Terminology Example p-hacking Summary

Lecture 7: Hypothesis testing part I Statistical Methods for Data Science

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Today

- Terminology
 - Experiment and parameter of interest
 - Null hypothesis and alternative hypothesis
 - Test statistic
 - Null distribution $f(s \mid H_0)$
 - ullet Significance level lpha, power and \emph{p} -value
- 2 Example
- p-hacking
- 4 Summary





Learning outcome

- Be able to explain the following terminology
 - Null hypothesis H_0 and alternative hypothesis H_A
 - Test statistic s
 - Null distribution $f(s \mid H_0)$
 - \bullet Significance level α and power
 - p-value
- Be able to design and interpret the one-sample z-test
- Be able to explain the concept of p-hacking





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- p-hacking



Example

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You need to help your chonker ducks lose weight. Which drug do you buy? Or should you just control their diet?

 If company A tested drug D on 30 ducks and the average weight loss after one month is 2.2 kg, would you buy drug D instead of regular diet control?





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- If company A tested drug D on 30 ducks and the average weight loss after one month is 2.2 kg, would you buy drug D instead of regular diet control?
- What if company A tested drug D on 30 ducks and the average weight loss after one month is 2.3 kg? Would you buy drug D instead of regular diet control in this case?





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- What if company A tested drug D on 100 ducks and the average weight loss after one month is 2.3 kg?





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- What if company A tested drug D on 100 ducks and the average weight loss after one month is 2.3 kg?
- Now company B tested drug E on 30 ducks and the average weight loss after one month is 2.5 kg, while drug D results in 2.3 kg weight loss with the same setup, would you buy drug E instead of drug D?





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How would you make your decision?





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 Hypothesis: a hypothesis is a proposed explanation for a phenomenon (wikipedia)





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 - $\bullet \ \, \mathsf{Hypothesis} + \mathsf{data} \to \mathsf{decision} \ \mathsf{on} \ \mathsf{rejecting/not} \ \mathsf{rejecting} \ \mathsf{the} \ \mathsf{hypothesis}$





Hypothesis testing: a list to go through

- A "boring" statement
- Experiment
- Data x, random variable X
- ullet Parameter of interest heta
- Parameter estimate $\hat{\theta}$
- Null hypothesis H_0
- Alternative hypothesis H_A
- Test statistic s
- Null distribution $f(s \mid H_0)$
- Significance level α
- p-value





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Experiment and parameter of interest





Experiment design

 Before formulating the statistical hypothesis, we need a "boring" statement: a claim that we would like to test against, e.g. drug D is not more effective than regular diet on average; drug E works the same as drug D on average



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Then we can use \bar{x} to approximate μ_D and check if it is greater than diet control (2.1 kg)





Experiment design (cont.)

- Example 2:
 - A "boring" statement: drug E and drug D work the same on average



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Then we use \bar{x} and \bar{y} to approximate μ_D and μ_E to see if they are the same





Experiment design (cont.)

 We make our decision by observing data; if the evidence does not support the "boring" statement, we reject the statement; otherwise, we do not reject the statement



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 a statement by showing counterexamples
- The logic here is: if a statement is true, then the evidence should support the statement

 if the evidence does not support the statement, the statement is considered false

 if the evidence supports the statement, the statement must be true



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Null hypothesis and alternative hypothesis





Hypotheses H_0 and H_A

Statistical hypothesis: a proposed distribution





Hypotheses H_0 and H_A

 Statistical hypothesis: a proposed distribution - a statement about the parameter of interest





Hypotheses $\overline{H_0}$ and $\overline{H_A}$

- Statistical hypothesis: a proposed distribution a statement about the parameter of interest
- \bullet Null hypothesis H_0 : the "boring" statement translated into a mathematical expression





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 - Example 1: drug D is not more effective than regular diet on average

$$H_0$$
: μ_D = 2.1



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• Example 2: drug E and drug D work the same on average (5 sec)



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 Alternative hypothesis H_A: a complementary alternative explanation to the "boring" statement



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 - Example 1: drug D is not more effective than regular diet on average

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 - Example 1: drug D is more effective than regular diet on average (5 sec)

$$H_A: \mu_D > 2.1$$

• Example 2: drug E and drug D do not work the same on average (5 sec)







Questions:

• Question 1: why are H_A : $\mu_D > 2.1$ and H_0 : $\mu_D = 2.1$ complementary to each other? What about H_A : $\mu_D < 2.1$?





Hypotheses H_0 and H_A (cont.)

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 Answer: no





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- Answer: an implicit assumption here is that μ_D will not be smaller than 2.1
- Question 2: can H_0 and H_A be ANYTHING I want? Like a magic mirror!? Answer: no
- Follow up question: what are the choices for H_0 and H_A ?





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For example, is a binary classifier more accurate than random?





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For example, is a binary classifier more accurate than random? $H_0: p = 50\%$



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- Null hypothesis H_0 : two cases
 - One-sample test: to test a data distribution against a theoretical probability distribution, i.e. for a given constant c

$$H_0: \theta = c$$

For example, is a binary classifier more accurate than random? $H_0: p = 50\%$

 Two-sample test: to test a data distribution against another data distribution, i.e.

$$H_0: \theta_1 = \theta_2$$

For example, is classifier A better than classifier B?





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For example, is classifier A better than classifier B? $H_0: p_A = p_B$

- We have seen one-sample test and two-sample test in the Q-Q plot lecture
- In practice, you can narrow down your choice of hypotheses by making a Q-Q plot





Choices for H_A

Given

$$H_0: \theta = \beta$$

where β can be either a constant (one-sample test) or a parameter from another data distribution (two-sample test)

- Alternative hypothesis H_A : H_A can be one-tailed or two-tailed
 - One-tailed:

$$H_A: \theta > \beta$$

or

$$H_A: \theta < \beta$$

Two-tailed:

$$H_A: \theta \neq \beta \iff \theta < \beta \text{ or } \theta > \beta$$





Summary: choices for H_0 and H_A

Putting everything together,

	One-sample test	Two-sample test
Two-tailed	$H_0: \theta = c, H_A: \theta \neq c$	$H_0: \theta_1 = \theta_2, H_A: \theta_1 \neq \theta_2$
One-tailed	$H_0: \theta = c, H_A: \theta > c$	$H_0: \theta_1 = \theta_2, H_A: \theta_1 > \theta_2$
	$H_0: \theta = c, H_A: \theta < c$	$H_0: \theta_1 = \theta_2, H_A: \theta_1 < \theta_2$

where θ , θ_1 , θ_2 are the parameters of interest and c is a constant





Terminology Example p-hacking Summary Experiment and parameter of interest Null hypothesis and alternative hypothesi **Test statistic**Null distribution $f(s \mid H_0)$ Significance level α , power and p-value





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Note: in this course, we only deal with null hypothesis where we are able to express the PDF/PMF $f(s \mid H_0)$, i.e. H_0 with an equal sign in them





Experiment and parameter of interest Null hypothesis and alternative hypothesi **Test statistic**Null distribution $f(s \mid H_0)$ Significance level α , power and p-value

Test statistic (cont.)

- Data: x_1, \dots, x_N
- Random variable: X_1, \dots, X_N i.i.d. Gaussian with known σ
- Parameter of interest: μ_D
- Parameter estimate: \bar{x}
- Null hypothesis: $H_0: \mu_D = 2.1$
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 - Recall: what is standardization?



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- Data: x_1, \dots, x_N
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- Parameter of interest: μ_D
- Parameter estimate: x̄
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- Test statistic: standardized \bar{x} assuming the null hypothesis
 - Recall: what is standardization?
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 - Data x: y = ^{x-μχ}/_{σx}
 - Recall: what are we trying to do? Decide how likely data follows the distribution described by the null hypothesis?



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Example 1. one-sample test

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Standardize \bar{x} (15 sec)





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Standardize \bar{x} (15 sec)

$$z = \frac{\bar{x} - 2.1}{\sigma / \sqrt{N}}$$





Example 2. two-sample test

- Data: x_1, \dots, x_{N_D} and y_1, \dots, y_{N_E}
- Random variable: X_1, \dots, X_{N_D} i.i.d. Gaussian with known σ_D ; Y_1, \dots, Y_{N_E} i.i.d. Gaussian with known σ_E ; X_i and Y_j independent
- Parameter of interest: μ_D , μ_E
- Parameter estimate: \bar{x} , \bar{y}
- Null hypothesis: $H_0: \mu_D = \mu_E \iff H_0: \mu_D \mu_E = 0$
- Test statistic: standardized $\bar{x} \bar{y}$ assuming the null hypothesis

$$z = \frac{\bar{x} - \bar{y}}{\sqrt{\sigma_D^2/N_D + \sigma_E^2/N_E}} \text{ (explained later)}$$



Terminology Example p-hacking Summary Experiment and parameter of interest Null hypothesis and alternative hypothesis Test statistic

Null distribution $f(s \mid H_0)$ Significance level α , power and p-value

Null distribution $f(s \mid H_0)$





Null distribution

- Null distribution $f(s \mid H_0)$: the distribution of the test statistic given the null hypothesis
- Example:
 - Data: x_1, \dots, x_N
 - Random variable: X_1, \dots, X_N i.i.d. Gaussian with known σ
 - Parameter of interest: μ
 - Parameter estimate: \bar{x}
 - Null hypothesis: $H_0: \mu = \mu_0$
 - Test statistic:

$$z = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{N}}$$

• Null distribution: standard Gaussian distribution



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Significance level α , power and p-value



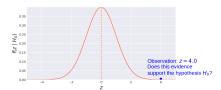


Significance level

Given a null hypothesis $H_0: \mu=2.1$ and the null distribution $f(s\mid H_0)$, we decide if we reject the hypothesis or not by observing data

- Run some experiments and collect data x_1, \dots, x_N
- Estimate the parameter of interest $\hat{\theta}$, e.g. $\hat{\mu} = \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$
- Standardize $\hat{\theta}$ assuming H_0 to compute the test statistic, e.g.

$$z = \frac{\bar{x} - 2.1}{\sigma / \sqrt{N}} = 4.0$$



• Does this evidence support the hypothesis H_0 ?



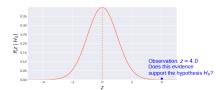


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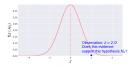


• Does this evidence support the hypothesis H_0 ? Probably not since it's so far away from the center?



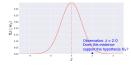


• What about this observation?





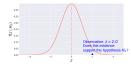
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• To be able to answer the question, you need to decide where you draw the line



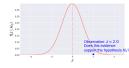
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 To be able to answer the question, you need to decide where you draw the line - define a rejection region by choosing a significance level



• What about this observation?



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- Significance level α : red area under the curve

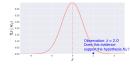


In these three images, $\alpha = 0.05$





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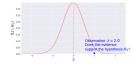
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More conservative \Rightarrow less probable to reject H_0 , which indicates a smaller rejection region

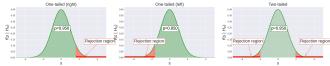




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More conservative \Rightarrow less probable to reject H_0 , which indicates a smaller rejection region Two-tailed H_A is more conservative





Experiment and parameter of interest Null hypothesis and alternative hypothes Test statistic Null distribution $f(s \mid H_0)$ Significance level α , power and p-value

Significance level (cont.)

What is needed for choosing a meaningful α ?

- Null distribution
- H_A one-tailed or two-tailed

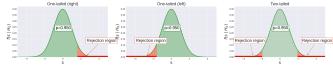




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Interpretation of lpha

ullet $\alpha = P(\textit{reject H}_0 \mid \textit{H}_0 \; \textit{is true})$ - the probability of making such a mistake



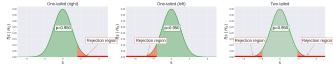
- The rejection region indicates that H_0 is **unlikely**, but the probability is not zero
- It is possible that H₀ is true, but our observation happens to fall in the rejection region
- If H₀ is true and our observation falls in the rejection region, we will mistakenly reject H₀
- ullet The probability of making this type of mistakes is lpha
- ullet Similar to the confidence interval, 1-lpha is called the **confidence level**





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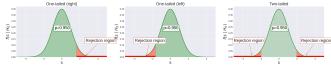
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Interpretation of α

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- Similar to the confidence interval, $1-\alpha$ is called the confidence level "with 95% confidence, rejecting H_0 is the right thing to do"
- Define the significance level before you run the experiments so that you can't cheat!





Experiment and parameter of interest Null hypothesis and alternative hypothesi Test statistic Null distribution $f(s \mid H_0)$ Significance level α , power and p-value

Significance level and power

• Contingency table:

	$y = H_A$	$y = H_0$
$\hat{y} = \text{reject } H_0$	TP	FP (Type I error)
$\hat{y} = \text{do not reject } H_0$	FN (Type II error)	TN





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• Significance level α : incorrectly rejecting H_0

$$\alpha = P(\mathsf{type}\;\mathsf{I}\;\mathsf{error})$$



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• Significance level α : incorrectly rejecting H_0

$$\alpha = P({\rm type\ I\ error})$$

Power: correctly rejecting H₀

$$\mathsf{power} = P(\mathsf{reject}\ \textit{H}_0 \mid \textit{H}_\textit{A}) = 1 - P(\mathsf{type}\ \mathsf{II}\ \mathsf{error})$$

Contingency table:

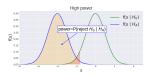
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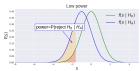
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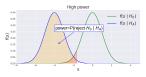
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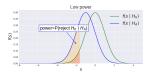
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• What is needed for computing the power?





Contingency table:

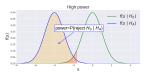
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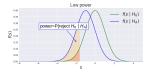
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$$\alpha = P(\text{type I error})$$

Power: correctly rejecting H₀

power =
$$P(\text{reject } H_0 \mid H_A) = 1 - P(\text{type II error})$$





• What is needed for computing the power? $f(s \mid H_0)$, $f(s \mid H_A)$

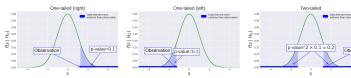




p-value

- p-value:
 - One-tailed:
 - Right tail: $p = P(S \ge s \mid H_0)$
 - Left tail: $p = P(S \le s \mid H_0)$
 - Two-tailed: $p = 2 \min (P(S \le s \mid H_0), P(S \ge s \mid H_0))$ Note: for example, if $f(s \mid H_0)$ is symmetric around zero and s < 0,

$$p = 2P(S \leq s \mid H_0)$$



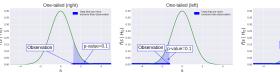
• What is needed for computing the p-value? (10 sec)

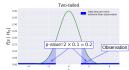
Observation

p-value

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- What is needed for computing the p-value? (10 sec)
 - Null distribution
 - \bullet Alternative hypothesis H_A to know one-tailed or two-tailed
 - Observation test statistic computed from data





Experiment and parameter of interest Null hypothesis and alternative hypothes Test statistic Null distribution $f(s \mid H_0)$ Significance level α , power and p-value

Summary: steps for hypothesis testing

- Step 1 Make a "boring" statement
- Step 2 Design an experiment
- Step 3 Describe the data generated from the experiment and the corresponding random variables
- Step 4 Describe the parameter of interest and their estimates
- Step 5 Translate the "boring" statement into a statistical hypothesis and call it the null hypothesis H_0
- Step 6 Find the expression for the **test statistic** *s*
- Step 7 Find the expression for the null distribution
- Step 8 Define an alternative hypothesis H_A : one-tailed or two-tailed
- Step 9 Choose a significance level α (the tail), which defines the rejection region
- Step 10 Collect data
- Step 11 Compute the test statistic from data
- Step 12 Compute the *p*-value
- Step 13 If p-value< α , i.e. the test statistic falls in the rejection region of the null distribution, then we reject the hypothesis H_0 ; otherwise, we fail to reject H_0 .





Today

- Terminology
- 2 Example
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$$z_0 = \frac{2.2 - 2.1}{0.6/\sqrt{30}} = 0.91$$









Step 12 Compute the *p*-value (20 secs):

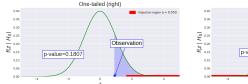
• For $H_A: \mu_D > 2.1$ (one-tailed): $p = P(Z \ge z_0 \mid H_0) = 0.1807 > \alpha$

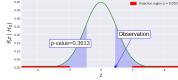


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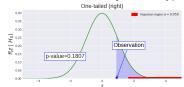


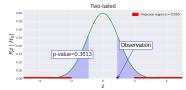
Two-tailed

Do not reject H_0 for both one-tailed and two-tailed H_A



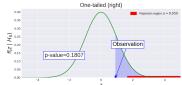
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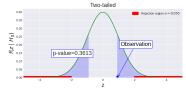




Do not reject H_0 for both one-tailed and two-tailed H_A What does it mean?

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Do not reject H_0 for both one-tailed and two-tailed H_A What does it mean? - Based on this test, you will stick to diet control instead of buying drug D.

What if $\bar{x} = 2.3$?





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- For $H_A: \mu_D \neq 2.1$ (two-tailed): $p = 2P(Z \geq z_0 \mid H_0) = 0.0679 > \alpha$

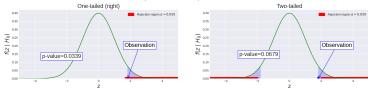
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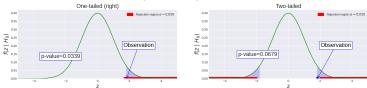
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Reject H_0 for one-tailed H_A ; do not reject H_0 for two-tailed H_A for the same confidence level $1 - \alpha = 5\%$



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Note: the two-tailed test is more conservative - if the data passes a two-tailed test, it is more conclusive than one-tailed test for the same confidence level





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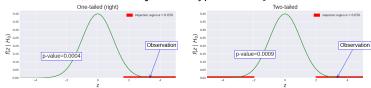
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- For $H_A: \mu_D > 2.1$ (one-tailed): $p = P(Z \ge z_0 \mid H_0) = 0.0004 < \alpha$
- For $H_A: \mu_D \neq 2.1$ (two-tailed): $p = 2P(Z \geq z_0 \mid H_0) = 0.0009 < \alpha$

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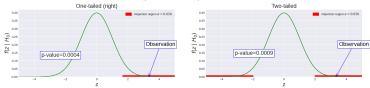
Reject H_0 for both one-tailed and two-tailed H_A

Note:

• With more data, it becomes more certain that we should reject H_0 in favor of H_A given the observation $\bar{x} = 2.3$



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This test is called **one-sample z-test**





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• p-value indicates how "surprising" the observation is

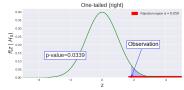


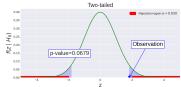


- p-value indicates how "surprising" the observation is
- "Surprising" observation usually means potential novelty



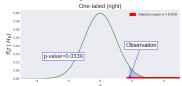
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- "Surprising" observation usually means potential novelty
- In one of the examples, we have shown that we reject the null hypothesis for the one-tailed test and we fail to reject the null hypothesis for the two-tailed test given the same significance level

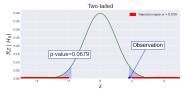






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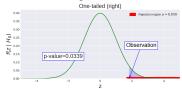


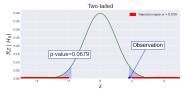


 In this example, if we use the two-tailed test, we will not claim that we have observed potential novelty with the experiment, whereas if we use the one-tailed test, we claim that we do observe potential novelty



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- In this example, if we use the two-tailed test, we will not claim that we have observed potential novelty with the experiment, whereas if we use the one-tailed test, we claim that we do observe potential novelty
- The conclusion we draw depends on which test we conduct





Variation of the p-value

• p-value is computed from data





Variation of the p-value

- p-value is computed from data
- Data is random p-value is random



Variation of the p-value

- p-value is computed from data
- Data is random p-value is random
- With the same experiment set up, if we switch to a different sample, p-value will be different



p-hacking

- Many factors can result in a different p-value
- p-hacking refers to situations where researchers are trying multiple things until they get the desired result
- This action can be a conscious decision, a subconscious decision or even an unconscious action
- p-hacking can be tricky to identify
- Suggestions to avoid p-hacking, e.g. one should always report effect sizes and confidence intervals
- Reference:
 - https://www.nature.com/news/ scientific-method-statistical-errors-1.14700
 - Why Most Published Research Findings Are False?













What should I do!?

• Be honest and explicit about your assumptions





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- Be "conservative"



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- Be skeptical about your result don't let go of any doubt!





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- Be skeptical about your result don't let go of any doubt!
- Assume the first success is always too good to be true try to prove yourself wrong - be a proper scientist



Today

- Terminology
- 2 Example
- p-hacking
- 4 Summary





Summary

So far:

- Data types and data containers
- Descriptive data analysis: descriptive statistics, visualization
- Probability distributions, events, random variables, PMF, PDF, parameters
- CDF, Q-Q plot, how to compare two distributions (data vs theoretical, data vs data)
- Modeling
- Parameter estimation: maximum likelihood estimation (MLE) and maximum a posteriori estimation (MAP)
- Classification, multinomial naive Bayes classifier, Gaussian naive Bayes classifier
- Central limit theorem, interval estimation
- Hypothesis test





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• More examples, test statistics; comparison of two classifiers





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More examples, test statistics; comparison of two classifiers

Before next lecture:

Steps for hypothesis testing



