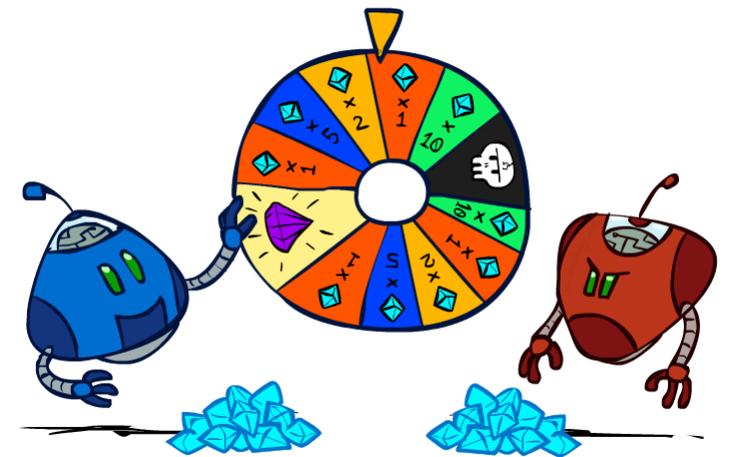


Reminder

- PS1 Due this Friday
- HW1 Due next Friday

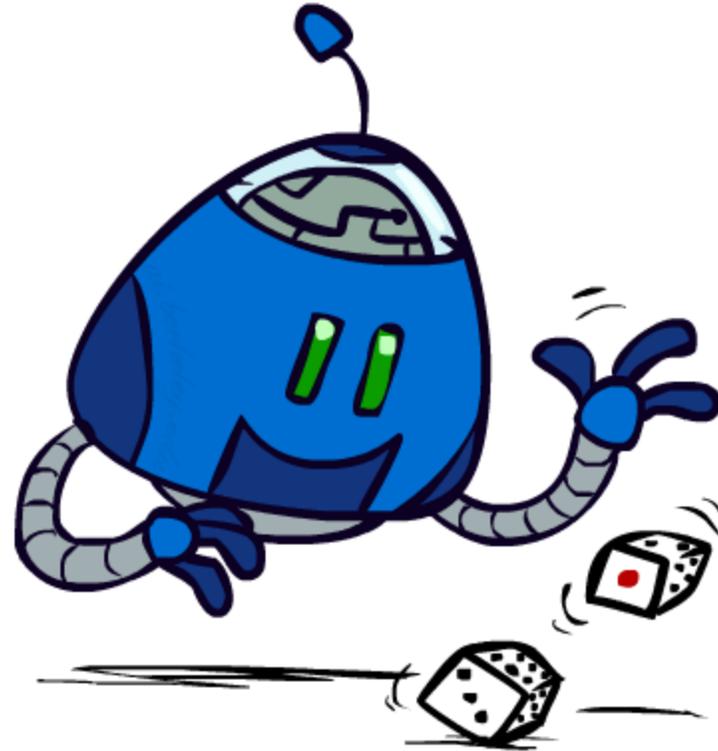
CSE 573: Artificial Intelligence

Hanna Hajishirzi
Expectimax – Complex Games

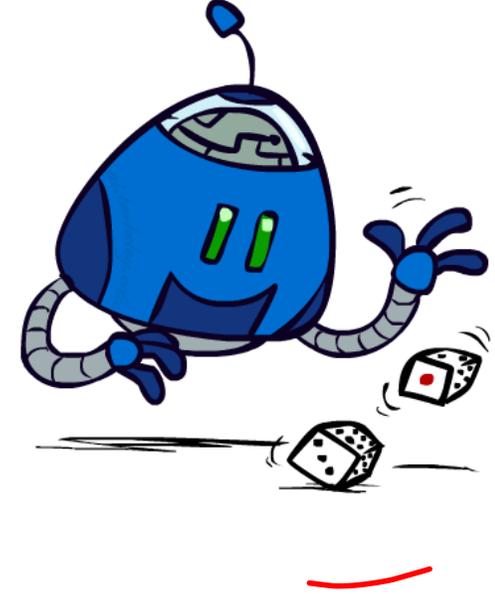
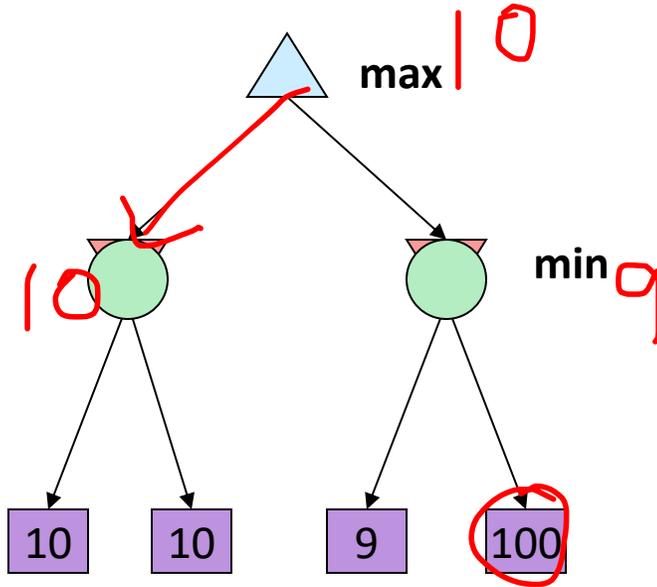
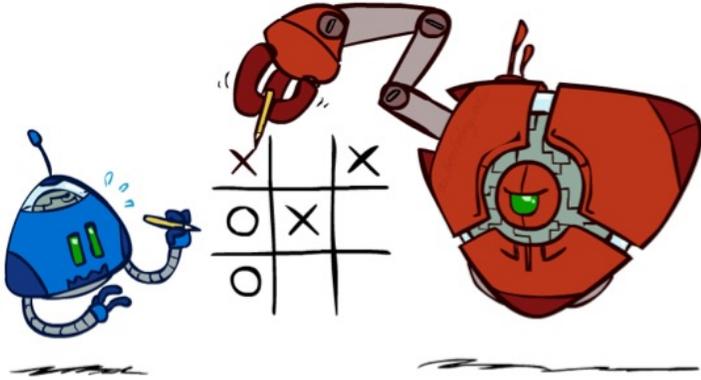


slides adapted from
Dan Klein, Pieter Abbeel ai.berkeley.edu
And Dan Weld, Luke Zettlemoyer

Uncertain Outcomes



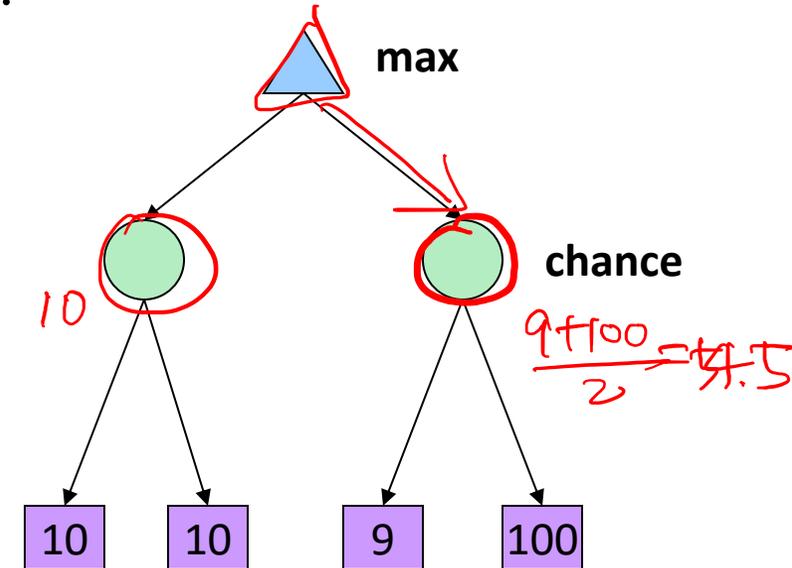
Worst-Case vs. Average Case



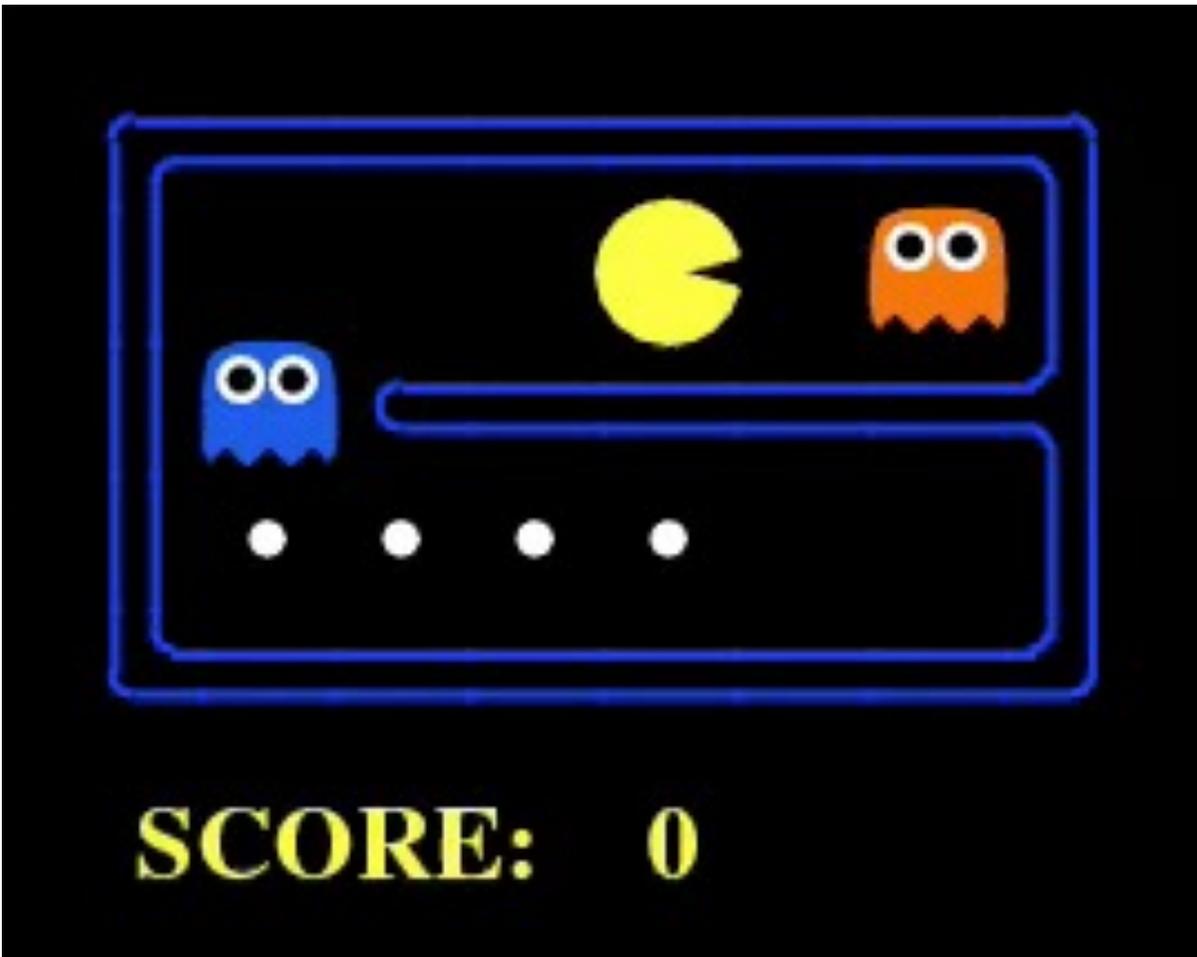
Idea: Uncertain outcomes controlled by chance, not an adversary!

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)



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):
```

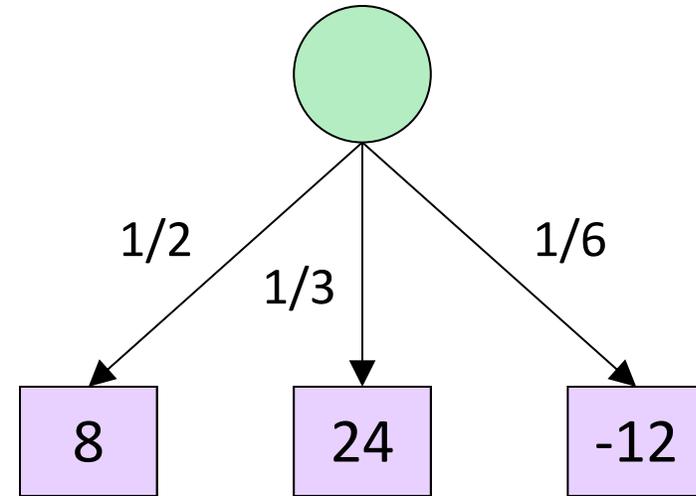
```
    initialize v =  $-\infty$   
    for each successor of state:  
        v = max(v, value(successor))  
    return v
```

```
def exp-value(state):
```

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

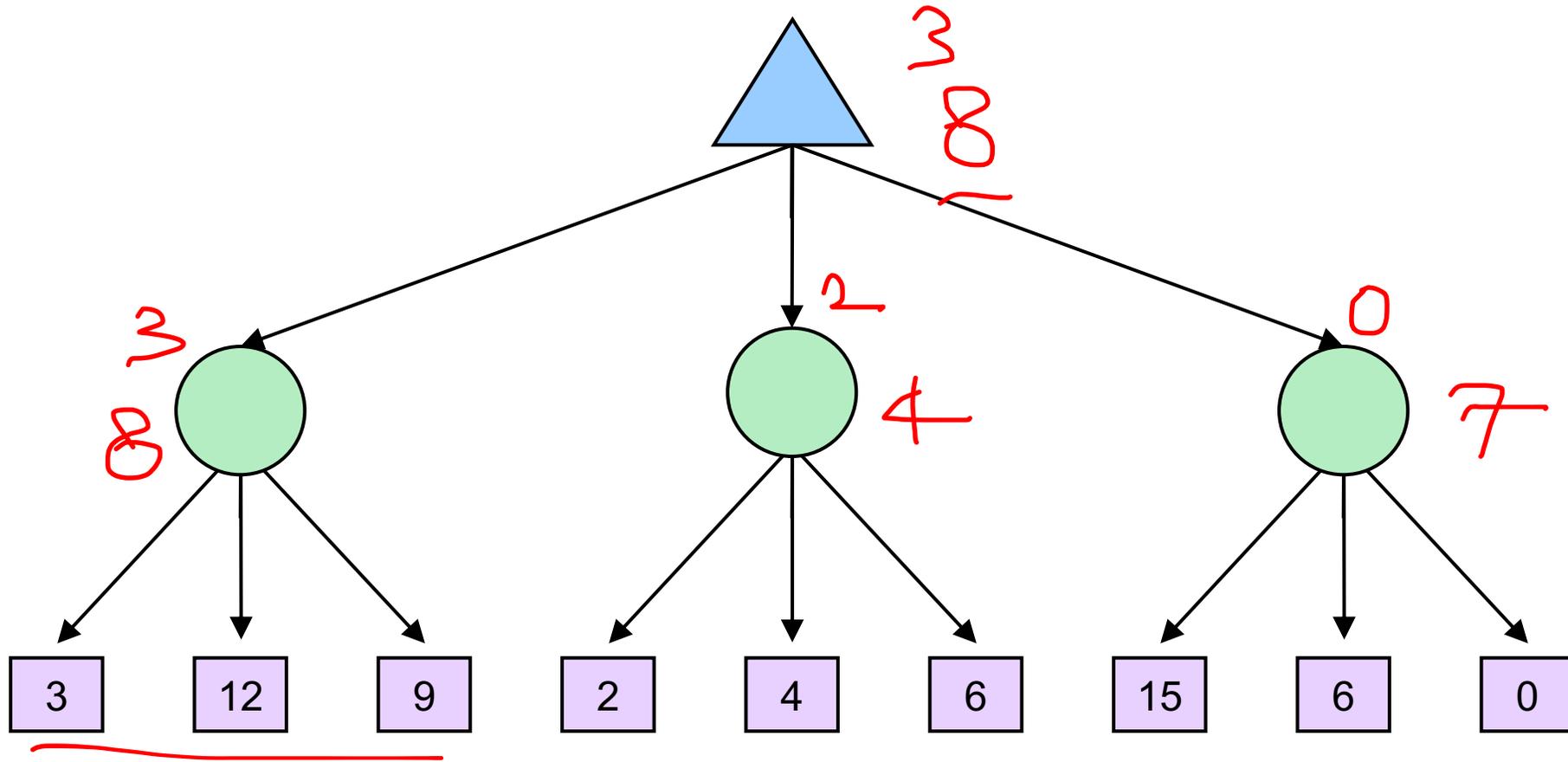
Expectimax Pseudocode

```
def exp-value(state):  
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    for each successor of state:  
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    return v
```

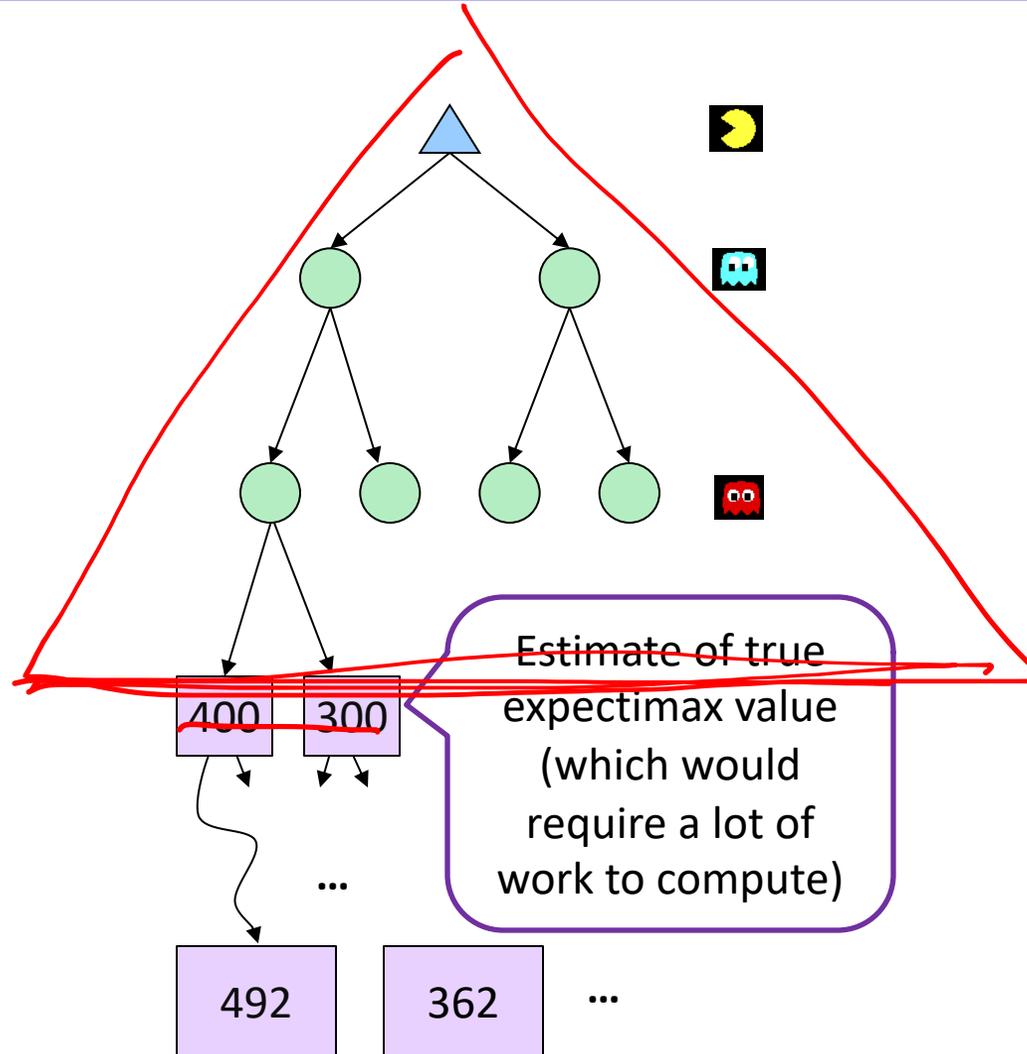


$$v = (1/2) (8) + (1/3) (24) + (1/6) (-12) = 10$$

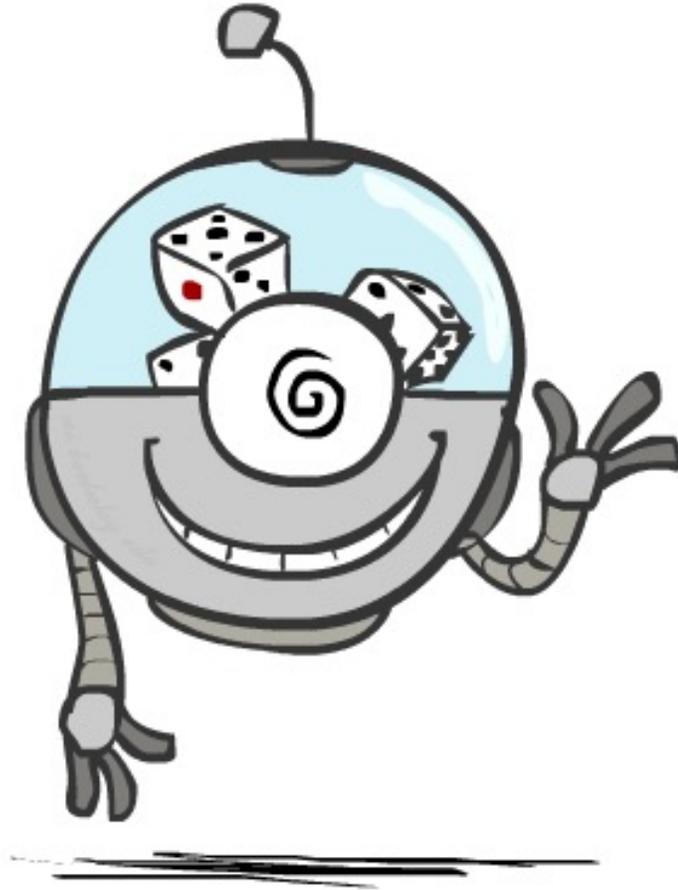
Expectimax Example



Depth-Limited Expectimax



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

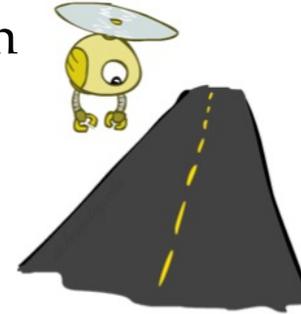
- Random variable: T = whether there's traffic
- Outcomes: T in {none, light, heavy}
- Distribution: $P(T=\text{none}) = 0.25$, $P(T=\text{light}) = 0.50$, $P(T=\text{heavy}) = 0.25$

- 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:

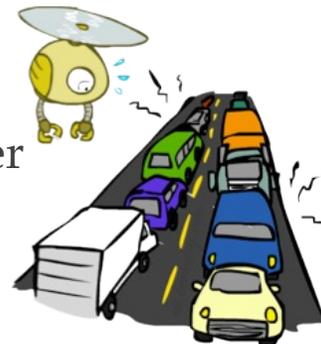
- $P(T=\text{heavy}) = 0.25$, $P(T=\text{heavy} \mid \text{Hour}=8\text{am}) = 0.60$
- We'll talk about methods for reasoning and updating probabilities later



0.25 → .1



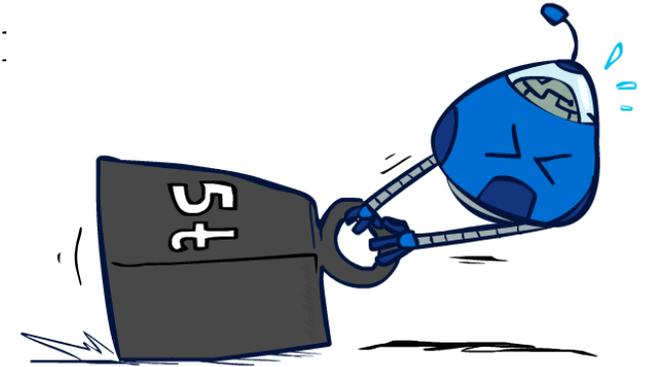
0.50 → .3



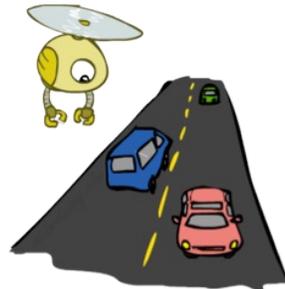
0.25 → .6

Reminder: Expectations

- The expected value of a function of a random variable : the average, weighted by the probability distribution over outcomes
- Example: How long to get to the airport?

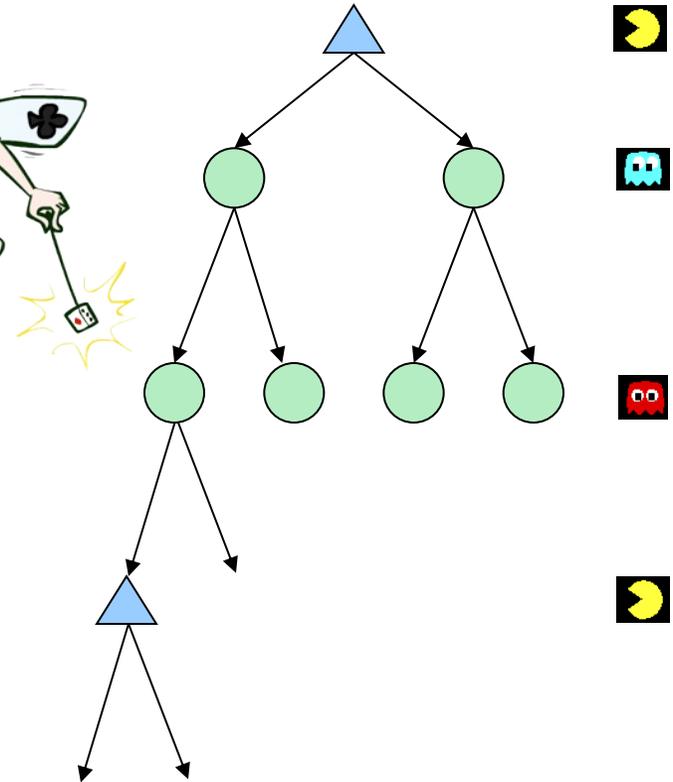


Time:	20 min		30 min		60 min			
	x	+	x	+	x			
Probability:	0.25		0.50		0.25		→	35 min



What Probabilities to Use?

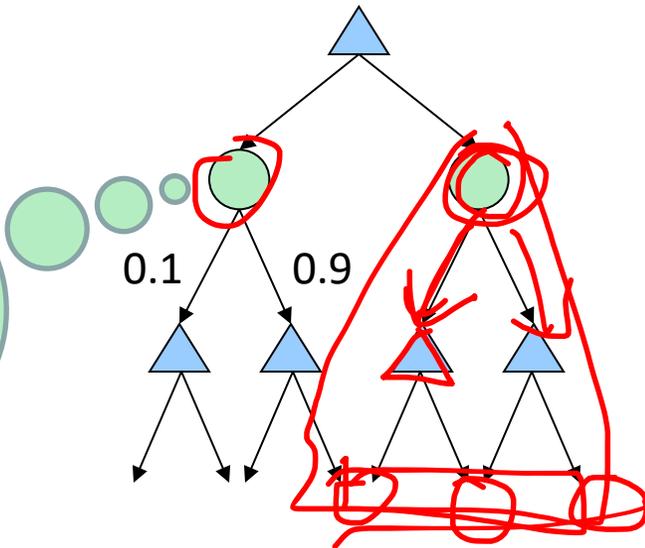
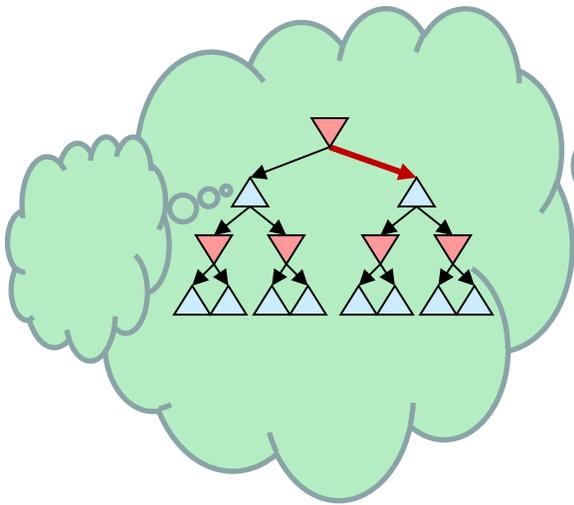
- In expectimax search, we have a probabilistic model of how the opponent (or environment) will behave in any state
 - Model could be a simple uniform distribution (roll a die)
 - Model could be sophisticated and require a great deal of computation
 - We have a chance node for any outcome out of our 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

80% / This kind of thing gets very slow very quickly L 100% R 0%

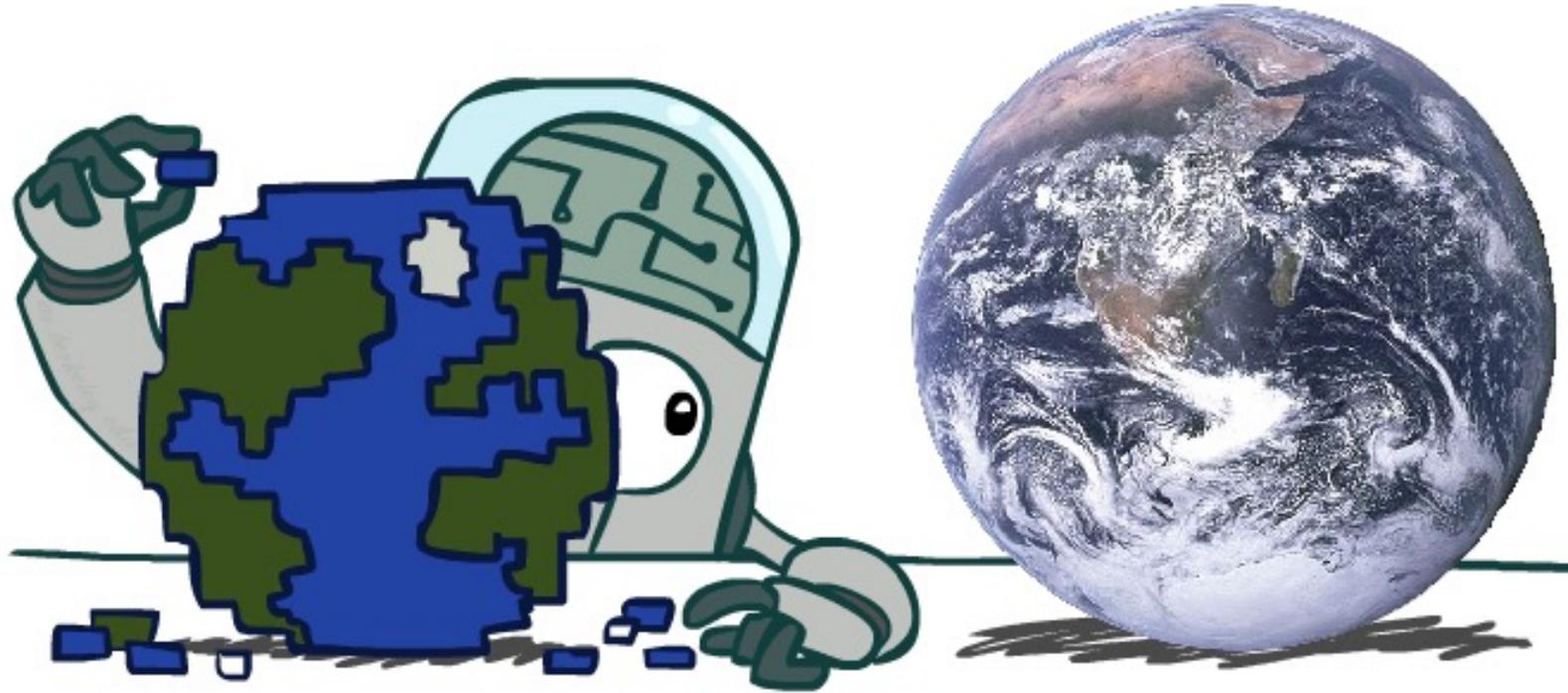
- Even worse if you have to simulate your opponent simulating you...

20% / ... except for minimax and maximax, which have the nice property that it all collapses into one game tree: L 50% R 50%

L: $0.8 \cdot 1 + 0.2 \cdot 0.5$

R: 10%

Modeling Assumptions



The Dangers of Optimism and Pessimism

Dangerous Optimism

Assuming chance when the world is adversarial

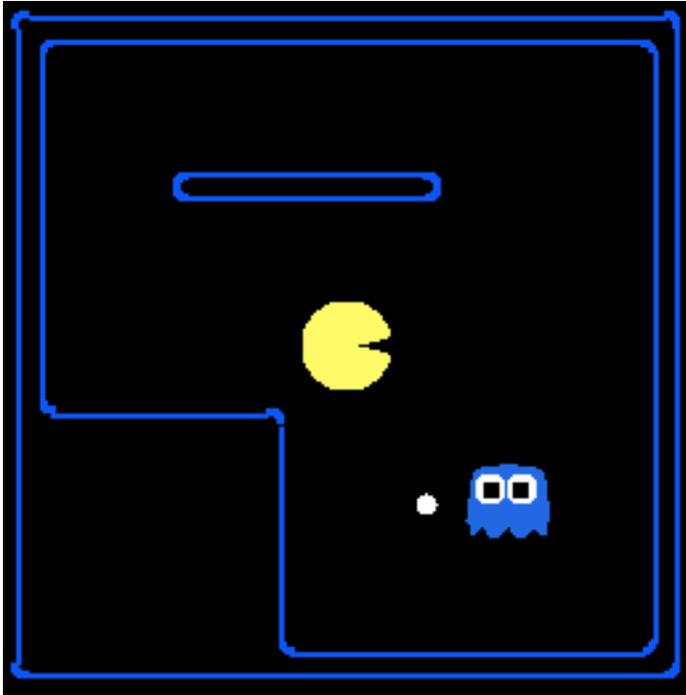


Dangerous Pessimism

Assuming the worst case when it's not likely



Assumptions vs. Reality

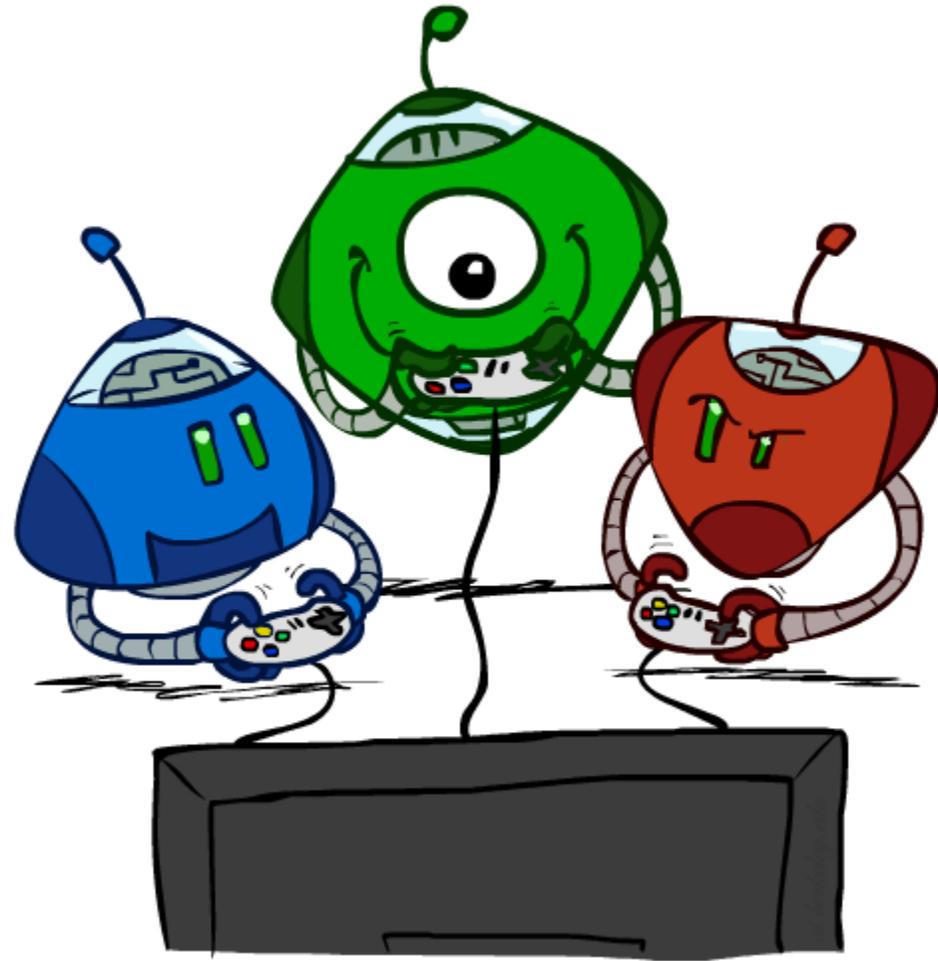


	Adversarial Ghost	Random Ghost
Minimax Pacman		
Expectimax Pacman		

Results from playing 5 games

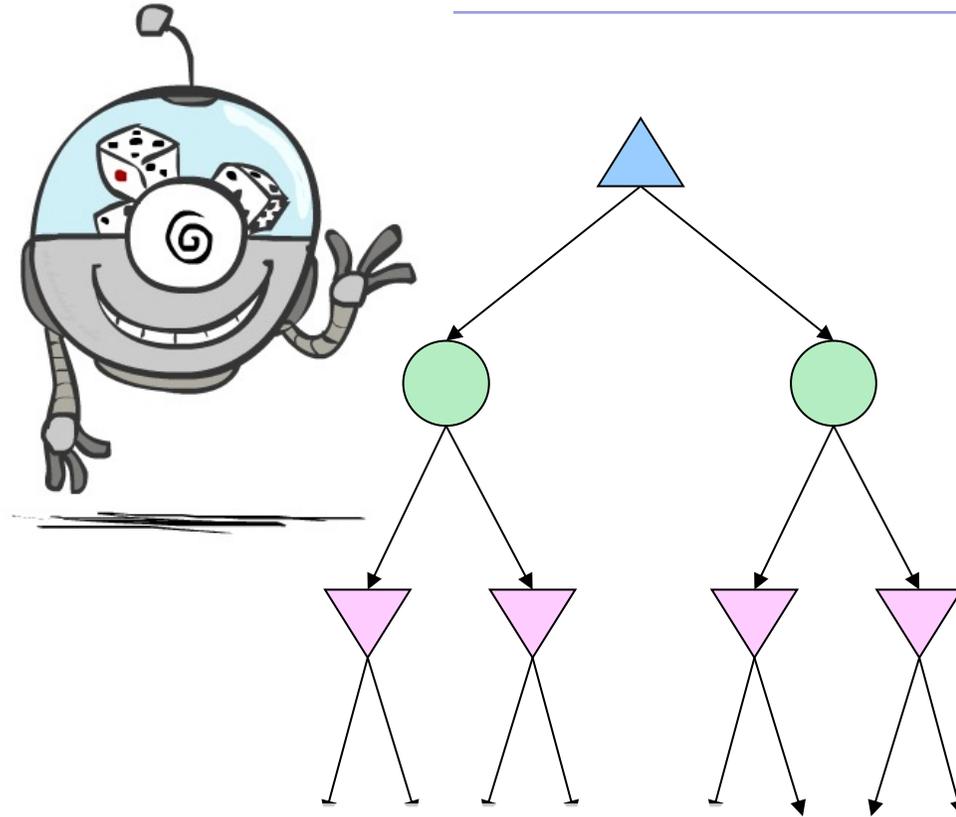
Pacman used depth 4 search with an eval function that avoids trouble
Ghost used depth 2 search with an eval function that seeks Pacman

Other Game Types



Mixed Layer 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



if *state* is a MAX node **then**

return the highest EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)

if *state* is a MIN node **then**

return the lowest EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)

if *state* is a chance node **then**

return average of EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)

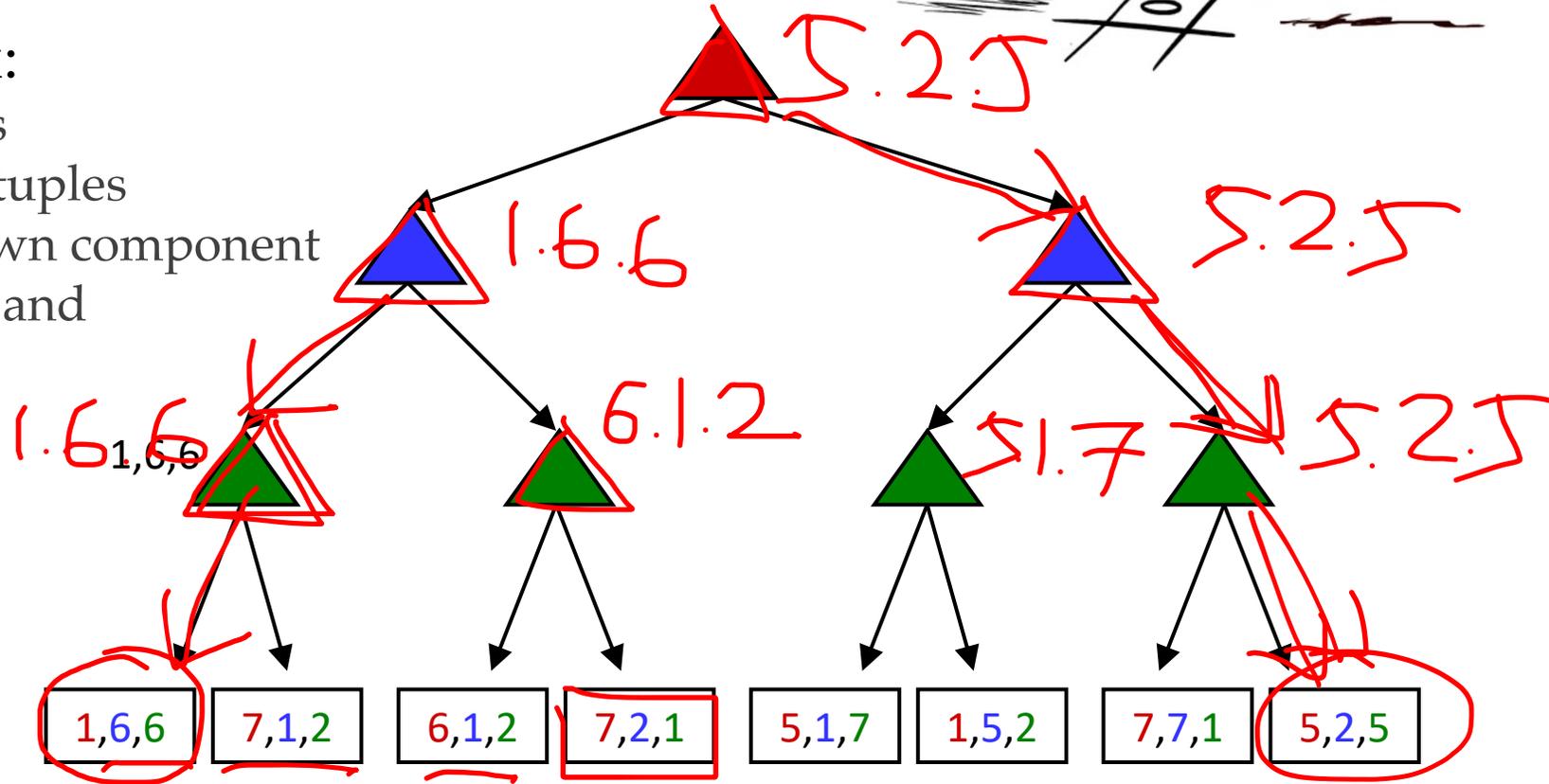
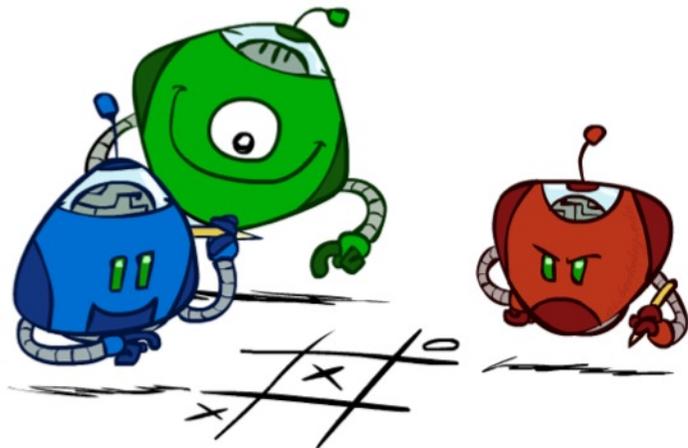
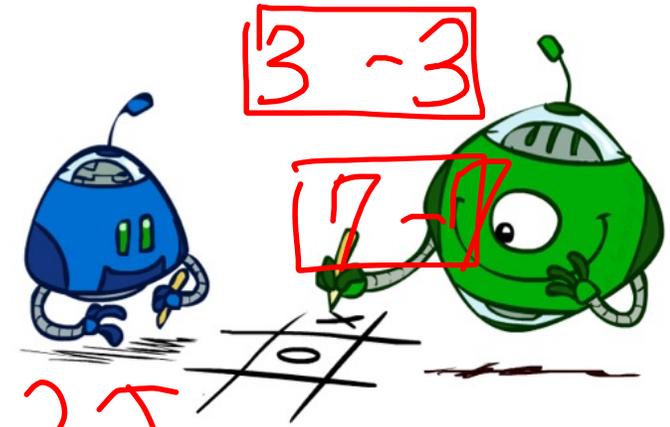
Example: Backgammon

- Dice rolls increase b : 21 possible rolls with 2 dice
 - Backgammon ≈ 20 legal moves
 - Depth 2 = $20 \times (21 \times 20)^3 = 1.2 \times 10^9$
- 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!



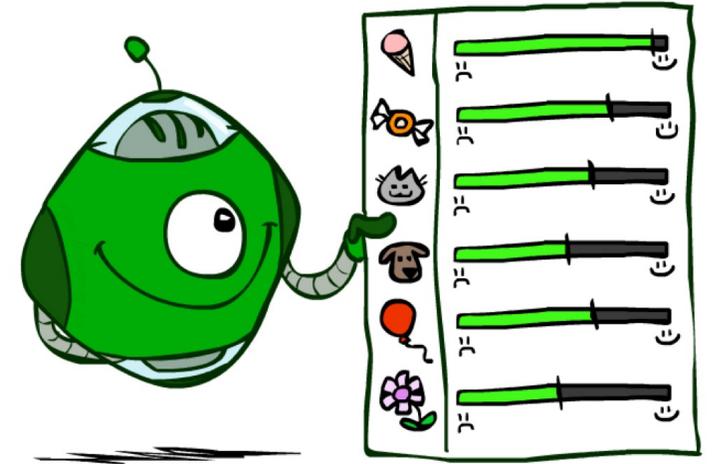
Multi-Agent Utilities

- 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...



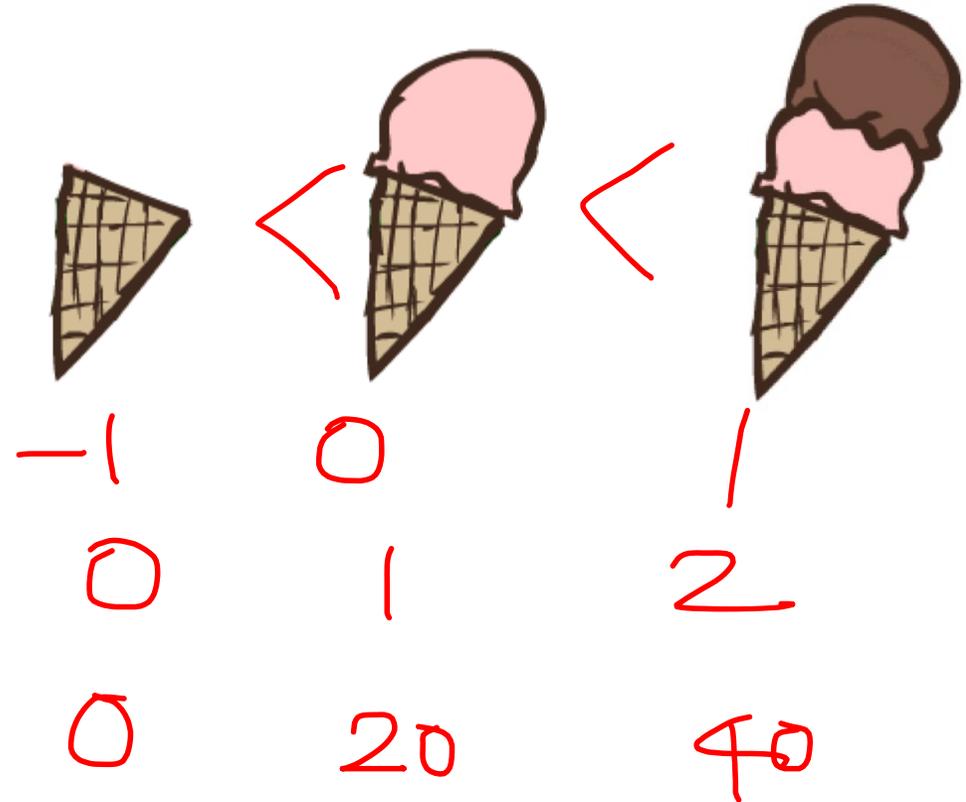
Utilities

- 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**

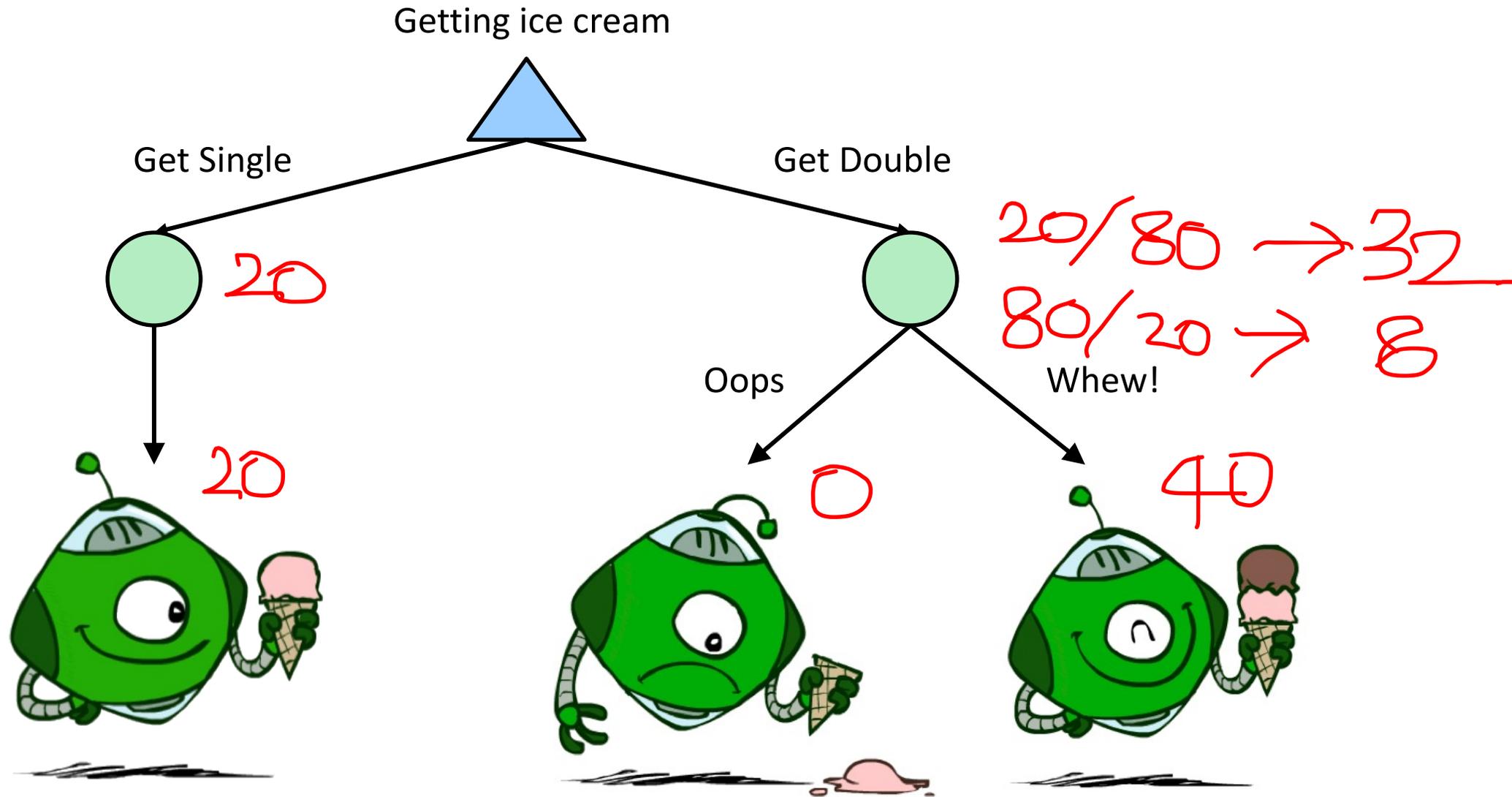


Utilities

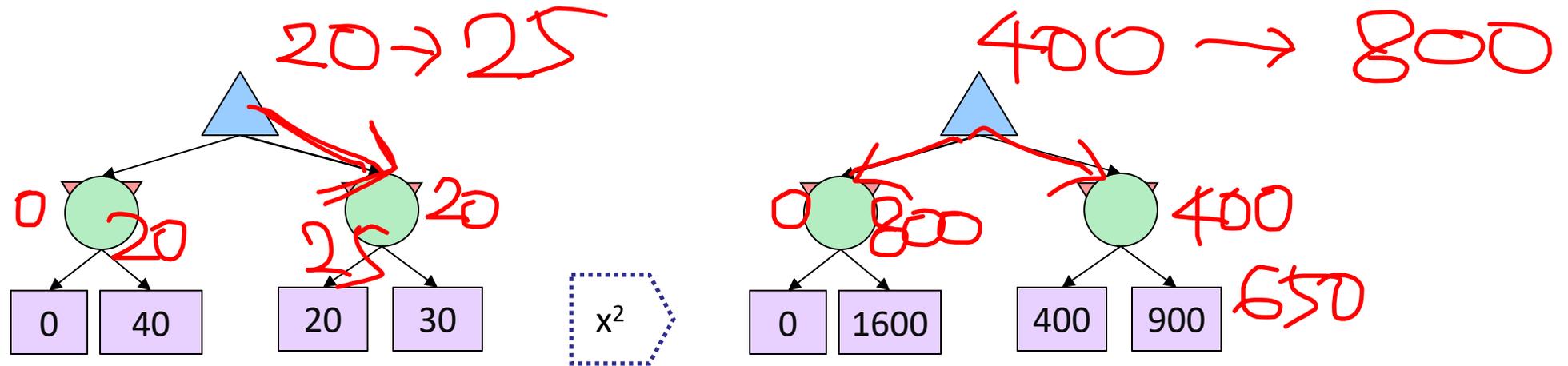
- Utilities are functions from outcomes (states of the world) to real numbers that describe an agent's preferences
- Where do utilities come from?
 - In a game, may be simple (+1/-1)
 - Utilities summarize the agent's goals
- We hard-wire utilities and let behaviors emerge



Utilities: Uncertain Outcomes



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 Topic: MDPs!
