors $f_1, \ldots, f_k$, that depend on X_i
- Remove X_i and $f_1, \ldots, f_k$
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

- Eliminate X_1



- Eliminate X_1
- Factors that depend on X_1:
  - o_1, t_1



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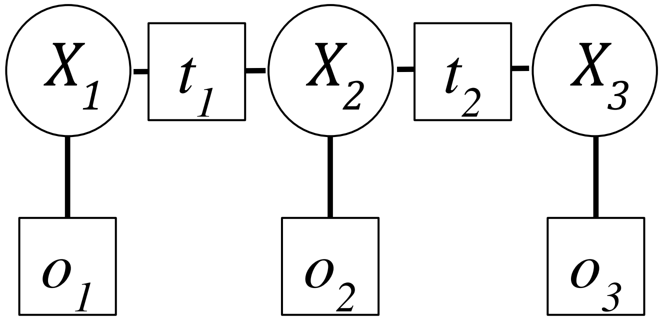

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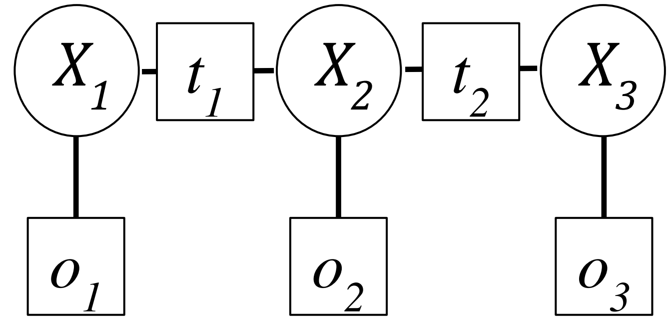
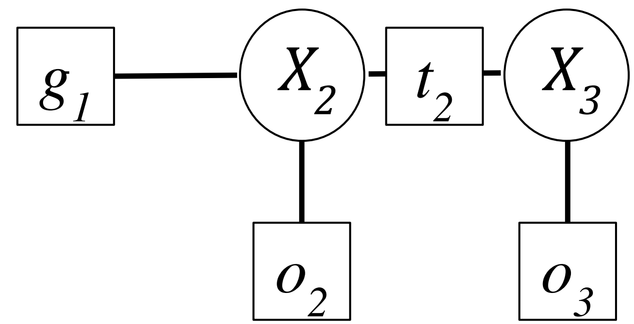
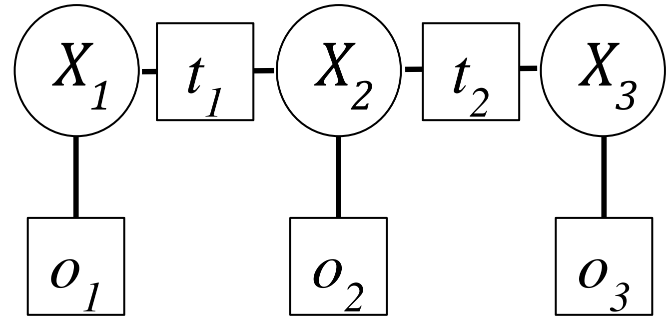
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$
- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$



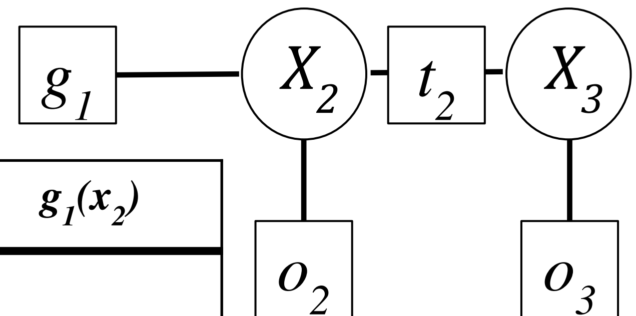


- Eliminate X_1
- Factors that depend on X_1:
  - o_1, t_1



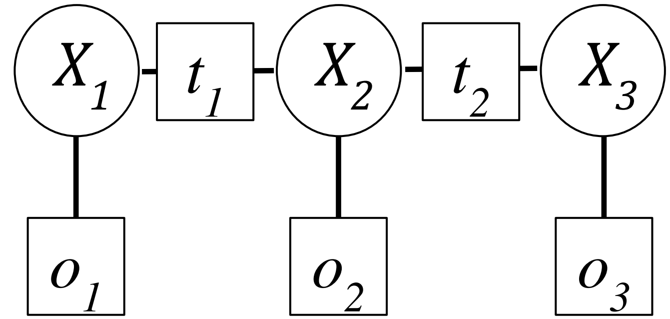
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

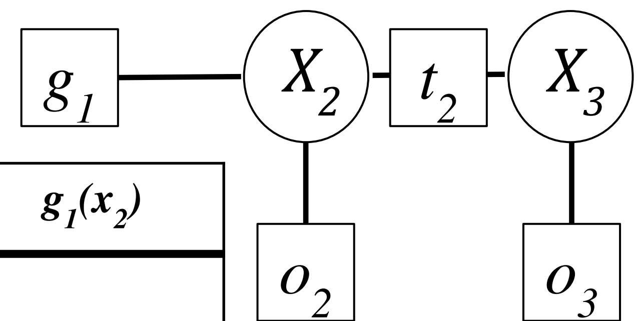
- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$



x_2	x_1	$o_1(x_1)$	$t_1(x_1, x_2)$	$o_1(x_1)\ t_1(x_1, x_2)$	$g_1(x_2)$
0	0				
0	1				
0	2				
1	0				
1	1				
1	2				
2	0				
2	1				
2	2				

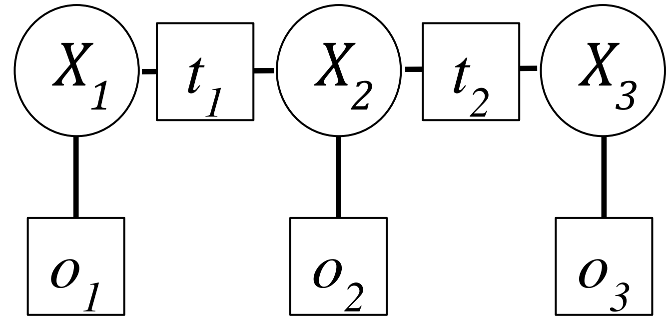
- Eliminate X_1
- Factors that depend on X_1:
  - o_1, t_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$
- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$





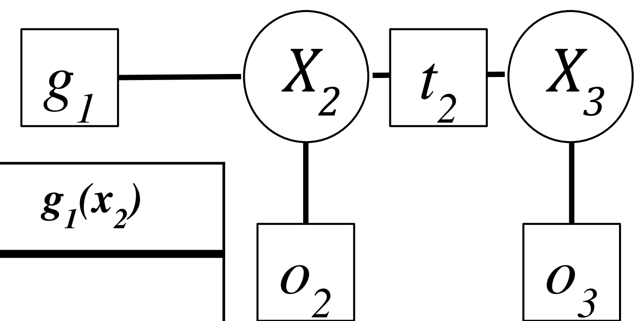
x_2	x_1	$o_1(x_1)$	$t_1(x_1, x_2)$	$o_1(x_1)\ t_1(x_1, x_2)$	$g_1(x_2)$
0	0	2			
0	1	1			
0	2	0			
1	0	2			
1	1	1			
1	2	0			
2	0	2			
2	1	1			
2	2	0			

- Eliminate X_1
- Factors that depend on X_1:
  - o_1, t_1



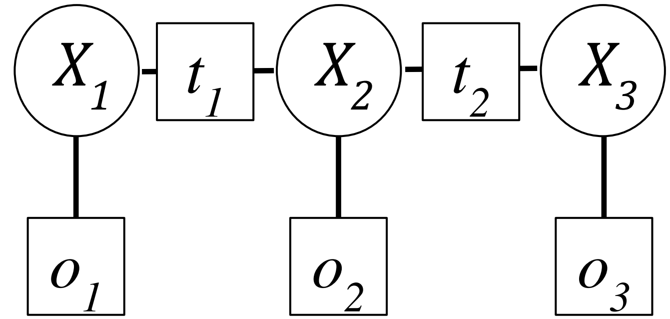
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$



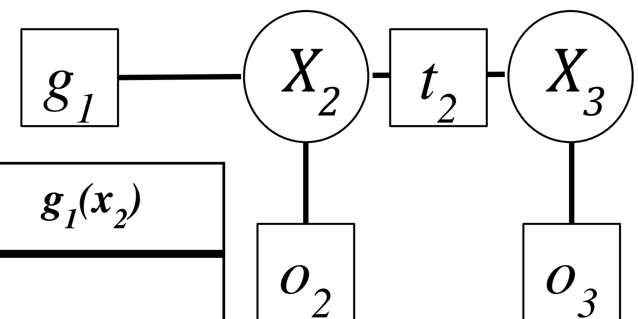
x_2	x_1	$o_1(x_1)$	$t_1(x_1, x_2)$	$o_1(x_1)\ t_1(x_1, x_2)$	$g_1(x_2)$
0	0	2	2		
0	1	1	1		
0	2	0	0		
1	0	2	1		
1	1	1	2		
1	2	0	1		
2	0	2	0		
2	1	1	1		
2	2	0	2		

- Eliminate X_1
- Factors that depend on X_1:
  - o_1, t_1



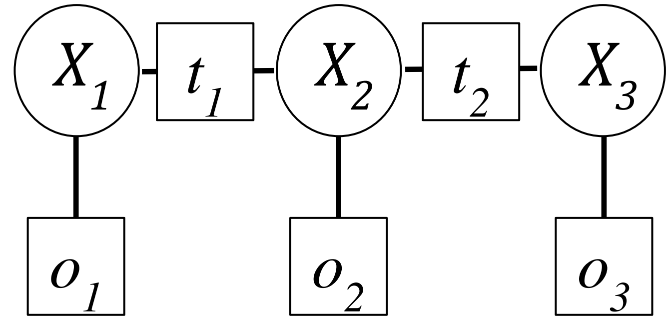
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$



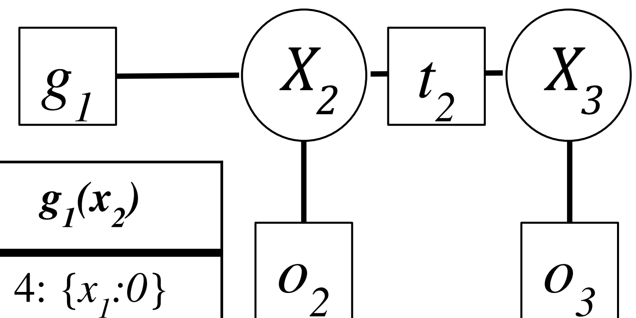
x_2	x_1	$o_1(x_1)$	$t_1(x_1, x_2)$	$o_1(x_1)\ t_1(x_1, x_2)$	$g_1(x_2)$
0	0	2	2	4	
0	1	1	1	1	
0	2	0	0	0	
1	0	2	1	2	
1	1	1	2	2	
1	2	0	1	0	
2	0	2	0	0	
2	1	1	1	1	
2	2	0	2	0	

- Eliminate X_1
- Factors that depend on X_1:
    - o_1, t_1



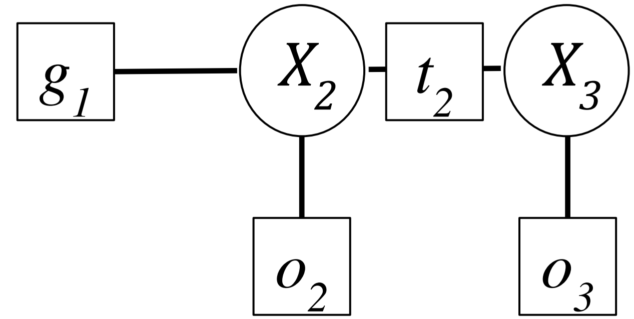
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

- $g_1(x_2) = \max_{x_1 \in \{0,1,2\}} o_1(x_1) \cdot t_1(x_1, x_2)$

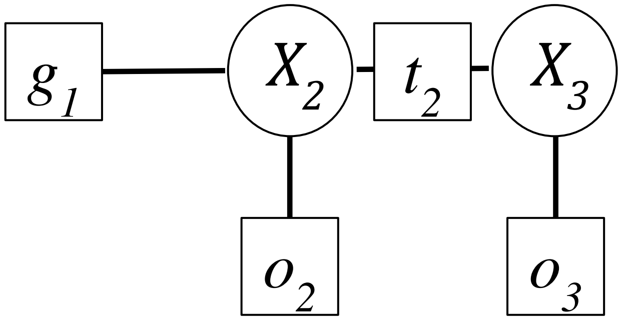


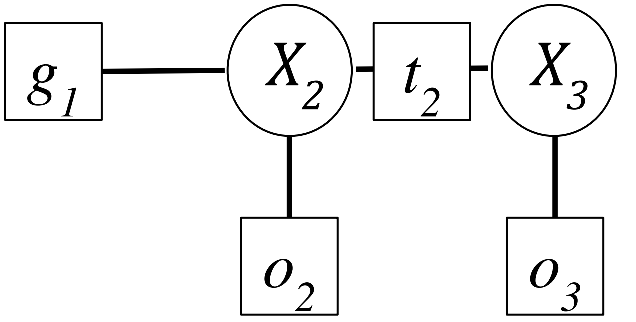
x_2	x_1	$o_1(x_1)$	$t_1(x_1, x_2)$	$o_1(x_1)\ t_1(x_1, x_2)$	$g_1(x_2)$
0	0	2	2	4	4: $\{x_1{:}0\}$
0	1	1	1	1	
0	2	0	0	0	
1	0	2	1	2	2: $\{x_1{:}\ 1\}$
1	1	1	2	2	
1	2	0	1	0	
2	0	2	0	0	1: $\{x_1{:}\ 1\}$
2	1	1	1	1	
2	2	0	2	0	

- Eliminate X_2



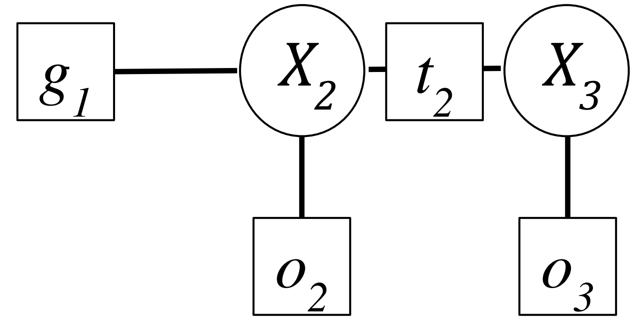
- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1

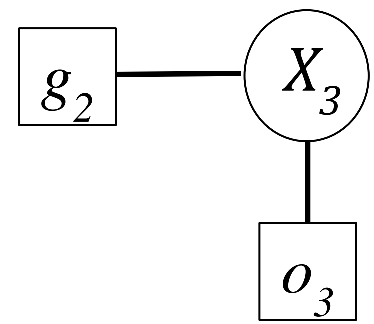




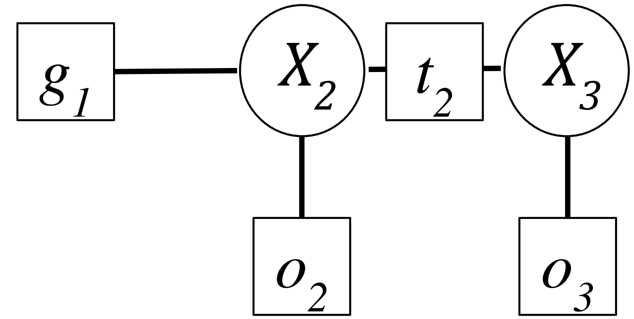
- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$
- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

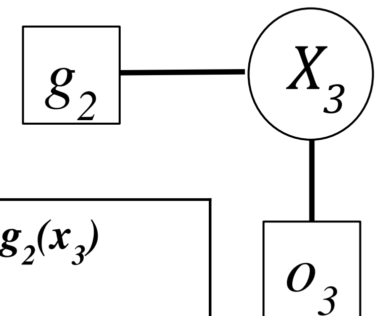




- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1



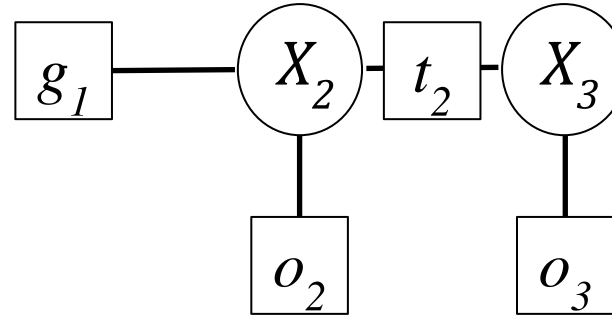
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$



- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

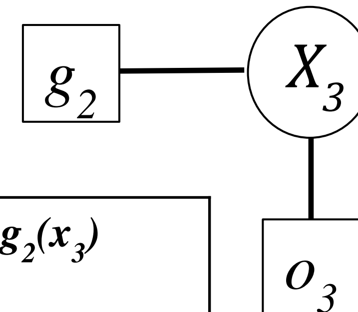
x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\, o_2(x_2)\, t_2(x_2, x_3)$	$g_2(x_3)$
0	0					
0	1					
0	2					
1	0					
1	1					
1	2					
2	0					
2	1					
2	2					

- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1

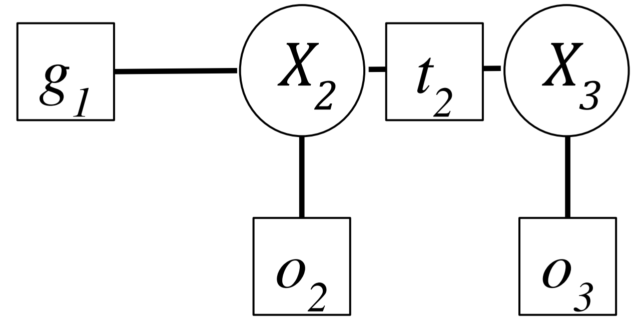


- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

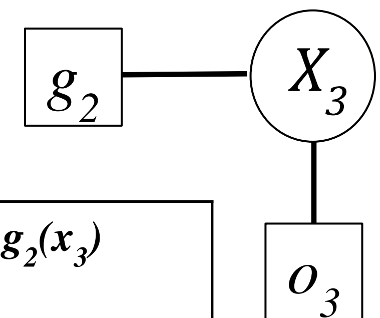
- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$



x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\ o_2(x_2)\ t_2(x_2, x_3)$	$g_2(x_3)$
0	0	4: $\{x_1{:}0\}$				
0	1	2: $\{x_1{:}\ 1\}$				
0	2	1: $\{x_1{:}\ 1\}$				
1	0	4: $\{x_1{:}0\}$				
1	1	2: $\{x_1{:}\ 1\}$				
1	2	1: $\{x_1{:}\ 1\}$				
2	0	4: $\{x_1{:}0\}$				
2	1	2: $\{x_1{:}\ 1\}$				
2	2	1: $\{x_1{:}\ 1\}$				



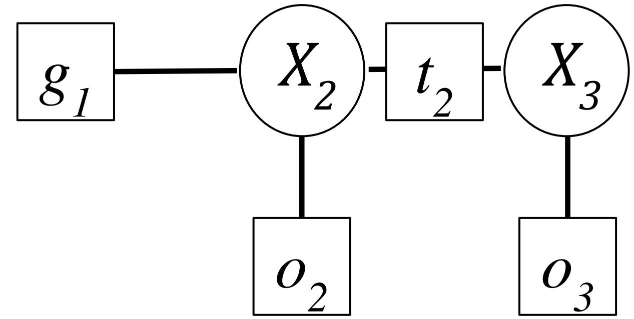
- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$



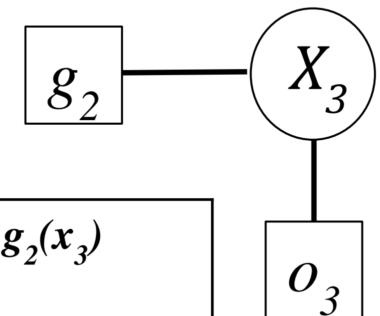
- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\, o_2(x_2)\, t_2(x_2, x_3)$	$g_2(x_3)$
0	0	4: $\{x_1{:}0\}$	0			
0	1	2: $\{x_1{:}\ 1\}$	1			
0	2	1: $\{x_1{:}\ 1\}$	2			
1	0	4: $\{x_1{:}0\}$	0			
1	1	2: $\{x_1{:}\ 1\}$	1			
1	2	1: $\{x_1{:}\ 1\}$	2			
2	0	4: $\{x_1{:}0\}$	0			
2	1	2: $\{x_1{:}\ 1\}$	1			
2	2	1: $\{x_1{:}\ 1\}$	2			

- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1

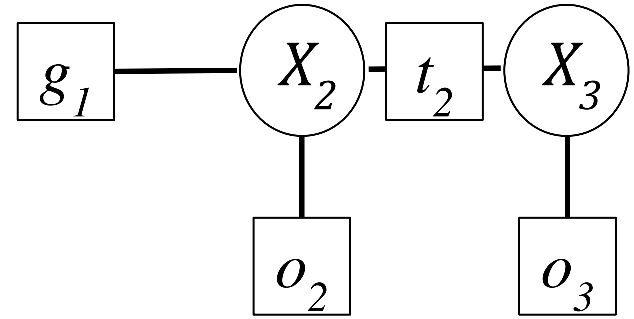


- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

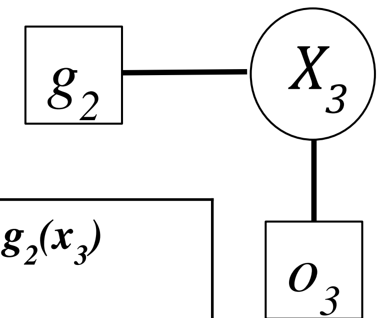


- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\ o_2(x_2)\ t_2(x_2, x_3)$	$g_2(x_3)$
0	0	4: $\{x_1{:}0\}$	0	2		
0	1	2: $\{x_1{:}\ 1\}$	1	1		
0	2	1: $\{x_1{:}\ 1\}$	2	0		
1	0	4: $\{x_1{:}0\}$	0	1		
1	1	2: $\{x_1{:}\ 1\}$	1	2		
1	2	1: $\{x_1{:}\ 1\}$	2	1		
2	0	4: $\{x_1{:}0\}$	0	0		
2	1	2: $\{x_1{:}\ 1\}$	1	1		
2	2	1: $\{x_1{:}\ 1\}$	2	2		

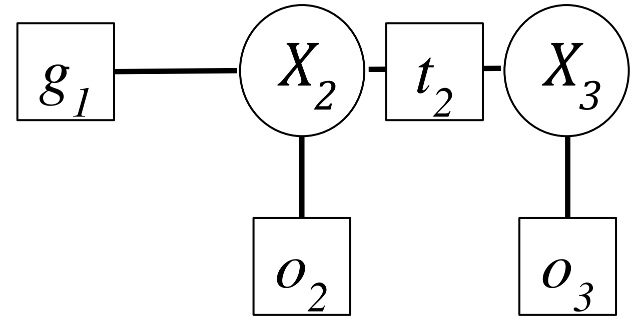


- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$

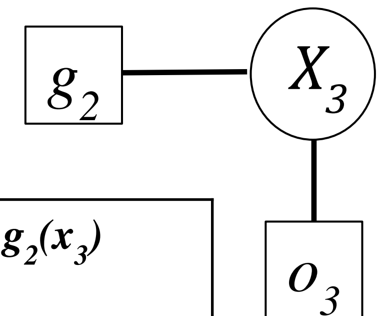


- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\ o_2(x_2)\ t_2(x_2, x_3)$	$g_2(x_3)$
0	0	4: $\{x_1{:}0\}$	0	2	0	
0	1	2: $\{x_1{:}\ 1\}$	1	1	2	
0	2	1: $\{x_1{:}\ 1\}$	2	0	2	
1	0	4: $\{x_1{:}0\}$	0	1	4	
1	1	2: $\{x_1{:}\ 1\}$	1	2	4	
1	2	1: $\{x_1{:}\ 1\}$	2	1	2	
2	0	4: $\{x_1{:}0\}$	0	0	0	
2	1	2: $\{x_1{:}\ 1\}$	1	1	2	
2	2	1: $\{x_1{:}\ 1\}$	2	2	4	



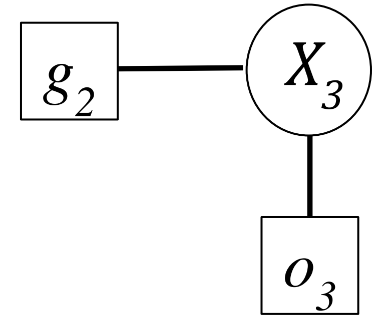
- Eliminate X_2
- Factors that depend on X_2:
  - o_2, t_2, g_1
- Add $f_{new}(x) = \max_{x_i} \prod_{j=1}^{k} f_j(x)$



- $g_2(x_3) = \max_{x_2 \in \{0,1,2\}} g_1(x_2) \cdot o_2(x_2) \cdot t_2(x_2, x_3)$

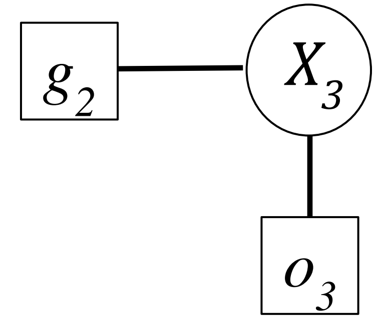
x_3	x_2	$g_1(x_2)$	$o_2(x_2)$	$t_2(x_2, x_3)$	$g_1(x_2)\ o_2(x_2)\ t_2(x_2, x_3)$	$g_2(x_3)$
0	0	4: $\{x_1{:}0\}$	0	2	0	2: $\{x_1: 1, x_2: 2\}$
0	1	2: $\{x_1: 1\}$	1	1	2	
0	2	1: $\{x_1: 1\}$	2	0	2	
1	0	4: $\{x_1{:}0\}$	0	1	4	4: $\{x_1: 1, x_2: 1\}$
1	1	2: $\{x_1: 1\}$	1	2	4	
1	2	1: $\{x_1: 1\}$	2	1	2	
2	0	4: $\{x_1{:}0\}$	0	0	0	4: $\{x_1: 1, x_2: 2\}$
2	1	2: $\{x_1: 1\}$	1	1	2	
2	2	1: $\{x_1: 1\}$	2	2	4	

- We are left with:



$$\max_{x_3 \in \{0,1,2\}} g_2(x_3) \cdot o_3(x_3)$$

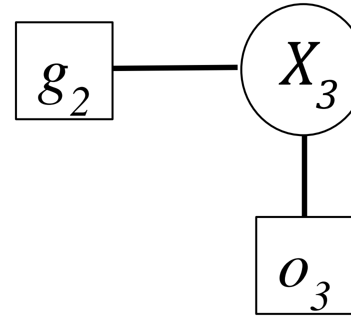
- We are left with:



$$\max_{x_3 \in \{0,1,2\}} g_2(x_3) \cdot o_3(x_3)$$

x_3	$g_2(x_3)$	$o_3(x_3)$	$g_2(x_3)\ o_3(x_3)$	***Optimal Weight***
0				
1				
2				

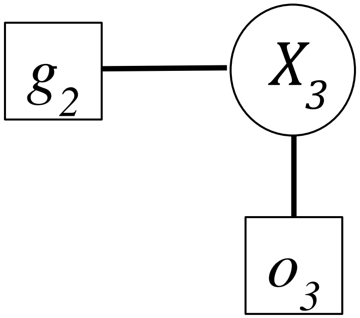
- We are left with:



$$\max_{x_3 \in \{0,1,2\}} g_2(x_3) \cdot o_3(x_3)$$

x_3	$g_2(x_3)$	$o_3(x_3)$	$g_2(x_3)\ o_3(x_3)$	*Optimal Weight*
0	2: $\{x_1 : 1,\ x_2 : 2\}$	0		
1	4: $\{x_1 : 1,\ x_2 : 1\}$	1		
2	4: $\{x_1 : 1,\ x_2 : 2\}$	2		

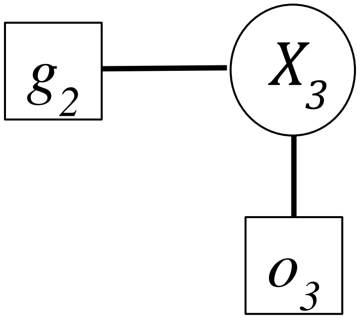
- We are left with:



$$\max_{x_3 \in \{0,1,2\}} g_2(x_3) \cdot o_3(x_3)$$

x_3	$g_2(x_3)$	$o_3(x_3)$	$g_2(x_3)\ o_3(x_3)$	***Optimal Weight***
0	2: $\{x_1 : 1,\ x_2 : 2\}$	0	2	
1	4: $\{x_1 : 1,\ x_2 : 1\}$	1	4	
2	4: $\{x_1 : 1,\ x_2 : 2\}$	2	8	

- We are left with:



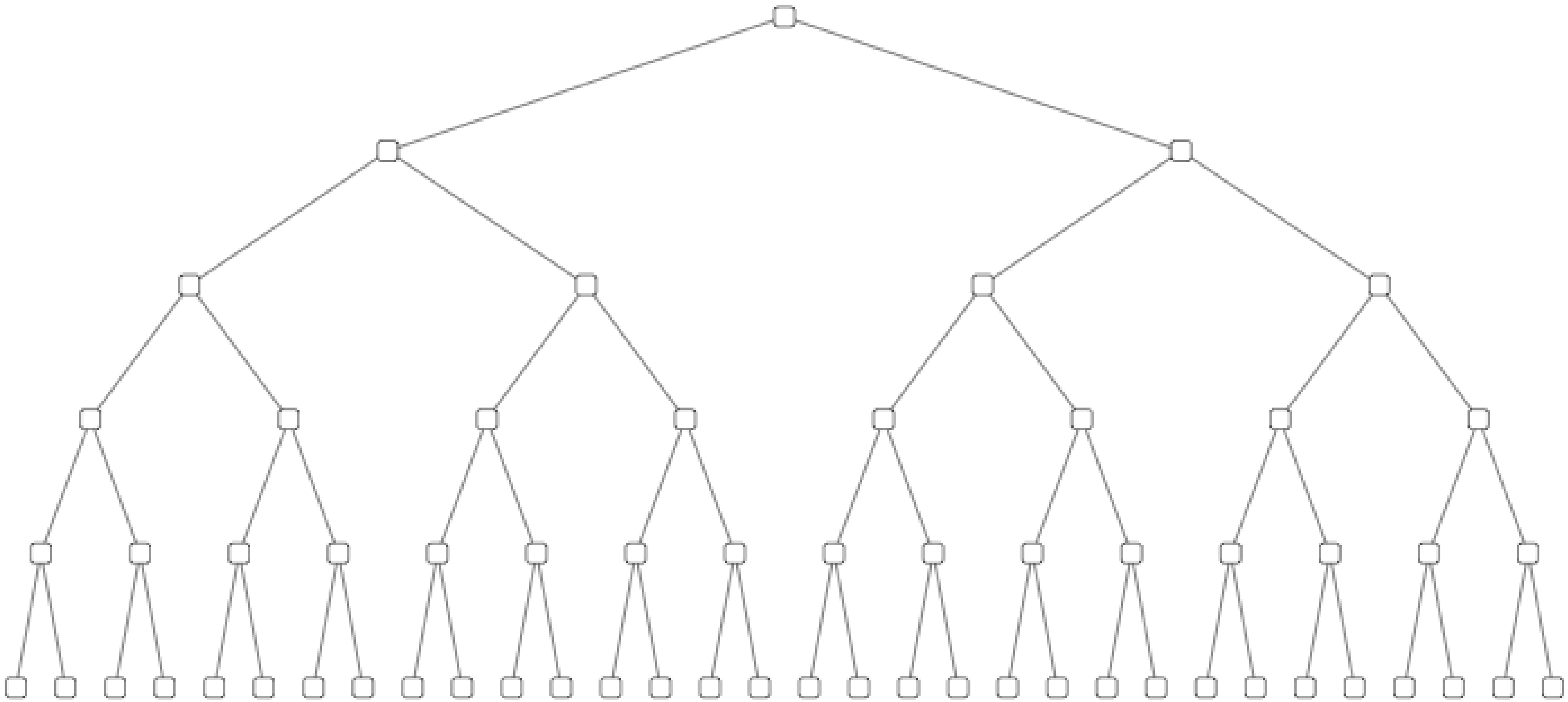
$$\max_{x_3 \in \{0,1,2\}} g_2(x_3) \cdot o_3(x_3)$$

x_3	$g_2(x_3)$	$o_3(x_3)$	$g_2(x_3)\, o_3(x_3)$	*Optimal Weight*
0	2: $\{x_1 : 1,\ x_2 : 2\}$	0	2	8: $\{x_1 : 1,\ x_2 : 2,\ x_3 : 2\}$
1	4: $\{x_1 : 1,\ x_2 : 1\}$	1	4	
2	4: $\{x_1 : 1,\ x_2 : 2\}$	2	8	

Search Techniques

- Backtracking
- Beam Search
- Gibbs Sampling
- Conditioning
- Elimination

Backtracking search



Search Techniques

- Backtracking
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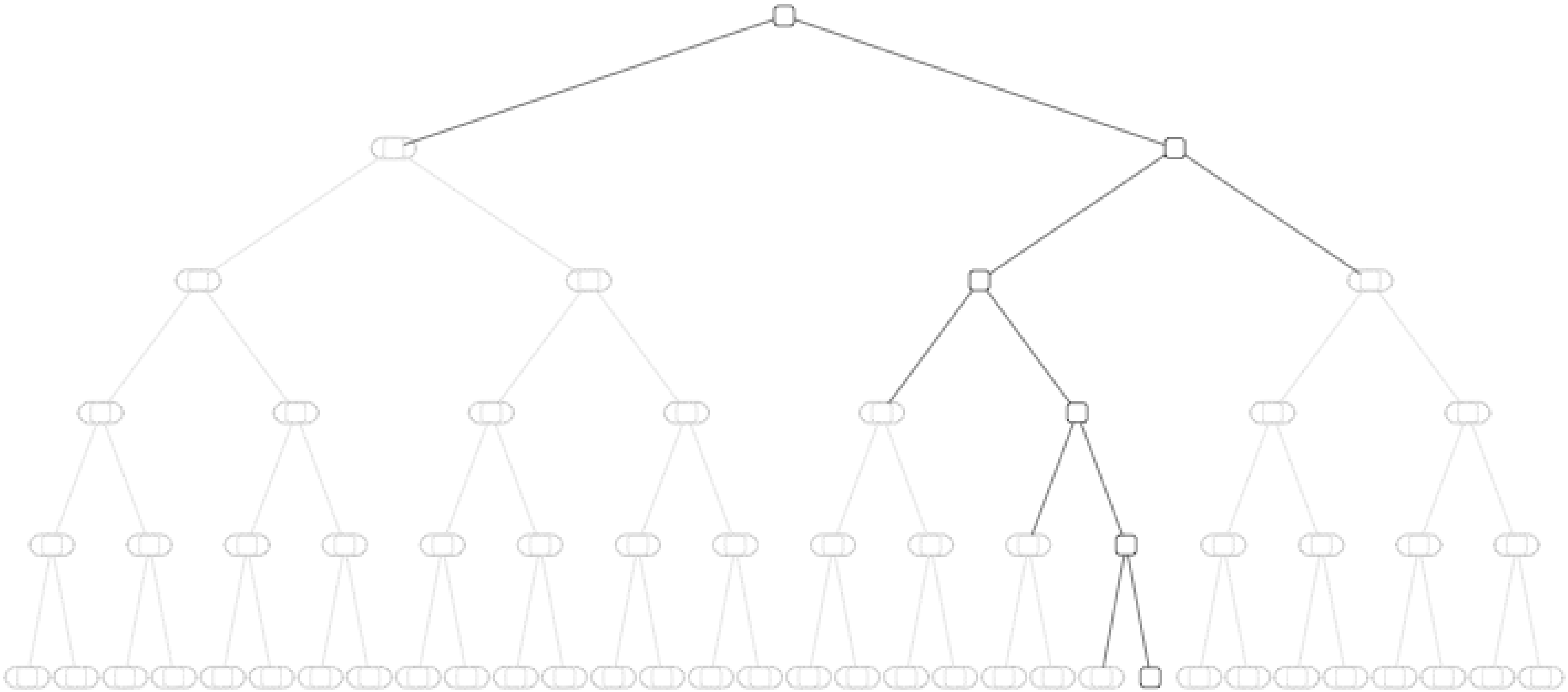
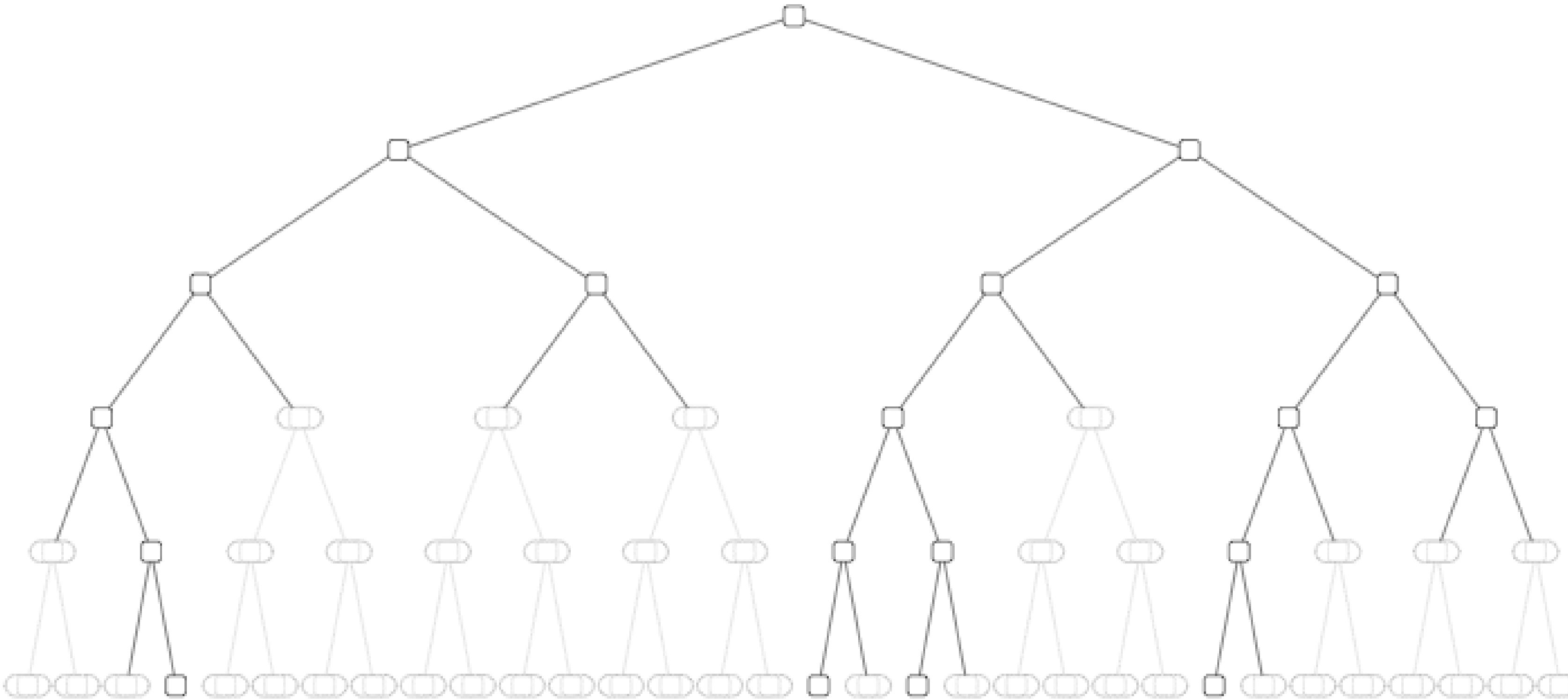
- Gibbs Sampling
- Conditioning
- Elimination

Greedy search



Beam search



Beam size $K = 4$

Search Techniques

- Backtracking
- Beam Search
- Iterated Conditional Modes
- Gibbs Sampling
- Conditioning
- Elimination

Gibbs sampling

Sometimes, need to go downhill to go uphill...

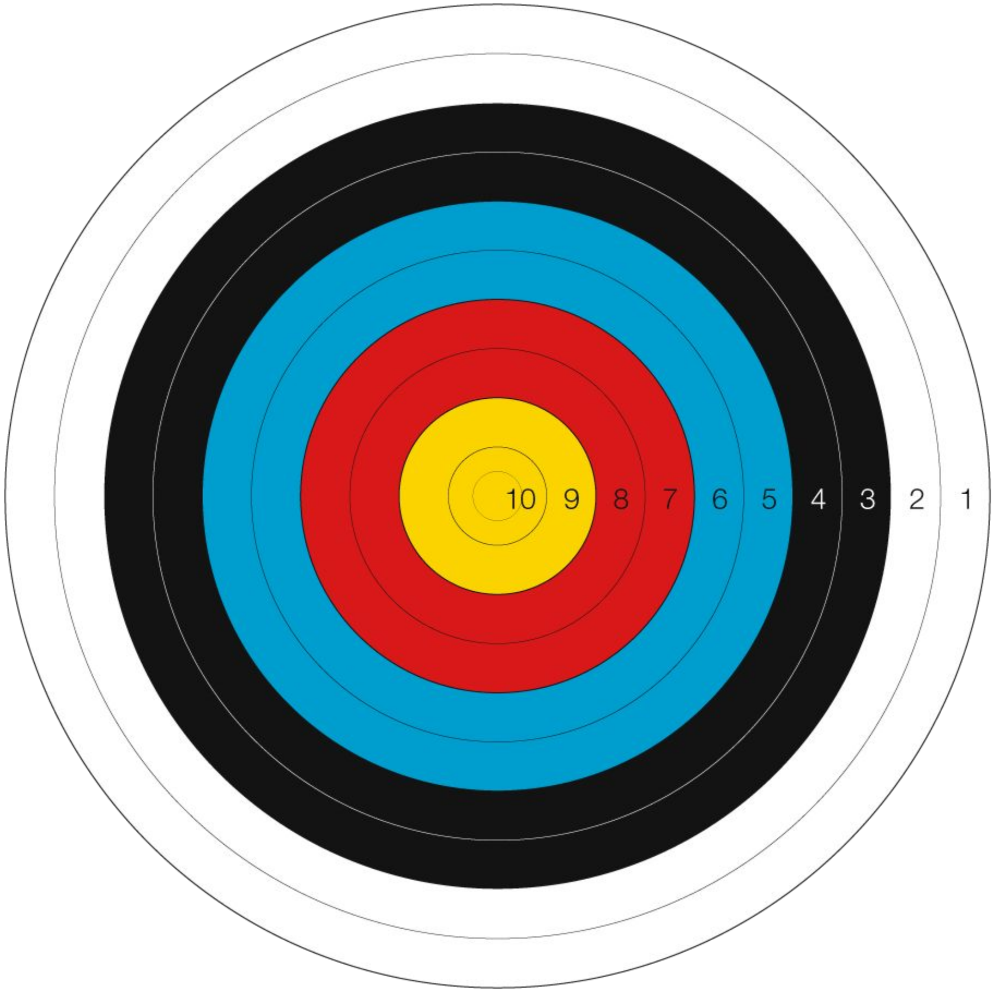
Key idea: randomness

Sample an assignment with probability proportional to its weight.

Example: Gibbs sampling

$$\text{Weight}(x \cup \{X_2 : 0\}) = 1 \quad \text{prob. } 0.2$$
$$\text{Weight}(x \cup \{X_2 : 1\}) = 2 \quad \text{prob. } 0.4$$
$$\text{Weight}(x \cup \{X_2 : 2\}) = 2 \quad \text{prob. } 0.4$$

Use Randomness

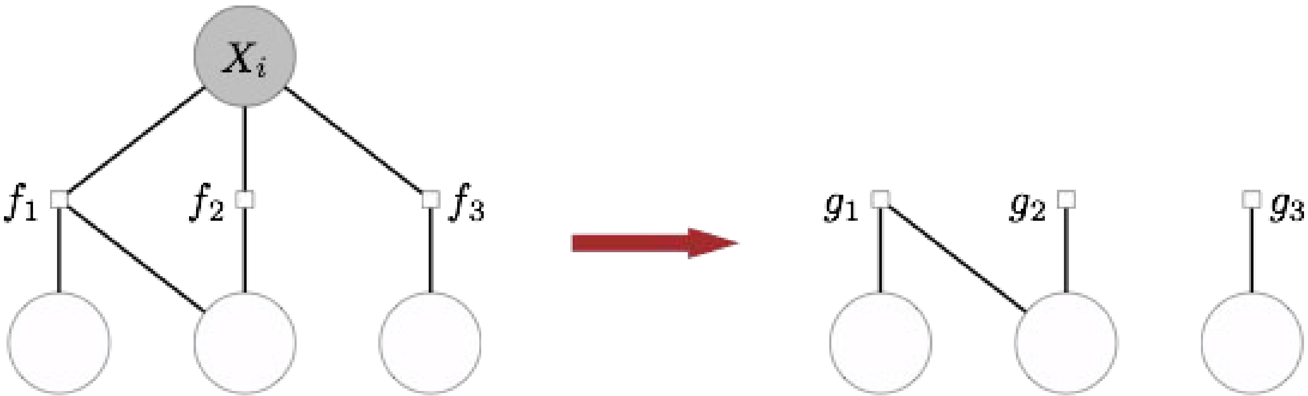


Search Techniques

- Backtracking
- Beam Search
- ICM
- Gibbs Sampling
- Conditioning
- Elimination

Conditioning: general

Graphically: remove edges from X_i to dependent factors



Definition: conditioning

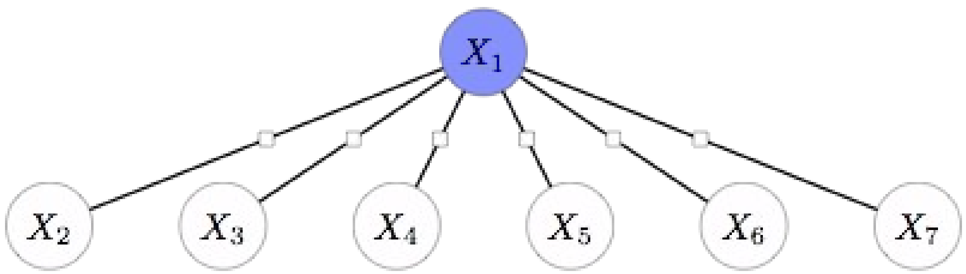
- To **condition** on a variable $X_i = v$, consider all factors $f_1, \dots, f_k$ that depend on X_i.
- Remove X_i and $f_1, \dots, f_k$.
- Add $g_j(x) = f_j(x \cup \{X_i : v\})$ for $j = 1, \dots, k$.

Using conditional independence

For each value $v =$ R, G, B:

Condition on $X_1 = v$.

Find the maximum weight assignment (easy).



R 3

G 6

B 1

maximum weight is 6

Search Techniques

- Backtracking
- Beam Search
- ICM
- Gibbs Sampling
- Conditioning
- Elimination