

Module 5: Introduction to Hypothesis Testing

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Research and Statistical Support

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Hypothesis Testing

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- The type of hypothesis testing done in much of the social sciences is called Null Hypothesis Significance Testing (NHST).

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 - Modern interpretation and use allows more precise specification.

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- Provides a basis for statistical testing.
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 - Provides the *first* piece of evidence for our empirical decisions.

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- But, theory can be *falsified* with more certainty.

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 - Therefore, we can use the standard normal distribution (Z-score distribution) as our comparison distribution.

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- Another way of saying this is: the Z-score, 1.64, represents the cutoff point between the lower 95% (or more precisely 94.95%) and the *top* 5% of scores.

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- Which is to say, evidence that he does not come from population 2, but instead he represents a different population, namely population 1.

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- To find the p value; look for 1.5 on the left and 0.03 on the top (of the table linked below) which corresponds to a Z-score of 1.53

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 - Thus, we have no evidence for population 1 and the idea that dogs on cartoons are smarter than dogs not on cartoons.
- Fail to reject the null hypothesis; we never say we *accept* the null or alternative hypothesis.

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- If it is less extreme than our stated critical p value (i.e., greater probability than .05), then we **fail to** reject the null hypothesis.
- We never accept either hypothesis, nor do we reject the alternative hypothesis. We either reject or fail to reject the null hypothesis.

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- If Z -crit is larger than Z -calc, we **fail to** reject because, it indicates our sample (population 1) is not extreme enough to differentiate it from population 2.
 - Interpretation: Population 1 is not significantly different from population 2 ($p > .05$); they are the same (or only population 2 exists).

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- A precise alternative hypothesis.
- We were not asking the question “is population 1 significantly **different** from population 2”, which is a more general, non-directional hypothesis and dictates a two-tailed test.

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- Because it is less specific; population 1 could be greater or less than population 2.

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 - Take .05 and split it; .025 at both ends = .05 as the critical level we generally use to determine statistical significance.

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- Directional Alternative Hypotheses

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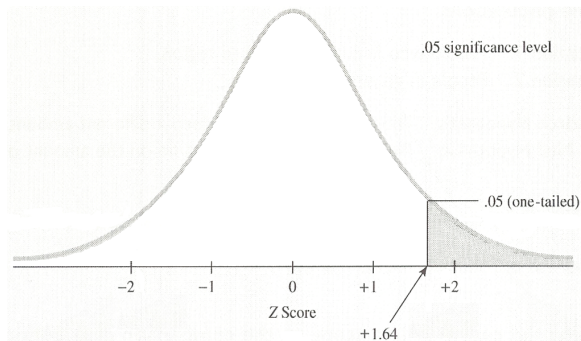
- Using $p = .05$ split in half, with one half ($p = .025$) at each end of the distribution.

Examples follow below.

Directional Alternative Hypothesis

Population 1 **greater** than population 2

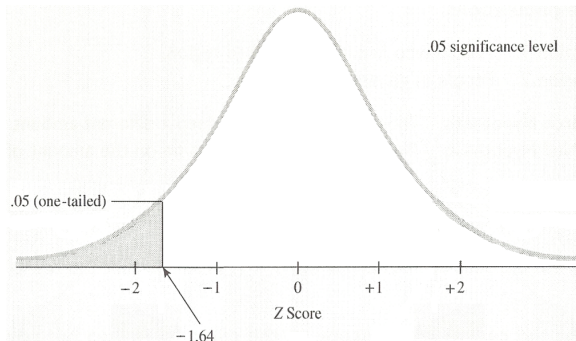
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Directional Alternative Hypothesis

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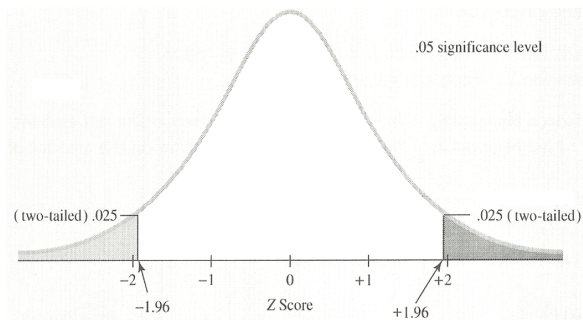
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Non-directional Alternative Hypothesis

Population 1 **different** than population 2

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 - Also called Beta error
 - Symbol: β

Decision Possibilities

		State of the World	
		H_0 true	H_0 false
Research Decision	Reject H_0	Type I error	Correct rejection
	Fail to reject H_0	Correct fail to reject	Type II error

More on Type I Error

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- This means, we are willing to run the risk of having a sample which is extreme enough (5% of the total population) to reject the null when the null is in fact true.
 - If Scooby's IQ was 160 but all the other cartoon dogs were especially dumb, we would reject the null when in fact there was no difference between the IQ of cartoon dogs (population 1) and the IQ dogs not in cartoons (population 2).

Type I Error continued

- The problem with Alpha is that we never know if we have committed the error, unless we fail to reject the null – in which case, we know for certain that we have not committed a Type I error.

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Type I Error continued

- The problem with Alpha is that we never know if we have committed the error, unless we fail to reject the null – in which case, we know for certain that we have not committed a Type I error.
 - But, we may have then committed a Type II error.
- If Scooby was especially dumb, but all the other cartoon dogs were especially bright, then we would have failed to reject the null, when in fact there was a significant difference in IQ between dogs in cartoons and dogs not in cartoons.

Decision Probabilities

		State of the World	
		H_0 true	H_0 false
Research Decision	Reject H_0	Type I $p = \alpha$	$p = 1 - \beta$ =Power
	Fail to reject H_0	$p = 1 - \alpha$	Type II $p = \beta$

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- The null is never true, strictly speaking.
 - There will always be some (numerical) difference between any two populations, so why do we use a 'null' hypothesis?
 - It provides a starting point; in later modules we will see that statistical significance is not "everything" and should not be the *only* thing we consider when making empirical decisions.

Concerns and Controversies continues on the next slide.

Concerns and Controversies continued

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Concerns and Controversies continued

- Most controversies come from mis-interpretation of or over-reliance on the p value.
 - It does not represent the probability of the Null hypothesis or the Alternative hypothesis.
 - Nor does it say anything about how likely your result is to replicate.
 - One study alone should never be used to make serious decisions; replication of findings across multiple samples must be done in order to have strong evidence for (and confidence in) research findings.

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All of these topics will be revisited consistently in future modules.

This concludes Module 5

Next time Module 6.

- Next time we'll begin covering Hypothesis Testing with means of Samples.
- Until next time; have a nice day.

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