

Lecture 7

Probabilistic Reasoning
CS 486/686
Oct 6, 2009

Outline

- Review probabilistic inference, independence and conditional independence
- Bayesian networks
 - What are they
 - What do they mean
 - How do we create them

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Probabilistic Inference

- By probabilistic inference, we mean
 - given a *prior* distribution Pr over variables of interest, representing degrees of belief
 - and given new evidence $E=e$ for some var E
 - Revise your degrees of belief: *posterior* Pr_e
- How do your degrees of belief change as a result of learning $E=e$ (or more generally $E=e$, for set E)

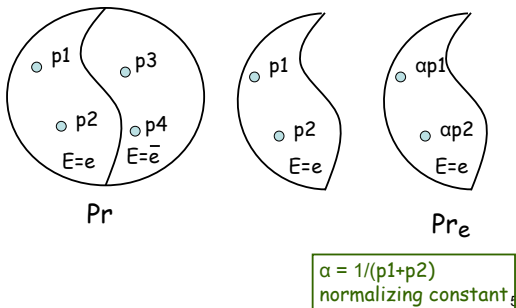
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Conditioning

- We define $Pr_e(\alpha) = Pr(\alpha / e)$
- That is, we produce Pr_e by *conditioning* the prior distribution on the observed evidence e

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Semantics of Conditioning



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Inference: Computational Bottleneck

- Semantically/conceptually, picture is clear; but several issues must be addressed

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Issue 1

- How do we specify the full joint distribution over a set of random variables X_1, X_2, \dots, X_n ?
 - **Exponential** number of possible worlds
 - e.g., if the X_i are boolean, then 2^n numbers (or $2^n - 1$ parameters/degrees of freedom, since they sum to 1)
 - These numbers are **not robust/stable**
 - These numbers are **not natural** to assess (what is probability that "Pascal wants a cup of tea; it's not raining or snowing in Montreal; robot charge level is low; ..."?)

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Issue 2

- Inference in this representation is **frightfully slow**
 - Must sum over exponential number of worlds to answer query $Pr(a)$ or to condition on evidence e to determine $Pr_e(a)$

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Small Example: 3 Variables

| | sunny | | ~sunny | |
|-----------|-------|-------|--------|-------|
| | cold | ~cold | cold | ~cold |
| headache | 0.108 | 0.012 | 0.072 | 0.008 |
| ~headache | 0.016 | 0.064 | 0.144 | 0.576 |

$$P(\text{headache}) = 0.108 + 0.012 + 0.072 + 0.008 = 0.2$$

$$P(\text{headache} \wedge \text{cold} \mid \text{sunny}) = P(\text{headache} \wedge \text{cold} \wedge \text{sunny}) / P(\text{sunny}) \\ = 0.108 / (0.108 + 0.012 + 0.016 + 0.064) = 0.54$$

$$P(\text{headache} \wedge \text{cold} \mid \sim \text{sunny}) = P(\text{headache} \wedge \text{cold} \wedge \sim \text{sunny}) / P(\sim \text{sunny}) \\ = 0.072 / (0.072 + 0.008 + 0.144 + 0.576) = 0.09$$

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Is there anything we can do?

- How do we avoid these two problems?
 - no solution in general
 - but in practice there is structure we can exploit
- We'll use conditional independence

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Independence

- Recall that x and y are **independent** iff:
 - $Pr(x) = Pr(x|y)$ iff $Pr(y) = Pr(y|x)$ iff $Pr(xy) = Pr(x)Pr(y)$
 - intuitively, learning y doesn't influence beliefs about x
- x and y are **conditionally independent given z** iff:
 - $Pr(x|z) = Pr(x|yz)$ iff $Pr(y|z) = Pr(y|xz)$ iff $Pr(xy|z) = Pr(x|z)Pr(y|z)$ iff ...
 - intuitively, learning y doesn't influence your beliefs about x *if you already know z*
 - e.g., learning someone's mark on 486 exam can influence the probability you assign to a specific GPA; but if you already knew the **final** 486 grade, learning the exam mark would *not* influence your GPA assessment

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Variable Independence

- Two **variables** X and Y are conditionally independent given variable Z iff x, y are conditionally independent given z for all $x \in \text{Dom}(X), y \in \text{Dom}(Y), z \in \text{Dom}(Z)$
 - Also applies to sets of variables X, Y, Z
 - Also to unconditional case (X, Y independent)
- If you know the value of Z (*whatever it is*), nothing you learn about Y will influence your beliefs about X
 - these definitions differ from earlier ones (which talk about events, not variables)

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What good is independence?

- Suppose (say, boolean) variables X_1, X_2, \dots, X_n are mutually independent
 - We can specify full joint distribution using only n parameters (linear) instead of $2^n - 1$ (exponential)
- How? Simply specify $Pr(x_1), \dots, Pr(x_n)$
 - From this we can recover the probability of any world or any (conjunctive) query easily
 - Recall $P(x,y)=P(x)P(y)$ and $P(x|y)=P(x)$ and $P(y|x)=P(y)$

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Example

- 4 independent boolean random variables X_1, X_2, X_3, X_4
- $P(x_1)=0.4, P(x_2)=0.2, P(x_3)=0.5, P(x_4)=0.8$

$$P(x_1, \sim x_2, x_3, x_4) = P(x_1)(1 - P(x_2))P(x_3)P(x_4) \\ = (0.4)(0.8)(0.5)(0.8) \\ = 0.128$$

$$P(x_1, x_2, x_3 | x_4) = P(x_1)P(x_2)P(x_3) \mathbf{1} \\ = (0.4)(0.2)(0.5)(1) \\ = 0.04$$

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The Value of Independence

- Complete independence reduces both *representation of joint* and *inference* from $O(2^n)$ to $O(n)!$
- **Unfortunately**, such complete mutual independence is very rare. Most realistic domains do not exhibit this property.
- **Fortunately**, most domains do exhibit a fair amount of conditional independence. We can exploit conditional independence for representation and inference as well.
- **Bayesian networks** do just this

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An Aside on Notation

- $Pr(X)$ for variable X (or set of variables) refers to the *(marginal) distribution* over X . $Pr(X|Y)$ refers to family of conditional distributions over X , one for each $y \in \text{Dom}(Y)$.
- Distinguish between $Pr(X)$ -- which is a distribution -- and $Pr(x)$ or $Pr(\sim x)$ (or $Pr(x_i)$ for nonboolean vars) -- which are numbers. Think of $Pr(X)$ as a function that accepts any $x_i \in \text{Dom}(X)$ as an argument and returns $Pr(x_i)$.
- Think of $Pr(X|Y)$ as a function that accepts any x_i and y_k and returns $Pr(x_i | y_k)$. Note that $Pr(X|Y)$ is not a single distribution; rather it denotes the family of distributions (over X) induced by the different $y_k \in \text{Dom}(Y)$

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Exploiting Conditional Independence

- Consider a story:
 - If Pascal woke up too early E , Pascal probably needs coffee C ; if Pascal needs coffee, he's likely grumpy G . If he is grumpy then it's possible that the lecture won't go smoothly L . If the lecture does not go smoothly then the students will likely be sad S .



E - Pascal woke too early G - Pascal is grumpy S - Students are sad
 C - Pascal needs coffee L - The lecture did not go smoothly

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Conditional Independence



- If you learned any of E, C, G , or L , would your assessment of $Pr(S)$ change?
 - If any of these are seen to be true, you would increase $Pr(s)$ and decrease $Pr(\sim s)$.
 - So S is *not independent* of E , or C , or G , or L .
- If you knew the value of L (true or false), would learning the value of E, C , or G influence $Pr(S)$?
 - Influence that these factors have on S is mediated by their influence on L .
 - Students aren't sad because Pascal was grumpy, they are sad because of the lecture.
 - So S is *independent* of E, C , and G , *given* L

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Conditional Independence



- So S is *independent* of E , and C , and G , *given* L
- Similarly:
 - S is *independent* of E , and C , *given* G
 - G is *independent* of E , *given* C
- This means that:
 - $\Pr(S | L, \{G, C, E\}) = \Pr(S | L)$
 - $\Pr(L | G, \{C, E\}) = \Pr(L | G)$
 - $\Pr(G | C, \{E\}) = \Pr(G | C)$
 - $\Pr(C | E)$ and $\Pr(E)$ don't "simplify"

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Conditional Independence

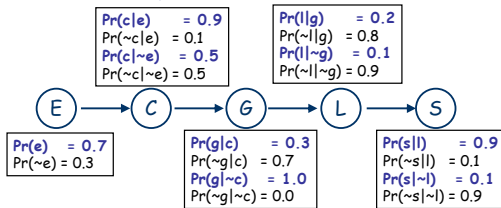


- By the chain rule (for any instantiation of $S \dots E$):
 - $\Pr(S, L, G, C, E) = \Pr(S | L, G, C, E) \Pr(L | G, C, E) \Pr(G | C, E) \Pr(C | E) \Pr(E)$
- By our independence assumptions:
 - $\Pr(S, L, G, C, E) = \Pr(S | L) \Pr(L | G) \Pr(G | C) \Pr(C | E) \Pr(E)$
- We can specify the full joint by specifying five *local conditional distributions*: $\Pr(S | L)$; $\Pr(L | G)$; $\Pr(G | C)$; $\Pr(C | E)$; and $\Pr(E)$

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Example Quantification



- Specifying the joint requires only 9 parameters (if we note that half of these are "1 minus" the others), instead of 31 for explicit representation
 - linear in number of vars instead of exponential!
 - linear generally if dependence has a chain structure

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Inference is Easy



- Want to know $P(g)$? Use sum out rule:

$$\begin{aligned}
 P(g) &= \sum_{c_i \in \text{Dom}(C)} \Pr(g | c_i) \Pr(c_i) \\
 &= \sum_{c_i \in \text{Dom}(C)} \Pr(g | c_i) \sum_{e_i \in \text{Dom}(E)} \Pr(c_i | e_i) \Pr(e_i)
 \end{aligned}$$

These are all terms specified in our local distributions!

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Inference is Easy



- Computing $P(g)$ in more concrete terms:
 - $P(c) = P(c|e)P(e) + P(c|\sim e)P(\sim e)$
 $= 0.8 * 0.7 + 0.5 * 0.3 = 0.78$
 - $P(\sim c) = P(\sim c|e)P(e) + P(\sim c|\sim e)P(\sim e) = 0.22$
 $\cdot P(\sim c) = 1 - P(c)$, as well
 - $P(g) = P(g|c)P(c) + P(g|\sim c)P(\sim c)$
 $= 0.7 * 0.78 + 0.0 * 0.22 = 0.546$
 - $P(\sim g) = 1 - P(g) = 0.454$

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Bayesian Networks

- The structure above is a *Bayesian network*.
 - *Graphical representation* of the direct dependencies over a set of variables + a set of *conditional probability tables (CPTs)* quantifying the strength of those influences.
- Bayes nets generalize the above ideas in very interesting ways, leading to effective means of representation and inference under uncertainty.

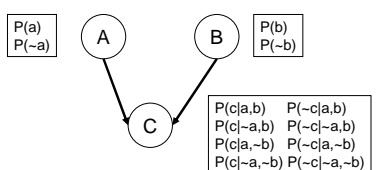
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Bayesian Networks

aka belief networks, probabilistic networks

- A BN over variables $\{X_1, X_2, \dots, X_n\}$ consists of:
 - a DAG whose nodes are the variables
 - a set of CPTs $(Pr(X_i | Parents(X_i)))$ for each X_i



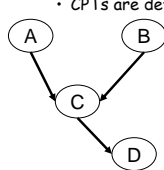
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Bayesian Networks

aka belief networks, probabilistic networks

- Key notions
 - parents of a node: $Par(X_i)$
 - children of node
 - descendants of a node
 - ancestors of a node
 - family: set of nodes consisting of X_i and its parents
 - CPTs are defined over families in the BN

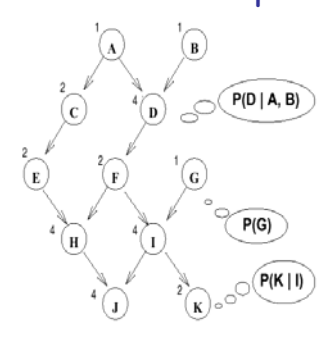


Parents(C)={A,B}
 Children(A)={C}
 Descendants(B)={C,D}
 Ancestors(D)={A,B,C}
 Family{C}={C,A,B}

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An Example Bayes Net



- A few CPTs are "shown"
- Explicit joint requires $2^{11} - 1 = 2047$ params
- BN requires only 27 params (the number of entries for each CPT is listed)

$P(D | A, B)$

$P(G)$

$P(K | I)$

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Semantics of a Bayes Net

- The structure of the BN means: every X_i is *conditionally independent of all of its nondescendants given its parents*.

$Pr(X_i | S \cup Par(X_i)) = Pr(X_i | Par(X_i))$

for any subset $S \subseteq NonDescendants(X_i)$

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Semantics of Bayes Nets

- If we ask for $P(x_1, x_2, \dots, x_n)$ we obtain
 - assuming an ordering consistent with network
- By the chain rule, we have:

$$P(x_1, x_2, \dots, x_n) = P(x_n | x_{n-1}, \dots, x_1) P(x_{n-1} | x_{n-2}, \dots, x_1) \dots P(x_1)$$

$$= P(x_n | Par(x_n)) P(x_{n-1} | Par(x_{n-1})) \dots P(x_1)$$
- Thus, the joint is recoverable using the parameters (CPTs) specified in an arbitrary BN

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Constructing a Bayes Net

- Given any distribution over variables X_1, X_2, \dots, X_n , we can construct a Bayes net that faithfully represents that distribution.

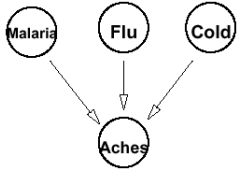
Take any ordering of the variables (say, the order given), and go through the following procedure for X_n down to X_1 . Let $Par(X_n)$ be any subset $S \subseteq \{X_1, \dots, X_{n-1}\}$ such that X_n is independent of $\{X_1, \dots, X_{n-1}\} - S$ given S . Such a subset must exist (convince yourself). Then determine the parents of X_{n-1} in the same way, finding a similar $S \subseteq \{X_1, \dots, X_{n-2}\}$, and so on. In the end, a DAG is produced and the BN semantics must hold by construction.

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Causal Intuitions

- The construction of a BN is simple
 - works with arbitrary orderings of variable set
 - but some orderings are much better than others!
 - generally, if ordering/dependence structure reflects causal intuitions, a more natural, compact BN results

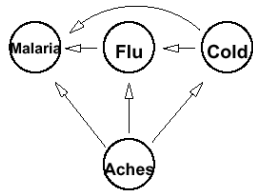


- In this BN, we've used the ordering Mal, Cold, Flu, Aches to build BN for distribution P for Aches
 - Variable can only have parents that come earlier in the ordering

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Causal Intuitions

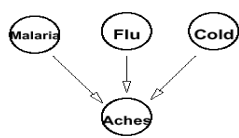
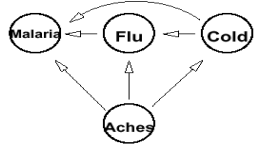
- Suppose we build the BN for distribution P using the opposite ordering
 - i.e., we use ordering Aches, Cold, Flu, Malaria
 - resulting network is more complicated!



- Mal depends on Aches; but it also depends on Cold, Flu *given* Aches
 - Cold, Flu *explain away* Mal given Aches
- Flu depends on Aches; but also on Cold *given* Aches
- Cold depends on Aches

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Compactness

1+1+1+8=11 numbers
1+2+4+8=15 numbers

In general, if each random variable is directly influenced by at most k others, then each CPT will be at most 2^k . Thus the entire network of n variables is specified by $n2^k$.

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Testing Independence

- Given BN, how do we determine if two variables X, Y are independent (given evidence E)?
 - we use a (simple) graphical property
- D-separation:** A set of variables E *d-separates* X and Y if it *blocks every undirected path* in the BN between X and Y .
- X and Y are conditionally independent given evidence E if E *d-separates* X and Y
 - thus BN gives us an easy way to tell if two variables are independent (set $E = \emptyset$) or cond. independent

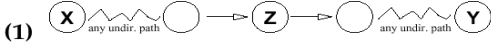
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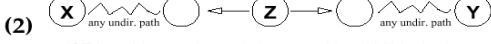
Blocking in D-Separation

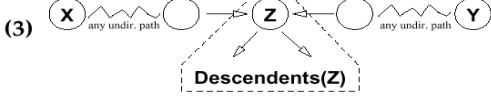
- Let P be an undirected path from X to Y in a BN. Let E be an evidence set. We say E *blocks path* P iff there is some node Z on the path such that:
 - Case 1:** one arc on P *goes into* Z and one *goes out* of Z , and $Z \in E$; or
 - Case 2:** both arcs on P leave Z , and $Z \in E$; or
 - Case 3:** both arcs on P enter Z and *neither Z , nor any of its descendants, are in E .*

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Blocking: Graphical View

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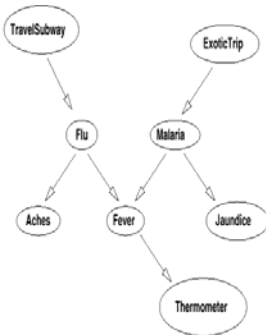
If Z in evidence, the path between X and Y blocked
- 

If Z in evidence, the path between X and Y blocked
- 

If Z is *not* in evidence and *no* descendent of Z is in evidence, then the path between X and Y is blocked

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D-Separation: Intuitions



1. Subway and Thermometer?
2. Aches and Fever?
3. Aches and Thermometer?
4. Flu and Malaria?
5. Subway and ExoticTrip?

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D-Separation: Intuitions

- Subway and Therm are dependent; but are independent given Flu (since Flu blocks the only path)
- Aches and Fever are dependent; but are independent given Flu (since Flu blocks the only path). Similarly for Aches and Therm (dependent, but indep. given Flu).
- Flu and Mal are indep. (given no evidence): Fever blocks the path, since it is *not in evidence*, nor is its descendant Therm. Flu, Mal are dependent given Fever (or given Therm): nothing blocks path now.
- Subway, ExoticTrip are indep.; they are dependent given Therm; they are indep. given Therm and Malaria. This for exactly the same reasons for Flu/Mal above.

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Next class

- Inference with Bayesian networks
- Section 14.4

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