

Central Limit Theorem and Confidence Intervals

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Learning Objectives

By the end of the day you should be able to...

- **Define** the normal distribution and the concept of normality.
- **Describe** the uses of the 68-95-99.7 rule and the z-score.
- **Describe** and apply the Central Limit Theorem.

Learning Objectives

By the end of the day you should be able to...

- **Describe** the relationship between the mean, the standard deviation, and the standard error of the mean.
- **Calculate** the standard error of the mean.
- **Define** and **calculate** a confidence interval.

Normality

and The Normal Distribution

The Normal Distribution

- aka "bell curve" or Gaussian distribution
- very commonly used in analysis
- often an **assumption** in modeling

Turn and Talk (6 minutes, 3 volunteers)

Assume that IQ is normally distributed with a mean (μ) of 100 and a standard deviation (σ) of 15, i.e.

$IQ \sim N(100, 15)$.

1. How much of the population is within two standard deviations (2σ) of the mean?
2. If I pick a random person, what is the probability that their IQ will be somewhere between 85 and 115?
3. What is the Z score associated with an IQ of 140? 145?

Python Time

go to notebook `central-limit-theorem.ipynb`

Central Limit Theorem

Motivation

I want to know the mean height of male Ewoks on Endor.

- I can't measure them all (the whole **population**)...
- So I will select a **sample** of 100
- Let's say that the mean height of all Ewoks is 1.02 meters

Calculating the mean height

- Collect a sample of 100 heights
- Calculate the mean height, \bar{h}

```
import numpy as np
```

```
heights = [0.95, 1.1, 1.02, 0.88, 0.87, ...]  
mean_height = np.mean(heights)
```

Calculating the mean height

Q: Is the mean height, \bar{h} , calculated in this manner, the **sample** or the **population** mean height?

- Raise one arm for **sample**
- Raise two arms for **population**

Calculating the mean height

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- Raise two arms for **population**

What would happen if I repeated this "experiment" and collected a different sample?

Multiple samples

Sample #	Mean Height
1	1.01
2	0.97
3	1.04
4	0.91
...	...

Multiple samples

Sample #	Mean Height
1	1.01
2	0.97
3	1.04
4	0.91
...	...

We need to make sense of the randomness in mean height!

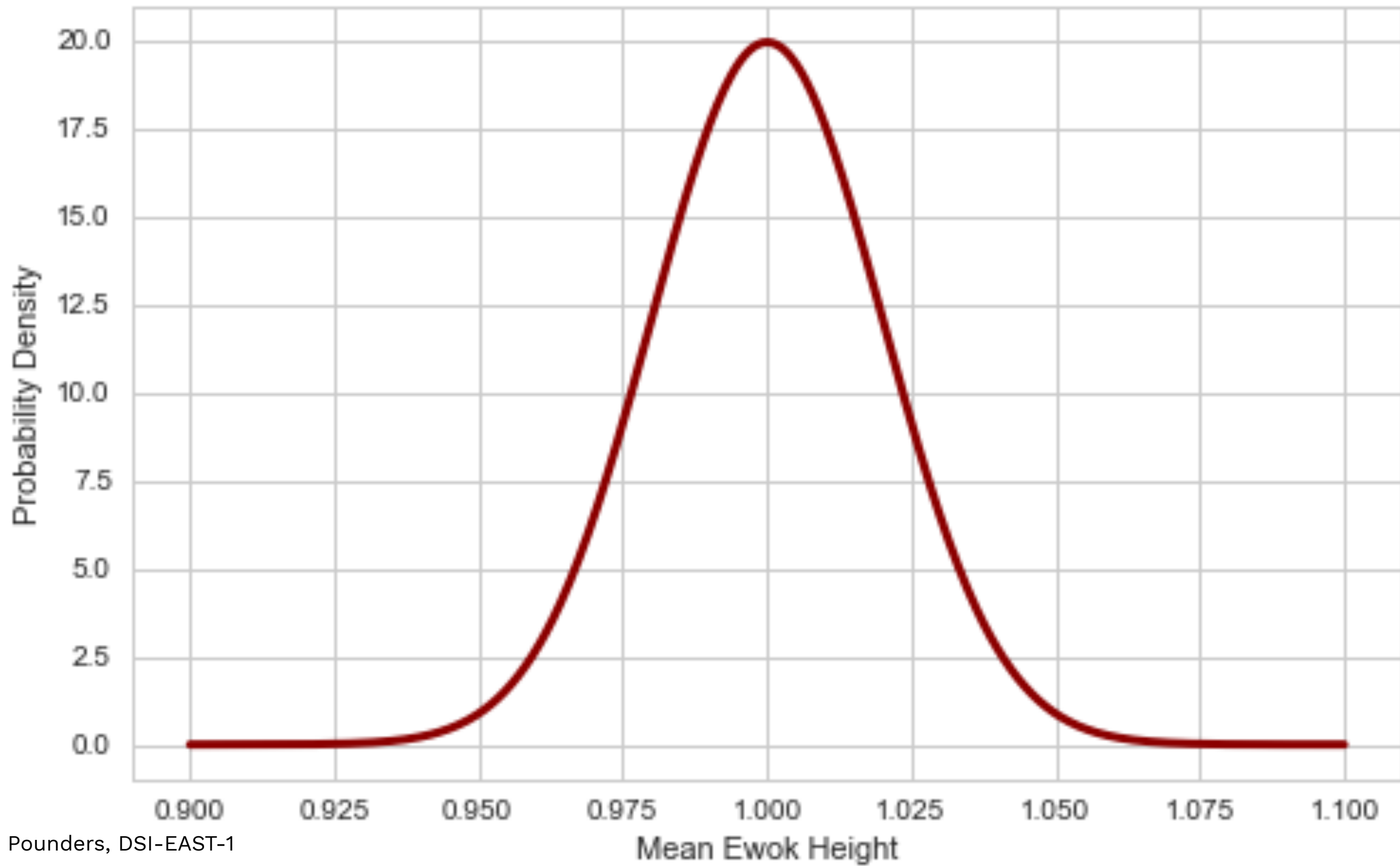
Understanding multiple samples

- An individual Ewok's height is a **random variable**
- The collection of mean heights from multiple samples is a **random variable**

Think of the sample mean as a data point from a known probability distribution.

Understanding multiple samples

- An individual Ewok's height is a **random variable**
 - Unknown probability distribution
- The collection of mean heights from multiple samples is a **random variable**
 - Normal probability distribution!!! (approximately)



Summary of Central Limit Theorem

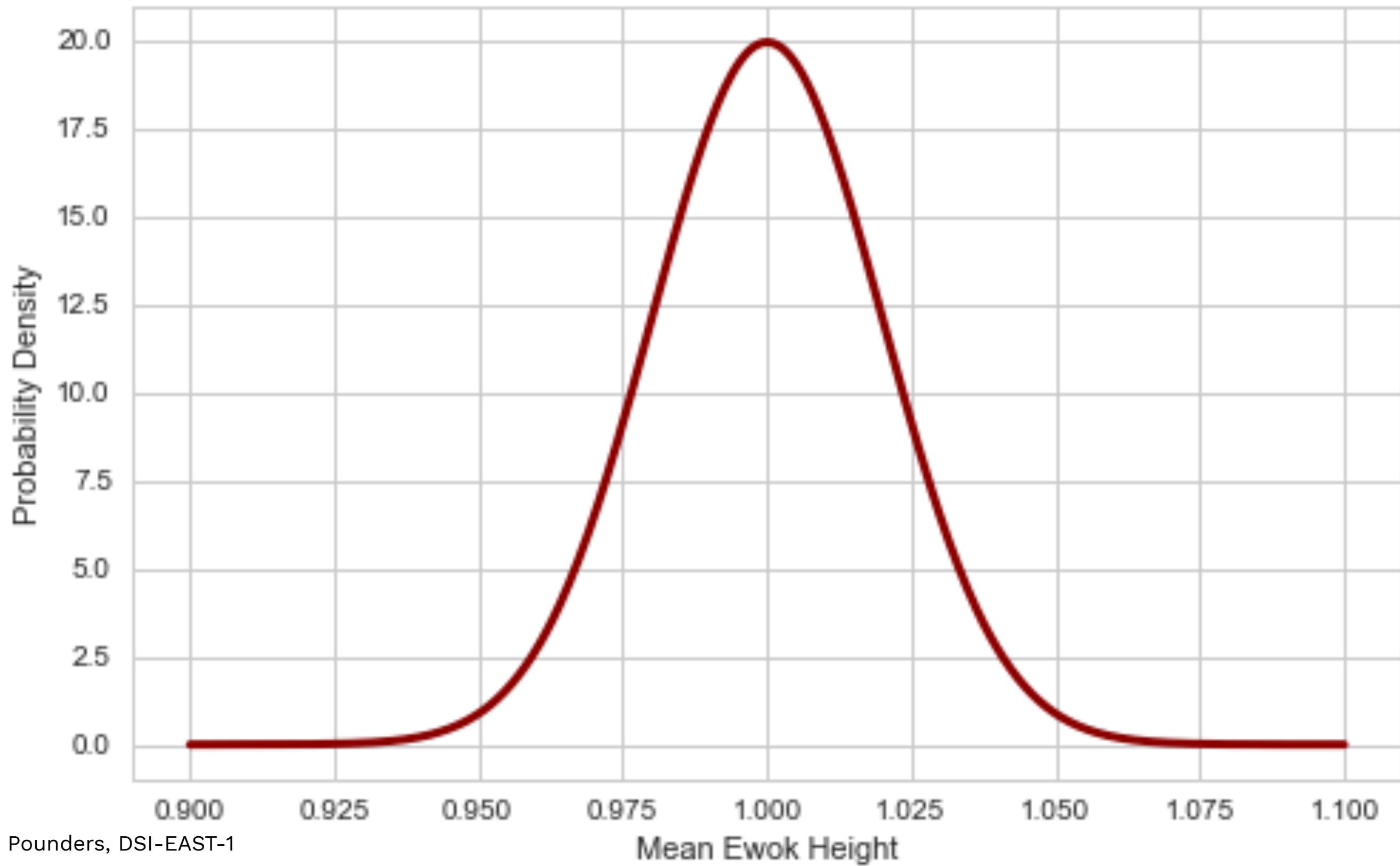
For samples of independent random variables (fixed sample size), the sample means are random **and normally distributed.**

Main implications and takeaways

- The distribution of the **sample mean** is called the **sampling distribution**
- The sampling distribution is approximately the **normal distribution**
- The standard deviation of the sampling distribution is called the **standard error**

$$\sigma_{\bar{h}} = \frac{\sigma}{\sqrt{n}}$$

The **standard error** represents the uncertainty of the sample mean relative to the true population mean.



CLT: Properties

— If $X \sim N(\mu, \sigma)$, then \bar{X} is exactly $N(\mu, \frac{\sigma}{\sqrt{n}})$

i.e.,

— If X is a **normal** random variable, the mean of a sample of X is **exactly normally distributed**

CLT: Properties

- If X is not normally distributed, then \bar{X} is approximately $N(\mu, \sigma/\sqrt{n})$ if the sample size n is at least 30.

i.e.,

- If X is **not** a normal random variable, then the mean of a sample of X is **approximately normally distributed** as long as the sample size is more than 30.

CLT: Practical Issue

$\bar{X} \sim N(\mu, \sigma/\sqrt{n})$, but μ and σ typically have to be replaced with sample estimates.

$$N(\mu, \sigma) \approx N(\bar{X}, s/\sqrt{n})$$

Python Time

go to notebook `central-limit-theorem.ipynb`

Reflect

Q: What is the most confusing part about central limit theorem or standard error?

Respond on slack.

Confidence Interval

What we got with CLT:

- sample mean is normally distributed...
- with mean μ and...
- standard deviation σ/n (aka standard error)

What we want next:

- give me a range of values that has a...
- 95% chance of including the true (population mean)

A confidence interval describes a **range of possible values for the true mean** based on a sample mean.

Confidence Interval

$$CI = \bar{x} \pm z \cdot \frac{s}{\sqrt{n}}$$

where

- \bar{x} is the sample mean
- z is a set z score
- s is the sample standard deviation
- n is the number of observations in sample

How to pick z ?

Confidence Interval

Pick z to establish level of confidence:

- 90% confidence... $z = 1.645$
- 95% confidence... $z = 1.96$
- 99% confidence... $z = 2.575$

Confidence Interval

Pick z to establish level of confidence:

- 90% confidence... $z = 1.645$
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What do we mean by "confidence"?

Confidence Interval

Suppose the 95% confidence interval for my average morning commute is 35 to 55 minutes.

Correct Interpretation

If I generated lots of samples from my commute history, and calculated a confidence interval for each, those intervals would contain the "true mean" of my commute 95% of the time.

Confidence Interval

Suppose the 95% confidence interval for my average morning commute is 35 to 55 minutes.

Not Quite Correct Interpretation

There is a 95% probability that my commute time each day will be between 35 and 55 minutes.

Python Time

go to notebook `confidence-intervals.ipynb`