

# 170E Week 8 Discussion Notes

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**Problem 1.** (Midterm 2 Problem 3, rephrased) A bag contains 5 red, 3 yellow, and 2 white marbles. We uniformly randomly pick 4 balls without replacement. Let  $R$  and  $Y$  denote the number of red and yellow balls selected, respectively.

- (a) Determine  $\text{supp}(R, Y)$ .
- (b) Find the joint density of  $(R, Y)$ .
- (c) Compute the marginal density  $f_R$ .

*Solution.* Let us start with (b). Observe that if we select  $r$  red and  $y$  yellow marbles, then we must select  $4 - r - y$  white marbles. Thus

$$f_{(R,Y)}(r, y) = \frac{1}{\binom{10}{4}} \binom{5}{r} \binom{3}{y} \binom{2}{4-r-y}.$$

For (a), we can use our answer for (b) as a guide. For  $f_{(R,Y)}(r, y)$  to be positive, we need  $r \in [5]$ ,  $y \in [3]$  and  $4 - r - y \in [2]$ . Moreover, since we only select 4 balls, we in fact have  $r \in [4]$ . Thus

$$\text{supp}(R, Y) = \{(r, y) \in [4] \times [3] \mid 4 - r - y \in [2]\}.$$

For (c), observe that if we select  $r$  red marbles, then we must select  $4 - r$  yellow or white marbles. Thus

$$f_R(r) = \frac{1}{\binom{10}{4}} \binom{5}{r} \binom{5}{4-r}. \quad \square$$

**Problem 2.** (Midterm 2 Problem 4, rephrased) Let  $Y$  be a continuous random variable supported on  $\mathbb{R}$ . We define the *entropy*  $H(Y)$  of  $Y$  as

$$H(Y) = - \int_{-\infty}^{\infty} f_Y(y) \log(f_Y(y)) \, dy.$$

Fix  $\mu, \sigma^2 \in \mathbb{R}$ .

- (a) Compute the entropy of  $Y \sim \text{Norm}(\mu, \sigma^2)$ .
- (b) Show that  $Y \sim \text{Norm}(\mu, \sigma^2)$  has maximal entropy among all random variables supported on  $\mathbb{R}$  with mean  $\mu$  and variance  $\sigma^2$ .

*Solution.* For (a), we directly compute

$$\begin{aligned}
H(Y) &= - \int_{-\infty}^{\infty} f_Y(y) \log(f_Y(y)) \, dy \\
&= - \int_{-\infty}^{\infty} f_Y(y) \log \left( \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2} (y - \mu)^2 \right) \right) \, dy \\
&= - \int_{-\infty}^{\infty} f_Y(y) \left( -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (y - \mu)^2 \right) \, dy \\
&= \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \mathbb{E}((Y - \mu)^2) \\
&= \frac{1}{2} \log(2\pi e \sigma^2),
\end{aligned}$$

where in the last equality we use that  $\mu_Y = \mu$ .

For (b), let  $X$  be a random variable supported on  $\mathbb{R}$  with mean  $\mu$  and variance  $\sigma^2$ . Recall from last week that the KL divergence  $D_{\text{KL}}(X \parallel Y)$  from  $X$  to  $Y$  is nonnegative. Thus

$$\begin{aligned}
0 &\leq D_{\text{KL}}(X \parallel Y) \\
&= \int_{-\infty}^{\infty} f_X(x) \log \left( \frac{f_X(x)}{f_Y(x)} \right) \, dx \\
&= -H(X) - \int_{-\infty}^{\infty} f_X(x) \log(f_Y(x)) \, dx \\
&= -H(X) - \int_{-\infty}^{\infty} f_X(x) \log \left( \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2} (x - \mu)^2 \right) \right) \, dx \\
&= -H(X) + \frac{1}{2} \log(2\pi e \sigma^2) \\
&= -H(X) + H(Y),
\end{aligned}$$

where in the second-to-last equality we use that  $\mu_X = \mu$  and  $\sigma_X^2 = \sigma^2$  to reuse the computation from (a). Thus  $H(Y) \geq H(X)$ .  $\square$

**Problem 3.** (Lecture notes Exercise 4.2, augmented) Let  $\mu_X, \mu_Y \in \mathbb{R}, \sigma_X, \sigma_Y > 0$ , and let  $\rho_{X,Y} \in [-1, 1]$ . Our definition of the bivariate normal distribution is via the pdf

$$f_{(X,Y)}(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho_{X,Y}^2}} \exp \left( -\frac{1}{2(1-\rho_{X,Y}^2)} Q(x, y) \right)$$

where

$$Q(x, y) = \left( \frac{x - \mu_X}{\sigma_X} \right)^2 + \left( \frac{y - \mu_Y}{\sigma_Y} \right)^2 - 2\rho_{X,Y} \frac{(x - \mu_X)(y - \mu_Y)}{\sigma_X\sigma_Y}.$$

(a) Consider the change of variables

$$Z_X = \frac{X - \mu_X}{\sigma_X} \quad \text{and} \quad Z_Y = \frac{Y - \mu_Y}{\sigma_Y}.$$

Show that  $(Z_X, Z_Y)$  is bivariate normal with  $\mu_{Z_X} = \mu_{Z_Y} = 0$  and  $\sigma_{Z_X} = \sigma_{Z_Y} = 1$  and  $\rho_{Z_X, Z_Y} = \rho_{X, Y}$ .

(b) Consider the change of variables

$$U_X = \frac{Z_X - \rho_{X, Y} Z_Y}{\sqrt{1 - \rho_{X, Y}^2}} \quad \text{and} \quad U_Y = Z_Y.$$

Show that  $(U_X, U_Y)$  is unit (means zero, variances one, zero correlation) bivariate normal.

(c) Show that for any bivariate normal, if  $\rho_{X, Y} = 0$ , then  $X$  and  $Y$  are independent.

(d) Deduce the means, variances, covariance, and correlation of  $X, Y$ .

*Solution.* For (a), an inverse transformation is

$$x(z_X, z_Y) = \sigma_X z_X + \mu_X \quad \text{and} \quad y(z_X, z_Y) = \sigma_Y z_Y + \mu_Y$$

which has Jacobian

$$J = \begin{pmatrix} \sigma_X & 0 \\ 0 & \sigma_Y \end{pmatrix}.$$

Thus by the bivariate change of variables theorem, we have

$$f_{(Z_X, Z_Y)}(z_X, z_Y) = |J| f_{(X, Y)}(x(z_X, z_Y), y(z_X, z_Y)) \\ = \frac{1}{2\pi\sqrt{1 - \rho_{X, Y}^2}} \exp\left(-\frac{1}{2(1 - \rho_{X, Y}^2)}(z_X^2 + z_Y^2 - 2\rho_{X, Y} z_X z_Y)\right).$$

This is the pdf of a bivariate normal with the claimed parameters.

For (b), an inverse transformation is

$$z_X(u_X, u_Y) = \sqrt{1 - \rho_{X, Y}^2} u_X + \rho_{X, Y} u_Y \quad \text{and} \quad z_Y(u_X, u_Y) = u_Y$$

which has Jacobian

$$J = \begin{pmatrix} \sqrt{1 - \rho_{X, Y}^2} & \rho_{X, Y} \\ 0 & 1 \end{pmatrix}.$$

Thus by the bivariate change of variables theorem, we have

$$f_{(U_X, U_Y)}(u_X, u_Y) = |J| f_{(Z_X, Z_Y)}(z_X(u_X, u_Y), z_Y(u_X, u_Y)) \\ = \frac{1}{2\pi} \exp\left(-\frac{1}{2(1 - \rho_{X, Y}^2)}((\sqrt{1 - \rho_{X, Y}^2} u_X + \rho_{X, Y} u_Y)^2 + u_Y^2 - 2\rho_{X, Y}(\sqrt{1 - \rho_{X, Y}^2} u_X + \rho_{X, Y} u_Y)u_Y)\right) \\ = \frac{1}{2\pi} \exp\left(-\frac{1}{2}(u_X^2 + u_Y^2)\right).$$

This is the pdf of a unit bivariate normal.

For (c), we simply note that when  $\rho_{X,Y} = 0$ , the pdf is

$$f_{(X,Y)}(x,y) = \frac{1}{2\pi\sigma_X\sigma_Y} \exp\left(-\frac{1}{2}\left(\left(\frac{x-\mu_X}{\sigma_X}\right)^2 + \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right)\right).$$

On the other hand, the marginal pdf of  $X$  is

$$\begin{aligned} f_{X|Y=y}(x) &= \int_{-\infty}^{\infty} f_{(X,Y)}(x,y) dy \\ &= \frac{1}{\sqrt{2\pi}\sigma_X} \exp\left(-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2\right) \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_Y} \exp\left(-\frac{1}{2}\left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right) dy \\ &= \frac{1}{\sqrt{2\pi}\sigma_X} \exp\left(-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2\right) \end{aligned}$$

and similarly for  $Y$ . Since the product of their marginals is their joint,  $X$  and  $Y$  are independent.

For (d), by (c), we have that  $U_X$  and  $U_Y$  are independent. We now backtrack to compute the desired quantities. For example,

$$\text{Cov}(Z_X, Z_Y) = \text{Cov}(\sqrt{1 - \rho_{X,Y}^2} U_X + \rho_{X,Y} U_Y, U_Y) = \rho_{X,Y}$$

so

$$\text{Cov}(X, Y) = \text{Cov}(\sigma_X Z_X + \mu_X, \sigma_Y Z_Y + \mu_Y) = \sigma_X \sigma_Y \rho_{X,Y}.$$

(In other words, we express  $X, Y$  in terms of  $Z_X, Z_Y$ , and then in terms of  $U_X, U_Y$ , for which all the quantities are already known.)  $\square$