

STAT 305: Chapter 6 - Part II

Hypothesis Testing

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Hypothesis Testing

Deciding What's True (Even If We're Just Guessing)

Let's Play A Game

A "Friendly" Introduction to Hypothesis Tests

My Game

The Rules

Let's Play A Game

The semester is getting a little intense! You are a livin'Let's break the tension with a friendly game.

Here are the rules:

- I have a new deck of cards. 52 Cards, 26 with Suits that are Red, 26 with Suits that are Black
- You draw a red-suited card, you give me a dollar
- You draw a black-suited card, I give you two dollars

Quick Questions

What is the expected number of dollars you will win playing this game?

Would you play this game?

Are We Forgetting Something?

My Game

The Rules

The Assumptions

Be Careful About Your Assumptions

Pause for a minute and think about what you are assuming is true when you play this game. For instance,

- You assume I'm going to shuffle the cards fairly
- You assume there are 52 cards in the deck
- You assume the deck has 26 red-suited cards in it
- You assume the deck has **a** red-suited card in it

How can we make sure the assumptions are safe??

- Shuffling assumption: watch me shuffle, make sure I'm not doing magic tricks, etc
- 52 Cards assumption: count the cards
- Red-suit assumption: Count the number of red cards

Whew! We can actually make sure all of our assumptions are good!

One Problem

I Refuse to Show You The Cards



Do You Trust Me?

My Game

The Rules

The
Assumptions

Our Assumptions

I'm not going to show you all the cards. In other words, I refuse to show you the *population of possible outcomes*. This is justified: we are in a statistics course after all.

So, let's start with our unverifiable assumption: Is it safe to assume that this is a fair game. Why would we make this assumption?

- You trust that I'm (basically) an honest person (*assumption of decency*)
- You trust that I'm getting paid enough that I wouldn't risk cheating students out of money (*assumption of practicality*)
- You saw the deck was new (*manufacturer trust assumption*)
- You want it to be an fair game because you would win lots of money if it was (*assumption in self-interest*)

My Game

The Rules

The
Assumptions

Our Assumptions

In statistical terminology, we wrap all these assumptions up into one assumption: our "**null hypothesis**" is that the game is not rigged - that the probability of you winning is 0.5

Null Hypothesis

The assumptions we are operate under in normal circumstances (i.e., what we believe is true). We wrap these assumptions up into a statistical/mathematical statement, but we will accept them unless we have reason to doubt them. We use the notation H_0 to refer to the null hypothesis.

In this case, we could say that the probability of winning is p and that would make our null hypothesis

$$H_0 : p = 0.5$$

My Game

The Rules

The
Assumptions

Our Assumptions

Of course our assumptions could be wrong. We call the other assumptions our "alternative hypothesis":

Alternative Hypothesis

The conditions that we do require proof to accept. We would have to change our beliefs based on evidence. We use the notation H_A (or sometimes, H_1) to refer to the alternative hypothesis.

In this case, we could say that our alternative to believing the game is "fair" is to believe the game is not fair, or that the probability of winning is not 0.5. We write:

$$H_A : p \neq 0.5$$

A Compromise

I Won't Show You All The Cards
But I Will Let You Test The Game

My Game

The Rules

The
Assumptions

The Test

Testing the Game

The test of whether or not the game is worth playing can be defined in term of whether or not our assumptions are true. In other words, we are going to test whether our null hypothesis is correct:

Hypothesis Tests

A **hypothesis test** is a way of checking if the outcomes of a random experiment are *statistically unusual* based on our assumptions. If we see really unusual results, then we have **statistically significant** evidence that allows us to **reject our null hypothesis**. If our assumptions lead to results that are not unusual, then we **fail to reject our null hypothesis**.

My Game

The Rules

The
Assumptions

The Test

Testing the Game

So how can we test the game? What if we tried a single round of the game?

- What are the probabilities of the outcome of a single game?
- If we draw a single card do we have enough evidence that the game is fair?
- Do we have enough evidence that the game is rigged?

Based on a single round of the game, both of the possible outcomes are pretty normal - that's not good enough.

If we draw a losing card, then we might be inclined to call the game unfair - even though a losing card is pretty common for a single round of the game

If we draw a winning card, then we might be inclined to call the game fair - even though a winning card may be common even when the game is not fair!

We can make lots of mistakes!!

My Game

The Rules

The
Assumptions

The Test

The Errors

The Mistakes We Might Make

We could of course be wrong: For instance, we could, just by random chance, see outcomes that are unusual for the assumptions we make and reject the assumptions even if (in reality they are true). This is called a "Type I Error"

Type I Error

When the results of a hypothesis test lead us to reject the assumptions, while the assumptions are actually true, we have committed a Type I Error.

My Game

The Mistakes We Might Make

The Rules

A common example of this is found in criminal court:

The
Assumptions

- We assume that a individual accused of a crime is innocent (our assumption)
- After examinig the evidence, we conclude that it is there is no reasonable doubt the person is not innocent (in other words, we reject the assumption because it is very unlikely to be true based on our evidence).

The Test

The Errors

- If the person truly is innocent, then we have committed a Type I error (rejecting assumptions that were true).

My Game

The Rules

The
Assumptions

The Test

The Errors

The Mistakes We Might Make

We could also make a different error: we could choose not to reject the assumptions when in reality the assumptions are wrong.

Type II Error

When the results of a hypothesis test lead us to fail to reject the assumptions, while the assumptions are actually false, we have committed a Type II Error.

My Game

The Mistakes We Might Make

The Rules

Again, if we consider the example of criminal court:

The
Assumptions

- We assume that a individual accused of a crime is innocent (our assumption)
- After examinig the evidence, we conclude that it is there is **not** evidence beyond a reasonable doubt the person is not innocent (in other words, the evidence is not enough to reject our assumption because it is still reasonable to doubt the accused's guilt).
- If the person truly is not innocent, then we have committed a Type II error (failing to reject assumptions that were false).

The Test

The Errors

In general, we want to make sure that a Type I error is unlikely. To take the example of court again,

- We commit a Type II error: a guilty person goes free
- We commit a Type I error: an innocent person goes to jail; the guilty person is still free

My Game

The Rules

The
Assumptions

The Test

The Errors

The Mistakes We Might Make

Let's go back to my game: We assume I am an honest person (i.e., we assume that the probability of winning a single game is $p = 0.5$)

Type I Error: Rejecting True Assumptions

- We gather evidence
- Looking at our evidence, we decide that the game was not fair even though it was.
- Fallout: you slander me, you disprove me, we have a fight, BOOOM.

Type II Error: Failing to Reject False Assumptions

- We gather evidence
- Looking at our evidence, we decide that the game was fair even though it was not.
- Fallout: you play the game and lose some money.

Ideally, we won't make either error. However, we can only base our decision on the evidence we can gather - the truth is out of our grasp!

My Game

Gathering Statistical Evidence

The Rules

Okay, so we don't want to make either error - that means we need good evidence.

The
Assumptions

Like we talked about before, even if the game is fair one test round of the game would not be enough to make a good decision since drawing a red-suited card and drawing a black-suited card are both pretty normal for a single round of the game.

The Test

The Errors

But what if we played the game 10 times in a row? After 10 rounds, do you think we would have enough evidence to make a decision about our assumption?

The Evidence

My Game

p-value

The Rules

If we assume the null hypothesis, then we can make some assumptions about what results are likely and what results are unlikely. We describe the likelihood of the results that we actually get using a **p-value**

The Assumptions

p-value

The Test

After gathering evidence (aka, data) we can determine the probability that we would have gotten the evidence we did if our assumptions were true. That probability is called the p-value. If the p-value is really, really small that means that the assumptions we started with are pretty unlikely and we reject our assumptions. If the p-value is not small, then the evidence collected (aka, the data) is pretty normal for our assumptions and we fail to reject our assumptions.

The Errors

The Evidence

p-value

My Game

p-value

The Rules

In other words, we collect evidence and determine a way to measure the whether or not our data was unusual *if our assumptions are true*.

The
Assumptions

If we have a very, very low chance of

The Test

- seeing both our results and
- having true assumptions then we reject the assumptions

The Errors

Going along with the terminology we have introduced, if we have a small p-value then we reject our null hypothesis.

The Evidence

p-value

My Game

Gathering Statistical Evidence

The Rules

In this game, if we assume that the game is fair, we have

The
Assumptions

- two outcomes: success (winning) and failure (losing)
- a constant chance of a successful outcome ($p = 0.5$), assuming the game is fair)
- independent rounds of the game (assuming fair shuffle, which we can check)

The Test

In other words, if we test the game 10 times we can model the number of successful outcomes as binomial: For X = the total number of wins,

The Errors

The Evidence

$$P(X = x) = \frac{10!}{x!} (0.5)^x (1 - 0.5)^{10-x}$$

p-value

This gives us a way of getting our p-value

Let's Test the Game

My Game

Gathering Statistical Evidence

The Rules

We played the game. Let's figure out whether our results were unusual or not.

The Assumptions

Again, we assume the game is fair and have decided that the number of times we win will follow a binomial distribution with probability function

The Test

$$P(X = x) = \frac{10!}{x!} (0.5)^x (1 - 0.5)^{10-x}$$

The Errors

Now we need to make a conclusion: do we accept or reject our assumptions? What do we consider unusual? Is it fair to decide after we play?

The Evidence

p-value

The Conclusion

My Game

Summary

The Rules

The
Assumptions

The Test

The Errors

The Evidence

p-value

The
Conclusion

- Sometimes we can know if something is true or not by examining the truth directly, but not always
- When we can't examine the truth, we need to test what we believe to be true
- A statistical test is a tool for testing our assumptions about what we believe
 - We state our assumed belief (generally our current beliefs, or the ethical beliefs, or the beliefs we hope are true, ...)
 - We come up with a way of collecting data that could validate or invalidate our assumption
 - We measure how likely it was that we would have gathered the data we did if our assumptions were correct
 - We reject the assumptions if our data is very unlikely we are our current beliefs

Now let's make everything
a little more formal

Section 6.3

Hypothesis Testing

Hypothesis testing

Last section illustrated how probability can enable confidence interval estimation. We can also use probability as a means to use data to quantitatively assess the plausibility of a trial value of a parameter.

Statistical inference is using data from the sample to draw conclusions about the population.

1. **Interval estimation (confidence intervals):**

Estimates population parameters and specifying the degree of precision of the estimate.

1. **Hypothesis testing:**

Testing the **validity** of statements about the population that are formed in terms of parameters.

Hypothesis Testing

Null

Definition:

Statistical **significance testing** is the use of data in the quantitative assessment of the plausibility of some trial value for a parameter (or function of one or more parameters).

Significance (or hypothesis) testing begins with the specification of a trial value (or **hypothesis**).

A **null hypothesis** is a statement of the form

$$\text{Parameter} = \#$$

or

$$\text{Function of parameters} = \#$$

for some $\#$ that forms the basis of investigation in a significance test. A null hypothesis is usually formed to embody a status quo/"pre-data" view of the parameter. It is denoted H_0 .

Hypothesis Testing

Null

Alternative

Definition:

An **alternative hypothesis** is a statement that stands in opposition to the null hypothesis. It specifies what forms of departure from the null hypothesis are of concern. An alternative hypothesis is denoted as H_a . It is of the form

$$\text{Parameter} \neq \#$$

or

$$\text{Parameter} > \# \quad \text{or} \quad \text{Parameter} < \#$$

Examples (testing the true mean value):

$$\begin{array}{lll} H_0 : \mu = \# & H_0 : \mu = \# & H_0 : \mu = \# \\ H_a : \mu \neq \# & H_a : \mu > \# & H_a : \mu < \# \end{array}$$

Often, the alternative hypothesis is based on an investigator's suspicions and/or hopes about the true state of affairs.

Hypothesis Testing

The **goal** is to use the data to debunk the null hypothesis in favor of the alternative.

Null

1. Assume H_0 .

2. Try to show that, under H_0 , the data are preposterous. (using probability)

Alternative

3. If the data are preposterous, reject H_0 and conclude H_a .

The outcomes of a hypothesis test consists of:

Hypothesis Testing

Null

Alternative

Probability of type I error

It is not possible to reduce both type I and type II errors at the same time. The approach is then to fix one of them.

We then fix the **probability of type I error** and try to minimize the probability of type II error.

We define the **probability of type I error** to be α (the significance level)

Hypothesis Testing

Null

Alternative

Example: [Fair coin]

Suppose we toss a coin $n = 25$ times, and the results are denoted by X_1, X_2, \dots, X_{25} . We use 1 to denote the result of a head and 0 to denote the results of a tail. Then $X_1 \sim \text{Binomial}(1, \rho)$ where ρ denotes the chance of getting heads, so $E(X_1) = \rho$, $\text{Var}(X_1) = \rho(1 - \rho)$. Given the result is you got all heads, do you think the coin is fair?

Null hypothesis : H_0 : the coin is fair or $H_0 : \rho = 0.5$

Alternative hypothesis : $H_a : \rho \neq 0.5$

If H_0 was correct, then

$$P(\text{results are all heads}) = (1/2)^{25} < 0.000001$$

I don't think this coin is fair (reject H_0 in favor of H_a)

Hypothesis Testing

In the real life, we may have data from many different kinds of distributions! Thus we need a universal framework to deal with these kinds of problems.

Null

We have $n = 25 \geq 25$ iid trials \Rightarrow By CLT we know if $H_0 : \rho = 0.5 (= E(X))$ then

Alternative

$$\frac{\bar{X} - \rho}{\sqrt{\rho(1 - \rho)/n}} \sim N(0, 1)$$

We observed $\bar{X} = 1$, so

$$\frac{\bar{X} - 0.5}{\sqrt{0.5(1 - 0.5)/25}} = \frac{1 - 0.5}{\sqrt{0.5(1 - 0.5)/25}} = 5$$

Then the probability of seeing as *wierd or wierder* data is

$$\begin{aligned} P(\text{Observing something wierd or wierder}) &= \\ P(Z \text{ bigger than } 5 \text{ or less than } -5) &= \\ &< 0.000001 \end{aligned}$$

Hypothesis Testing

Significance tests for a mean

Null

Definition:

A **test statistic** is the particular form of numerical data summarization used in a significance test.

Alternative

Definition:

A **reference (or null) distribution** for a test statistic is the probability distribution describing the test statistic, provided the null hypothesis is in fact true.

P-value

Definition:

The **observed level of significance or p -value** in a significance test is the probability that the reference distribution assigns to the set of possible values of the test statistic that are *at least as extreme as* the one actually observed.

Hypothesis Testing

Significance tests for a mean

Null

In the previous example, the test statistic was

$$\frac{\bar{X} - \rho}{\sqrt{\rho(1 - \rho)/n}} \sim N(0, 1)$$

Alternative

In the previous example, the null distribution was $N(0, 1)$

P-value

In the previous example, the p-value was < 0.000001

Hypothesis Testing

Significance tests for a mean

Null

In other words:

Let K be the test statistics value based on the data

Alternative

Say

P-value

$$H_0 : \mu = \mu_0$$

$$H_a : \mu \neq \mu_0$$

$P(\text{observing data as or more extreme as } K)$

$$= P(Z < -K \text{ or } Z > k)$$

is defined as the **p-value**

Hypothesis Testing

Null

Alternative

P-value

Significance tests for a mean

Based on our results from Section 6.2 of the notes, we can develop hypothesis tests for the true mean value of a distribution in various situations, given an iid sample X_1, \dots, X_n where $H_0 : \mu = \mu_0$.

Let K be the value of the test statistic, $Z \sim N(0, 1)$, and $T \sim t_{n-1}$. Here is a table of p -values that you should use for each set of conditions and choice of H_a .

Situation	K	$H_a : \mu \neq \mu_0$	$H_a : \mu < \mu_0$	$H_a : \mu > \mu_0$
$n \geq 25, \sigma$ known	$\frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$	$P(Z > K)$	$P(Z < K)$	$P(Z > K)$
$n \geq 25, \sigma$ unknown	$\frac{\bar{x} - \mu_0}{s/\sqrt{n}}$	$P(Z > K)$	$P(Z < K)$	$P(Z > K)$
$n < 25, \sigma$ unknown	$\frac{\bar{x} - \mu_0}{s/\sqrt{n}}$	$P(T > K)$	$P(T < K)$	$P(T > K)$

Hypothesis Testing

Null

Alternative

P-value

Steps to perform a hypothesis test

1. State H_0 and H_1
2. State α , significance level, usually a small number (0.1, 0.05 or 0.01)
3. State form of the test statistic, its distribution under the null hypothesis, and all assumptions
4. Calculate the test statistic and p-value
5. Make a decision based on the p-value(if p-value $< \alpha$, reject H_0 otherwise we fail to reject H_0)
6. Interpret the conclusion using the concept of the problem

Hypothesis Testing

Null

Alternative

P-value

Example:[Cylinders]

The strengths of 40 steel cylinders were measured in MPa. The sample mean strength is 1.2 MPa with a sample standard deviation of 0.5 MPa. At significance level $\alpha = 0.01$, conduct a hypothesis test to determine if the cylinders meet the strength requirement of 0.8 MPa.

Hypothesis Testing

Example: [Concrete beams]

10 concrete beams were each measured for flexural strength (MPa). The data is as follows.

Null

[1] 8.2 8.7 7.8 9.7 7.4 7.8 7.7 11.6 11.3 11.8

Alternative

The sample mean was 9.2 MPa and the sample variance was 3.0933 MPa. Conduct a hypothesis test to find out if the flexural strength is different from 9.0 MPa.

P-value

Hypothesis Testing Using Confidence Interval

Hypothesis Testing

Null

Alternative

P-value

Hypothesis testing using the CI

We can also use the $1 - \alpha$ confidence interval to perform hypothesis tests (instead of p -values). The confidence interval will contain μ_0 when there is little to no evidence against H_0 and will not contain μ_0 when there is strong evidence against H_0 .

Hypothesis Testing

Null

Alternative

P-value

CI method

Hypothesis testing using the CI

Steps to perform a hypothesis test using a confidence interval:

1. State H_0 and H_1
2. State α , significance level
3. State the form of $100(1 - \alpha)\%$ CI along with all assumptions necessary. (use one-sided CI for one-sided tests and two-sided CI for two sided tests)
4. Calculate the CI
5. Based on $100(1 - \alpha)\%$ CI, either reject H_0 (if μ_0 is not in the interval) or fail to reject (if μ_0 is in the interval)
6. Interpret the conclusion in the content of the problem

Hypothesis Testing

Null

Alternative

P-value

CI method

Example:[Breaking strength of wire, cont'd]

Suppose you are a manufacturer of construction equipment. You make 0.0125 inch wire rope and need to determine how much weight it can hold before breaking so that you can label it clearly. You have breaking strengths, in kg, for 41 sample wires with sample mean breaking strength 91.85 kg and sample standard deviation 17.6 kg. Using the appropriate 95% confidence interval, conduct a hypothesis test to find out if the true mean breaking strength is above 85 kg.

Steps:

1- $H_0 : \mu = 85$ vs. $H_1 : \mu > 85$

2- $\alpha = 0.05$

Hypothesis Testing

Null

Alternative

P-value

CI method

Example:[Breaking strength of wire, cont'd]

3- One-sided test and we care about the lower bound. So, we use $(\bar{X} - z_{1-\alpha} \frac{s}{\sqrt{n}}, +\infty)$.

4- From the example in previous set of slides, the CI is $(87.3422, +\infty)$.

5- Since $\mu_0 = 85$ is not in the CI, we **reject** H_0 .

6- There is **significant evidence** to conclude that the true mean breaking strength of wire is greater than the 85kg. Hence the requirement is met.

Hypothesis Testing

Example: [Concrete beams, cont'd]

10 concrete beams were each measured for flexural strength (MPa). The data is as follows.

Null

[1] 8.2 8.7 7.8 9.7 7.4 7.8 7.7 11.6 11.3 11.8

Alternative

The sample mean was 9.2 MPa and the sample variance was $3.0933 (MPa)^2$. At $\alpha = 0.01$, test the hypothesis that the true mean flexural strength is 10 MPa using a confidence interval. Steps:

P-value

$$1- H_0 : \mu = 10 \text{ vs. } H_1 : \mu \neq 10$$

$$2- \alpha = 0.01$$

3- This is two-sided test with $n = 10$ and 100
($1 - \alpha$) % CI is

$$(\bar{X} - t_{(n-1, 1-\alpha/2)} \frac{s}{\sqrt{n}}, \bar{X} + t_{(n-1, 1-\alpha/2)} \frac{s}{\sqrt{n}})$$

CI method

Hypothesis Testing

Null

Alternative

P-value

CI method

Example:[Breaking strength of wire, cont'd]

4- Check that the CI is (7.393, 11.007).

5- Since $\mu_0 = 10$ is within the CI, we **fail** to reject H_0 .

6- There is **not enough evidence** to conclude that the true mean flexural strength is different from 10 Mpa.

Hypothesis Testing

Example:[Paint thickness, cont'd]

Consider the following sample of observations on coating thickness for low-viscosity paint.

Null

[1] 0.83 0.88 0.88 1.04 1.09 1.12 1.29 1.31 1.48 1.49 1.59 1.62
1.65 1.71 [15] 1.76 1.83

Alternative

Using $\alpha = 0.1$, test the hypothesis that the true mean paint thickness is 1.00 mm. Note, the 90\% confidence interval for the true mean paint thickness was calculated from before as (1.201, 1.499).

P-value

CI method

1- $H_0 : \mu = 1.0 \text{ vs. } H_1 : \mu \neq 1.0$

2- $\alpha = 0.1$

3- This is two-sided test with $n = 16$, σ unknown, so 100 (1 - α) % CI is

$$\left(\bar{X} - t_{(n-1, 1-\alpha/2)} \frac{s}{\sqrt{n}}, \bar{X} + t_{(n-1, 1-\alpha/2)} \frac{s}{\sqrt{n}} \right)$$

Hypothesis
Testing

Null

Alternative

P-value

CI method

Example:[Breaking strength of wire, cont'd]

4- The CI is (1.201, 1.499).

5- Since $\mu_0 = 1$ is not in the the CI, we **reject** H_0 .

6- There is **enough evidence** to conclude that the true mean paint thickness is not 1mm.

Section 6.4

Inference for matched pairs and two-sample data

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Inference for matched pairs and two-sample data

An important type of application of confidence interval estimation and significance testing is when we either have *paired data* or *two-sample data*.

Recall: Matched pairs

Paired data is bivariate responses that consists of several determinations of basically the same characteristics

Example:

- Practice SAT scores *before* and *after* a preperation course
- Severity of a disease *before* and *after* a treatment
- Fuel economy of cars *before* and *after* testing new formulations of gasoline

Hypothesis
Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Inference for matched pairs and two-sample data

One simple method of investigating the possibility of a consistent difference between paired data is to

1. Reduce the measurements on each object to a single difference between them
2. Methods of confidence interval estimation and significance testing applied to differences (using Normal or t distributions when appropriate)

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Example:[Fuel economy]

Twelve cars were equipped with radial tires and driven over a test course. Then **the same twelve cars** (with the same drivers) were equipped with regular belted tires and driven over the same course.

After each run, the cars gas economy (in km/l) was measured. Using significance level $\alpha = 0.05$ and the method of critical values, test for a difference in fuel economy between the radial tires and belted tires.

Construct a 95% confidence interval for **true mean difference due to tire type**. (i.e μ_d)

car	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0	12.0
radial	4.2	4.7	6.6	7.0	6.7	4.5	5.7	6.0	7.4	4.9	6.1	5.2
belted	4.1	4.9	6.2	6.9	6.8	4.4	5.7	5.8	6.9	4.7	6.0	4.9

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Example:[Fuel economy]

car	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0	12.0
radial	4.2	4.7	6.6	7.0	6.7	4.5	5.7	6.0	7.4	4.9	6.1	5.2
belted	4.1	4.9	6.2	6.9	6.8	4.4	5.7	5.8	6.9	4.7	6.0	4.9
d	0.1	-0.2	0.4	0.1	-0.1	0.1	0.0	0.2	0.5	0.2	0.1	0.3

Since we have paired data, the first thing to do is to find the differences of the paired data. ($d = d_1 - d_2$, where d_1 is associated with radial and d_2 is associated with belted tires.)

Then writing down the information available:

$$n = 12, \quad \bar{d} = 0.142, \quad s_d = 0.198$$

$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i, \quad s_d^2 = \frac{1}{n-1} \sum_{i=1}^n (d_i - \bar{d})^2$$

Then we just need to apply steps of hypothesis testing.

Note that the null hypothesis here is that **there is no difference between the gas economy recorded of the two different tires.**(i.e $\mu_d = 0$)

Hypothesis
Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Example:[Fuel economy]

1- $H_0 : \mu_d = 0$ vs. $H_1 : \mu_d \neq 0$

2- $\alpha = 0.05$

3- I will use the test statistics $K = \frac{\bar{d}-0}{s_d/\sqrt{n}}$ which has a t_{n-1} distribution assuming that

- H_0 is true and
- d_1, d_2, \dots, d_{12} are iid $N(\mu_d, \sigma_d^2)$

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Example:[Breaking strength of wire, cont'd]

$$4- K = \frac{0.421}{0.198/\sqrt{12}} = 2.48 \sim t_{(11,0.975)}.$$

$$\begin{aligned} p - value &= P(|T| > K) = P(|T| > 2.48) \\ &= P(T > 2.48) + P(T < -2.48) \\ &= 1 - P(T < 2.48) + P(T < -2.48) \\ &(\text{by software}) = 1 - 0.9847 + 0.9694 = 0.03 \end{aligned}$$

5- Since $p\text{-value} < 0.05$, we **reject** H_0 .

6- There is **enough evidence** to conclude that fuel economy differs between radial and belted tires.

Hypothesis Testing

Example:[Breaking strength of wire, cont'd]

A two-sided 95% confidence interval for the true mean fuel economy **difference** is

Null

$$(\bar{d} - t_{(n-1, 1-\alpha/2)} \frac{s_d}{\sqrt{n}}, \bar{d} + t_{(n-1, 1-\alpha/2)} \frac{s_d}{\sqrt{n}})$$

Alternative

P-value

$$= (0.142 - t_{(11, 0.975)} \frac{0.198}{\sqrt{12}}, 0.142 + t_{(11, 0.975)} \frac{0.198}{\sqrt{12}})$$

CI method

$$= (0.142 - 2.2 \frac{0.198}{\sqrt{12}}, 0.142 + 2.2 \frac{0.198}{\sqrt{12}})$$

Matched Pairs

$$= (0.0164, 0.2764)$$

Two-sample

Note that $d = d_1 - d_2$, so the interpretation will be:

We are 95% confident that the radial tires get between 0.0166 km/l and 0.2674 km/l more in fuel economy than belted tires on average

Hang on for a Second

Let's review slide 58 again

Hypothesis Testing

Example:[Breaking strength of wire, cont'd]

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

$$\begin{aligned} p - value &= P(|T| > K) = P(|T| > 2.48) \\ &= P(T > 2.48) + P(T < -2.48) \\ &= 1 - P(T < 2.48) + P(T < -2.48) \\ (\text{by software}) &= 1 - 0.9847 + 0.9694 = 0.03 \end{aligned}$$

We have seen t-student table

How do we get that p-value using **software** !!!

What is happening?

Hypothesis
Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Unlike *standard Normal distribution* table which gives us probability under the standard Normal curve, *t* tables are quantile tables.

i.e We use the *t* table (Table B.4 in Vardeman and Jobe) to calculate **quantiles**.

To have exact probabilities, we need software.

Table B.4
t Distribution Quantiles

ν	$Q(.9)$	$Q(.95)$	$Q(.975)$	$Q(.99)$	$Q(.995)$	$Q(.999)$	$Q(.9995)$
1	3.078	6.314	12.706	31.821	63.657	318.317	636.607
2	1.886	2.920	4.303	6.965	9.925	22.327	31.598
3	1.638	2.353	3.182	4.541	5.841	10.215	12.924
4	1.533	2.132	2.776	3.747	4.604	7.173	8.610
5	1.476	2.015	2.571	3.365	4.032	5.893	6.869

The approach in calculating p-value when
t distribution is involved

Hypothesis Testing

Two important points:

Null

P-value and α are both probabilities. (so $\in [0, 1]$).

Alternative

They are areas under the curve in tails under *null hypothesis*.

P-value

CI method

Matched Pairs

Two-sample

Hypothesis Testing

Null

Alternative

P-value

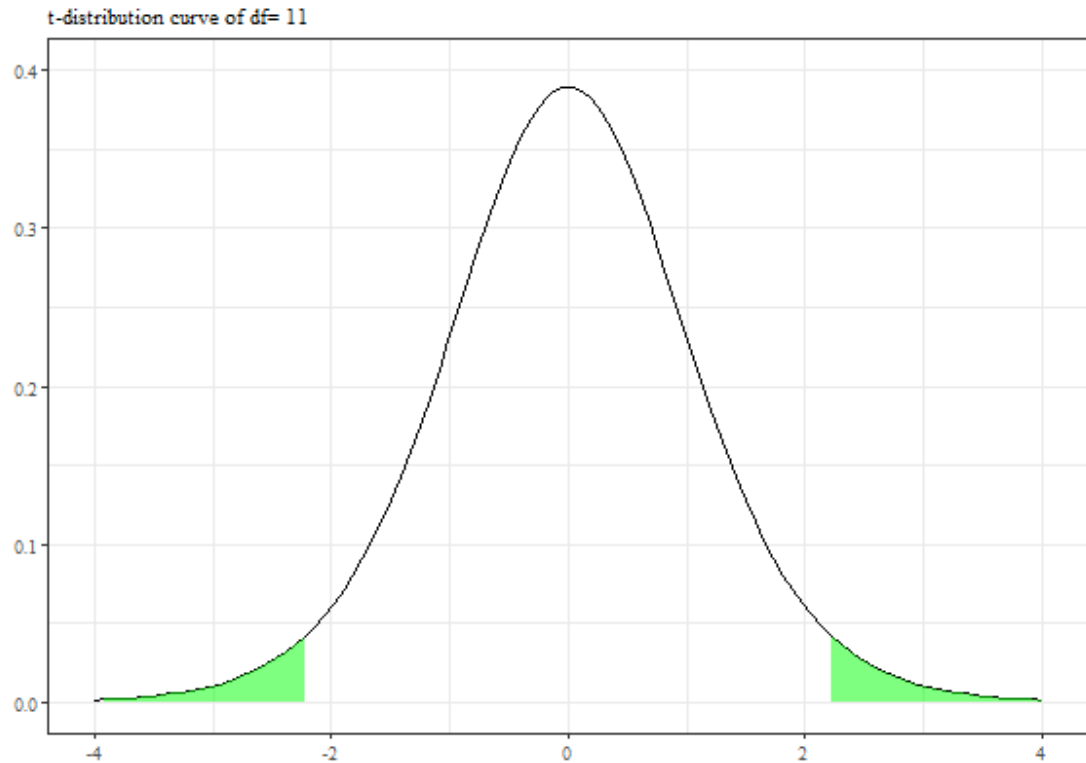
CI method

Matched Pairs

Two-sample

For a random variable with $\sim t_{(11,0.975)}$:

By the t table, the t quantile of $t_{(11,0.975)}$ is 2.2.



Hypothesis
Testing

For the critical value we calculated under the null hypothesis:

Null

The critical value calculated is $K = 2.34$

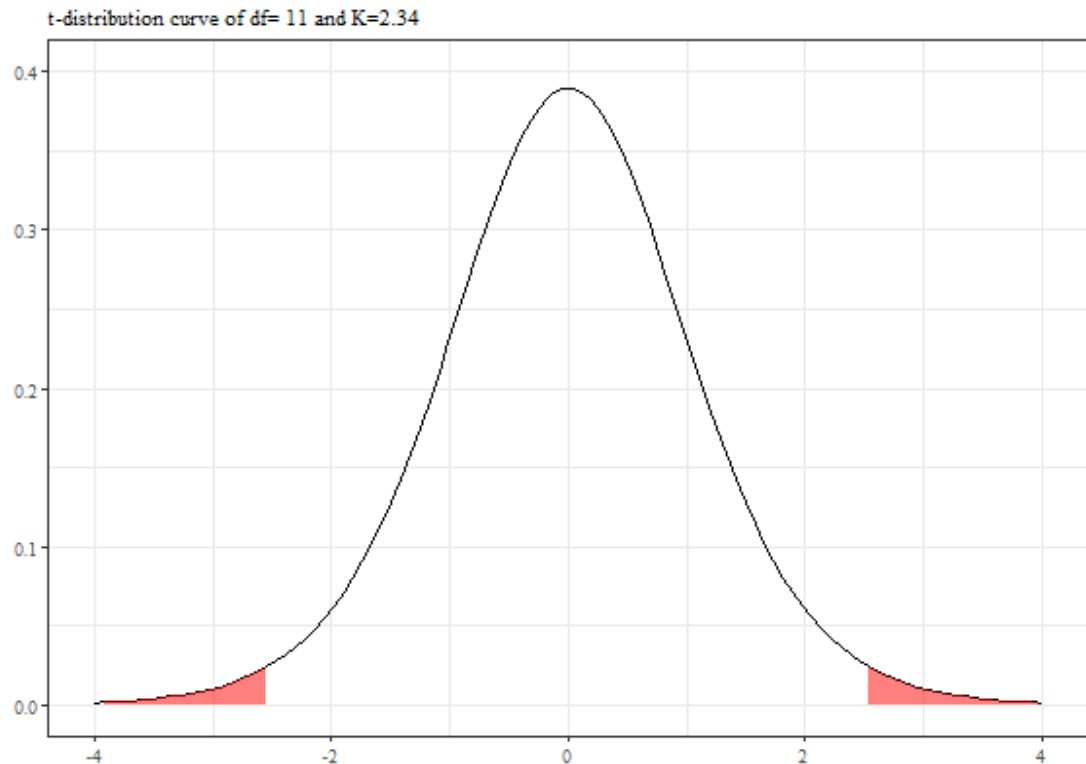
Alternative

P-value

CI method

Matched Pairs

Two-sample



Hypothesis Testing

Both together

Null

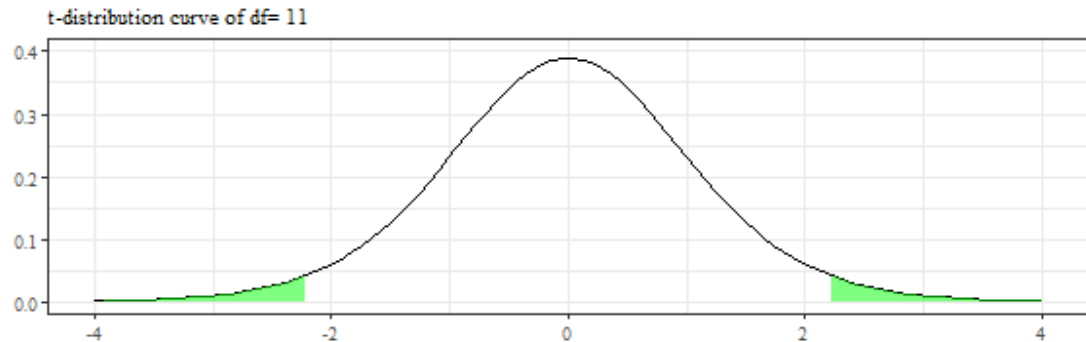
Alternative

P-value

CI method

Matched Pairs

Two-sample



We reject the null if $p\text{-value} < \alpha$.

Remember p-value and α are areas under the curve

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Example:[End-cut router]

Consider the operation of an end-cut router in the manufacture of a company's wood product. Both a leading-edge and a trailing-edge measurement were made on each wooden piece to come off the router.

Is the leading-edge measurement different from the trailing-edge measurement for a typical wood piece?

Do a hypothesis test at $\alpha = 0.05$ to find out. Make a two-sided 95% confidence interval for the true mean of the difference between the measurements.

piece	1.000	2.000	3.000	4.000	5.000
leading_edge	0.168	0.170	0.165	0.165	0.170
trailing_edge	0.169	0.168	0.168	0.168	0.169

Two-Sample Data

Hypothesis Testing

Two-sample data

Null

Paired differences provide inference methods of a special kind for comparison. Methods that can be used to compare two means where two different *unrelated* samples will be discussed next.

Alternative

P-value

CI method

Matched Pairs

Two-sample

SAT score of high school A vs. high school B

Severity of a disease in men vs. women

Height of Liverpool soccer players vs. Manchester United soccer players

Fuel economy of gas formula type A vs. formula type B

Hypothesis
Testing

Two-sample data

Null

Notations:

Alternative

P-value

CI method

Matched Pairs

Two-sample

Large Samples

Hypothesis Testing

Large samples ($n_1 \geq 25, n_2 \geq 25$)

The difference in sample means $\bar{x}_1 - \bar{x}_2$ is a natural statistic to use in comparing μ_1 and μ_2 .

Null

i.e

Alternative

$$E(\bar{X}_1) = \mu_1 \quad E(\bar{X}_2) = \mu_2 \quad \text{Var}(\bar{X}_1) = \frac{\sigma_1^2}{n_1} \quad \text{Var}(\bar{X}_2) = \frac{\sigma_2^2}{n_2}$$

P-value

If σ_1 and σ_2 are **known**, then we have

CI method

$$E(\bar{X}_1 - \bar{X}_2) = E(\bar{X}_1) - E(\bar{X}_2) = \mu_1 - \mu_2$$

Matched Pairs

$$\text{Var}(\bar{X}_1 - \bar{X}_2) = \text{Var}(\bar{X}_1) + \text{Var}(\bar{X}_2) = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$$

Two-sample

Hypothesis Testing

Large samples ($n_1 \geq 25, n_2 \geq 25$)

If, in addition, n_1 and n_2 are large,

Null

$\bar{X}_1 \sim N(\mu_1, \frac{\sigma_1^2}{n_1})$ is independent of $\bar{X}_2 \sim N(\mu_2, \frac{\sigma_2^2}{n_2})$ (by CLT).

Alternative

So that $\bar{X}_1 - \bar{X}_2$ is **approximately Normal** (trust me)

P-value

$$Z = \frac{\bar{X}_1 - \bar{X}_2 - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim N(0, 1)$$

CI method

Matched Pairs

Two-sample

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Large samples ($n_1 \geq 25, n_2 \geq 25$)

So, if we want to test $H_0 : \mu_1 - \mu_2 = \#$ with some alternative hypothesis, σ_1 and σ_2 are known, and $n_1 \geq 25, n_2 \geq 25$, then we use the statistic

$$K = \frac{\bar{X}_1 - \bar{X}_2 - (\#)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

which has a $N(0, 1)$ distribution if

1. H_0 is true
2. The sample 1 points are iid with mean μ_1 and variance σ_1^2 , and the sample 2 points are iid with mean μ_2 and variance σ_2^2 .
3. Sample I is independent of sample II

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Large samples ($n_1 \geq 25, n_2 \geq 25$)

The confidence intervals (2-sided, 1-sided upper, and 1-sided lower, respectively) for $\mu_1 - \mu_2$ are:

- *Two-sided* $100(1 - \alpha)\%$ confidence interval for $\mu_1 - \mu_2$

$$(\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha/2} * \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$$

- *One-sided* $100(1 - \alpha)\%$ confidence interval for $\mu_1 - \mu_2$ with a upper confidence bound

$$(-\infty, (\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha} * \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}})$$

- *One-sided* $100(1 - \alpha)\%$ confidence interval for μ with a lower confidence bound

$$((\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha} * \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}), +\infty)$$

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Large samples ($n_1 \geq 25, n_2 \geq 25$)

If σ_1 and σ_2 are **unknown**, and $n_1 \geq 25, n_2 \geq 25$, then we use the statistic

$$K = \frac{\bar{X}_1 - \bar{X}_2 - (\#)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

and confidence intervals (2-sided, 1-sided upper, and 1-sided lower, respectively) for $\mu_1 - \mu_2$:

- *Two-sided* $100(1 - \alpha)\%$ confidence interval for $\mu_1 - \mu_2$

$$(\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha/2} * \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Large samples ($n_1 \geq 25, n_2 \geq 25$)

- *One-sided* 100(1 - α)% confidence interval for $\mu_1 - \mu_2$ with a upper confidence bound

$$(-\infty, (\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha} * \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}})$$

- *One-sided* 100(1 - α)% confidence interval for μ with a lower confidence bound

$$((\bar{x}_1 - \bar{x}_2) \pm z_{1-\alpha} * \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}), +\infty)$$

Hypothesis Testing

Example:[Anchor bolts]

Null

An experiment carried out to study various characteristics of anchor bolts resulted in 78 observations on shear strength (kip) of 3/8-in. diameter bolts and 88 observations on strength of 1/2-in. diameter bolts.

Alternative

Let Sample 1 be the 1/2 in diameter bolts and Sample 2 be the 3/8 in diameter bolts.

P-value

Using a significance level of $\alpha = 0.01$, find out if the 1/2 in bolts are more than 2 kip stronger (in shear strength) than the 3/8 in bolts. Calculate and interpret the appropriate 99% confidence interval to support the analysis.

CI method

- $n_1 = 88, n_2 = 78$

Matched Pairs

- $\bar{x}_1 = 7.14, \bar{x}_2 = 4.25$

Two-sample

- $s_1 = 1.68, s_2 = 1.3$

Hypothesis
Testing

Example:[Anchor bolts]

- $n_1 = 88, n_2 = 78$
- $\bar{x}_1 = 7.14, \bar{x}_2 = 4.25$
- $s_1 = 1.68, s_2 = 1.3$

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Small Samples

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Small samples

If $n_1 < 25$ or $n_2 < 25$, then we need some **other assumptions** to hold in order to complete inference on two-sample data.

We need two independent samples to be iid
Normally distributed and $\sigma_1^2 \approx \sigma_2^2$

A test statistic to test $H_0 : \mu_1 - \mu_2 = \#$ against some alternative is

$$K = \frac{\bar{X}_1 - \bar{X}_2 - (\#)}{S_p \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

where S_p^2 is called **pooled sample variance** and is defined as

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

Hypothesis Testing

Small samples

Also assuming

Null

- H_0 is true,
- The sample 1 points are iid $N(\mu_1, \sigma_1^2)$, the sample 2 points are iid $N(\mu_2, \sigma_2^2)$,
- and the sample 1 points are independent of the sample 2 points and $\sigma_1^2 \approx \sigma_2^2$.

Alternative

P-value

Then

CI method

$$K = \frac{\bar{X}_1 - \bar{X}_2 - (\#)}{S_p \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \sim t_{(n_1+n_2-2)}$$

Matched Pairs

Two-sample

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Small samples

$1 - \alpha$ confidence intervals (2-sided, 1-sided upper, and 1-sided lower, respectively) for $\mu_1 - \mu_2$ under these assumptions are of the form:

(let $\nu = n_1 + n_2 - 2$)

- *Two-sided* $100(1 - \alpha)\%$ confidence interval for $\mu_1 - \mu_2$

$$(\bar{x}_1 - \bar{x}_2) \pm t_{(\nu, 1-\alpha/2)} * S_p \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$$

- *One-sided* $100(1 - \alpha)\%$ confidence interval for $\mu_1 - \mu_2$ with a upper confidence bound

$$(-\infty, (\bar{x}_1 - \bar{x}_2) + t_{(\nu, 1-\alpha)} * S_p \sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)})$$

Hypothesis Testing

Null

Alternative

P-value

CI method

Matched Pairs

Two-sample

Small samples

- *One-sided* $100(1 - \alpha)\%$ confidence interval for μ with a lower confidence bound

$$((\bar{x}_1 - \bar{x}_2) - t_{(\nu, 1-\alpha)} * S_p \sqrt{(\frac{1}{n_1} + \frac{1}{n_2})}, +\infty)$$

Hypothesis Testing

Small samples

Example:[Springs]

Null

The data of W. Armstrong on spring lifetimes (appearing in the book by Cox and Oakes) not only concern spring longevity at a 950 N/ mm² stress level but also longevity at a 900 N/ mm² stress level.

Alternative

P-value

Let sample 1 be the 900 N/ mm² stress group and sample 2 be the 950 N/ mm² stress group.

CI method

900 N/mm2 Stress	950 N/mm2 Stress
216, 162, 153, 216, 225, 216, 306, 225, 243, 189	225, 171, 198, 189, 189, 135, 162, 135, 117, 162

Matched Pairs

Two-sample

Hypothesis Testing

Small samples

Example:[Springs]

Null

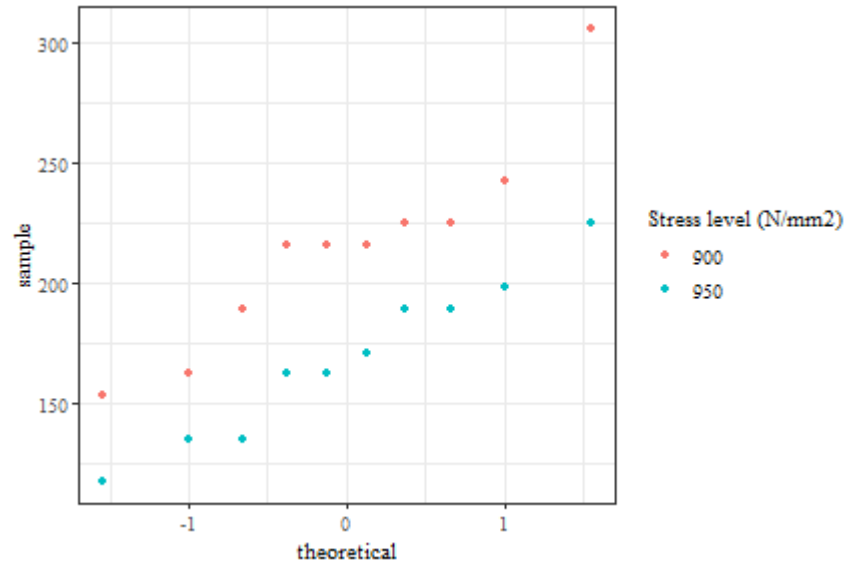
Alternative

P-value

CI method

Matched Pairs

Two-sample



Let's do a hypothesis test to see if the sample 1 springs lasted significantly longer than the sample 2 springs.

Hypothesis Testing

Small samples

Example:[Stopping distance]

Null

Suppose μ_1 and μ_2 are true mean stopping distances (in meters) at 50 mph for cars of a certain type equipped with two different types of breaking systems.

Alternative

Suppose $n_1 = n_2 = 6$, $\bar{x}_1 = 115.7$, $\bar{x}_2 = 129.3$, $s_1 = 5.08$, and $s_2 = 5.38$.

P-value

Use significance level $\alpha = 0.01$ to test $H_0 : \mu_1 - \mu_2 = -10$ vs. $H_A : \mu_1 - \mu_2 < -10$.

CI method

Construct a 2-sided 99% confidence interval for the true difference in stopping distances.

Matched Pairs

Two-sample