

# Probability and Stochastic Processes I - Lecture 8

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## II.5 Transformations and Change of Variables

- suppose we have a random vector  $\mathbf{X} \in R^k$  and we transform this to be a new random vector  $\mathbf{Y} = T(\mathbf{X}) \in R^l$
- given the probability distribution of  $\mathbf{X}$ , whether specified by a probability function  $p_{\mathbf{X}}$  or a density  $f_{\mathbf{X}}$ , determine the probability function or density of  $\mathbf{Y}$

### discrete case

- so suppose  $\mathbf{X}$  has prob. function  $p_{\mathbf{X}}$  and now we want

$$p_{\mathbf{Y}}(\mathbf{y}) = P_{\mathbf{Y}}(\{\mathbf{y}\}) = P_{\mathbf{X}}(T^{-1}\{\mathbf{y}\}) = \sum_{\mathbf{x} \in T^{-1}\{\mathbf{y}\}} p_{\mathbf{X}}(\mathbf{x})$$

**Example II.5.1** - suppose  $p_{\mathbf{X}}(0, 1) = 1/2$ ,  $p_{\mathbf{X}}(1, 0) = 1/3$ ,  $p_{\mathbf{X}}(1, 1) = 1/6$  and  $y = T(x_1, x_2) = x_1 + x_2$

- so  $Y$  takes the values 1 and 2 (only) with positive probability and since  $T^{-1}\{1\} = \{(0, 1), (1, 0)\}$  then  $p_Y(1) = 1/2 + 1/3 = 5/6$  and since  $T^{-1}\{2\} = \{(1, 1)\}$  then  $p_Y(2) = 1/6$

## Example II.5.2 Projections

- suppose  $k \geq 2$  and  $(y_1, y_2) = T(x_1, \dots, x_k) = (x_1, x_2)$  projection on the first two coordinates, then

$$T^{-1}\{\mathbf{y}\} = T^{-1}\{(y_1, y_2)'\} = \{(x_1, \dots, x_k) : x_1 = y_1, x_2 = y_2\}$$

$$\begin{aligned} p_Y(y_1, y_2) &= P_{\mathbf{X}}(T^{-1}\{\mathbf{y}\}) = \sum_{\mathbf{x} \in T^{-1}\{\mathbf{y}\}} p_{\mathbf{X}}(\mathbf{x}) \\ &= \sum_{(x_1, \dots, x_k) : x_1 = y_1, x_2 = y_2} p_{\mathbf{X}}(x_1, \dots, x_k) \\ &= \sum_{(x_3, \dots, x_k) \in R^{k-2}} p_{\mathbf{X}}(y_1, y_2, x_3, \dots, x_k) \end{aligned}$$

- also if  $y = T(x_1, \dots, x_k) = x_2$  projection on the second coordinate, then

$$T^{-1}\{y\} = T^{-1}\{y\} = \{(x_1, \dots, x_k) : x_2 = y\}$$

$$\begin{aligned} p_Y(y) &= \sum_{(x_1, \dots, x_k) : x_2 = y} p_{\mathbf{X}}(x_1, \dots, x_k) \\ &= \sum_{(x_1, x_3, \dots, x_k) \in R^{k-2}} p_{\mathbf{X}}(x_1, y, x_3, \dots, x_k) \end{aligned}$$

- so the general approach for finding the probability functions of projections is to take the joint probability function and sum out all the remaining variables

**Example II.5.3** *Multinomial*( $n, p_1, \dots, p_k$ ) *distribution*

- when let  $\mathbf{X} = (X_1, \dots, X_k)' \sim \text{multinomial}(n, p_1, \dots, p_k)$  then  $p_{\mathbf{X}}$  is only positive on  $\mathbf{a} \in R^k$  when

$$a_i \in \{0, \dots, n\} \text{ and } a_1 + \dots + a_k = n \quad (*)$$

and has

$$p_{\mathbf{X}}(\mathbf{a}) = \binom{n}{a_1 \ a_2 \ \dots \ a_k} p_1^{a_1} \dots p_k^{a_k}$$

- suppose  $k \geq 2$  and  $(y_1, y_2) = T(x_1, \dots, x_k) = (x_1, x_2)$  so we want the distribution of  $\mathbf{Y} = (X_1, X_2)'$

- by (\*)  $y_1, y_2, a_3, \dots, a_k \in \{0, \dots, n\}$  and  $y_1 + y_2 + a_3 + \dots + a_k = n$  iff

$$a_3, \dots, a_k \in \{0, \dots, n - y_1 - y_2\} \text{ and } a_3 + \dots + a_k = n - y_1 - y_2 \quad (**)$$

- therefore

$$\begin{aligned} p_Y(y_1, y_2) &= \sum_{(a_3, \dots, a_k) \text{ sat. (**)}} \binom{n}{y_1 \ y_2 \ a_3 \ \dots \ a_k} p_1^{y_1} p_2^{y_2} p_3^{a_3} \dots p_k^{a_k} \\ &= \frac{n!}{y_1! y_2! (n - y_1 - y_2)!} p_1^{y_1} p_2^{y_2} \sum_{(a_3, \dots, a_k) \text{ sat. (**)}} \frac{(n - y_1 - y_2)!}{a_3! \dots a_k!} p_3^{a_3} \dots p_k^{a_k} \\ &= \binom{n}{y_1 \ y_2 \ n - y_1 - y_2} p_1^{y_1} p_2^{y_2} (1 - p_1 - p_2)^{n - y_1 - y_2} \times \\ &\quad \sum_{(a_3, \dots, a_k) \text{ sat.g (**)}} \binom{n - y_1 - y_2}{a_3 \ \dots \ a_k} \left( \frac{p_3}{1 - p_1 - p_2} \right)^{a_3} \dots \left( \frac{p_k}{1 - p_1 - p_2} \right)^{a_k} \\ &= \binom{n}{y_1 \ y_2 \ n - y_1 - y_2} p_1^{y_1} p_2^{y_2} (1 - p_1 - p_2)^{n - y_1 - y_2} \end{aligned}$$

since the second term is the sum of all

$$\text{multinomial} \left( n - y_1 - y_2, \frac{p_3}{1 - p_1 - p_2}, \dots, \frac{p_k}{1 - p_1 - p_2} \right)$$

probabilities and so  $(X_1, X_2) \sim \text{multinomial}(n, p_1, p_2, 1 - p_1 - p_2)$  ■

**Exercise II.5.1** If  $\mathbf{X} = (X_1, \dots, X_k)' \sim \text{multinomial}(n, p_1, \dots, p_k)$  then prove  $X_j \sim \text{binomial}(n, p_j) = \text{multinomial}(n, p_j, 1 - p_j)$ .

**note** - these results for the multinomial are easy to see intuitively since the multinomial arises by categorizing  $n$  independent observations into  $k$  mutually disjoint categories and when we project onto  $l$  coordinates we are now categorizing into  $l + 1$  mutually disjoint categories

**Exercise II.5.2** Use the above note to determine the distribution of  $Y = X_1 + \dots + X_l$  for  $l \leq k$  when

$$(X_1, \dots, X_k)' \sim \text{multinomial}(n, p_1, \dots, p_k).$$

**note** - in the discrete case if  $T$  is 1-1 ( $T(\mathbf{x}_1) = T(\mathbf{x}_2)$  iff  $\mathbf{x}_1 = \mathbf{x}_2$ ) then

$$p_{\mathbf{Y}}(\mathbf{y}) = P_{\mathbf{X}}(T^{-1}\{\mathbf{y}\}) = p_{\mathbf{X}}(T^{-1}\{\mathbf{y}\})$$

whenever  $T^{-1}\{\mathbf{y}\} \neq \emptyset$

- depending on the transformation  $T$  it could be that  $\mathbf{Y} = T(\mathbf{X})$  has a discrete distribution no matter what kind of distribution  $\mathbf{X}$  has

### Example II.5.4

- suppose  $T(\mathbf{x}) = \mathbf{c} \in R^l$  for every  $\mathbf{x}$ , then

$$p_{\mathbf{Y}}(\mathbf{y}) = P_{\mathbf{X}}(T^{-1}\{\mathbf{y}\}) = \begin{cases} P_{\mathbf{X}}(R^k) = 1 & \text{if } \mathbf{y} = \mathbf{c} \\ P_{\mathbf{X}}(\phi) = 0 & \text{if } \mathbf{y} \neq \mathbf{c} \end{cases}$$

and the distribution of  $\mathbf{Y}$  is *degenerate* at  $\mathbf{c}$

- suppose  $X \sim N(0, 1)$  so  $P(X \leq 0) = P(X > 0) = 1/2$ , then if

$$Y = T(X) = I_{(-\infty, 0]}(X) = \begin{cases} 1 & \text{if } X \leq 0 \\ 0 & \text{if } X > 0 \end{cases}$$

then

$$p(1) = P(X \leq 0) = 1/2 \text{ and } p(0) = P(X > 0) = 1/2$$

so  $Y \sim \text{Bernoulli}(1/2)$  ■

**Definition II.5.1** For  $A \subset \Omega$  the function  $I_A : \Omega \rightarrow \mathbb{R}^1$  given by

$$I_A(\omega) = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \in A^c \end{cases}$$

is called the *indicator function* of  $A$ . ■

**Exercise II.5.3** If  $(\Omega, \mathcal{A}, P)$  is a probability model and  $A \in \mathcal{A}$  then  $Y = I_A$  is a random variable with  $Y \sim \text{Bernoulli}(P(A))$ .