



# UNIVERSITY OF LONDON

## Probability and Statistics: To $p$ , or not to $p$ ?

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### 5.2 Type I and Type II errors

In any hypothesis test there are two types of **inferential decision error** which could be committed.

Clearly, we would like to reduce the probabilities of these errors as much as possible. These two types of error are called a Type I error and a Type II error.

- **Type I error**: rejecting  $H_0$  when it is true. This can be thought of as a ‘false positive’. Denote the probability of this type of error by  $\alpha$ .
- **Type II error**: failing to reject  $H_0$  when it is false. This can be thought of as a ‘false negative’. Denote the probability of this type of error by  $\beta$ .

Both errors are undesirable and, depending on the context of the hypothesis test, it could be argued that either one is worse than the other.

However, on balance, a Type I error is usually considered to be more problematic.<sup>1</sup>

The possible **decision space** can be presented as:

		Decision made	
		$H_0$ not rejected	$H_0$ rejected
True state of nature	$H_0$ true	Correct decision	<b>Type I error</b>
	$H_1$ true	<b>Type II error</b>	Correct decision

For example, if  $H_0$  was being ‘not guilty’ and  $H_1$  was being ‘guilty’, a Type I error would be finding an innocent person guilty (bad for him/her), while a Type II error would be finding a guilty person innocent (bad for the victim/society, but admittedly good for him/her!).

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<sup>1</sup>Thinking back to trials by jury, conventional wisdom is that it is better to let 100 guilty people walk free than to convict a single innocent person. While you are welcome to disagree, this view is consistent with Type I errors being more problematic.

The complement of a Type II error, that is  $1 - \beta$ , is called the **power** of the test – the probability that the test will reject a false null hypothesis. Hence power measures the ability of the test to reject a false  $H_0$ , and so we seek the most powerful test for any testing situation.

Unlike  $\alpha$ , we do not control test power. However, we can increase it by increasing the sample size,  $n$  (a larger sample size will inevitably improve the accuracy of our statistical inference).

These concepts can be summarised as **conditional probabilities**.

	Decision	
	$H_0$ not rejected	$H_0$ rejected
$H_0$ true	$1 - \alpha$	$P(\text{Type I error}) = \alpha$
$H_1$ true	$P(\text{Type II error}) = \beta$	Power = $1 - \beta$

We have:

$$P(H_0 \text{ not rejected} | H_0 \text{ is true}) = 1 - \alpha$$

$$P(H_0 \text{ rejected} | H_0 \text{ is true}) = \alpha$$

$$P(H_0 \text{ not rejected} | H_1 \text{ is true}) = \beta$$

$$P(H_0 \text{ rejected} | H_1 \text{ is true}) = 1 - \beta.$$

Other things equal, if you decrease  $\alpha$  you increase  $\beta$  and vice-versa. Hence there is a trade-off.

## Significance level

Since we control for the probability of a Type I error,  $\alpha$ , what value should this be?

Well, in general we test at the  $100\alpha\%$  significance level, for  $\alpha \in [0, 1]$ . The default choice is  $\alpha = 0.05$ , i.e. we test at the 5% significance level. Of course, this value of  $\alpha$  is subjective, and a different significance level may be chosen. The severity of a Type I error in the context of a specific hypothesis test might for example justify a more conservative or liberal choice for  $\alpha$ .

In fact, noting our look at confidence intervals in Section 4.6, we could view the **significance level as the complement of the confidence level**.<sup>2</sup> For example:

- a 90% confidence level equates to a 10% significance level
- a 95% confidence level equates to a 5% significance level
- a 99% confidence level equates to a 1% significance level.

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<sup>2</sup>Strictly speaking, this would apply to so-called ‘two-tailed’ hypothesis tests.