

# Expected values

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# Expected values

- ▶ The **expected value** or **mean** of a random variable is the center of its distribution
- ▶ For discrete random variable  $X$  with PMF  $p(x)$ , it is defined as follows

$$E[X] = \sum_x xp(x).$$

where the sum is taken over the possible values of  $x$

- ▶  $E[X]$  represents the center of mass of a collection of locations and weights,  $\{x, p(x)\}$

# Example

Find the center of mass of the bars

```
## Loading required package: MASS  
  
## Loading required package: HistData  
  
## Loading required package: Hmisc  
  
## Loading required package: lattice  
  
## Loading required package: survival  
  
## Loading required package: Formula  
  
## Loading required package: ggplot2
```

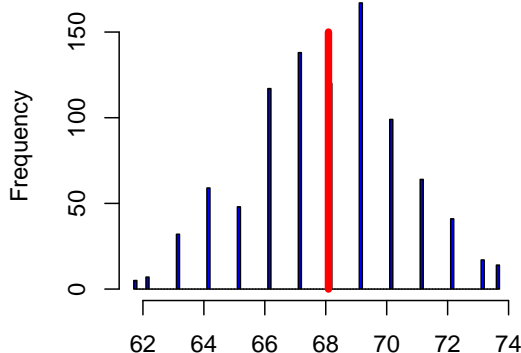
## Using manipulate

```
library(manipulate)
myHist <- function(mu){
  hist(galton$child,col="blue",breaks=100)
  lines(c(mu, mu), c(0, 150),col="red",lwd=5)
  mse <- mean((galton$child - mu)^2)
  text(63, 150, paste("mu = ", mu))
  text(63, 140, paste("Imbalance = ", round(mse, 2)))
}
manipulate(myHist(mu), mu = slider(62, 74, step = 0.5))
```

## The center of mass is the empirical mean

```
hist(galton$child,col="blue",breaks=100)  
meanChild <- mean(galton$child)  
lines(rep(meanChild,100),seq(0,150,length=100),col="red",
```

**Histogram of galton\$child**

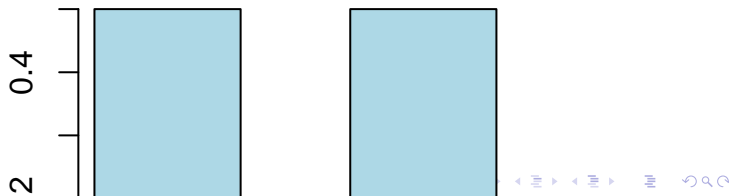


## Example

- ▶ Suppose a coin is flipped and  $X$  is declared 0 or 1 corresponding to a head or a tail, respectively
- ▶ What is the expected value of  $X$ ?

$$E[X] = .5 \times 0 + .5 \times 1 = .5$$

- ▶ Note, if thought about geometrically, this answer is obvious; if two equal weights are spaced at 0 and 1, the center of mass will be .5



## Example

- ▶ Suppose that a die is rolled and  $X$  is the number face up
- ▶ What is the expected value of  $X$ ?

$$E[X] = 1 \times \frac{1}{6} + 2 \times \frac{1}{6} + 3 \times \frac{1}{6} + 4 \times \frac{1}{6} + 5 \times \frac{1}{6} + 6 \times \frac{1}{6} = 3.5$$

- ▶ Again, the geometric argument makes this answer obvious without calculation.

# Continuous random variables

- ▶ For a continuous random variable,  $X$ , with density,  $f$ , the expected value is defined as follows

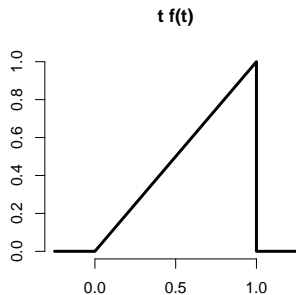
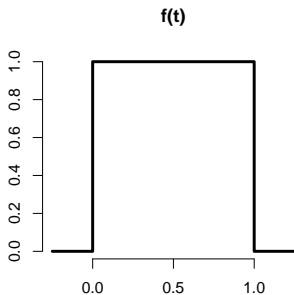
$$E[X] = \text{the area under the function } tf(t)$$

- ▶ This definition borrows from the definition of center of mass for a continuous body



# Example

- ▶ Consider a density where  $f(x) = 1$  for  $x$  between zero and one
- ▶ (Is this a valid density?)
- ▶ Suppose that  $X$  follows this density; what is its expected value?



# Rules about expected values

- ▶ The expected value is a linear operator
- ▶ If  $a$  and  $b$  are not random and  $X$  and  $Y$  are two random variables then
- ▶  $E[aX + b] = aE[X] + b$
- ▶  $E[X + Y] = E[X] + E[Y]$

## Example

- ▶ You flip a coin,  $X$  and simulate a uniform random number  $Y$ , what is the expected value of their sum?

$$E[X + Y] = E[X] + E[Y] = .5 + .5 = 1$$

- ▶ Another example, you roll a die twice. What is the expected value of the average?
- ▶ Let  $X_1$  and  $X_2$  be the results of the two rolls

$$E[(X_1 + X_2)/2] = \frac{1}{2}(E[X_1] + E[X_2]) = \frac{1}{2}(3.5 + 3.5) = 3.5$$

## Example

1. Let  $X_i$  for  $i = 1, \dots, n$  be a collection of random variables, each from a distribution with mean  $\mu$
2. Calculate the expected value of the sample average of the  $X_i$

$$\begin{aligned} E \left[ \frac{1}{n} \sum_{i=1}^n X_i \right] &= \frac{1}{n} E \left[ \sum_{i=1}^n X_i \right] \\ &= \frac{1}{n} \sum_{i=1}^n E[X_i] \\ &= \frac{1}{n} \sum_{i=1}^n \mu = \mu. \end{aligned}$$

## Remark

- ▶ Therefore, the expected value of the **sample mean** is the population mean that it's trying to estimate
- ▶ When the expected value of an estimator is what its trying to estimate, we say that the estimator is **unbiased**

# The variance

- ▶ The variance of a random variable is a measure of *spread*
- ▶ If  $X$  is a random variable with mean  $\mu$ , the variance of  $X$  is defined as

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

the expected (squared) distance from the mean - Densities with a higher variance are more spread out than densities with a lower variance

- ▶ Convenient computational form

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

- ▶ If  $a$  is constant then  $\text{Var}(aX) = a^2 \text{Var}(X)$
- ▶ The square root of the variance is called the **standard deviation**
- ▶ The standard deviation has the same units as  $X$

## Example

- ▶ What's the sample variance from the result of a toss of a die?
- ▶  $E[X] = 3.5$
- ▶  $E[X^2] = 1^2 \times \frac{1}{6} + 2^2 \times \frac{1}{6} + 3^2 \times \frac{1}{6} + 4^2 \times \frac{1}{6} + 5^2 \times \frac{1}{6} + 6^2 \times \frac{1}{6} = 15.17$
- ▶  $Var(X) = E[X^2] - E[X]^2 \approx 2.92$

## Example

- ▶ What's the sample variance from the result of the toss of a coin with probability of heads (1) of  $p$ ?
- ▶  $E[X] = 0 \times (1 - p) + 1 \times p = p$
- ▶  $E[X^2] = E[X] = p$
- ▶  $Var(X) = E[X^2] - E[X]^2 = p - p^2 = p(1 - p)$



# Interpreting variances

- ▶ Chebyshev's inequality is useful for interpreting variances
- ▶ This inequality states that

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

- ▶ For example, the probability that a random variable lies beyond  $k$  standard deviations from its mean is less than  $1/k^2$

$$2\sigma \rightarrow 25\%$$

$$3\sigma \rightarrow 11\%$$

$$4\sigma \rightarrow 6\%$$

- ▶ Note this is only a bound; the actual probability might be quite a bit smaller

## Example

- ▶ IQs are often said to be distributed with a mean of 100 and a sd of 15
- ▶ What is the probability of a randomly drawn person having an IQ higher than 160 or below 40?
- ▶ Thus we want to know the probability of a person being more than 4 standard deviations from the mean
- ▶ Thus Chebyshev's inequality suggests that this will be no larger than 6%
- ▶ IQs distributions are often cited as being bell shaped, in which case this bound is very conservative
- ▶ The probability of a random draw from a bell curve being 4 standard deviations from the mean is on the order of  $10^{-5}$  (one thousandth of one percent)

# Example

- ▶ A former buzz phrase in industrial quality control is Motorola's "Six Sigma" whereby businesses are suggested to control extreme events or rare defective parts
- ▶ Chebyshev's inequality states that the probability of a "Six Sigma" event is less than  $1/6^2 \approx 3\%$
- ▶ If a bell curve is assumed, the probability of a "six sigma" event is on the order of  $10^{-9}$  (one ten millionth of a percent)