

Homework 2

(Due on Friday before 09:50. Please submit your completed assignment to a TA by email or in-person.)

AI policy. The use of AI tools to complete the assignment is not permitted.

Please complete the questions below using the concepts and techniques introduced in the lectures.

Markov-equivalence

1.1. Show that the graphs $A \leftarrow B \rightarrow C$ and $A \rightarrow B \rightarrow C$ are Markov-equivalent.

[*Hint:* think about the definition of Markov equivalence. Note also that the chain rule implies that $P(X|Y)P(Y) = P(Y|X)P(X)$ for all X and Y .]

1.2. Show that the DAG $A \rightarrow B$ and the unconnected DAG $A \quad B$ are not Markov-equivalent.

[*Hint:* we simply need to find at least one joint distribution that can be factorized with respect to one DAG but not the other.]

Categorizing blickets

A toy creature has three features: Color (either *red* or *blue*), Shape (either *round* or *square*), Texture (either *soft* or *hard*).

Some of these creatures emit a special kind of radiation that can be detected by a scientific instrument called a ‘blicket detector’. For this reason these creatures are called ‘blickets’.

You are trying to figure out what makes a creature a blicket. Armed with your blicket detector, you have tested whether four different individual creatures are blickets. Here are these 4 observations. Data $D = \{(o_i, y_i)\}_{i=1}^4$:

Observation	Color	Shape	Texture	Blicket?
o_1	red	round	soft	yes
o_2	red	square	soft	yes
o_3	blue	round	hard	no
o_4	blue	square	soft	no

On the basis of these data, one can evaluate hypotheses about what makes something a blicket. Suppose that hypotheses about “what makes something a blicket” are generated by this grammar:

$$H \rightarrow A \text{ (0.6)} \quad H \rightarrow (H \wedge H) \text{ (0.25)} \quad H \rightarrow (H \vee H) \text{ (0.15)}$$

$$A \rightarrow \text{red} \mid \text{blue} \mid \text{round} \mid \text{square} \mid \text{soft} \mid \text{hard} \quad (\text{each } \frac{1}{6})$$

- 2.1.** Compute the prior probability of the following hypotheses, and show every production rule used:

$$\begin{aligned}h_1 &= \text{red.} \\h_2 &= (\text{red} \wedge \text{soft}). \\h_3 &= (\text{red} \vee \text{round}). \\h_4 &= ((\text{red} \wedge \text{soft}) \vee \text{round}).\end{aligned}$$

- 2.2.** Compare the prior probabilities $P(h_1)$, $P(h_2)$, $P(h_3)$, and $P(h_4)$. Explain why the probabilities differ.
- 2.3.** Let us assume a likelihood function such that for each individual observation o_i , $P(o_i|H) = .1$ if the hypothesis makes an incorrect prediction about whether the creature is a blicket, and $P(o_i|H) = .9$ if the hypothesis makes a correct prediction. Then we have the likelihood:

$$P(D|H) = P(o_1|H)P(o_2|H)P(o_3|H)P(o_4|H).$$

Compute the likelihoods $P(D|h_1)$, $P(D|h_2)$, $P(D|h_3)$, and $P(D|h_4)$.

- 2.4.** Compare the posterior probabilities $P(h_1|D)$, $P(h_2|D)$, $P(h_3|D)$, and $P(h_4|D)$. Note that you don't need to compute the exact value of each probability, only their relative ranking. [*Hint:* The normalizing constant in Bayes' rule, $P(D)$, is the same for all $P(H_i|D)$.]

Parsimony bias

Let $n_A(h)$ be the number of atomic predicates in a hypothesis h . Let $n_B(h)$ be the number of binary connectives, meaning uses of $\wedge$ or $\vee$.

For example,

$$h = (\text{red} \wedge \text{soft})$$

has

$$n_A(h) = 2, \quad n_B(h) = 1.$$

- 3.1.** For the grammar above, argue that every complete derivation satisfies

$$n_A(h) = n_B(h) + 1.$$

Hint: think of the derivation tree as a full binary tree.

- 3.2.** Parsimony bias is the cognitive tendency to favor simpler explanations or models, also known as Occam's razor. Explain why PCFG creates a parsimony bias.

(In)Tractability

The hypothesis space $\mathcal{H}$ contains all rules generated by the PCFG. Since the grammar is recursive, $\mathcal{H}$ is infinite.

- 4.1. Give three different valid hypotheses generated by the grammar that contain exactly one binary connective.
- 4.2. Give three different valid hypotheses generated by the grammar that contain exactly two binary connectives.
- 4.3. Roughly explain why the number of hypotheses grows quickly as the number of connectives increases.
- 4.4. The posterior normalizer is

$$P(D) = \sum_{h \in \mathcal{H}} P(D | h) P(h).$$

Explain why computing this sum exactly is difficult.

- 4.5. Even if many long hypotheses have small prior probability, why can we not always ignore all of them?

Required Reflection

In 3–5 sentences, explain one mistake you initially made or one step in the homework that you found non-obvious. Your explanation should refer to a specific part of your solution.

This reflection is required for getting any credit at all.