

# Mathematical Statistics I

## Chapter 4: Expected Values

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1. Discrete random variables
2. Continuous random variables
3. Expectation of functions of random variables
4. Variance and Standard Deviation

# Discrete random variables

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# Introduction

- This material comes primarily from Rice (2007, Chapter 4).
- We will cover the ideas of expected value, variance, as well as higher-order moments.
- This includes topics such as conditional expectation, which is one of the fundamental ideas behind many branches of statistics and machine learning.
- For instance, most regression / prediction algorithms are built with the idea of minimizing some conditional expectation.

## Expectation: Discrete random variables

### Definition: Expectation of discrete random variables

Let  $X$  be a discrete random variable with pmf  $p(x)$ , which takes values in the space  $\mathcal{X}$ . The **expected value** of  $X$  is

$$E(X) = \sum_{x \in \mathcal{X}} x p(x),$$

provided that  $\sum_{x \in \mathcal{X}} |x| p(x) < \infty$ ; otherwise, the expectation is not defined.

- This is not the most mathematically precise definition of expectation, but a more complete treatment of the topic is outside the scope of this course (See Resnick, 2019).

## Expectation: Discrete random variables II

- The concept of the expected value parallels the notion of a *weighted average*.
- That is, we weight each possibility  $x \in \mathcal{X}$  by their corresponding probability:  $\sum_x x p(x)$ .
- $E(X)$  is also referred to as the **mean** of  $X$ , and is typically denoted  $\mu$  or  $\mu_X$ .
- If the function  $p$  is thought of as a weight, then  $E(X)$  is the center; that is, if we place the mass  $p(x_i)$  at the points  $x_i$ , then the balancing point is  $E(X)$ .
- Like with the pmf and cdf, we often use subscripts to denote which probability law we are using for the expectation, if it is not clear:  $E_X(X)$ .

## Expectation: Discrete random variables III

### Roulette

A roulette wheel has the numbers 1 through 36, as well as 0 and 00. If you bet \$1 that an odd number comes up, you win or lose \$1 according to whether that event occurs. If  $X$  denotes your net gain,  $X = 1$  with probability  $18/38$  and  $X = -1$  with probability  $20/38$ . The expected value of  $X$  is

$$E(X) = 1 \times \frac{18}{38} + (-1) \times \frac{20}{38} = -\frac{1}{19}.$$

- As you might imagine, the expected value coincides in the limit with the actual average loss per game, if you play many games (Chapter 5).

## Expectation: Discrete random variables IV

- Most casino games have a negative expected value by design; you may win some money, but if a large number of games are played, the house will come out on top.



## Expectation: Discrete random variables V

### Geometric Random Variable

Suppose that items are produced in a plant are independently defective with probability  $p$ . If items are inspected one by one until a defective item is found, then how many items must be inspected on average?

*Solution:*

## Expectation: Discrete random variables VI

### Poisson Distribution

The  $\text{Poisson}(\lambda)$  distribution has pmf  $p(k) = \frac{\lambda^k}{k!} e^{-\lambda}$ , for all  $k \geq 0$ . Thus, if  $X \sim \text{Pois}(\lambda)$ , then what is  $E[X]$ ?

*Solution:*

## Continuous random variables

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# Expectation: Continuous random variables

## Definition: Expectation of continuous random variables

Let  $X$  be a continuous random variable with pdf  $f(x)$ , which takes values in the space  $\mathcal{X}$ . The **expected value** of  $X$  is

$$E(X) = \int_{x \in \mathcal{X}} x f(x) dx.$$

provided that  $\int_{x \in \mathcal{X}} x f(x) dx < \infty$ , otherwise the expectation is undefined.

- As before, this is not the most mathematically precise definition of expectation, but a more complete treatment of the topic is outside the scope of this course (See Resnick, 2019).

## Expectation: Continuous random variables II

- We can still think of  $E(X)$  as the center of mass of the density.

## Expectation: Continuous random variables III

### Gamma Density

If  $X$  follows a gamma density with parameters  $\alpha$  and  $\lambda$ , then the pdf of  $X$  is

$$f(x) = \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}, \quad x \geq 0.$$

Find  $E(X)$ .

*Solution.*

## **Expectation of functions of random variables**

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# Functions of random variables

- We are often interested in functions of random variables:  
 $Y = g(X)$ .
- Ideas that we have already covered enable us to calculate  $E(Y)$ .
- For instance, you could use the change-of-variables theorem to get the density of  $Y$ , then use the definition to calculate  $E[Y]$ .
- Fortunately, we don't have to do this. We can instead calculate  $E[Y]$  by integrating (or summing) with respect to  $X$ :

$$E[g(X)] = \int_{x \in \mathcal{X}} g(x) f(x) dx.$$

- We will justify this for the discrete analog.



## Functions of random variables II

### Theorem 4.1: Expectation of transformed random variables

Suppose that  $X$  is a random variable and that  $Y = g(X)$  for some function  $g$ . Then,

- If  $X$  is discrete with pmf  $p(x)$ :

$$E(Y) = \sum_x g(x) p(x),$$

provided that  $\sum_x |g(x)|p(x) < \infty$ .

- If  $X$  is continuous with pdf  $f(x)$ :

$$E(Y) = \int_{-\infty}^{\infty} g(x) f(x) dx,$$

provided that  $\int |g(x)|f(x) dx < \infty$ .

## Functions of random variables: proof

*Proof:*

## Functions of random variables: proof II

- The proof for the continuous case is similar, but does require a measure-theoretic approach to integration.
- One important thing to note is that  $g(E(X))$  is not usually equal to  $E(g(x))$ .
- For example, let  $Z$  be a standard normal. We know that  $E[Z] = 0$ , because it's symmetric. However,  $P(|Z| > 0) = 1$ , thus we can readily deduce that  $E[|Z|] \geq 0 = |E[Z]|$ .
- An immediate consequence is that if for all non-negative random variables  $X$  that have finite expectation, if  $g(x) \leq x$  for some function  $g$ , then  $E[g(X)] \leq E[X]$ .

## Expected value of indicator functions

- An interesting example is **indicator** functions.
- For example, suppose that  $X$  is a random variable. Then  $Y = 1[X \in A]$  for some  $A \subset \mathcal{X}$  is a random variable.
- Example: Let  $X$  follow a standard normal distribution, and  $A = [-1, 1]$ . Then  $Y = 1[X \in A]$  is defined as the random variables such that  $Y(\omega) = 1$  if  $X(\omega) \in A$ , and  $Y(\omega) = 0$  otherwise.

## Expected value of indicator functions II

- Expectations of indicator variables are **probabilities**:

$$\begin{aligned} E(Y) &= E(1[X \in A]) \\ &= \int_{x \in \mathcal{X}} 1[X \in A] f(x) dx \\ &= \int_{x \in A} f(x) dx = P(X \in A). \end{aligned}$$

- This fact is useful for deriving some important inequalities.
- Let  $X$  be a continuous random variable with expectation  $E(X)$ . From our definition, this implies that  $\int |x| f(x) dx < \infty$ .

## Expected value of indicator functions III

- Now suppose that for some random variable  $Y = g(X)$  such that  $|Y| \leq |X|$ . Then, if  $Y$  has a pdf, we can deduce that  $\int |y| f(x) dx < \infty$ , and therefore  $E[Y]$  exists.
- Now suppose that  $\varphi$  is a non-decreasing, non-negative function, and that for some  $a \in \mathbb{R}$ ,  $\varphi(a) > 0$ . Then, for all  $x \geq a$ ,  $\varphi(x)/\varphi(a) \geq 1$ .
- Define  $Y = 1[X \geq a]$ . Note that for all possible outcomes  $\omega \in \Omega$ ,

$$Y = 1[X \geq a] \leq \varphi(X)/\varphi(a)1[X \geq a] \leq \varphi(X)/\varphi(a).$$

## Expected value of indicator functions IV

- Taking expectations of both sides,

$$E(1[X \geq a]) = P(X \geq a) \leq \frac{E[\varphi(X)]}{\varphi(a)} = E[\varphi(X)/\varphi(a)].$$

- This inequality is known as **Markov's (general) inequality**, and is very useful for bounding the probability of particular events.
- Specifically, if  $\varphi(x) = |x|^p$ , with  $p > 0$ , then because  $|X|$  is always positive,  $\varphi$  is non-negative, non-decreasing, and therefore

$$P(|X| \geq a) \leq \frac{E[|X|^p]}{a^p},$$

- If we restrict ourselves to the case where  $X$  is non-negative, we get the most standard version of the inequality:

$$P(X \geq a) \leq E(X)/a.$$

## Expected value of indicator functions V

### Markov's Inequality in Action

Suppose that an individual is taken randomly from a population that has an average salary of \$50,000. If we assume that salary from the population is approximately independently and identically distributed, we can provide an upper-bound for the probability that the individual is wealthy.

Let  $X_i$  be the salary of individual  $i$ , randomly drawn from said population. Even though all we know is the average salary, Markov's inequality tells us that:

$$P(X \geq 200,000) \leq \frac{50,000}{200,000} = \frac{1}{4}.$$



## Expected value of indicator functions VI

- Returning to expectations of functions of random variables, we can extend to the multi-variate case

## Expected value of indicator functions VII

### Theorem 4.2: functions of multiple variables

Suppose that  $X_1, \dots, X_n$  are jointly distributed RVs and  $Y = g(X_1, \dots, X_n)$ . Then

- IF  $X_i$  are discrete with pmf  $p(x_1, \dots, x_n)$ , then

$$E(Y) = \sum_{x_1, \dots, x_n} g(x_1, \dots, x_n) p(x_1, \dots, x_n).$$

- If  $X_i$  are continuous with pdf  $f(x_1, \dots, x_n)$ , then

$$E(Y) = \int_{\mathcal{X}_1, \dots, \mathcal{X}_n} g(x_1, \dots, x_n) f(x_1, \dots, x_n) dx_1 \dots, dx_n.$$

In both cases, we need the sum (or integral) of  $|g|$  to converge.

## Expected value of indicator functions VIII

- The proof for the discrete case of Theorem 4.2 follows directly that of Theorem 4.1
- An immediate consequence of Theorem 4.2 is the following

### Corollary 4.2.1

If  $X$  and  $Y$  are independent random variables, and  $g$  and  $h$  are fixed functions, then

$$E[g(X)h(Y)] = \left( E[g(X)] E[h(Y)] \right),$$

provided that the expectations on the right-hand side exist.

## Expected value of indicator functions IX

### Example: Breaking sticks

A stick of unit-length is broken randomly (uniformly) in two places. What is the average length of the middle piece?

We will interpret this problem to mean that the locations of the two break-points are independent uniform random variables,  $U_1$  and  $U_2$ , and we need to computing  $E|U_1 - U_2|$ .

*Solution:*

# Linear Combinations of Random Variables

- A useful property of expectation is that it is a **linear operator**.

## Theorem 4.3: Linear combinations

If  $X_1, \dots, X_n$  are jointly distributed random variables with expectations  $E(X_i)$ , respectively, and  $Y = a + \sum_{i=1}^n b_i X_i$ , then,

$$E(Y) = a + \sum_{i=1}^n b_i E(X_i).$$

# Linear Combinations of Random Variables II

*Proof.*

## Linear Combinations of Random Variables III

- The previous theorem is extremely useful for calculating expected values.
- An obvious example is **sums** of random variables, such as the arithmetic average.
- It's also useful because some distributions can be expressed as the sum of other distributions.
- For instance, we saw in a previous example that the sum of two exponential random variables has a Gamma distribution. Thus, if we know the mean of an exponential, we can readily calculate the mean of a Gamma distribution.

# Linear Combinations of Random Variables IV

## Expectation of a binomial distribution

Let  $Y$  follow a Binomial( $p, q$ ) distribution. Find the expected value of  $Y$ .

*Solution:*



# Linear Combinations of Random Variables V

## Example: Baseball Card Collection

Suppose that you collect baseball cards, that there are  $n$  distinct cards, and that on each trial you are equally likely to get a card of any of the types. How many trials would you expect to go through until you had a complete set of cards?

## Linear Combinations of Random Variables VI

### Example: Group Testing

Suppose that a large number,  $n$  of blood samples are screened for a rare disease. If each sample is taken individually,  $n$  tests will be required. An alternative approach is group individuals into  $m$  groups of size  $k$ , pool the blood samples for each group together and perform a test on the pooled sample. If the pooled test is negative, we know all individuals in the group do not have the rare disease; however, if the test is positive, we can then do tests on each individual in the smaller group. What is the expected number of tests that will be conducted using this approach?

## Linear Combinations of Random Variables VII

### Example: Counting DNA “words”

Within DNA patterns, we might be interested in finding the number of times a particular combination of letters (or “word”) occurs in a DNA sequence. This can be useful for determining if a region of DNA has unusually large occurrences of specific sequences. Assume each sequence is randomly composed of letters  $A, C, G, T$ , and that for each location in the sequence, each letter has probability  $1/4$ . For example, consider occurrence of the “word”  $TATA$ .

*ACTATATAGATATA*

In the above sequence, we would count  $TATA$  3 times (counting overlaps). In a sequence of length  $N$ , what is the expected number of times a word of length  $q$  occurs?

## Some comments on expected values

- An important thing to notice about the theorem for linear combinations is that we do not require independence.
- The last example demonstrates this principle. Though  $I_n$  is Bernoulli distributed,  $\sum_n I_n$  is **NOT** binomial distributed, because the  $I_n$  are not independent.
- As an example, if our word is  $TATA$ , then  $I_1 = 1$  implies that  $I_2 = 0$ , since a  $TATA$  at position 1 implies that the second letter starts with  $A$ , and thus  $TATA$  cannot occur at position 2.
- Despite this, we can still calculate the expected value of a sum by taking the sum of expected values.

## Some comments on expected values II

- The expected value can be used as an indication of the central value of the density or frequency function.
- Because of this, the expected value is sometimes referred to as a **location parameter**.
- The expected value is not the only type of location parameter. For instance, the *median* is also a type of location parameter.
- We have seen a lot of parallel between the expected value of a discrete random variable and that of a continuous random variable. This is not a coincidence.
- Specifically, we generally just “swap” and integration with summation, and pdf with pmfs.

## Some comments on expected values III

- With a more rigorous definition of expectation, we could define expectation as a **Lebesgue-Stieltjes** integral, with respect to some measure  $P$ .
- That is,  $E(X) = \int_{\Omega} X dP$ , where  $P$  is a probability measure. If the probability measure is a counting measure, then the integral *is* a sum.
- Note that this definition does not require the existence of a pdf; in fact, there distributions where the expectation is well-defined, but the pdf is not. These types of distributions do not come up often in standard examples.

# **Variance and Standard Deviation**

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# Variance

- The expected value is useful for summarizing the average or expected behavior of a random variable.
- We are also often interested in the “spread” of a random variable.
- That is, if the expected value is the center (or location) of a distribution, we want an indication of how dispersed a distribution is around this center.
- The two most common ways to express this idea is the **variance** and **standard deviation** of a random variable.



## Variance II

### Definition: Variance

If  $X$  is a random variable with expected value  $E(X)$ , then the **variance** of  $X$  is

$$\text{Var}(X) = E\left[(X - E(x))^2\right],$$

provided the expectation exists.

- If  $X$  is a discrete random variable, then by Theorem 4.1,

$$\text{Var}(X) = \sum_i (x_i - \mu)^2 p(x_i),$$

where  $\mu = E[X]$ .

## Variance III

- If  $X$  is a continuous random variable, then

$$\text{Var}(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

## Variance IV

### Definition: Standard deviation

If  $X$  is a random variable, then the standard deviation of  $X$  is the square-root of the variance, provided it exists.

- The variance is often denoted by  $\sigma^2$ , and the standard deviation  $\sigma$ .
- Because  $(X - E(x))^2 \geq 0$ ,  $\text{Var}(X) \geq 0$ .
- Formally, the variance is the mean of the squared distance between  $X$  and  $E[X]$ . If most values of  $X$  are close to the mean, this value is small; and vice-versa if most values of  $X$  are far away from  $E[X]$ .
- By this definition, the units for the variance are squared units.

## Variance $V$

- That is, if  $X$  is measured in meters, then the variance is measured in square-meters, and the standard deviation is measured in meters.

### Theorem 4.4: linear transformation of a single variable

Let  $X$  be a random variable, and assume that  $\text{Var}(X)$  exists. Then if  $Y = a + bX$ , then  $\text{Var}(Y) = b^2\text{Var}(X)$ .

*Proof.*

## Variance VII

- This result makes a lot of sense: adding a constant only “shifts” a distribution, it does not affect the spread.
- The multiplier does change the spread, and because we’re squaring the difference, the multiplier is also squared.
- From this result, we can also see that the standard deviation also changes in a natural way.
- Specifically, if  $\sigma_Y, \sigma_X$  denote the standard deviations of  $X$  and  $Y$ , respectively, then

$$\sigma_Y = |b|\sigma_X.$$

- We take the absolute value, because variance and standard deviation are always positive, though the multiplier  $b$  might be negative.

## Variance VIII

### Example: Bernoulli distribution

Let  $X$  be a Bernoulli( $p$ ) distributed random variable. What is the variance of  $X$ ?

### Example: Normal distribution

Let  $X \sim N(\mu, \sigma^2)$ . What is  $\text{Var}(X)$ ?



## Variance X

- Using the definition of variance, we will derive a very famous inequality.

### Theorem 4.5: Chebyshev's Inequality

Let  $X$  be a random variable with  $E[X] = \mu$ , and  $\text{Var}(X) = \sigma^2$ . Then for any  $t > 0$ ,

$$P(|X - \mu| > t) \leq \frac{\sigma^2}{t^2}.$$

- This theorem bounds the probability that the difference between  $X$  and  $E[X]$  is larger than  $t$ .

## Variance XI

- If  $\sigma^2$  is small, then the probability that  $X$  deviates far away from the mean is also small.
- By letting  $t = k\sigma$ , we get a bound on the probability that a variable will be  $k$ -standard deviations away from the mean:

$$P(|X - \mu| > k\sigma) \leq \frac{1}{k^2},$$

- For instance, the probability that any arbitrary random variable  $X$  will be more than  $4\sigma$  away from  $E[X]$  is less than  $1/16$ .
- While applicable to all random variables with well-defined variances, it is not the most optimal bound we can achieve.

## Variance XII

- For instance, if  $X \sim N(\mu, \sigma^2)$ , then
$$P(|X - \mu| > 2\sigma) = 0.05 < 1/4$$

### **Corollary: zero variance**

Let  $X$  be a random variable with  $\text{Var}(X) = 0$ . Then
$$P(X = \mu) = 1.$$

### Theorem 4.6: Variance Calculation

Let  $X$  be a random variable such that  $\text{Var}(X)$  exists. Then

$$\text{Var}(X) = E(X^2) - [E(X)]^2 = E(X^2) - \mu^2,$$

where  $\mu = E(X)$ .

## Variance XIV

- Theorem 4.5 is sometimes useful to help us calculate the variance of a random variable.
- Other times, the variance is known, and the theorem helps us calculate  $E(X^2)$ .

### Example: Uniform distribution

Let  $X \sim U(0, 1)$ . Use Theorem 4.5 to find  $\text{Var}(X)$ .

# References and Acknowledgements

Resnick S (2019). *A probability path*. Springer.

Rice JA (2007). *Mathematical statistics and data analysis*, volume 371. 3 edition. Thomson/Brooks/Cole Belmont, CA.

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