

# Parametric Statistics

## Conditional Expectation, Moments

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## Last Time

- ▶ Expectation is a summary of a distribution.
- ▶ We can compute the expectation of a function of an RV using LOTUS.
- ▶ Properties of expectation.
- ▶ Variance is a summary of how spread out a distribution is.
- ▶ Covariance describes how much two variables vary together.
- ▶ Correlation is covariance without scale.

# Lecture Summary

4.7 Conditional Expectations

4.4 Moments

## Conditional Expectation

Let  $X$  and  $Y$  be random variables such that the mean of  $Y$  exists and is finite. The conditional expectation (or conditional mean) of  $Y$  given  $X = x$  is denoted by  $E(Y | x)$  and is defined to be the expectation of the conditional distribution of  $Y$  given  $X = x$ .

For example, if  $Y$  has a continuous conditional distribution given  $X = x$  with conditional p.d.f.  $g_2(y | x)$ , then

$$E(Y | x) = \int_{-\infty}^{\infty} yg_2(y | x)dy.$$

Similarly, if  $Y$  has a discrete conditional distribution given  $X = x$  with conditional p.f.  $g_2(y | x)$ , then

$$E(Y | x) = \sum_{\text{All } y} yg_2(y | x).$$

# Conditional Expectation

- ▶ Conditional distributions are distributions, so they have expectations and variances.
- ▶  $E(Y|X = x) = \sum_y yP(y|X = x)$  is the conditional expectation of  $Y$  if you know  $X = x$  (a number).
- ▶  $E(Y|X) = h(X)$  is a function of  $X$ . For every possible value  $x$  of  $X$ ,  $E(Y|X)$  takes the value  $E(Y|X = x)$ . So  $E(Y|X)$  is a random variable.
- ▶ Law of total expectation/Law of iterated expectations:

$$E[E(Y|X)] = E(Y)$$

# Conditional Variance

## Definition

For every given value  $x$ , let  $\text{Var}(Y | x)$  denote the variance of the conditional distribution of  $Y$  given that  $X = x$ . That is,

$$\text{Var}(Y | x) = E \{ [Y - E(Y | x)]^2 | x \} .$$

We call  $\text{Var}(Y | x)$  the conditional variance of  $Y$  given  $X = x$ .

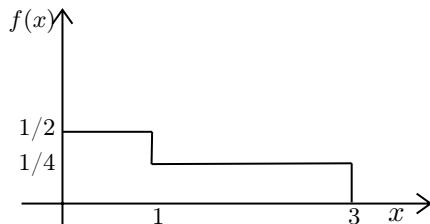
## Law of total variance

If  $X$  and  $Y$  are arbitrary random variables for which the necessary expectations and variances exist, then

$$\text{Var}(Y) = E[\text{Var}(Y | X)] + \text{Var}[E(Y | X)]$$

We call  $\text{Var}(Y | x)$  the conditional variance of  $Y$  given  $X = x$ .

## Using the laws of total expectation and variance



- ▶  $Y \sim \text{Bernoulli}(0.5)$ .
- ▶  $X|Y = 0 \sim \text{Uniform}([0, 1])$ .
- ▶  $X|Y = 1 \sim \text{Uniform}([1, 3])$
- ▶ Find  $E(X|Y)$ ,  $\text{Var}(X|Y)$ .
- ▶ Find  $E(X)$ ,  $\text{Var}(X)$ .

# Moments and Central Moments

## Definition (Moments and Central Moments)

Let  $X$  be a random variable and  $k$  be a positive integer.

The expectation  $E(X^k)$  is the  $k$ -th moment of  $X$ .

The expectation  $E[(X - E(X))^k]$  is the  $k$ -th central moment of  $X$ .

- ▶ The first moment is the mean:  $\mu = E(X^1)$ .
- ▶ The first central moment is zero:  
$$E[(X - E(X))^1] = E(X - \mu) = E(X) - E(X) = 0$$
- ▶ The second central moment is the variance:  
$$E[(X - E(X))^2] = Var(X)$$



## Moments and Central Moments

- ▶ The  $k$  th moment exists if and only if  $E(|X|^k) < \infty$ .
- ▶ If the random variable  $X$  is bounded ( $\Pr(a \leq X \leq b) = 1$ ), then all moments of  $X$  must necessarily exist.
- ▶ It is possible, however, that all moments of  $X$  exist even though  $X$  is not bounded.
- ▶ If  $E(|X|^k) < \infty$  for some positive integer  $k$ , then  $E(|X|^j) < \infty$  for every positive integer  $j$  such that  $j < k$ .
- ▶ If the distribution of  $X$  is symmetric with respect to its mean  $\mu$ , and if the central moment  $E[(X - \mu)^k]$  exists for a given odd integer  $k$ , then the value of  $E[(X - \mu)^k]$  will be 0.

# Skewness

Let  $X$  be a random variable with mean  $\mu$ , standard deviation  $\sigma$ , and finite third moment. The skewness of  $X$  is defined to be  $E[(X - \mu)^3] / \sigma^3$ .

- ▶ The reason for dividing the third central moment by  $\sigma^3$  is to make the skewness measure only the lack of symmetry rather than the spread of the distribution.

# Skewness

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- ▶ The reason for dividing the third central moment by  $\sigma^3$  is to make the skewness measure only the lack of symmetry rather than the spread of the distribution.
- ▶ Let's compute the skewness of the Bernoulli distribution.
  - ▶ with  $p = 0.5$
  - ▶ with  $p = 0.1$

# Moment Generating Functions

## Definition

Let  $X$  be a random variable. The function

$$\psi(t) = E(e^{tX}), t \in R$$

is called the moment generating function (m.g.f.) of  $X$ .

Let  $X$  be a random variables whose m.g.f.  $\psi(t)$  is finite for  $t$  in an open interval around zero. Then the  $n$ -th moment of  $X$  is finite, for  $n = 1, 2, \dots$ , and

$$E(X^n) = \left. \frac{d^n \psi(t)}{dt^n} \right|_{t=0}$$

# Properties of Moment Generating Functions

- ▶  $\psi(aX + b) = e^{bt}\psi_X(at)$ .
- ▶ Let  $Y = \sum_{i=1}^n X_i$  where  $X_1, \dots, X_n$  are independent random variables with m.g.f  $\psi_i(t)$  for  $i = 1, \dots, n$ . Then

$$\psi_Y(t) = \prod_{i=1}^n \psi_i(t)$$

- ▶ Let  $X$  and  $Y$  be two random variables with m.g.f.'s  $\psi_X(t)$  and  $\psi_Y(t)$ . If the m.g.f.'s are finite and  $\psi_X(t) = \psi_Y(t)$  for all values of  $t$  in an open interval around zero, then  $X$  and  $Y$  have the same distribution.

# Finding the p.f.'s for sums of random variables

- ▶ Find the mgf of Binomial( $n,p$ ).

## Sum of Binomials is a Binomial

If  $X_1$  and  $X_2$  are independent random variables, and if  $X_i$  has the binomial distribution with parameters  $n_i$  and  $p$  ( $i = 1, 2$ ), then  $X_1 + X_2$  has the binomial distribution with parameters  $n_1 + n_2$  and  $p$ .

# Mean and Median

## Median

Let  $X$  be a random variable. Every number  $m$  with the following property is called a median of the distribution of  $X$  :

$$\Pr(X \leq m) \geq 1/2 \quad \text{and} \quad \Pr(X \geq m) \geq 1/2.$$

## Mean Squared Error/M.S.E

The number  $E[(X - d)^2]$  is called the mean squared error (M.S.E.) of the prediction  $d$ .

## Mean Absolute Error/M.A.E.

The number  $E(|X - d|)$  is called the mean absolute error (M.A.E.) of the prediction  $d$ .

# Mean and Median

## Mean minimizes M.S.E.

Let  $X$  be a random variable with finite variance  $\sigma^2$ , and let  $\mu = E(X)$ . For every number  $d$ ,

$$E[(X - \mu)^2] \leq E[(X - d)^2]$$

## Median minimizes M.A.E.

Let  $X$  be a random variable with finite mean, and let  $m$  be a median of the distribution of  $X$ . For every number  $d$ ,

$$E(|X - m|) \leq E(|X - d|).$$

Equality holds if and only if  $d$  is also a median of the distribution of  $X$ .



# Recap

- ▶ Conditional Expectation, Conditional Variance are functions of the conditioning variable.
- ▶ Law of total expectation/law of total variance can help us compute variances and expectations of complex functions.
- ▶ The means of powers  $X^k$  of an RV  $X$  are called moments of  $X$ .
- ▶ They can help us derive distributions of sums of independent random variables and prove limiting properties of distributions.