# ROB311 Quiz 2

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## Contents

# Probabilistic Inference Problems

## 1 Bayesian Networks

**Definition**: Vertices represent random variables and edges represent dependencies between variables.

### 1.1 Junction

**Definition**: A **junction** $\mathcal{J}$ consists of three vertices, $X_1$, $X_2$, and $X_3$, connected by two edges, $e_1$ and $e_2$:

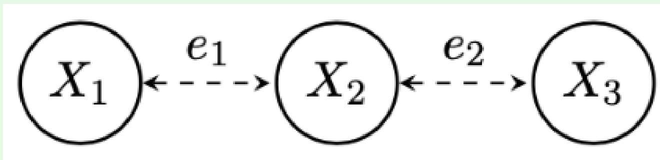



Figure 1

- $X_1$ and $X_2$ are not independent, $X_2$ and $X_3$ are not independent, but when is $X_1$ and $X_3$ independent?

#### 1.1.1 Causal Chain

**Definition**: A causal chain is a junction $\mathcal{J}$ s.t.

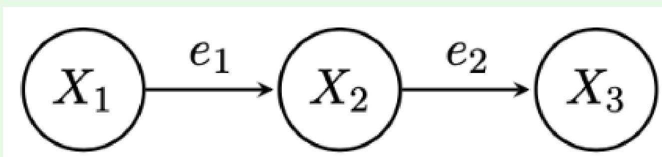



Figure 2

- $X_1$ and $X_3$ are not independent (unconditionally), but are independent given $X_2$.

**Notes**:
- **Analogy:** Given $X_2$, $X_1$ and $X_3$ are independent. Why? $X_2$'s door closes when you know $X_2$, so $X_1$ and $X_3$ are independent.
- **Distinction b/w Causal and Dependence:** $X_1$ and $X_2$ are dependent. However, from a causal perspective, $X_1$ is influencing $X_2$ (i.e. $X_1 \rightarrow X_2$).

**Warning**: $X_1$ is influeincing $X_2$ and $X_2$ is influencing $X_3$.

#### 1.1.2 Common Cause

**Definition**: A common cause is a junction $\mathcal{J}$ s.t.

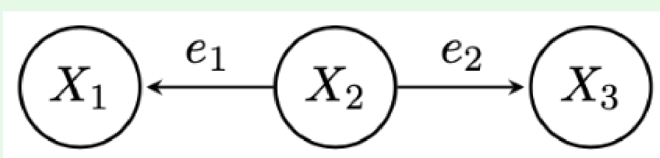



Figure 3

- $X_1$ and $X_3$ are not independent (unconditionally), but are independent given $X_2$.

**Notes**:
- **Analogy:** Given $X_2$, $X_1$ and $X_3$ are independent. Why? Consider the following example:
  - Let $X_2$ represent whether a person smokes or not, $X_1$ represent whether they have yellow teeth, $X_3$ represent whether they have lung cancer.
- Without knowing $X_2$, observing $X_1$ provides information about $X_3$ because yellow teeth are associated with smoking, which in turn increases the likelihood of lung cancer.
- If $X_2$ is known, then knowing whether a person has yellow teeth provides no additional information about whether they have lung cancer beyond what is already known from smoking status.

### 1.1.3 Common Effect

**Definition**: A common effect is a junction $\mathcal{J}$ s.t.

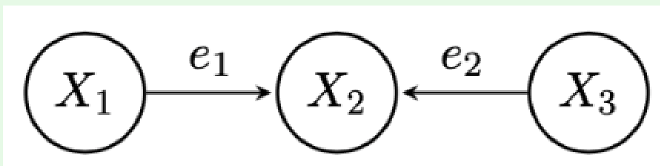



Figure 4

- $X_1$ and $X_3$ are independent (unconditionally), but are not independent given $X_2$ or any of $X_2$'s descendents.

**Notes**:
- **Analogy:** Consider the following example:
  - Let $X_2$ represent whether the grass is wet, $X_1$ represent whether it rained, $X_3$ represent whether the sprinkler was on.
- Without knowing whether the grass is wet ($X_2$), the occurrence of rain ($X_1$) and the sprinkler being on ($X_3$) are independent events. The rain may occur regardless of the sprinkler, and vice versa.
- However, once we observe that the grass is wet ($X_2$), the two events become dependent:
  - If we learn that the sprinkler was not on, then the wet grass must have been caused by rain.
  - If we learn that it did not rain, then the wet grass must have been caused by the sprinkler.

## 1.2 Dependence Separation

### 1.2.1 Blocked

**Definition**: $\mathcal{J} = (\{X_1, X_2, X_3\}, \{e_1, e_2\})$ is **blocked** given $\mathcal{K} \subseteq \mathcal{V}$ if $X_1$ and $X_3$ are independent given $\mathcal{K}$.

### 1.2.2 Blocked Undirected Path

**Definition**: An undirected path,

$$p = \langle (X_1, e_1, X_2), \ldots, (X_{|p|-1}, e_{|p|-1,|p|}, X_{|p|}) \rangle,$$

is **blocked** given $\mathcal{K} \subseteq \mathcal{V}$ if any of its junctions,

$$\mathcal{J}^{(n)} = \{(X_{n-1}, X_n, X_{n+1}), (e_{n-1}, e_n)\},$$

is blocked given $\mathcal{K}$.

### 1.2.3 Independence

**Theorem**: Any two variables, $X_1$ and $X_2$, in a Bayesian network, $\mathcal{B} = (\mathcal{V}, \mathcal{E})$, are independent given $\mathcal{K} \subseteq \mathcal{V}$ if every undirected path is blocked.

### 1.2.4 Consequence of Dependence Separation

**Theorem**: For any variable, $X \in \mathcal{V}$, it can be shown that $X$ is independent of $X$'s non-descendants, $\mathcal{V} \setminus \mathrm{des}(X)$, given $X$'s parents, $\mathrm{pts}(X)$.

**Notes**:

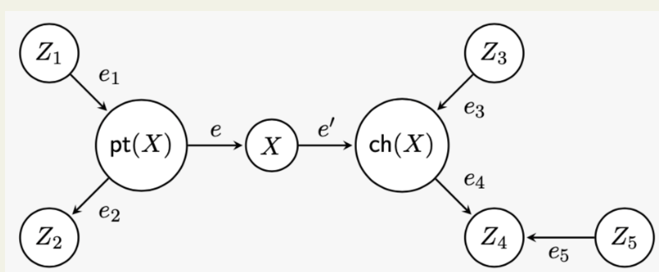



Figure 5

- Given $X$'s parent, apply junction rules to determine that $X$ is independent of its non-descendants.
- $\mathcal{J} = \{(Z_1, \mathrm{pt}(X), X), (e_1, e)\}$ shows that $Z_1$ and $X$ are independent given $\mathrm{pt}(X)$ (causal chain).
- $\mathcal{J} = \{(Z_2, \mathrm{pt}(X), X), (e_2, e)\}$ shows that $Z_2$ and $X$ are independent given $\mathrm{pt}(X)$ (common cause).
- Given $\mathrm{ch}(X)$'s parent, apply junction rules to determine that $\mathrm{ch}(X)$ is independent of its non-descendants.
- $\mathcal{J} = \{\mathrm{pt}(X), X, \mathrm{ch}(X)), (e, e')\}$ shows that $\mathrm{pt}(X)$ and $\mathrm{ch}(X)$ are independent given $X$ (causal chain).
- Given $Z_4$'s parent, apply junction rules to determine that $Z_4$ is independent of its non-descendants.
- $\mathcal{J} = \{X, \mathrm{ch}(X), Z_4, (e', e_4)\}$ shows that $X$ and $Z_4$ are independent given $\mathrm{ch}(X)$ (causal chain).
- CHECK THIS OVER AGAIN WITH

# 2 Probabilistic Inference

## 2.1 Problem Setup

**Definition**: Given a Bayesian network, $\mathcal{B} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{X_1, \ldots, X_{|\mathcal{V}|}\}$, we want to find the value of:

$$\text{pr}(\mathbf{Q} \mid \mathbf{E}) := \text{pr}(Q_1, \ldots, Q_{|\mathbf{Q}|} \mid E_1, \ldots, E_{|\mathbf{E}|}) = \frac{\sum_{\mathcal{V} \setminus (\mathbf{Q} \cup \mathbf{E})} p(X_1, \ldots, X_{|\mathcal{V}|})}{\sum_{\mathcal{V} \setminus \mathbf{E}} p(X_1, \ldots, X_{|\mathcal{V}|})}$$

$$\text{pr}(\mathbf{Q} \mid \mathbf{E}) \propto \sum_{\mathcal{V} \setminus (\mathbf{Q} \cup \mathbf{E})} \left( p(X_1) \prod_{i \neq 1} p(X_i \mid \text{pts}(X_i)) \right)$$

- $\mathbf{Q} = \{Q_1, \ldots, Q_{|\mathbf{Q}|}\}$: Query variables
- $\mathbf{E} = \{E_1, \ldots, E_{|\mathbf{E}|}\} \subseteq \mathcal{V}$: Evidence variables
- $\mathbf{Q} \cap \mathbf{E} = \emptyset$.

## 2.2 Method 1: Bayesian Network Inference

### 2.2.1 Markov Blanket

**Definition**: The **Markov blanket** of a variable $X$, denoted $\text{mbk}(X)$, consists of the following variables:
- $X$'s children
- $X$'s parents
- The other parents of $X$'s children, excluding $X$ itself.

which is when a variable, $X$, is "eliminated", the resulting factor's scope is the Markov blanket of $X$.

### 2.2.2 Graphical Interpretation

**Notes**: Pictorially, eliminating $X$ is equivalent to replacing all hyper-edges that include $X$ with their union minus $X$, and then removing $X$.

### 2.2.3 Elimination Ordering

**Definition**: The order that the variables are eliminated.

### 2.2.4 Elimination Width

**Definition**: The **elimination width** of a sequence of hyper-graphs is the # of variables in the hyper-edge within the sequence with the most variables.

### 2.2.5 Heuristics for Elimination Ordering

**Definition**: Choose the elimination ordering to minimize the elimination width using the following heuristics:
1. Eliminate variable with the fewest parents.
2. Eliminate variable with the smallest domain for its parents, where

$$|\operatorname{dom}(\text{pts}(X))| = \prod_{Z \in \text{pnt}(X)} |\operatorname{dom}(Z)|.$$

3. Eliminate variable with the smallest Markov blanket.
4. Eliminate variable with the smallest domain for its Markov blanket, where

$$|\operatorname{dom}(\text{mbk}(X))| = \prod_{Z \in \text{embk}(X)} |\operatorname{dom}(Z)|.$$

## 2.3 Method 2: Inference via Sampling

**Definition**: Generate a large # of samples and then approximate as:

$$p(\mathbf{Q} \mid \mathbf{E}) \approx \frac{\text{\# of samples w/ } \mathbf{Q} \text{ and } \mathbf{E}}{\text{\# of samples w/ } \mathbf{E}}.$$

- As # of samples $\to \infty$, the approximation becomes exact.

### 2.3.1 Inference via Sampling with Likelihood Weighting

**Motivation**: Most of the samples are wasted since they are not consistent with the evidence.

**Definition**: Generate a large # of samples and then approximate as:

$$p(\mathbf{Q} \mid \mathbf{E}) \approx \frac{\text{weight of samples w/ } \mathbf{Q} \text{ and } \mathbf{E}}{\text{weight of samples w/ } \mathbf{E}}.$$

- Weight for each sample: Probability of forcing the evidence, i.e. probability of the evidence given the sample.

## 2.4 Canonical Problems:

**Example**:

1. **Given:** Caveman is deciding whether to go hunt for meat. He must take into account several factors:
   - Weather
   - Possibility of over-exertion
   - Possibility encountering lion

   These factors can result in Cavemen's death. His decision will ultimately depend on the **chances** of his death.
2. **Binary Variables:**
   - $W = \{\text{Sun}, \text{Rainy}\}$: Weather
   - $H$: Whether the Cavemen goes hunting or not.
   - $L$: Whether the Cavemen encounters a lion or not.
   - $T$: Whether the Cavement is tired or not.
   - $D$: Whether the Cavemen dies or not
3. **Problem:** Cavemen must decide whether to go hunting or not.
   - He must consider the conditional probabilities (i.e. dependence) of each event.

**Warning**: Have to be discrete.

#### 2.4.1 Undirected Path Blocked?

**Process:**
1. **Given:** Undirected path $p$ and $\mathcal{K}$
2. Check if any of the junctions on the undirected path are blocked given $\mathcal{K}$.
   - i.e. Check if $X_1$ and $X_3$ of the junction are independent given $\mathcal{K}$.

#### 2.4.2 Independence

**Process:**
1. Given a Bayesian network w/ 2 variables to find independence.
2. Find all undirected paths between the 2 variables in the Bayesian network.
3. Identify a set of variables, $\mathcal{K}$, that blocks all undirected paths.
4. If all undirected paths are blocked, then the 2 variables are independent given $\mathcal{K}$.

**Example:**
1. **Given:** Bayesian network.

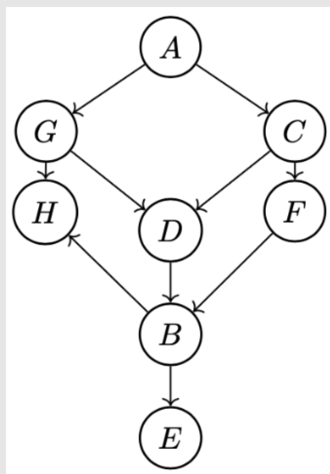



Figure 6

2. **Problem:** $A$ and $E$ are
   - independent if $\mathcal{K} =$
   - not necessarily independent for $\mathcal{K} =$
3. **Soln:**
   (a) **Undirected Paths:**
   - $A \to G \to H \to B \to E$
   - $A \to G \to D \to B \to E$
   - $A \to C \to F \to B \to E$
   - $A \to C \to D \to B \to E$

**Example**: **Independent:**

| $\mathcal{K}$ |
|---|
| $\{G, C\}$ |

- $A \iff G \iff H \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(A, G, H), (e_1, e_2)\}$ is blocked given $G$ since $A, H$ independent given $G$ (causal chain)
- $A \iff G \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(A, G, D), (e_1, e_2)\}$ is blocked given $G$ since $A, D$ independent given $G$ (causal chain)
- $A \iff C \iff F \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(A, C, F), (e_1, e_2)\}$ is blocked given $C$ since $A, F$ independent given $C$ (causal chain)
- $A \iff C \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(A, C, D), (e_1, e_2)\}$ is blocked given $C$ since $A, D$ independent given $C$ (causal chain)

$\{D, F\}$

- $A \iff G \iff H \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(G, H, B), (e_1, e_2)\}$ is blocked NOT given $H$ since $G, B$ independent NOT given $H$ (common effect)
- $A \iff G \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(G, D, B), (e_1, e_2)\}$ is blocked given $D$ since $G, B$ independent given $D$ (causal chain)
- $A \iff C \iff F \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(C, F, B), (e_1, e_2)\}$ is blocked given $F$ since $C, B$ independent given $F$ (causal chain)
- $A \iff C \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(C, D, B), (e_1, e_2)\}$ is blocked given $D$ since $C, B$ independent given $D$ (causal chain)

**Not Necessarily Independent:**

| $\mathcal{K}$ |
|---|
| $\{H, D, F\}$ |

- $A \iff G \iff H \iff B \iff E$ is unblocked given $\mathcal{K}$ since $\mathcal{J} = \{(G, H, B), (e_1, e_2)\}$ is unblocked given $H$ since $G, B$ not independent given $H$ (common effect)
- $A \iff G \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(G, D, B), (e_1, e_2)\}$ is blocked given $D$ (causal chain) since $G, B$ independent given $D$ (causal chain)
- $A \iff C \iff F \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(C, F, B), (e_1, e_2)\}$ is blocked given $F$ since $C, B$ independent given $F$ (causal chain)
- $A \iff C \iff D \iff B \iff E$ is blocked given $\mathcal{K}$ since $\mathcal{J} = \{(C, D, B), (e_1, e_2)\}$ is blocked given $D$ since $C, B$ independent given $D$ (causal chain)

### 2.4.3 Bayesian Inference

**Process:**

1. Given Bayesian network w/ variables and their conditional probabilities.
2. Find the probability of the query variable given the evidence variable, $p(\mathbf{Q} \mid \mathbf{E})$.
3. Use $p(\mathbf{Q} \mid \mathbf{E}) = \dfrac{\sum_{\mathcal{V}\setminus(\mathbf{Q}\cup\mathbf{E})} p(X_1, \ldots, X_{|\mathcal{V}|})}{\sum_{\mathcal{V}\setminus\mathbf{E}} p(X_1, \ldots, X_{|\mathcal{V}|})}$.
4. Determine $p(X_1)\prod_{i\neq 1} p(X_i \mid \text{pts}(X_i))$ using the Bayesian network.
5. Write out the summation of the numerator in an order using heuristics to determine elimination ordering.
6. Start with inner summation and work outwards.
7. Calculate the probability of the query variable(s) given the evidence variable(s).

**Example**:

1. **Given:**

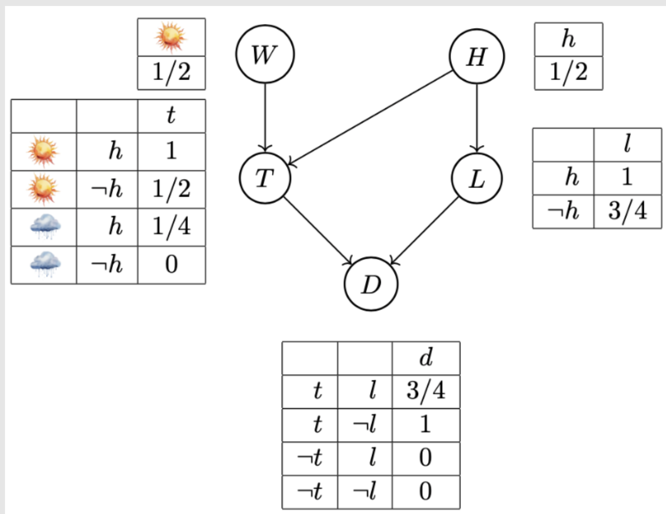



Figure 7

| Variables | Values |
|---|---|
| $W$ | $P(\text{Sunny}) = 0.5 \mid P(\text{Rainy}) = 0.5$ |
| $H$ | $P(h) = 0.5 \mid P(\neg h) = 0.5$ |
| $T$ | $P(t \mid \text{Sunny}, h) = 1 \mid P(t \mid \text{Sunny}, \neg h) = 0.5 \mid P(t \mid \text{Rainy}, h) = 0.25 \mid P(t \mid \text{Rainy}, \neg h) = 0$<br>$P(\neg t \mid \text{Sunny}, h) = 0 \mid P(\neg t \mid \text{Sunny}, \neg h) = 0.5 \mid P(\neg t \mid \text{Rainy}, h) = 0.75 \mid P(\neg t \mid \text{Rainy}, \neg h) = 1$ |
| $L$ | $P(l \mid h) = 1 \mid P(l \mid \neg h) = 0.75$<br>$P(\neg l \mid h) = 0 \mid P(\neg l \mid \neg h) = 0.25$ |
| $D$ | $P(d \mid t, l) = 0.75 \mid P(d \mid t, \neg l) = 1 \mid P(d \mid \neg t, l) = 0 \mid P(d \mid \neg t, \neg l) = 0$<br>$P(\neg d \mid t, l) = 0.25 \mid P(\neg d \mid t, \neg l) = 0 \mid P(\neg d \mid \neg t, l) = 1 \mid P(\neg d \mid \neg t, \neg l) = 1$ |

2. **Problem:** $p(d \mid h)$?
3. **Soln:**
   (a) $p(d \mid h) = \dfrac{p(d, h)}{p(h)} = \dfrac{\sum_{W,T,L} p(W, h, T, L, d)}{\sum_{W,T,L,D} p(W, h, T, L, d)}$ by definition of query and evidence equations.
   (b) $p(W, h, T, L, D) = p(h)p(W)p(L \mid h)p(t \mid W, h)p(D \mid T, L)$ by Bayesian network and $p(X_1, \ldots, X_{|\mathcal{V}|}) = p(X_1)\prod_{i\neq 1} p(X_i \mid \text{pts}(X_i))$.

**Summation**

$$\text{Numerator}: p(h) \underbrace{\sum_L p(L \mid h) \underbrace{\sum_T p(D \mid T, L) \underbrace{\sum_W p(W) p(T \mid W, h)}_{g_1(T)}}_{g_2(L,D)}}_{g_3(D)}$$

$$g_1(T) = p(\text{Sunny})p(T \mid \text{Sunny}, h) + p(\text{Rainy})p(T \mid \text{Rainy}, h)$$

$g_1(t) = p(\text{Sunny})p(t \mid \text{Sunny}, h) + p(\text{Rainy})p(t \mid \text{Rainy}, h) = 0.5 \cdot 1 + 0.5 \cdot 0.25 = 0.625$
$g_1(\neg t) = p(\text{Sunny})p(\neg t \mid \text{Sunny}, h) + p(\text{Rainy})p(\not t \mid \text{Rainy}, h) = 0.5 \cdot 0 + 0.5 \cdot 0.75 = 0.375$

$$g_2(L, D) = p(D \mid t, L)g_1(t) + p(D \mid \neg t, L)g_1(\neg t)$$

$g_2(l, d) = p(d \mid t, l)g_1(t) + p(d \mid \neg t, l)g_1(\neg t) = 0.75 \cdot 0.625 + 0 \cdot 0.375 = 0.46875$
$g_2(l, \neg d) = p(\neg d \mid t, l)g_1(t) + p(\neg d \mid \neg t, l)g_1(\neg t) = 0.25 \cdot 0.625 + 1 \cdot 0.375 = 0.53125$
$g_2(\neg l, d) = p(d \mid t, \neg l)g_1(t) + p(d \mid \neg t, \neg l)g_1(\neg t) = 1 \cdot 0.625 + 0 \cdot 0.375 = 0.625$
$g_2(\neg l, \neg d) = p(\neg d \mid t, \neg l)g_1(t) + p(\neg d \mid \neg t, \neg l)g_1(\neg t) = 0 \cdot 0.625 + 1 \cdot 0.375 = 0.375$

$$g_3(D) = p(h)p(l \mid h)g_2(l, D) + p(h)p(\neg l \mid h)g_2(\neg l, D)$$

$g_3(d) = p(h)p(l \mid h)g_2(l, d) + p(h)p(\neg l \mid h)g_2(\neg l, d) = (0.5)(1)(0.46875) + (0.5)(0)(0.625) = 0.234375$
$g_3(\neg d) = p(h)p(l \mid h)g_2(l, \neg d) + p(h)p(\neg l \mid h)g_2(\neg l, \neg d) = (0.5)(1)(0.53125) + (0.5)(0)(0.375) = 0.265625$

$$p(d \mid h) = \frac{g_3(d)}{g_3(d) + g_3(\neg d)} = \frac{0.234375}{0.234375 + 0.265625} = \frac{0.234375}{0.5} = 0.46875$$

**Example**:

| **Summation** |
|---|
| $$\text{Numerator}: p(h)\underbrace{\sum_L p(L \mid h)\underbrace{\sum_W p(W)\underbrace{\sum_T p(T \mid W, h)p(D \mid T, L)}_{g_1(W,D,L)}}_{g_2(D,L)}}_{g_3(D)}$$ |
| $$\text{Numerator}: p(h)\underbrace{\sum_W p(W)\underbrace{\sum_T p(T \mid W, h)\underbrace{\sum_L p(L \mid h)p(D \mid T, L)}_{g_1(D,T)}}_{g_2(D,W)}}_{g_3(D)}$$ |
| $$\text{Numerator}: p(h)\underbrace{\sum_W p(W)\underbrace{\sum_L p(L \mid h)\underbrace{\sum_T p(T \mid W, h)p(D \mid T, L)}_{g_1(W,D,L)}}_{g_2(W,D)}}_{g_3(D)}$$ |
| $$\text{Numerator}: p(h)\underbrace{\sum_T p(T \mid W, h)\underbrace{\sum_W p(W)\underbrace{\sum_L p(L \mid h)p(D \mid T, L)}_{g_1(D,T)}}_{g_2(D,T)}}_{g_3(D)}$$ |
| $\dots$ |

### 2.4.4 Hypergraph

**Process:** Process of eliminating a variable.

1. HOW TO DO THIS?

**Example**:

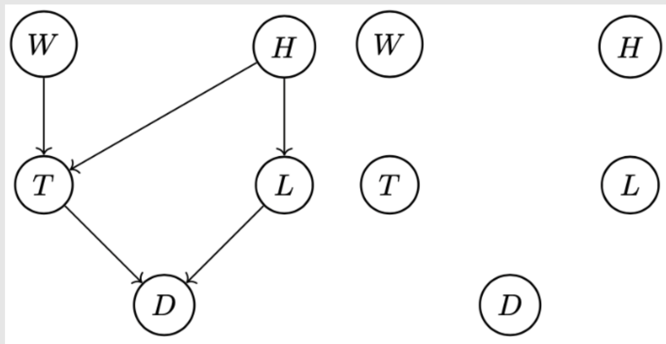



Figure 8

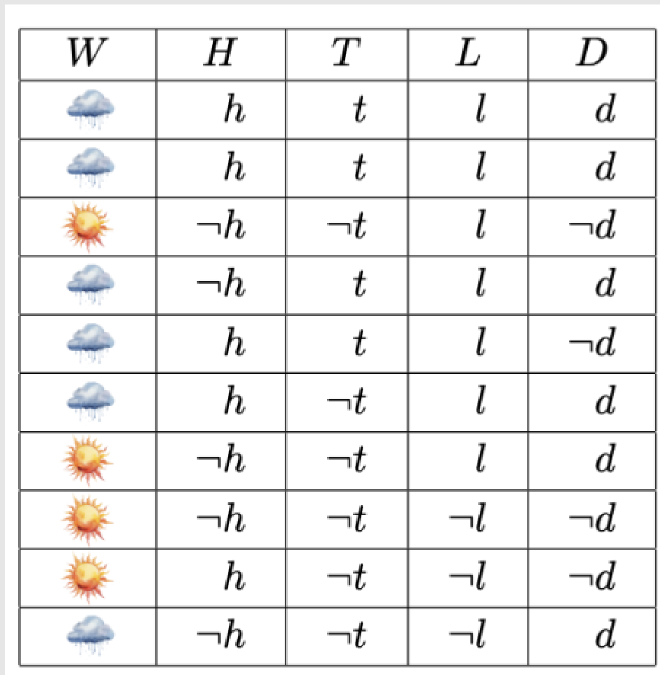
#### 2.4.5 Inference via Sampling

**Process:**

1. Given samples
2. Calculate number of samples w/ the query and evidence variables.
3. Calculate number of samples w/ the evidence variables.
4. Approximate the probability of the query variable given the evidence variable by dividing the # of samples w/ the query and evidence variables by the # of samples w/ the evidence variables.

**Example:**

1. **Given:** Samples



| $W$ | $H$ | $T$ | $L$ | $D$ |
|---|---|---|---|---|
| 🌧 | $h$ | $t$ | $l$ | $d$ |
| 🌧 | $h$ | $t$ | $l$ | $d$ |
| ☀ | $\neg h$ | $\neg t$ | $l$ | $\neg d$ |
| 🌧 | $\neg h$ | $t$ | $l$ | $d$ |
| 🌧 | $h$ | $t$ | $l$ | $\neg d$ |
| 🌧 | $h$ | $\neg t$ | $l$ | $d$ |
| ☀ | $\neg h$ | $\neg t$ | $l$ | $d$ |
| ☀ | $\neg h$ | $\neg t$ | $\neg l$ | $\neg d$ |
| ☀ | $h$ | $\neg t$ | $\neg l$ | $\neg d$ |
| 🌧 | $\neg h$ | $\neg t$ | $\neg l$ | $d$ |

Figure 9

2. **Problem:** Find the probability of $p(d \mid h)$.
3. **Soln:** $p(d \mid h) \approx \frac{\#\text{ of samples w/ } d \text{ and } h}{\#\text{ of samples w/ } h} = \frac{3}{5} = 0.6$.

# 3 Markov

## 3.1 General

### 3.1.1 Random Process

**Definition:** Time-varying random variables $S_0, S_1, S_2, \ldots$.

### 3.1.2 Markov Process

**Definition:** Random process + depends on previous time step only (memoryless)
- w.l.o.g. states can contain history of previous states.

## 3.2 Markov Chains (MCs)

**Summary:** In a **Markov Chain**, we assume that:
- there are no agents
- state transitions occur automatically
- $S_t$ is the state *after* transition $t$
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, \ldots, S_{t-2} \mid S_{t-1}$$

  - $S_t$ is independent of all previous states given $S_{t-1}$

| **Name** | **Function:** |
|---|---|
| initial state distribution | $p_0(s) := \mathbb{P}[S_0 = s]$ |
| transition distribution | $p(s'\|s) := \mathbb{P}[S_{t+1} = s'\|S_t = s]$ |
| Prob. that state of the env. after $T$ transitions is $s$ | $p_T(s) := \mathbb{P}[S_T = s] = \sum_{s'} p_{T-1}(s')p(s\|s')$ |

- $p_{T-1}(s')$: Prob. $s'$ at $T$-1 (given)
  - $p_0(s)$: Base case
- $p(s|s')$: Prob. $s$ given $s'$ (from graph)

### 3.2.1 Bayesian Network

**Notes**: $S_0, S_1, S_2, \ldots$ form a **Bayesian Network**:

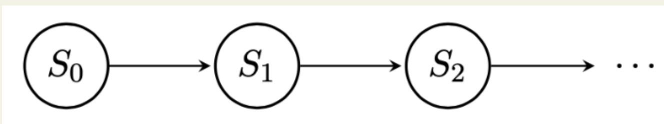



Figure 10

## 3.3 Markov Reward Processes (MRPs)

**Summary:** In a **Markov Reward Process**, we assume that:

- there is one agent
- state transitions occur automatically (i.e. agent has no control over actions)
- $S_t$ is the state *after* transition $t$
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, \dots, S_{t-2} \mid S_{t-1}$$

  - $S_t$ is independent of all previous states given $S_{t-1}$
- $R_t$ is the reward for transition $t$, i.e., $(S_{t-1}, \varnothing, S_t)$

| **Name** | **Function:** |
|---|---|
| Initial state distribution | $p_0(s) := \mathbb{P}[S_0 = s]$ |
| Transition distribution | $p(s'\|s) := \mathbb{P}[S_{t+1} = s'\|S_t = s]$ |
| Reward function | $r(s, s') :=$ reward for transition $(s, \varnothing, s')$ |
| Discount factor | $\gamma \in [0, 1]$ |
| Return after $T$ transitions | $U_T = \sum_{t=1}^{T} \gamma^{t-1} R_t = U_{T-1} + \gamma^{T-1} R_T$ |

- i.e. The (possibly discounted) sum of the rewards after $T$ transitions (sequence of rewards)
- **Why?**
  - Future rewards are less valuable than immediate rewards.
  - Won't converge if sum goes to $\infty$ if $\gamma = 1$.

| | |
|---|---|
| Expected return after $T$ transitions | $\mathbb{E}[U_T] = \mathbb{E}[U_{T-1}] + \gamma^{T-1}\mathbb{E}[R_t] = \mathbb{E}[U_{T-1}] + \gamma^{T-1} \sum_{s,s'} p_{T-1}(s) p(s'\|s) r(s, s')$ |

- $p_{T-1}(s)p(s'|s)$: Prob. $s \to s'$
- $r(s, s')$: rwd $s \to s'$
- $\mathbb{E}[U_0] := 0$: Base case

### 3.3.1 Bayesian Network

**Notes**: $S_0, R_1, S_1, R_2, S_2, \dots$ form a **Bayesian Network**:

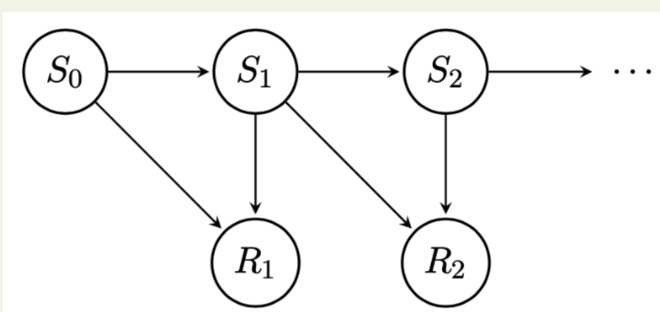



Figure 11

## 3.4 Markov Decision Processes (MDPs)

### 3.4.1 Setup

**Summary:** In a **Markov Decision Process (MDP)**, we assume that:

- there is one agent
- state transitions occur manually (after each action)
- $S_t$ is the state *after* transition $t$
- $A_t$ is the action inducing transition $t$
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, A_1, \ldots, S_{t-2}, A_{t-1} \mid S_{t-1}, A_t$$

  - $S_t$ is independent of all previous states and actions given $S_{t-1}$ and $A_t$
- $R_t$ is the reward for transition $t$, i.e., $(S_{t-1}, A_t, S_t)$

**Summary:**

<table>
<tr><th>Name</th><th>Function:</th></tr>
<tr><td>initial state distribution</td><td>$p_0(s) := \mathbb{P}[S_0 = s]$</td></tr>
<tr><td>transition distribution</td><td>$p(s'|s, a) := \mathbb{P}[S_t = s'|A_t = a, S_{t-1} = s]$</td></tr>
<tr><td>reward function</td><td>$r(s, a, s') :=$ reward for transition $(s, a, s')$</td></tr>
<tr><td>a time-invariant policy for choosing actions</td><td>$\pi(a|s) := \mathbb{P}[A_t = a|S_t = s]$</td></tr>
<tr><td>Maximum number of transitions<br><ul><li>A Markov Decision Process can be either:<ul><li>Finite: $T_{\max}$ is finite</li><li>Infinite: $T_{\max}$ is infinite<ul><li>For infinite MDPs, we must have $\gamma < 1$.</li></ul></li></ul></li></ul></td><td>$T_{\max}$</td></tr>
<tr><td>Prob. that state of the env. after $T$ transitions is $s$<br><ul><li>$p_{T-1}(s)$: Prob. $s'$ at $T$-1</li><li>$\pi(a|s')$: Action $a$ from $s'$</li><li>$p(s|s', a)$: Prob. $s$ given $s', a$</li></ul></td><td>$p_T(s) = \sum_{a,s'} p_{T-1}(s)\pi(a|s')p(s|s', a)$</td></tr>
<tr><td>Expected return after $T$ transitions<br><ul><li>$\mathbb{E}_\pi[R_t] = \sum_{s,a,s'} p_{T-1}(s)\pi(a \mid s)p(s' \mid s, a)r(s, a, s')$</li><li>$\mathbb{E}_\pi[U_0] = 0$: Base case.</li></ul></td><td>$\mathbb{E}_\pi[U_T]=\mathbb{E}_\pi[U_{T-1}] + \gamma^{T-1}\mathbb{E}_\pi[R_t]$</td></tr>
<tr><td>Future return after $\tau$ transitions<br><ul><li>Starting at $\tau + 1$ for the future return.</li></ul></td><td>$$\begin{aligned} G_\tau &= \sum_{t=\tau+1}^{T} \gamma^{t-(\tau+1)} R_t \\ &= R_{\tau+1} + \gamma G_{\tau+1} \end{aligned}$$</td></tr>
<tr><td>Expected future return after $\tau$ transitions given $S_\tau{=}s$<br><ul><li>$\mathbb{E}_\pi[G_{T_{\max}} \mid S_{T_{\max}} = s] = 0$: Base case.</li></ul></td><td>$$\begin{aligned} &\mathbb{E}_\pi[G_\tau \mid S_\tau{=}s]=\mathbb{E}_\pi[R_{\tau+1} \mid S_\tau{=}s] + \gamma\mathbb{E}_\pi[G_{\tau+1} \mid S_\tau{=}s] \\ &= \sum_{a,s'} \pi(a \mid s)p(s' \mid s, a) \left(r(s, a, s') + \gamma\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1}{=}s']\right) \end{aligned}$$</td></tr>
</table>

**Summary:**

| **Name** | **Function:** |
|---|---|
| Value function | $v_\pi(s,T) := \mathbb{E}_\pi[G_{T_{\max}-T} \mid S_{T_{\max}-T} = s] = \sum_{a,s'} \pi(a \mid s) p(s' \mid s,a) \left(r(s,a,s') + \gamma v_\pi(s', T-1)\right)$ |

- Value of state $s$ under the policy $\pi$ with $T$ transitions remaining.
  - i.e. How good the state is at time $T$ (e.g. If $v(s,T) = 5$, then the expected future return at $T$ is 5).
- $v(s,0) = 0$ for all $s$: Base case

| | |
|---|---|
| Optimal action | $a^*(s,T) = \arg\max_{a \in \mathcal{A}(s)} \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma v_{\pi^*}(s', T-1)\right) = \arg\max_{a \in \mathcal{A}(s)} q^*(s,a,T)$ |
| Optimal policy | $\pi^*(a \mid s,T) = \arg\max_{\pi(a\mid s,T)} \mathbb{E}_\pi[G_\tau \mid S_\tau = s] = \begin{cases} 1 & \text{if } a = a^*(s,T) \\ 0 & \text{otherwise} \end{cases}$ |

- Choose $\pi(\cdot \mid s)$ to maximize the expected future return after $T$ transitions given $S_\tau = s$.
- **Note:** Policy always depends on transitions remaining so may omit.

| | |
|---|---|
| Optimal value function | $v^*(s,T) = \max_a \sum_{s'} p(s' \mid a,s) \left(r(s,a,s') + \gamma v^*(s', \tau+1)\right)$ |

- Assume we use an optimal policy $\pi^*$.
- $v^*(s,0) = 0$ for all $s$: Base case.

| | |
|---|---|
| Q function (quality) | $q_\pi(s,a,T) := \mathbb{E}_\pi[G_{T_{\max}-T} \mid S_{T_{\max}-T} = s, A_{T_{\max}-(T-1)} = a] = \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma \sum_{a'} \pi(a' \mid s') q_\pi(s',a',T-1)\right)$ |

- Quality of move $(s,a)$ under policy $\pi$ with $T$ transitions remaining.
- $q_\pi(s,a,0) = 0$ for all $s,a$: Base case.

| | |
|---|---|
| Optimal Q function | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$ |

- $q^*(s,a,0) = 0$ for all $s,a$: Base case.

| | |
|---|---|
| IDK Expected Return | $\mathbb{E}_\pi[U_{T_{\max}}] = \sum_s \mathbb{E}_\pi[G_0 \mid S_0 = s] p_0(s) = \sum_s v_\pi(s,0) p_0(s)$ |

- $G_0 = U_{T_{\max}}$

| | |
|---|---|
| IDK Optimal Expected Return | $\max_\pi \mathbb{E}[U_{T_{\max}}] = \sum_s v^*(s,0) p_0(s)$ |

### 3.4.2 Bayesian Network

**Notes**: $S_0, A_1, R_1, S_1, A_2, R_2, S_2, \ldots$ form a **Bayesian Network**:

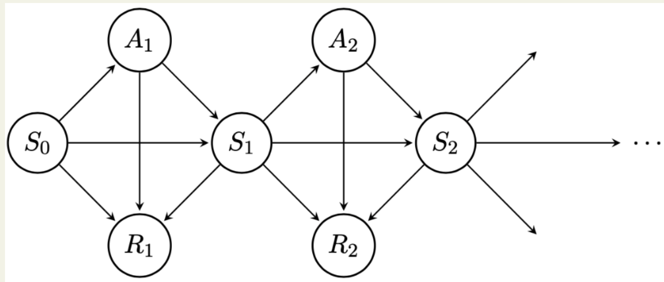



Figure 12

### 3.4.3 Intuition on Formulae

**Notes**:

$$\mathbb{E}_\pi[R_{\tau+1} \mid S_\tau = s] = \sum_{a,s'} \pi(a \mid s)p(s' \mid a,s)r(s,a,s')$$

- $\pi(a \mid s)p(s' \mid a,s)$: Prob. of getting to $s'$ from $s$ w/ action $a$
- $r(s,a,s')$: Reward of getting to $s'$ from $s$ w/ action $a$

$$\mathbb{E}_\pi[G_{\tau+1} \mid S_\tau = s] = \sum_{a,s'} \pi(a \mid s)p(s' \mid a,s)\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1} = s']$$

- $\pi(a \mid s)p(s' \mid a,s)$: Prob. of getting to $s'$ from $s$ w/ action $a$
- $\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1} = s']$: Expected future return at $\tau+1$ from $s'$ at $\tau+1$.
- $\sum_{a,s'}$: Sum over all possible future states and current actions to get expected future return at $\tau+1$ from $s$ at $\tau$.

## 3.5 Canonical Examples

### 3.5.1 Markov Chains

**Example**:

1. **Given:** Caveman needs to predict the weather, $W$, which is either sunny or rainy. Suppose the weather tomorrow depends on the weather today:

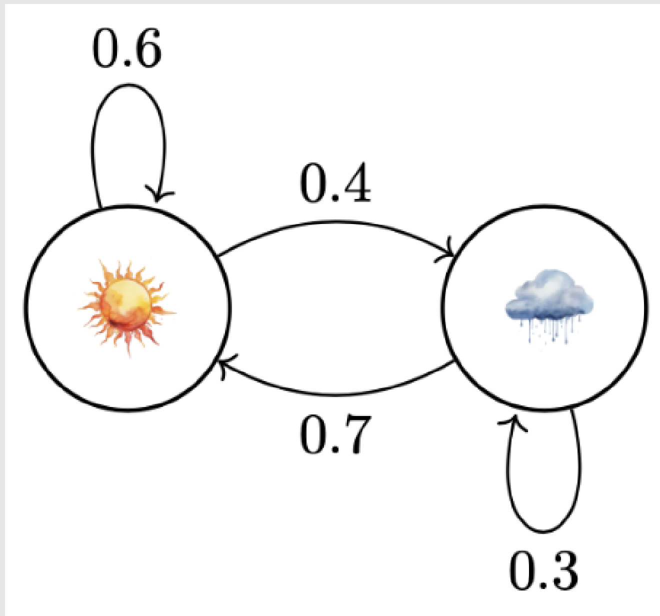



Figure 13

2. **Problem:** Caveman wants to predict the weather on a given day.

### 3.5.2 Markov Reward Processes

**Example**:

1. **Given:** Caveman needs to predict the weather, $W$, which is either sunny or rainy. Suppose the weather tomorrow depends on the weather today:

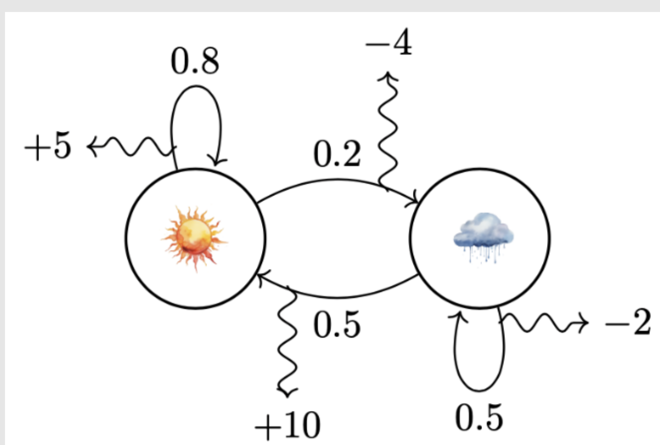



Figure 14

   - Depending on the transition, caveman may feel happier/sadder. This is quantified w/ the rewards.

2. **Problem:** Caveman wants to predict the weather on a given day that maximizes his happiness.

### 3.5.3 Markov Decision Processes

**Example**:
1. **Given:**

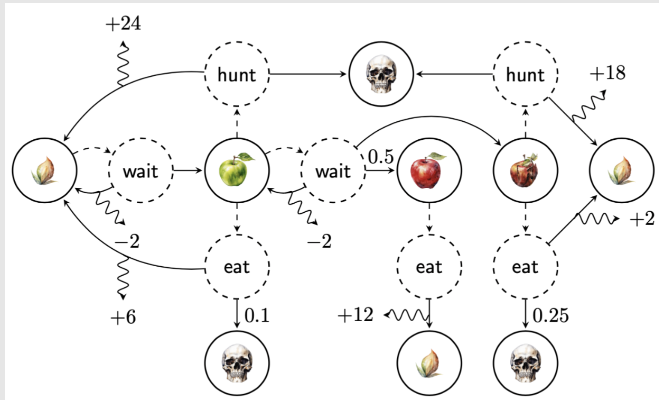



Figure 15

- Solid straight line: Outcome of action $a$ from state $s$.
- Dotted straight line: Choice of action (policy) from state $s$.
  - If policy known, then reduced to MRP.
- Squiggly line: Reward for action $a$ from state $s$ to state $s'$.
- Assume uniform probability.
  - Since $\sum p = 1$, therefore count # of arrows going out of $s$ and divide by 1 to get $p$.
- Same states have the same connections (i.e. all can use them just to hard to draw)

2. **Problem:** Find the optimal policy for $\gamma = 1$ and $T_{\max} = 5$.
3. **Soln:**

**Example**:

| $T$ | $s$ | $a$ | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$ |
|---|---|---|---|
| 0 | - | - | 0 |

- Best Action: $a^*(s,0) = \text{NA}$

| | | | |
|---|---|---|---|
| 1 | seed | wait | $q^*(\text{seed}, \text{wait}, 1) = \underbrace{0.5(-2+0)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{ga}} = -1$ |

- Best Action: $a^*(\text{seed}, 1) = \text{wait}$

| | | | |
|---|---|---|---|
| 1 | ga | wait | $q^*(\text{ga}, \text{wait}, 1) = \underbrace{0.25(-2+0)}_{s'=\text{ga}} + \underbrace{0.5(0+0)}_{s'=\text{rea}} + \underbrace{0.25(0+0)}_{s'=\text{roa}} = -0.5$ |
| 1 | ga | eat | $q^*(\text{ga}, \text{eat}, 1) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+0)}_{s'=\text{seed}} = 5.4$ |
| 1 | ga | hunt | $q^*(\text{ga}, \text{hunt}, 1) = \underbrace{0.5(24+0)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 12$ |

- Best Action: $a^*(\text{ga}, 1) = \text{hunt}$

| | | | |
|---|---|---|---|
| 1 | rea | eat | $q^*(\text{rea}, \text{eat}, 1) = \underbrace{1(12+0)}_{s'=\text{seed}} = 12$ |

- Best Action: $a^*(\text{rea}, 1) = \text{eat}$

| | | | |
|---|---|---|---|
| 1 | roa | eat | $q^*(\text{roa}, \text{eat}, 1) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+0)}_{s'=\text{seed}} = 1.5$ |
| 1 | roa | hunt | $q^*(\text{roa}, \text{hunt}, 1) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+0)}_{s'=\text{seed}} = 9$ |

- Best Action: $a^*(\text{roa}, 1) = \text{hunt}$

| | | | |
|---|---|---|---|
| 1 | dead | - | $q^*(\text{dead}, -, 1) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$ |

- Best Action: $a^*(s,1) = -$

- Optimal Policy w/ 1 Transition Remaining: $\pi^*(a \mid s, 1) = \begin{cases} 1 & \text{if } a = a^*(s,1) \\ 0 & \text{otherwise} \end{cases}$

**Example**:

| $T$ | $s$ | $a$ | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\Big(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\Big)$ |
|---|---|---|---|
| 2 | seed | wait | $q^*(\text{seed}, \text{wait}, 2) = \underbrace{0.5(-2-1)}_{s'=\text{seed}} + \underbrace{0.5(0+12)}_{s'=\text{ga}} = 4.5$ |

- Best Action: $a^*(\text{seed}, 2) = \text{wait}$

| | | | |
|---|---|---|---|
| 2 | ga | wait | $q^*(\text{ga}, \text{wait}, 2) = \underbrace{0.25(-2+12)}_{s'=\text{ga}} + \underbrace{0.5(0+12)}_{s'=\text{rea}} + \underbrace{0.25(0+9)}_{s'=\text{roa}} = 10.75$ |
| 2 | ga | eat | $q^*(\text{ga}, \text{eat}, 2) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6-1)}_{s'=\text{seed}} = 4.5$ |
| 2 | ga | hunt | $q^*(\text{ga}, \text{hunt}, 2) = \underbrace{0.5(24-1)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 11.5$ |

- Best Action: $a^*(\text{ga}, 2) = \text{hunt}$

| | | | |
|---|---|---|---|
| 2 | rea | eat | $q^*(\text{rea}, \text{eat}, 2) = \underbrace{1(12-1)}_{s'=\text{seed}} = 11$ |

- Best Action: $a^*(\text{rea}, 2) = \text{eat}$

| | | | |
|---|---|---|---|
| 2 | roa | eat | $q^*(\text{roa}, \text{eat}, 2) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2-1)}_{s'=\text{seed}} = 0.5$ |
| 2 | roa | hunt | $q^*(\text{roa}, \text{hunt}, 2) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18-1)}_{s'=\text{seed}} = 8.5$ |

- Best Action: $a^*(\text{roa}, 2) = \text{hunt}$

| | | | |
|---|---|---|---|
| 2 | dead | - | $q^*(\text{dead}, -, 2) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$ |

- Best Action: $a^*(s, 2) = -$

- Optimal Policy w/ 2 Transitions Remaining: $\pi^*(a \mid s, 2) = \begin{cases} 1 & \text{if } a = a^*(s,2) \\ 0 & \text{otherwise} \end{cases}$

**Example**:

| $T$ | $s$ | $a$ | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$ |
|---|---|---|---|
| 3 | seed | wait | $q^*(\text{seed},\text{wait},3) = \underbrace{0.5(-2+4.5)}_{s'=\text{seed}} + \underbrace{0.5(0+11.5)}_{s'=\text{ga}} = 7$ |

- Best Action: $a^*(\text{seed},3) = \text{wait}$

| | | | |
|---|---|---|---|
| 3 | ga | wait | $q^*(\text{ga},\text{wait},3) = \underbrace{0.25(-2+11.5)}_{s'=\text{ga}} + \underbrace{0.5(0+11)}_{s'=\text{rea}} + \underbrace{0.25(0+8.5)}_{s'=\text{roa}} = 10$ |
| 3 | ga | eat | $q^*(\text{ga},\text{eat},3) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+4.5)}_{s'=\text{seed}} = 9.45$ |
| 3 | ga | hunt | $q^*(\text{ga},\text{hunt},3) = \underbrace{0.5(24+4.5)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 14.25$ |

- Best Action: $a^*(\text{ga},3) = \text{hunt}$

| | | | |
|---|---|---|---|
| 3 | rea | eat | $q^*(\text{rea},\text{eat},3) = \underbrace{1(12+4.5)}_{s'=\text{seed}} = 16.5$ |

- Best Action: $a^*(\text{rea},3) = \text{eat}$

| | | | |
|---|---|---|---|
| 3 | roa | eat | $q^*(\text{roa},\text{eat},3) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+4.5)}_{s'=\text{seed}} = 4.875$ |
| 3 | roa | hunt | $q^*(\text{roa},\text{hunt},3) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+4.5)}_{s'=\text{seed}} = 11.25$ |

- Best Action: $a^*(\text{roa},3) = \text{hunt}$

| | | | |
|---|---|---|---|
| 3 | dead | - | $q^*(\text{dead},-,3) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$ |

- Best Action: $a^*(s,3) = -$

- Optimal Policy w/ 3 Transitions Remaining: $\pi^*(a \mid s,3) = \begin{cases} 1 & \text{if } a = a^*(s,3) \\ 0 & \text{otherwise} \end{cases}$

**Example**:

| $T$ | $s$ | $a$ | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$ |
|---|---|---|---|
| 4 | seed | wait | $q^*(\text{seed}, \text{wait}, 4) = \underbrace{0.5(-2+7)}_{s'=\text{seed}} + \underbrace{0.5(0+14.25)}_{s'=\text{ga}} = 9.625$ |

- Best Action: $a^*(\text{seed}, 4) = \text{wait}$

| | | | |
|---|---|---|---|
| 4 | ga | wait | $q^*(\text{ga}, \text{wait}, 4) = \underbrace{0.25(-2+14.25)}_{s'=\text{ga}} + \underbrace{0.5(0+16.5)}_{s'=\text{rea}} + \underbrace{0.25(0+11.25)}_{s'=\text{roa}} = 14.125$ |
| 4 | ga | eat | $q^*(\text{ga}, \text{eat}, 4) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+7)}_{s'=\text{seed}} = 11.7$ |
| 4 | ga | hunt | $q^*(\text{ga}, \text{hunt}, 4) = \underbrace{0.5(24+7)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 15.5$ |

- Best Action: $a^*(\text{ga}, 4) = \text{hunt}$

| | | | |
|---|---|---|---|
| 4 | rea | eat | $q^*(\text{rea}, \text{eat}, 4) = \underbrace{1(12+7)}_{s'=\text{seed}} = 19$ |

- Best Action: $a^*(\text{rea}, 4) = \text{eat}$

| | | | |
|---|---|---|---|
| 4 | roa | eat | $q^*(\text{roa}, \text{eat}, 4) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+7)}_{s'=\text{seed}} = 6.75$ |
| 4 | roa | hunt | $q^*(\text{roa}, \text{hunt}, 4) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+7)}_{s'=\text{seed}} = 12.5$ |

- Best Action: $a^*(\text{roa}, 4) = \text{hunt}$

| | | | |
|---|---|---|---|
| 4 | dead | - | $q^*(\text{dead}, -, 4) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$ |

- Best Action: $a^*(s, 4) = -$

- Optimal Policy w/ 4 Transitions Remaining: $\pi^*(a \mid s, 4) = \begin{cases} 1 & \text{if } a = a^*(s,4) \\ 0 & \text{otherwise} \end{cases}$

**Example**:

| $T$ | $s$ | $a$ | $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a) \Big( r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1) \Big)$ |
|---|---|---|---|
| 5 | seed | wait | $q^*(\text{seed}, \text{wait}, 5) = \underbrace{0.5(-2+9.625)}_{s'=\text{seed}} + \underbrace{0.5(0+15.5)}_{s'=\text{ga}} = 11.5625$ |

- Best Action: $a^*(\text{seed}, 5) = \text{wait}$

| | | | |
|---|---|---|---|
| 5 | ga | wait | $q^*(\text{ga}, \text{wait}, 5) = \underbrace{0.25(-2+15.5)}_{s'=\text{ga}} + \underbrace{0.5(0+19)}_{s'=\text{rea}} + \underbrace{0.25(0+12.5)}_{s'=\text{roa}} = 16$ |
| 5 | ga | eat | $q^*(\text{ga}, \text{eat}, 5) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+9.625)}_{s'=\text{seed}} = 14.0625$ |
| 5 | ga | hunt | $q^*(\text{ga}, \text{hunt}, 5) = \underbrace{0.5(24+9.625)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 16.8125$ |

- Best Action: $a^*(\text{ga}, 5) = \text{hunt}$

| | | | |
|---|---|---|---|
| 5 | rea | eat | $q^*(\text{rea}, \text{eat}, 5) = \underbrace{1(12+9.625)}_{s'=\text{seed}} = 21.625$ |

- Best Action: $a^*(\text{rea}, 5) = \text{eat}$

| | | | |
|---|---|---|---|
| 5 | roa | eat | $q^*(\text{roa}, \text{eat}, 5) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+9.625)}_{s'=\text{seed}} = 8.71875$ |
| 5 | roa | hunt | $q^*(\text{roa}, \text{hunt}, 5) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+9.625)}_{s'=\text{seed}} = 13.8125$ |

- Best Action: $a^*(\text{roa}, 5) = \text{hunt}$

| | | | |
|---|---|---|---|
| 5 | dead | - | $q^*(\text{dead}, -, 5) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$ |

- Best Action: $a^*(s, 5) = -$

- Optimal Policy w/ 5 Transitions Remaining: $\pi^*(a \mid s, 5) = \begin{cases} 1 & \text{if } a = a^*(s,5) \\ 0 & \text{otherwise} \end{cases}$