



Statistical Data Analysis 2

Exercises # 1

Ewa Szczurek
Lukasz Kozlowski
September 20, 2018

Problem 1: Conditional independence

Let X, Y, Z be random variables. X and Y are said to be *conditionally independent* given Z (in symbols $X \perp Y \mid Z$) if

$$P(X, Y \mid Z) = P(X \mid Z)P(Y \mid Z).$$

This condition is equivalent to

$$P(X \mid Y, Z) = P(X \mid Z).$$

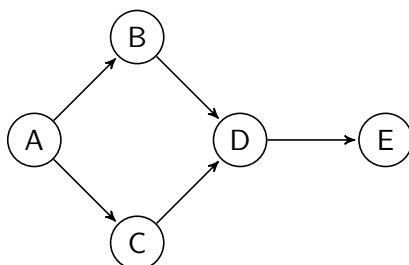
Using the laws of probability, show that this equivalence holds (show both directions of the proof).

Solution:

- If the defining property holds, then we have by the laws of probability:
$$P(X \mid Y, Z) = \frac{P(X, Y, Z)}{P(Y, Z)} = \frac{P(X, Y \mid Z)P(Z)}{P(Y, Z)} = \frac{P(X \mid Z)P(Y \mid Z)P(Z)}{P(Y, Z)} = \frac{P(X \mid Z)P(Y, Z)}{P(Y, Z)} = P(X \mid Z).$$
- The converse is shown as follows:
$$P(X, Y \mid Z) = P(X \mid Y, Z)P(Y \mid Z) = P(X \mid Z)P(Y \mid Z).$$

Problem 2: Markov blanket

Consider the following graphical structure of a Bayesian network:



Determine the Markov blanket $MB(C)$ of the node C and show that the conditional probability $P(C \mid A, B, D, E)$ can be expressed as

$$P(C \mid A, B, D, E) = P(C \mid MB(C)).$$

Solution: By the law of total probability we have

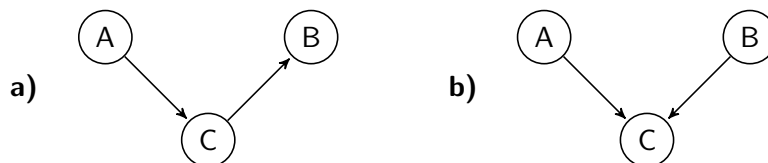
$$\begin{aligned}
 P(C | A, B, D, E) &= \frac{P(A)P(B | A)P(C | A)P(D | B, C)P(E | D)}{\sum_C P(A)P(B | A)P(C | A)P(D | B, C)P(E | D)} \\
 &= \frac{P(A)P(B | A)P(C | A)P(D | B, C)P(E | D)}{P(A)P(B | A)P(E | D) \sum_C P(C | A)P(D | B, C)} \\
 &= \frac{P(C | A)P(D | B, C)}{\sum_C P(C | A)P(D | B, C)}
 \end{aligned}$$

Since this expression does not depend on E we have

$$P(C | A, B, D, E) = P(C | A, B, D)$$

Problem 3: Conditional independence and BNs

Consider the following graphical structures, corresponding to (different) Bayesian networks. For which network does the statement $A \perp B | C$ hold? For which does the statement $A \perp B$ hold? Prove your answers by the laws of probability.



Solution:	$A \perp B C$	a)	b)
	$A \perp B$	Yes	No
		No	Yes

Explanation for the conditional independences:

- For a) we have $P(A, B, C) = P(B | C)P(C | A)P(A)$.
Inserting this and using Bayes' rule we get the conditional probability:
 $P(A, B | C) = \frac{P(A, B, C)}{P(C)} = P(B | C) \frac{P(C | A)P(A)}{P(C)} = P(B | C)P(A | C) \Leftrightarrow A \perp B | C$
- For b) we have $P(A, B, C) = P(C | A, B)P(A)P(B)$.
Consequently, we have

$$\begin{aligned}
 P(A, B | C) &= \frac{P(A, B, C)}{P(C)} = \frac{P(C | A, B)P(A)P(B)}{P(C)} \\
 &= \frac{P(C | A, B)P(A)P(B)P(C | A)}{P(C)P(C | A)} = \frac{P(A | C)P(C | A, B)P(B)}{P(C | A)} \\
 &= \frac{P(A | C)P(C | A, B)P(B)P(C | B)P(C)}{P(C | A)P(C | B)P(C)} = P(A | C)P(B | C) \frac{P(C | A, B)P(C)}{P(C | A)P(C | B)}
 \end{aligned}$$

Since the last term will only equal 1 in special cases, in general $A \perp B | C$ does not hold.

Explanation for the marginal independences:

- For a) applying Bayes' rule, we get

$$\begin{aligned}
 P(A, B) &= \sum_C P(A, B, C) = \sum_C P(B | C)P(C | A)P(A) \\
 &= \sum_C \frac{P(C | B)P(B)P(C | A)P(A)}{P(C)} = P(A)P(B) \sum_C \frac{P(C | B)P(C | A)}{P(C)}.
 \end{aligned}$$

Therefore, $A \perp B$ does not generally hold.

- For b) we have $P(A, B, C) = P(C | A, B)P(A)P(B)$. Marginalizing over C :
 $\sum_C P(A, B, C) = \sum_C P(C | A, B)P(A)P(B)$ yields $P(A, B) = P(A)P(B) \Leftrightarrow A \perp B$

Problem 4: Conjugate distributions

Let X be a binomially distributed random variable with parameters $N \in \mathbb{N}$ and $\theta \in [0, 1]$. Further, assume that a prior $P(\theta)$ of the parameter θ is *beta distributed* with parameters α, β , i.e. its probability density function is given by

$$\rho(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt}$$

Show that the prior $P(\theta)$ is conjugate to the binomial likelihood $L(\theta) := P(X | \theta)$. In other words, show that the posterior distribution $P(\theta | X)$, which is defined as

$$P(\theta | X) = \frac{P(X | \theta)P(\theta)}{P(X)}$$

also obeys a beta distribution with suitable parameters.

Solution: Given that

$$P(\theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha, \beta)}, \quad \text{where } B(\cdot, \cdot) \text{ is the beta function, and}$$

$$P(X | \theta) = \binom{N}{x} \theta^x (1-\theta)^{N-x},$$

we obtain

$$\begin{aligned} P(\theta | X) &= \frac{P(X | \theta)P(\theta)}{P(X)} = \frac{P(X | \theta)P(\theta)}{\int_0^1 P(X | \theta)P(\theta) d\theta} \\ &= \frac{\binom{N}{x} \theta^{\alpha+x-1} (1-\theta)^{\beta+N-(x+1)} (B(\alpha, \beta))^{-1}}{\int_0^1 \binom{N}{x} \theta^{\alpha+x-1} (1-\theta)^{\beta+N-(x+1)} (B(\alpha, \beta))^{-1} d\theta} \\ &= \frac{\theta^{\alpha+x-1} (1-\theta)^{\beta+N-(x+1)}}{\int_0^1 \theta^{\alpha+x-1} (1-\theta)^{\beta+N-x-1} d\theta} = \frac{\theta^{\alpha+x-1} (1-\theta)^{\beta+N-x-1}}{B(\alpha+x, \beta+N-x)} \end{aligned}$$

Therefore $P(\theta | X)$ is beta distributed with parameters $\alpha + x$ and $\beta + N - x$.