Uncertain Outcomes
Worst-Case vs. Average Case

Idea: Uncertain outcomes controlled by chance, not an adversary!
Expectimax Search

- Why wouldn’t we know what the result of an action will be?
  - Explicit randomness: rolling dice
  - Unpredictable opponents: the ghosts respond randomly
  - Unpredictable humans: humans are not perfect
  - Actions can fail: when moving a robot, wheels might slip

- Values should now reflect average-case (expectimax) outcomes, not worst-case (minimax) outcomes

- **Expectimax search:** compute the average score under optimal play
  - Max nodes as in minimax search
  - Chance nodes are like min nodes but the outcome is uncertain
  - Calculate their **expected utilities**
  - I.e. take weighted average (expectation) of children

- Later, we’ll learn how to formalize the underlying uncertain-result problems as **Markov Decision Processes**
Video of Demo Min vs. Exp (Min)
Video of Demo Min vs. Exp (Exp)
Expectimax Pseudocode

```
def value(state):
    if the state is a terminal state: return the state’s utility
    if the next agent is MAX: return max-value(state)
    if the next agent is EXP: return exp-value(state)

def max-value(state):
    initialize v = -∞
    for each successor of state:
        v = max(v, value(successor))
    return v

def exp-value(state):
    initialize v = 0
    for each successor of state:
        p = probability(successor)
        v += p * value(successor)
    return v
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def exp-value(state):
    initialize v = 0
    for each successor of state:
        p = probability(successor)
        v += p * value(successor)
    return v

v = (1/2) (8) + (1/3) (24) + (1/6) (-12) = 10
Expectimax Example

The diagram illustrates a decision tree for a game, with nodes representing the states and branches representing the moves. The numbers at each node represent the scores, with the branches leading to the opponent's moves labeled as 'Opponent' and the agent's moves labeled as 'Agent.' The diagram shows the expected value for each decision point, guiding the agent to make the optimal choice.
Expectimax Pruning?
Depth-Limited Expectimax

Estimate of true expectimax value (which would require a lot of work to compute)
Probabilities
Reminder: Probabilities

- A **random variable** represents an event whose outcome is unknown
- A **probability distribution** is an assignment of weights to outcomes

**Example: Traffic on freeway**
- Random variable: \( T \) = whether there’s traffic
- Outcomes: \( T \) in \{none, light, heavy\}
- Distribution: \( P(T=\text{none}) = 0.25, P(T=\text{light}) = 0.50, P(T=\text{heavy}) = 0.25 \)

**Some laws of probability (more later):**
- Probabilities are always non-negative
- Probabilities over all possible outcomes sum to one

**As we get more evidence, probabilities may change:**
- \( P(T=\text{heavy}) = 0.25, P(T=\text{heavy} \mid \text{Hour}=8am) = 0.60 \)
- We’ll talk about methods for reasoning and updating probabilities later
Reminder: Expectations

- The expected value of a function of a random variable is the average, weighted by the probability distribution over outcomes.

Example: How long to get to the airport?

<table>
<thead>
<tr>
<th>Time</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 min</td>
<td>0.25</td>
</tr>
<tr>
<td>30 min</td>
<td>0.50</td>
</tr>
<tr>
<td>60 min</td>
<td>0.25</td>
</tr>
</tbody>
</table>

\[
35 \text{ min} = 0.25 \times 20 \text{ min} + 0.50 \times 30 \text{ min} + 0.25 \times 60 \text{ min}
\]
What Probabilities 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 (roll a die)
  ○ 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
  ○ The model might say that adversarial actions are likely!

○ For now, assume each chance node magically comes along with probabilities that specify the distribution over its outcomes

Having a probabilistic belief about another agent’s action does not mean that the agent is flipping any coins!
Quiz: Informed Probabilities

- Let’s say you know that your opponent is actually running a depth 2 minimax, using the result 80% of the time, and moving randomly otherwise.
- Question: What tree search should you use?

  - Answer: Expectimax!

  - To figure out EACH chance node’s probabilities, you have to run a simulation of your opponent.
  - This kind of thing gets very slow very quickly.
  - Even worse if you have to simulate your opponent simulating you…
  - ... except for minimax and maximax, which have the nice property that it all collapses into one game tree.
Modeling Assumptions
The Dangers of Optimism and Pessimism

Dangerous Optimism
Assuming chance when the world is adversarial

Dangerous Pessimism
Assuming the worst case when it’s not likely
Assumptions vs. Reality

Pacman used depth 4 search with an eval function that avoids trouble.
Ghost used depth 2 search with an eval function that seeks Pacman.
Video of Demo World Assumptions
Random Ghost – Expectimax Pacman
Video of Demo World Assumptions
Adversarial Ghost – Minimax Pacman
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Assumptions vs. Reality

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<tr>
<td></td>
<td>Avg. Score: 483</td>
<td>Avg. Score: 493</td>
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<td></td>
<td></td>
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<tr>
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<td>Won 5/5</td>
</tr>
<tr>
<td></td>
<td>Avg. Score: -303</td>
<td>Avg. Score: 503</td>
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Results from playing 5 games

Pacman used depth 4 search with an eval function that avoids trouble
Ghost used depth 2 search with an eval function that seeks Pacman
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Why not minimax?

- Worst case reasoning is too conservative
- Need average case reasoning
Other Game Types
E.g. Backgammon

- Expecti-minimax
  - Environment is an extra “random agent” player that moves after each min/max agent
  - Each node computes the appropriate combination of its children

```plaintext
if state is a MAX node then
    return the highest \text{ExpectiMinimax-Value} of Successors(state)

if state is a MIN node then
    return the lowest \text{ExpectiMinimax-Value} of Successors(state)

if state is a chance node then
    return average of \text{ExpectiMinimax-Value} of Successors(state)
```
Example: Backgammon

- Dice rolls increase $b$: 21 possible rolls with 2 dice
  - Backgammon $\approx$ 20 legal moves
  - Depth 2 = $20 \times (21 \times 20)^2 = 1.2 \times 10^9$

- As depth increases, probability of reaching a given search node shrinks
  - So usefulness of search is diminished
  - So limiting depth is less damaging
  - But pruning is trickier...

- Historic AI: TDGammon uses depth-2 search + very good evaluation function + reinforcement learning: world-champion level play

- 1st AI world champion in any game!
Multi-Agent Utilities

- What if the game is not zero-sum, or has multiple players?

- Generalization of minimax:
  - Terminals have utility tuples
  - Node values are also utility tuples
  - Each player maximizes its own component
  - Can give rise to cooperation and competition dynamically…
Utilities

- Utilities: values that we assign to every state

- Why should we average utilities? Why not minimax?

- Principle of maximum expected utility:
  - A rational agent should choose the action that maximizes its expected utility, given its knowledge
Utilities

- Utilities are functions from outcomes (states of the world) to real numbers that describe an agent’s preferences.

- Where do utilities come from?
  - In a game, may be simple (+1/-1)
  - Utilities summarize the agent’s goals

- We hard-wire utilities and let behaviors emerge
Utilities: Uncertain Outcomes

Getting ice cream

Get Single

Get Double

Oops

Whew!
What Utilities to Use?

- 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
Next Time: MDPs!