

ROB311 Quiz 2

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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 influencing 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 descendants.

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,

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

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, $\mathcal{V} \setminus \text{des}(X)$, given X 's parents, $\text{pts}(X)$.

Notes:

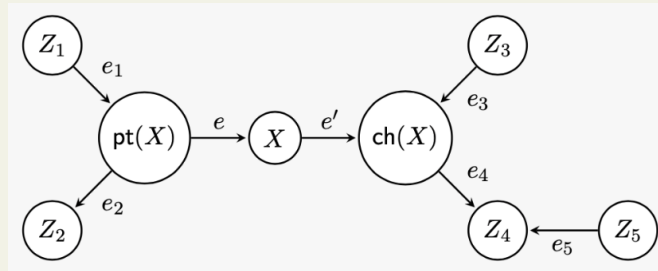


Figure 5

2 Probabilistic Inference

2.1 Problem Setup

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

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

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

- $\mathbf{Q} = \{Q_1, \dots, Q_{|\mathbf{Q}|}\}$: Query variables
- $\mathbf{E} = \{E_1, \dots, E_{|\mathbf{E}|}\} \subseteq \mathcal{V}$: 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

Definition: 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

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

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

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

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 $\rightarrow \infty$, 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:**
 - $W = \{\text{Sun, Rainy}\}$: 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 Path Blocked?

Process:

- Know when a path is blocked. More than one path b/w 2 variables, then all paths need to be blocked.

Example:

2.4.2 Independence

Process:

- 1.

Example:

1. **Given:** Bayesian network.

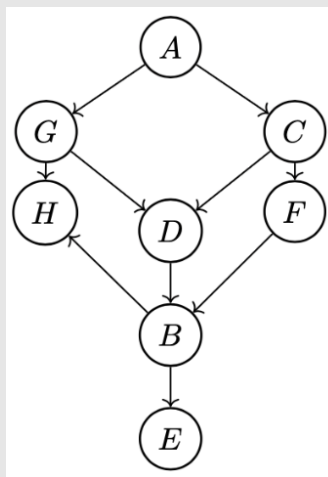


Figure 6

2. **Problem:** A and E are
 - independent if $\mathcal{K} =$
 - not necessarily independent for $\mathcal{K} =$

2.4.3 Hypergraph

Process:

1.

2.4.4 Bayesian Inference

Process:

1.

Example:

1. Given:

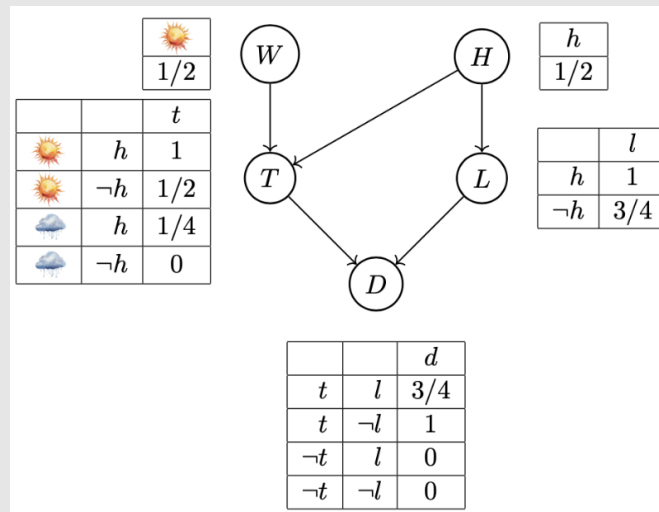


Figure 7

2. Problem:

2.4.5 Inference via Sampling

Process:

- 1.

Example:

1. **Given:**
2. **Problem:**

3 Markov

3.1 Markov Chains (MCs)

3.1.1 Setup

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:

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

- 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	$p_T(s) := \mathbb{P}[S_T = s]$ $= \sum_{s'} p_{T-1}(s') p(s s')$

3.1.2 Bayesian Network

Definition: S_0, S_1, S_2, \dots form a **Bayesian Network**:

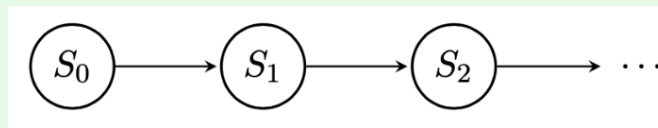


Figure 8

3.2 Markov Reward Processes (MRPs)

3.2.1 Setup

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., $(S_{t-1}, \emptyset, S_t)$

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	$r(s, s') := \text{reward for transition } (s, \emptyset, s')$
Discount factor	$\gamma \in [0, 1]$
Return after T transitions	$U_T = \sum_{t=1}^T \gamma^{t-1} R_t$ $= U_{T-1} + \gamma^{T-1} R_T$
<ul style="list-style-type: none"> • The (possibly discounted) sum of the rewards after T transitions 	
Expected return after T transitions	$\mathbb{E}[U_T] = \mathbb{E}[U_{T-1}] + \gamma^{T-1} \mathbb{E}[R_T]$ $= \mathbb{E}[U_{T-1}] + \gamma^{T-1} \sum_{s, s'} p_{T-1}(s) p(s' s) r(s, s')$
<ul style="list-style-type: none"> • $p_{T-1}(s)p(s' s)$: Prob. $s \rightarrow s'$ • $r(s, s')$: rwd $s \rightarrow s'$ • $\mathbb{E}[U_0] := 0$. 	

3.2.2 Bayesian Network

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

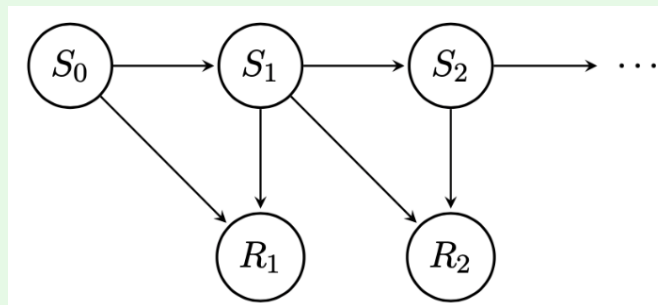


Figure 9

3.3 Markov Decision Processes (MDPs)

3.3.1 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:

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

- 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:

Name	Function:
initial state distribution	$p_0(s) := \mathbb{P}[S_0 = s]$
transition distribution	$p(s' s, a) := \mathbb{P}[S_t = s' A_t = a, S_{t-1} = s]$
reward function	$r(s, a, s') := \text{reward for transition } (s, a, s')$
a time-invariant policy for choosing actions	$\pi(a s) := \mathbb{P}[A_t = a S_t = s]$
Maximum number of transitions	T_{\max}
<ul style="list-style-type: none"> A Markov Decision Process can be either: <ul style="list-style-type: none"> Finite: T_{\max} is finite Infinite: T_{\max} is infinite * For infinite MDPs, we must have $\gamma < 1$. 	
Prob. that state of the env. after T transitions is s	$p_T(s) = \sum_{a, s'} p_{T-1}(s) \pi(a s') p(s s', a)$
<ul style="list-style-type: none"> $p_{T-1}(s)$: Prob. s' at $T-1$ $p(a s')$: Action a from s' $p(s s', a)$: Prob. s given s', a 	
Expected return after T transitions	$\mathbb{E}_\pi[U_T] = \mathbb{E}_\pi[U_{T-1}] + \gamma^{T-1} \mathbb{E}_\pi[R_T]$
<ul style="list-style-type: none"> $\mathbb{E}_\pi[R_t] = \sum_{s, a, s'} p_{T-1}(s) \pi(a s) p(s' s, a) r(s, a, s')$ $\mathbb{E}_\pi[U_0] = 0$. 	
Future return after τ transitions	$G_\tau = \sum_{t=\tau+1}^T \gamma^{t-(\tau+1)} R_t$ $= R_{\tau+1} + \gamma G_{\tau+1}$
<ul style="list-style-type: none"> Starting at $\tau + 1$ for the future return. 	
Expected future return after τ transitions given $S_\tau = s$	$\mathbb{E}_\pi[G_\tau S_\tau = s] = \mathbb{E}_\pi[R_{\tau+1} S_\tau = s] + \gamma \mathbb{E}_\pi[G_{\tau+1} S_\tau = s]$ $= \sum_{a, s'} \pi(a s) p(s' s, a) (r(s, a, s') + \gamma \mathbb{E}_\pi[G_{\tau+1} S_{\tau+1} = s'])$
<ul style="list-style-type: none"> $\mathbb{E}_\pi[G_{T_{\max}} S_{T_{\max}} = s] = 0$. $\mathbb{E}_\pi[R_{\tau+1} S_\tau = s] = \sum_{a, s'} \pi(a s) p(s' a, s) r(s, a, s')$ <ul style="list-style-type: none"> $\pi(a s) p(s' a, s)$: Prob. of getting to s' from s w/ action a $r(s, a, s')$: Reward of getting to s' from s w/ action a $\mathbb{E}_\pi[G_{\tau+1} S_\tau = s] = \sum_{a, s'} \pi(a s) p(s' a, s) \mathbb{E}_\pi[G_{\tau+1} S_{\tau+1} = s']$ <ul style="list-style-type: none"> $\pi(a s) p(s' a, s)$: Prob. of getting to s' from s w/ action a $\mathbb{E}_\pi[G_{\tau+1} S_{\tau+1} = s']$: 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 τ. 	

Summary:

Name	Function:
Optimal policy	$\pi^*(\cdot s) = \arg \max_{\pi(\cdot s)} \mathbb{E}_\pi[G_\tau S_\tau = s]$ <ul style="list-style-type: none"> Choose $\pi(\cdot s)$ to maximize the expected future return given $S_\tau = s$.
Value function	$v_\pi(s, \tau) := \mathbb{E}_\pi[G_\tau S_\tau = s]$ $= \sum_{a, s'} \pi(a s) p(s' s, a) (r(s, a, s') + \gamma v_\pi(s', \tau + 1))$ <ul style="list-style-type: none"> $v(s, T) = 0$ for all s.
Optimal value function	$v^*(s, \tau) = \max_a \sum_{s'} p(s' a, s) (r(s, a, s') + \gamma v^*(s', \tau + 1))$ <ul style="list-style-type: none"> Taking the optimal $\pi(\cdot s)$ (i.e., π^*) gives the recurrence above. $v^*(s, T) = 0$ for all s.
Expected Return	$\mathbb{E}_\pi[U_{T_{\max}}] = \sum_s \mathbb{E}_\pi[G_0 S_0 = s] p_0(s)$ $= \sum_s v_\pi(s, 0) p_0(s)$ <ul style="list-style-type: none"> $G_0 = U_{T_{\max}}$
Optimal Expected Return	

3.3.2 Bayesian Network

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

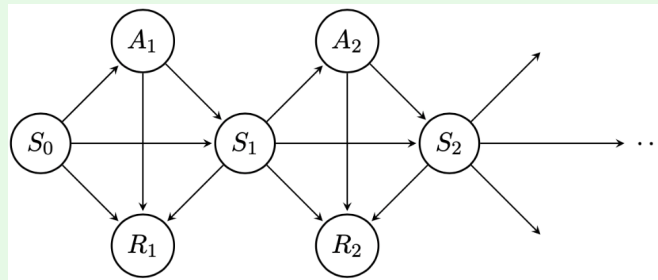


Figure 10