6.867 Machine learning | Prof. Tommi Jaakkola | Week 13, Tuesday, November 26th, 2013 | Lecture 23

Lecture 23: Inference in Bayesian networks

Final will be on December 10, 7-10pm.

Today we'll try to infer more on *arbitrary graphs*.

Directed acyclic graph (DAG)

Such graphs capture independence properties.

- They have nodes from 1, ..., n
- Random variables are associated with the nodes $x_1, ..., x_n$
- Each node has a parent pa_i , i = 1, ..., n. $X_{pa_i} = \{X_j\}_{j \in pa_i}$
- If the graph is acyclic then there exists a node with no parent: $\exists k \text{ s.t. } X_{pa_k} = \emptyset$



Probabilities on any such graph can be computed as follows:

$$P(x_1, \dots, x_n) = \prod_{i=1\dots n} P_i(x_i | x_{pa_i})$$

- s_1 is a a parent of x_1

- s_1 and s_2 are ancestors of x_2
- s_2 and x_2 are descendants of s_1
- This is an "open V-structure," E = earthquake, B = burglary, A = alarm
- $E \perp B$ (E and B are independent of each other)



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6.867 Machine learning | Prof. Tommi Jaakkola | Week 13, Tuesday, November 26th, 2013 | Lecture 23 P(E=A) = 0.01 P(B=A) = 0.04

$$P(A = I | E, B) = \begin{cases} A, E = A & \text{ord} & B = A \\ 0, & 0. & W \end{cases}$$

If we apply our graph inference rule:

$$P(x_1, \dots, x_n) = \prod_{i=1\dots n} P_i(x_i | x_{pa_i})$$

We get:

$$P(E,B) = \sum_{A} P(E,B,A) = \sum_{A} P(A|E,B)P(E)P(B) = P(E)P(B)\sum_{A} P(A|E,B) = P(E)P(B)$$

Are $E \perp B \mid A$? If I know there was an alarm, that implies either an earthquake or a burglary occurred so I cannot set the variables independently. Thus, they are not independent given A. This is called **induced dependence**.

$$P(B = 1 | A = 1) = .5$$

Now we can include a "radio report" event in the graph, such that if an earthquake occurred, a radio report will be released with probability 1. Now we can ask if $R \perp B$? Yes.



What is P(B = 1 | R = 1, A = 1) = .01 = P(B = 1)

Why is that? "Explaining away" phenomenon (See <u>http://www.cs.ubc.ca/~murphyk/Bayes/bnintro.html</u>). Now, we can add a *"will leave"* event in the graph.

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6.867 Machine learning | Prof. Tommi Jaakkola | Week 13, Tuesday, November 26th, 2013 | Lecture 23 Is $L \perp B \mid A$? No.

How to read off independence statements from the graph

D-separation (and independence), says $x_i \perp x_j \mid x_k$, if *i* and *j* are separated (no path between them) by *k* in the *moralized* ancestral graph.

How can we answer such independence questions?

- 1. Keep only x_i, x_j, x_k and their ancestors (prune the graph)
- 2. "marry" the parents of all the nodes (in my initial notes I had just "of the 3 nodes"): you draw an edge between any two pair of parents
 - a. After this point you can think of it as an undirected graph
- 3. $x_i \perp x_i \mid x_k$ is true if k separates i and j in the resulting graph





P(E, B, R, A) = P(E)P(B|E)P(R|E, B)P(A|E, B, R)

$B \perp E$

$R\perp B\mid E$

$A \perp R \mid E, B$

P(E, B, R, A) = P(E)P(B|E)P(R|E, B)P(A|E, B, R) = P(E)P(B)P(R|E)P(A|E, B)

What does this mean: Variable is independent of its preceding non-parents given the parents.

A variable is conditionally independent of its non-descendants given its immediate parents.

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6.867 Machine learning | Prof. Tommi Jaakkola | Week 13, Tuesday, November 26th, 2013 | Lecture 23 Equivalence of graphs

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Definition: Graph G and G' are equivalent iff they make the same independence assumptions.

Two graphs are equivalent if:

- they have the same set of edges (undirected)
- they have the same open v-structures

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