

**MATH 3339**  
**Statistics for the Sciences**  
**Live Lecture Help**

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Session 9

Office Hours: see schedule in the "Office Hours" channel on Teams  
Course webpage: [www.casa.uh.edu](http://www.casa.uh.edu)

When you email me you **MUST** include the following

- MATH 3339 Section 20024 and a description of your issue in the **Subject Line**
- Your name and ID# in the **Body**
- Complete sentences, punctuation, and paragraph breaks
- Email messages to the class will be sent to your Exchange account (user@cougarnet.uh.edu)

# Using R and R-Studio

1. Download R from <https://cran.r-project.org/>
2. Download R-Studio from <https://www.rstudio.com/>

# Outline

- 1 Updates and Announcements
- 2 Recap
- 3 Student submitted questions

# Updates and Announcements

- Test 1 total is "Test 1" + "Test 1 FR".
- Test 2 is in 4 weeks.
- I will replace one lower test grade with Final Exam grade.

# PDF of a Normal Distribution

A continuous random variable  $X$  is said to have a **Normal distribution** with parameters  $\mu$  and  $\sigma$  (or  $\mu$  and  $\sigma^2$ ), where  $-\infty < \mu < \infty$  and  $0 < \sigma$ , if the pdf of  $X$  is:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

For all  $-\infty < x < \infty$ .

The cdf of  $X$  when  $X \sim N(\mu, \sigma)$  is:

$$F(x) = P(X \leq x) = \int_{-\infty}^x f(t)dt = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}\sigma} e^{-(t-\mu)^2/2\sigma^2} dt$$

# Standard Normal Distribution

When  $X \sim N(\mu, \sigma)$ , we can standardize the values by forming:

$$Z = \frac{X - \mu}{\sigma}$$

where  $\mu_Z = 0$  and  $\sigma_Z = 1$  to get the pdf:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$$

The cdf of  $Z \sim N(0, 1)$  is

$$\Phi(z) = P(Z \leq z) = \int_{-\infty}^z \phi(t) dt = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$$



# Normal Approximation to Binomial

Let  $X$  be a binomial random variable based on  $n$  trials with success probability  $p$ . Then if the binomial probability histogram is not too skewed,  $X$  has an approximate Normal distribution with  $\mu = np$  and  $\sigma = \sqrt{np(1-p)}$ . In particular, for  $x$  a possible value of  $X$ ,

$$\begin{aligned} P(X \leq x) &= \text{Binom}(x; n, p) \\ &\approx (\text{area under the normal curve to the left of } x + 0.5) \\ &= \Phi\left(\frac{x + 0.5 - np}{\sqrt{np(1-p)}}\right) \end{aligned}$$

In practice, the approximation is adequate provided that both  $np \geq 10$  and  $n(1-p) \geq 10$ .

# Shape of the Sample Mean Distribution

- If a population has a Normal distribution, then the sample mean  $\bar{X}$  of  $n$  independent observations also has a Normal distribution with mean  $\mu$  and standard deviation  $\sigma/\sqrt{n}$ .
- **Central limit theorem:** For *any* population, when  $n$  is large ( $n \geq 30$ ), the sampling distribution of the sample mean  $\bar{X}$  is approximately a Normal distribution with mean  $\mu$  and standard deviation  $\sigma/\sqrt{n}$ .

## Notes about finding probabilities for $\bar{X}$

- We have a sample size  $n$ . Thus the standard deviation changes by that value  $\text{SD}(\bar{X}) = \sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$ .
- The mean stays the same.  $\text{mean}(\bar{X}) = \mu_{\bar{X}} = \mu$ .
- If we know that the original distribution is Normal **or** we have a large enough sample ( $n \geq 30$ ). We can use the Normal distributions to find the probabilities.

# Sample Proportions

- The population proportion is  $p$  a parameter. In some cases we do not know the population proportion, thus we use the sample proportion,  $\hat{p}$  to estimate  $p$ .
- The sample proportion is calculated by:  $\hat{p} = \frac{X}{n}$
- $X$  = the number of observations of interest in the sample or the number of "successes" in the sample.
- $n$  = the sample size or number of observations.
- Recall that  $X \sim \text{Bin}(n, p)$  and can be approximated by the Normal distribution with  $\mu_x = E(X) = np$  and  $\sigma_X = SD(X) = \sqrt{np(1-p)}$  as long as  $np \geq 10$  and  $n(1-p) \geq 10$ .
- Now we want to know how is  $\hat{p} = \frac{X}{n}$  distributed. Thus we want to know  $\mu_{\hat{p}} = E(\hat{p})$  and  $\sigma_{\hat{p}} = SD(\hat{p})$ .

# Shape of the distribution of $\hat{p}$

We can use the **Normal distribution** as long as

- The sampled values must be random and independent of each other. This can be tested by **10% Condition**: The sample size must be no larger than 10% of the population.
- The sample size,  $n$  must be large enough. This can be tested by **Success / Failure Condition**: The sample size has to be big enough so that both  $np$  and  $n(1 - p)$  at least 10.

## Center of the distribution of $\hat{p}$

- The center is the mean (expected value):  $\mu_{\hat{p}} = p$  the proportion of success.
- $\hat{p} = \frac{X}{n}$  where  $X$  is the number of **successes** out of  $n$  observations. Thus  $X$  has a binomial distribution with parameters  $n$  and  $p$ .

- The mean of  $X$  is:

$$\mu_X = E(X) = np$$

- Thus the mean of  $\hat{p}$  is:

$$\mu_{\hat{p}} = E(\hat{p}) = E\left(\frac{X}{n}\right) = \frac{\mu_X}{n} = \frac{np}{n} = p$$

# Spread of the distribution of $\hat{p}$

- The spread is the standard deviation  $\sigma_{\hat{p}} = \sqrt{\frac{p(1-p)}{n}}$ .
- The variance of  $X$  is:

$$\sigma_X^2 = \text{Var}(X) = np(1-p)$$

- The variance of  $\hat{p}$  is:

$$\sigma_{\hat{p}}^2 = \text{Var}(\hat{p}) = \text{Var}\left(\frac{X}{n}\right) = \frac{\text{Var}(X)}{n^2} = \frac{np(1-p)}{n^2} = \frac{p(1-p)}{n}$$

# Unbiased Estimators

- If we desire to estimate a parameter, we want to know that we are using a good estimator. We prefer for the estimator statistic to be an **unbiased** estimate of the parameter.
- A point estimator  $\hat{\theta}$  is said to be an **unbiased estimator** of  $\theta$  if  $E(\hat{\theta}) = \theta$  for every possible value of  $\theta$ .
- If  $\hat{\theta}$  is not unbiased, the difference  $E(\hat{\theta}) - \theta$  is called the **bias** of  $\hat{\theta}$ .



# Standard Error

- The **standard error** of an estimator  $\hat{\theta}$  is its standard deviation  
 $SE(\hat{\theta}) = \sqrt{Var(\hat{\theta})}$ .

- Examples of standard errors

- ▶  $SE(\bar{X}) = \frac{\sigma}{\sqrt{n}}$ .
  - ▶  $SE(\hat{p}) = \sqrt{\frac{p(1-p)}{n}}$ .

$X$        $\mu_X$      $\sigma_X$   
 $X_1, X_2, X_3, \dots, X_n, \bar{X}, S$

- The problem is that often we do not know  $\sigma$  or  $p$ , for example. To get around this we can use the estimators for these parameters. Then we have the **estimated standard error**.
- Again we need to know how these estimators  $\hat{\theta}$  are being distributed.

# What we use for estimating?

- A **confidence interval** is a range of possible values that is likely to contain the unknown population parameter we are seeking.
- First, we must have a **level of confidence**.
- Then based on this level we will compute a **margin of error**.
- Last, we can say that we are  $-\%$  confident that the true population parameter falls within our confidence interval.

# The confidence interval

The  $1 - \alpha$  confidence interval for  $\mu$ , given that we know the population standard deviation is:

$$\bar{x} \pm z_{\alpha/2} \left( \frac{\sigma}{\sqrt{n}} \right)$$

# Margin of Error

The margin of error is

$$m = \text{critical value} \times \text{standard error}$$

For means (given the population standard deviation is known), the margin of error is:

$$m = z_{\alpha/2} \left( \frac{\sigma}{\sqrt{n}} \right)$$

What is the margin of error for the mean monthly cell phone bill?

# T distribution

- Used for the inference of the population mean. When population standard deviation  $\sigma$  is unknown.
- The distribution of the population is basically bell-shape.

- Formula for  $t$ :

$$t = \frac{\bar{x} - \mu}{s/\sqrt{n}} = \frac{\sqrt{n}(\bar{x} - \mu)}{s}$$

- Use t-table, or `qt(probability,df)` in R.
- Degrees of freedom:  $df = n - 1$ .

## Critical value when $\sigma$ unknown

- When  $\sigma$  is **unknown** we use  $t$ -distribution.
- With degrees of freedom,  $df = n - 1$ .
- The critical value is  $t_{\alpha/2}$  where the area between  $-t_{\alpha/2}$  and  $+t_{\alpha/2}$  under the T-curve is the confidence level  $C = 1 - \alpha$ .
- $t_{\alpha/2}$  is found in T-table using the row according to the degrees of freedom and the column according to the confidence level at the bottom of the table.
- In R use `qt((1 + C)/2, df)`.

# Confidence Interval for $\mu$ Recap

- Z-confidence interval, given the population standard deviation,  $\sigma$  is **known**

$$\bar{x} \pm z_{\alpha/2} \left( \frac{\sigma}{\sqrt{n}} \right)$$

- T-confidence interval, given that the population standard deviation,  $\sigma$  is **unknown**

$$\bar{x} \pm t_{\alpha/2, n-1} \left( \frac{s}{\sqrt{n}} \right)$$

# Choosing Sample Size

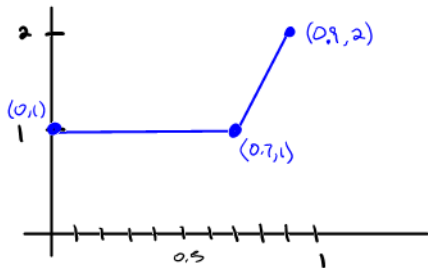
You can have both a high confidence while at the same time a small margin of error by taking enough observations.

- Sample size for confidence intervals of means.

$$n > \left( \frac{z_{\alpha/2} \sigma}{m} \right)^2$$



Think about a density curve that consists of two line segments. The first goes from the point  $(0, 1)$  to the point  $(0.7, 1)$ . The second goes from  $(0.7, 1)$  to  $(0.9, 2)$  in the  $xy$ -plane. What percent of observations fall between 0.7 and 0.9?



$$(0.7, 1) \rightarrow (0.9, 2)$$

$$m = \frac{\Delta y}{\Delta x} = \frac{2-1}{0.9-0.7} = \frac{1}{0.2} = 5$$

$$\begin{aligned} \text{Line: } y-1 &= 5(x-0.7) \\ y &= 5x - 3.5 + 1 \\ y &= 5x - 2.5 \end{aligned}$$

The blue "curve" is graph of  $f(x)$

$$\text{What is } f(x) = \begin{cases} 1 & \text{if } 0 \leq x \leq 0.7 \\ 5x - 2.5 & \text{if } 0.7 < x \leq 0.9 \\ 0 & \text{otherwise} \end{cases}$$

$$f(x) = \begin{cases} 1 & \text{if } 0 \leq x \leq 0.7 \\ 5x - 2.5 & \text{if } 0.7 < x \leq 0.9 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \text{Is } 1 &= \int_{-\infty}^{\infty} f(x) dx = \int_0^{0.7} 1 dx + \int_{0.7}^{0.9} (5x - 2.5) dx \\ &= x \Big|_0^{0.7} + \left[ \frac{5}{2} x^2 - 2.5x \right]_{0.7}^{0.9} \\ &= 0.7 + \frac{5}{2} \left[ 0.9^2 - 0.9 - (0.7^2 - 0.7) \right] \\ &= 0.7 + \frac{5}{2} \left[ 0.81 - 0.9 - 0.49 + 0.7 \right] \\ &= 0.7 + \frac{5}{2} \cdot 0.12 = 0.7 + 0.3 = 1 \quad \checkmark \end{aligned}$$

$$\text{So, } P(0.7 \leq x \leq 0.9) = \int_{0.7}^{0.9} f(x) dx = \boxed{0.3} \quad (\text{see above})$$

Consider a spinner that, after a spin, will point to a number between zero and 1 with "uniform probability". Determine the probability:  $P(\frac{1}{9} \leq X \leq \frac{23}{45})$ .

What is  $f(x)$  here?  $f(x) = \frac{1}{1-0} = 1$

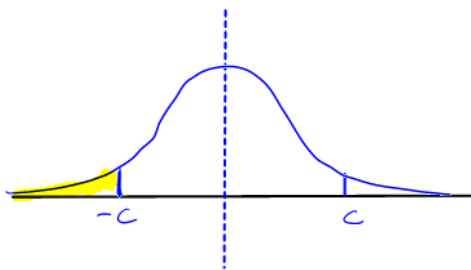
$$X \sim \text{Unif}(0,1) \quad F(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } 0 \leq x \leq 1 \\ 1 & \text{if } x \geq 1 \end{cases}$$

$$P(\frac{1}{9} \leq X \leq \frac{23}{45}) = P(X \leq \frac{23}{45}) - P(X \leq \frac{1}{9})$$

$$= F(\frac{23}{45}) - F(\frac{1}{9})$$

$$= \frac{23}{45} - \frac{1}{9}$$

$$= \frac{18}{45} = \frac{2}{5} = 0.4$$



$$\begin{aligned} p &= P(Z \leq -c) = P(Z \geq c) \\ &= 1 - P(Z \leq c) \end{aligned}$$

$$P(Z \leq c) = 1 - P(Z \leq -c)$$

$$c = z_{\text{norm}}(1 - p)$$

$$-c = -z_{\text{norm}}(1 - p)$$

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