

Decision Theory

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Decision Theory

What does it mean to make an optimal decision?

- Asked by economists to study consumer behavior
- Asked by MBAs to maximize profit
- Asked by leaders to allocate resources
- Asked in OR to maximize efficiency of operations
- Asked in AI to model intelligence

- Asked (sort of) by any intelligent person every day



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Utility Functions

- A *utility function* is a mapping from **world states** to **real numbers**
- Sometimes called a *value function*
- Rational or optimal behavior viewed as maximizing expected utility:

$$\max_a \sum_s P(s | a) U(s)$$

a = actions, s = states

Are Utility Functions Natural?

- Some have argued that people don't really have utility functions
 - What is the utility of the current state?
 - What was your utility at 8:00pm last night?
 - *Utility elicitation* is difficult problem



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- It's easy to communicate *preferences*
- Theorem (sorta): Given a plausible set of assumptions about your preferences, there must exist a consistent utility function

Axioms of Utility Theory

- Orderability: $(A \succ B) \vee (A \prec B) \vee (A \sim B)$
- Transitivity: $(A \succ B) \wedge (B \succ C) \Rightarrow (A \succ C)$
- Continuity: $A \succ B \succ C \Rightarrow \exists p[p, A; 1 - p, C] \sim B$ Bet/gamble
between A and C
- Substitutability: $A \sim B \Rightarrow [p, A; 1 - p, C] \sim [p, B; 1 - p, C]$
- Monotonicity: $A \succ B \Rightarrow (p \geq q \Leftrightarrow [p, A; 1 - p, B] \geq [q, A; 1 - q, B])$
- Decomposability: $[p, A; (1 - p), [q, B; (1 - q), C]] \sim [p, A; (1 - p)q, B; (1 - p)(1 - q), C]$

Consequences of Preference Axioms

- Utility Principle

- There exists a real-valued function U:

$$U(A) > U(B) \Leftrightarrow A \succ B \quad \longleftarrow \text{A preferred to B}$$

$$U(A) = U(B) \Leftrightarrow A \sim B \quad \longleftarrow \text{Indifferent between A and B}$$

- Expected Utility Principle

- The utility of a lottery can be calculated as:

Lottery that results in S_i with prob p_i \longrightarrow

$$U([p_1, S_1; \dots; p_n, S_n]) = \sum_i p_i U(S_i)$$

More Consequences

- Scale invariance
- Shift invariance

Maximizing Utility

- Suppose you want to be famous
- You can be either (N,M,C)
 - Nobody
 - Modestly Famous
 - Celebrity
- Your utility function:
 - $U(N) = 20$
 - $U(M) = 50$
 - $U(C) = 100$
- You have to decide between going to grad school and becoming a professor (G) or going to Hollywood and becoming an actor (A)



Outcome Probabilities

- $P(N|G)=0.5$, $P(M|G)=0.4$, $P(C|G)=0.1$
- $P(N|H)=0.6$, $P(M|H)=0.2$, $P(C|H)=0.2$
- Maximize expected utility: $U(N) = 20$, $U(M) = 50$, $U(C) = 100$

$$EU_G = 0.5(20) + 0.4(50) + 0.1(100) = 40$$

$$EU_H = 0.6(20) + 0.2(50) + 0.2(100) = 42$$

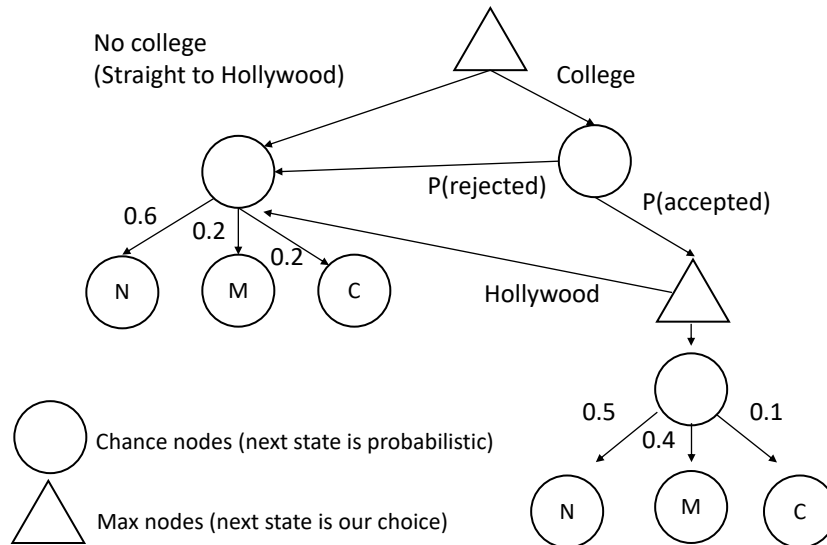
Hollywood wins!

Multiple Time Steps

- Suppose my utility is still defined purely in terms of fame (N, M, or C)
- ...but I'm **still in high school**
- Now I need to decide whether to go to college or not

- Represent this is a tree

Decision Theory as a Tree (DAG)

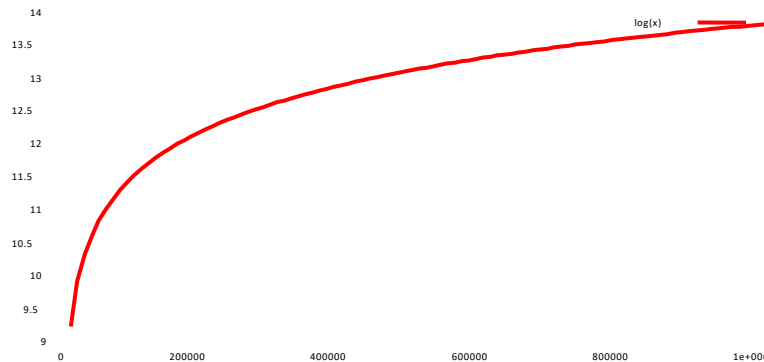


Decision Theory as a Recursive Tree Calculation

- Observe: Choosing to go to college depends upon the values of the grad school/Hollywood decision
- In general:
 - Decision theory requires us to work **backwards** from future to
 - Expectimax is decision theory!
 - **Exponential** amount of calculation since tree of possible outcomes can grow exponentially with depth

Utility of Money

- How much happier are you with an extra \$1M?
- How much happier is Jeff Bezos with an extra \$1M?
- Some have proposed:

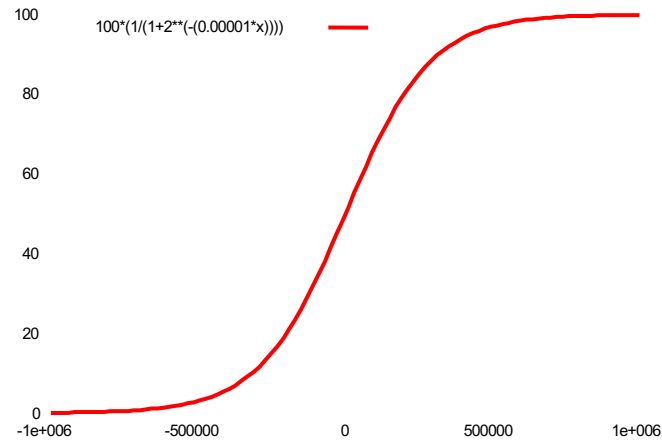


Utility of Money

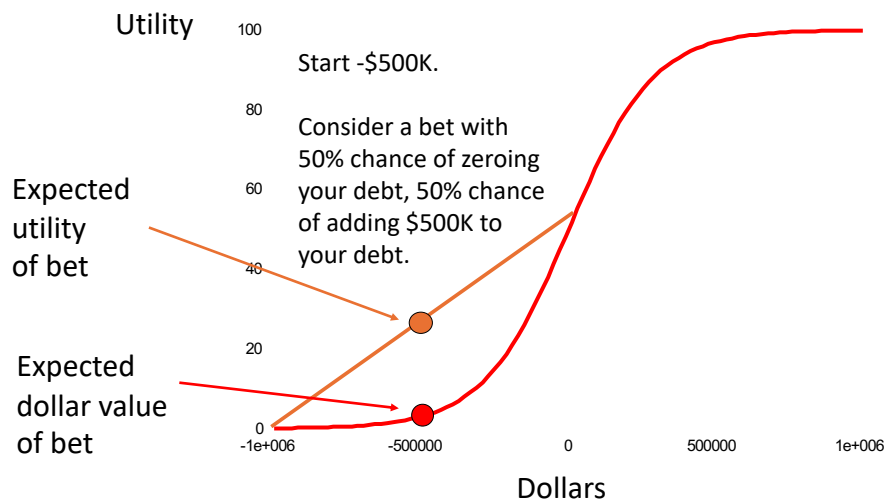
- $U(\text{money})$ should drop slowly in negative region too
- If you're solvent, losing \$1M is pretty bad
- If already \$10M in debt, losing another \$1M isn't that bad
- Utility of money is probably sigmoidal (S shaped)

A Sigmoidal Utility Function

$$U(\$X) = 100 \frac{1}{1 + 2^{-0.00001X}}$$



Sigmoidal Utility and Gambling



Value of Information

- Many choices are choices about acquiring information:
 - Medical tests (x-rays, CT-scans, mammograms, etc.)
 - Pregnancy tests
 - Pre-purchase house/car inspections
 - Hiring consultants
 - Hiring a trainer
 - Funding research
 - Checking one's own credit score
 - Checking somebody else's credit score
 - Background checks
 - Drug tests
 - Real time stock prices
- Information is rarely free
- How do we determine what it is worth to us?

Value of Information

- Expected utility of action a with evidence E :

$$EU_E(A|E) = \max_{a \in A} \sum_i P(S_i | E, a) U(S_i)$$

- Expected utility given new evidence E' - **after** E' is known

$$EU_{E,E'}(A|E,E') = \max_{a \in A} \sum_i P(S_i | E, E', a) U(S_i)$$

- Expected value of knowing E' (**Value of Perfect Information**) – **before** E' is known

$$VPI_E(E') = \left(\sum_{E'} P(E'|E) EU_{E,E'}(A|E,E') \right) - EU_E(A|E)$$

Expected utility given
New information
(weighted)

Previous
Expected
utility

VPI Example

- Should you pay to subscribe for (more timely) traffic information?
- Assume:
 - Time = cost = -utility
 - Cost of taking highway to work (w/o traffic_jam) = 15
 - Cost of taking highway to work (w/traffic_jam) = 30
 - Cost of taking local roads to work = 20
 - $P(\text{traffic_jam}) = 0.15$
- Steps:
 - Determine optimal decision w/o information: $EU(A|\{\})$
 - Determine optimal decisions given information: $EU_T(A|T)$
 - Compute expected value of optimal decisions given T
 - Estimate value of information (difference in prev. slide)

VPI for Traffic Info

- Cost of local roads = 20
 - Cost of highway = $0.15 \cdot 30 + 0.85 \cdot 15 = 17.25$
 - Traffic = true case: Take local roads; cost = 20
 - Traffic = false case: Take highway; cost = 15
 - Expected cost: $0.15 \cdot 20 + 0.85 \cdot 15 = 15.75$
 - Value = 1.5
- $\left. \begin{array}{l} \text{Cost of highway} \\ \text{Expected cost} \end{array} \right\} EU(A|\{\})$
 $\left. \begin{array}{l} \text{Traffic = true case} \\ \text{Traffic = false case} \end{array} \right\} EU_T(A|T)$
 $\left. \begin{array}{l} \text{Expected cost} \\ \text{Value} \end{array} \right\} \text{Expectation}$
 $\left. \begin{array}{l} \text{Value} \end{array} \right\} \text{VPI}$

- **Important:** In this case, the optimal choice given the information was trivial. In general, we may do more computation to determine the optimal choice given new information – not all decisions are “one shot”

Properties of VPI

- VPI is non-negative!
- VPI is not additive
- VPI is easy to compute and is often used to determine how much you should pay for **one** extra piece of information. Why is this myopic?

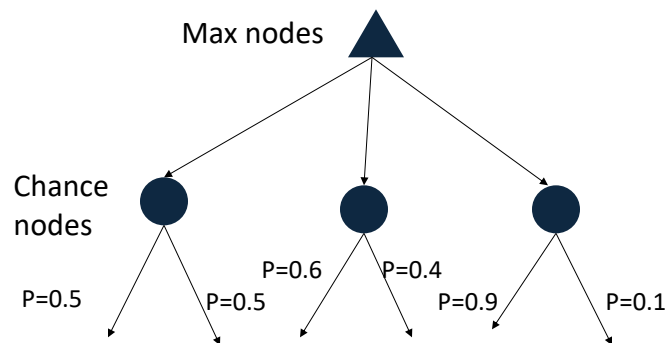
For example, knowing X and Y together, may be no more helpful than knowing just one

More Properties of VPI

- Acquiring information optimally is very difficult
- Need to construct a conditional plan for every possible outcome before you ask for even the first piece of information
 - Suppose you're a doctor planning to treat a patient
 - Picking the optimal test to do first requires that you consider all subsequent tests and all possible treatments as a result of these tests
- General versions of this problem are intractable – because we need to build a tree, and trees are exponential in depth

Value of information as Search

- States = States are “information states” that include your state of knowledge, not necessarily exact states of world
- Actions may be actual actions in the world, or actions that acquire information



How Information is Doled Out

- VPI = Value of Perfect Information
- In practice, information is:
 - Partial
 - Imperfect
- Partial information:
 - We learn about some state variables, but don't learn the exact state of the world
 - Example: We can see a traffic camera at one intersection, but we don't have coverage of our entire route
- Imperfect information:
 - We learn something that may not be reliable
 - Example: There may be a lag in our traffic data
- Our framework can handle this by introducing an extra variable.
(We get perfect information about the observed variable, and this influences the distribution over the others.)

Conclusions

- Decision theory: **framework for optimal decision making**
- Principle: *Maximize Expected Utility*
- Easy to describe in principle
- Efficient application to multistep problems can require advanced planning and probabilistic reasoning techniques