

# STAT 302 Review of Chapters 5 – 7

(November, 2012)

## 1. Multivariate Probability Distributions

### (a) Bivariate discrete distributions

- Joint distribution  $p(x_1, x_2) = P(X_1 = x_1, X_2 = x_2)$ .
- Marginal distribution  $P(X_1 = x_1) = \sum_{x_2} p(x_1, x_2)$ ,  $P(X_2 = x_2) = \sum_{x_1} p(x_1, x_2)$ .
- Conditional distribution  $P(X_1 = x_1 | X_2 = x_2) = P(X_1 = x_1, X_2 = x_2) / P(X_2 = x_2)$ .

Note: (i)  $\sum_{x_1} \sum_{x_2} p(x_1, x_2) = 1$ ; (ii)  $\sum_{x_1} P(X_1 = x_1 | X_2 = x_2) = 1$  for any fixed  $x_2$ . These results may be used to verify your answers.

### (b) Bivariate continuous distributions

- Joint pdf  $f(x_1, x_2)$ : for any area  $A$  in the plane,

$$p((X_1, X_2) \in A) = \int \int_A f(x_1, x_2) dx_1 dx_2.$$

(Please review techniques for double integrations.)

- Marginal pdf:  $f_1(x_1) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2$ ,  $f_2(x_2) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_1$ .
- Conditional pdf:  $f(x_1 | x_2) = f(x_1, x_2) / f_2(x_2)$  for  $f_2(x_2) > 0$ .

Note: (i)  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 dx_2 = 1$ . (ii)  $\int_{-\infty}^{\infty} f(x_1 | x_2) dx_1 = 1$  for any fixed  $x_2$ . (These two results may be used to verify your answers.) (iii)  $P(a < X < b | x_2) = \int_a^b f(x_1 | x_2) dx_1$  for any fixed  $x_2$ .

## 2. Expectation, Variance, Covariance, Correlation, and Independence.

### a. Covariance and Correlation

Covariance and correlation describe the (linear) relationship between two random variables.

Covariance:  $Cov(X_1, X_2) = E(X_1 X_2) - E(X_1)E(X_2)$ .

Correlation:  $\rho(X_1, X_2) = \frac{Cov(X_1, X_2)}{\sqrt{V(X_1)V(X_2)}}$ ,  $-1 \leq \rho \leq 1$ .

Properties:

$$E(h(X_1, X_2)) = \int \int h(x_1, x_2) f(x_1, x_2) dx_1 dx_2, \quad \text{for any function } h(x_1, x_2),$$

$$V\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 V(X_i) + 2 \sum_{i < j} a_i a_j Cov(X_i, X_j), \quad \text{for any constants } a_i,$$

$$Cov\left(\sum_{i=1}^n a_i X_i, \sum_{j=1}^m b_j Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m a_i b_j Cov(X_i, Y_j), \quad \text{for any constants } a_i, b_j.$$

## b. Independence

Random variables  $X_1$  and  $X_2$  are independent if  $f(x_1, x_2) = f(x_1)f(x_2)$ , for all  $x_1, x_2$ , when  $X_1$  and  $X_2$  are continuous, or  $P(X_1 = x_1, X_2 = x_2) = P(X_1 = x_1)P(X_2 = x_2)$ , for every  $x_1, x_2$ , when  $X_1$  and  $X_2$  are discrete. If  $X_1$  and  $X_2$  are independent, the  $Cov(X_1, X_2) = 0$ .

## c. Functions of Random Variables

Let  $Y = h(X)$ , where  $h(x)$  is a known function. We want to find the distribution of  $Y$  if the distribution of  $X$  is given.

- General approach: (i) If  $X$  is discrete,

$$P(Y = y) = \sum_{\{x: h(x)=y\}} P(X = x).$$

- (ii) If  $X$  is continuous, first find the cdf of  $Y$

$$F_Y(y) = P(Y \leq y) = \int_{\{x: h(x) \leq y\}} f_X(x) dx,$$

then find the pdf of  $Y$  via

$$f_Y(y) = dF_Y(y)/dy.$$

The above methods work for general problems, including bivariate case, but sometimes the methods can be tedious. In some cases, the following method may be preferable.

- If  $h(x)$  is monotone and differentiable, then

$$f_Y(y) = f_X(h^{-1}(y)) \left| \frac{dx}{dy} \right|.$$

- For multivariate cases, sometimes we can use the condition method illustrated in class.

## d. Common distributions in statistics

The following distributions are widely used in statistics: the t-distribution, the  $\chi^2$ -distribution, and the F distribution. It is important to know how these distributions are obtained, but it is not necessary to remember their density functions.

## 3. Limit Theorems

Sequences of random variables may converge in different ways: converge in probability, converge in distribution, etc.

$X_n$  converges to  $X$  in probability if for any  $\epsilon > 0$

$$P(|X_n - X| > \epsilon) \rightarrow 0.$$

$X_n$  converges to  $X$  in distribution if  $F_n(x)$  (the cdf of  $X_n$ ) converges to  $F(x)$  (the cdf of  $X$ ) at every  $x$  where  $F(x)$  is continuous. Remark:  $X_n$  converges to  $X$  in distribution if the mgf of  $X_n$   $M_n(t)$  converges to the mgf of  $X$   $M(t)$  at every  $t$ .

The Central Limit Theorem: If  $X_1, \dots, X_n$  are i.i.d. with  $E(X_i) = \mu$  and  $V(X_i) = \sigma^2 < \infty$ , then

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \rightarrow N(0, 1) \text{ in distribution.}$$

*Note: This review may NOT include all the materials covered in class. The final exam will cover all the materials given in class.*