Ch2 - Testing

ECO 204
Statistics For Business and Economics - II

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Outline

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Testing : Key Ideas

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What is Testing, Errors and Different Types of Tests

- In this chapter we will learn a new technique in inferential statistic, known as *Hypothesis Testing*, or in short often we just say - *Testing*.
- Testing problem is slightly different than estimation, here
  - First, we start with *two competing* hypotheses about the unknown population parameter, one is called *"Null Hypothesis"* and the other one is *"Alternative Hypothesis"*. We then use the sample data to reject or accept the Null Hypothesis.

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- *Question is* -

What is a hypothesis?

Ans: It's simply a conjecture about the population parameter.

- Let's see an example.

Testing, Errors and Different Types of Tests

- Continuing from the problem we introduced in the last chapter, suppose we have an information that the unknown population mean income μ is less than $24,000$, now we would like to test whether $\mu < 24,000$, is true, to do this we can form two hypotheses as follows,

$$H_0 : \mu \geq 24,000 \quad \textit{Null Hypothesis}$$
$$H_a : \mu < 24,000 \quad \textit{Alternative Hypothesis}$$

- Now after we are done with constructing the hypotheses, we use a random sample (or data) to either *reject the Null* or *accept the Null*. Acceptance is sometimes written as *fail to reject*, however in this chapter we will avoid these philosophical issues!

- Two important points,

  i) What we believe is written in the alternative (this is often the convention, however not necessary!)

  ii) Notice! Everything is happening around Null. So we are either rejecting the Null or accepting the Null (Why? We will come back to the answer later!)

- Since in practice we never know where is μ, so in this setting we can make two types of errors, which are known as *Type I Error* and *Type II Error*, and also there are two scenarios where we are correct, let's see this now

Testing, Errors and Different Types of Tests

		Population Reality	
		H_0 True	H_a True
Conclusion	Accept H_0	Correct Conclusion	Type II Error
	Reject H_0	Type I Error	Correct Conclusion

- Before interpreting the table, first of all, always remember

  we do not know what is μ

- Now the table says, if the hypothesized Null is actually true and after the testing we accept Null, then there is no error, but if the hypothesized Null is true and we reject the Null then we will make an error and the error is called Type-I error....Can you interpret other cells of the table?
- Ideally we want to construct a test that minimizes both of these errors, but actually for a fixed sample size, this is impossible. So the idea is we fix the Type-I error and look for a test which minimizes the Type-II error. We won't go to more theoretical details here... in our testing procedure we will always *fix Type-I error* and our procedure will minimize Type-II error...
- Let's replace the hypothesized information $24,000$ with μ_0, essentially this is the value of the unknown parameter where we are dividing the parameter set. In this case we will now think about following three formations of testing

Two Tail test

$$H_0 : \mu = \mu_0$$
$$H_a : \mu \neq \mu_0$$

Upper Tail test

$$H_{0:} : \mu \leq \mu_0$$
$$H_a : \mu > \mu_0$$

Lower Tail test

$$H_{0:} : \mu \geq \mu_0$$
$$H_a : \mu < \mu_0$$

- Together the last two tests are called - *One tail tests*. The word tail is coming from the tail of the Normal distribution...but you will understand later why this naming...

Testing : Key Ideas

Test Statistic and Sampling Distribution in Testing

Test Statistic and Sampling Distribution in Testing

- In the hypothesis testing again we will use the *sampling distribution of $\overline{X}$*. Recall before we called $\overline{X}$ an estimator of μ.
- In the Hypothesis testing we won't call this an estimator, rather we will call it a *Test Statistic*. In general often a *Test Statistic* is same or very similar to a point estimator, but its a *Statistic*, which is simply *a function of the random sample*
- When a *Statistic* is used for estimation we call it an *Estimator*. Similarly, when a *Statistic* is used for *Testing* we call it a *Test Statistic*. These are just some naming conventions that you need to know.

Test Statistic and Sampling Distribution in Testing

- For example $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$ is a function of random sample, so this is a statistic. When we use it for point estimation, we call this point estimator, but if we use it for hypothesis testing we call it a *Test Statistic*.
- Before we said the distribution of the estimator is called *sampling distribution*, actually more generally the probability distribution of a *Statistic* is called *Sampling Distribution*. So here the distribution of $\overline{X}$ is a sampling distribution (old stuff!)
- Again we will use the three old results (below we always assume i.i.d.)

Test Statistic and Sampling Distribution in Testing

- **Result 1:** If the *population data is normal* with μ and σ^2, then $\overline{X} \sim \mathcal{N}(\mu, \sigma^2/n)$, we can use this if *we know σ*. In this case we often use Z statistic, where

$$Z = \frac{\overline{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \text{ and } Z \sim \mathcal{N}(0, 1)$$

- **Result 2:** If the *population data is normal*, but *we don't know σ*, then we use T statistic, where

$$T = \frac{\overline{X} - \mu}{\frac{S}{\sqrt{n}}} \text{ and } T \sim t_{n-1}$$

  where S is the sample standard deviation, Note that in these cases,

$$\mathbb{E}(\overline{X}) = \mu \text{ and } \mathbb{V}(\overline{X}) = \frac{\sigma^2}{n}$$

  however in the second case we cannot calculate the variance, hence we use an estimator of the variance, which is S^2/n, and we can write this as,

$$\widehat{\mathbb{V}}(\overline{X}) = \frac{S^2}{n}$$

Test Statistic and Sampling Distribution in Testing

- **Result 3:** If the *population data is not normal* we cannot use *exact distributions* like above, rather we need to *use an approximation following Central Limit Theorem (CLT)*, in that case, we use the statistic

$$Z = \frac{\overline{X} - \mathbb{E}\left(\overline{X}\right)}{\sqrt{\widehat{\mathbb{V}}(\overline{X})}} \text{ when } n \text{ is large,} \qquad \text{so } Z \overset{approx}{\sim} \mathcal{N}(0,1)$$

  where $\widehat{\mathbb{V}}(\overline{X})$ is the estimator for the variance of $\overline{X}$. Important is Z follows $\mathcal{N}(0,1)$ when the sample size n becomes very large, this is called *Asymptotic Normality* of the sample mean.

Test Statistic and Sampling Distribution in Testing

CLT in Bernoulli case:
Note it's an approximation and the data may or not be normal. For example, if the population distribution is Bernoulli (i.e., 0 or 1 data, think about Gender), then target parameter is

$$\mathbb{E}(X) = p \text{ where } \mathbb{P}(X = 1) = p$$

In practice we never know p, so we can propose the following estimator for p

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \text{ in this case it is } \textit{sample proportion}$$

It is possible to show that (we skip the proof but it's very easy under i.i.d. assumption)

$$\mathbb{E}(\overline{X}) = p \text{ and } \mathbb{V}(\overline{X}) = \frac{p(1-p)}{n}$$

since we don't know p, we use an estimator of the variance $\mathbb{V}(\overline{X})$, which is

$$\widehat{\mathbb{V}}(\overline{X}) = \frac{\overline{X}(1-\overline{X})}{n}$$

this gives the following Z

$$Z = \frac{\overline{X} - p}{\sqrt{\widehat{\mathbb{V}}(\overline{X})}} \text{ and } Z \overset{approx}{\sim} \mathcal{N}(0,1) \text{ when } n \text{ is large}$$

Test Statistic and Sampling Distribution in Testing

so in this case, in large sample the approximate sampling distribution of the sample proportion is normal with the estimated standard error

$$\sqrt{\widehat{\mathbb{V}}(\overline{X})} = \sqrt{\frac{\overline{X}(1-\overline{X})}{n}}$$

if you are curious about the exact distribution of the sample proportion in finite samples, it is $\mathrm{Bin}(n, p)$ with scaling $\frac{1}{n}$, this means the values will be $0, 1/n, 2/n, \ldots, 1$

Z Test (σ known)

Example and Steps

The following example is slightly modified from Anderson et al. (2020)).

The Bangladesh Golf Federation (BGF) establishes rules that manufactures of golf equipment must meet if their products are to be acceptable for use in BGF events. Company ABC uses a high-technology manufacturing process to produce golf balls with a mean driving distance of 295 *yards. This is what it advertises to sell its balls.*

Sometimes, however, the process gets out of adjustment and produces golf balls with a mean driving distance different from 295 *yards. When the mean distance falls below* 295 *yards, the company worries about losing sales because the golf balls do not provide as much distance as advertised. When the mean distance goes above than* 295 *yards, ABC also worries because golf balls may be rejected by the BGF for exceeding the overall distance standard concerning carry and roll.*

ABC's quality control department takes time to time a sample of 50 *golf balls to monitor the manufacturing process. It calculated the sample mean of* 50 *golf balls and found it is to be* 297.6.

For this sample, now the department wants to do hypothesis testing to determine whether the process has fallen out of adjustment. Develop the null and alternative hypotheses and do the testing at 5% *level of significance, and also do the test, suppose somehow the quality control team knows that population standard deviation of all golf balls is* $\sigma = 12$.

- How do we develop the Null and Alternative Hypothesis? Note that, both below and above of 295 is problematic for the company. So the proper formation is, (notice here $\mu_0 = 295$)

$$H_0 : \mu = 295$$
$$H_a : \mu \neq 295$$

- From the story, we know
  - $n = 50$
  - $\bar{x} = 297.6$
  - $\alpha = 0.05$
  - $\mu_0 = 295$
  - $\sigma = 12$
- What does the company want? It's clear that the company would like to accept the Null. This is because if the company rejects the Null then it's costly, why? maybe because it has to change its entire production process.
- We will directly use standard normal distribution (although not necessary in this case), which we denoted with $\mathcal{N}(0, 1)$ to do the testing of the ABC company, here are the steps

Different z-Tests

First Example and Steps

Algorithm 1: Two Tail Test : σ known

Input: $\overline{x}$, σ, n, μ_0, α

Output: Reject H_0 or Accept H_0

Formulate the hypotheses H_0 and H_a properly such that

$$H_0 : \mu = \mu_0$$
$$H_a : \mu \neq \mu_0$$

Calculate the value of the Z Statistic which is z_{calc} using the formula

$$z_{\text{calc}} = \frac{\overline{x} - \mu_0}{\sigma / \sqrt{n}}$$

Calculate the critical values $z_{\alpha/2}$ and $z_{1-\alpha/2}$ using $\mathcal{N}(0,1)$

if $z_{calc} \geq z_{1-\frac{\alpha}{2}}$ *or* $z_{calc} \leq z_{\frac{\alpha}{2}}$ **then**

  Reject H_0

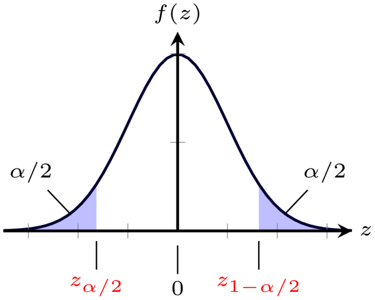
else

  Accept H_0

Recall here the critical values are such that,

$$\mathbb{P}(Z \leq z_{\frac{\alpha}{2}}) = \alpha/2 \quad \text{and} \quad \mathbb{P}(Z \leq z_{1-\frac{\alpha}{2}}) = 1 - \alpha/2$$

here is the picture of critical values...



The R code is also very simple, here it is

R code - sigma known, two-tail (using standard normal)

```
# First give the data and calculate zcalc
n <- 50
xbar <- 297.6
alpha <- 0.05
mu0 <- 295
sigma <- 12

zcalc <- (xbar - mu0)/(sigma/sqrt(n))

# check the value
zcalc
# [1] 1.532065

# (alpha/2) quantile of the standard normal
qnorm(alpha/2)
# [1] -1.959964


# (1 - alpha/2) quantile of the standard normal
qnorm(1 - alpha/2)
# [1] 1.959964
```

- In our problem, $z_{\text{calc}} = 1.532$
- Also
  - $z_{\alpha/2} = z_{.025} = -1.96$, this is the .025th quantile or 2.5th percentile of the standard normal distribution.
  - $z_{1-\alpha/2} = z_{.975} = 1.96$, this is the .975th quantile or 97.5th percentile of the standard normal distribution.
- So we can see that

$$-1.96 < 1.532 < 1.96$$

or

$$z_{\alpha/2} < z_{\text{calc}} < z_{1-\alpha/2}$$

- So this means our transformed sample mean 1.532 does not fall in the rejection region, so *we accept the Null*....bottomline the ABC company is happy
- Now we can adjust the problem slightly for example,

Problem Changed... (modified for upper-tail test)

ABC only checks whether the average distance is *at max* 295, but worries if the average distance exceeds 295.

- This happens when the company is worried about the golf balls being rejected by the BGF for exceeding the overall distance standard concerning carry and roll. In this case, the company is worried about the average distance exceeding 295 yards. So the proper formation of the hypotheses is, (notice here $\mu_0 = 295$)

$$H_0 : \mu \leq 295$$
$$H_a : \mu > 295$$

- Note the word upper is coming from the alternative hypothesis.
- Similarly, we can think about

Problem Changed... (modified for lower-tail test)

ABC only checks whether the average distance is *at least* 295, but worries if the average distance is below 295.

- This happens when the company is worried about losing sales because the golf balls do not provide as much distance as advertised. In this case, the company is worried about the average distance falling below 295 yards. So the proper formation of the hypotheses is, (notice here $\mu_0 = 295$)

$$H_0 : \mu \geq 295$$
$$H_a : \mu < 295$$

- This is called the lower tail test,
- The steps are similar,

Different z-Tests

First Example and Steps

Algorithm 2: Upper Tail Test : σ known

Input: $\overline{x}$, σ, n, μ_0, α
Output: Reject H_0 or Accept H_0

Formulate the hypotheses H_0 and H_a properly such that

$$H_0 : \mu \leq \mu_0$$
$$H_a : \mu > \mu_0$$

Calculate the value of the Z Statistic which is z_{calc} using the formula

$$z_{\text{calc}} = \frac{\overline{x} - \mu_0}{\sigma/\sqrt{n}}$$

Calculate the critical values $z_{\alpha/2}$ and $z_{1-\alpha/2}$ using $\mathcal{N}(0,1)$

if $z_{calc} \geq z_{1-\alpha}$ **then**
  Reject H_0
else
  Accept H_0

Different z-Tests

First Example and Steps

Algorithm 3: Lower Tail Test : σ known

Input: $\overline{x}$, σ, n, μ_0, α

Output: Reject H_0 or Accept H_0

Formulate the hypotheses H_0 and H_a properly such that

$$H_0 : \mu \geq \mu_0$$
$$H_a : \mu < \mu_0$$

Calculate the value of the Z Statistic which is z_{calc} using the formula

$$z_{\text{calc}} = \frac{\overline{x} - \mu_0}{\sigma / \sqrt{n}}$$

Calculate the critical values $z_{\alpha/2}$ and $z_{1-\alpha/2}$ using $\mathcal{N}(0, 1)$

if $z_{calc} \leq z_\alpha$ **then**

  Reject H_0

else

  Accept H_0

- The codes are similar, and you should be able to adjust it...

t-Tests (σ un-known)

Example and Steps

- The t-test is more practical since the assumption of known σ is strange, however in this case we can calculate sample standard deviation s which is

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n-1}}$$

- The whole process will be similar to z-test however we will calculate the value of the T-statistic which is

$$t_{\text{calc}} = \frac{\overline{X} - \mu_0}{\frac{s}{\sqrt{n}}}$$

- And then compare this with the t values we can get from the t_{n-1} distribution.

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