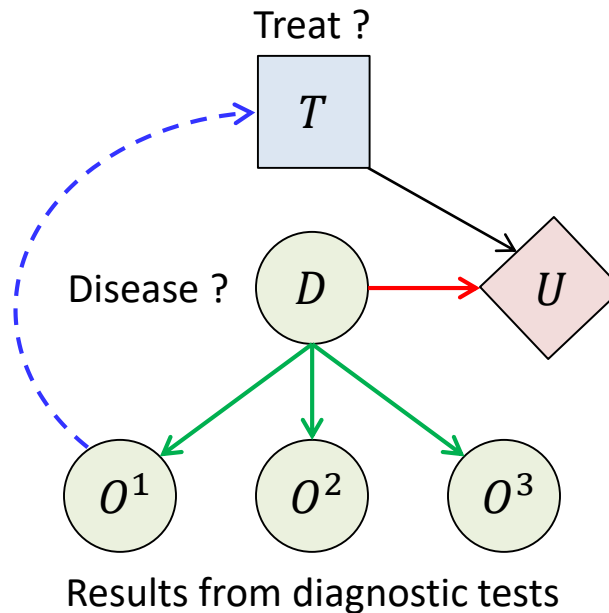





L11. Influential Diagram

Introduction

Bayesian Network + **Decision node** + **Utility node** = **Decision network (Influential Diagram)**

- make rational decisions based on a probabilistic model and utility function



-  **A chance node** corresponds to a random variable
-  **A decision node** corresponds to each decision to be made
-  **A utility node** corresponds to an additive utility component

How to compare the plausibility of different statements?

A : “We can be a millionaire if we go to graduate school”

vs

B : “We can be a millionaire if we go to Samsung”

- If you believe A more than B , you can write $A \succ B$
- If you believe B more than A , you can write $A \prec B$
- If you have the same belief, you can write $A \sim B$

Constraints on Rational Preference

Assumptions about relationships of \succ and \sim

- Completeness (comparability) : either $A \succ B$, $A \prec B$ or $A \sim B$
- Transitivity : if $A \succ B$ and $B \succ C$, then $A \succ C$
- Continuity : if $A \succ B \succ C$, there exists a probability p such that $[A: p; C: 1 - p] \sim B$
- Monotonicity: if $A \succ B$, then for any C and probability p , $[A: p; C: 1 - p] \succ [B: p; C: 1 - p]$

The degree of belief can be represented by a real-valued function:

- $P(A) > P(B)$ if and only if $A \succ B$
- $P(A) = P(B)$ if and only if $A \sim B$

- Just as beliefs can be subjective, so can preferences.
- Preference operators can be used to compare preferences over uncertain outcomes. That is, a lottery is a set of probabilities $p_{1:n}$ associated with a set of outcomes $S_{1:n}$.

$$[S_1:p_1; S_2:p_2; \dots; S_n:p_n]$$

- The utility of a lottery is given by

$$U([S_1:p_1; S_2:p_2; \dots; S_n:p_n]) = \sum_{i=1}^n p_i U(S_i)$$

Maximum Expected Utility Principle

- Reach rational decisions with imperfect knowledge of the state of the world.
- Expected utility of taking action a given that we observe o and take action a :

Probabilistic model Utility function

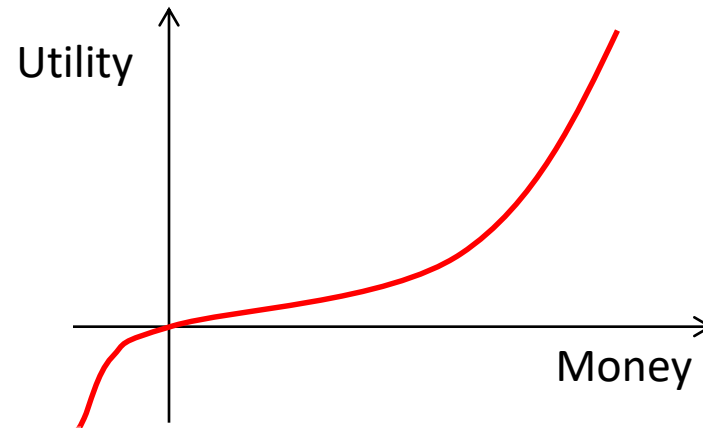
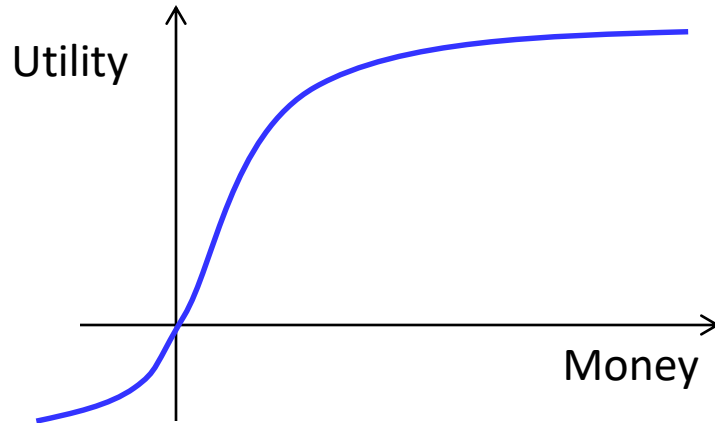
$$EU(a|o) = \sum_{s'} P(s'|o, a) U(s')$$

- The principle of maximum expected utility : a rational agent should choose the action that maximizes expected utility:

$$a^* = \operatorname{argmax}_a EU(a|o)$$

Utility of Money

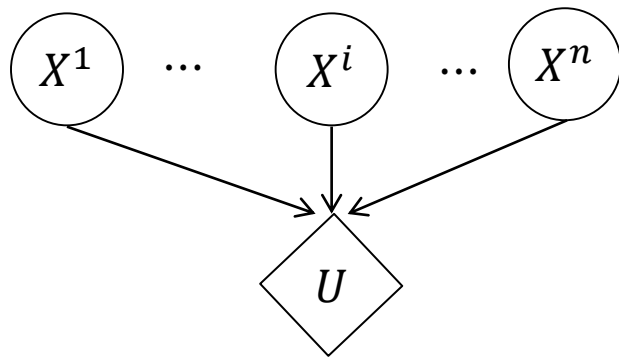
- Monetary values are often used to infer utility function.
Ex) cost of property, human loss damage caused by natural disasters
- It is well known that the relationship between utility and money may not be linear as shown below;



A: Winning 1\$ with a probability 1 vs **B:** Winning 100\$ with a probability 0.01

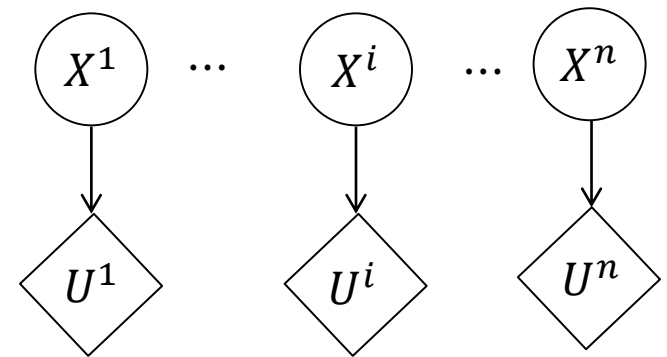
- **Risk averse** : Preference for A (Utility function is concave)
- **Risk neutral** : There is no difference between A and B (Utility function is a linear)
- **Risk seeking** : Preference for B (Utility function is convex)

Multiple Variable Utility Function



$$U(X^{1:n})$$

Assumption:
Sum of single-variable
utility **function**



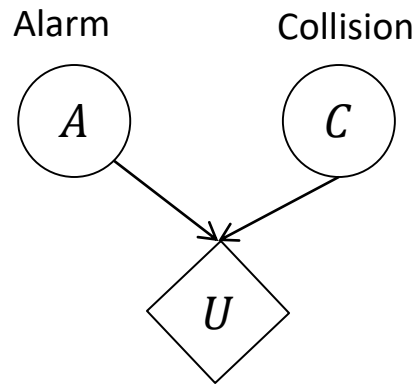
$$U(X^{1:n}) = \sum_{i=1}^n U(X^i)$$

- If X^i is a binary variable,
 2^n parameters are required to specify $U(X^{1:n})$
- If X^i is a binary variable,
 $2n$ parameters are required to specify $U(X^{1:n})$

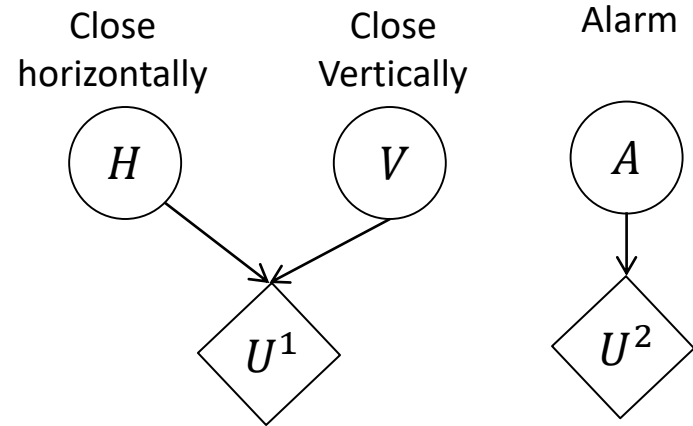
Different additive decomposition can be explicitly imposed on the network structure!

Multiple Variable Utility Function

Example : Collision avoidance system



A	C	U
a^0	c^0	$U(a^0, c^0)$
a^0	c^1	$U(a^0, c^1)$
a^1	c^0	$U(a^1, c^0)$
a^1	c^1	$U(a^1, c^1)$

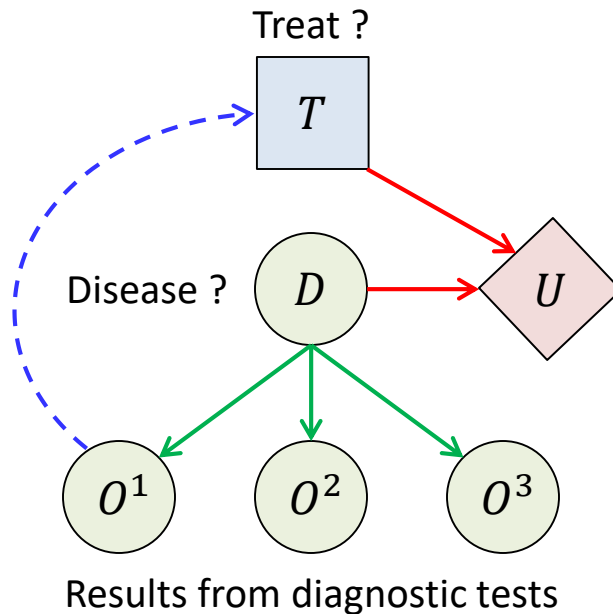


Additive decomposition of
utility function

$$U(h, v, a) = U^1(h, v) + U^2(a)$$

Decision Network

Bayesian Network + **Decision node** + **Utility node** = **Decision network (Influential Diagram)**



T	D	$U(T, D)$
0	0	0
0	1	-10
1	0	-1
1	1	-1

→ Conditional edge

→ Functional edge

----> Information edge
(often omitted)

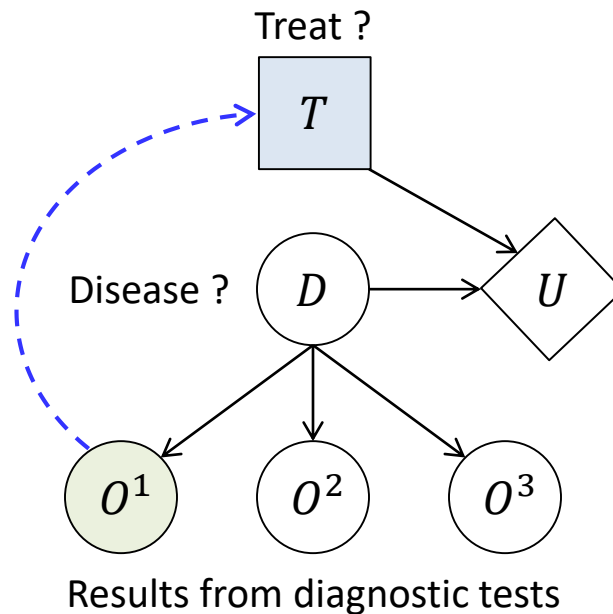
○ A **chance node** corresponds to a random variable

□ A **decision node** corresponds to each decision to be made

◇ A **utility node** corresponds to an additive utility component

Decision Network

Assume we only have a single observation $O^1 = 1 (= o_1^1)$ from test 1



$$\begin{aligned} EU(t^1|o_1^1) &= \sum_{o_3} \sum_{o_2} \sum_d P(d, o_2, o_3|t^1, o_1^1) U(t^1, d, o_1^1, o_2, o_3) \\ &= \sum_d \underbrace{P(d|t^1, o_1^1)}_{\text{Can be computed using many inference methods}} U(t^1, d) \end{aligned}$$

Can be computed using many inference methods

Compare $EU(t^0|o_1^1)$ and $EU(t^1|o_1^1)$ and choose the treatment that leads to maximum EU

Value of Information

- It may be beneficial to administer additional diagnostic tests to reduce the uncertainty about the disease. Then, how to choose a test type to be conducted?
- Expected utility of optimal action given observation o :

$$EU^*(o) = \operatorname{argmax}_a EU(a|o)$$

- The value of information (VOI) about new variable o^{new} (**unobserved**) given the current observation o (**observed**):

$$VOI(o^{new}|o) = \left(\sum_{o^{new}} P(o^{new}|o) EU^*(o^{new}, o) \right) - EU^*(o)$$
$$VOI(o^{new}|o) \geq 0 \quad \forall o^{new}, o$$

- The value of information about a variable is the increase in expected utility with the observation of that variable
- VPI can only capture the increase in expected utility → need to consider the cost associated with observing the new information

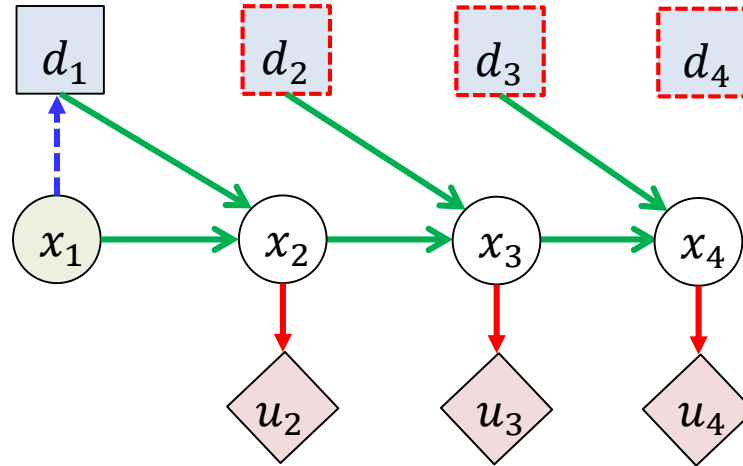
Sequential Decision Making : Partial Ordering

- The sequential decision making problems can be solved by exploiting structure in the problem based on Bayesian Network and the corresponding inference routines
- The sequential decision making problem will be extended later to problems in **control theory** and **reinforcement learning**
- Influential Diagram defines a partial ordering of the nodes:

$$\mathcal{X}_0 < D_1 < \mathcal{X}_1 < D_2, \dots, < \mathcal{X}_{n-1} < D_n < \mathcal{X}_n$$

with \mathcal{X}_k being the variables revealed between decision D_k and D_{k+1}

Sequential Decision Making : Partial Ordering



- Transition probability :

$$p(x_{t+1}|x_t, d_t)$$

- Utility is

$$U(x_{1:4}) = \sum_{t=2}^4 u(x_t)$$

- The probability of the sequence

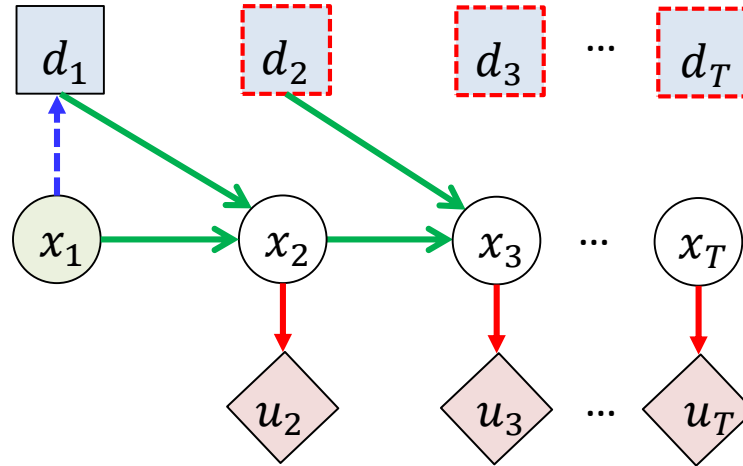
$$p(x_{2:4}|x_1, d_{1:3}) = \prod_{t=1}^3 p(x_{t+1}|x_t, d_t) = p(x_2|x_1, d_1)p(x_3|x_2, d_2)p(x_4|x_3, d_3)$$

- At time $t = 1$, we want to made the decision d_1 that will lead to maximized expected total utility

$$U(d_1|x_1) = \sum_{x_2} \max_{d_2} \sum_{x_3} \max_{d_3} p(x_{2:4}|x_1, d_{1:3}) U(x_{2:4})$$

$$U(d_1|x_1) = \sum_{x_2} \max_{d_2} \sum_{x_3} \max_{d_3} \prod_{t=1}^3 p(x_{t+1}|x_t, d_t) \sum_{t=2}^4 u(x_t)$$

Sequential Decision Making : Partial Ordering



- Transition probability :

$$p(x_{t+1}|x_t, d_t)$$

- Utility is

$$U(x_{1:T}) = \sum_{t=2}^T u(x_t)$$

- The probability of the sequence

$$p(x_{2:T}|x_1, d_{1:T-1}) = \prod_{t=1}^{T-1} p(x_{t+1}|x_t, d_t)$$

- At time $t = 1$, we want to make the decision d_1 that will lead to maximized expected total utility

$$U(d_1|x_1) = \sum_{x_2} \max_{d_2} \sum_{x_3} \max_{d_3} \sum_{x_4} \dots \max_{d_{T-1}} \sum_{x_T} p(x_{2:T}|x_1, d_{1:T-1}) U(x_{2:T})$$

$$U(d_1|x_1) = \sum_{x_2} \max_{d_2} \sum_{x_3} \max_{d_3} \sum_{x_4} \dots \max_{d_{T-1}} \sum_{x_T} \prod_{t=1}^{T-1} p(x_{t+1}|x_t, d_t) \sum_{t=2}^T u(x_t)$$

Sequential Decision Making : Partial Ordering

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with \mathcal{X}_k being the variables revealed between decision D_k and D_{k+1}

- The optimal first decision $D_1 = d_1$ is determined by computing

$$U(d_1|x_0) \equiv \sum_{\mathcal{X}_1} \max_{D_2} \dots \sum_{\mathcal{X}_{n-1}} \max_{D_n} \sum_{\mathcal{X}_n} \prod_{i \in \mathcal{L}} p(x_i | \text{pa}(x_i)) \sum_{j \in \mathcal{T}} U_j(\text{pa}(u_j))$$

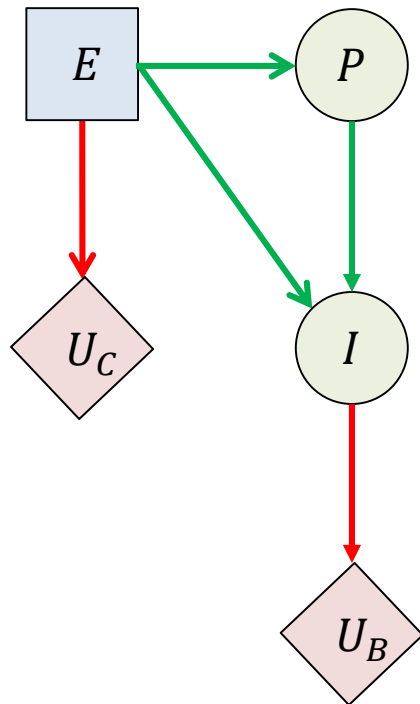
$\text{pa}(x_i) := \text{Parent nodes of } x_i$

\mathcal{L} is a set of random variables and \mathcal{T} is a set of utility variables

- The optimal first decision D_1^* is determined as

$$d_1^* = \operatorname{argmax}_{d_1} U(d_1|x_0)$$

Example: Should I do a PhD?



Do PhD to wind a Nobel Prize?

The ordering : $E^* < \{I, P\}$

Domains

- $\text{dom}(E) = \{\text{do PhD, no PhD}\}$
- $\text{dom}(P) = \{\text{prize, no prize}\}$
- $\text{dom}(I) = \{\text{low, average, high}\}$

Utilities

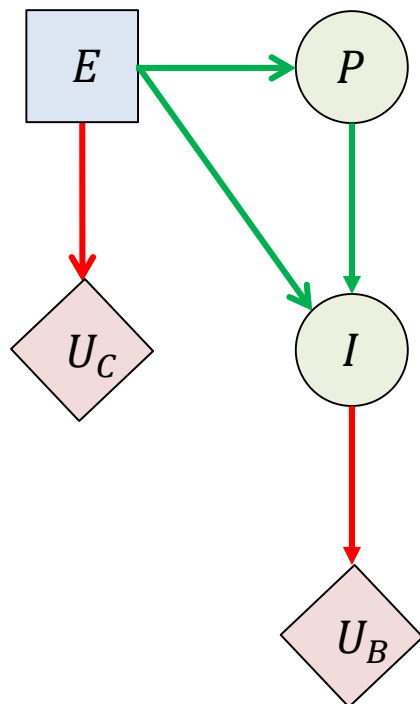
- $U_C(\text{do PhD}) = -50000$, $U_C(\text{no PhD}) = 0$
- $U_B(\text{low}) = 100000$, $U_B(\text{average}) = 200000$, $U_B(\text{high}) = 500000$

Probabilities

- $p(\text{win Nobel Prize}|\text{no PhD}) = 0.0000001$, $p(\text{win Nobel Prize}|\text{do PhD}) = 0.001$
- $p(\text{low}|\text{do PhD, no prize}) = 0.1$, $p(\text{average}|\text{do PhD, no prize}) = 0.5$, $p(\text{high}|\text{do PhD, no prize}) = 0.4$
- $p(\text{low}|\text{no PhD, no prize}) = 0.2$, $p(\text{average}|\text{no PhD, no prize}) = 0.6$, $p(\text{high}|\text{no PhD, no prize}) = 0.2$
- $p(\text{low}|\text{do PhD, prize}) = 0.01$, $p(\text{average}|\text{do PhD, prize}) = 0.04$, $p(\text{high}|\text{do PhD, prize}) = 0.95$
- $p(\text{low}|\text{no PhD, prize}) = 0.01$, $p(\text{average}|\text{no PhD, prize}) = 0.04$, $p(\text{high}|\text{no PhD, prize}) = 0.95$



Example: Should I do a PhD?



Do PhD to wind a Nobel Prize?

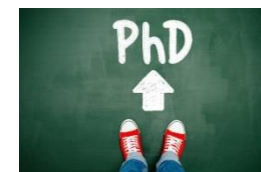
The ordering : $E^* < \{I, P\}$

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- $\text{dom}(P) = \{\text{prize, no prize}\}$
- $\text{dom}(I) = \{\text{low, average, high}\}$

Utilities

- $U_C(\text{do PhD}) = -50000$, $U_C(\text{no PhD}) = 0$
- $U_B(\text{low}) = 100000$, $U_B(\text{average}) = 200000$, $U_B(\text{high}) = 500000$



Probabilities

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- $p(\text{low}|\text{no PhD, prize}) = 0.01$, $p(\text{average}|\text{no PhD, prize}) = 0.04$, $p(\text{high}|\text{no PhD, prize}) = 0.95$

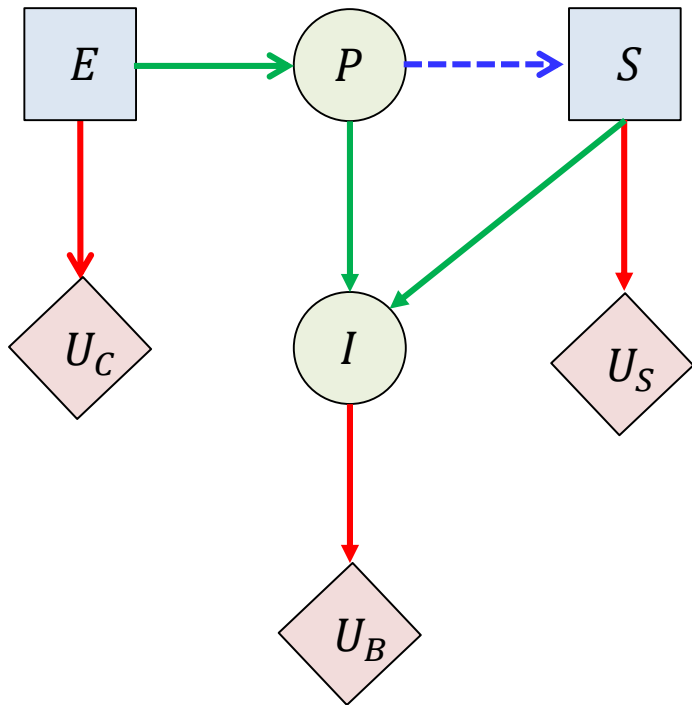
The expected utility of Education is

$$U(E) = \sum_{I,P} p(I|E,P)p(P|E)[U_C(E) + U_B(I)]$$

$$U(\text{do PhD}) = 260174$$

$$U(\text{no PhD}) = 240000$$

Example: PhD and start-up companies



Do PhD to wind a Nobel Prize and start-up?

The ordering : $E^* < P < S^* < I$

Domains

- $\text{dom}(E) = \{\text{do PhD, no PhD}\}$
- $\text{dom}(P) = \{\text{prize, no prize}\}$
- $\text{dom}(I) = \{\text{low, average, high}\}$
- $\text{dom}(S) = \{\text{yes, no}\}$

Utilities

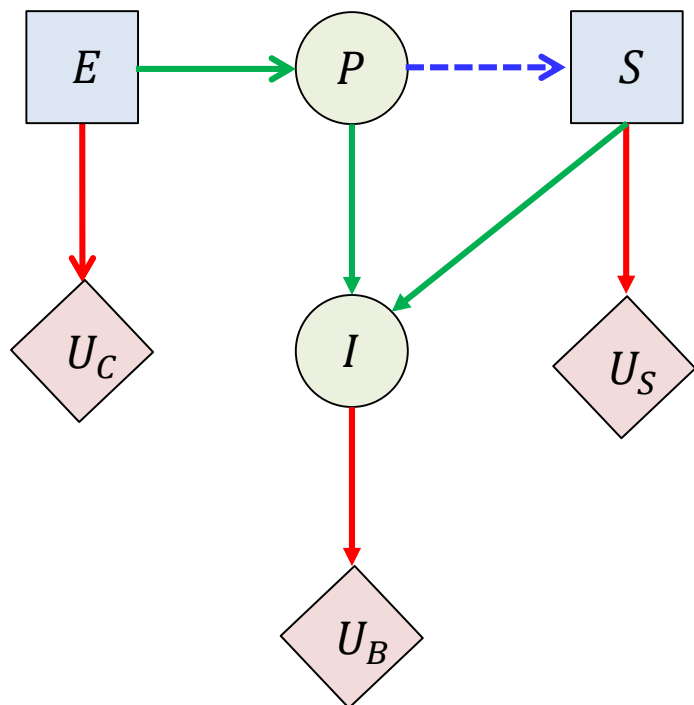
- $U_C(\text{do PhD}) = -50000$, $U_C(\text{no PhD}) = 0$
- $U_B(\text{low}) = 100000$, $U_B(\text{average}) = 200000$, $U_B(\text{high}) = 500000$
- $U_S(\text{start up}) = -200000$, $U_S(\text{no start up}) = 0$

Probabilities

- $p(\text{win Nobel Prize}|\text{no PhD}) = 0.0000001$, $p(\text{win Nobel Prize}|\text{do PhD}) = 0.001$
- $p(\text{low}|\text{do PhD, no prize}) = 0.1$, $p(\text{average}|\text{do PhD, no prize}) = 0.5$, $p(\text{high}|\text{do PhD, no prize}) = 0.4$
- $p(\text{low}|\text{no PhD, no prize}) = 0.2$, $p(\text{average}|\text{no PhD, no prize}) = 0.6$, $p(\text{high}|\text{no PhD, no prize}) = 0.2$
- $p(\text{low}|\text{do PhD, prize}) = 0.01$, $p(\text{average}|\text{do PhD, prize}) = 0.04$, $p(\text{high}|\text{do PhD, prize}) = 0.95$
- $p(\text{low}|\text{no PhD, prize}) = 0.01$, $p(\text{average}|\text{no PhD, prize}) = 0.04$, $p(\text{high}|\text{no PhD, prize}) = 0.95$
- $p(\text{low}|\text{start up, no prize}) = 0.1$, $p(\text{average}|\text{start up, no prize}) = 0.5$, $p(\text{high}|\text{start up, no prize}) = 0.4$
- $p(\text{low}|\text{no start up, no prize}) = 0.2$, $p(\text{average}|\text{no start up, no prize}) = 0.6$, $p(\text{high}|\text{no start up, no prize}) = 0.2$
- $p(\text{low}|\text{start up, prize}) = 0.005$, $p(\text{average}|\text{start up, prize}) = 0.005$, $p(\text{high}|\text{start up, prize}) = 0.99$
- $p(\text{low}|\text{no start up, prize}) = 0.05$, $p(\text{average}|\text{no start up, prize}) = 0.15$, $p(\text{high}|\text{no start up, prize}) = 0.8$



Example: PhD and start-up companies



Do PhD to wind a Nobel Prize and start-up?

The ordering : $E^* < P < S^* < I$

Domains

- $\text{dom}(E) = \{\text{do PhD, no PhD}\}$
- $\text{dom}(P) = \{\text{prize, no prize}\}$
- $\text{dom}(I) = \{\text{low, average, high}\}$
- $\text{dom}(S) = \{\text{yes, no}\}$

Utilities

- $U_C(\text{do PhD}) = -50000$, $U_C(\text{no PhD}) = 0$
- $U_B(\text{low}) = 100000$, $U_B(\text{average}) = 200000$, $U_B(\text{high}) = 500000$
- $U_S(\text{start up}) = -200000$, $U_S(\text{no start up}) = 0$



- Our interest is to advise whether or not it is desirable to take a PhD, bearing in mind that later one may or may not win the Nobel Prize, and may or may not form a start-up company
- The expected optimal utility for any state E is

$$U(E) = \sum_P \max_S \sum_I p(I|S, P) p(P|E) [U_C(E) + U_B(I) + U_S(S)]$$

(where we assume that the optimal decisions are taken in the future)

$$U(\text{do PhD}) = 190195$$

$$U(\text{no PhD}) = 240002$$