# **1**A

## Machine Learning II ID: 5684926 Tristan Scheidemann

### 1A-1.

Let  $X \sim B(1, p)$  and  $Y \sim Exp(\lambda)$  with mass  $f_X(x) = p^x \cdot (1 - p)^{1 - x}$ ,  $x \in \{0, 1\}$  and density  $f_Y(y) = \lambda e^{-\lambda y}$ , with  $y \in [0, \infty)$ .

The joint pdf is then given by

$$f_{X,Y}(x,y) = \begin{cases} (1-p) \cdot \lambda e^{-\lambda y} &, & iff \ x = 0 \\ p \cdot \lambda e^{-\lambda y} &, & iff \ x = 1 \end{cases}$$

which is a mixture of a continuous Y and discrete X.

Proof

$$f_{X,Y}(x,y) = \underbrace{f_X(x)f_Y(y)}_{X,Y \ independence} = \begin{cases} (1-p) \cdot \lambda e^{-\lambda y} &, & iff \ x = 0 \\ p \cdot \lambda e^{-\lambda y} &, & iff \ x = 1 \end{cases}.$$

Additionally,  $f_{X,Y}$  is a valid density function, because:

(i) 
$$f_{XY} \ge 0$$
,  $\forall x, y \in \{0,1\} \times \mathbb{R}^+$ .

(ii) 
$$f_{X,Y}(x,y) = \int_0^\infty \sum_{i=0}^1 f(x=i,y) \, dy = \int_0^\infty (1-p) \cdot \lambda e^{-\lambda y} dy + \int_0^\infty p \cdot \lambda e^{-\lambda y} dy = 1.$$

#### 1A-2.

We have the following constraints:

Given the above restrictions R, we have to prove / disprove:

$$R \Longrightarrow P(B,C|X) = P(B|X) \cdot P(C|X)$$

Solution: Transform the joint probability P(B, C|X) into  $P(B, C|X) = P(C|B, X) \cdot P(B|X)$ .

Excluding the degenerate case P(B|X) = 0, this leads to:

$$P(B,C|X) = P(B|X) \cdot P(C|X)$$

$$\Leftrightarrow P(C|B,X) \cdot P(B|X) = P(B|X) \cdot P(C|X)$$

$$\Leftrightarrow P(C|B,X) = P(C|X)$$

$$\Leftrightarrow \frac{P(C,B,X)}{P(B,X)} = P(C|X).$$

The above only holds iff P(C|B,X) = P(C|X), which is generally not true, so conditional independence of A,B and A,C is not sufficient for transitivity.

#### 1A-4.

Definition of the events:

G = Person is guilty,

T = Person passes the test.

(i) The negations  $\overline{T}$ ,  $\overline{G}$  can be read as *not*.

$$P(G|\bar{T}) = \frac{P(\bar{T}|G) \cdot P(G)}{P(\bar{T})} = \frac{\frac{5}{6} \cdot \frac{1}{3}}{\frac{7}{18}} = \frac{5}{7},$$
with
$$P(\bar{T}|G) = \frac{5}{6},$$

$$P(G) = \frac{1}{3},$$

$$P(\bar{T}) = P(G) \cdot P(\bar{T}|G) + P(\bar{G}) \cdot P(\bar{T}|\bar{G}) = \frac{1}{3} \cdot \frac{5}{6} + \frac{2}{3} \cdot \frac{1}{6} = \frac{7}{18}$$
(ii)
$$P(G|\bar{T},\bar{T}) = \frac{P(\bar{T},\bar{T}|G)}{P(\bar{T},\bar{T})} = \underbrace{\frac{P(\bar{T}|G) \cdot P(\bar{T}|G)}{P(\bar{T},\bar{T})}}_{conditional independence} = \frac{\left(\frac{5}{6}\right)^2}{\frac{1}{3} \cdot \left(\frac{5}{6}\right)^2 + \frac{2}{3} \cdot \left(\frac{1}{6}\right)^2} = 0.\overline{925}.$$

Using the conditional independence of  $P(\overline{T}, \overline{T}|G)$  and independence of testing  $P(\overline{T}, \overline{T}|G)$ .

#### 1A-5.

$$E[X] = \sum_{i=1}^{6} i \cdot P(X=i) = (1+2+3) \cdot \frac{1}{12} + (4+5) \cdot \frac{1}{6} + 6 \cdot \frac{5}{12} = 4.5.$$

$$Var[X] = E[X^{2}] - E[X]^{2} = \left[ (1+4+9) \cdot \frac{1}{12} + (16+25) \cdot \frac{1}{6} + 36 \cdot \frac{5}{12} \right] - 4.5^{2} = \frac{271}{12} - 4.5^{2}$$

$$= 2 \cdot \frac{3}{12}$$

$$E[X_1 + E_2] = 2 \cdot E[X_1] = 9.$$

# 1A-6.

$$E[(X - E[X])(Y - E[Y])] = E[XY - XE[Y] - YE[X] + E[X]E[Y]]$$

$$= E[XY] - E[Y]E[X] - E[X]E[Y] + E[X]E[Y]$$

$$= E[XY] - E[X]E[Y]$$

$$= 0.$$

$$E[XY] = \int_{y_0}^{y_1} \int_{x_0}^{x_1} xy \cdot f_{X,Y}(x,y) dx dy = \int_{y_0}^{y_1} y \int_{x_0}^{x_1} x \cdot \underbrace{f_X(x)f_y(y)}_{independence} dx dy$$

$$= \int_{y_0}^{y_1} y f_y(y) \int_{x_0}^{x_1} x f_X(x) dx dy = \int_{y_0}^{y_1} y f_y(y) \cdot E[X] dy = E[X] \int_{y_0}^{y_1} y f_y(y) dy$$

$$= E[X]E[Y].$$

Utilizing that \*E[XY] = E[X]E[Y] if X, Y are independent.