Decision Networks
[RN2] Sections 16.5, 16.6
[RN3] Sections 16.5, 16.6

CS 486/686
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Outline

- Decision Networks
 - Aka Influence diagrams
- Value of information

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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

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Sample Decision Network

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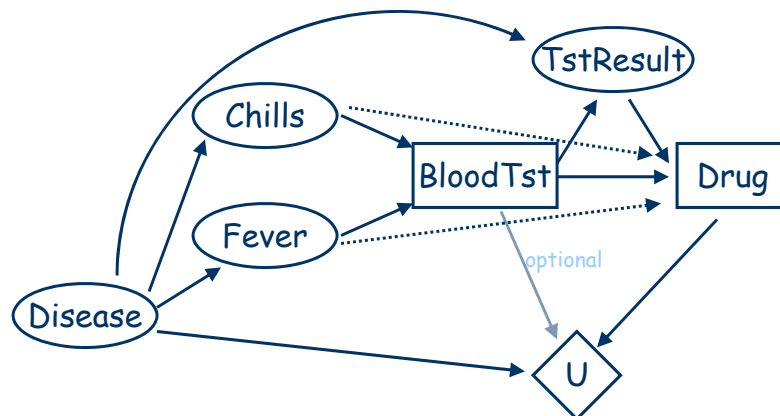
Decision Networks: Chance Nodes

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

Pr(f|flu) = .5
Pr(f|mal) = .3
Pr(f|none) = .05

Pr(pos|flu,bt) = .2
Pr(neg|flu,bt) = .8
Pr(null|flu,bt) = 0
Pr(pos|mal,bt) = .9
Pr(neg|mal,bt) = .1
Pr(null|mal,bt) = 0
Pr(pos|no,bt) = .1
Pr(neg|no,bt) = .9
Pr(null|no,bt) = 0
Pr(pos|D,~bt) = 0
Pr(neg|D,~bt) = 0
Pr(null|D,~bt) = 1

Fever

TstResult

Disease

BloodTst

Pr(flu) = .3
Pr(mal) = .1
Pr(none) = .6
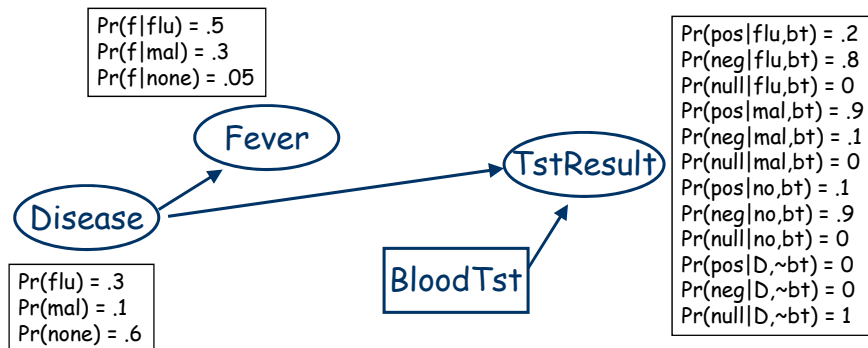
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Decision Networks: Decision Nodes

- **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)
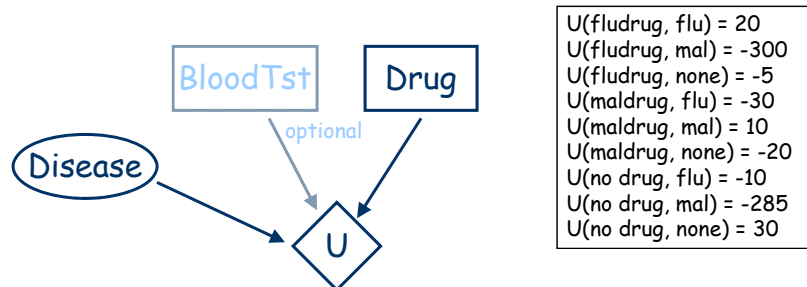
Chills

BloodTst   BT ∈ {bt, ~bt}

Fever

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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

BloodTst   Drug

optional

Disease

U

| 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 |

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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)
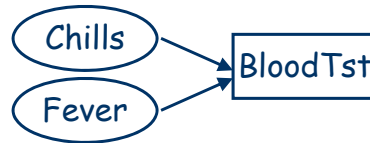 - thus all parents of D_i are parents of D_j

Chills

BloodTst   Drug

Fever

Dashed arcs ensure the no-forgetting property
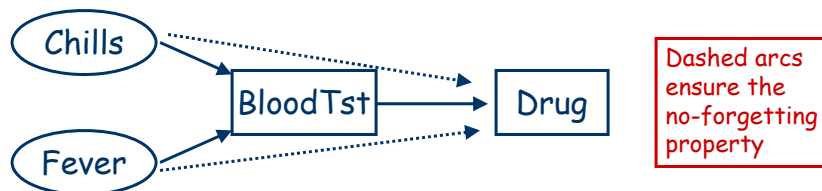
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Policies

- 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$_i$
  - δ_i : *Dom(Par(D$_i$))* → *Dom(D$_i$)*
  - δ_i associates a decision with each parent asst for D$_i$
- For example, a policy for BT might be:
  - δ_{BT} (c,f) = bt
  - δ_{BT} (c,~f) = ~bt
  - δ_{BT} (~c,f) = bt
  - δ_{BT} (~c,~f) = ~bt

Chills → BloodTst
Fever →

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Value of a Policy

- *Value of policy δ* is the expected utility given that decisions 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 :

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

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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: $\delta_D(c,f,bt,pos) = md$
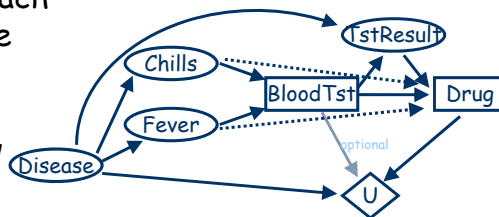
Computing the Best Policy

- 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)

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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
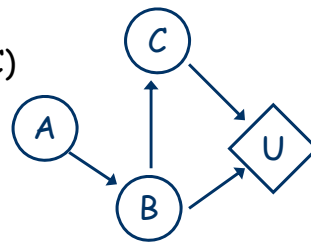- Can do same for *fd,no* to decide which is best

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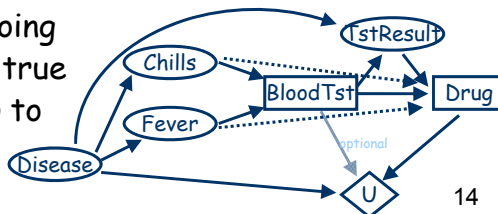
Computing Expected Utilities

- 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

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

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

- Just eliminate variables
  in the usual way

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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

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

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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
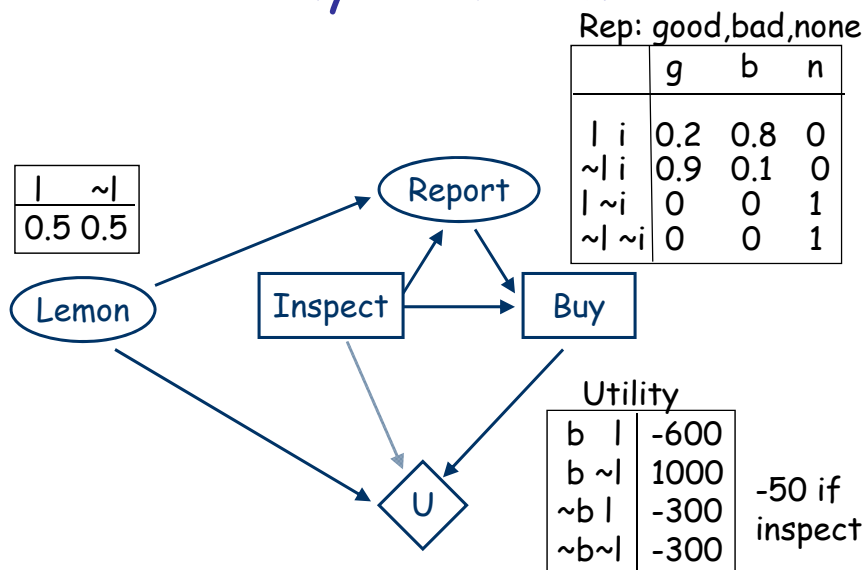
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A Decision Net Example

- 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.

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Car Buyer's Network

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

l	~l
0.5	0.5

Report

Lemon   Inspect   Buy

Utility

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

-50 if inspect

U

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Evaluate Last Decision: Buy (1)

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

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Evaluate Last Decision: Buy (2)

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

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Evaluate Last Decision: Buy (3)

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

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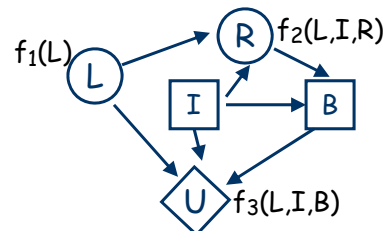
Restriction: replace $f_2(L,I,R)$ by $f_4(L) = f_2(L,i,g)$
  replace $f_3(L,I,B)$ by $f_5(L,B) = f_3(L,i,B)$
Step 1: Add $f_6(B)= \Sigma_L\ f_1(L)\ f_4(L)\ f_5(L,B)$
  Remove: $f_1(L)$, $f_4(L)$, $f_5(L,B)$
Last factor: $f_6(B)$ is proportional to the expected utility of buy and ~buy. Select action with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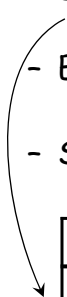
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Alternatively

- 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 = parents(U)
  - $EU(dec|evidence) = \sum_X Pr(X|dec,evidence) \, U(X)$
  - Compute $Pr(X|dec,evidence)$ by variable elimination
  - Multiply $Pr(X|dec,evidence)$ by $U(X)$
  - Summout X

Evaluate First Decision: Inspect

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

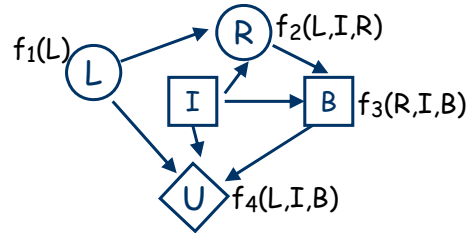|	P(R,L | i)	δ_{Buy}	U(L, i, δ_{Buy})
g,l	0.1	buy	-600 - 50 = -650
b,l	0.4	~buy	-300 - 50 = -350
g,~l	0.45	buy	1000 - 50 = 950
b,~l	0.05	~buy	-300 - 50 = -350

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

$f_1(L)$ R $f_2(L,I,R)$
L I B $f_3(R,I,B)$
U $f_4(L,I,B)$

N.B. $f3(R,I,B) = \delta_B(R,I)$

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.

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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(~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

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