Reasoning Under Uncertainty: Bnet Inference

(Variable elimination)

Computer Science cpsc322, Lecture 29

(Textbook Chpt 6.4)

March, 20, 2009

Lecture Overview

- Recap Learning Goals previous lecture
- Bnets Inference
  - Intro
  - Factors
  - Variable elimination Intro

Learning Goals for Wed's class

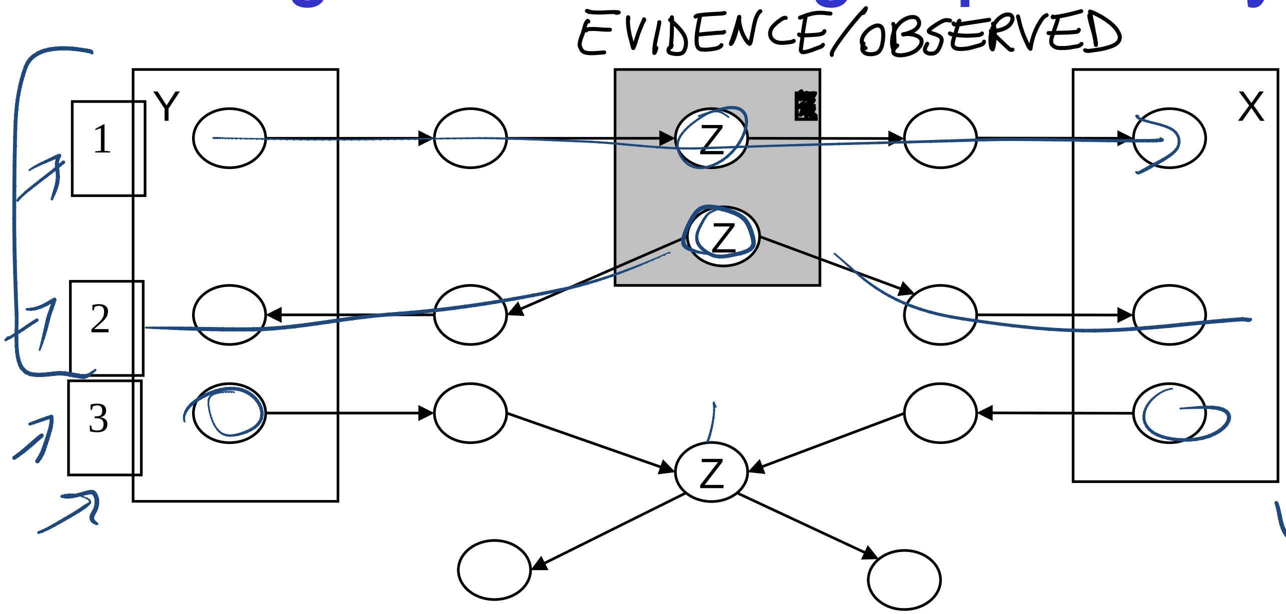
You can:

- In a Belief Net, determine whether one variable is independent of another variable, given a set of observations.

- Define and use **Noisy-OR** distributions. Explain assumptions and benefit.

- Implement and use a **naïve Bayesian classifier**. Explain assumptions and benefit.

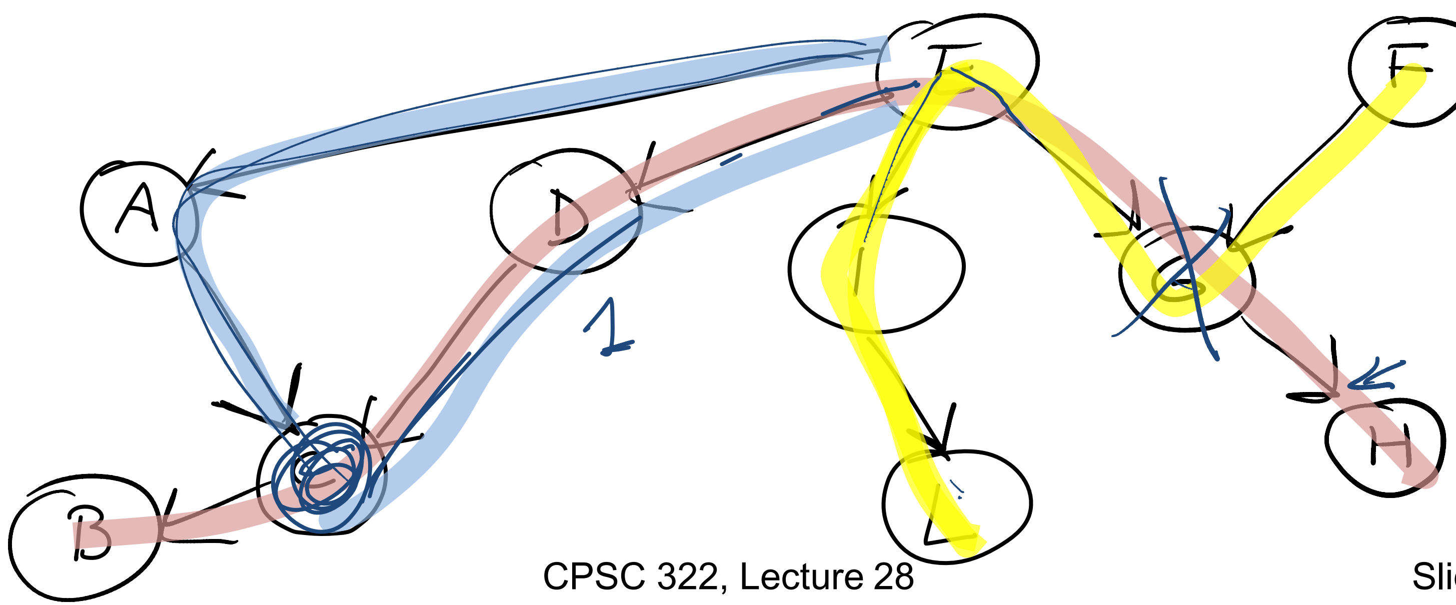
3 Configuration blocking dependency (belief propagation)



✓ 2 Indep(B, H {E})

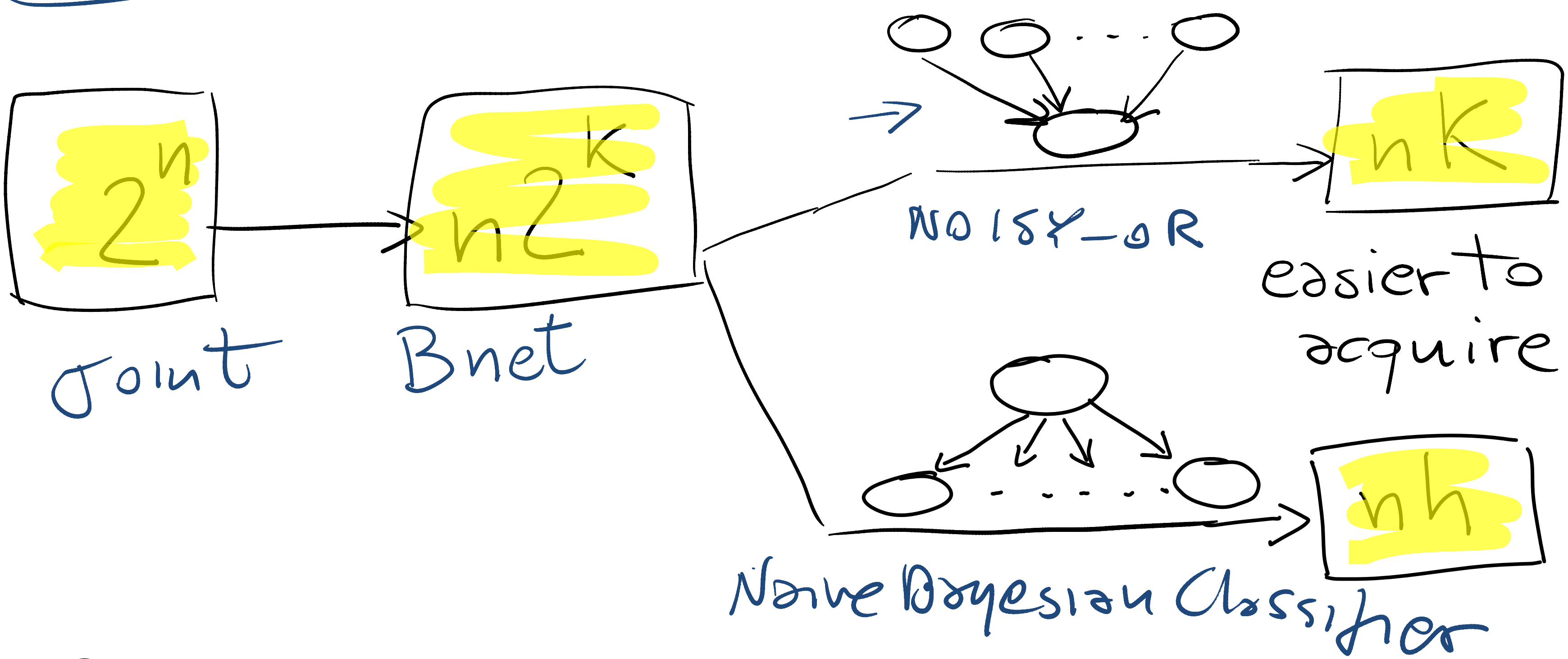
✗ Indep(E, C {D})

✓ 3 Indep(L, F {C})



Bnets: Compact Representations

n Boolean variables, k max. number of parents



Only one parent with h possible values

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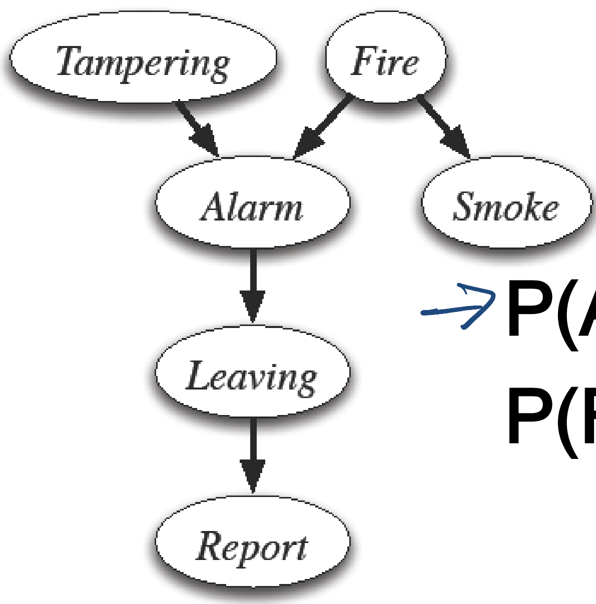
Bnet Inference

- **Our goal:** compute probabilities of variables in a belief network

  What is the posterior distribution over one or ~~more variables~~, conditioned on one or more observed variables?



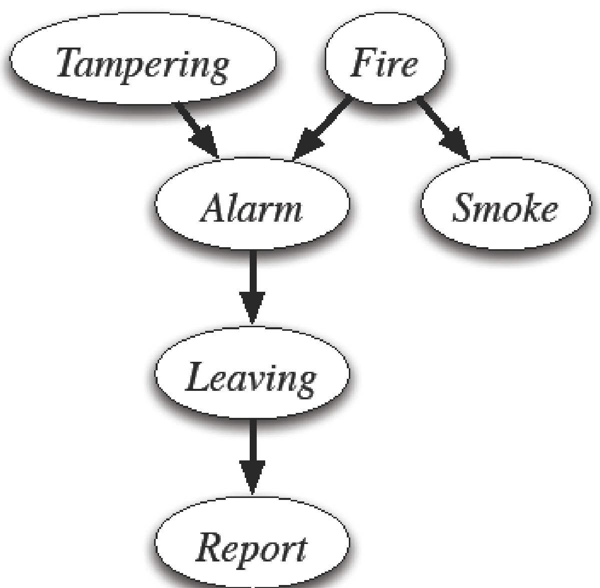
examples

→ P(Alarm| Smoke = f)

P(Fire | Smoke = t ,Leaving = f)

Bnet Inference: General

- Suppose the variables of the belief network are $X_1,\ldots,X_n$.
- Z is the query variable
- *$Y_1=v_1, \ldots, Y_j=v_j$ are the observed variables (with their values)*
- $Z_1, \ldots, Z_k$ are the remaining variables
- What we want to compute: $\boxed{P(Z \mid Y_1 = v_1, \ldots, Y_j = v_j)}$



Example:

P(L | S = t , R = f)

$Z \Leftrightarrow L$

$Y_1 Y_2 \Leftrightarrow S, R$

$Z_1 Z_2 Z_3 \Leftrightarrow T, F, A$

What do we need to compute?

Remember conditioning and marginalization…

$$P(L \mid S = t, R = f) = \frac{P(L, S=t, R=f)}{P(S=t, R=f)}$$

① ② ③

L	*S*	*R*	*P(L, S=t, R=f)*
t	t	f	.3
f	t	f	.2

Do they have to sum up to one?

no

② = .5

③

L	*S*	*R*	*P(L | S=t, R=f)*
t	t	f	.6
f	t	f	.4

In general.....

conditional prob

$$P(Z \mid Y_1 = v_1, \ldots, Y_j = v_j) = \frac{P(Z, Y_1 = v_1, \ldots, Y_j = v_j)}{P(Y_1 = v_1, \ldots, Y_j = v_j)} = \frac{\boxed{P(Z, Y_1 = v_1, \ldots, Y_j = v_j)}}{\boxed{\sum_Z P(Z, Y_1 = v_1, \ldots, Y_j = v_j)}}$$

1

2

- We only need to **compute the** numerator and then **normalize**
- This can be framed in terms of **operations between factors** (that satisfy the semantics of probability)

Lecture Overview

- Recap Bnets
- Bnets Inference
  - Intro
  - **Factors**
  - Variable elimination Algo

Factors

- A **factor** is a representation of a function from a tuple of random variables into a number. [0, 1]
- We will write factor f on variables $X_1, \ldots, X_j$ as $f(X_1, \ldots, X_n)$
- A factor denotes one or more (possibly partial) distributions over the given tuple of variables

  - e.g., $P(X_1, X_2)$ is a factor $f(X_1, X_2)$ — Distribution
  - e.g., $P(X_1, X_2, X_3 = v_3)$ is a factor $f(X_1, X_2)_{X3 = v3}$ — Partial distribution
  - e.g., $P(Z \mid X,Y)$ is a factor $f(Z,X,Y)$ — Set of Distributions
  - e.g., $P(X_1, X_3 = v_3 \mid X_2)$ is a factor $f(X_1, X_2)_{X3 = v3}$ — Set of partial Distributions

$P(Z \mid X\,Y)$

f(X,Y,Z)

X	Y	Z	val
t	t	t	0.1
t	t	f	0.9
t	f	t	0.2
t	f	f	0.8
f	t	t	0.4
f	t	f	0.6
f	f	t	0.3
f	f	f	0.7

Manipulating Factors:

We can make new factors out of an existing factor

- Our first operation: we can *assign* some or all of the variables of a factor.

f(X,Y,Z):

X	Y	Z	val
t	t	t	0.1
t	t	f	0.9
t	f	t	0.2
t	f	f	0.8
~~f~~	~~t~~	~~t~~	~~0.4~~
~~f~~	~~t~~	~~f~~	~~0.6~~
~~f~~	~~f~~	~~t~~	~~0.3~~
~~f~~	~~f~~	~~f~~	~~0.7~~

What is the result of assigning X= t ?

$f(X{=}t, Y, Z)$

$f(X, Y, Z)_{X_1 = v_1}$

More examples of assignment

r(X,Y,Z):

X	Y	Z	val
t	t	t	0.1
t	t	f	0.9
t	f	t	0.2
t	f	f	0.8
f	t	t	0.4
f	t	f	0.6
f	f	t	0.3
f	f	f	0.7

r(X=t,Y,Z):

Y	Z	val
~~t~~	~~t~~	~~0.1~~
t	f	0.9
~~f~~	~~t~~	~~0.2~~
f	f	0.8

r(X=t,Y,Z=f):

Y	val
t	.9
f	.8

r(X=t,Y=f,Z=f):

val
.8

Summing out a variable example

Our second operation: we can ***sum out*** a variable, say X_1 with domain $\{v_1, \dots, v_k\}$, from factor $f(X_1, \dots, X_j)$, resulting in a factor on $X_2, \dots, X_j$ defined by:

$f_3(A,B,C)$:

A	B	C	val
t	t	t	0.03
t	t	f	0.07
t	f	t	0.54
t	f	f	0.36
f	t	t	0.06
f	t	f	0.14
f	f	t	0.48
f	f	f	0.32

$\sum_B f_3(A,C)$:

A	C	val
t	t	.57
t	f	.43
f	t	
f	f	

$$\left(\sum_{X_1} f\right)(X_2, \dots, X_j) = f(X_1 = v_1, X_2, \dots, X_j) + \dots + f(X_1 = v_k, X_2, \dots, X_j)$$

Multiplying factors

•Our third operation: factors can be *multiplied* together.

$f_1(A,B)$:

A	B	Val
t	t	0.1
t	f	0.9
f	t	0.2
f	f	0.8

$f_2(B,C)$:

B	C	Val
t	t	0.3
t	f	0.7
f	t	0.6
f	f	0.4

$f_1(A,B) \times f_2(B,C)$:

A	B	C	val
t	t	t	.03
t	t	f	.07
t	f	t	.54
t	f	f	
f	t	t	
f	t	f	
f	f	t	
f	f	f	

Multiplying factors: Formal

- The **product** of factor $f_1(A, B)$ and $f_2(B, C)$, where B is the variable in common, is the factor $(f_1 \times f_2)(A, B, C)$ defined by:

$$(f_1 \times f_2)(A, B, C) = f_1(A, B)\, f_2(B, C)$$

Note1: it's defined on all A, B, C triples, obtained by multiplying together the appropriate pair of entries from f_1 and f_2.

Note2: A, B, C can be sets of variables ✓

Factors Summary

- A factor is a representation of a function from a tuple of random variables into a number.
  - $f(X_1, \dots, X_j)$.

- We have defined three operations on factors: <

1. Assigning one or more variables
   - $f(X_1=v_1, X_2, \dots, X_j)$ is a factor on $X_2, \dots, X_j$, also written as $f(X_1, \dots, X_j)_{X_1=v_1}$ resulting factor is smaller

   < same

2. Summing out variables
   - $(\sum_{X_1} f)(X_2, \dots, X_j) = f(X_1=v_1, \dots, X_j) + \dots + f(X_1=v_k, \dots, X_j)$

3. Multiplying factors > resulting factor is bigger
   - $(f_1 \times f_2)(A, B, C) = f_1(A, B)\, f_2(B, C)$

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Variable Elimination Intro

- Suppose the variables of the belief network are $X_1, \ldots, X_n$.
- Z is the query variable
- *$Y_1=v_1, \ldots, Y_j=v_j$ are the observed variables (with their values)*
- $Z_1, \ldots, Z_k$ are the remaining variables
- What we want to compute: $\boxed{P(Z \mid Y_1 = v_1, \ldots, Y_j = v_j)}$
- We show before that what we actually need to compute is

$$\boxed{P(Z, Y_1 = v_1, \ldots, Y_j = v_j)}$$

This can be computed in terms of **operations between factors** (that satisfy the semantics of probability)

Variable Elimination Intro

- If we express the joint as a factor,

observed　　　　　　　sum out

$f(Z, Y_1, \ldots, Y_j, Z_1, \ldots, Z_j)$

assign

- We can compute $\boxed{P(Z, Y_1{=}v_1, \ldots, Y_j{=}v_j)}$ by ??
  - **assigning** $Y_1{=}v_1, \ldots, Y_j{=}v_j$
  - and **summing out** the variables $Z_1, \ldots, Z_k$

$$P(Z, Y_1 = v_1, \ldots, Y_j = v_j) = \boxed{\sum_{Z_k} \cdots \sum_{Z_1}} f(Z, Y_1, \ldots, Y_j, Z_1, \ldots, Z_k)_{Y_1 = v_1, \ldots, Y_j = v_j}$$

this is the joint TOO BIG!

Are we done?　no

Learning Goals for today's class

You can:

- Define **factors**. Derive new factors from existing factors. Apply operations to factors, including assigning, summing out and multiplying factors.

- (*Minimally*) Carry out **variable elimination** by using factor representation and using the factor operations. Use techniques to simplify variable elimination.

Next Class

Variable Elimination

- The algorithm
- An example

Course Elements

- Two Practice Exercises on Bnet available.
- Assignment 3 is due on Monday!
- Assignment 4 will be available on Wednesday and due on Apr the 8th (last class).