

Experiment Design Revisited

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Before we Begin

- Go to the github repo:
 - □ https://github.com/Mollinetti/Statistics-R
- Download the script for this class! (in the 'scripts' folder, class_3_5.r!)
- Run the first lines to load/install the required libraries

Agenda

- Experiment Design
 - □ Factorial Design
 - □ Full factorial x Partial
- Review: The medicine experiment

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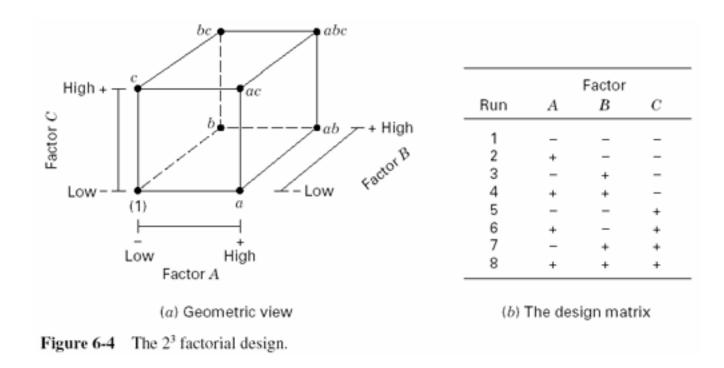


- From the previous lectures, we know have the competence to design "simple" experiments
- Simple, we mean with one variable that follows normality (for now)
- Remember: Before anything, begin with the RESEARCH QUESTION

- THE P-VALUE DOES NOT PROVE/DISPROVE ANYTHING
- If the experiment does not turn the way you want, blame the design/research question, but do not blame the p-value.

- Experiment Design
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An experiment has Factors and Levels





- Factor: Category of a variable
- Levels: Degrees of variations of the factors
- Example: Heart Dataset
 - Sex is a factor, male/female are levels
 - □ Cp is a factor, none/mild/medium/acute are levels



- Most processes can be described in terms of several controllable variables, Experimenters can determine which subset of the process variables has the greatest influence on process performance. Results of such an experiment can lead to:
 - Improved process yield
 - Reduced variability in the process and closer conformance to nominal or target requirements
 - 3. Reduced design and development time
 - 4. Reduced cost of operation
 - 5. Ease of reproducibility

- For categorical variables it is easy to define levels
- For numerical variables, a interval of fixed values (bins) is the recommended approach
 - Ex: values ranging from 0 to 1 we discretize into 4 bins

- Experiments involves permutation of levels and factors
- Bounded by 2ⁿ permutations (very easy to explode!)
- One has to carefully define the levels and factors of their experiments

- Experiment Design
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- Full factorial design: explore all possible permutations of levels and factors
 - Able to explore any and every interaction
 - However, it is restricted to a small number of factors/levels
- Fractional design: some levels have fixed values
 - □ Explore only desired permutations
 - □ Does not explore all the possibilities



- Example: "We want to test the effects of a new medicine on people ranging from 18 to 60 years old"
 - ☐ How many factors?
 - How many levels for each factor?
 - □ Should we go for partial or full-factorial?

- Experiment Design
 - □ Factorial Design
 - □ Full factorial x Partial
- Review: The medicine experiment

- Time to put all of our knowledge so far in practice!
- Let's do the following experiment:
 - "Suppose you want to test the effects of a new medicine that helps people with symptoms of insomnia. There are three groups: Control, Test and Placebo. Variable measured is the mean amount of sleep for fixed days. Suppose you have a stringent constraint on budget and measurements takes a copious amount of labor, so mistakes are not allowed. You are allowed to conduct a pilot study with 6 candidates before the main experiment."

- We will use the "sleep_exp_pilot.csv" dataset for the pilot study
- For the main experiment we will use the "sleep_exp_main.csv" dataset
- Slides with the R symbol at the corner: refer to the R code!



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- Verify whether the sleep medicine has any effect on the target population
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- Verify whether the sleep medicine has any effect on the target population
- Placebo is considered to account for bias!
- Now, let's go for our SEVEN STEPS

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired α and β
- 4. Determine the test statistic and critical region
- 5. Calculate sample size
- 6. Calculate statistic
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest mean of populations
- 2. Define your H_0 and H_1
- 3. Determine desired α and β
- 4. Determine the test statistic and critical region
- 5. Calculate sample size
- Calculate statistic
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1 H_0 : same mean H_1 : not the same mean (two-sided)
- 3. Determine desired α and β
- 4. Determine the test statistic and critical region
- 5. Calculate sample size
- 6. Calculate statistic
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired α and β standard 95% and 85%
- 4. Determine the test statistic and critical region
- 5. Calculate sample size
- 6. Calculate statistic
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired α and β
- Determine the test statistic and critical region
 t-test + validations
- 5. Calculate sample size
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- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired lpha and eta
- Determine the test statistic and critical region
- 5. Calculate sample size Power-t-test for the pilot study (z-test)
- 6. Calculate statistic
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired α and β
- Determine the test statistic and critical region
- 5. Calculate sample size
- 6. Calculate statistic p-values and means
- 7. Decide whether or not to reject H_0

- 1. Identify the parameter of interest
- 2. Define your H_0 and H_1
- 3. Determine desired α and β
- Determine the test statistic and critical region
- 5. Calculate sample size
- 6. Calculate statistic
- 7. Decide whether or not to reject H_0 based on the t-test+ validation



- We know that the expected mean value of a healthy person is 7 hours.
- Our minimal observable difference value δ^* is 1 hour





- Let's start by step 4: calculating power and the ideal sample size.
- Run the power-t-test for the pilot experiment example and for the desired power



- Having decided our ideal sample size n, we conducted measurements with n samples
- Open the "sleep_exp_main.csv"
- Let's validate our data, for every column test:
 - □ Normality qq-plot + shapiro-wilk
 - ☐ Heteroscedascity fligner-kileen + residuals scatterplot
 - ☐ Independence* Durbin-watson



- Now, let's decide whether we will do a paired or a pooled t-test
- Let's verify the correlation and covariance of each column
- Do we need to reduce the noise of the test?
- Was each observation obtained homogeneously?
- Based on that we make our choice and run the test

- For each test, what was the p-value?
- What can be said about H_0 ?
- What can we concur about the results? Is the medicine effective? How so?





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