Review of Statistical TheoryPart 3

Dragos Ailoae

dailoae@gradcenter.cuny.edu

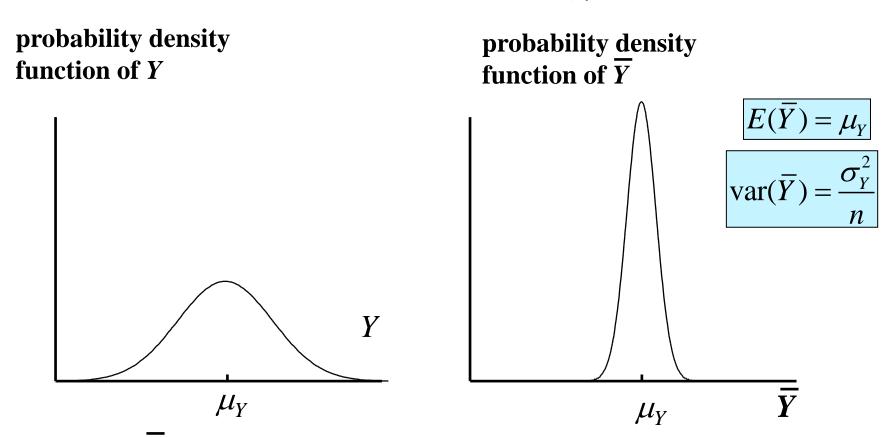
Advanced Economics and Business Statistics ECON-4400w - Spring 2022

> Brooklyn College Sep 14, 2022

- 1. The probability framework for statistical inference
- 2. Estimation
- 3. Hypothesis Testing
- 4. Confidence intervals

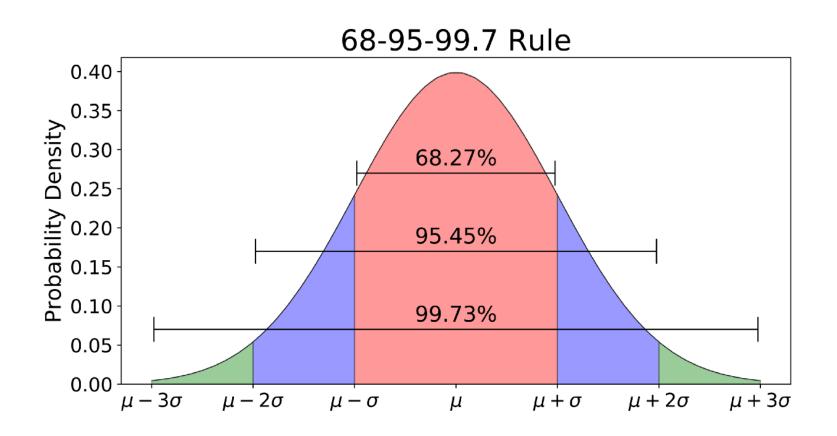
Distribution of the sample mean

In this illustration, Y and \overline{Y} are both centered around μ_Y , but the dispersion differs.

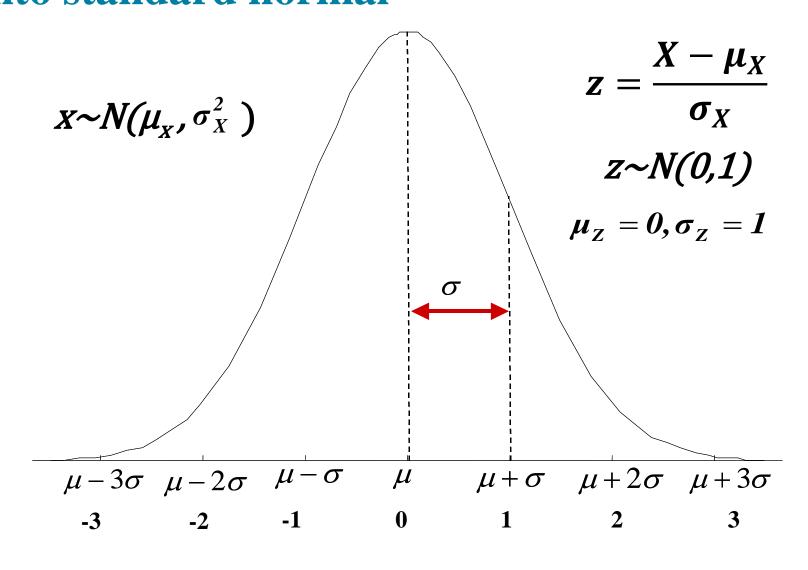


Note that \overline{Y} is normally distributed even when the underlying random variable Y is not! Remember in our CLT simulation Y was uniformly distributed.

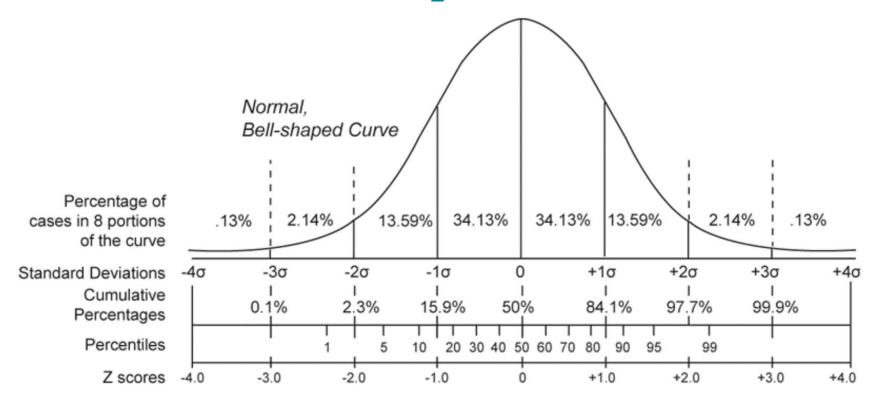
The normal distribution



All normal distributions can be translated into standard normal



The standard normal profile



- For other values see statistical tables like the one in textbook Appendix or here: https://www.edu.github.io/BC4400F22/Admin/StatsTables.pdf#page=2
- https://demonstrations.wolfram.com/AreaOfANormalDistribution/

Hypothesis Testing

The *hypothesis testing* problem (for the mean): make a provisional decision based on the evidence at hand whether a null hypothesis is true, or instead that some alternative hypothesis is true. That is, test

- H_0 : $E(Y) = \mu_{Y,0}$ vs. H_1 : $E(Y) > \mu_{Y,0}$ (1-sided, >)
- H_0 : $E(Y) = \mu_{Y.0}$ vs. H_1 : $E(Y) < \mu_{Y.0}$ (1-sided, <)
- H_0 : $E(Y) = \mu_{Y.0}$ vs. H_1 : $E(Y) \neq \mu_{Y.0}$ (2-sided)

Some terminology for testing statistical hypotheses (1 of 2)

p-value = probability of drawing a statistic (e.g. \bar{Y}) at least as adverse to the null as the value actually computed with your data, assuming that the null hypothesis is true.

The *significance level* of a test is a pre-specified probability of incorrectly rejecting the null, when the null is true.

Calculating the p-value based on \bar{Y} :

$$p - \text{value} = \boxed{\Pr[|\overline{Y} - \mu_{Y,0}| > |\overline{Y}^{act} - \mu_{Y,0}|]}$$

Where \bar{Y}^{act} is the value of \bar{Y} actually observed (nonrandom)

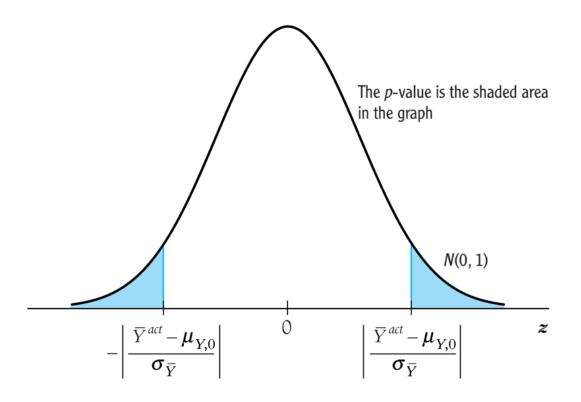
Some terminology for testing statistical hypotheses (2 of 2)

- To compute the p-value, you need the to know the sampling distribution of \bar{Y} , which is complicated if n is small.
- If *n* is large, you can use the normal approximation (CLT):

$$\begin{split} p\text{-value} &= \Pr_{H_0}[|\overline{Y} - \mu_{Y,0}| > |\overline{Y}^{act} - \mu_{Y,0}|], \\ &= \Pr_{H_0}[|\frac{\overline{Y} - \mu_{Y,0}}{\sigma_Y/\sqrt{n}}| > |\frac{\overline{Y}^{act} - \mu_{Y,0}}{\sigma_Y/\sqrt{n}}|] \\ &= \Pr_{H_0}[|\frac{\overline{Y} - \mu_{Y,0}}{\sigma_{\overline{Y}}}| > |\frac{\overline{Y}^{act} - \mu_{Y,0}}{\sigma_{\overline{Y}}}|] \end{split}$$

 \cong probability under left + right N(0,1) tails where $\sigma_{\bar{Y}} = \text{std.}$ dev. of the distribution of $\bar{Y} = \sigma_Y / \sqrt{n}$.

Calculating the p-value with σ_{γ} known:



- For large n, p-value = the probability that a N(0,1) random variable falls outside $|(\bar{Y}^{act} \mu_{Y,0})/\sigma_{\bar{Y}}|$
- In practice, $\sigma_{\bar{y}}$ is unknown it must be estimated

Estimator of the variance of Y:

$$s_Y^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \overline{Y})^2 = \text{"sample variance of } Y\text{"}$$

Fact:

If $(Y_1,...,Y_n)$ are i.i.d. and $E(Y^4) < \infty$, then

$$s_Y^2 \xrightarrow{p} \sigma_Y^2$$

The Standard Error of \overline{Y}

KEY CONCEPT

3.4

The standard error of \overline{Y} is an estimator of the standard deviation of \overline{Y} . The standard error of \overline{Y} is denoted $SE(\overline{Y})$ or $\hat{\sigma}_{\overline{Y}}$. When Y_1, \ldots, Y_n are i.i.d.,

$$SE(\overline{Y}) = \hat{\sigma}_{\overline{Y}} = s_Y / \sqrt{n}.$$
 (3.8)

Computing the p-value with σ_Y^2 estimated:

$$\begin{aligned} p\text{-value} &= \Pr_{H_0}[|\overline{Y} - \mu_{Y,0}| > |\overline{Y}^{act} - \mu_{Y,0}|], \\ &= \Pr_{H_0}[|\frac{\overline{Y} - \mu_{Y,0}}{\sigma_Y/\sqrt{n}}| > |\frac{\overline{Y}^{act} - \mu_{Y,0}}{\sigma_Y/\sqrt{n}}|] \\ &\cong \Pr_{H_0}[|\frac{\overline{Y} - \mu_{Y,0}}{s_Y/\sqrt{n}}| > |\frac{\overline{Y}^{act} - \mu_{Y,0}}{s_Y/\sqrt{n}}|] \quad \text{(large } n) \end{aligned}$$

SO

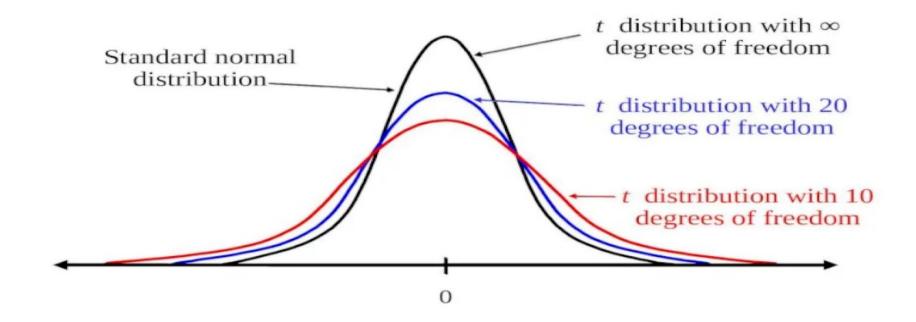
$$p$$
-value = $Pr_{H_0}[|t| > |t^{act}|]$ (σ_Y^2 estimated)

 \cong probability under normal tails outside $|t^{act}|$

where
$$t = \frac{\overline{Y} - \mu_{Y,0}}{s_Y / \sqrt{n}}$$
 (the usual *t*-statistic)

The Student-t distribution

The t-distribution is used when n is **small** and σ is **unknown**.



The Student-t distribution

- For n > 30, the *t*-distribution and N(0,1) are very close (as *n* grows large, the t_{n-1} distribution converges to N(0,1))
- The *t*-distribution is an artifact from days when sample sizes were small and "computers" were people
- For historical reasons, statistical software typically uses the *t*-distribution to compute *p*-values but this is irrelevant when the sample size is moderate or large.
- For these reasons, in this class we will focus on the large-*n* approximation given by the CLT

The average adult male height in a certain country is 170 cm. We suspect that the men in a certain city in that country might have a different average height due to some environmental factors. We pick a random sample of size 9 from the adult males in the city and obtain the following values for their heights (in cm):

176.2 157.9 160.1 180.9 165.1 167.2 162.9 155.7 166.2

Assume that the height distribution in this population is normally distributed. Here, we need to decide between

$$H_0$$
: $\mu = 170$
 H_1 : $\mu \neq 170$

Based on the observed data, is there enough evidence to reject H_0 at significance level $\alpha = 0.05$?

Solution:

Let's first compute the sample mean and the sample standard deviation. The sample mean is

$$\bar{X} = \frac{X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9}{9}$$
= 165.8

The sample variance is given by

$$S^{2} = \frac{1}{9-1} \sum_{k=1}^{9} (X_{k} - \bar{X})^{2} = 68.01$$

The sample standard deviation is given by $S = \sqrt{S^2} = 8.25$

Now, our test statistic is

$$W(X_1, X_2, \dots, X_9) = \frac{\overline{X} - \mu_0}{\frac{S}{\sqrt{n}}} = \frac{165.8 - 170}{\frac{8.25}{3}} = -1.52$$

Thus, |W| = 1.52. Also, we have

$$t_{\frac{\alpha}{2},n-1} = t_{0.025,8} \approx 2.31$$

Thus, we conclude

$$|W| \le t_{\frac{\alpha}{2}, n-1}$$

Therefore, we cannot reject H_0 . In other words, we do not have enough evidence to conclude that the average height in the city is different from the average height in the country.

Achievement test scores of all high school seniors in a state have mean 60 and variance 64. A random sample of n=100 students from one large high school had a mean score of 58. Is there evidence to suggest that this high school is inferior?

Hint: calculate the probability that the sample mean is at most 58 when n=100.

Let \bar{X} denote the mean of a random sample of n=100 scores from a population with $\mu=60$ and $\sigma^2=64$. We want to approximate $P(\bar{X} \leq 58)$. We know from the Central Limit Theorem that $(\bar{X}-\mu)/(\sigma/\sqrt{n})$ has a distribution that can be approximated by a standard normal distribution. Using the standard normal table we have:

$$P(\bar{X} \le 58) = P\left(\frac{\bar{X} - 60}{8/\sqrt{100}} \le \frac{58 - 60}{.8}\right) \approx P(Z \le -2.5) = .0062$$

Because this probability is so small, it is unlikely that the sample from the school of interest can be regarded as a random sample from a population with $\mu = 60$ and $\sigma^2 = 64$. The evidence suggests that the average score for this high school is lower than the overall average of $\mu = 60$.

- 1. The probability framework for statistical inference
- 2. Estimation
- 3. Testing
- 4. Confidence intervals

Confidence Intervals

- A 95% *confidence interval* for μ_Y is an interval that contains the true value of μ_Y in 95% of repeated samples.
- Digression: What is random here? The values of $Y_1,...,Y_n$ and thus any functions of them including the confidence interval. The confidence interval will differ from one sample to the next. The population parameter, μ_Y , is not random; we just don't know it.

Confidence Intervals

A 95% confidence interval can always be constructed as the set of values of μ_Y not rejected by a hypothesis test with a 5% significance level.

$$\{\mu_{Y}: \left| \frac{\overline{Y} - \mu_{Y}}{s_{Y}} \right| \le 1.96\} = \{\mu_{Y}: -1.96 \le \frac{\overline{Y} - \mu_{Y}}{s_{Y}} \le 1.96\}$$

$$= \{\mu_{Y}: -1.96 \frac{s_{Y}}{\sqrt{n}} \le -\mu_{Y} \le 1.96 \frac{s_{Y}}{\sqrt{n}}\}$$

$$= \{\mu_{Y}\in (\overline{Y} - 1.96 \frac{s_{Y}}{\sqrt{n}}, \overline{Y} + 1.96 \frac{s_{Y}}{\sqrt{n}})\}$$

This confidence interval relies on the large-n results that \overline{Y} is approximately normally distributed and $s_Y^2 \xrightarrow{p} \sigma_Y^2$.

Confidence interval example

In a sample of 25, $\bar{x} = 1.63$ and s = 0.51. Construct a 95 percent confidence interval for μ .

Solution:

2.064 is the 95% critical value from a t distribution with 24 degrees of freedom. Thus, the confidence interval is $1.63 \pm [2.064(0.51)/5]$ or [1.4195,1.8405].

Summary:

From the two assumptions of:

- 1. simple random sampling of a population, that is, $\{Y_i, i = 1,...,n\}$ are i.i.d.
- 2. $0 < E(Y^4) < \infty$

we developed, for large samples (large n):

- Theory of estimation (sampling distribution of \bar{Y})
- Theory of hypothesis testing (large-n distribution of t-statistic and computation of the p-value)
- Theory of confidence intervals