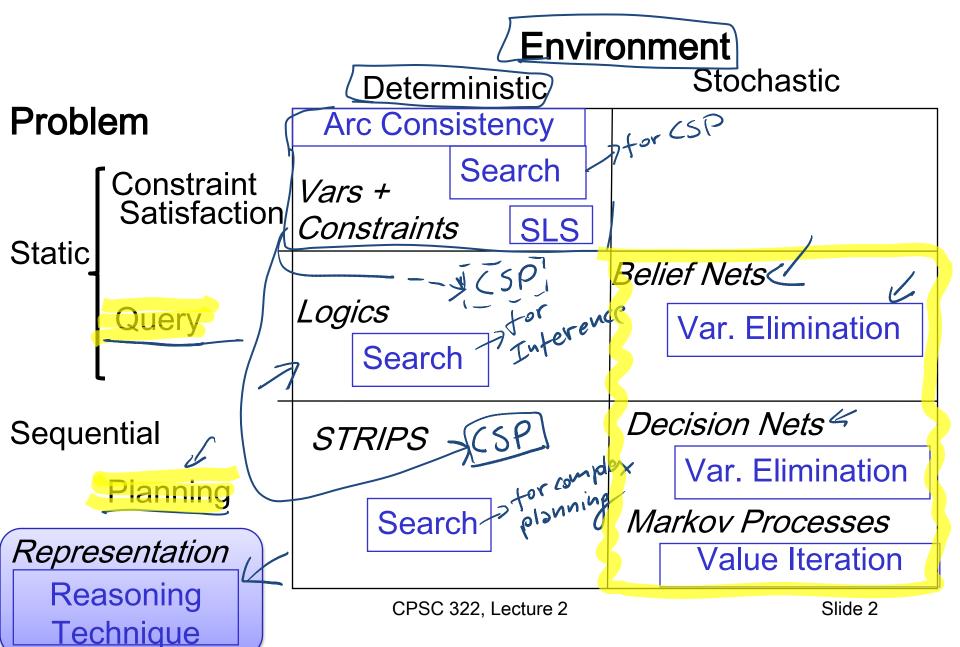
# Reasoning Under Uncertainty: Belief Networks

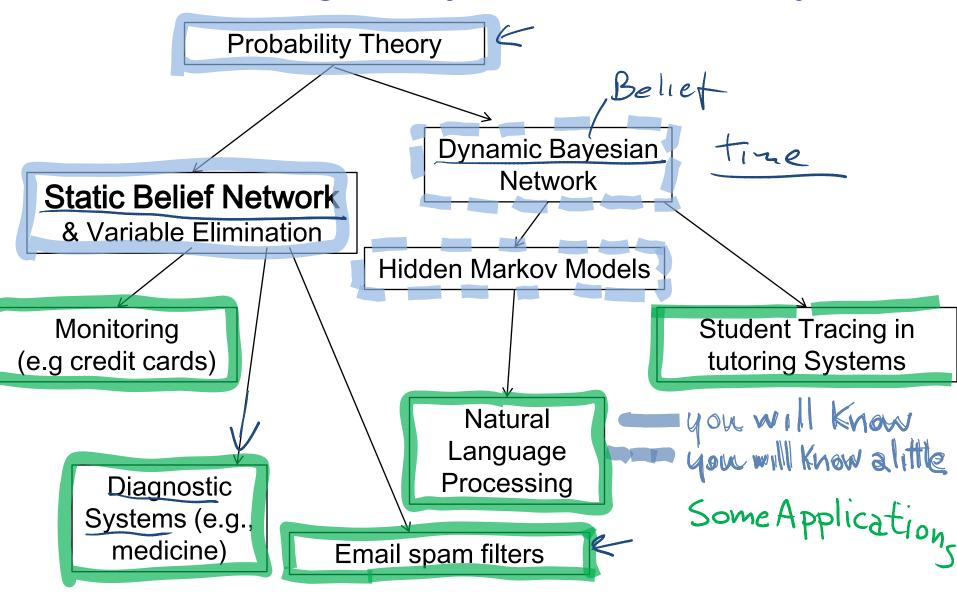
Computer Science cpsc322, Lecture 27
(Textbook Chpt 6.3)

March, 16, 2009

# Big Picture: R&R systems



#### **Answering Query under Uncertainty**



# **Key points Recap**

- We model the environment as a set of .Y.⇒r >
  - X1...Xn P(x1...Xn) rondom
- Why the joint is not an adequate representation?

"Representation, reasoning and learning" are "exponential" in ..... # vars

Solution: Exploit marginal&conditional independence

$$P(X|Y) = P(X) \qquad P(X|YZ) = P(X|Z)$$

But how does independence allow us to simplify the joint? CHAIN RULE!

#### **Lecture Overview**

- Belief Networks
  - Build sample BN
  - Intro Inference, Compactness, Semantics
  - More Examples

#### **Belief Nets: Burglary Example**

There might be a burglar in my house



The anti-burglar alarm in my house may go off



I have an agreement with two of my neighbors, **John** and **Mary**, that they **call** me if they hear the alarm go off when I am at work

**Minor earthquakes** may occur and sometimes the set off the alarm.

Variables: BAMTE

Joint has 2<sup>5</sup> entries/probs

-..--

# **Belief Nets: Simplify the joint**

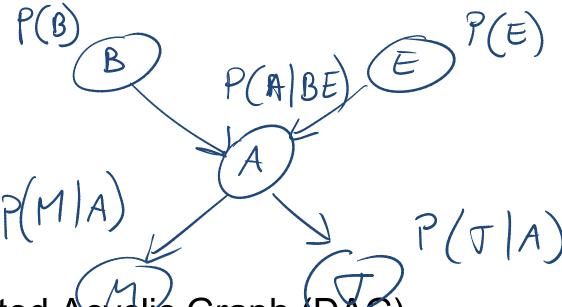
- Typically order vars to reflect causal knowledge (i.e., causes before effects)
  - A burglar (B) can set the alarm (A) off
  - An earthquake (E) can set the alarm (A) off
  - The alarm can cause Mary to call (M)
  - The alarm can cause John to call (J)

Apply Chain Rule
$$- = P(B) P(E|B) P(A|B,E) P(M|BEA) P(J|BEAM)$$

 Simplify according to marginal&conditional independence

#### **Belief Nets: Structure + Probs**

- Express remaining dependencies as a network
  - Each var is a node
  - For each var, the conditioning vars are its parents
  - Associate to each node corresponding conditional probabilities



Directed Acyclic Graph (DAG)

Slide 8

# P(B)

#### **Burglary: complete BN**



P(B=T)	P(B=F)
.001	.999

Butglary

Earthquake

P(E=T)	P(E=F)
.002	.998

P(A/B,E)

В	E	P(A=T   B,E)	P(A=F   B,E)
> T	T	.95	.05
Т	F	.94	.06
F	Т	.29	.71
F	F	<u>.001</u>	.999

John Calls

PGIA)

A	P(J=T   A)	P(J=F   Á)
Т	.90	.10
F	.05	.95

Alarm

Mory Colls) P(M/A)

A	$P(M=T \mid A)$	P(M=F   A)
Т	.70	.30
F	.01	.99

Vcall for any other reasons

#### **Lecture Overview**

- Belief Networks
  - Build sample BN
  - Intro Inference, Compactness, Semantics
  - More Examples

# Burglary Example: Bnets inference

Our BN can answer any probabilistic query that can be answered by processing the joint!

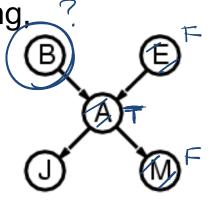
(Ex1) I'm at work,

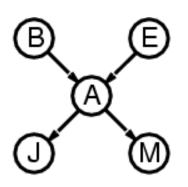
- neighbor John calls to say my alarm is ringing.
- neighbor Mary doesn't call.
- No news of any earthquakes.
- Is there a burglar?

(Ex2) I'm at work,

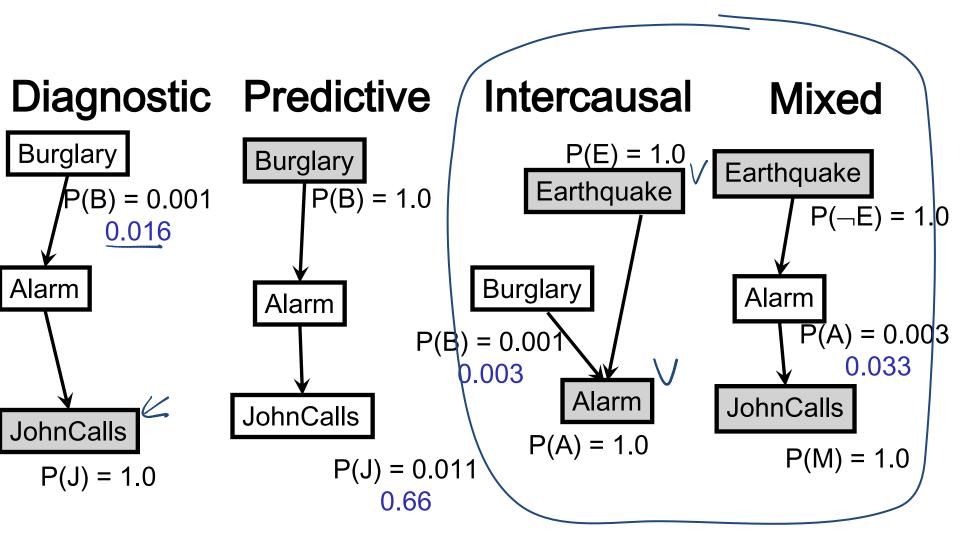
- Receive message that neighbor John called ,
- News of minor earthquakes.
- Is there a burglar?







# Bayesian Networks – Inference Types



#### LCPT

# BNnets: Compactness T

P(B=T)	P(B=F)
.001	.999



CPT

「レンナル	19WaKe
COLU	19Wary
<b>&gt;</b>	

P(E=T)	P(E=F)
.002	.998

1

< 1	PT	

В	E	$P(A=T \mid B,E)$	P( <u>A=</u> F   <u>B</u> , <u>E</u> )
Т	T	.95	.05
Т	F	.94	.06
F	T	.29	.71
F	F	.001	.999

John Calls

Α	P(J=T   A)	P(J=F   A)
T	.90	.10
F	05	95

Alarm

Mory Calls

CPT		
<b>A</b>	P(M=T   A)	P(M=F   A)
T	.70	.30
F	.01	.99
	-	-

1+1+4+2+2=10

Canditional Probability **BNets: Compactness** 

2<sup>K</sup> possible combinations

In General:

ACPT for boolean  $X_i$  with k boolean parents has  $\frac{1}{2}$  rows for the combinations of parent values

Each row requires one number  $p_i$  for  $X_i = true$  (the number for  $X_i = false$  is just  $1-p_i$ )

each row 15 a distrib. for Xi

If each variable has no more than k parents, the complete network requires O(N/2) numbers

For k < n, this is a substantial improvement,

• the numbers required grow linearly with *n*, vs.  $O(2^n)$  for the full joint distribution

#### **BNets: Construction General Semantics**

The full joint distribution can be defined as the product of conditional distributions:

$$P(X_1, ..., X_n) = \prod_{i=1}^n P(X_i / X_1, ..., X_{i-1})$$
 (chain rule)

Simplify according to marginal&conditional independence

- Express remaining dependencies as a network
  - Each var is a node
  - For each var, the conditioning vars are its parents
  - Associate to each node corresponding conditional probabilities

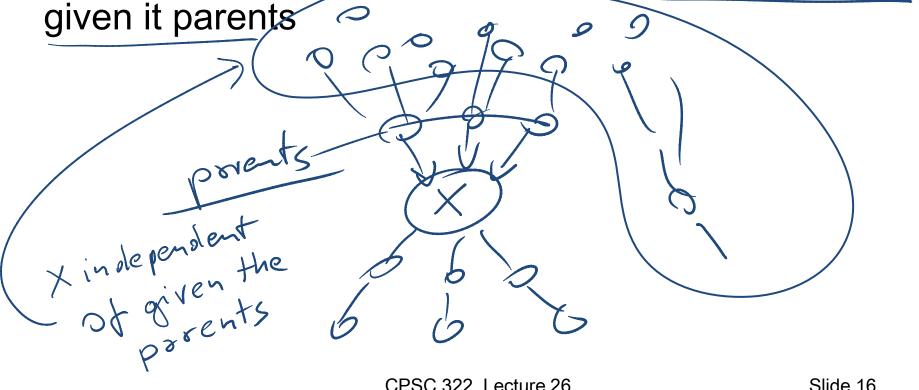
$$P(X_1, \ldots, X_n) = \prod_{i=1}^n P(X_i | Parents(X_i))$$

# **BNets: Construction General Semantics** (cont')

$$P(X_1, \ldots, X_n) = \prod_{i=1}^n P(X_i | Parents(X_i))$$

n

Every node is independent from its non-descendants



#### **Lecture Overview**

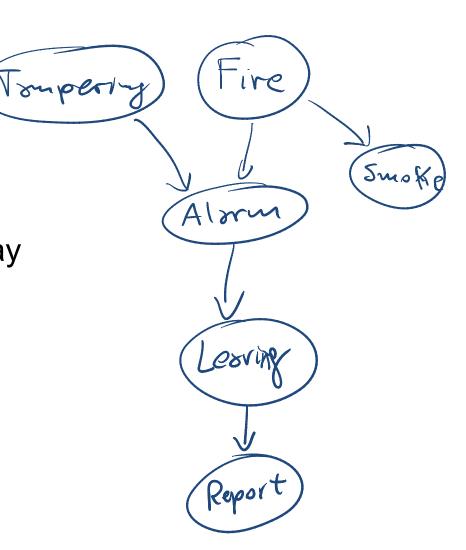
- Belief Networks
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# Other Examples: Fire Diagnosis (textbook Ex. 6.10)

Suppose you want to diagnose whether there is a fire in a building

 you receive a noisy report about whether everyone is leaving the building.

- if everyone is leaving, this may have been caused by a fire alarm.
- if there is a fire alarm, it may have been caused by a fire or by tampering
- if there is a fire, there may be smoke raising from the bldg.



cture 26 Slide 18

# Other Examples (cont')

 Make sure you explore and understand the Fire Diagnosis example (we'll expand on it to study Decision Networks)



• Electrical Circuit example (textbook ex 6.11)



- Patient's aching hands example (ex. 6.14)
- Several other examples on



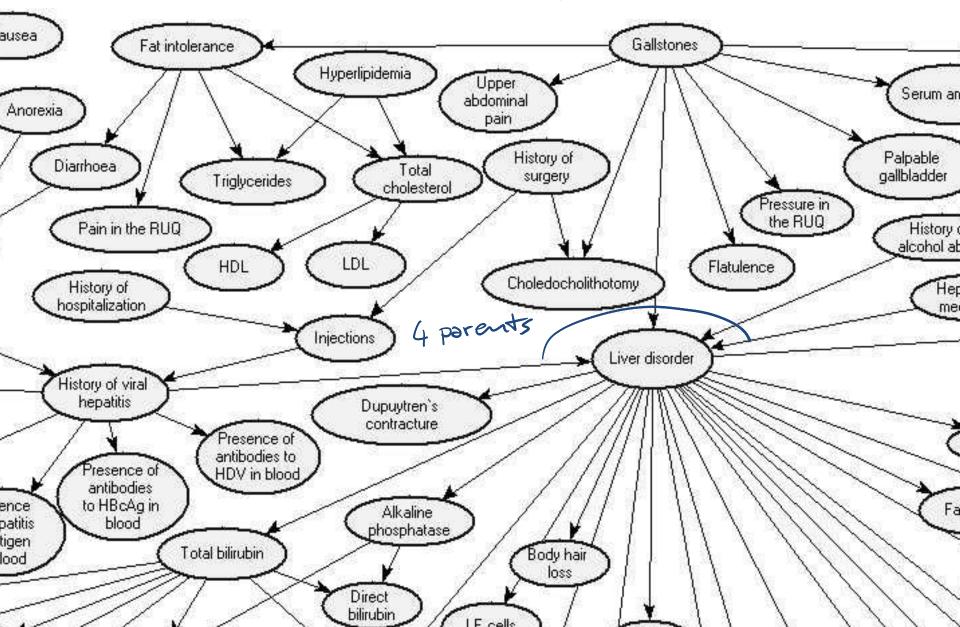
#### Realistic BNet: Liver Diagnosis Source: Onisko et al., 1999 wis Nausea Headache Fat intolerance Gallstones Lipase Hyperlipidemia Upper Serum amylase abdominal Diabetes Anorexia pain Vomiting History of Palpable Diarrhoea gallbladder surgery Triglycerides Obesity cholestero Pressure in the RUQ Blood Pain in the RUQ History of sugar alcohol abuse HDL LDL Flatulence Iron Choledocholithotomy History of Hepatotoxic Blood hospitalization medications Abnormal transfusion carbohydrate Injections metabolism Liver disorder Presence of History of viral antibodies to hepatitis HBsAg in blood Dupuytren's Alcohol contracture intolerance Presence of Hepatomegaly antibodies to Presence of Presence of HDV in blood hepatitis B antibodies surface antigen to HBcAg in resence Fatigue Enlarged Alkaline Hepatalgia in blood of hepatitis blood phosphatase B antigen Total bilirubin Body hair in blood loss Serum Itching in encephalopathy urea pregnancy bilirubin LE cells 5athological Alpha Impaired Jaundice fetoprotein resistances consciousness International Apathy **ESR** normalized ratio Increased Jaundice in of prothrombin liver density pregnancy Antimitochondrial Total proteins antibodies Musculo-skeleta LDH Platelet Irregular Jaundice liver edge AST count symptoms Smooth muscle ALT antibodies Ascites Antinuclear Gamma globulin Irregular antibodies Liver Albumin GGTP Edema liver palms Beta globulin Haemorrhagie erythemic diathesis Weight Alpha1 eruptions globulin gain lgG. Minute IgM. Vascular haemorrhagie spiders

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### Realistic BNet: Liver Diagnosis

Source: Onisko et al., 1999



# Learning Goals for today's class

#### You can:

Build a Belief Network for a simple domain

Classify the types of inference

Compute the representational saving in terms on number of probabilities required

#### **Next Class**

Bayesian Networks Representation  $\angle$ 



- Additional Dependencies encoded by BNets
- More compact representations for CPT
- Very simple but extremely useful Bnet (Bayes Classifier)

# **Belief network summary**

- A belief network is a directed acyclic graph (DAG) that effectively expresses independence assertions among random variables.
- The parents of a node X are those variables on which X directly depends.
- Consideration of causal dependencies among variables typically help in constructing a Bnet