CS 581 – Advanced Artificial Intelligence

Topic: Decision Making Under Uncertainty

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Motivation

- The agent needs reason in an uncertain world
- Uncertainty can be due to
  - Noisy sensors (e.g., temperature, GPS, camera, etc.)
  - Imperfect data (e.g., low resolution image)
  - Missing data (e.g., lab tests)
  - Imperfect knowledge (e.g., medical diagnosis)
  - Exceptions (e.g., all birds fly except ostriches, penguins, birds with injured wings, dead birds, …)
  - Changing data (e.g., flu seasons, traffic conditions during rush hour, etc.)
  - …
- The agent still must act (e.g., step on the breaks, diagnose a patient, order a lab test, …)

What to do?

- Probability of a given email being spam is 0.6. Where should that email be delivered?
- Probability of rain is 0.6. I don't like carrying my umbrella around, but I also don't like getting wet. Should I take my umbrella?
- Probability of a given patient suffering from a heart disease is 0.6. Should more tests be conducted and if so, which ones and in which order? What should the treatment plan be?
- Probability of the product selling is 0.6. If we spend $100K in ads, the probability goes up to 0.7. Is $100K on ads justified?

Rational Agent

- Given world states, a utility function, actions, transitions, evidence, and probabilities,
- A rational agent chooses the action that maximizes expected utility

$$action = \underset{a}{\text{argmax}}\, EU(a|\text{e})$$

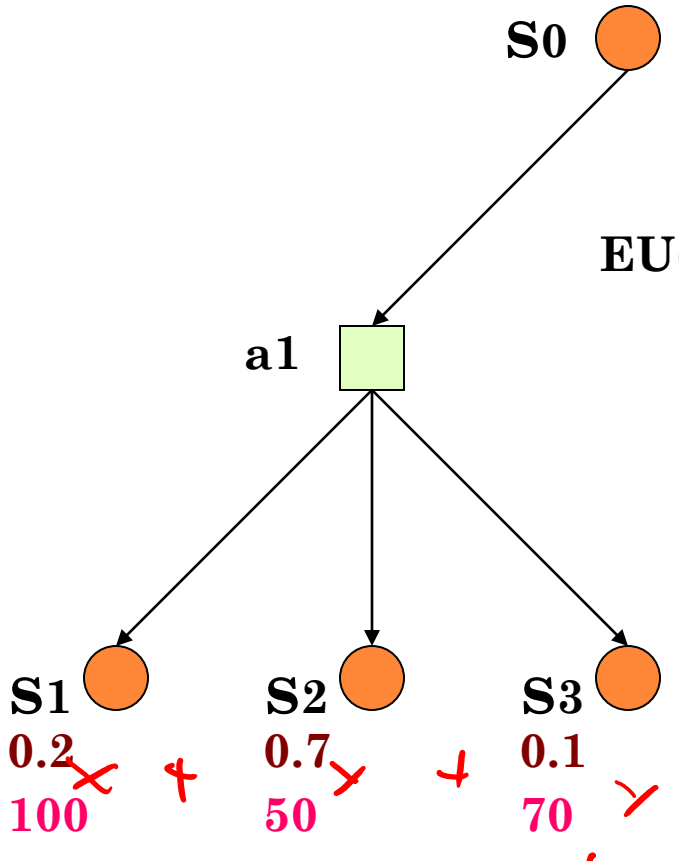
Uncertainty Representation

- Covered
  - Probability background (marginal, conditional, independence, Bayes rule, …)
  - Probabilistic classification (naïve Bayes, logistic regression, neural networks)
- Skipped
  - Bayesian networks (covered in CS 480 and CS 583)

Utility Theory

- Lottery: n possible outcomes with probabilities
  - $[p_1, \mathrm{S}_1; p_2, \mathrm{S}_2; \ldots p_n, \mathrm{S}_n]$
  - Each S_i can be an atomic state or another lottery
- **Expected utility of a lottery**
  - $EU([p_1, S_1;\ p_2, S_2;\ \ldots\ pn, Sn]) = \sum_{i=1}^{n} p_i U(S_i)$

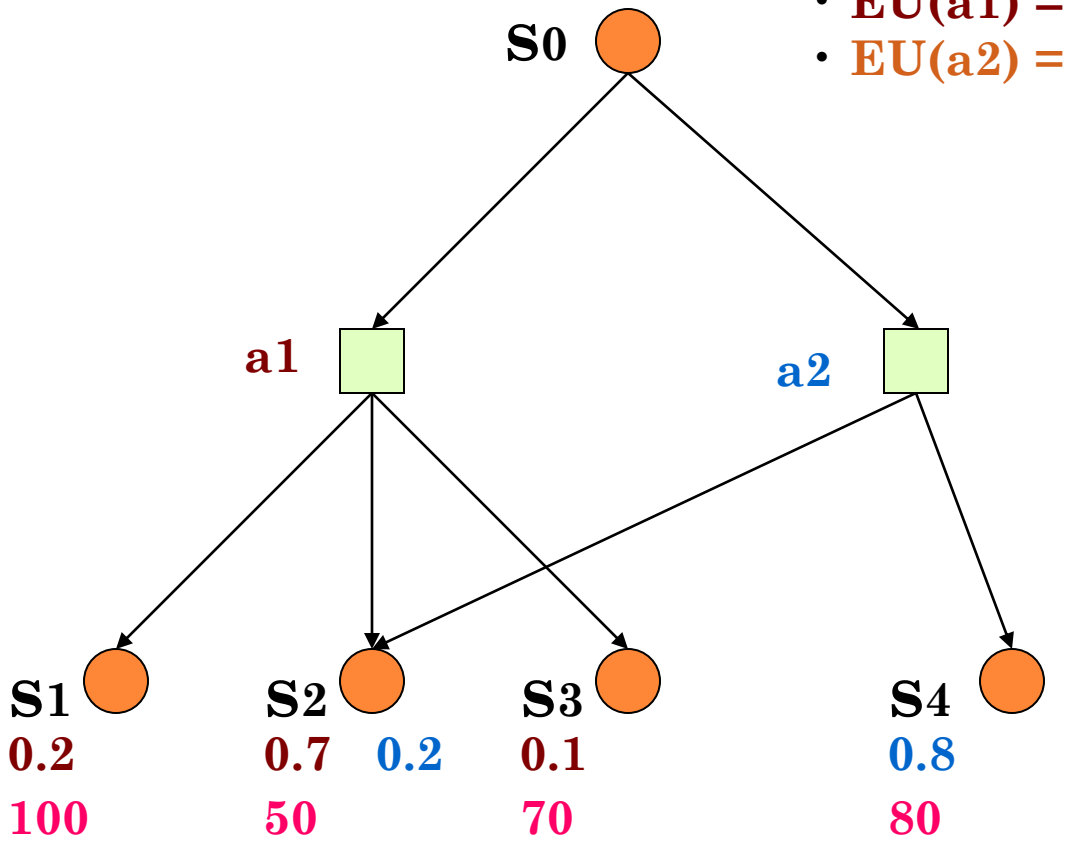
One Action Example



EU(a1) = 100 x 0.2 + 50 x 0.7 + 70 x 0.1
= 20 + 35 + 7
= 62

Two Actions Example

- EU(a1) = 62
- EU(a2) = 0.2*50+0.8*80 = 74



Utility ≠ Money

- Most agents prefer more money to less money,
  - But this does not mean money behaves as a utility function
- For example, which lottery would you prefer
  - L_1: [1, \$1 Million] ~ 1M
  - L_2: [0.5, \$0; 0.5, \$2.5 Million] 1.25M
- If money served as a utility function, then you'd prefer L_2 no matter what, but the answer *often* depends on how much money you currently have
  - The utility of money depends on what you *prefer*
    - If you are short on cash, a little more *certain* money can help
    - If you are already billionaire, you might take the risk
    - Or if you are swimming in debt, you might like to gamble

Utility ≠ Money

- Let's say you currently have \$k and let S_k represent the state of having \$k
- $EU(L_1) = U(S_{k+1M})$
- $EU(L_2) = 0.5*U(S_k) + 0.5*U(S_{k+2.5M})$
- The rational choice depends on your preferences for S_k, S_{k+1M}, and $S_{k+2.5M}$
  - i.e, it depends on the values of $U(S_k)$, $U(S_{k+1M})$, and $U(S_{k+2.5M})$
- $U(S_i)$ does not have to be a linear function of i, and for people it often is not

Which Action To Take?

- Given
  - A probability distribution
  - Choice of actions and their effects on the distribution
  - Evidence
  - A utility function (as a function of states and possibly actions)
- Find
  - Which action maximizes the expected utility?

A simple Spam Filtering Example

- Given an email:
  - P(s | e) = 0.6
  - P(~s | e) = 0.4
- Actions:
  - deliverIntoSpamFolder (dS)
  - deliverIntoInboxFolder (dI)
- Utility function:
  - U(dS, s) = 200
  - U(dI, ~s) = 100
  - U(dI, s) = -100
  - U(dS, ~s) = -500
- Where should this email be delivered and why?

Umbrella Example

$t \Rightarrow p \times c + (1-p) \cdot b$

$\neg t \Rightarrow p \times d + (1-p) \cdot a$

- Check the weather:
  - P(r) = p
  - P(~r) = 1-p
- Actions:
  - takeUmbrella (t)
  - ~takeUmbrella (~t)
- Utility function:
  - U(~r, ~t) = a
  - U(~r, t) = b
  - U(r, t) = c
  - U(r, ~t) = d
- When should you take the umbrella?

Value of Information

- If I can buy more information to help with my decision, up to how much should I pay for that information?
  - Currency here is in "utility" units
- Value of information
  - Expected utility after the information is acquired
    - Minus
  - Expected utility before the information is acquired
- There is one catch: we do not know the content of the information before we acquire it
  - Solution: take an expectation over the possible outcomes

Value of Information – All Binary

- Probability of state:
  - P(s) = p, P(~s) = 1-p
- Actions
  - a, ~a
- Additional info, E
  - P(s | e) = q, P(~s | e) = 1-q
  - P(s | ~e) = r, P(~s | ~e) = 1-r
  - P(e) = v, P(~e) = 1-v
- Utilities
  - U(s, a) = u1
  - U(s, ~a) = u2
  - U(~s, a) = u3
  - U(~s, ~a) = u4
- What is the value of E? VOI(E)?

Next

- Multi-armed bandit
- Markov decision processes
- Reading
  - Chapter 17 of the AI book by Stuart & Russel (http://aima.cs.berkeley.edu/)
  - Chapters 2 and 3 of the RL book by Sutton & Barto (http://www.incompleteideas.net/book/the-book-2nd.html)

Multi-armed Bandit

Setup

- K slot machines
  - Each one is a one-armed bandit
- Unknown reward functions
  - The distribution of rewards for each machine are unknown
- Limited resources
  - Have a limited number of tries (or alternatively, future rewards are discounted)
- Can gather information
  - Each try gives a (potentially) zero/negative reward, but also is useful for information gathering purposes
- Main objective
  - Maximize rewards
- Exploration vs exploitation trade-off
  - How should you balance exploitation (sticking with a machine that looks good) versus exploration (trying new machines)?

Notation

- A_t: action at time t
- R_t: reward at time t
- Sequence of actions and rewards:
  $A_1, R_1, A_2, R_2, \cdots, A_T, R_T$
- $q_*(a) = E[R_t \mid A_t = a]$
  - Not given; otherwise, the solution is trivial
- $Q_t(a)$: Average reward for action a, up to, excluding, time t
  - Estimated using prior experiences
  - If action a has never been taken before time t, $Q_t(a)$ is initialized to a default value

Optimal Strategy

- $\underset{a}{\operatorname{argmax}}\, q_*(a)$
- At time t, choose the action that has the highest expected reward
- Challenge
  - We do not know $q_*(a)$

Greedy Strategy (Exploit only)

- $\underset{a}{\text{argmax}}\, Q_t(a)$
- Calculate the average reward for each action, up to time t, and choose the maximum one
- Problems
  - Initial values of $Q_t(a)$ plays a big role
  - It simply tries the best action it has found; purely exploitation
  - Could easily miss other actions that are better but not tried

Random Strategy (Explore Only)

- Choose an action at random
- Good
  - Explores all the time
- Bad
  - Does not exploit; does not learn

Epsilon Greedy

- Given an exploration parameter ϵ
- At each step t:
  - With probability ϵ, choose a random action (explore)
  - With probability $1 - \epsilon$, choose the current best action: $\underset{a}{\operatorname{argmax}}\, Q_t(a)$ (exploit)
- $\epsilon = 0$ is fully greedy, and $\epsilon = 1$ is fully random

Simulation Setup

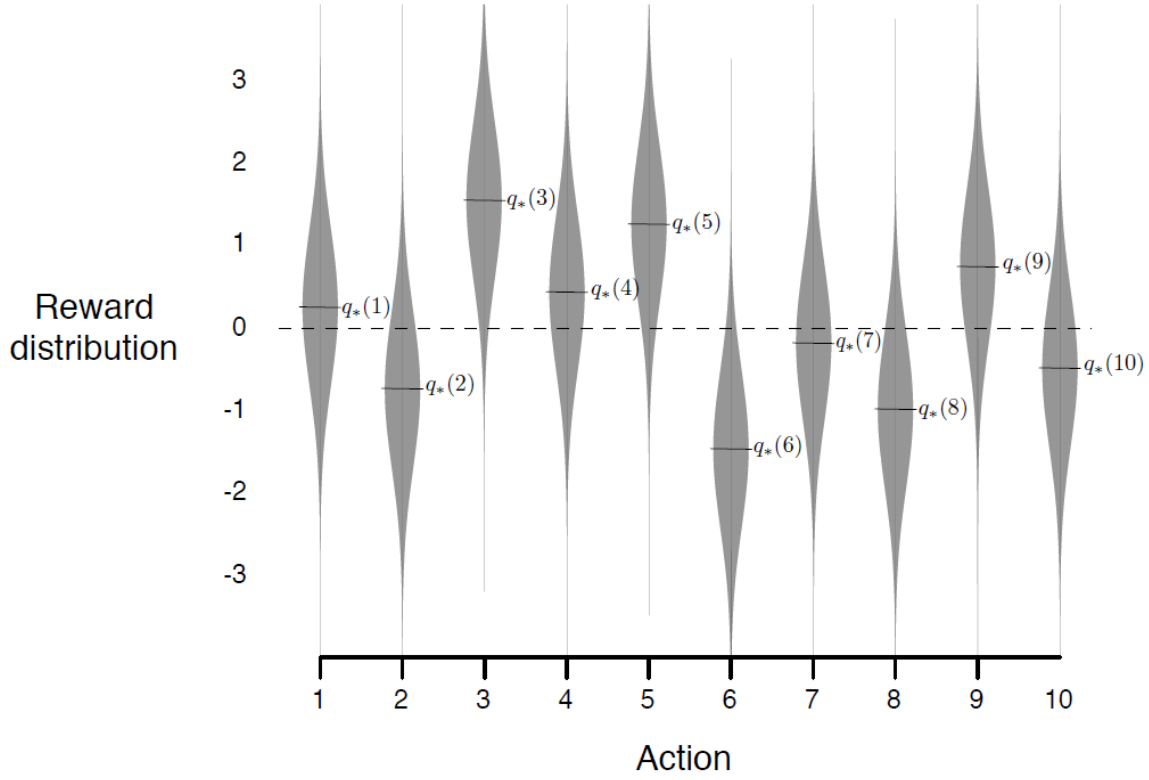


Figure 2.1: An example bandit problem from the 10-armed testbed. The true value $q_*(a)$ of each of the ten actions was selected according to a normal distribution with mean zero and unit variance, and then the actual rewards were selected according to a mean $q_*(a)$, unit-variance normal distribution, as suggested by these gray distributions.

Figure from http://www.incompleteideas.net/book/the-book-2nd.html

Simulation Results

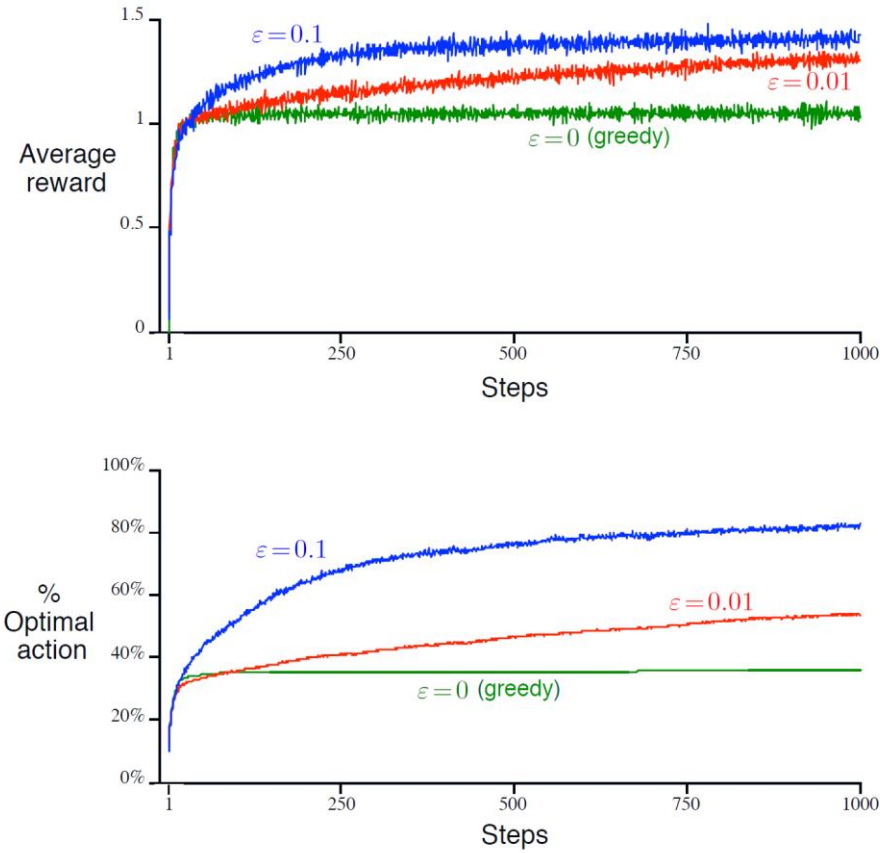


Figure 2.2: Average performance of ε-greedy action-value methods on the 10-armed testbed. These data are averages over 2000 runs with different bandit problems. All methods used sample averages as their action-value estimates.

Figure from http://www.incompleteideas.net/book/the-book-2nd.html

UCB

- The upper-confidence bound (UCB) method calculates the upper bound on the mean for each slot and chooses the machine with max value
  - $Q_t(a) + c\sqrt{\frac{\ln(t)}{N_t(a)}}$, where $N_t(a)$ is the number of times the action a is tried and c is the trade-off parameter
- The term in the square root is a measure of uncertainty in $Q_t(a)$; and hence the name upper confidence bound
  - The upper confidence is derived using the Chernoff-Hoeffding bound
- The exploration grows with *ln(t)*, shrinks with $N_t(a)$
- We've seen this before; where?

Simulation Results

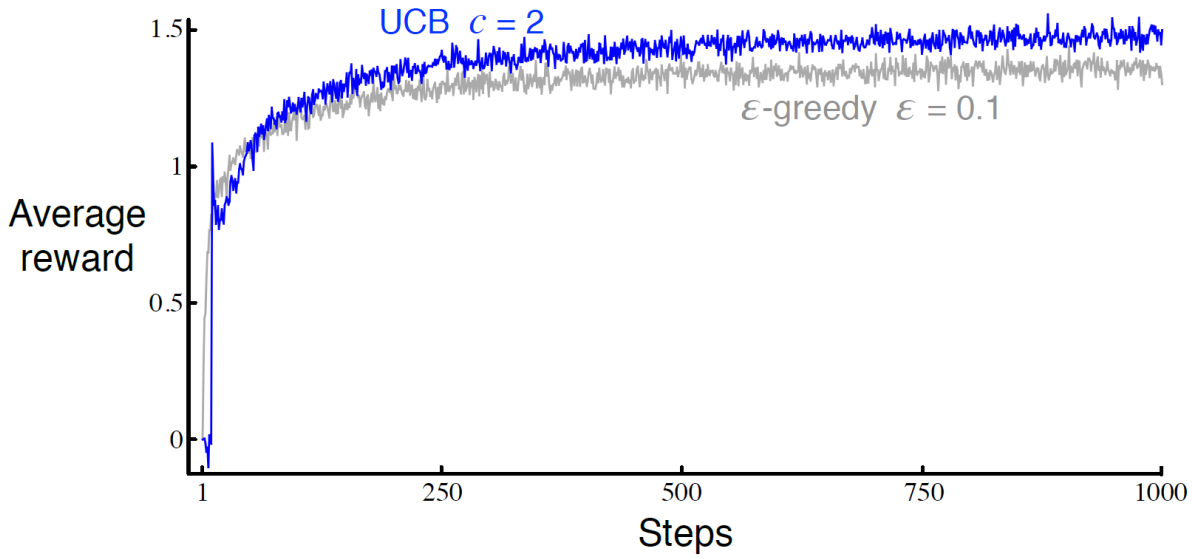


Figure 2.4: Average performance of UCB action selection on the 10-armed testbed. As shown, UCB generally performs better than ε-greedy action selection, except in the first k steps, when it selects randomly among the as-yet-untried actions.

Figure from http://www.incompleteideas.net/book/the-book-2nd.html

A Running Average Computation

$$
\begin{aligned}
Q_{n+1} &= \frac{1}{n}\sum_{i=1}^{n} R_i \\
&= \frac{1}{n}\left(R_n + \sum_{i=1}^{n-1} R_i\right) \\
&= \frac{1}{n}\left(R_n + (n-1)\frac{1}{n-1}\sum_{i=1}^{n-1} R_i\right) \\
&= \frac{1}{n}\Big(R_n + (n-1)Q_n\Big) \\
&= \frac{1}{n}\Big(R_n + nQ_n - Q_n\Big) \\
&= Q_n + \frac{1}{n}\Big[R_n - Q_n\Big],
\end{aligned}
$$

Figure from http://www.incompleteideas.net/book/the-book-2nd.html

Update Rule

- $Q_{n+1} = Q_n + \frac{1}{n}(R_n - Q_n)$
- new = old + stepSize*(target – old)
- For computing the exact average, stepSize is a function of n

Non-stationary Rewards

- What if the reward distribution changes over time?
- We'd like to give recent rewards more weight
- A simple approach
  - $Q_{n+1} = Q_n + \alpha(R_n - Q_n)$
- Earlier rewards have lower weights

$$
\begin{aligned}
Q_{n+1} &= Q_n + \alpha(R_n - Q_n) \\
&= \alpha R_n + (1-\alpha)Q_n \\
&= \alpha R_n + (1-\alpha)[\alpha R_{n-1} + (1-\alpha)Q_{n-1}]
\end{aligned}
$$

Markov Decision Processes

Problem Setting

- The world is represented through states
- At each state, an agent is given 0 (terminal states) or more actions to choose from
- Each action moves the agent, probabilistically, to a state (could be the current state) and results, probabilistically, in a reward (could be zero, negative, positive)
- The agent needs to maximize the sum of the rewards it accumulates over time
- Greedy strategy with respect to immediate rewards often do not work; the agent needs to consider the long-term consequences of its actions

Markov Decision Process

- A sequential decision-making process
- Stochastic environment
- Markov transition model
- Additive rewards
- Applications: planning
  - Search Google
  - http://www.it.uu.se/edu/course/homepage/aism/st11/MDPApplications1.pdf

MDP Diagram Example

- See OneNote

Notation

- $P(s' | s, a)$ Probability of arriving at state s' given we are at state s and take action a
- $R(s, a, s')$ The reward the agent receives when it transitions from state s to state s' via action a
- $\pi(s)$ The action recommended by policy π at state s
- π^* Optimal policy
- $U^{\pi}(s)$ The expected utility obtained via executing policy π starting at state s
- $U^{\pi^*}(s)$ is abbreviated as $U(s)$
- $Q(s, a)$ The expected utility of taking action a at state s
- γ Discount factor [0, 1]

Running Example

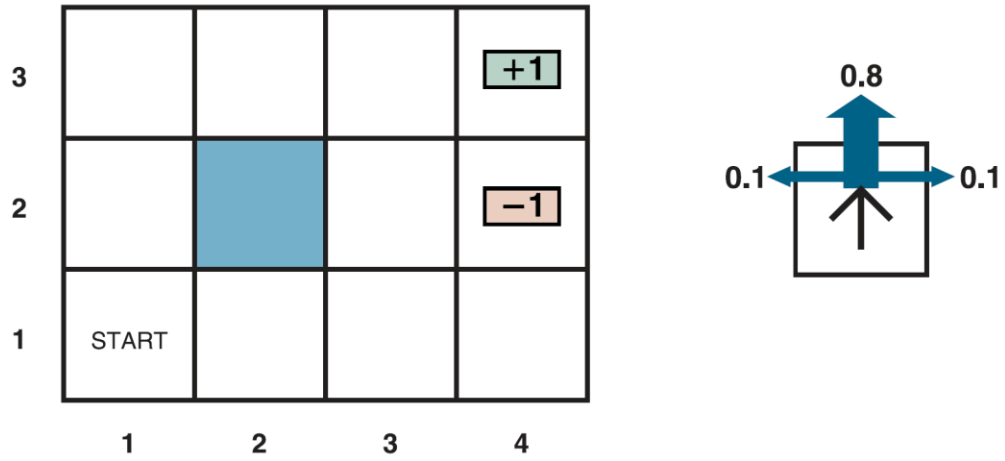


Figure 17.1 (a) A simple, stochastic 4×3 environment that presents the agent with a sequential decision problem. (b) Illustration of the transition model of the environment: the "intended" outcome occurs with probability 0.8, but with probability 0.2 the agent moves at right angles to the intended direction. A collision with a wall results in no movement. Transitions into the two terminal states have reward +1 and –1, respectively, and all other transitions have a reward of –0.04.

Figure from http://aima.cs.berkeley.edu/figures.pdf

Solution?

- A fixed action sequence is not the answer due to stochasticity
  - For example, [Up, Up, Right, Right, Right] is not a solution
  - It would be a solution if the environment was deterministic
- A solution must specify the agent should do in any state that the agent might reach
  - This is called a **policy**
- Policy notation: $\boldsymbol{\pi}$
  - $\pi(s)$ specifies what action the agent should take at state s
- An **optimal policy** is the one that maximizes the expected utility
  - $\boldsymbol{\pi^*}$

Running Example

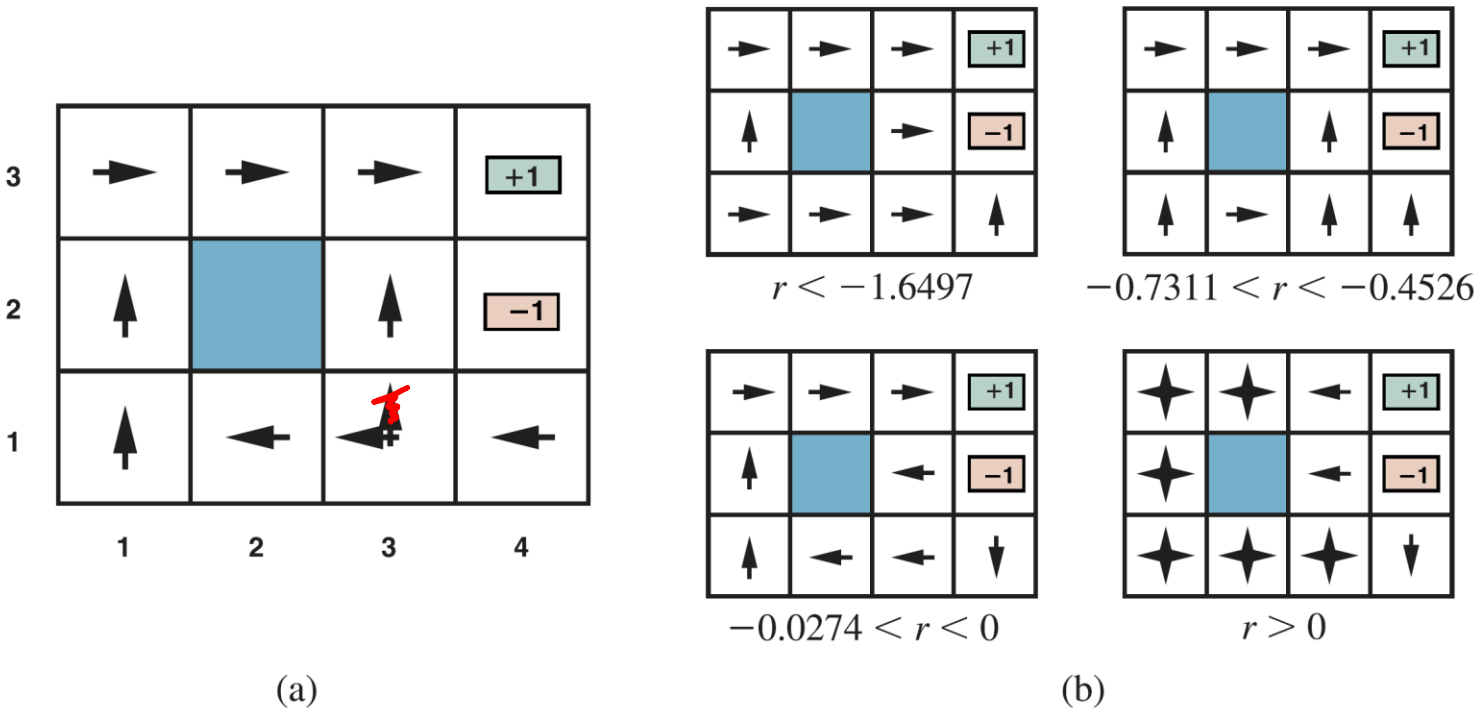


Figure 17.2 (a) The optimal policies for the stochastic environment with $r = -0.04$ for transitions between nonterminal states. There are two policies because in state (3,1) both *Left* and *Up* are optimal. (b) Optimal policies for four different ranges of r.

Figure from http://aima.cs.berkeley.edu/figures.pdf

Utility of States

- The agent receives a reward at each state
- Utility of a state s given a policy π is the expected reward that the agent will get starting from state s and taking actions according to policy π
- Let S_t denote the state that the agent reaches at time t
- $U^{\pi}(s) = E[\sum_{t=0}^{\infty} \gamma^t R(S_t, \pi(S_t), S_{t+1})]$
- The expectation is with respect to the transition probabilities

The optimal Policy

- The optimal policy is the one that maximizes the expected utility
  - $\pi_s^* = \underset{\pi}{\text{argmax}}\, U^{\pi}(s)$
- Remember that π_s^* is a policy; that is, it recommends an action for each state, regardless of whether it is the starting state or not
- It is optimal when the starting state is s
- When the rewards are discounted, the optimal policy is independent of the start state
  - The optimality of the policy does not depend on the starting state but of course the action sequence depends on the starting state
- True utility of each state is defined as $U^{\pi^*}(s)$ -- the expected rewards the agent will receive if it executes the optimal policy starting at s

U(S) VS R(S, A, S')

- *R(s, a, s')* is the short-term immediate reward the agent receives when it transitions from state s to state s' via action a
- *U(s)* is the long-term cumulative reward from s onward
- $U^{\pi}(s) = E[\sum_{t=0}^{\infty} \gamma^t R(S_t, \pi(S_t), S_{t+1})]$

Bellman Optimality Equation

$$U(s) = \max_{a \in A(s)} \sum_{s'} P(s' | s, a)[R(s, a, s') + \gamma U(s')]$$

Action-Utility Function $Q(s, a)$

- $Q(s, a)$ The expected utility of taking action a at state s
- $Q(s, a) = \sum_{s'} P(s' | s, a)[R(s, a, s') + \gamma U(s')]$
- $U(s) = \max_{a \in A(s)} Q(s, a)$
- $Q(s, a) = \sum_{s'} P(s' | s, a)[R(s, a, s') + \gamma \max_{a' \in A(s')} Q(s', a')]$
  - Bellman optimality equation for the Q function

Running Example

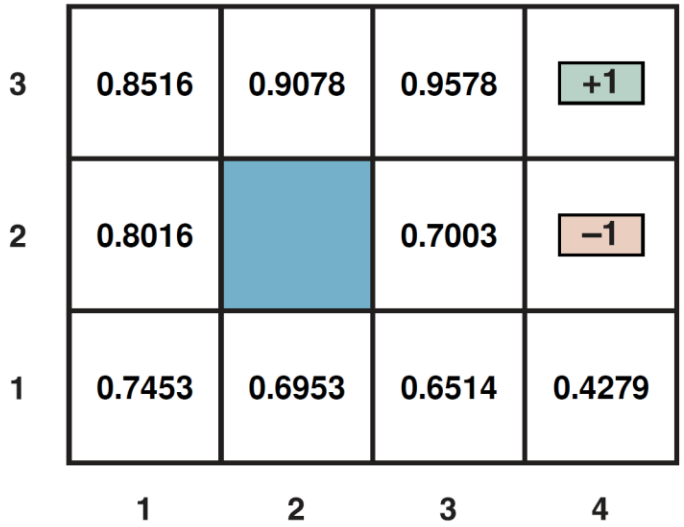


Figure 17.3 The utilities of the states in the 4×3 world with $\gamma = 1$ and $r = -0.04$ for transitions to nonterminal states.

Figure from http://aima.cs.berkeley.edu/figures.pdf

Q(S, A)

					UP			
0.8516	0.9078	0.9578	1		0.81722	0.86718	0.91702	0
0.8016		0.7003	-1		0.8016		0.70027	0
0.7453	0.6953	0.6514	0.4279		0.74534	0.65591	0.63256	-0.70007
					DOWN			
					0.77722	0.86718	0.71102	0
					0.71656		0.45515	0
					0.7003	0.65591	0.59344	0.41025
					LEFT			
					0.8066	0.82284	0.85205	0
					0.76097		0.68116	0
					0.71093	0.6953	0.65141	0.42791
					RIGHT			
					0.85156	0.9078	0.95781	0
					0.76097		-0.64708	0
					0.67093	0.62018	0.43749	0.24911
					MAX			
					0.85156	0.9078	0.95781	0
					0.8016		0.70027	0
					0.74534	0.6953	0.65141	0.42791

Exercise

- Confirm that the utilities given in the previous slide satisfy the Bellman equations

How to Find π^*

- $\pi^*(s) = \underset{a \in A(s)}{\text{argmax}} \sum_{s'} P(s' \mid s, a)[R(s, a, s') + \gamma U(s')]$
- However, we are not given $U(s)$
- Two algorithms for finding optimal policies

1. Value iteration
2. Policy iteration

Value Iteration

- $U(s) = \max_{a \in A(s)} \sum_{s'} P(s' | s, a)[R(s, a, s') + \gamma U(s')]$
- n possible states, n Bellman equations, one for each state
- However, these are non-linear equations, due to the max operator
- One approach: iterative
  - Start with an initial guess (could be random)
  - Iterate until convergence

Policy Iteration

- Start with an initial policy π_0
- Alternate between

1. Policy evaluation: given policy π_i, calculate U^{π_i}
2. Policy improvement: Calculate a new MEU policy π_{i+1}, using the utilities calculated in the previous step

- Stop when utilities no longer change

Next

- Reinforcement learning
  - In fact, we already covered many of the fundamentals of RL
    - Value iteration, policy iteration, exploration vs exploitation trade-off
  - We are now ready to make the leap from MDPs to RL
  - RL can be considered as solving an MDP where the transition and reward dynamics are unknown