

# **Machine Learning: Assignment Sheet #2**

Due on February 22, 2022 at 10:00

**Group HB**

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## Problem 2.1

We consider the chance experiment of a fair coin that is tossed four times.

a) Give the sample space.

The sample space is:

$$\Omega = \{(HHHH), (HHHT), (HHTH), (HTHH), (THHH), (HHTT), (HTHT), (THHT), (THTH), (TTHH), (HTTH), (HTTT), (THTT), (TTHT), (TTTH), (TTTT)\}$$

b) Define the random variable  $X$  to be the number of heads,  $Y$  as the number of tails and  $Z$  as  $Z = |X - Y|$ .

Random variables  $X$ ,  $Y$ ,  $Z$  are defined as following:

$$\begin{array}{llll} X(TTTT) = 0, & X(TTTH) = 1, & X(TTHT) = 1, & X(THTT) = 1 \\ X(HTTT) = 1, & X(HHTT) = 2, & X(HTHT) = 2, & X(THHT) = 2 \\ X(THTH) = 2, & X(TTHH) = 2, & X(HTTH) = 2, & X(HHHT) = 3 \\ X(HHTH) = 3, & X(HTHH) = 3, & X(THHH) = 3, & X(HHHH) = 4 \end{array}$$

$$\begin{array}{llll} Y(TTTT) = 4, & Y(TTTH) = 3, & Y(TTHT) = 3, & Y(THTT) = 3 \\ Y(HTTT) = 3, & Y(HHTT) = 2, & Y(HTHT) = 2, & Y(THHT) = 2 \\ Y(THTH) = 2, & Y(TTHH) = 2, & Y(HTTH) = 2, & Y(HHHT) = 1 \\ Y(HHTH) = 1, & Y(HTHH) = 1, & Y(THHH) = 1, & Y(HHHH) = 0 \end{array}$$

$$\begin{array}{llll} Z(TTTT) = 4, & Z(TTTH) = 2, & Z(TTHT) = 2, & Z(THTT) = 2 \\ Z(HTTT) = 2, & Z(HHTT) = 0, & Z(HTHT) = 0, & Z(THHT) = 0 \\ Z(THTH) = 0, & Z(TTHH) = 0, & Z(HTTH) = 0, & Z(HHHT) = 2 \\ Z(HHTH) = 2, & Z(HTHH) = 2, & Z(THHH) = 2, & Z(HHHH) = 4 \end{array}$$

c) Compute the joint PMF of  $(X, Z)$ .

The PMF of variables  $X$  and  $Z$  is defined as following:

$$p(0, 4) = p(\{(TTTT)\} \cap \{(TTTT), (HHHH)\}) = p(\{(TTTT)\}) = \frac{1}{16}$$

$$\begin{aligned} p(1, 1) &= p(\{(TTTH), (TTHT), (THTT), (HTTT)\} \cap \{(TTTH), (TTHT), (THTT), \\ & (HTTT), (HHHT), (HHTH), (HTHH), (THHH)\}) = p(\{(TTTH), (TTHT), (THTT), (HTTT)\}) = \frac{1}{4} \end{aligned}$$

$$\begin{aligned} p(2, 0) &= p(\{(HHTT), (HTHT), (THHT), (THTH), (TTHH), (HTTH)\} \cap \{(HHTT), (HTHT), (THHT), \\ & (THTH), (TTHH), (HTTH)\}) = p(\{(HHTT), (HTHT), (THHT), (THTH), (TTHH), (HTTH)\}) = \frac{3}{8} \end{aligned}$$

$$\begin{aligned} p(3, 1) &= p(\{(HHHT), (HHTH), (HTHH), (THHH)\} \cap \{(TTTH), (TTHT), (THTT), \\ & (HTTT), (HHHT), (HHTH), (HTHH), (THHH)\}) = p(\{(HHHT), (HHTH), (HTHH), (THHH)\}) = \frac{1}{4} \end{aligned}$$

$$p(4, 4) = p(\{(HHHH)\} \cap \{(TTTT), (HHHH)\}) = p(\{(HHHH)\}) = \frac{1}{16}$$

PMF for the other values of  $X$  and  $Z$  is  $p(X, Z) = P(\emptyset) = 0$

d) Compute the expectation  $E(Y)$ . The expectation  $E(Y)$  is computed as following:

$$E(Y) = \sum_{y \in R_y} y \cdot P(Y = y) = 0 \cdot \frac{1}{16} + 1 \cdot \frac{1}{4} + 2 \cdot \frac{6}{16} + 3 \cdot \frac{4}{16} + 4 \cdot \frac{1}{16} = \frac{32}{16} = 2$$

## Problem 2.2

We consider the chance experiment of a fair dice that is rolled two times. Let  $X_1$  be the outcome of the first roll, while  $X_2$  is the outcome of the second roll.

a) Describe the chance experiment by its sample space, and define the random variables.

The sample space is:

$$\Omega = \{11, 12, 13, 14, 15, 16, 21, 22, 23, 24, 25, 26, 31, 32, 33, 34, 35, 36, 41, 42, 43, 44, 45, 46, 51, 52, 53, 54, 55, 56, 61, 62, 63, 64, 65, 66\}$$

Definition of  $X_1$

$$\begin{array}{llllll} X_1(11) = 1 & X_1(12) = 1 & X_1(13) = 1 & X_1(14) = 1 & X_1(15) = 1 & X_1(16) = 1 \\ X_1(21) = 2 & X_1(22) = 2 & X_1(23) = 2 & X_1(24) = 2 & X_1(25) = 2 & X_1(26) = 2 \\ X_1(31) = 3 & X_1(32) = 3 & X_1(33) = 3 & X_1(34) = 3 & X_1(35) = 3 & X_1(36) = 3 \\ X_1(41) = 4 & X_1(42) = 4 & X_1(43) = 4 & X_1(44) = 4 & X_1(45) = 4 & X_1(46) = 4 \\ X_1(51) = 5 & X_1(52) = 5 & X_1(53) = 5 & X_1(54) = 5 & X_1(55) = 5 & X_1(56) = 5 \\ X_1(61) = 6 & X_1(62) = 6 & X_1(63) = 6 & X_1(64) = 6 & X_1(65) = 6 & X_1(66) = 6 \end{array}$$

Definition of  $X_2$

$$\begin{array}{llllll} X_2(11) = 1 & X_2(12) = 2 & X_2(13) = 3 & X_2(14) = 4 & X_2(15) = 5 & X_2(16) = 6 \\ X_2(21) = 1 & X_2(22) = 2 & X_2(23) = 3 & X_2(24) = 4 & X_2(25) = 5 & X_2(26) = 6 \\ X_2(31) = 1 & X_2(32) = 2 & X_2(33) = 3 & X_2(34) = 4 & X_2(35) = 5 & X_2(36) = 6 \\ X_2(41) = 1 & X_2(42) = 2 & X_2(43) = 3 & X_2(44) = 4 & X_2(45) = 5 & X_2(46) = 6 \\ X_2(51) = 1 & X_2(52) = 2 & X_2(53) = 3 & X_2(54) = 4 & X_2(55) = 5 & X_2(56) = 6 \\ X_2(61) = 1 & X_2(62) = 2 & X_2(63) = 3 & X_2(64) = 4 & X_2(65) = 5 & X_2(66) = 6 \end{array}$$

b) Compute the conditional expectation  $E[X_1 X_2 | X_2 = x_2]$ .

$$\begin{aligned} E[X_1 + X_2 | X_2 = x_2] &= E[X_1 | X_2 = x_2] + E[X_2 | X_2 = x_2] \\ &= E[X_1] + x_2 \\ &= 3.5 + x_2 \end{aligned}$$

$E[X_1 | X_2 = x_2] = E[X_1]$  holds due to the independence between the two variables (they refer to two different rolls of the fair dice)

c) Compute the conditional expectation  $E[X_1 X_2 | X_2 = x_2]$ .

$$\begin{aligned} E[X_1 X_2 | X_2 = x_2] &= x_2 E[X_1 | X_2 = x_2] \\ &= x_2 E[X_1] \\ &= 3.5 \cdot x_2 \end{aligned}$$

$E[X_1 | X_2 = x_2] = E[X_1]$  holds due to the independence between the two variables (they refer to two different rolls of the fair dice)

d) Compute the conditional variance  $\text{Var}(X_1^2 X_2 | X_2 = x_2)$ .

By definition of variance, it can be computed as:

$$\begin{aligned}
 \text{Var}(X_1^2 X_2 | X_2 = x_2) &= E[(X_1^2 X_2 - E[X_1^2 X_2 | X_2 = x_2])^2 | X_2 = x_2] \\
 &= E[X_1^4 X_2^2 - 2X_1^2 X_2 E[X_1^2 X_2 | X_2 = x_2] + E[X_1^2 X_2 | X_2 = x_2]^2 | X_2 = x_2] \\
 &= x_2^2 E[X_1^4 | X_2 = x_2] - 2E[X_1^2 X_2 x_2 E[X_1^2 | X_2 = x_2] | X_2 = x_2] \\
 &\quad + E[x_2^2 E[X_1^2 | X_2 = x_2]^2 | X_2 = x_2] \\
 &= x_2^2 E[X_1^4] - 2E[X_1^2 X_2 x_2 E[X_1^2] | X_2 = x_2] + E[x_2^2 E[X_1^2]^2 | X_2 = x_2] \\
 &= x_2^2 E[X_1^4] - 2x_2^2 E[X_1^2 E[X_1^2]] + x_2^2 E[E[X_1^2]^2] \\
 &= x_2^2 E[X_1^4] - 2x_2^2 E[X_1^2] E[X_1^2] + x_2^2 E[X_1^2]^2
 \end{aligned}$$

Substituting the expected values for  $X_1^4$  and  $X_1^2$

$$E[X_1^2] = \frac{91}{6} \quad E[X_1^4] = \frac{2275}{6}$$

$$\begin{aligned}
 \text{Var}(X_1^2 X_2 | X_2 = x_2) &= x_2^2 E[X_1^4] - 2x_2^2 E[X_1^2] E[X_1^2] + x_2^2 E[X_1^2]^2 \\
 &= x_2^2 \left( \frac{2275}{6} - 2 \frac{91}{6} \frac{91}{6} + \left( \frac{91}{6} \right)^2 \right) \\
 &= x_2^2 \frac{2275 \cdot 6 - 91^2}{36} \\
 &= x_2^2 \frac{5369}{36} \\
 &\approx 149.14 \cdot x_2^2
 \end{aligned}$$

## Problem 2.3

Let  $(X, Y)$  be random variables describing the two coordinates of points that are uniformly distributed in a triangle that is bound  $-1 \leq x \leq 1, y \geq 0$  and the two lines  $y = 1 + x$  and  $y = 1 - x$ .

Firstly, we find the joint probability density function PDF by the property:

$$\int_x \int_y p(x, y) \cdot dy \cdot dx = 1$$

We set the  $p(x, y)$  to be a constant  $c$ .

$$\begin{aligned}
 \int_{-1}^0 \int_0^{1+x} c \cdot dy \cdot dx + \int_0^1 \int_0^{1-x} c \cdot dy \cdot dx &= 1 \\
 \int_{-1}^0 c \cdot (1+x) \cdot dx + \int_0^1 c \cdot (1-x) \cdot dx &= 1 \\
 c - \frac{c}{2} + c - \frac{c}{2} &= 1 \\
 c = 1 &\Rightarrow p(x, y) = 1
 \end{aligned}$$

a) Find  $P(X \geq -0.5)$ .

$$\begin{aligned}
 P(X \geq -0.5) &= 1 - P(X < -0.5) \\
 P(X \geq -0.5) &= 1 - \int_{-1}^{-0.5} \int_0^{1+x} p(x, y) \cdot dy \cdot dx \\
 P(X \geq -0.5) &= 1 - \int_{-1}^{-0.5} \int_0^{1+x} 1 \cdot dy \cdot dx \\
 P(X \geq -0.5) &= 1 - \int_{-1}^{-0.5} (1+x) \cdot dx \\
 P(X \geq -0.5) &= 1 - \left( \frac{x^2}{2} + x \right) \Big|_{-1}^{-0.5} \\
 P(X \geq -0.5) &= 1 - \left( \frac{1}{8} - \frac{1}{2} \right) - \left( \frac{1}{2} - 1 \right) = \frac{7}{8}
 \end{aligned}$$

b) Find  $P(Y \geq 0.5)$ .

For each value of  $Y$ , the value of  $X$  goes from  $y - 1$  to  $1 - y$

$$\begin{aligned}
 P(Y \geq 0.5) &= \int_{0.5}^1 \int_{y-1}^{1-y} p(x, y) \cdot dx \cdot dy \\
 P(Y \geq 0.5) &= \int_{0.5}^1 \int_{y-1}^{1-y} 1 \cdot dx \cdot dy \\
 P(Y \geq 0.5) &= \int_{0.5}^1 (2 - 2 \cdot y) \cdot dy \\
 P(Y \geq 0.5) &= 2 \cdot y - y^2 \Big|_{0.5}^1 \\
 P(Y \geq 0.5) &= (2 - 1) - \left( 1 - \frac{1}{4} \right) = \frac{1}{4}
 \end{aligned}$$

c) Find the marginal densities and expectations of  $X$  and  $Y$ .

$$p_X(x) = \int_Y p(x, y) \cdot dy$$

Since the values of  $Y$  vary from 0 to  $1 - |x|$ :

$$\begin{aligned}
 p_X(x) &= \int_0^{1-|x|} p(x, y) \cdot dy \\
 p_X(x) &= 1 - |x|
 \end{aligned}$$

The marginal density of  $Y$ :

$$p_Y(y) = \int_X p(x, y) \cdot dx$$

The values of  $X$  varies from  $y - 1$  to  $1 - y$ , so the marginal density can be written as:

$$p_Y(y) = \int_{y-1}^{1-y} 1 \cdot dx = 2 - 2 \cdot y$$

The expectation value of  $X$ :

$$E[X] = \int_X \int_Y x \cdot p(x, y) dy \cdot dx$$

$$E[X] = \int_{-1}^1 \int_0^{1-|x|} x dy \cdot dx$$

$$E[X] = \int_{-1}^1 x \cdot (1 - |x|) \cdot dx$$

Sine we have absolute value of  $x$ , we can split the integral into 2 intervals:

$$E[X] = \int_{-1}^0 x \cdot (1 + x) \cdot dx + \int_0^1 x \cdot (1 - x) \cdot dx$$

$$E[X] = \left( \frac{x^3}{3} + \frac{x^2}{2} \right) \Big|_{-1}^0 + \left( -\frac{x^3}{3} + \frac{x^2}{2} \right) \Big|_0^1 = -\left( \frac{-1}{3} + \frac{1}{2} \right) + \left( \frac{-1}{3} + \frac{1}{2} \right) = 0$$

The expectation value of  $Y$ :

$$E[Y] = \int_Y \int_X y \cdot p(x, y) dx \cdot dy$$

$$E[Y] = \int_0^1 \int_{y-1}^{1-y} y \cdot dx \cdot dy$$

$$E[Y] = \int_0^1 2 \cdot y - 2 \cdot y^2 \cdot dy$$

$$E[Y] = \left( y^2 - \frac{2 \cdot y^3}{3} \right) \Big|_0^1 = \left( 1 - \frac{2}{3} \right) = \frac{1}{3}$$

## Programming Problem 2.1

a) Generate a random set of two-dimensional points and plot them as a scatter plot.

```
1 size = 100
2 points = np.random.rand(size, 2)
3
4 fig = plt.figure()
5 ax = fig.add_subplot(1, 1, 1)
6
7 ax.scatter(points[:, 0], points[:, 1])
8 plt.show()
```

b) Plot the density of the 2D Gaussian distribution  $\mathcal{N}(\mu, \Sigma)$  with  $\mu = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$  and  $\Sigma = \begin{pmatrix} 1 & 0.25 \\ 0.25 & 1 \end{pmatrix}$ .

```
1 def two_dimensional_gaussian(mean, cov, pos):
2     cov_det = np.linalg.det(cov)
3     cov_inv = np.linalg.inv(cov)
4
5     N = np.sqrt((2 * np.pi) ** 2 * cov_det)
6
7     fac = np.einsum('...k,kl,...l->...', pos - mean, cov_inv, pos - mean)
8
9     return np.exp(-fac / 2) / N
10
11 sample = 100
12
13 X = np.linspace(-3, 3, sample)
14 Y = np.linspace(-2, 4, sample)
15 X, Y = np.meshgrid(X, Y)
```

```
16
17 pos = np.empty(X.shape + (2,))
18 pos[:, :, 0] = X
19 pos[:, :, 1] = Y
20
21 mean = np.array([0, 1])
22 cov = np.array([[1, 0.25], [0.25, 1]])
23
24 dst = two_dimensional_gaussian(mean, cov, pos)
25
26 fig = plt.figure(figsize=(15, 15))
27 ax = fig.add_subplot(projection='3d')
28
29 ax.plot_surface(X, Y, dst, linewidth=1, cmap=cm.jet)
30
31 ax.set_zlim(-0.05, 0.2)
32 ax.set_zticks(np.linspace(0, 0.2, 5))
33 ax.view_init(20, -20)
34
35 plt.show()
```