

HWS) VB2182

(1) Doors X, Y, Z :-

first = first pick by contestant
car = car is hidden
host = host opened the door

(I) $P(\text{car} = X) = 1/3$; $P(\text{car} = Y) = 1/3$; $P(\text{car} = Z) = 1/3$

(II)

$$P(\text{car} = a | \text{first pick} = b) = P(\text{car} = a)$$

$\forall a, b$ belong to $\{X, Y, Z\}$ Sample Size

car and first pick are independent

Say I
picked door "X"
and
host opened
door "Z"

$$P(\text{host} = Z | \text{car} = Z, \text{first} = X) = 0$$

$$P(\text{host} = Z | \text{car} = Y, \text{first} = X) = 1$$

$$P(\text{host} = Z | \text{car} = X, \text{first} = X) = 1/2$$

By Bayes' theorem,

$$P(\text{car} = X | \text{host} = Z, \text{first} = X) = \frac{P(\text{host} = Z | \text{car} = X, \text{first} = X) \times P(\text{car} = X | \text{first} = X)}{\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X) \times P(\text{car} = m | \text{first} = X)}$$

$$\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X) \times P(\text{car} = m | \text{first} = X)$$

Using (II)

$$= \frac{P(\text{host} = Z | \text{car} = X, \text{first} = X) \times P(\text{car} = X)}{\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X) \times P(\text{car} = m)}$$

$$\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X) \times P(\text{car} = m)$$

$$\left[\frac{P(\text{car} = m)}{= 1/3} = P(\text{car} = X) \right] = \frac{P(\text{host} = Z | \text{car} = X, \text{first} = X)}{\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X)}$$

$$\sum_{m=1}^3 P(\text{host} = Z | \text{car} = m, \text{first} = X)$$

$$P(\text{car} = X | \text{host} = Z, \text{first} = X) = \frac{1/2}{0 + 1/2 + 1} = \frac{1/2}{3/2} = \frac{1}{3} \quad \text{--- (IV)}$$

$$\Rightarrow P(\text{car} = Y | \text{host} = Z, \text{first} = 1) = 1 - \frac{1}{3} = \frac{2}{3} \quad \text{--- (V)}$$

As (V) > (IV), I will get better chance by switching to door Y.

From definition of Bayesian Network, and using Bayes Ball rules.

(2)

As per Bayesian networks

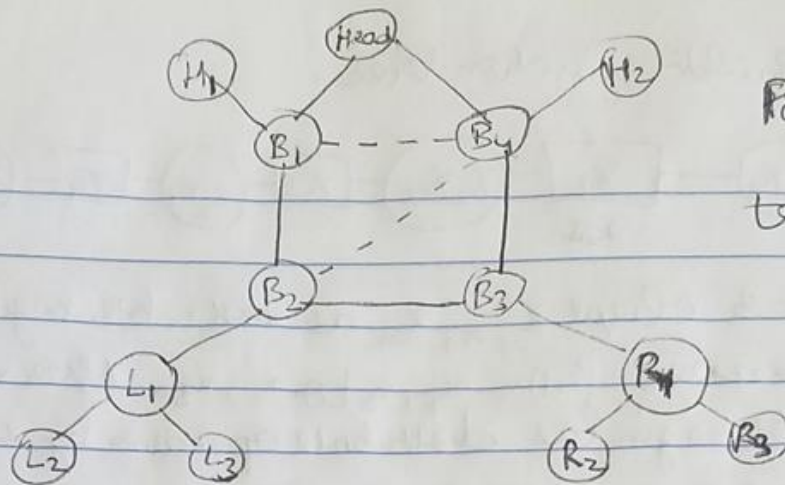
12

$$P(x_1, x_2, x_3, x_4, x_5) = P(x_1) P(x_2/x_1) P(x_3) \\ P(x_4/x_1, x_3) P(x_5/x_2, x_4)$$

Using Bayes Ball rules

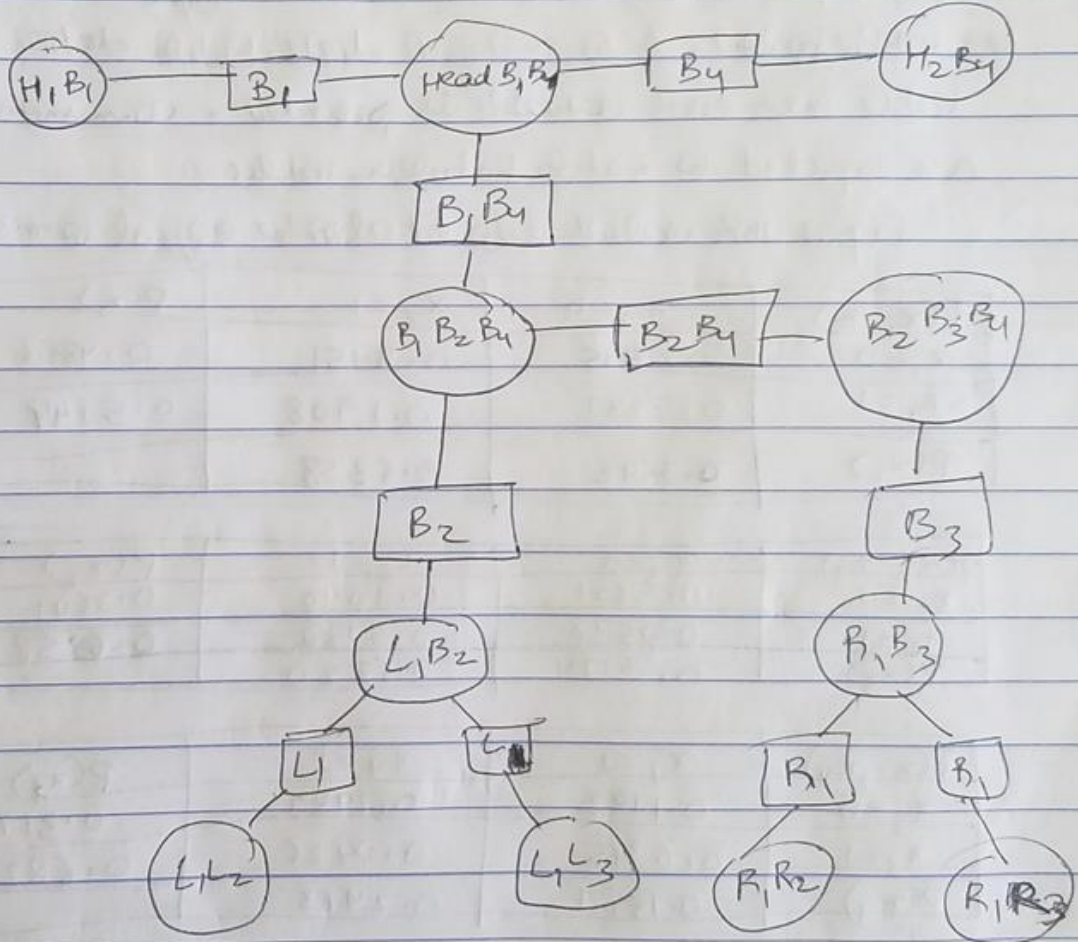
1. FALSE (goes through 1, hence dependent)
2. FALSE (goes through 5, hence dependent)
3. TRUE (no go through x_2 ~~such that~~ for dependency)
4. FALSE (goes through 3-4-1-2-5, hence dependent)
5. TRUE (no go through x_i for dependency)
6. FALSE (goes through 1-2-5-4-3, hence dependent)
7. TRUE (no go through x_i for dependency)
8. TRUE (no go through x_i for dependency)
9. FALSE (goes through 3-4-5-2, hence dependent)
10. FALSE (goes through 3-4-1-2, hence dependent)

③



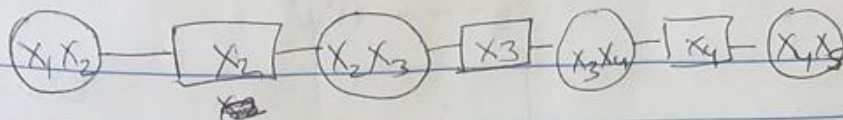
Postmeralization
and
triangularization

constructed Junction tree:



(4)

Building junction tree:



Lets pick clique x_{n-1}, x_n as root. We begin w/ sending message from x_1, x_2 to x_2, x_3 . After reaching the root, we begin the distribute operation by sending the information from x_{n-1}, x_n to x_{n-2}, x_{n-1} .

After sending all the info, all marginalizing the table joint probability distributions over clique's are given in the tables below. Also marginal distributions determined from table over each variable is provided. Common marginals are expected to match between tables.

Separators values should also be equal to marginals

$P(x_1, x_2)$	$x_2=0$	$x_2=1$	$P(x_1)$
$x_1=0$	0.0405	0.4451	0.4856
$x_1=1$	0.3237	0.1908	0.5144
$P(x_2)$	0.3642	0.6358	

$P(x_2, x_3)$	$x_3=0$	$x_3=1$	$P(x_2)$
$x_2=0$	0.2601	0.1040	0.3641
$x_2=1$	0.0578	0.5780	0.6358
$P(x_3)$	0.3179	0.6820	

$P(x_3, x_4)$	$x_4=0$	$x_4=1$	$P(x_3)$
$x_3=0$	0.1192	0.1987	0.3179
$x_3=1$	0.6395	0.0426	0.6821
$P(x_4)$	0.7587	0.2413	

$P(x_4, x_5)$	$x_5=0$	$x_5=1$	$P(x_4)$
$x_4=0$	0.5690	0.1897	0.7587
$x_4=1$	0.0603	0.1810	0.2413
$P(x_5)$	0.6293	0.3707	

Code:

```
clc; clear variables;

values_of_p = cell(4, 1);
values_of_p{1} = [0.1, 0.7; 0.8, 0.3];
values_of_p{2} = [0.5, 0.1; 0.1, 0.5];
values_of_p{3} = [0.1, 0.5; 0.5, 0.1];
values_of_p{4} = [0.9, 0.3; 0.1, 0.3];
marg = values_of_p;
n = size(marg,1);
seprt = ones(n-1,2);
%Left To Right
for i=1:n-1
    seprt(i,:) = sum(marg{i});
    marg{i+1} = marg{i+1}.*(seprt(i,:)'*[1,1]);
end
%Right to Left
for i=1:n-1
    seprts_old = seprt(n-i,:);
    seprt(n-i,:) = sum(marg{n-i+1},2)';
    marg{n-i} = marg{n-i}.*([1;1]*(seprt(n-i,:)./seprts_old));
end
%Normalizing
for i=1:n
    marg{i} = marg{i}/sum(sum(marg{i}));
end
disp('Marginal Values Calculated:');
for i=1:n
    val = marg{i};
    disp(val);
end
```

Marginals Values Calculated:	
0.0405	0.4451
0.3237	0.1908
0.2601	0.1040
0.0578	0.5780
0.1192	0.1987
0.6395	0.0426
0.5690	0.1897
0.0603	0.1810

Q5: Use ArgMax Junction Tree Algorithm (JTA), where we replace sums with max in JTA, find the biggest separators. The emotional states are most likely here:

Day 1	Day 2	Day 3	Day 4	Day 5
Happy	Angry	Angry	Angry	Angry

Code:

```
clc; clear variables;
emis_p = [0.4, 0.1, 0.3, 0.2; 0.1, 0.4, 0.2, 0.3];
init = [1; 0];
obs_st = [1, 4, 2, 2, 3];
trans_p = [0.8, 0.2; 0.2, 0.8];
t_size = size(trans_p, 1); nsize = size(obs_st, 2);
val1 = zeros(t_size, t_size, nsize); val2 = zeros(t_size, nsize);
val2(:, 1) = init;
% L to R
for i = 2:nsize
    val = obs_st(1, i);
    val1(:, :, i) = diag(val2(:, i - 1)) * trans_p * diag(emis_p(:, val));
    val2(:, i) = max(val1(:, :, i));
end
% R to L
for i = nsize-1:-1:1
    val2_new = max(val1(:, :, i + 1), [], 2);
    val1(:, :, i) = val1(:, :, i) * diag(val2_new ./ val2(:, i));
    val2(:, i) = val2_new;
end
[~, V] = max(val2);
```

```
>> V
```

```
V =
```

```
     1     2     2     2     2
```