Lecture 11

June 6, 2006
CS 486/686

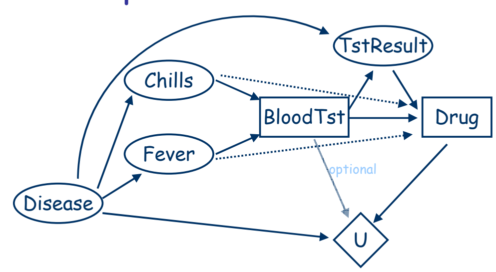
Outline

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

Decision Networks

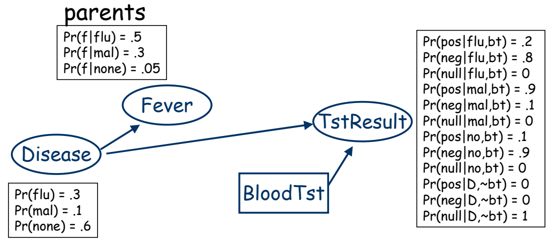
- *Decision networks* (also known as *influence diagrams*) provide a way of representing sequential decision problems
  - basic idea: represent the variables in the problem as you would in a BN
  - add decision variables – variables that you "control"
  - add utility variables – how good different states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

Sample Decision Network



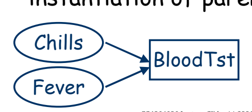
Decision Networks: Chance Nodes

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



Decision Networks: Decision Nodes

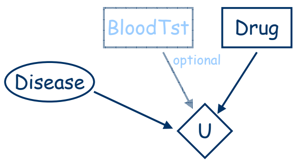
- **Decision nodes**
  - variables decision maker sets, denoted by squares
  - parents reflect *information available* at time decision is to be made
- In example decision node: the actual values of Ch and Fev will be observed before the decision to take test must be made
  - agent can make *different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



BT ∈ {bt, ~bt}

Decision Networks: Value Node

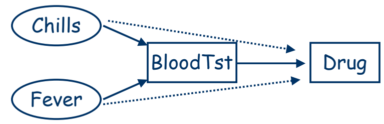
- **Value node**
  - specifies utility of a state, denoted by a diamond
  - utility depends *only on state of parents* of value node
  - generally: only one value node in a decision network
- Utility depends only on disease and drug



U(fludrug, flu) = 20
U(fludrug, mal) = -300
U(fludrug, none) = -5
U(maldrug, flu) = -30
U(maldrug, mal) = 10
U(maldrug, none) = -20
U(no drug, flu) = -10
U(no drug, mal) = -285
U(no drug, none) = 30

Decision Networks: Assumptions

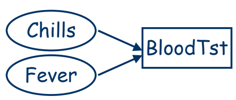
- Decision nodes are totally ordered
  - decision variables D_1, D_2, …, D_n
  - decisions are made in sequence
  - e.g., BloodTst (yes,no) decided before Drug (fd,md,no)
- *No-forgetting property*
  - any information available when decision D_i is made is available when decision D_j is made (for $i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



Dashed arcs ensure the no-forgetting property

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:
  - $\delta_{BT}(c,f) = bt$
  - $\delta_{BT}(c,\sim f) = \sim bt$
  - $\delta_{BT}(\sim c,f) = bt$
  - $\delta_{BT}(\sim c,\sim f) = \sim bt$



Value of a Policy

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

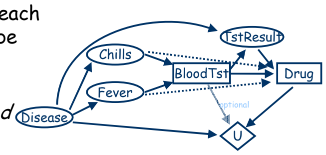
$$EU(\delta) = \Sigma_{\mathbf{X}} P(\mathbf{X}, \delta(\mathbf{X}))\, U(\mathbf{X}, \delta(\mathbf{X}))$$

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

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: $\delta_D(c,f,bt,pos) = md$

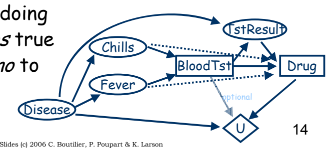


Computing the Best Policy

- 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)

Computing the Best Policy

- How do we compute these expected values?
  - suppose we have asst <*c,f,bt,pos*> 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) = Σ_{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



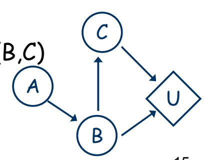
Computing Expected Utilities

- The preceding 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 = $\Sigma_{A,B,C}$ P(A,B,C) U(B,C)

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

- Just eliminate variables in the usual way



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

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 δ(**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
  - it's successor decisions (optimized) are just normal nodes in the BNs (with CPTs)

Decision Network Notes

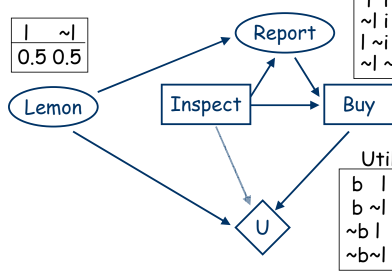
- Decision networks commonly used by decision analysts to help structure decision problems
- Much work put into computationally effective techniques to solve these
  - common trick: replace the decision nodes with random variables at outset and solve a plain Bayes net (a subtle but useful transformation)
- 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

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.

Car Buyer's Network

l	~l
0.5	0.5



Rep: good,bad,none

	g	b	n
l i	0.2	0.8	0
~l i	0.9	0.1	0
l ~i	0	0	1
~l ~i	0	0	1

Utility

b l	-600
b ~l	1000
~b l	-300
~b~l	-300

-50 if inspect

Evaluate Last Decision: Buy (1)

- EU(B|I,R) = Σ_L P(L|I,R,B) U(L,I,B)
- I = i, R = g:
  - EU(buy) = P(l|i,g,buy) U(l,i,buy) + P(~l|i,g,buy) U(~l,i,buy)
    = .18*-650 + .82*950 = 662
  - EU(~buy) = P(l|i,g,~buy) U(l,i,~buy) + P(~l|i,g,~buy) U(~l,i,~buy)
    = -300 - 50 = -350 (-300 indep. of lemon)
  - So optimal δ_{Buy} *(i,g) = buy*

Evaluate Last Decision: Buy (2)

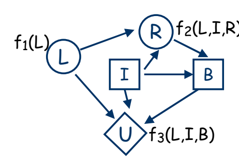
- I = i, R = b:
  - EU(buy) = P(l|i,b,buy) U(l,i,buy) + P(~l|i,b,buy) U(~l,i,buy)
    = .89*-650 + .11*950 = -474
  - EU(~buy) = P(l|i,b,~buy) U(l,i,~buy) + P(~l|i, b,~buy) U(~l,i,~buy)
    = -300 - 50 = -350 (-300 indep. of lemon)
  - So optimal δ_{Buy} *(i,b) = ~buy*

Evaluate Last Decision: Buy (3)

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

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 $f_5(L,B) = f_2(L,i,B)$
Step 1: Add $f_6(B) = \Sigma_L f_1(L) f_4(L) f_5(L,B)$
Remove: $f_1(L)$, $f_4(L)$, $f_5(L,B)$
Last factor: $f_6(B)$ is the unscaled expected utility of buy and ~buy. Select action with highest (unscaled) expected utility.
Repeat for EU(B|i,b), EU(B|~i,n)

Alternatively

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

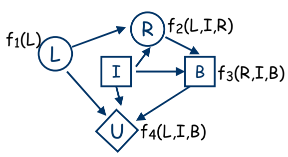
Evaluate First Decision: Inspect

- EU(I) = $\Sigma_{L,R}$ P(L,R|i) U(L,i,δ_{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) = 187.5
  - EU(~i) = P(n,l|~i) U(l,~i,buy) + P(n,~l|~i) U(~l,~i,buy) = .5*-600 + .5*1000 = 200
  - So optimal $\delta_{Inspect}$ *() = ~inspect*

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

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. f3(R,I,B) = δ_B(R,I)
Step 1: Add f_5(R,I,B)= Σ_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)= Σ_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)= Σ_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.

Value of Information

- So optimal policy is: don't inspect, buy the car
  - EU = 200
  - Notice that the EU of inspecting the car, then buying it iff you get a good report, is 237.5 less the cost of the inspection (50). So inspection not worth the improvement in EU.
  - Suppose inspection cost $25: would it be worth it?
    - EU = 237.5 – 25 = 212.5 > EU(~i)
  - The *expected value of information* associated with inspection is 37.5 (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 $37.5 for the report

Next Class

- Reasoning under uncertainty over time
  - Inference in temporal models
  - Hidden Markov Models
  - Dynamic Bayesian Networks
- Russell and Norvig: Chapter 15