ECON 0150 | Economic Data Analysis The economist's data analysis pipeline.

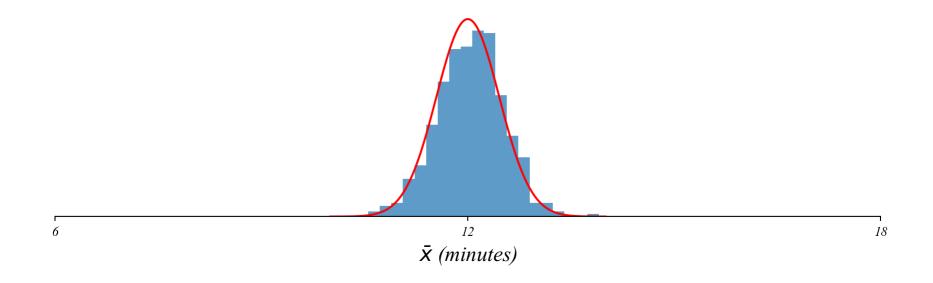
Part 3.3 | Central Limit Theorem and Confidence Intervals

$A \underset{\textit{We found \bar{x} follows a normal distribution around μ... now what?}{Big Question}$

- > how can we use this to learn about the population?
- > lets systematize how "close" \bar{x} and μ are

The Distribution of \bar{x}

Remember: sample means follow a normal distribution with mean (μ) and standard error $(SE = \frac{\sigma}{\sqrt{n}})$.



$$> \mu = 12$$
 and $\sigma = 2.5$ and $n = 30$.

Why $SE = \sigma / \sqrt{n}$?

The standard error (SE) measures the precision of the estimate.

Consider n independent observations, each with variance σ^2 .

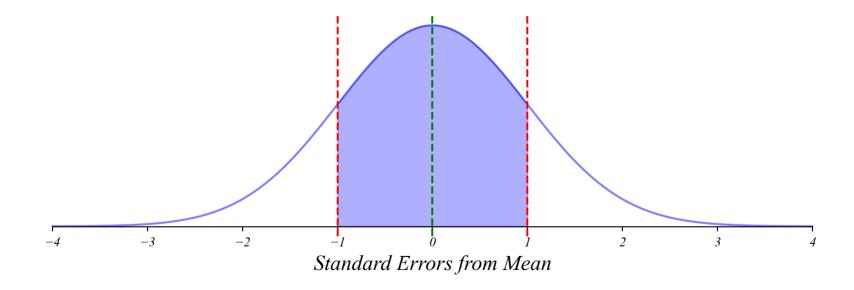
- 1. The sum of n samples has variance $n\sigma^2 \left(VAR(a) + VAR(b) = VAR(a+b) \right)$
- 2. Divide by n to find that the mean of n is $\frac{\sigma^2}{n} \left(nVAR(a) = VAR(n^2a) \right)$

Therefore the standard error is $\sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$.

Confidence Intervals

If we know σ *, we can calculate probabilities.*

> what's the probability \bar{x} is within one standard error of μ ?

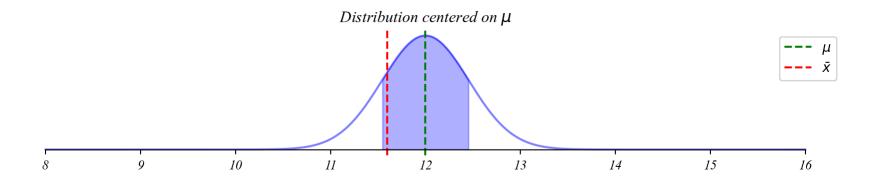


$$> P(|\bar{x} - \mu| \le \frac{\sigma}{\sqrt{n}}) \approx 0.68$$

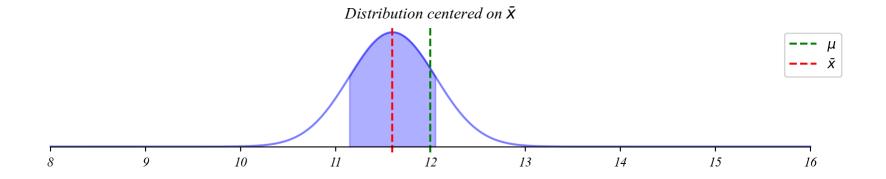
- > so 68% of the time \bar{x} will fall within $[\mu \frac{\sigma}{\sqrt{n}}, \mu + \frac{\sigma}{\sqrt{n}}]$
- > we call $\left[\mu \frac{\sigma}{\sqrt{n}}, \mu + \frac{\sigma}{\sqrt{n}}\right]$ a 68% confidence interval

Two Perspectives $\textit{There are two mathematically equivalent perspectives to think about "closeness" between μ and \bar{x}. }$

Perspective 1: probability \bar{x} is close to μ

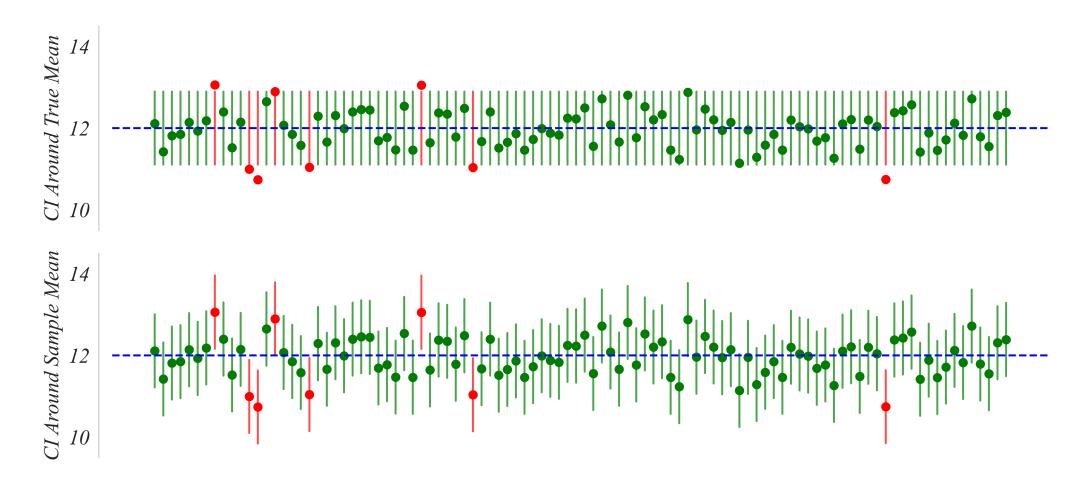


Perspective 2: probability μ is close to \bar{x}



Difference Center Points

There are two mathematically equivalent perspectives to think about "closeness" between μ and \bar{x} .



> this is huge! we can center the confidence interval around \bar{x} instead of μ !

Using Confidence Intervals Example: $\bar{x} = 102.3$, s = 1.6, and n = 100

Question 1: what's the probability μ is closer than 0.1 to \bar{x} ?

```
1 distance = 0.1
2 \text{ se} = \text{s} / \text{np.sqrt(n)}
3 probability = stats.norm.cdf(distance/se) - stats.norm.cdf(-distance/se)
```

Question 2: what's the 95% CI?

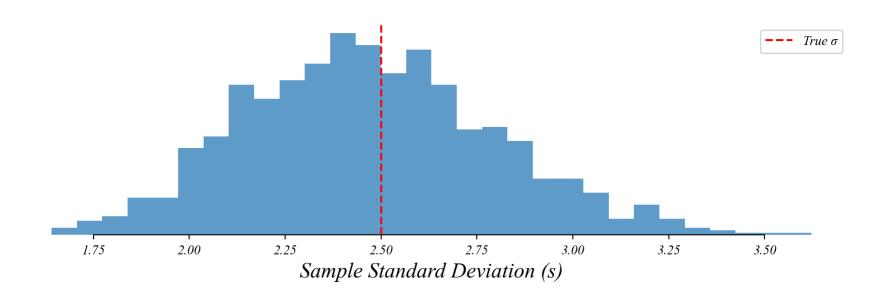
```
1 se = s / np.sqrt(n)
2 ci = stats.norm.interval(0.95, loc=x_bar, scale=se)
```

One Problem Remains

We don't know σ either!

- > we used \bar{x} to estimate μ
- > can we use s to estimate σ ?
- > yes, but there's a catch...

Using s Instead of σ Sample standard deviation (s) has its own sampling variability.

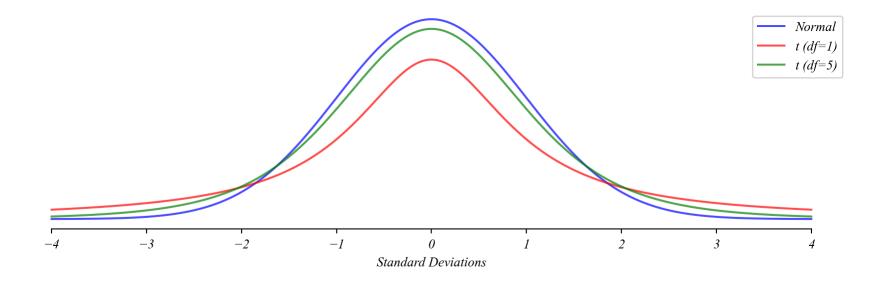


> this adds extra uncertainty to our interval

Normal vs t-Distribution

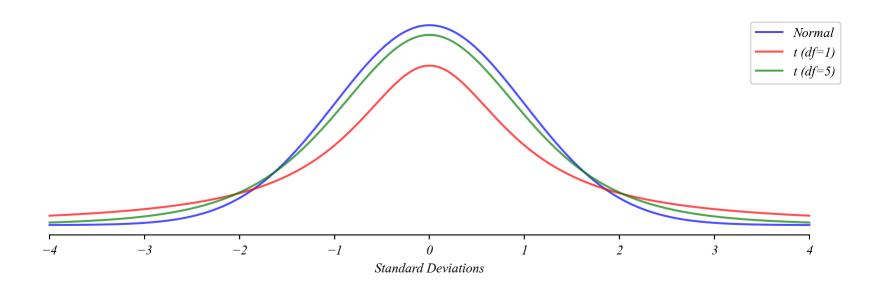
The t-distribution precisely accounts for the variation in s around σ .

- $> \bar{x}$ follows a normal distribution with μ and σ
- > key insight: since s is random, using it instead σ introduces another r.v.
- > this gives us the t-distribution with n-1 degrees of freedom



The t-Distribution

... acounts for the extra uncertainty in s around σ .



- > t-distribution has heavier tails than normal
- > approaches normal as sample size (n) increases

Putting It All Together Now we can quantify our uncertainty about an unknown μ .

- 1. \bar{x} follows a normal distribution around μ .
- 2. We can center the distribution on \bar{x} instead.
- 3. Using s adds uncertainty, captured by t-distribution.
- 4. We can use the t-distribution to make probability statements about μ .

Example: Wait Times

Calculate the 95% confidence interval for waiting times.

Generate some sample data.

```
1 sample = np.random.normal(12, 2.5, 30)
```

Calculate sample statistics.

```
1 x_bar = np.mean(sample)
2 s = np.std(sample, ddof=1)
3 n = len(sample)
4 se = s / np.sqrt(n)
```

Calculate how many standard errors the 95% CI is from \bar{x} .

```
1 t_crit = stats.t.ppf(0.975, n-1)
```

Calculate the CI from the critical value.

```
1 margin = t_crit * se
2 ci = [x_bar - margin, x_bar + margin]
```

- > if we took many samples, 95% of the time this interval would contain the truth
- > we often just say: "we're 95% confident the truth is in this interval"

Extra Questions

- 1. How would the confidence interval change if we:
 - *Increased sample size?*
 - Wanted 99% confidence instead?
 - *Had a more variable population?*
- 2. Why use t-distribution instead of normal?
- 3. What does "95% confident" really mean?
- 4. How could this help with economic decision-making?