

Uncertainty and Utility

CSE 4617: Artificial Intelligence



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Recap: Probabilities

- Random Variable \rightarrow An even whose outcome is unknown
- Probability Distribution \rightarrow Assignment of weights to outcomes based on their chance
- Probabilities can't be negative
- Sum of all possible outcomes = 1

Example: Getting that internship

- Random variable: $I \rightarrow$ whether you got the internship
- Outcome: $I \in \{\text{none, good one, bad one}\}$
- Distribution: $P(I=\text{none}) = 0.1$, $P(I=\text{good}) = 0.4$, $P(I=\text{bad}) = 0.5$



Recap: Probabilities

- Expected value \rightarrow Average, weighted by the probability distribution over outcomes
- Sum of the values multiplied by their chance of occurring

Time:

20 min

30 min

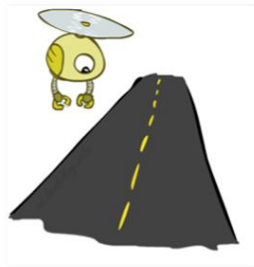
60 min

Probability:

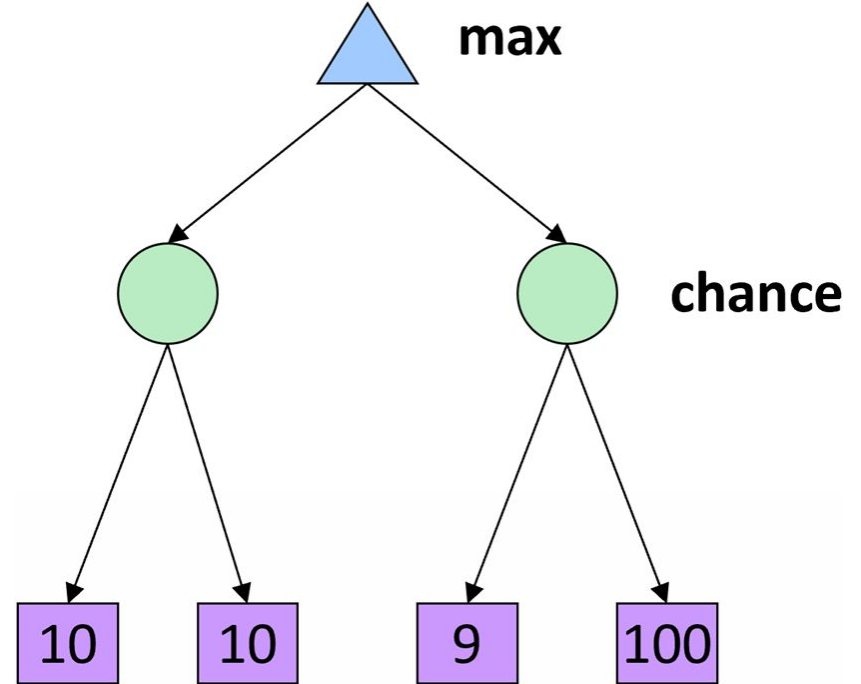
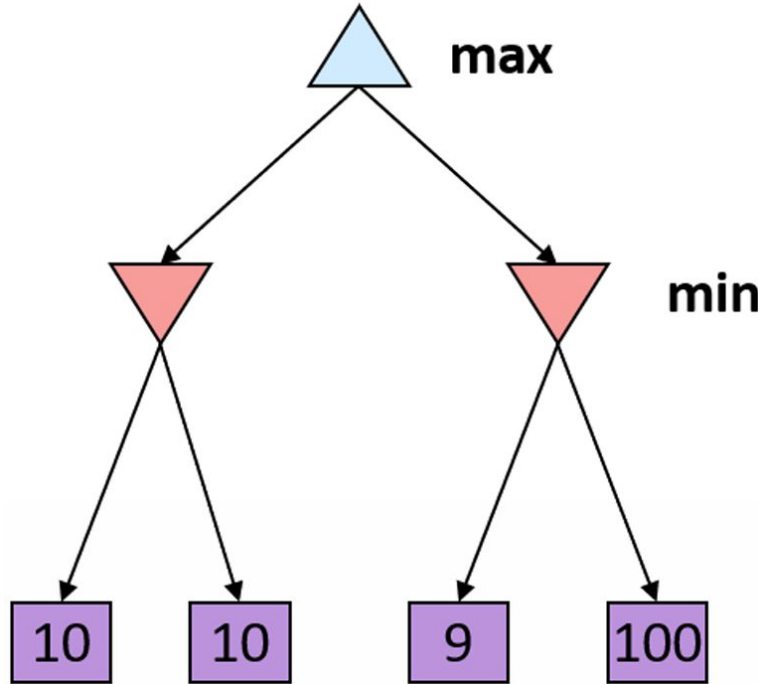
0.25

0.50

0.25



Worst-case scenario vs. Average-case scenario



Worst-case scenario vs. Average-case scenario

- How wouldn't we know what the results of an action would be?
 - Explicit randomness → Dice roll, coin flip
 - Unpredictable opponents → Sometimes, opponents are not entirely rational agents
 - Failed actions → Wheel slip, traffic congestion
- Values should reflect average-case outcomes, not worst-case outcomes
 - Max nodes are the same as mini-max
 - Chance nodes are replacing min nodes but the outcome has probabilities attached with it
 - Calculate the **expected utilities** → Take weighted average of children

Minimax Algorithm

```
VALUE (state) → returns utility value of the state
  if state is TERMINAL: then return utility
  if state is MAX-AGENT: then return MAX-VALUE (state)
  if state is MIN-AGENT: then return MIN-VALUE (state)
```

```
MAX-VALUE (state) → returns utility value of a state
  v ←  $-\infty$ 
  for successor in state:
    v = max (v, VALUE (successor))
  return v
```

```
MIN-VALUE (state) → returns utility value of a state
  v ←  $+\infty$ 
  for successor in state:
    v = min (v, VALUE (successor))
  return v
```

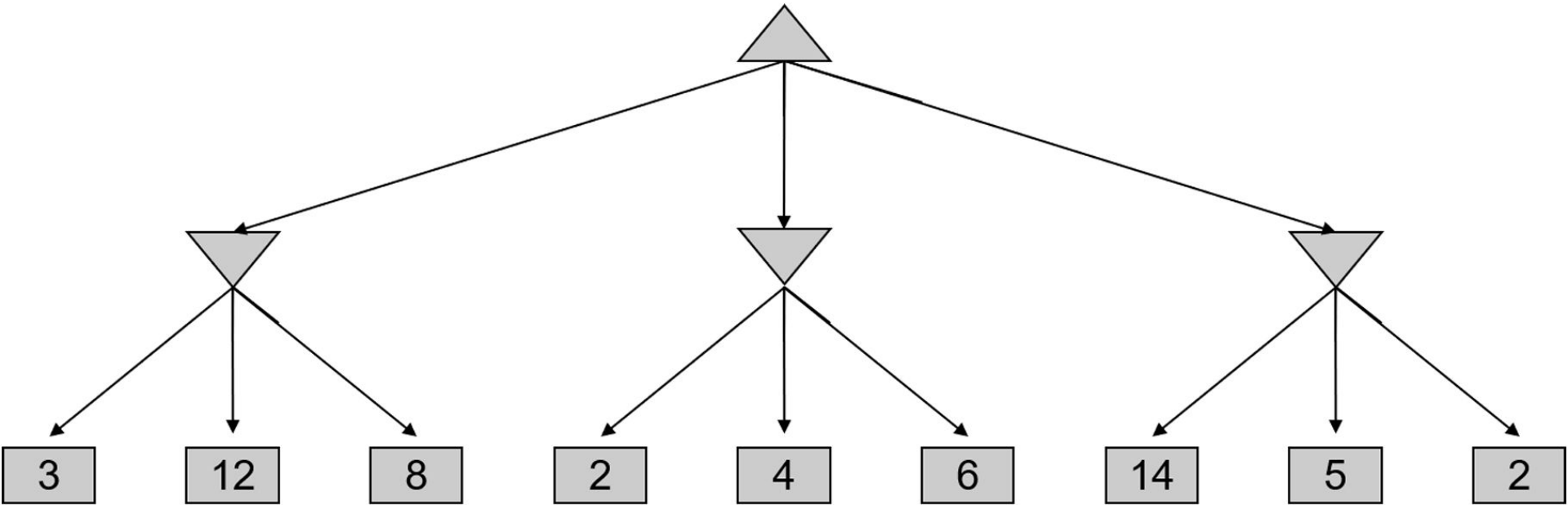
Expectimax Algorithm

```
VALUE (state) → returns utility value of the state
  if state is TERMINAL: then return utility
  if state is MAX-AGENT: then return MAX-VALUE (state)
  if state is EXP-AGENT: then return EXP-VALUE (state)
```

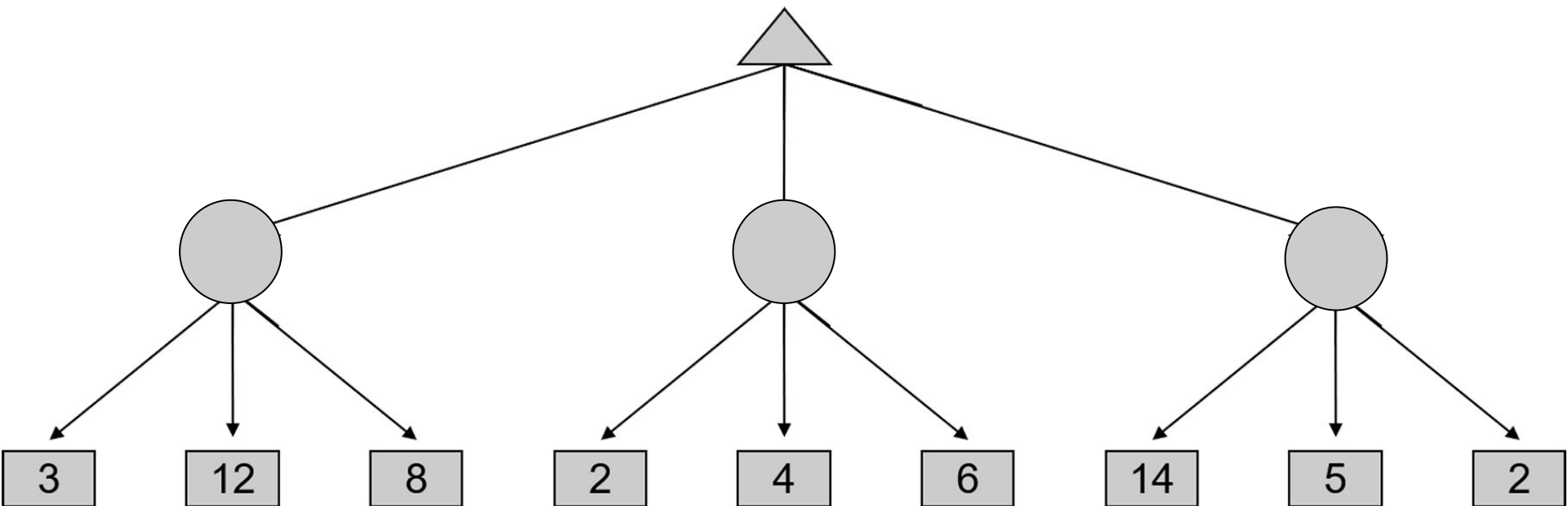
```
MAX-VALUE (state) → returns utility value of a state
   $v \leftarrow -\infty$ 
  for successor in state:
     $v = \max (v, \text{VALUE} (\textit{successor}))$ 
  return v
```

```
MIN-VALUE (state) → returns expected utility value of a state
   $v \leftarrow 0$ 
  for successor in state:
     $p \leftarrow \text{probability} (\textit{successor})$ 
     $v += p * \text{VALUE} (\textit{successor})$ 
  return v
```

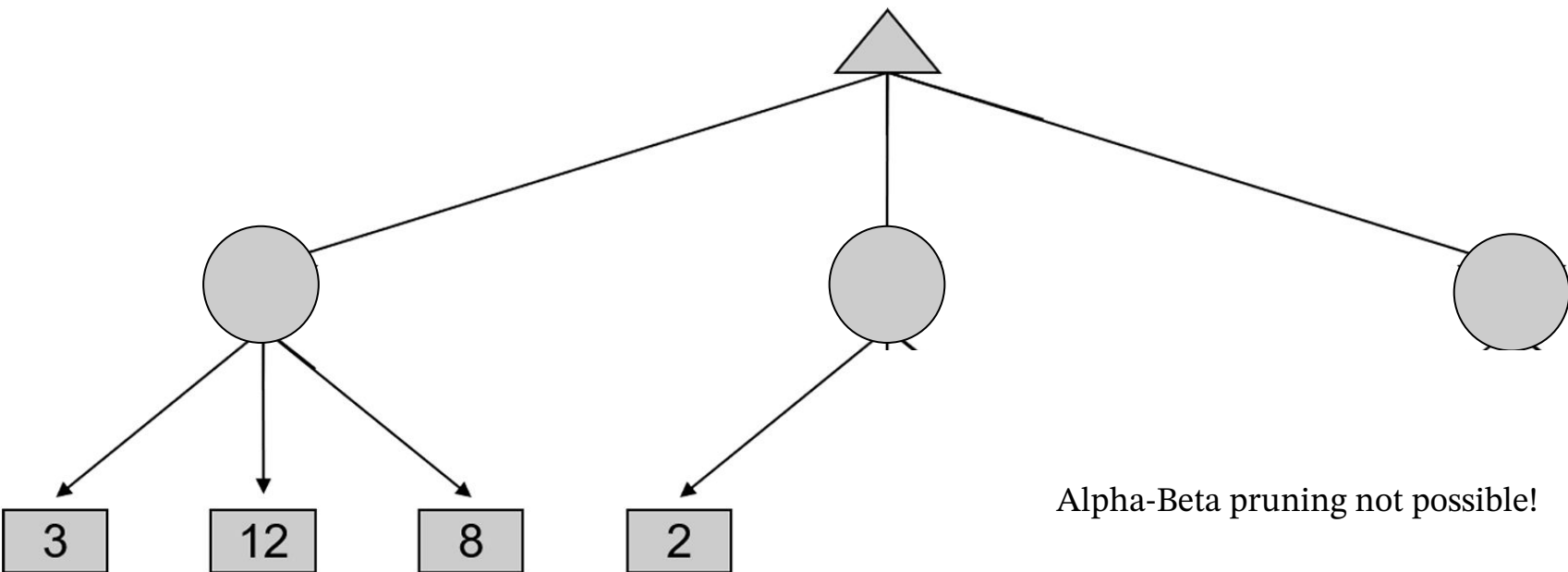
Minimax Algorithm



Expectimax Algorithm



Expectimax Pruning?

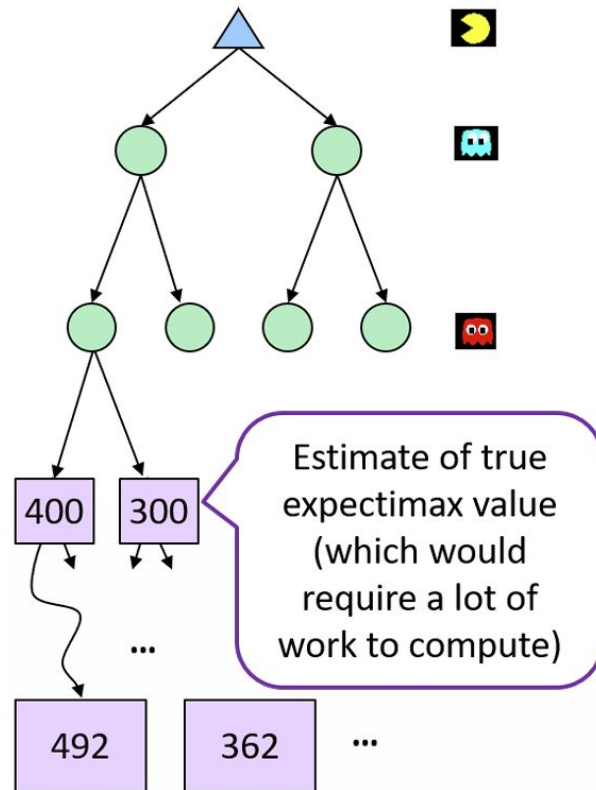


Depth Limited Expectimax

In demanding games like chess, we can not search to the leaves!

Depth-limited Search:

- Search only to a limited depth in the tree
- Replace terminal utilities with an evaluation function for non-terminal positions
- Guarantee of optimal play is gone
- The more depth you check, the better your moves become
- Use **iterative deepening** or a better outcome



What Probability Model to Use?

- In expectimax search, we have a probabilistic model of how the opponent (or environment) will behave in any state
 - Model could be a simple uniform distribution
 - Model could be sophisticated and require a great deal of computation
 - We have a chance node for any outcome out of our control: opponent or environment
- Assume each chance node magically comes along with probabilities that specify the distribution over its outcomes
- Having a chance node to model an opponent's action does not mean that the agent is also following the same distribution → It is just an estimate!

News: Cops are looking for a man who stole 6 orange cats built a fighting ring and put lasagna in the middle to determine who is the real Garfield



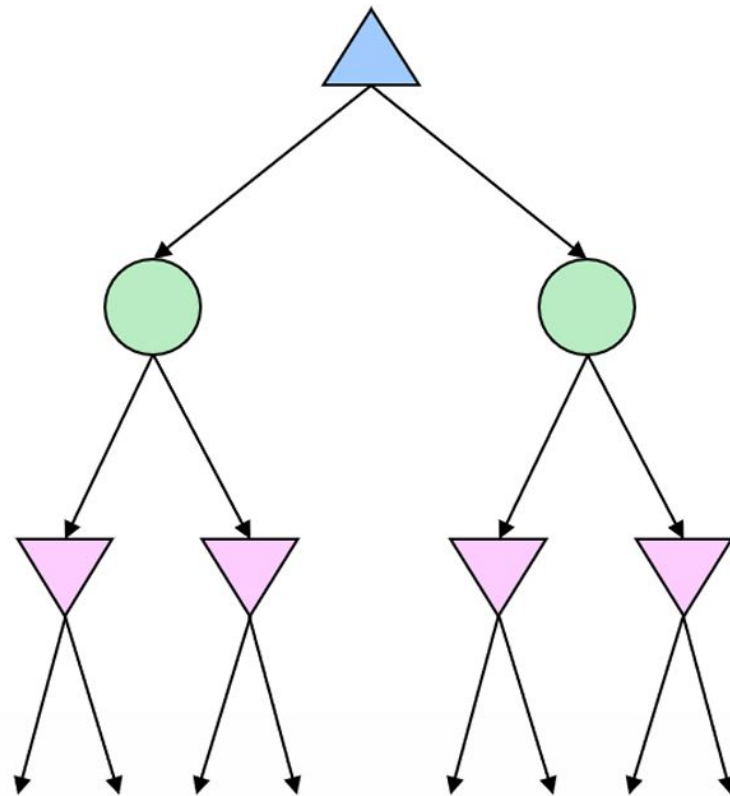
Dangers of Optimism and Pessimism

	Adversarial Ghost	Random Ghost
Minimax Pacman	Won 5/5 Avg. Score: 483	Won 5/5 Avg. Score: 493
Expectimax Pacman	Won 1/5 Avg. Score: -303	Won 5/5 Avg. Score: 503

Other Types of Games

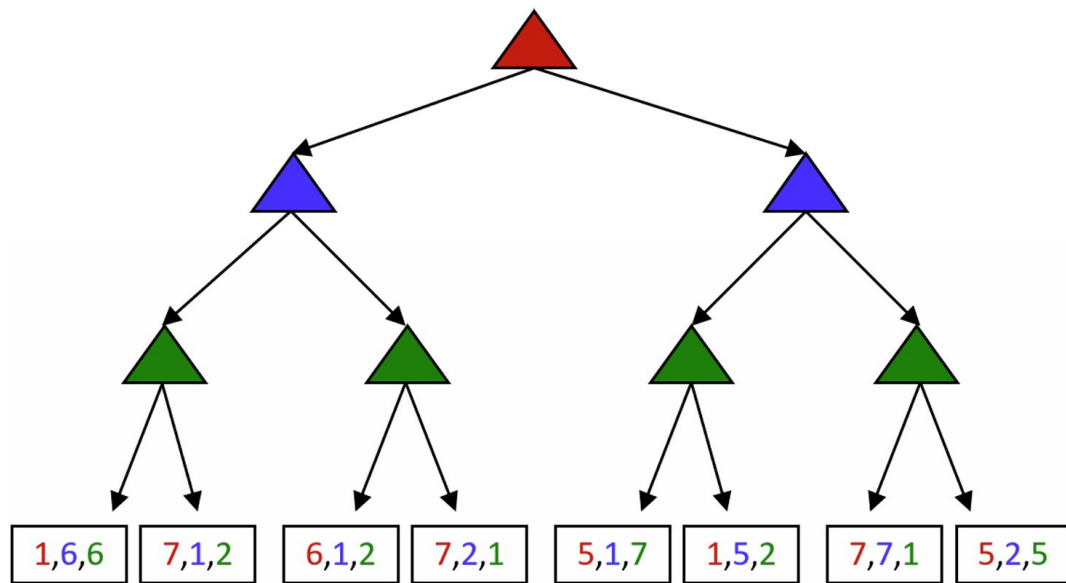
Mixed Layer Type Games

- Expectiminimax
 - Environment is an extra “random agent” player that moves after each min/max agent
 - Each node computes the appropriate combination of its children
- Examples could be:
 - Backgammon
 - Ludo
 - Snakes and Ladders
 - Uno



Mixed Layer Type Games

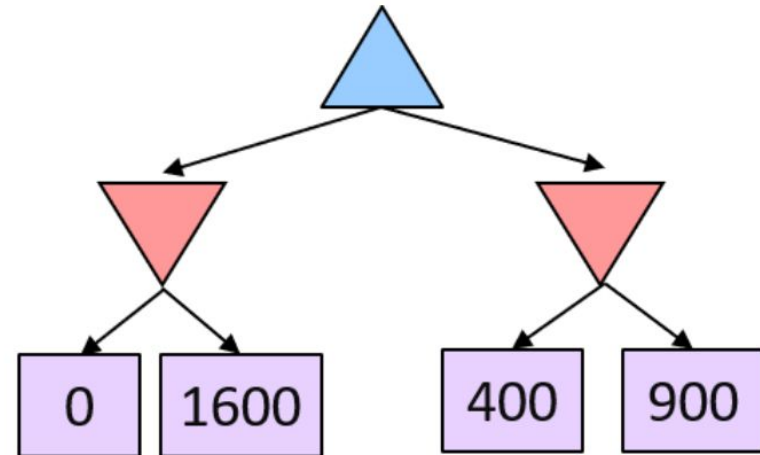
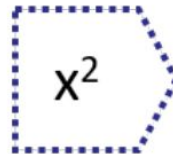
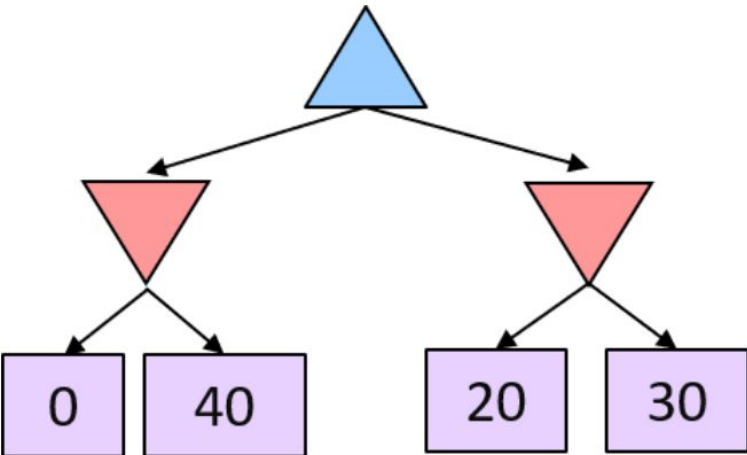
- What if a game is not zero-sum or has multiple players?
- Terminals have utility tuples
- Node values are also utility tuples
- Each player maximizes its own component \rightarrow Not zero-sum



Utilities

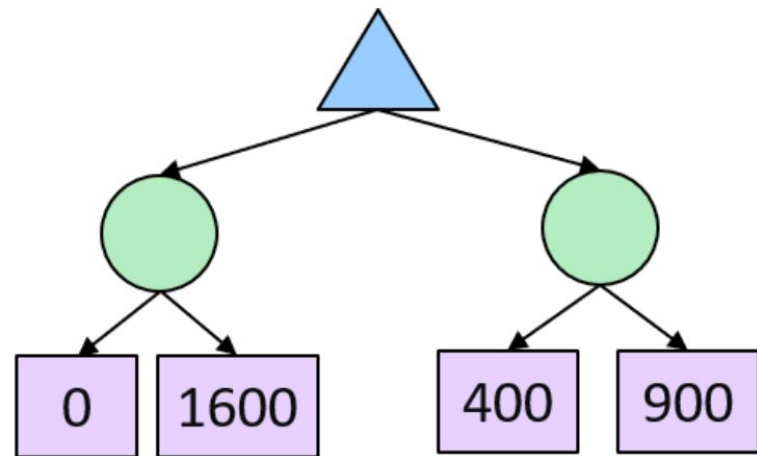
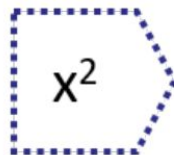
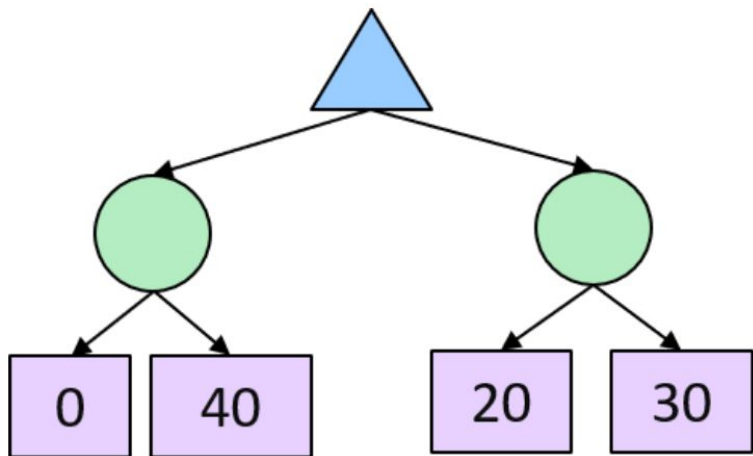
Utilities

- Principle of maximum expected utility
 - A rational agent should choose the action that **maximizes its expected utility**, given its knowledge as noted by its model of the world
- But what do these numbers really mean? Can we let an agent decide?



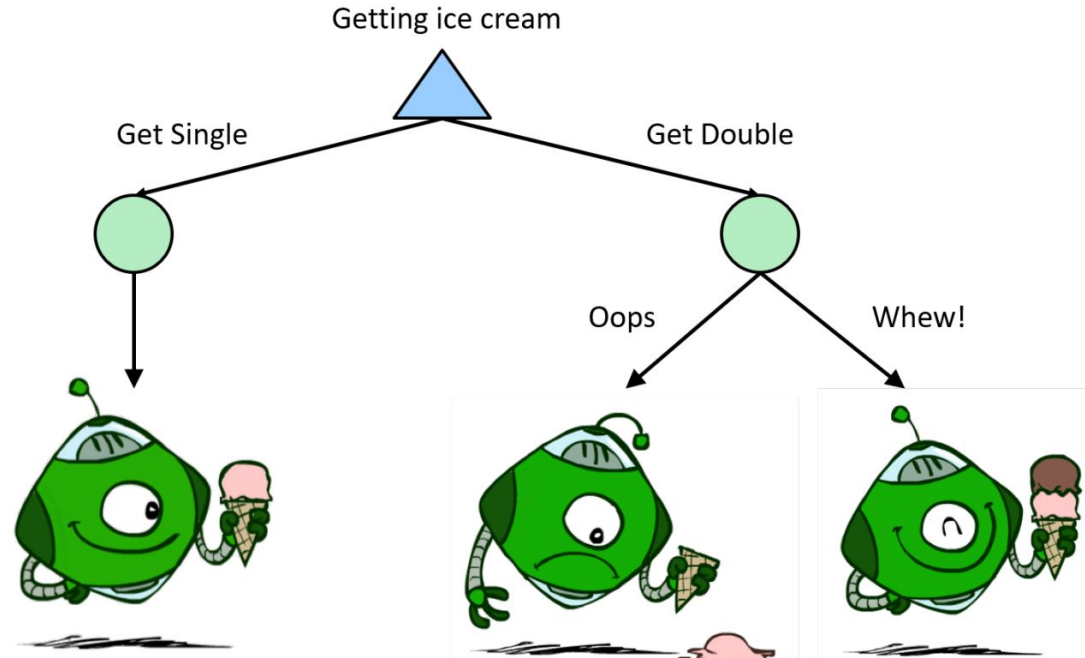
Utilities

- For worst-case minimax reasoning, terminal function scale doesn't matter
 - We just want better states to have higher evaluations (get the ordering right)
 - We call this insensitivity to **monotonic transformations**
- For average-case expectimax reasoning, we need magnitudes to be meaningful



Utilities

- Utilities are real numbers that describe the agent's **preference**
- Any “rational” preference can be summarized as a utility function → Proof?



Preferences

- Prizes $\rightarrow A, B$
- Lottery $\rightarrow L=[p, A; (1-p), B]$
- Preference $\rightarrow A \succ B$ Indifference $\rightarrow A \sim B$
- Lottery doesn't mean an actual game of lottery, any event with multiple outcomes and probability values for those outcomes can be considered as a lottery



Rational Preference

- We want some constraints on preferences before we call them rational, such as:
 - Transitivity: $(A \succ B) \wedge (B \succ C) \rightarrow (A \succ C)$
 - Orderability: $(A \succ B) \vee (B \succ A) \vee (A \sim B)$
 - Continuity: $A \succ B \succ C \rightarrow \exists_p [p, A; (1 - p), C] \sim B$
 - Substitutability: $A \sim B \rightarrow [p, A; (1 - p), C] \sim [p, B; (1 - p), C]$
 - Monotonicity: $A \succ B \rightarrow (p \geq q \leftrightarrow [p, A; (1 - p), B] \succcurlyeq [q, A; (1 - q), B])$
- **Theorem:** Rational preferences imply behavior describable as maximization of expected utility

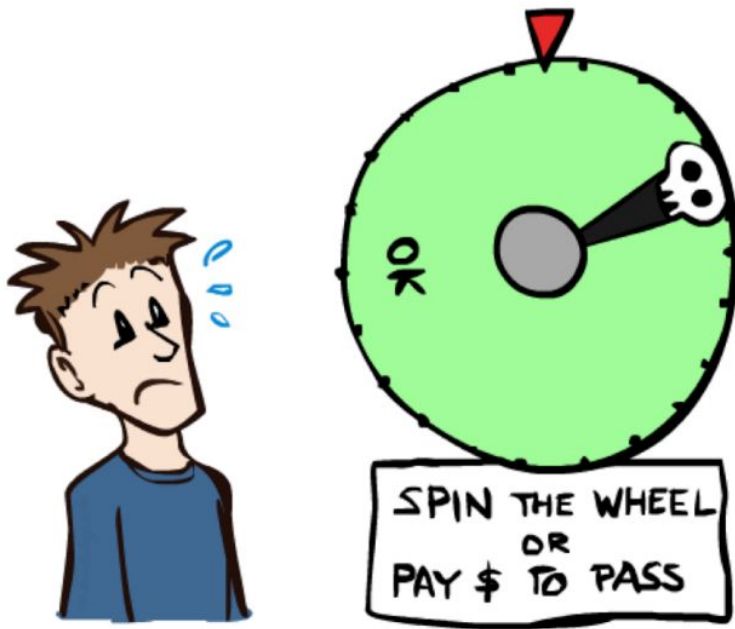
MEU Principle

- [Ramsey, 1931; von Neumann & Morgenstern, 1944]
 - Given any preferences satisfying these constraints, there exists a real-valued function U such that:
 - $A \succcurlyeq B \leftrightarrow U(A) \geq U(B)$ where, $U(p_1, S_1; p_2, S_2; \dots) = \sum_i p_i U(S_i)$
- Choose the action that maximizes expected utility
- An agent can be **entirely rational** (consistent with MEU) without ever representing or manipulating utilities and probabilities

Human Utilities

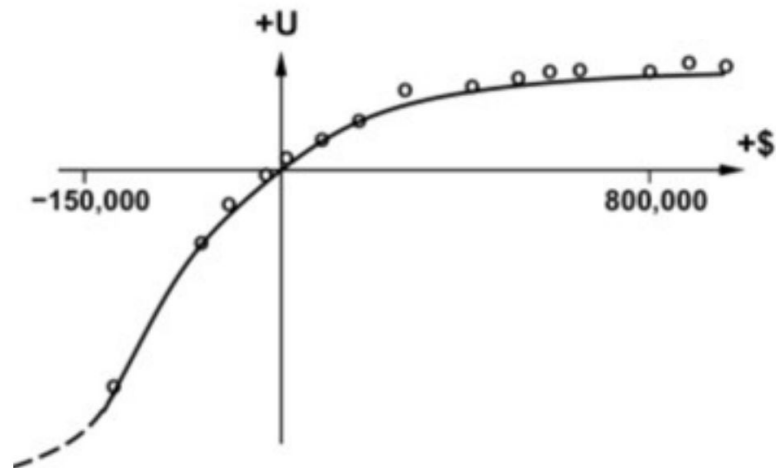
Human Utilities

- Utilities map states to real numbers
- Standard approach to assess human utilities:
 - Compare a prize A to a standard lottery L_p between:
 - Best possible prize with prob p
 - Worst possible prize with prob $(1-p)$
 - Adjust lottery probability p until indifference: $A \sim L_p$



Utility of Money

- Money **does not behave** as a utility function
- Given a lottery $L = [p, \$X; (1-p), \$Y]$
 - Expected monetary value (EMV) $\rightarrow p \times X + (1-p) \times Y$
 - Utility $U(L) \rightarrow p \times U(\$X) + (1-p) \times U(\$Y)$
 - Usually, $U(L) < U(\text{EMV}(L))$
- People are risk-averse in usual scenarios
- When deep in debt, people are risk-prone
- Useful when modeling complex functions like **insurance premium**



Are Humans Rational?

Thank you

Additional Resources

- [AI 101: Monte Carlo Tree Search](#)
- [What's the Use of Utility Functions?](#)
- [Eliezer Yudkowsky – AI Alignment: Why It's Hard, and Where to Start](#)