

## Experiments Design and Analysis

Fotis E. Psomopoulos

(cc

CODATA-RDA Advanced Bioinformatics Workshop, 19-23 August 2019, Trieste, Italy



2

### A short intro ... to me 🙂

Get rights and content

**Bioinformatics** 

#### earch paper

*De novo* comparative transcriptome analysis of genes involved in fruit morphology of pumpkin cultivars with extreme size difference and development of EST-SSR markers

Aliki Xanthopoulou<sup>a, b</sup>, Ioannis Ganopoulos<sup>6</sup>, Fotis Psomopoulos<sup>6</sup>, Maria Manio<sup>,</sup> Jaki<sup>6</sup>, Theodoros Moysiadis<sup>a</sup>, Aliki Kapazoglou<sup>a</sup>, Maslin Osathanunkul<sup>e</sup>, Sofia Michailidou<sup>a</sup>, Apostolos Kalivas<sup>4</sup>, B **Show more** 

https://doi.org/10.1016/j.gene.2017.04.035



Cloud

Computing

Bioinformatics and Data Mining

- tools and pipelines to address domain-specific questions
- genome-aware methods
- Bioinformatics and Cloud Computing
  - workflows and pipelines on cloud infrastructures
  - standardization and reusability

Front. G .net., 23 June 2015 | http://dx.doi.org/10.3389/fgene.2015.00193

PERSPEC /IVE ARTICLE

Future opportunities and trends for einfrastructures and life sciences: going beyond the grid to enable life science data analysis

🚰 Afonso M. S. Duarte<sup>14</sup>, 🚰 Fotis E. Psomopoulos<sup>2,34</sup>, 🔔 Christophe Blanchet<sup>4</sup>, 🚱 Alexandre M. J. J. Bonvin<sup>5</sup>, 📓 Manuel Corpas<sup>5</sup>, ి Alain Franc<sup>7</sup>, 🞆 Rafael C. Jimenez<sup>8</sup>, 🛓 Jesus M. de Lucas<sup>9</sup>, இ Tommi Nyrönen<sup>10</sup>, L Gergely Sipos<sup>11</sup> and 🔔 Stephanie B. Suhr<sup>12</sup>

Monday, August 19th 2018

Data Mining

Journal of Big Data

Data-aware optimization of bioinformatics workflows in hybrid clouds

Authors Authors and affiliations

Athanassios M. Kintsakis 🖂 , Fotis E. Psomopoulos, Pericles A. Mitkas

Experiment Design and Analysis

### Bioinformatics Group @ INAB | CERTH



3

Training

NGS Data Analysis using Cloud Computing (Oct 2015)



Experiment Design and Analysis

#### Research

- NGS Workflows
- Omics Data Integration
- Data Mining

1<sup>st</sup> Software Carpentry Workshop (Oct 2016)





 $\succ$ 

 $\succ$ 

Maria Kotouza, PhD Student

Maria Tsayopoulou, PhD Student







CERTH Main Building

Monday, August 19th 2018



elixir



Experiment Design and Analysis



### What is an experiment?

An experiment is characterized by the **treatments** and **experimental units** to be used, the way treatments are **assigned** to units, and the **responses** that are measured.

- Experiments allow us to set up a <u>direct comparison</u> between the treatments of interest.
- 2. We can design experiments to minimize any bias in the comparison.
- 3. We can design experiments so that the error in the comparison is small.
- 4. Most important, we are in control of experiments, and having that control allows us to make stronger inferences about the nature of differences that we see in the experiment. Specifically, we may make <u>inferences about</u> <u>causation</u>.

CODATA INR3

5

#### CODATA INAS

6

### **Components of an Experiment**

Treatments, units, and assignment method specify the experimental design

- An alternative definition is:
  - "treatment design" is the selection of treatments to be used
  - "experiment design" is the selection of units and assignment of treatments
- Note that there is no mention of a method for analyzing the results.
  - analysis is **not** part of the design
  - However: it is often useful to consider the analysis when planning an experiment.





### Why Think About Experimental Design?



Experiment Design and Analysis

### Crisis in Reproducible Research

Retracted publications by year of Entrez record creation



Experiment Design and Analysis

CODATA INRS

elixir

۲

RDA

8

http://neilfws.github.io/PubMed/pmretract/pmretract.html

# Consequences of Poor Experimental Design...

- Cost of experimentation.
  We have a responsibility to donors!
- Limited & Precious material esp. clinical samples.
- Immortalization of data sets in public databases and methods in the literature. Our bad science begets more bad science.
- Ethical concerns of experimentation: animals and clinical samples.

Slides adapted from "Designing Functional Genomics Experiments for Successful Analysis", by Rory Stark, 18/09/2017, CRUK-CI



CODATA INRS



### A good experiment design

Not all experimental designs are created equal!

- A good experimental design must
  - 1. Avoid systematic error
  - 2. Be precise

CODATA INAS

eli

11

- 3. Allow estimation of error
- 4. Have broad validity
- Let's see these aspects one at a time!

Slides adapted from Gary W. Oehlert, "A First Course in Design and Analysis of Experiments", 2010 - ISBN 0-7167-3510-5

### 1. Design to avoid systematic error

- Comparative experiments estimate differences in response between treatments.
- If an experiment has systematic error, then the comparisons will be biased, no matter how precise our measurements are or how many experimental units we use.

If responses for units receiving **treatment one** are measured with **instrument A** and responses for **treatment two** are measured with **instrument B**,

then we don't know if any observed differences are due to treatment effects or instrument miscalibrations.

CODATA INAS

12



CODATA INAS

13

### 2. Design to increase precision

- Even without systematic error, there will be random error in the responses, and this will lead to random error in the treatment comparisons.
- Experiments are precise when this random error in treatment comparisons is small.
- Precision depends on the size of the random errors in the responses, the number of units used, and the experimental design used.

### 14

eli

CODATA INAS

### 3. Design to estimate error

- Experiments must be designed so that we have an estimate of the size of random error.
- This permits statistical inference:

We will see those in practice later.

- for example, confidence intervals or tests of significance.
- We cannot do inference without an estimate of error! Sadly, experiments that cannot estimate error continue to be run.

Experiment Design and Analysis

## 4. Design to widen validity

- The conclusions we draw from an experiment are <u>applicable to the</u> <u>experimental units we used in the experiment</u>.
- If the units are actually a statistical sample from some population of units, then the conclusions are also valid for the population.
- Beyond this, we are extrapolating, and the extrapolation might or might not be successful.

We compare two different drugs for treating attention deficit disorder and our subjects are **pre-adolescent boys** from **our clinic**.

- We <u>might</u> have a fair case that our results would hold for <u>pre-adolescent boys elsewhere</u>, but even that might not be true if our clinic's population of subjects is unusual in some way.
- The results are even less compelling for older boys or for girls.

CODATA INAS



### Keeping a common vocabulary

1. Treatments

CODATA INAS

elixir

() BY **RDA** 

- 2. Experimental units
- 3. Responses
- 4. Measurement units
- 5. Randomization
- 6. Control
- 7. Factors
- 8. Confounding
- 9. Experimental Error
- 10. Blinding

### Terms and concepts (1/5)

- 1. Treatments are the different procedures we want to compare.
  - different kinds or amounts of fertilizer in agronomy
  - different long distance rate structures in marketing
  - different temperatures in a reactor vessel in chemical engineering
- 2. Experimental units are the things to which we apply the treatments.
  - plots of land receiving fertilizer
  - groups of customers receiving different rate structures
  - batches of feedstock processing at different temperatures



🕾 CODATA INR3

17

### Terms and concepts (2/5)

- 3. **Responses** are <u>outcomes that we observe</u> after applying a treatment to an experimental unit (a measure of what happened in the experiment; we often have more than one response)
  - nitrogen content or biomass of corn plants
  - profit by customer group
  - yield and quality of the product per ton of raw material
- 4. **Measurement units** (or response units) are the actual objects on which the response is measured. These may differ from the experimental units.
  - (e.g. in different fertilizers on the nitrogen content of corn plants) Different field plots are the experimental units, but the measurement units might be a subset of the corn plants on the field plot, or a sample of leaves, stalks, and roots from the field plot.

CODATA INR3



### Terms and concepts (3/5)

- 5. Randomization is the use of a known, understood probabilistic mechanism for the assignment of treatments to units.
  - Other aspects of an experiment can also be randomized: for example, the order in which units are evaluated for their responses.
- 6. Control has several different uses in design.
  - An experiment is <u>controlled</u> because we as experimenters assign treatments to experimental units. Otherwise, we would have an observational study.
  - A <u>control treatment</u> is a "standard" treatment that is used as a baseline or basis of comparison for the other treatments.
    - This control treatment might be the treatment in common use, or it might be a null treatment (no treatment at all).
    - e.g. a study on the efficacy of fertilizer could give some fields no fertilizer at all.



19

CODATA INA3

### Terms and concepts (4/5)

#### 7. Factors combine to form treatments.

- The baking treatment for a cake involves a given time at a given temperature. The treatment is the combination of time and temperature, but we can vary the time and temperature separately. Thus we speak of a time factor and a temperature factor.
- Individual settings for each factor are called <u>levels of the factor</u>.
- 8. **Confounding** occurs when the effect of one factor or treatment cannot be distinguished from that of another factor or treatment.
  - Except in very special circumstances, <u>confounding should be avoided</u>.
  - e.g. planting corn variety A in Minnesota and corn variety B in Iowa. In this experiment, we cannot distinguish location effects from variety effects—the variety factor and the location factor are confounded.

🕾 codata INR3

20

### Terms and concepts (5/5)

#### 9. Experimental Error is the random variation present in all experimental results.

- Different experimental units will give different responses to the same treatment, and it is often true that applying the same treatment over and over again to the same unit will result in different responses in different trials.
- Experimental error does not refer to conducting the wrong experiment or dropping test tubes.
- **10. Blinding** occurs when the evaluators of a response do not know which treatment was given to which unit.
  - helps <u>prevent bias</u> in the evaluation, even unconscious bias from well-intentioned evaluators.
  - Double blinding occurs when both the evaluators of the response and the (human subject) experimental units do not know the assignment of treatments to units.

🕾 CODATA INR3

Monday, August 19th 2018





### Ok, let's go back to our initial question:

### What is a good experimental design?

Experiment Design and Analysis



(RDA)

elixir

### A Well-Designed Experiment

Should have:

CODATA INAS

- 1. Clear Objectives
- 2. Focus and Simplicity
- 3. Sufficient Power
- 4. Randomized Comparisons
- And be:
  - 1. Precise
  - 2. Unbiased
  - 3. Amenable to statistical analysis
  - 4. Reproducible



Experiment Design and Analysis





elixir

 $(\mathbf{i})$ 

(RDA)

### Aspects of Experimental Design

- Experimental Factors
- Variability
  - 1. Sources of Variance
  - 2. Replicates
- Bias

CODATA INAS

- 1. Confounding factors
- 2. Randomization wherever a decision is to be made
  - Controls for **both** measured and unmeasured factors
- 3. Controls

### **Experimental Factors**

- Factors: Aspects of Experiment that change and influence the outcome of the experiment
  - e.g. time, weight, drug, gender, ethnicity, country, plate, cage etc.
- Variable type depends on type of measurement
  - Categorical (**nominal**) , e.g. gender
  - Categorical with ordering (ordinal), e.g. tumor grade
  - Discrete, e.g. shoe size, number of cells
  - **Continuous**, e.g. body weight in kg, height in cm
- Independent or Dependent Variables
  - Independent variable (IV): what you change
  - Dependent variable (DV): what changes due to IV
  - "If (independent variable), then (dependent variable)"

CODATA INAS



### Sources of Variation

#### Biological "Noise"

CODATA INAS

26

- Biological processes are inherently stochastic
- Single cells, cell populations, individuals, organs, species....
- Timepoints, cell cycle, synchronized vs. unsynchronized
- Technical Noise
  - Reagents, antibodies, temperatures, pollution
  - Platforms, runs, operators

Consider in advance and control replication required to capture variance



27

### Types of Replication

#### Biological Replication

In vivo

CODATA INAS

- Patients
- Mice
- In vitro
  - Different cell lines
  - Re-growing cells (passages)
- Technical Replication
  - Experimental protocol
  - Measurement platform (i.e. sequencer)



# How many samples? Why do you need replicates?

- Calculating appropriate sample sizes
  - Power calculations

🕾 CODATA INR3

- Planning for precision
- Resource equation
- Power: the probability of detecting an effect of a specified size if present.
  - Identify and control the sources of variability
    - Biological variability
    - Technical variability
  - Using appropriate numbers of samples (sample size/replicates)
  - Power calculations estimate sample size required to detect an effect <u>if degree of variability</u> <u>is known</u>
    - Depends on  $\delta$ , n, sd, a, H<sub>A</sub>
  - If adding samples increases variability, that alone won't add power!



### 29

elix

CODATA INAS

### Confounding Factors

- Aka Extraneous, hidden, lurking or masking factors, or the third variable or mediator variable.
- May mask an actual association or falsely demonstrate an apparent association between the independent and dependent variables.
- Hypothetical example would be a study of coffee drinking and lung cancer.





### Confounding factors

- Inadequate management and monitoring of confounding factors
  - one of the most common causes of researchers wrongly assuming that a correlation leads to a causality.
- If a study does not consider confounding factors, don't believe it!

CODATA INAS



eli

### Solutions!

CODATA INAS

eli

31

Randomization



- Statistical analysis assume randomized comparisons
- May not see issued caused by non-randomized comparisons
- Make every decision random not arbitrary
- Blinding
  - Especially important where subjective measurements are taken
  - Every experiment should reach its potential degree of blinding



10 11 12

Day 3, Plate 3

**Treatment 2** 

### Randomized Block Design

 Blocking is the arranging of experimental units in groups (blocks) that are similar to one another



- RBD across plates so that each plate contains spatially randomized equal proportions of:
  - 1. Control

CODATA INAS

eli

 $(\mathbf{i})$ 

33

- 2. Treatment 1
- 3. Treatment 2

controlling plate effects.

### All good in theory, but in practice?

TEACHING

TRAINING



Experiment Design and Analysis

Monday, August 19th 2018



elizir

### **Experimental Design Practical Questions I**

- 1. What are your objectives?
- 2. What are you measuring?
- 3. What are your primary sample groups of interest?
- 4. What controls will you use each type of sample group?
- 5. What constitutes a replicate in this experiment? Are they biological or technical? How many samples/replicates should be collected?
- 6. Sketch out the design as a matrix, with sample numbers
- 7. What sample group comparisons (contrasts) will you make with the data? Which gene set(s) will you use for pathway analysis?
- 8. What are possible confounding factors and sources of bias?

🕾 CODATA INR3

### Experimental Design Practical Questions II

- 9. How will you confirm effective silencing?
- 10. What information about your experiment should be recorded to help identify any problems should there be any?
- 11. Will you be multiplexing samples? How will you assign barcodes? Will you use pooled libraries? How many pools? How will samples be assigned to pools?
- 12. What are the sequencing parameters you need to be aware of (e.g. sequencing type and depth)?
- 13. What other types of data might be useful to assay, and how might the sequencing parameters need to change to accommodate this?
- 14. Can you think of any other design related issues that could/should be addressed?



36

CODATA INA3







38

Let's do an experiment!



Experiment Design and Analysis





### The setup

- 150 individuals
- 50 of each treatment
- Treatment lasts 1 week
- We have 3 incubators/greenhouses/tanks/cages which each hold 50 individuals







Experiment Design and Analysis

Monday, August 19th 2018

elizir



Discuss in groups!

- Let's do the blue treatment in week 1, green treatment in week 2 and red treatment in week 3
  - because ... reasons!

The twist!

- You have 3 undergrads. How should they split the data collection work?
- They are also available for just two days to do the library prep.
- And! You just have 2 lanes per Sequencer available

CODATA INAS

eli



43

### Let's actually do this in R/RStudio

Experiment Design and Analysis

