# Elementary Statistics – Principles of Hypothesis Testing

Dr. Ab Mosca (they/them)

# Plan for Today

- Hypothesis Testing
  - Statistical Inference
  - Central Limit Theorem
  - Normal Distribution

# Warm Up: Statistics and Cls

In statistics, we want to know about populations, but we only have sample data to work with.

So we estimate population parameters using *sample statistics*.

- Sample mean:  $\bar{x}$
- Sample proportion:  $\hat{p}$

Sample statistics are random variables

### Practice:

Let an experiment be rolling a loaded die (loaded to land on six 50% of the time) 1000 times and counting the proportion of sixes. In this scenario, what is p, and what is  $\hat{p}$ ?

If I repeat this experiment 100 times and construct a 95% confidence interval (CI) of  $\hat{p}$  each time, how many CI's would you expect to capture p?

# Models of Statistical Inference

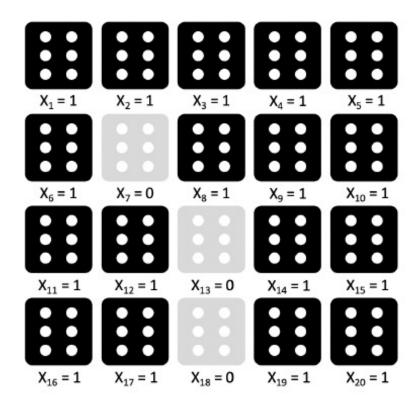
Our sample statistics represent our best guess for the true population parameter. We know this best guess is not perfect; we expect error (variability) die to the sampling process.

Because we can't know the truth directly we:

- 1. Construct a confidence interval
  - Expresses the uncertainty that we have in our estimate
  - Describes the range of plausible values given our observed data
- 2. Conduct a hypothesis test
  - Posits a specific explanation for how data were generated
  - Checks if the observed data is consistent with that explanation

Loaded Die?

Recall an experiment where we gathered data by rolling a die 20 times. We observed 17 sixes:



This feels like evidence that the die is loaded, but how compelling is it? Is there a compelling alternative explanation for this data?

What if the die was fair?

The Role of Random
Chance

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# The Role of Random Chance

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So...

If the die was truly fair, just how unusual would be be to observe 17 sixes in 20 rolls?

We can quantify this with a hypothesis test

#### 1. Two competing and complementary claims about the world:

**Null Hypothesis** ( $H_0$ ) is a statement about the population that represents the status quo (i.e. that nothing, or null, is different).

Pieces to a Hypothesis Test

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Ex.  $H_0$ : the die is fair

 $H_0$ : the die rolls sixes with a probability of  $\frac{1}{6}$ 

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Ex.  $H_0$ : the die is not fair

 $H_0$ : the die rolls sixes with a probability other than 1/6

$$H_0: p \neq \frac{1}{6}$$

#### 1. Two competing and complementary claims about the world

A null hypothesis ( $H_0$ ) and an alternative hypothesis ( $H_A$ )

Ex. 
$$H_0$$
:  $p = \frac{1}{6}$ ,  $H_A$ :  $p \neq \frac{1}{6}$ 

#### 2. Test Statistic

A metric calculated with observed data that summarized how compatible the data are with  $H_0$ 

What is our test statistic for our die experiment where we observed 17 sixes in 20 rolls?

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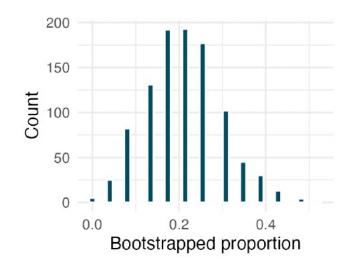
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$$\hat{p} = \frac{17}{20} = 0.85$$

#### 3. Null Distribution

The sampling distribution for our chosen test statistic under the assumption that our null hypothesis is true.

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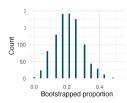
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#### 4. P-value

The probability of obtaining a test statistic as rare or more rare than our observed test statistic if the null hypothesis were true.

**P-value** is a conditional probability that tells us how unusual our test statistic would be *given the null hypothesis is true*.

Ex. p-value = 
$$P(\hat{p} \ge 0.85 | p = \frac{1}{6})$$

A *high p-value* implies it is *highly likely to observe our sample* statistic if the null hypothesis it true.

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When we see a high p-value we "Fail to reject  $H_0$ "

A *low p-value* implies it is *highly unlikely to observe our sample* statistic if the null hypothesis is true.

When we see a low p-value we "Reject  $H_0$ "

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What is the delineation between a high and low p-value?

Before we perform hypothesis testing we choose a threshold for high vs low p-values. We call this threshold  $\alpha$ 

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If p-value \leq \alpha we reject H_0
If p-value > \alpha we fail to reject H_0
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When a p-value  $\leq \alpha$  we say **a statistically significant difference** exists.

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Let  $\alpha = 0.05$ . What would we do with respect to  $H_0$  if we calculated a p-value of 0.01? 0.15?

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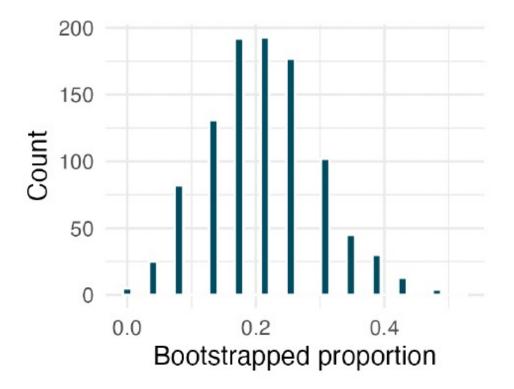
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How do we get the p-value?

### P-Values

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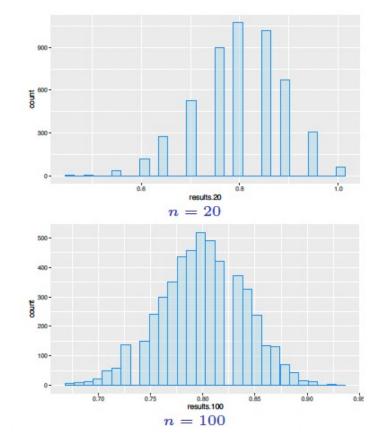
How do we get the p-value? From our null distribution, generated with bootstrap.

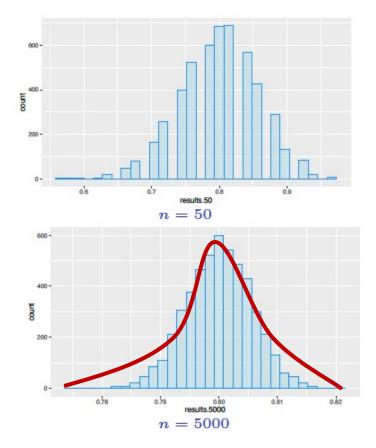


# Under increased sample sizes, sampling distributions (of continuous random variables) form a *density curve*.

Ex. n = rolls,  $\hat{p}$  = proportion of sixes

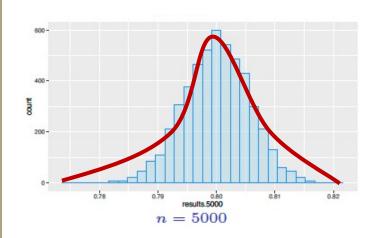
# Null Distribution

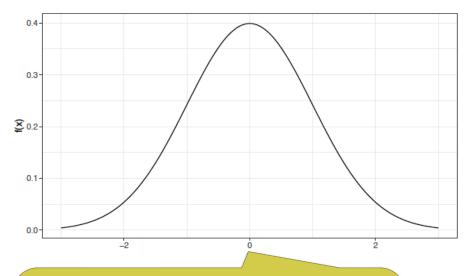




The *central limit theorem* states if observations in a sample are independent and the size of the sample is large, then the sampling distribution of a parameter is well-approximated the Normal distribution.

# Central Limit Theorem

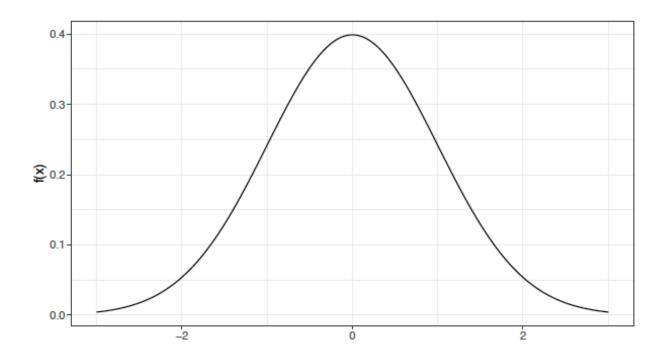




Symmetric, unimodal, bell-shaped

# Normal Distribution

The *Normal distribution* describes a continuous random variable whose density curve is symmetric, unimodal, and bell-shaped.



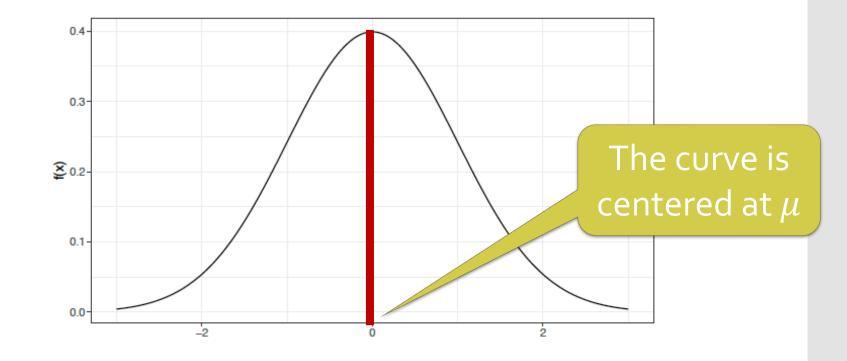
We write  $X \sim Norm(\mu, \sigma)$  where  $\mu$  is the mean of the random variable, X, and  $\sigma$  is its standard deviation.

When  $\mu = 0$ ,  $\sigma = 1$  we call the distribution the **standard Normal distribution**.

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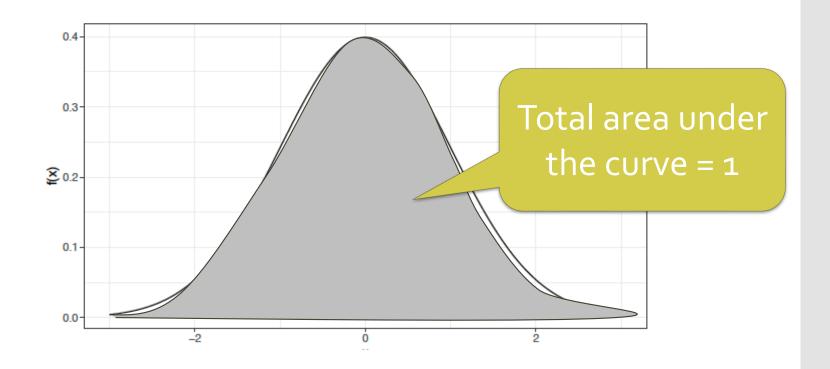
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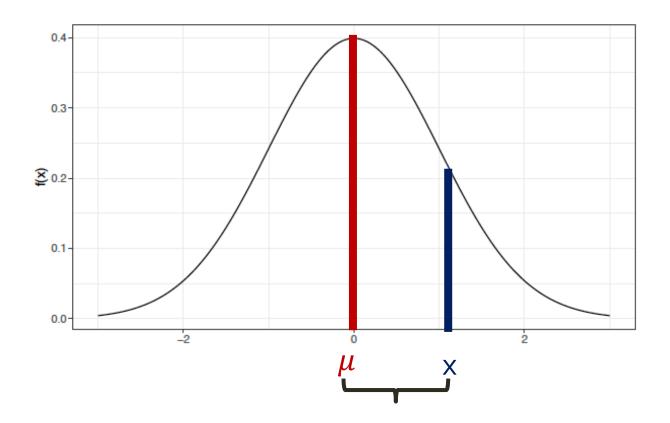
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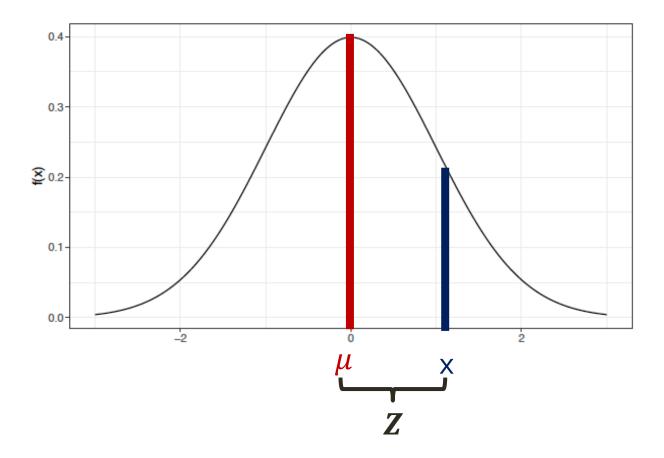
Normal distribution:  $X \sim Norm(\mu, \sigma)$ ,  $\mu$  is the mean of the random variable, X, and  $\sigma$  is its standard deviation.



For any observation, x, we can quantify how unusual it is by looking at how many  $\sigma$ 's away from  $\mu$  it falls.

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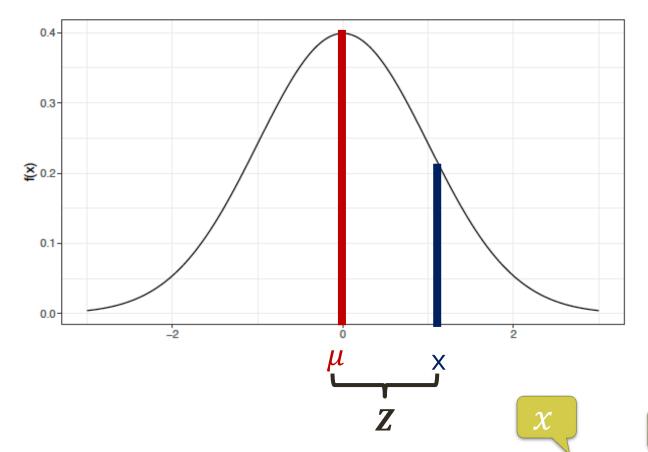
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For any observation, x, we can quantify how unusual it is by looking at how many  $\sigma$ 's away from  $\mu$  it falls, this is called a **z**-score.

# Z-scores

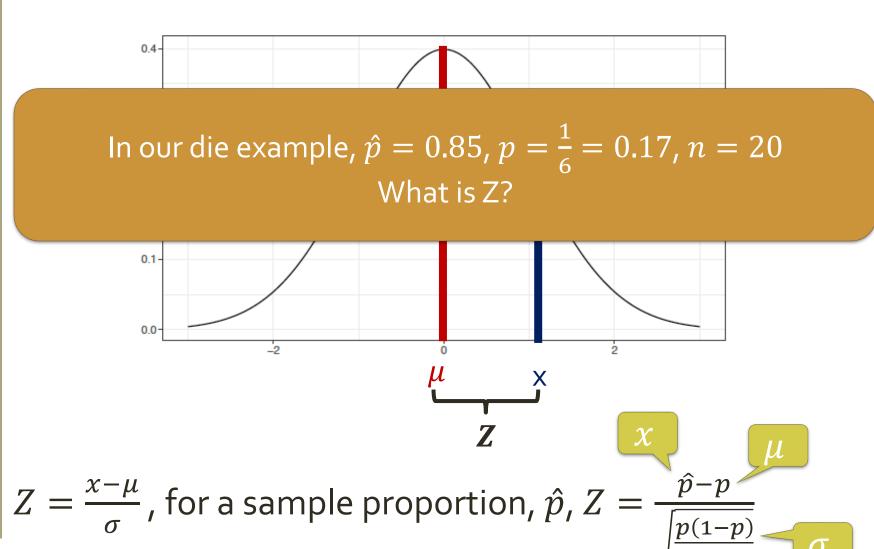
The **z-score** of an observation characterizes the number of standard deviations it falls above or below the mean.



$$Z = \frac{x-\mu}{\sigma}$$
, for a sample proportion,  $\hat{p}$ ,  $Z = \frac{\hat{p}-p}{\sqrt{\frac{p(1-p)}{n}}}$ 

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The **z-score** of an observation characterizes the number of standard deviations it falls above or below the mean.

0.4-

If we rolled 40 times and saw 10 sixes, what would Z be?

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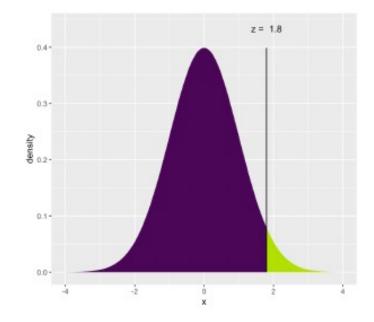
Probability that of seeing an observation less than or equal to x:

$$P(Z \le -1.33)$$



Area under the curve to the left of the z-score = probability of seeing a smaller z-score. Often called the *percentile*.

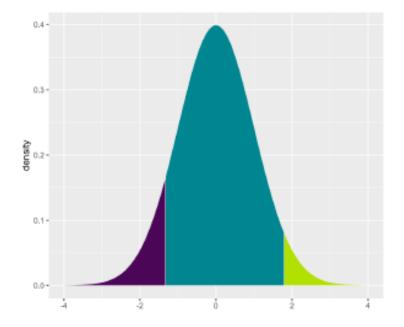
Probability that of seeing an observation greater than x:



Area under the curve to the right of the z-score = probability of seeing a larger z-score.

Probability that of seeing an observation between two x's:

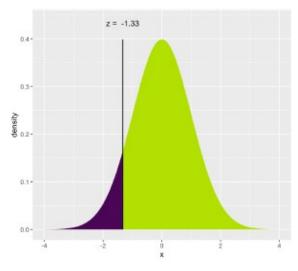
$$P(-1.33 \le Z \le 1.8)$$

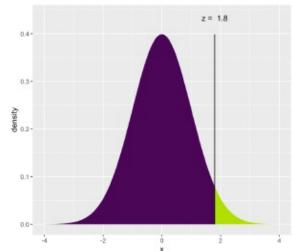


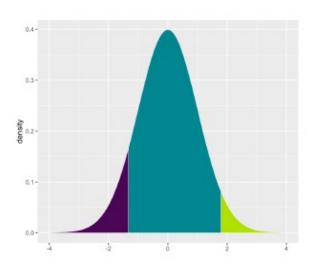
Area under the curve between the two values. Equivalent to  $P(Z \le 1.8) - P(Z \le -1.33)$ .

$$P(Z \le -1.33)$$

$$P(-1.33 \le Z \le 1.8)$$







Calculating area under the standard normal distribution (Norm(0, 1)) for a z-score, z.

#### Option 1:

z-score table: <a href="https://www.z-table.com/">https://www.z-table.com/</a>

#### Option 2:

• online calculator: <a href="https://www.calculator.net/z-score-calculator.html">https://www.calculator.net/z-score-calculator.html</a>

#### Option 3:

regular scientific calculator

#### Option 4:

excel =NORMSDIST(Z)

#### What str the percentiles for z = 8.1, and for z = 1.34?

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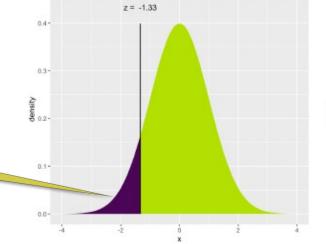
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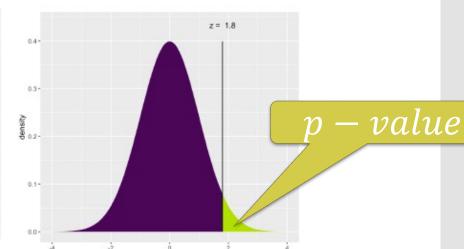
### **Z**-scores

- value









# Given the percentile 1 for z = 8.1 (from $\hat{p}=0.85$ ), what is the p-value? Given the percentile 0.91 for z = 1.34. (from $\hat{p}=0.25$ ), what is the p-value?

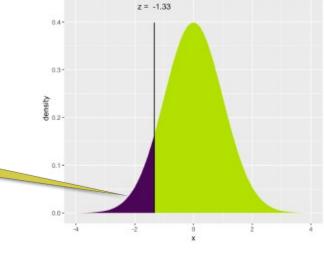
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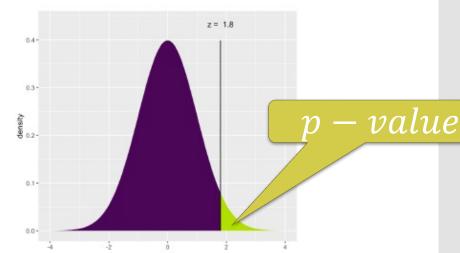
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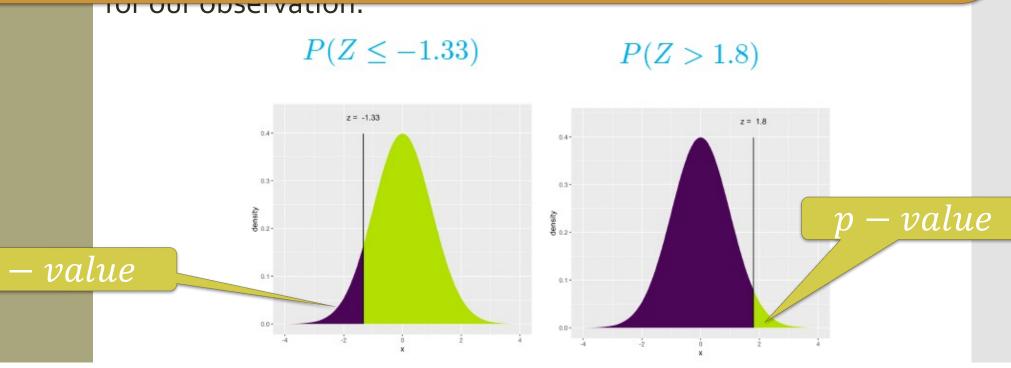




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If we use  $\alpha=0.05$ , do we reject or fail to reject our  $H_0$  that the die is fair in each of these experiments?





For any normally-distributed random variable:

- about 68% of the distribution is within 1  $\sigma$  of  $\mu$
- about 95% of the distribution is within 2  $\sigma$ 's of  $\mu$
- about 99.7% of the distribution is within 3  $\sigma$ 's of  $\mu$

