Lecture 13: Central Limit Theorem + Confidence Intervals

Chapter 4.4 + 4.2

Goals for Today

- Discuss the Central Limit Theorem
- Introduce confidence intervals
- Interpretation

Recap

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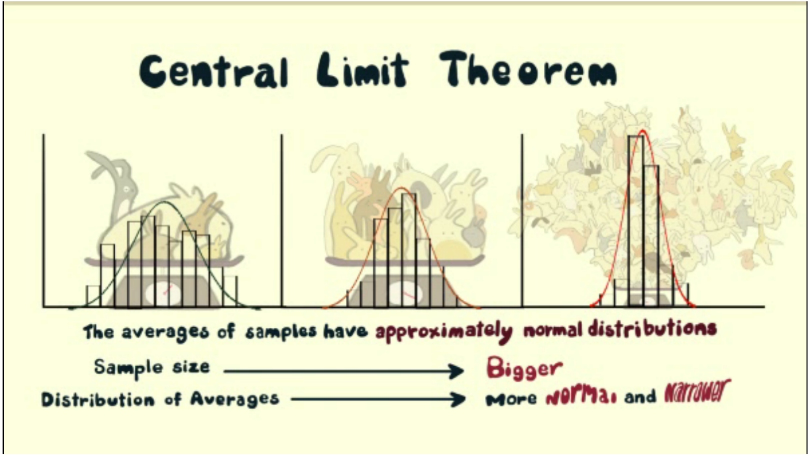
- The sampling distribution characterizes the (random) behavior of point estimates (like $\overline{x}$).
- The standard deviation of a sampling distribution is the standard error: it quantifies the uncertainty/variability of point estimates.

Illustrative Image of Sampling Distribution

Central Limit Theorem



Central Limit Theorem

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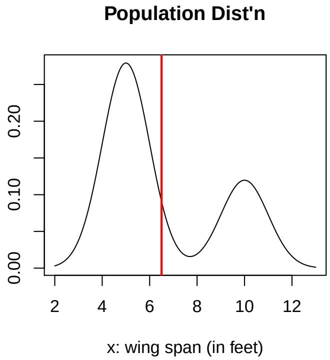

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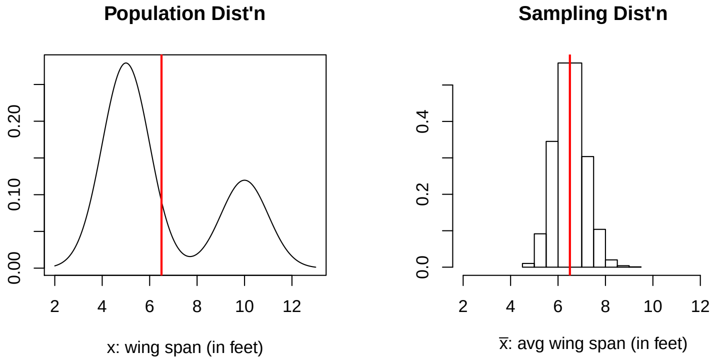

Central Limit Theorem

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Answer: So we can use the Normal table on p.409 of the book to calculate areas/percentiles/probabilities! We call this using the normal model.

	Second decimal place of Z									
Z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Definition

For a sample $x_1, \ldots, x_n$ of independent observations, if n is "large" enough to counteract the skew of the population distribution, then the sampling distribution of $\overline{x}$ is approximately Normal with

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Recall: If we don't know σ, we can plug in its point estimate s if the two conditions are satisfied.

Conditions for the Normal Model

Example of Skew vs *n*

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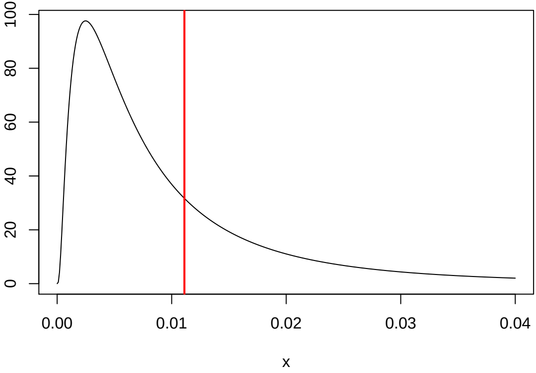

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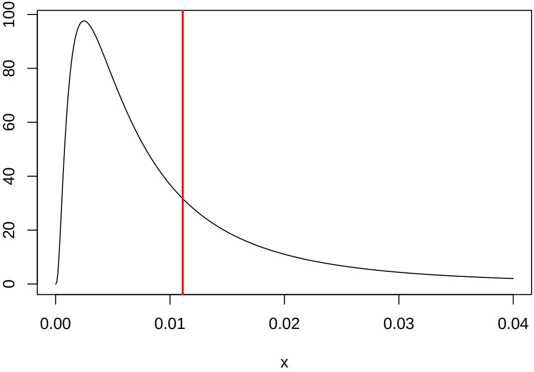

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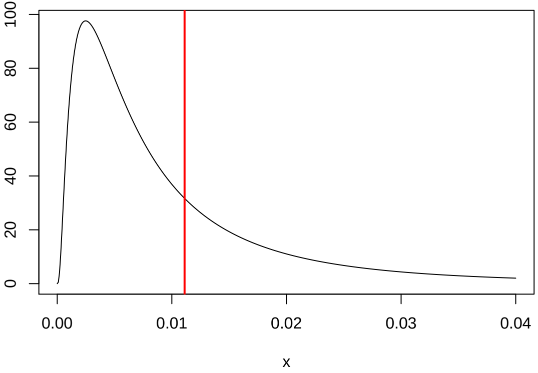
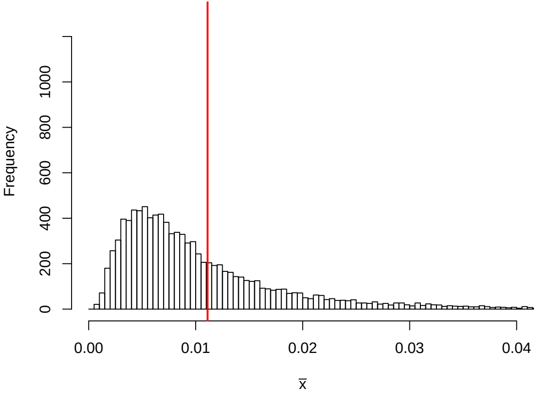


This is where your individual observations x_i come from. Now compare 10000 values of $\overline{x}$'s based on different n: 2, 10, 30, 75.

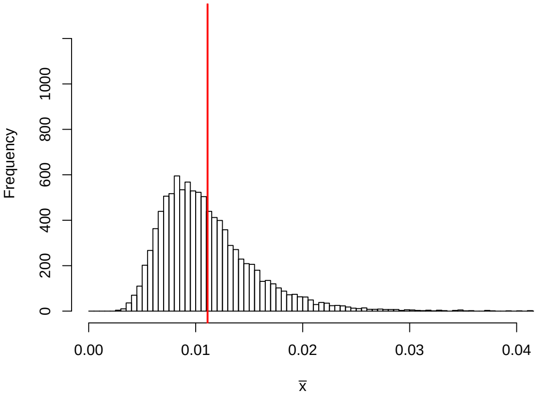
Example of Skew vs n

For 10000 values of $\overline{x}$ based on samples of size $n = 2$, the sampling distribution is:



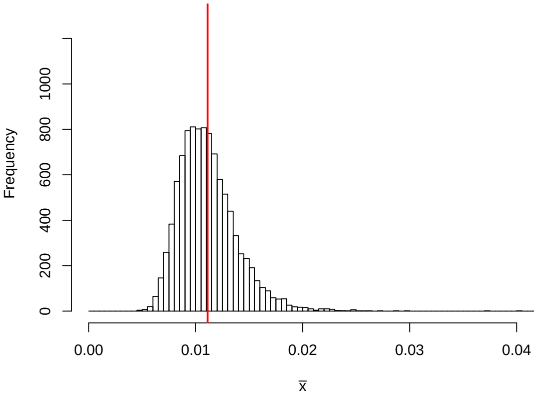
Example of Skew vs n

For 10000 values of $\overline{x}$ based on samples of size $n = 10$, the sampling distribution is:



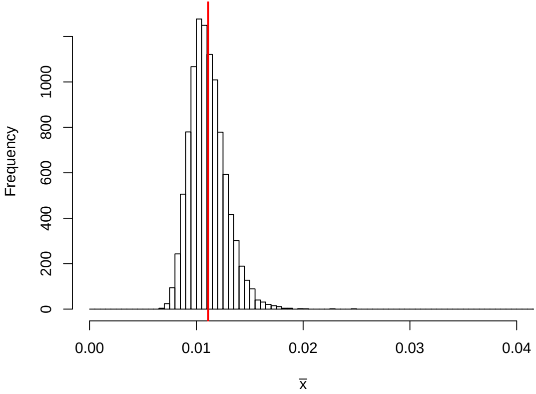
Example of Skew vs n

For 10000 values of $\overline{x}$ based on samples of size $n = 30$, the sampling distribution is:



Example of Skew vs n

For 10000 values of $\overline{x}$ based on samples of size $n = 75$, the sampling distribution is:



i.e. more normal and more narrow

Intuition of a Confidence Interval

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Using just the point estimate:

Using a confidence interval:

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Recall the example of 1000 instances of $\overline{x}$ based on $n = 100$. Each observation came from a population distribution that was Normal with $\mu = 5$ & $\sigma = 2$.

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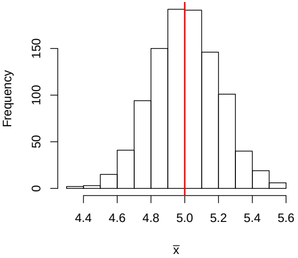

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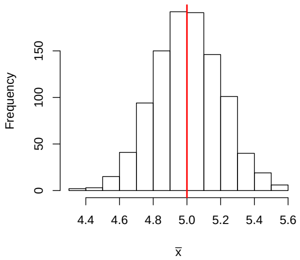

We observed the sampling distribution

- is centered at μ
- has spread $SE = \frac{\sigma}{\sqrt{n}} = \frac{2}{\sqrt{100}} = 0.2$

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- the SE is the standard deviation of the sampling distribution
- roughly 95% of the time $\overline{x}$ will be within 2 SE of μ if the sampling distribution is normal

If the interval spreads out 2 SE from $\overline{x}$, we can be roughly "95% confident" that we have captured the true parameter μ.

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Confidence Intervals

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- Wrong, yet common, interpretation: There is a 95% chance that the C.I. captures the true population mean μ. The probability is 0 or 1: either it does or it doesn't.
- Correct, interpretation: If we were to repeat this sampling procedure 100 times, we expect 95 (i.e. 95%) of calculated C.I.'s to capture the true μ

Illustration: How to Interpret a Confidence Interval

In Chapter 4 there is an example of finish times (in minutes) from the 2012 Cherry Blossom 10 mile run with $n = 16,924$ participants. In this case, we can compute the true population mean $\mu = 94.52$.

Illustration: How to Interpret a Confidence Interval

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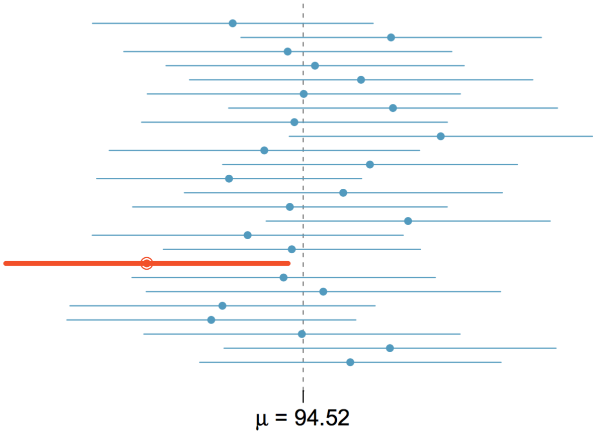
Say we take 25 (random) samples of size $n = 100$ and for each sample we compute:

- $\overline{x}$
- s
- and hence the 95% CI: $\left[\overline{x} - 1.96 \times \frac{s}{\sqrt{n}},\ \overline{x} + 1.96 \times \frac{s}{\sqrt{n}}\right]$

How to Interpret a Confidence Interval

Of the 25 CI's based on 25 different samples of size $n = 100$, one of them (in red) did not capture the true population mean μ:



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Intrepretation: the interpretation is not that there is a 95% chance that $[41.6, 48.4]$ captures the true %'age. Rather, that if we were to take 20 such polls, 19 of them would capture the true %'age.

Next Time

Hypothesis Testing: we can perform statistical tests on population parameters such as μ:

Define:

- Null and alternative hypotheses.
- Testing hypotheses using confidence intervals.
- Types of errors