

# Bayes Nets for representing and reasoning about uncertainty

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## What we'll discuss

- Recall the numerous and dramatic benefits of Joint Distributions for describing uncertain worlds
- Reel with terror at the problem with using Joint Distributions
- Discover how Bayes Net methodology allows us to built Joint Distributions in manageable chunks
- Discover there's still a lurking problem...
- ...Start to solve that problem

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Bayes Nets: Slide 2

## Why this matters

- In Andrew's opinion, the most important technology in the Machine Learning / AI field to have emerged in the last 10 years.
- A clean, clear, manageable language and methodology for expressing what you're certain and uncertain about
- Already, many practical applications in medicine, factories, helpdesks:
  - $P(\text{this problem} \mid \text{these symptoms})$
  - anomalousness of this observation
  - choosing next diagnostic test  $\mid$  these observations

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Active Data  
Collection

Inference

Anomaly  
Detection

## Ways to deal with Uncertainty

- Three-valued logic: True / False / Maybe
- Fuzzy logic (truth values between 0 and 1)
- Non-monotonic reasoning (especially focused on Penguin informatics)
- Dempster-Shafer theory (and an extension known as quasi-Bayesian theory)
- Possibilistic Logic
- Probability

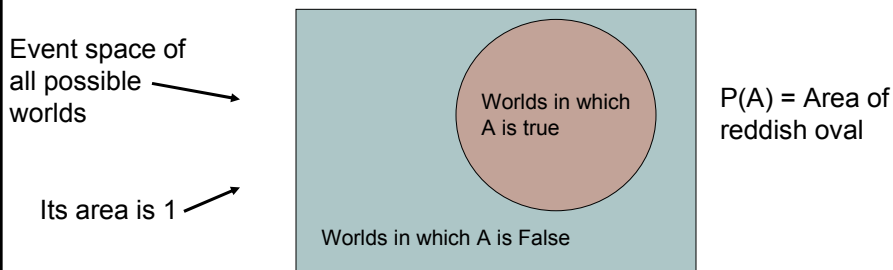
## Discrete Random Variables

- A is a Boolean-valued random variable if A denotes an event, and there is some degree of uncertainty as to whether A occurs.
- Examples
  - A = The US president in 2023 will be male
  - A = You wake up tomorrow with a headache
  - A = You have Ebola

# Probabilities

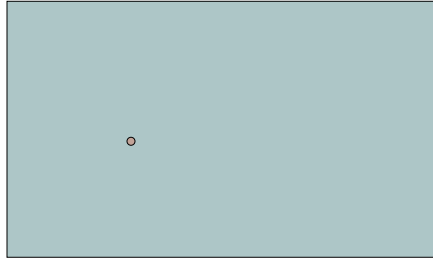
- We write  $P(A)$  as “the fraction of possible worlds in which  $A$  is true”
- We could at this point spend 2 hours on the philosophy of this.
- But we won't.

# Visualizing $A$



## Interpreting the axioms

- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1$
- $P(\text{False}) = 0$
- $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$

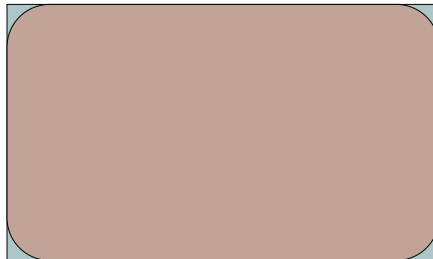


The area of A can't get any smaller than 0

And a zero area would mean no world could ever have A true

## Interpreting the axioms

- $0 \leq P(A) \leq 1$
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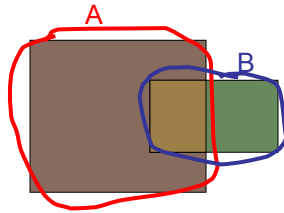


The area of A can't get any bigger than 1

And an area of 1 would mean all worlds will have A true

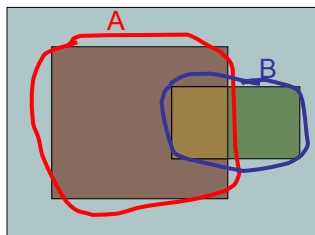
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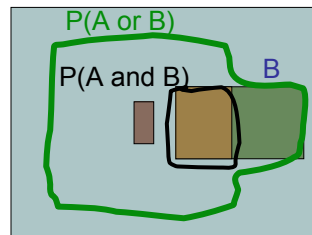


# Interpreting the axioms

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- $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$



Simple addition and subtraction



## These Axioms are Not to be Trifled With

- There have been attempts to do different methodologies for uncertainty
  - Fuzzy Logic
  - Three-valued logic
  - Dempster-Shafer
  - Non-monotonic reasoning
- But the axioms of probability are the only system with this property:

If you gamble using them you can't be unfairly exploited by an opponent using some other system [di Finetti 1931]

## Theorems from the Axioms

- $0 \leq P(A) \leq 1$ ,  $P(\text{True}) = 1$ ,  $P(\text{False}) = 0$
- $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$

From these we can prove:

$$P(\text{not } A) = P(\sim A) = 1 - P(A)$$

- How?

## Side Note

- I am inflicting these proofs on you for two reasons:
  1. These kind of manipulations will need to be second nature to you if you use probabilistic analytics in depth
  2. Suffering is good for you

## Another important theorem

- $0 \leq P(A) \leq 1$ ,  $P(\text{True}) = 1$ ,  $P(\text{False}) = 0$
- $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$

From these we can prove:

$$P(A) = P(A \wedge B) + P(A \wedge \sim B)$$

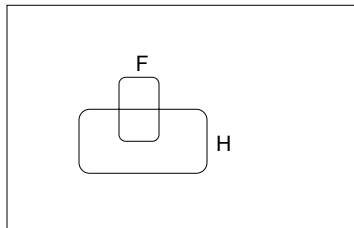
- How?

# Conditional Probability

- $P(A|B)$  = Fraction of worlds in which B is true that also have A true

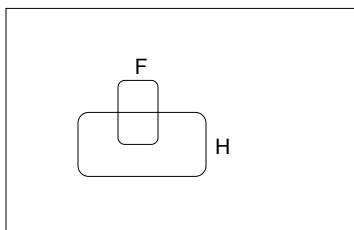
H = "Have a headache"  
 F = "Coming down with Flu"

$P(H) = 1/10$   
 $P(F) = 1/40$   
 $P(H|F) = 1/2$



"Headaches are rare and flu is rarer, but if you're coming down with 'flu there's a 50-50 chance you'll have a headache."

# Conditional Probability



H = "Have a headache"  
 F = "Coming down with Flu"

$P(H) = 1/10$   
 $P(F) = 1/40$   
 $P(H|F) = 1/2$

$P(H|F)$  = Fraction of flu-inflicted worlds in which you have a headache

$$= \frac{\text{\#worlds with flu and headache}}{\text{\#worlds with flu}}$$

$$= \frac{\text{Area of "H and F" region}}{\text{Area of "F" region}}$$

$$= \frac{P(H \wedge F)}{P(F)}$$

## Definition of Conditional Probability

$$P(A|B) = \frac{P(A \wedge B)}{P(B)}$$

## Corollary: The Chain Rule

$$P(A \wedge B) = P(A|B) P(B)$$

## Bayes Rule

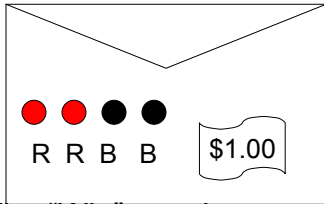
$$P(B|A) = \frac{P(A \wedge B)}{P(A)} = \frac{P(A|B) P(B)}{P(A)}$$

This is Bayes Rule

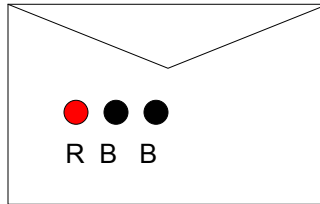
**Bayes, Thomas (1763)** An essay towards solving a problem in the doctrine of chances. *Philosophical Transactions of the Royal Society of London*, 53:370-418



# Using Bayes Rule to Gamble



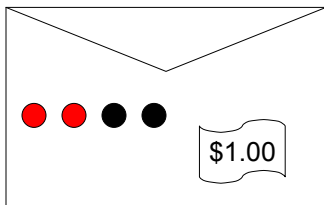
The "Win" envelope has a dollar and four beads in it



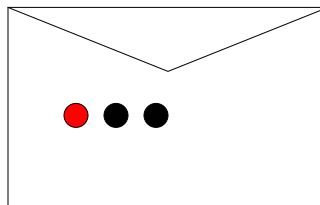
The "Lose" envelope has three beads and no money

Trivial question: someone draws an envelope at random and offers to sell it to you. How much should you pay?

# Using Bayes Rule to Gamble



The "Win" envelope has a dollar and four beads in it



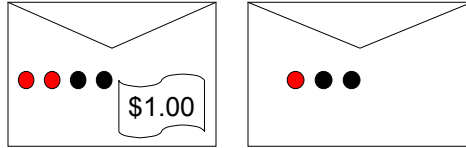
The "Lose" envelope has three beads and no money

Interesting question: before deciding, you are allowed to see one bead drawn from the envelope.

Suppose it's black: How much should you pay?

Suppose it's red: How much should you pay?

## Calculation...



## Multivalued Random Variables

- Suppose  $A$  can take on more than 2 values
- $A$  is a *random variable with arity  $k$*  if it can take on exactly one value out of  $\{v_1, v_2, \dots, v_k\}$
- Thus...

$$P(A = v_i \wedge A = v_j) = 0 \text{ if } i \neq j$$

$$P(A = v_1 \vee A = v_2 \vee \dots \vee A = v_k) = 1$$

## An easy fact about Multivalued Random Variables:

- Using the axioms of probability...  
 $0 \leq P(A) \leq 1$ ,  $P(\text{True}) = 1$ ,  $P(\text{False}) = 0$   
 $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$
- And assuming that A obeys...

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- It's easy to prove that

$$P(A = v_1 \vee A = v_2 \vee A = v_i) = \sum_{j=1}^i P(A = v_j)$$

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$$P(B \wedge [A = v_1 \vee A = v_2 \vee A = v_i]) = \sum_{j=1}^i P(B \wedge A = v_j)$$

- And thus we can prove

$$P(B) = \sum_{j=1}^k P(B \wedge A = v_j)$$

## More General Forms of Bayes Rule

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|\sim A)P(\sim A)}$$

$$P(A|B \wedge X) = \frac{P(B|A \wedge X)P(A \wedge X)}{P(B \wedge X)}$$

## More General Forms of Bayes Rule

$$P(A=v_i|B) = \frac{P(B|A=v_i)P(A=v_i)}{\sum_{k=1}^{n_A} P(B|A=v_k)P(A=v_k)}$$

## Useful Easy-to-prove facts

$$P(A | B) + P(\neg A | B) = 1$$

$$\sum_{k=1}^{n_A} P(A = v_k | B) = 1$$

## The Joint Distribution

*Example: Boolean variables A, B, C*

Recipe for making a joint distribution  
of M variables:

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*Example: Boolean variables A, B, C*

Recipe for making a joint distribution of M variables:

1. Make a truth table listing all combinations of values of your variables (if there are M Boolean variables then the table will have  $2^M$  rows).

A	B	C
0	0	0
0	0	1
0	1	0
0	1	1
1	0	0
1	0	1
1	1	0
1	1	1

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Recipe for making a joint distribution of M variables:

1. Make a truth table listing all combinations of values of your variables (if there are M Boolean variables then the table will have  $2^M$  rows).
2. For each combination of values, say how probable it is.

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	0.10

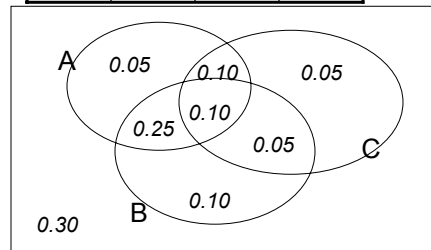
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Recipe for making a joint distribution of M variables:

1. Make a truth table listing all combinations of values of your variables (if there are M Boolean variables then the table will have  $2^M$  rows).
2. For each combination of values, say how probable it is.
3. If you subscribe to the axioms of probability, those numbers must sum to 1.

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	0.10



## Using the Joint

gender	hours_worked	wealth	prob
Female	v0:40.5-	poor	0.253122
		rich	0.0245895
	v1:40.5+	poor	0.0421768
		rich	0.0116293
Male	v0:40.5-	poor	0.331313
		rich	0.0971295
	v1:40.5+	poor	0.134106
		rich	0.105933

Once you have the JD you can ask for the probability of any logical expression involving your attribute

$$P(E) = \sum_{\text{rows matching } E} P(\text{row})$$

## Using the Joint

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$$P(\text{Poor Male}) = 0.4654$$

$$P(E) = \sum_{\text{rows matching } E} P(\text{row})$$

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$$P(\text{Poor}) = 0.7604$$

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# Inference with the Joint

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$$P(E_1 | E_2) = \frac{P(E_1 \wedge E_2)}{P(E_2)} = \frac{\sum_{\text{rows matching } E_1 \text{ and } E_2} P(\text{row})}{\sum_{\text{rows matching } E_2} P(\text{row})}$$

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$$P(\text{Male} | \text{Poor}) = 0.4654 / 0.7604 = 0.612$$

# Joint distributions

- Good news

Once you have a joint distribution, you can ask important questions about stuff that involves a lot of uncertainty

- Bad news

Impossible to create for more than about ten attributes because there are so many numbers needed when you build the damn thing.

# Using fewer numbers

Suppose there are two events:

- M: Manuela teaches the class (otherwise it's Andrew)
- S: It is sunny

The joint p.d.f. for these events contain four entries.

If we want to build the joint p.d.f. we'll have to invent those four numbers. OR WILL WE??

- We don't have to specify with bottom level conjunctive events such as  $P(\sim M \wedge S)$  IF...
- ...instead it may sometimes be more convenient for us to specify things like:  $P(M)$ ,  $P(S)$ .

But just  $P(M)$  and  $P(S)$  don't derive the joint distribution. So you can't answer all questions.

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- ... it may sometimes be more convenient for us to specify things like:  $P(M)$ ,  $P(S)$ .

But just  $P(M)$  and  $P(S)$  are not enough to derive the joint distribution. So you can't answer the question: **What extra assumption can you make?**

## Independence

"The sunshine levels do not depend on and do not influence who is teaching."

This can be specified very simply:

$$P(S \mid M) = P(S)$$

This is a powerful statement!

It required extra domain knowledge. A different kind of knowledge than numerical probabilities. It needed an understanding of causation.

# Independence

From  $P(S \mid M) = P(S)$ , the rules of probability imply: (*can you prove these?*)

- $P(\sim S \mid M) = P(\sim S)$
- $P(M \mid S) = P(M)$
- $P(M \wedge S) = P(M) P(S)$
- $P(\sim M \wedge S) = P(\sim M) P(S)$ ,  $P(M \wedge \sim S) = P(M) P(\sim S)$ ,  
 $P(\sim M \wedge \sim S) = P(\sim M) P(\sim S)$

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 $P(\sim M \wedge \sim S) = P(\sim M) P(\sim S)$
- And in general:  
$$P(M=u \wedge S=v) = P(M=u) P(S=v)$$
  
for each of the four combinations of  
$$u = \text{True/False}$$
  
$$v = \text{True/False}$$

# Independence

We've stated:

$$P(M) = 0.6$$

$$P(S) = 0.3$$

$$P(S | M) = P(S)$$

From these statements, we can derive the full joint pdf.

M	S	Prob
T	T	
T	F	
F	T	
F	F	

And since we now have the joint pdf, we can make any queries we like.

# A more interesting case

- M : Manuela teaches the class
- S : It is sunny
- L : The lecturer arrives slightly late.

Assume both lecturers are sometimes delayed by bad weather. Andrew is more likely to arrive late than Manuela.

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Let's begin with writing down knowledge we're happy about:

$P(S \mid M) = P(S)$ ,  $P(S) = 0.3$ ,  $P(M) = 0.6$   
Lateness is not independent of the weather and is not independent of the lecturer.

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Lateness is not independent of the weather and is not independent of the lecturer.

We already know the Joint of S and M, so all we need now is

$$P(L \mid S=u, M=v)$$

in the 4 cases of  $u/v = \text{True/False}$ .

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$$\begin{array}{ll} P(S \mid M) = P(S) & P(L \mid M \wedge S) = 0.05 \\ P(S) = 0.3 & P(L \mid M \wedge \sim S) = 0.1 \\ P(M) = 0.6 & P(L \mid \sim M \wedge S) = 0.1 \\ & P(L \mid \sim M \wedge \sim S) = 0.2 \end{array}$$

Now we can derive a full joint p.d.f. with a “mere” six numbers instead of seven\*

*\*Savings are larger for larger numbers of variables.*

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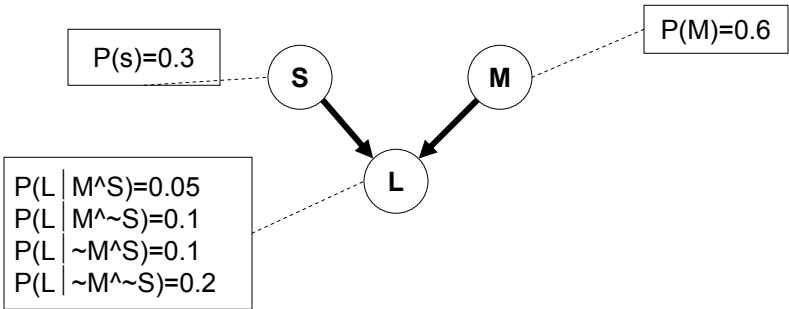
Question: Express

$$P(L=x \wedge M=y \wedge S=z)$$

in terms that only need the above expressions, where x,y and z may each be True or False.

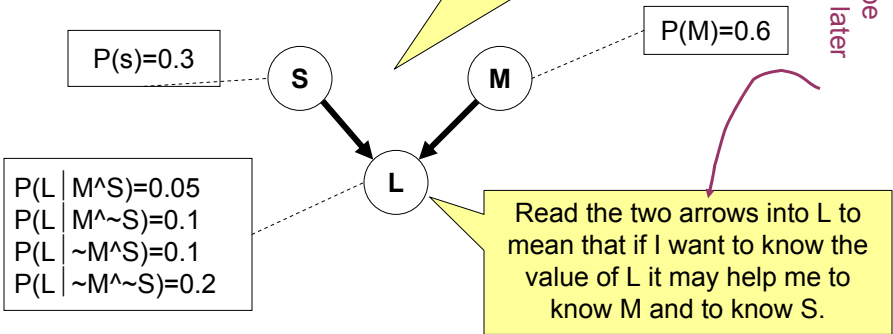
# A bit of notation

$P(S   M) = P(S)$	$P(L   M \wedge S) = 0.05$
$P(S) = 0.3$	$P(L   M \wedge \sim S) = 0.1$
$P(M) = 0.6$	$P(L   \sim M \wedge S) = 0.1$
	$P(L   \sim M \wedge \sim S) = 0.2$



# A bit of notation

$P(S   M) = P(S)$	$P(L   M \wedge S) = 0.05$
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## An even cuter trick

Suppose we have these three events:

- M : Lecture taught by Manuela
- L : Lecturer arrives late
- R : Lecture concerns robots

Suppose:

- Andrew has a higher chance of being late than Manuela.
- Andrew has a higher chance of giving robotics lectures.

What kind of independence can we find?

How about:

- $P(L \mid M) = P(L)$  ?
- $P(R \mid M) = P(R)$  ?
- $P(L \mid R) = P(L)$  ?

## Conditional independence

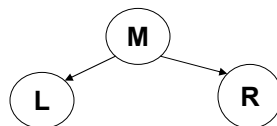
Once you know who the lecturer is, then whether they arrive late doesn't affect whether the lecture concerns robots.

$$P(R \mid M, L) = P(R \mid M) \text{ and} \\ P(R \mid \sim M, L) = P(R \mid \sim M)$$

We express this in the following way:

“R and L are conditionally independent given M”

..which is also notated by the following diagram.



Given knowledge of M, knowing anything else in the diagram won't help us with L, etc.

## Conditional Independence formalized

R and L are conditionally independent given M if  
for all  $x,y,z$  in  $\{T,F\}$ :

$$P(R=x \mid M=y \wedge L=z) = P(R=x \mid M=y)$$

More generally:

Let  $S_1$  and  $S_2$  and  $S_3$  be sets of variables.

Set-of-variables  $S_1$  and set-of-variables  $S_2$  are  
conditionally independent given  $S_3$  if for all  
assignments of values to the variables in the sets,

$$P(S_1\text{'s assignments} \mid S_2\text{'s assignments} \ \& \ S_3\text{'s assignments}) = P(S_1\text{'s assignments} \mid S_3\text{'s assignments})$$

### Example:

R and L are  
for all  $x,y,z$

$$P(R=x \mid M=y \wedge L=z)$$

More generally:

Let  $S_1$  and  $S_2$  and  $S_3$  be sets of variables.

Set-of-variables  $S_1$  and set-of-variables  $S_2$  are  
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$$P(S_1\text{'s assignments} \mid S_2\text{'s assignments} \ \& \ S_3\text{'s assignments}) = P(S_1\text{'s assignments} \mid S_3\text{'s assignments})$$

“Shoe-size is conditionally independent of Glove-size given  
height weight and age”

means

forall  $s,g,h,w,a$

$$P(\text{ShoeSize}=s \mid \text{Height}=h, \text{Weight}=w, \text{Age}=a)$$

=

$$P(\text{ShoeSize}=s \mid \text{Height}=h, \text{Weight}=w, \text{Age}=a, \text{GloveSize}=g)$$

Example:

R and L are

for all x,y,z

$P(R=x)$

More general

Let  $S_1$  and  $S_2$  and  $S_3$  be sets of variables

Set-of-variables  $S_1$  and set-of-variables  $S_2$  are conditionally independent given  $S_3$  if for all assignments of values to the variables in the sets,

$$P(S_1\text{'s assignments} \mid S_2\text{'s assignments} \ \& \ S_3\text{'s assignments}) = P(S_1\text{'s assignments} \mid S_3\text{'s assignments})$$

“Shoe-size is conditionally independent of Glove-size given height weight and age”

does not mean

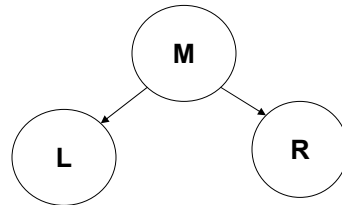
forall s,g,h

$$P(\text{ShoeSize}=s \mid \text{Height}=h)$$

=

$$P(\text{ShoeSize}=s \mid \text{Height}=h, \text{GloveSize}=g)$$

## Conditional independence



We can write down  $P(M)$ . And then, since we know L is only directly influenced by M, we can write down the values of  $P(L \mid M)$  and  $P(L \mid \sim M)$  and know we've fully specified L's behavior. Ditto for R.

$$P(M) = 0.6$$

$$P(L \mid M) = 0.085$$

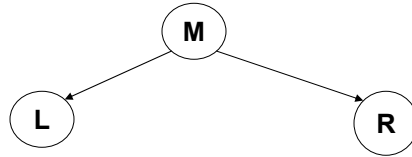
$$P(L \mid \sim M) = 0.17$$

$$P(R \mid M) = 0.3$$

$$P(R \mid \sim M) = 0.6$$

'R and L conditionally independent given M'

## Conditional independence



$$P(M) = 0.6$$

$$P(L \mid M) = 0.085$$

$$P(L \mid \sim M) = 0.17$$

$$P(R \mid M) = 0.3$$

$$P(R \mid \sim M) = 0.6$$

Conditional Independence:

$$P(R \mid M, L) = P(R \mid M),$$

$$P(R \mid \sim M, L) = P(R \mid \sim M)$$

Again, we can obtain any member of the Joint prob dist that we desire:

$$P(L=x \wedge R=y \wedge M=z) =$$

## Assume five variables

T: The lecture started by 10:35

L: The lecturer arrives late

R: The lecture concerns robots

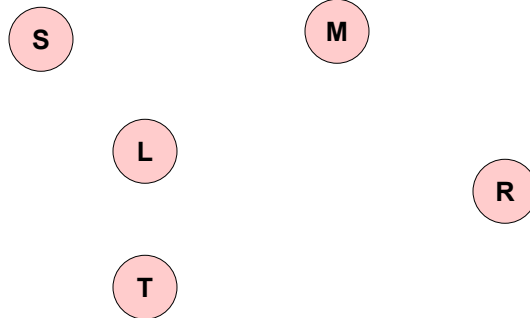
M: The lecturer is Manuela

S: It is sunny

- T only directly influenced by L (i.e. T is conditionally independent of R,M,S given L)
- L only directly influenced by M and S (i.e. L is conditionally independent of R given M & S)
- R only directly influenced by M (i.e. R is conditionally independent of L,S, given M)
- M and S are independent

# Making a Bayes net

T: The lecture started by 10:35  
L: The lecturer arrives late  
R: The lecture concerns robots  
M: The lecturer is Manuela  
S: It is sunny

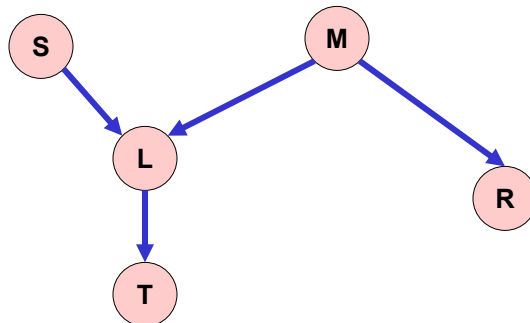


Step One: add variables.

- Just choose the variables you'd like to be included in the net.

# Making a Bayes net

T: The lecture started by 10:35  
L: The lecturer arrives late  
R: The lecture concerns robots  
M: The lecturer is Manuela  
S: It is sunny

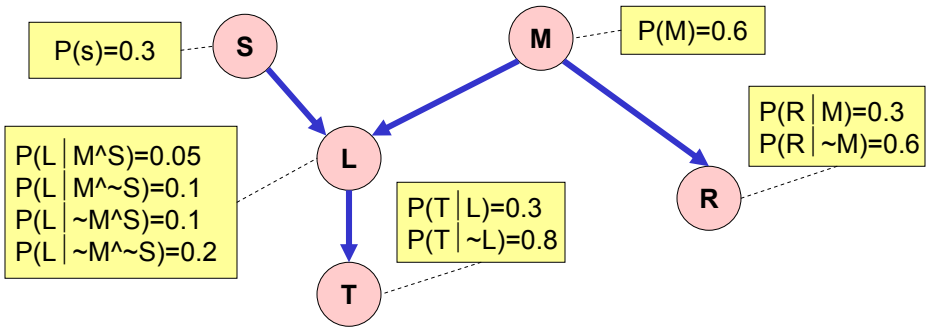


Step Two: add links.

- The link structure must be acyclic.
- If node  $X$  is given parents  $Q_1, Q_2, \dots, Q_n$  you are promising that any variable that's a non-descendent of  $X$  is conditionally independent of  $X$  given  $\{Q_1, Q_2, \dots, Q_n\}$

# Making a Bayes net

T: The lecture started by 10:35  
 L: The lecturer arrives late  
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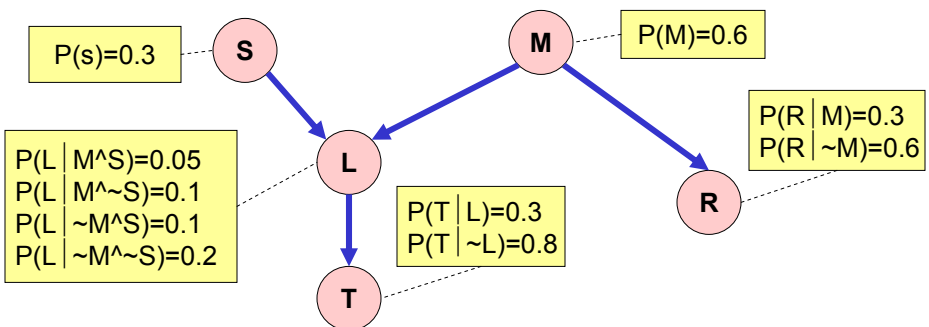


Step Three: add a probability table for each node.

- The table for node X must list  $P(X|Parent Values)$  for each possible combination of parent values

# Making a Bayes net

T: The lecture started by 10:35  
 L: The lecturer arrives late  
 R: The lecture concerns robots  
 M: The lecturer is Manuela  
 S: It is sunny



- Two unconnected variables may still be correlated
- Each node is conditionally independent of all non-descendants in the tree, given its parents.
- You can deduce many other conditional independence relations from a Bayes net. See the next lecture.

## Bayes Nets Formalized

A Bayes net (also called a belief network) is an augmented directed acyclic graph, represented by the pair  $V, E$  where:

- $V$  is a set of vertices.
- $E$  is a set of directed edges joining vertices. No loops of any length are allowed.

Each vertex in  $V$  contains the following information:

- The name of a random variable
- A probability distribution table indicating how the probability of this variable's values depends on all possible combinations of parental values.

## Building a Bayes Net

1. Choose a set of relevant variables.
2. Choose an ordering for them
3. Assume they're called  $X_1 \dots X_m$  (where  $X_1$  is the first in the ordering,  $X_2$  is the second, etc)
4. For  $i = 1$  to  $m$ :
  1. Add the  $X_i$  node to the network
  2. Set  $Parents(X_i)$  to be a minimal subset of  $\{X_1 \dots X_{i-1}\}$  such that we have conditional independence of  $X_i$  and all other members of  $\{X_1 \dots X_{i-1}\}$  given  $Parents(X_i)$
  3. Define the probability table of  $P(X_i = k \mid \text{Assignments of } Parents(X_i) )$ .

## Example Bayes Net Building

Suppose we're building a nuclear power station.

There are the following random variables:

GRL : Gauge Reads Low.

CTL : Core temperature is low.

FG : Gauge is faulty.

FA : Alarm is faulty

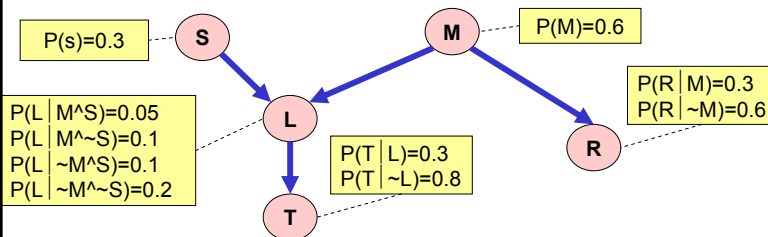
AS : Alarm sounds

- If alarm working properly, the alarm is meant to sound if the gauge stops reading a low temp.
- If gauge working properly, the gauge is meant to read the temp of the core.

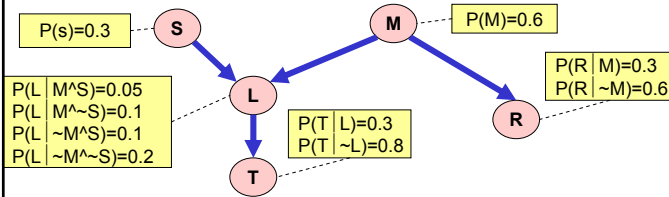
## Computing a Joint Entry

How to compute an entry in a joint distribution?

E.G: What is  $P(S \wedge \sim M \wedge L \sim R \wedge T)$ ?



# Computing with Bayes Net



$$\begin{aligned}
 &P(T \wedge \sim R \wedge L \wedge \sim M \wedge S) = \\
 &P(T \mid \sim R \wedge L \wedge \sim M \wedge S) * P(\sim R \wedge L \wedge \sim M \wedge S) = \\
 &P(T \mid L) * P(\sim R \wedge L \wedge \sim M \wedge S) = \\
 &P(T \mid L) * P(\sim R \mid L \wedge \sim M \wedge S) * P(L \wedge \sim M \wedge S) = \\
 &P(T \mid L) * P(\sim R \mid \sim M) * P(L \wedge \sim M \wedge S) = \\
 &P(T \mid L) * P(\sim R \mid \sim M) * P(L \mid \sim M \wedge S) * P(\sim M \wedge S) = \\
 &P(T \mid L) * P(\sim R \mid \sim M) * P(L \mid \sim M \wedge S) * P(\sim M \mid S) * P(S) = \\
 &P(T \mid L) * P(\sim R \mid \sim M) * P(L \mid \sim M \wedge S) * P(\sim M) * P(S).
 \end{aligned}$$

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Bayes Nets: Slide 71

# The general case

$$\begin{aligned}
 &P(X_1=x_1 \wedge X_2=x_2 \wedge \dots \wedge X_{n-1}=x_{n-1} \wedge X_n=x_n) = \\
 &P(X_n=x_n \mid X_{n-1}=x_{n-1} \wedge \dots \wedge X_2=x_2 \wedge X_1=x_1) = \\
 &P(X_n=x_n \mid X_{n-1}=x_{n-1} \wedge \dots \wedge X_2=x_2 \wedge X_1=x_1) * P(X_{n-1}=x_{n-1} \wedge \dots \wedge X_2=x_2 \wedge X_1=x_1) = \\
 &P(X_n=x_n \mid X_{n-1}=x_{n-1} \wedge \dots \wedge X_2=x_2 \wedge X_1=x_1) * P(X_{n-1}=x_{n-1} \mid \dots \wedge X_2=x_2 \wedge X_1=x_1) * \\
 &P(X_{n-2}=x_{n-2} \wedge \dots \wedge X_2=x_2 \wedge X_1=x_1) = \\
 &\vdots \\
 &= \\
 &\prod_{i=1}^n P((X_i = x_i) \mid ((X_{i-1} = x_{i-1}) \wedge \dots \wedge (X_1 = x_1))) \\
 &= \\
 &\prod_{i=1}^n P((X_i = x_i) \mid \text{Assignments of Parents}(X_i))
 \end{aligned}$$

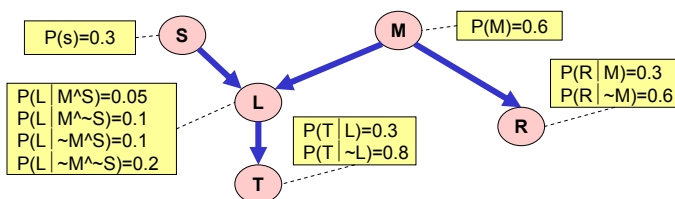
So any entry in joint pdf table can be computed. And so any **conditional probability** can be computed.

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Bayes Nets: Slide 72

# Where are we now?

- We have a methodology for building Bayes nets.
- We don't require exponential storage to hold our probability table. Only exponential in the maximum number of parents of any node.
- We can compute probabilities of any given assignment of truth values to the variables. And we can do it in time linear with the number of nodes.
- So we can also compute answers to any questions.



E.G. What could we do to compute  $P(R | T, \sim S)$ ?

# Where are we now?

Step 1: Compute  $P(R^{\wedge}T^{\wedge}\sim S)$

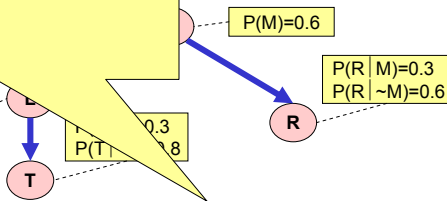
Step 2: Compute  $P(\sim R^{\wedge}T^{\wedge}\sim S)$

Step 3: Return

$$P(R^{\wedge}T^{\wedge}\sim S)$$

$$P(R^{\wedge}T^{\wedge}\sim S) + P(\sim R^{\wedge}T^{\wedge}\sim S)$$

$P(L | M^{\wedge}S)=0.05$   
 $P(L | M^{\wedge}\sim S)=0.1$   
 $P(L | \sim M^{\wedge}S)=0.1$   
 $P(L | \sim M^{\wedge}\sim S)=0.2$



E.G. What could we do to compute  $P(R | T, \sim S)$ ?

# Where are we now?

Step 1: Compute  $P(R \wedge T \wedge \sim S)$

Sum of all the rows in the Joint that match  $R \wedge T \wedge \sim S$

Step 2: Compute  $P(\sim R \wedge T \wedge \sim S)$

Sum of all the rows in the Joint that match  $\sim R \wedge T \wedge \sim S$

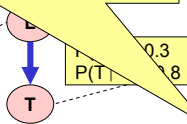
Step 3: Return

$$P(R \wedge T \wedge \sim S)$$

---


$$P(R \wedge T \wedge \sim S) + P(\sim R \wedge T \wedge \sim S)$$

$P(L \wedge M \wedge S)$	=0.05
$P(L \wedge M \wedge \sim S)$	=0.1
$P(L \wedge \sim M \wedge S)$	=0.1
$P(L \wedge \sim M \wedge \sim S)$	=0.2



$P(M) = 0.6$

$P(R | M) = 0.3$   
 $P(R | \sim M) = 0.6$

E.G. What could we do to compute  $P(R | T, \sim S)$ ?

# Where are we now?

Step 1: Compute  $P(R \wedge T \wedge \sim S)$

4 joint computes

Sum of all the rows in the Joint that match  $R \wedge T \wedge \sim S$

Step 2: Compute  $P(\sim R \wedge T \wedge \sim S)$

Sum of all the rows in the Joint that match  $\sim R \wedge T \wedge \sim S$

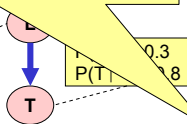
Step 3: Return

$$P(R \wedge T \wedge \sim S)$$

---


$$P(R \wedge T \wedge \sim S) + P(\sim R \wedge T \wedge \sim S)$$

$P(L \wedge M \wedge S)$	=0.05
$P(L \wedge M \wedge \sim S)$	=0.1
$P(L \wedge \sim M \wedge S)$	=0.1
$P(L \wedge \sim M \wedge \sim S)$	=0.2



$P(R | \sim M) = 0.6$

Each of these obtained by the "computing a joint probability entry" method of the earlier slides

4 joint computes

E.G. What could we do to compute  $P(R | T, \sim S)$ ?

## The good news

We can do inference. We can compute any conditional probability:

$P(\text{Some variable} \mid \text{Some other variable values})$

$$P(E_1 \mid E_2) = \frac{P(E_1 \wedge E_2)}{P(E_2)} = \frac{\sum_{\text{joint entries matching } E_1 \text{ and } E_2} P(\text{joint entry})}{\sum_{\text{joint entries matching } E_2} P(\text{joint entry})}$$

## The good news

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Suppose you have  $m$  binary-valued variables in your Bayes Net and expression  $E_2$  mentions  $k$  variables.

How much work is the above computation?

## The sad, bad news

Conditional probabilities by enumerating all matching entries in the joint are expensive:

**Exponential in the number of variables.**

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**Exponential in the number of variables.**

But perhaps there are faster ways of querying Bayes nets?

- In fact, if I ever ask you to manually do a Bayes Net inference, you'll find there are often many tricks to save you time.
- So we've just got to program our computer to do those tricks too, right?

# The sad, bad news

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**Exponential in the number of variables.**

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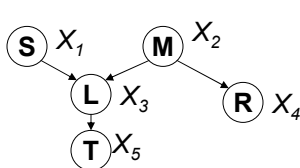
- In fact, if I ever ask you to manually do a Bayes Net inference, you'll find there are often many tricks to save you time.
- So we've just got to program our computer to do those tricks too, right?

**Sadder and worse news:**

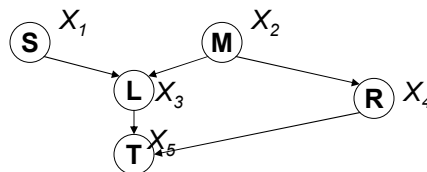
**General querying of Bayes nets is NP-complete.**

# Bayes nets inference algorithms

A poly-tree is a directed acyclic graph in which no two nodes have more than one path between them.



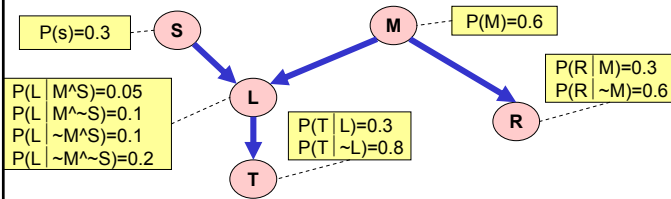
A poly tree



Not a poly tree  
(but still a legal Bayes net)

- If net is a poly-tree, there is a linear-time algorithm (see a later Andrew lecture).
- The best general-case algorithms convert a general net to a poly-tree (often at huge expense) and calls the poly-tree algorithm.
- Another popular, practical approach (doesn't assume poly-tree): Stochastic Simulation.

# Sampling from the Joint Distribution



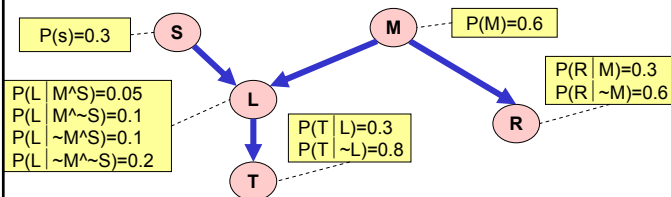
It's pretty easy to generate a set of variable-assignments at random with the same probability as the underlying joint distribution.

How?

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Bayes Nets: Slide 83

# Sampling from the Joint Distribution



1. Randomly choose S. S = True with prob 0.3
2. Randomly choose M. M = True with prob 0.6
3. Randomly choose L. The probability that L is true depends on the assignments of S and M. E.G. if steps 1 and 2 had produced S=True, M=False, then probability that L is true is 0.1
4. Randomly choose R. Probability depends on M.
5. Randomly choose T. Probability depends on L

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Bayes Nets: Slide 84

# A general sampling algorithm

Let's generalize the example on the previous slide to a general Bayes Net.

As in Slides 16-17, call the variables  $X_1 \dots X_n$ , where  $Parents(X_i)$  must be a subset of  $\{X_1 \dots X_{i-1}\}$ .

For  $i=1$  to  $n$ :

1. Find parents, if any, of  $X_i$ . Assume  $n(i)$  parents. Call them  $X_{p(i,1)}, X_{p(i,2)}, \dots, X_{p(i,n(i))}$ .
2. Recall the values that those parents were randomly given:  $x_{p(i,1)}, x_{p(i,2)}, \dots, x_{p(i,n(i))}$ .
3. Look up in the lookup-table for:  
 $P(X_i=True \mid X_{p(i,1)}=x_{p(i,1)}, X_{p(i,2)}=x_{p(i,2)} \dots X_{p(i,n(i))}=x_{p(i,n(i))})$
4. Randomly set  $x_i=True$  according to this probability

$x_1, x_2, \dots, x_n$  are now a sample from the joint distribution of  $X_1, X_2, \dots, X_n$ .

# Stochastic Simulation Example

Someone wants to know  $P(R = True \mid T = True \wedge S = False)$

We'll do lots of random samplings and count the number of occurrences of the following:

- $N_c$  : Num. samples in which  $T=True$  and  $S=False$ .
- $N_s$  : Num. samples in which  $R=True, T=True$  and  $S=False$ .
- $N$  : Number of random samplings

Now if  $N$  is big enough:

$N_c / N$  is a good estimate of  $P(T=True \text{ and } S=False)$ .

$N_s / N$  is a good estimate of  $P(R=True, T=True, S=False)$ .

$P(R \mid T \wedge \sim S) = P(R \wedge T \wedge \sim S) / P(T \wedge \sim S)$ , so  $N_s / N_c$  can be a good estimate of  $P(R \mid T \wedge \sim S)$ .

# General Stochastic Simulation

Someone wants to know  $P(E_1 \mid E_2)$

We'll do lots of random samplings and count the number of occurrences of the following:

- $N_c$  : Num. samples in which  $E_2$
- $N_s$  : Num. samples in which  $E_1$  and  $E_2$
- $N$  : Number of random samplings

Now if  $N$  is big enough:

$N_c / N$  is a good estimate of  $P(E_2)$ .

$N_s / N$  is a good estimate of  $P(E_1, E_2)$ .

$P(E_1 \mid E_2) = P(E_1 \wedge E_2) / P(E_2)$ , so  $N_s / N_c$  can be a good estimate of  $P(E_1 \mid E_2)$ .

# Likelihood weighting

Problem with Stochastic Sampling:

With lots of constraints in  $E$ , or unlikely events in  $E$ , then most of the simulations will be thrown away, (they'll have no effect on  $N_c$ , or  $N_s$ ).

Imagine we're part way through our simulation.

In  $E_2$  we have the constraint  $X_i = v$

We're just about to generate a value for  $X_i$  at random. Given the values assigned to the parents, we see that  $P(X_i = v \mid \text{parents}) = p$ .

Now we know that with stochastic sampling:

- we'll generate " $X_i = v$ " proportion  $p$  of the time, and proceed.
- And we'll generate a different value proportion  $1-p$  of the time, and the simulation will be wasted.

Instead, always generate  $X_i = v$ , but weight the answer by weight " $p$ " to compensate.

# Likelihood weighting

Set  $N_c := 0$ ,  $N_s := 0$

1. Generate a random assignment of all variables that matches  $E_2$ . This process returns a weight  $w$ .
2. Define  $w$  to be the probability that this assignment would have been generated instead of an unmatching assignment during its generation in the original algorithm. Fact:  $w$  is a product of all likelihood factors involved in the generation.
3.  $N_c := N_c + w$
4. If our sample matches  $E_1$  then  $N_s := N_s + w$
5. Go to 1

Again,  $N_s / N_c$  estimates  $P(E_1 \mid E_2)$

# Case Study I

Pathfinder system. (Heckerman 1991, Probabilistic Similarity Networks, MIT Press, Cambridge MA).

- Diagnostic system for lymph-node diseases.
- 60 diseases and 100 symptoms and test-results.
- 14,000 probabilities
- Expert consulted to make net.
  - 8 hours to determine variables.
  - 35 hours for net topology.
  - 40 hours for probability table values.
- Apparently, the experts found it quite easy to invent the causal links and probabilities.
- Pathfinder is now outperforming the world experts in diagnosis. Being extended to several dozen other medical domains.

## Questions

- What are the strengths of probabilistic networks compared with propositional logic?
- What are the weaknesses of probabilistic networks compared with propositional logic?
- What are the strengths of probabilistic networks compared with predicate logic?
- What are the weaknesses of probabilistic networks compared with predicate logic?
- (How) could predicate logic and probabilistic networks be combined?

## What you should know

- The meanings and importance of independence and conditional independence.
- The definition of a Bayes net.
- Computing probabilities of assignments of variables (i.e. members of the joint p.d.f.) with a Bayes net.
- The slow (exponential) method for computing arbitrary, conditional probabilities.
- The stochastic simulation method and likelihood weighting.