

Lecture 11 Decision Networks

October 20, 2009
CS 486/686

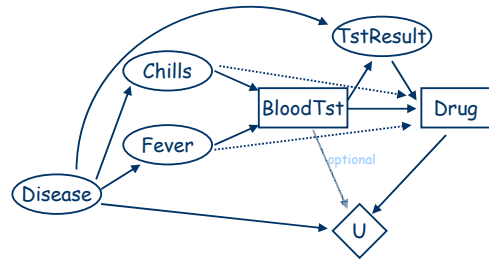
Outline

- Decision Networks
 - Aka Influence diagrams
- Value of information
- Russell and Norvig: Sect 16.5-16.6

Decision Networks

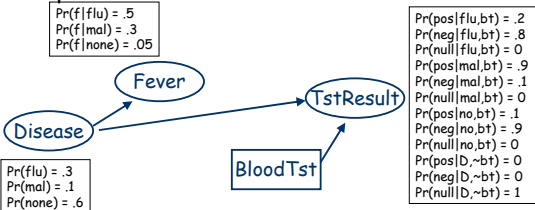
- *Decision networks* (also known as *influence diagrams*) provide a way of representing sequential decision problems
 - basic idea: represent the variables in the problem as you would in a BN
 - add decision variables - variables that you "control"
 - add utility variables - how good different states are

Sample Decision Network



Decision Networks: Chance Nodes

- **Chance nodes**
 - random variables, denoted by circles
 - as in a BN, probabilistic dependence on parents



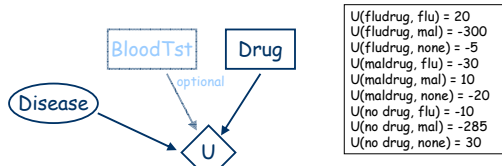
Decision Networks: Decision Nodes

- **Decision nodes**
 - variables set by decision maker, denoted by squares
 - parents reflect *information available* at time decision is to be made
- Example: the actual values of Ch and Fev will be observed before the decision to take test must be made
 - agent can make *different decisions* for each instantiation of parents (i.e., policies)



Decision Networks: Value Node

- **Value node**
 - specifies utility of a state, denoted by a diamond
 - utility depends *only on state of parents* of value node
 - generally: only one value node in a decision network
- Utility depends only on disease and drug

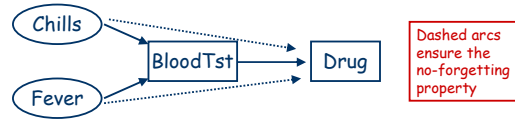


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7

Decision Networks: Assumptions

- Decision nodes are totally ordered
 - decision variables D_1, D_2, \dots, D_n
 - decisions are made in sequence
 - e.g., BloodTst (yes,no) decided before Drug (fd,md,no)
- **No-forgetting property**
 - any information available when decision D_i is made is available when decision D_j is made (for $i < j$)
 - thus all parents of D_i are parents of D_j

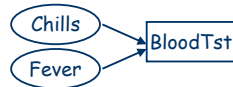


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8

Policies

- Let $Par(D_i)$ be the parents of decision node D_i
 - $Dom(Par(D_i))$ is the set of assignments to parents
- A policy δ is a set of mappings δ_i , one for each decision node D_i
 - $\delta_i : Dom(Par(D_i)) \rightarrow Dom(D_i)$
 - δ_i associates a decision with each parent asst for D_i
- For example, a policy for BT might be:
 - $\delta_{BT}(c,f) = bt$
 - $\delta_{BT}(c,\sim f) = \sim bt$
 - $\delta_{BT}(\sim c,f) = bt$
 - $\delta_{BT}(\sim c,\sim f) = \sim bt$



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9

Value of a Policy

- **Value of a policy** δ is the expected utility given that decision nodes are executed according to δ
- Given asst \mathbf{x} to the set \mathbf{X} of all chance variables, let $\delta(\mathbf{x})$ denote the asst to decision variables dictated by δ
 - e.g., asst to D_1 determined by its parents' asst in \mathbf{x}
 - e.g., asst to D_2 determined by its parents' asst in \mathbf{x} along with whatever was assigned to D_1
 - etc.
- Value of δ :

$$EU(\delta) = \sum_{\mathbf{x}} P(\mathbf{X}, \delta(\mathbf{X})) U(\mathbf{X}, \delta(\mathbf{X}))$$

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10

Optimal Policies

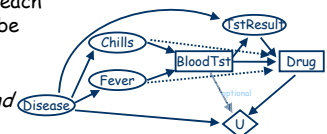
- An **optimal policy** is a policy δ^* such that $EU(\delta^*) \geq EU(\delta)$ for all policies δ
- We can use the dynamic programming principle yet again to avoid enumerating all policies
- We can also use the structure of the decision network to use **variable elimination** to aid in the computation

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11

Computing the Best Policy

- We can work backwards as follows
- First compute optimal policy for Drug (last dec'n)
 - for each asst to parents (C,F,BT,TR) and for each decision value (D = md,fd,none), **compute the expected value** of choosing that value of D
 - set policy choice for each value of parents to be the value of D that has max value
 - eg: $\delta_D(c,f,bt,pos) = md$



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12

Computing the Best Policy

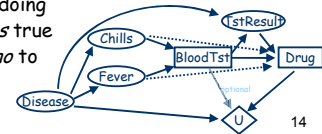
- Next compute policy for BT given policy $\delta_D(C, F, BT, TR)$ just determined for Drug
 - since $\delta_D(C, F, BT, TR)$ is fixed, we can treat Drug as a normal random variable with deterministic probabilities
 - i.e., for any instantiation of parents, value of Drug is fixed by policy δ_D
 - this means we can solve for optimal policy for BT just as before
 - only uninstantiated vars are random vars (once we fix *its* parents)

13

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Computing the Best Policy

- How do we compute these expected values?
 - suppose we have asst $\langle c, f, bt, pos \rangle$ to parents of Drug
 - we want to compute EU of deciding to set Drug = md
 - we can run **variable elimination!**
- Treat C, F, BT, TR, Dr as evidence
 - this reduces factors (e.g., U restricted to bt, md depends on Dis)
 - eliminate remaining variables (e.g., only Disease left)
 - left with factor: **$EU(md|c, f, bt, pos) = \sum_{Dis} P(Dis|c, f, bt, pos, md) U(Dis, bt, md)$**
- We now know EU of doing $Dr=md$ when c, f, bt, pos true
- Can do same for fd, no to decide which is best



14

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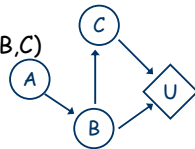
Computing Expected Utilities

- The preceding slide illustrates a general phenomenon
 - computing expected utilities with BNs is quite easy
 - utility nodes are just factors that can be dealt with using variable elimination

$$EU = \sum_{A,B,C} P(A,B,C) U(B,C)$$

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

- Just eliminate variables in the usual way



15

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Optimizing Policies: Key Points

- If a decision node D has no decisions that follow it, we can find its policy by instantiating each of its parents and computing the expected utility of each decision for each parent instantiation
 - no-forgetting means that all other decisions are instantiated (they must be parents)
 - its easy to compute the expected utility using VE
 - the number of computations is quite large: we run expected utility calculations (VE) for each parent instantiation together with each possible decision D might allow
 - policy: choose max decision for each parent instant'n

16

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Optimizing Policies: Key Points

- When a decision D node is optimized, it can be treated as a random variable
 - for each instantiation of its parents we now know what value the decision should take
 - just treat policy as a new CPT: for a given parent instantiation x , D gets $\delta(x)$ with probability 1 (all other decisions get probability zero)
- If we optimize from last decision to first, at each point we can optimize a specific decision by (a bunch of) simple VE calculations
 - its successor decisions (optimized) are just normal nodes in the BNs (with CPTs)

17

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Decision Network Notes

- Decision networks commonly used by decision analysts to help structure decision problems
- Much work put into computationally effective techniques to solve these
 - common trick: replace the decision nodes with random variables at outset and solve a plain Bayes net (a subtle but useful transformation)
- Complexity much greater than BN inference
 - we need to solve a number of BN inference problems
 - one BN problem for each setting of decision node parents and decision node value

18

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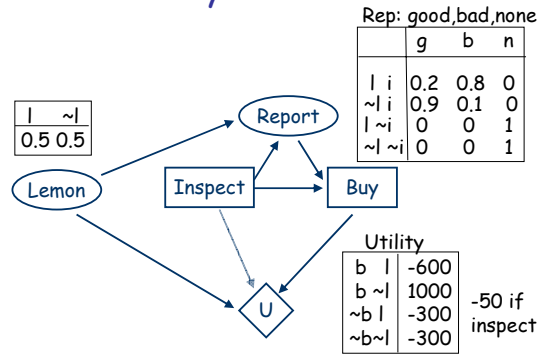
A Decision Net Example

- Setting: you want to buy a used car, but there's a good chance it is a "lemon" (i.e., prone to breakdown). Before deciding to buy it, you can take it to a mechanic for inspection. S/he will give you a report on the car, labeling it either "good" or "bad". A good report is positively correlated with the car being sound, while a bad report is positively correlated with the car being a lemon.
- The report costs \$50 however. So you could risk it, and buy the car without the report.
- Owning a sound car is better than having no car, which is better than owning a lemon.

19

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Car Buyer's Network



20

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Evaluate Last Decision: Buy (1)

- $EU(B|I,R) = \sum_L P(L|I,R,B) U(L,I,B)$
- $I = i, R = g$:
 - $EU(\text{buy}) = P(|i,g,\text{buy}) U(i,i,\text{buy}) + P(\sim|i,g,\text{buy}) U(\sim|i,i,\text{buy})$
 $= .18 \cdot -650 + .82 \cdot 950 = 662$
 - $EU(\sim\text{buy}) = P(|i,g,\sim\text{buy}) U(i,i,\sim\text{buy}) + P(\sim|i,g,\sim\text{buy}) U(\sim|i,i,\sim\text{buy})$
 $= -300 - 50 = -350$ (-300 indep. of lemon)
 - So optimal $\delta_{Buy}(i,g) = \text{buy}$

21

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Evaluate Last Decision: Buy (2)

- $I = i, R = b$:
 - $EU(\text{buy}) = P(|i,b,\text{buy}) U(i,i,\text{buy}) + P(\sim|i,b,\text{buy}) U(\sim|i,i,\text{buy})$
 $= .89 \cdot -650 + .11 \cdot 950 = -474$
 - $EU(\sim\text{buy}) = P(|i,b,\sim\text{buy}) U(i,i,\sim\text{buy}) + P(\sim|i,b,\sim\text{buy}) U(\sim|i,i,\sim\text{buy})$
 $= -300 - 50 = -350$ (-300 indep. of lemon)
 - So optimal $\delta_{Buy}(i,b) = \sim\text{buy}$

22

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Evaluate Last Decision: Buy (3)

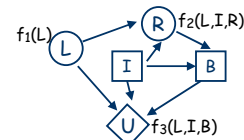
- $I = \sim i, R = n$
 - $EU(\text{buy}) = P(|\sim i,n,\text{buy}) U(i,\sim i,\text{buy}) + P(\sim|\sim i,n,\text{buy}) U(\sim|\sim i,i,\text{buy})$
 $= .5 \cdot -600 + .5 \cdot 1000 = 200$
 - $EU(\sim\text{buy}) = P(|\sim i,n,\sim\text{buy}) U(i,\sim i,\sim\text{buy}) + P(\sim|\sim i,n,\sim\text{buy}) U(\sim|\sim i,i,\sim\text{buy})$
 $= -300$ (-300 indep. of lemon)
 - So optimal $\delta_{Buy}(\sim i,n) = \text{buy}$
- So optimal policy for Buy is:
 - $\delta_{Buy}(i,g) = \text{buy}$; $\delta_{Buy}(i,b) = \sim\text{buy}$; $\delta_{Buy}(\sim i,n) = \text{buy}$
- Note: we don't bother computing policy for $(i,\sim n)$, $(\sim i,g)$, or $(\sim i,b)$, since these occur with probability 0

23

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Using Variable Elimination

Factors: $f_1(L)$ $f_2(L,I,R)$
 $f_3(L,I,B)$
Query: $EU(B)?$
Evidence: $I = i, R = g$
Elim. Order: L



- Restriction: replace $f_2(L,I,R)$ by $f_4(L) = f_2(L,i,g)$
 replace $f_3(L,I,B)$ by $f_5(L,B) = f_3(L,i,B)$
- Step 1: Add $f_6(B) = \sum_L f_1(L) f_4(L) f_5(L,B)$
 Remove: $f_1(L), f_4(L), f_5(L,B)$
- Last factor: $f_6(B)$ is proportional to the expected utility of buy and $\sim\text{buy}$. Select action with highest value.
 Repeat for $EU(B|i,b), EU(B|\sim i,n)$

24

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Alternatively

- N.B.: variable elimination for decision networks computes expected utility that are **not scaled**...
- Can still pick best action, since utility scale is not important (relative magnitude is what matters)
- If we want exact expected utility:
 - Let $X = \text{parents}(U)$
 - $EU(\text{dec}|\text{evidence}) = \sum_X \Pr(X|\text{dec}, \text{evidence}) U(X)$
 - Compute $\Pr(X|\text{dec}, \text{evidence})$ by variable elimination
 - Multiply $\Pr(X|\text{dec}, \text{evidence})$ by $U(X)$
 - Summout X

25

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Evaluate First Decision: Inspect

- $EU(I) = \sum_{L,R} P(L,R|i) U(L,i, \delta_{Buy}(I,R))$
 - where $P(R,L|i) = P(R|L,i)P(L|i)$
 - $EU(i) = (.1)(-650) + (.4)(-350) + (.45)(950) + (.05)(-350) = 205$
 - $EU(\sim i) = P(n, I|\sim i) U(I, \sim i, \text{buy}) + P(n, \sim I|\sim i) U(\sim I, \sim i, \text{buy}) = .5 * -600 + .5 * 1000 = 200$
 - So optimal $\delta_{Inspect}(I) = \text{inspect}$

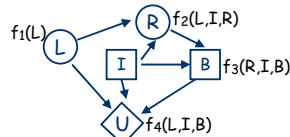
	$P(R,L i)$	δ_{Buy}	$U(L, i, \delta_{Buy})$
g, I	0.1	buy	-600 - 50 = -650
b, I	0.4	~buy	-300 - 50 = -350
g, ~I	0.45	buy	1000 - 50 = 950
b, ~I	0.05	~buy	-300 - 50 = -350

26

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Using Variable Elimination

Factors: $f_1(L)$ $f_2(L,I,R)$
 $f_3(R,I,B)$ $f_4(L,I,B)$
Query: $EU(I)?$
Evidence: none
Elim. Order: L, R, B



N.B. $f_3(R,I,B) = \delta_B(R,I)$

Step 1: Add $f_5(R,I,B) = \sum_L f_1(L) f_2(L,I,R) f_4(L,I,B)$
 Remove: $f_1(L)$ $f_2(L,I,R)$ $f_4(L,I,B)$

Step 2: Add $f_6(I,B) = \sum_R f_3(R,I,B) f_5(R,I,B)$
 Remove: $f_3(R,I,B)$ $f_5(R,I,B)$

Step 3: Add $f_7(I) = \sum_B f_6(I,B)$
 Remove: $f_6(I,B)$

Last factor: $f_7(I)$ is the expected utility of inspect and ~inspect.
 Select action with highest expected utility.

27

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Value of Information

- So optimal policy is: inspect the car and if the report is good buy, otherwise don't buy
 - $EU = 205$
 - Notice that the EU of inspecting the car, then buying it iff you get a good report is 205 (i.e., 255 - 50 (cost of inspection)) which is greater than 200. So inspection improves EU.
 - Suppose inspection cost is \$60: would it be worth it?
 - $EU = 255 - 60 = 195 < EU(\sim i)$
 - The *expected value of information* associated with inspection is 55 (it improves expected utility by this amount ignoring cost of inspection). How? Gives opportunity to change decision (~buy if bad).
 - You should be willing to pay up to \$55 for the report

28

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Next Class

- Probabilistic reasoning over time (Chapter 15)
 - Dynamic Bayesian networks
 - Markov models

29

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