Institute of Data

2019

Data Science and AI

Module 3
Part 2:

Data Science Practice 1/2

Agenda: Module 3 Part 2

- Defining Data Science
- Hypothesising
- Statical Evidence
- Statical Proof
- Causation
- Statical Inferences

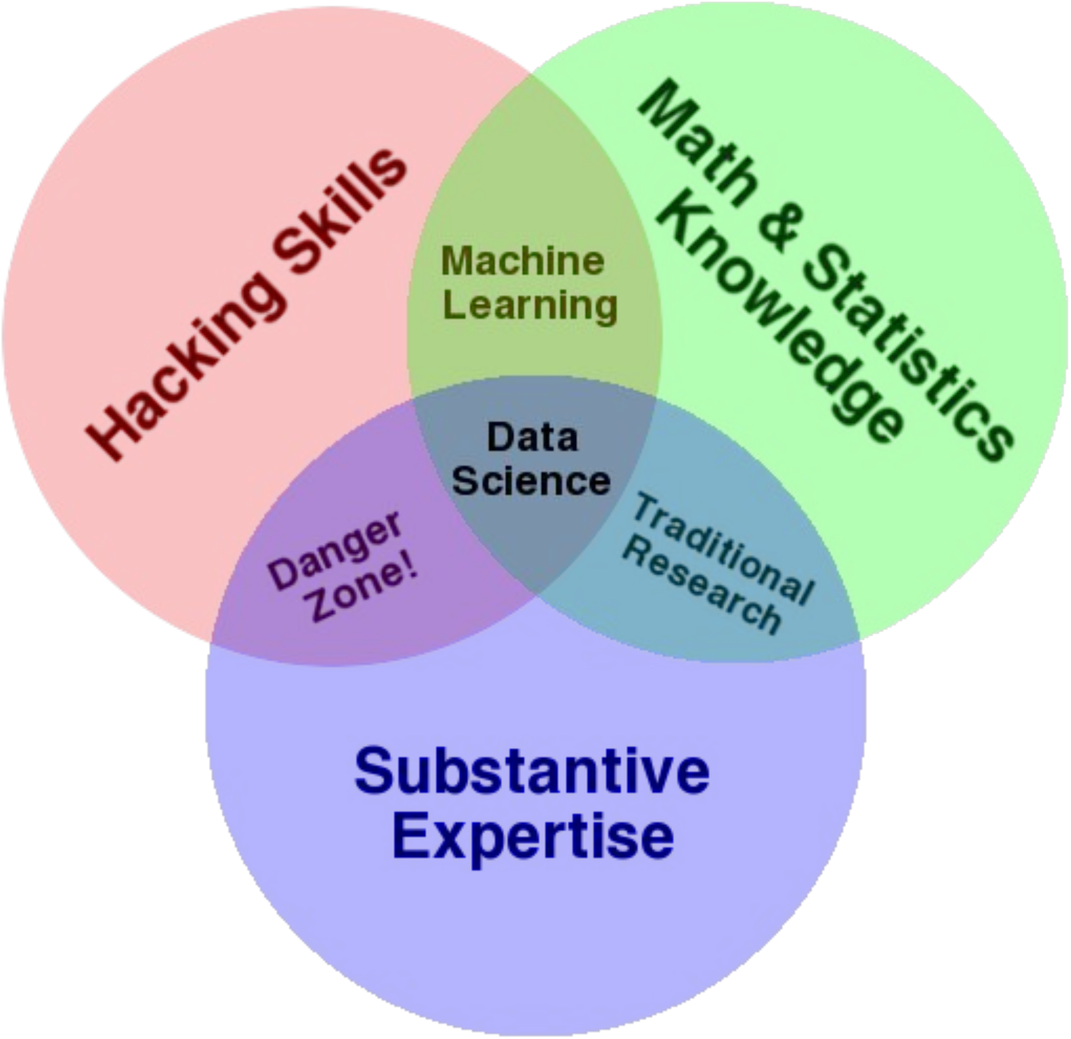
Institute of Data

Defining Data Science

- What is data science?
- Users and use cases
- What makes a data scientist?
- The data science pipeline
- Testable hypotheses

What is Data Science?

- cutting-edge techniques and tools for analysing data
- an interdisciplinary approach to problem-solving
- business analysis on steroids
- the application of scientific method to practical problems



Drew Conway

Who Uses Data Science?

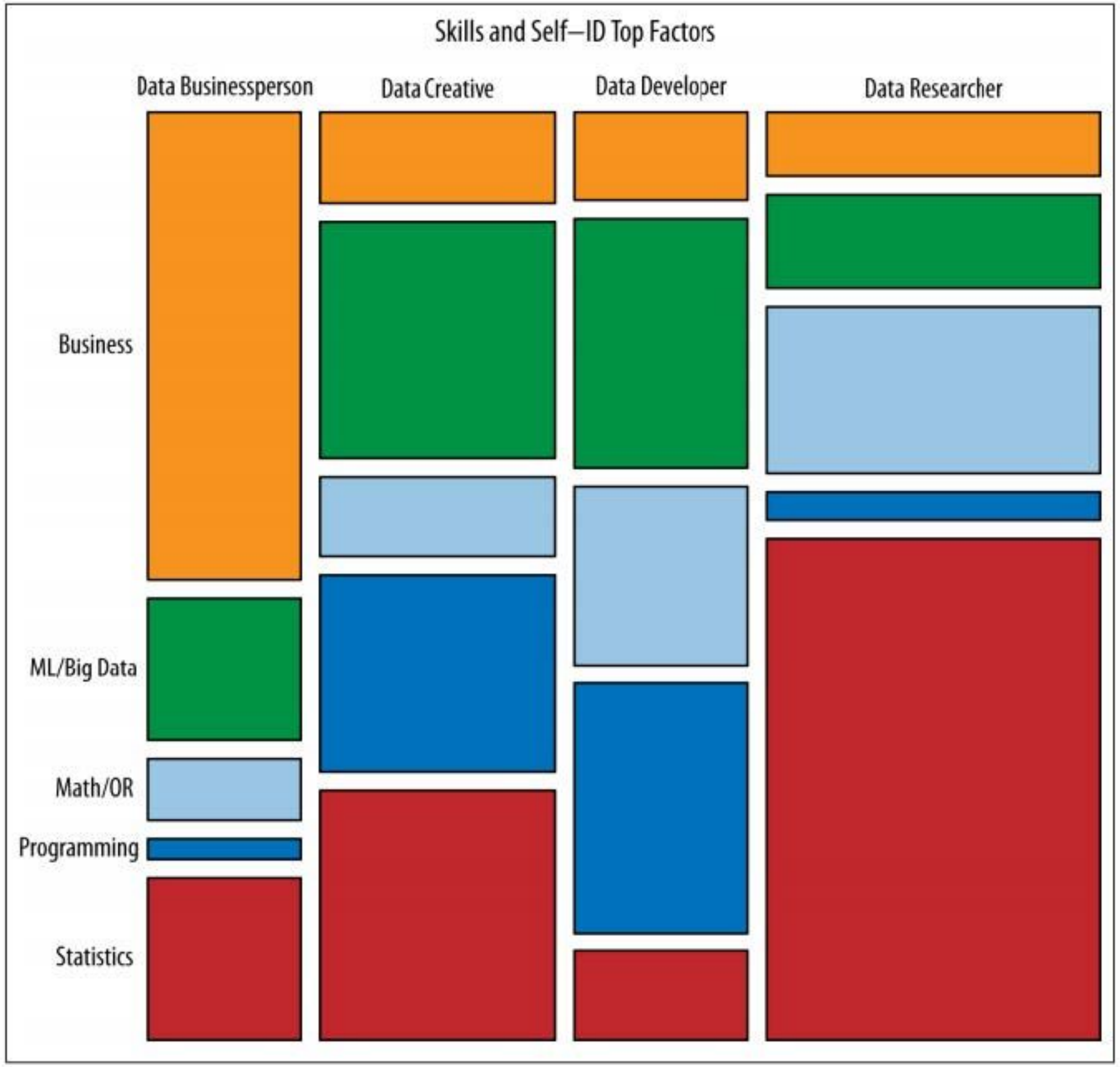
Where do data scientists come from?

What are their typical strengths?

	Hacking Skills	Math & Stats	Substantive Expertise	Methodology	Abstraction	Communication
Data Science program graduates						
Scientists (especially physics)						
Statisticians						
Developers						
Business Analysts						

Relative Strengths

- These roles prioritize different skill sets.
- All roles involve some part of each skillset.
- *Where are your ambitions?*
- *Where are your strengths and weaknesses?*



The Data Science Pipeline

Define
- objectives
- data sources
- strategy

→

Prepare
- wrangle
- clean
- profile
- munge

→

Analyse
- model
- predict
- revise
- enhance

→

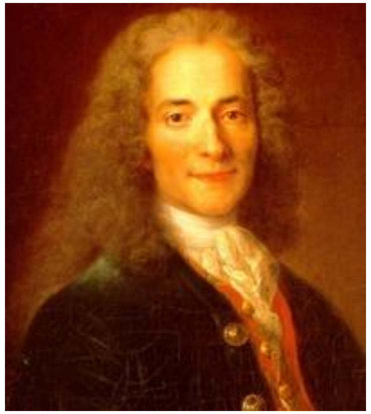
Deliver
- visualise
- summarise
- advise / build
- deploy

Defining the Problem

Every Solution Begins with a Question

- any business problem, decision-support tool, or clever data product begins life with a well-defined need:
  - a set of questions that frame an analysis
- sets up for a successful process
- establishes the basis for reproducibility
- creates scope for future expansion

"A problem well stated is half solved."
— Charles Kettering



"Judge a man by his questions rather than by his answers."
— Voltaire

What is your question?

- What is your name?
- What is your quest?
- What is the average airspeed of an unladen sparrow?

How to specify the question

A business challenge may be vague:

- "How can we grow our online market share?"

Data science questions need to be focused:

- "Is our website achieving sufficient user engagement?"
- "Are we presenting our products effectively to website visitors?"
- "Are our prices competitive?"
- "Is this market niche saturated?"

> Even these examples are a bit vague, but we could break each one down into a series of more granular questions with quantitative domains

The Elements of a Good Question

Specific	The dataset and key variables are clearly defined.
Measurable	The type of analysis and major assumptions are articulated.
Attainable	The available data are amenable to the question and unlikely to be biased.
Reproducible	The analysis can be repeated by another person or at another time.
Time-bound	The time period and population to which the analysis pertains is clearly stated.

Knowledge check

Does this question follow the SMART framework:

“Is there an association between number of passengers with carry-on luggage and delayed take-off time?”

Knowledge check

How about this (revised) question:

"Is there an association between the number of passengers (on JetBlue, Delta, and United domestic flights) with carry-on luggage and delayed take-off time in the data from flightstats.com between January 2015 and December 2015?"

Dataset Characteristics

- What would we look for if we wanted to be able to describe a dataset?
  - size, completeness
  - accuracy, precision
  - periodicity, stationarity
  - variance, heteroskedasticity
  - bias
    - missing variables
  - correlated variables
    - due to causation or covariation
  - correlated samples
    - time series / Markov series
    - contaminated or prejudiced sampling
    - study design

Data Temporality

Cross-sectional

- ‘static’
- treated as a snapshot in time
- causality is simultaneous

Longitudinal

- ‘time series’
- treated as a series of snapshots with a temporal or serial dependence

Dynamic

- ‘streaming’
- continuously accumulated or refreshed

Variables in Data Science

Features
Predictors

Independent variables
Inputs

A *predictor* is a *feature* that is useful in modelling the *response*. Specifically, its inclusion enables a *model* to account for more of the *variance* in the response.

Responses
Outcomes

Dependent variables
Outputs

A covariate is a variable that is possibly predictive of the response. It could also represent an interacting variable.

A confounding variable is one which influences the response but has not been measured (i.e. it introduces bias).

Data Preparation

def: Tidy data: the end goal of data cleaning and munging

- each variable should be in one column
- each observation should comprise one row
- each type of observational unit should form one table
- key columns for linking multiple tables
- top row contains (sensible) variable names
- in general, save data as one file per table

this is Codd's 3rd normal form from RDBMS theory

- search: "hadley wickham's tidy data paper"

Lab 3.2.1: Hypothesising

- Purpose:
  - To create a testable hypothesis
- Resources:
  - ‘titanic.csv’
- Instructions:
  1. You should already be familiar with the ‘titanic’ dataset from the last module’s homework. Now, think about what stories the data might tell, and devise a hypothesis that could be tested.
  2. Provide some data profiling results to support your assertion that this hypothesis is testable.

Institute of Data

Statistical Evidence

- What is statistical proof?
- Revisiting the null hypothesis
- The Student's *t*-test

Statistical Proof

Can a hypothesis be proved?

- in science, no theory (or hypothesis) can actually be proved
  - must explain known phenomenon
  - must make testable predictions
  - *will gain acceptance if it survives rigorous testing*

How can a hypothesis be tested?

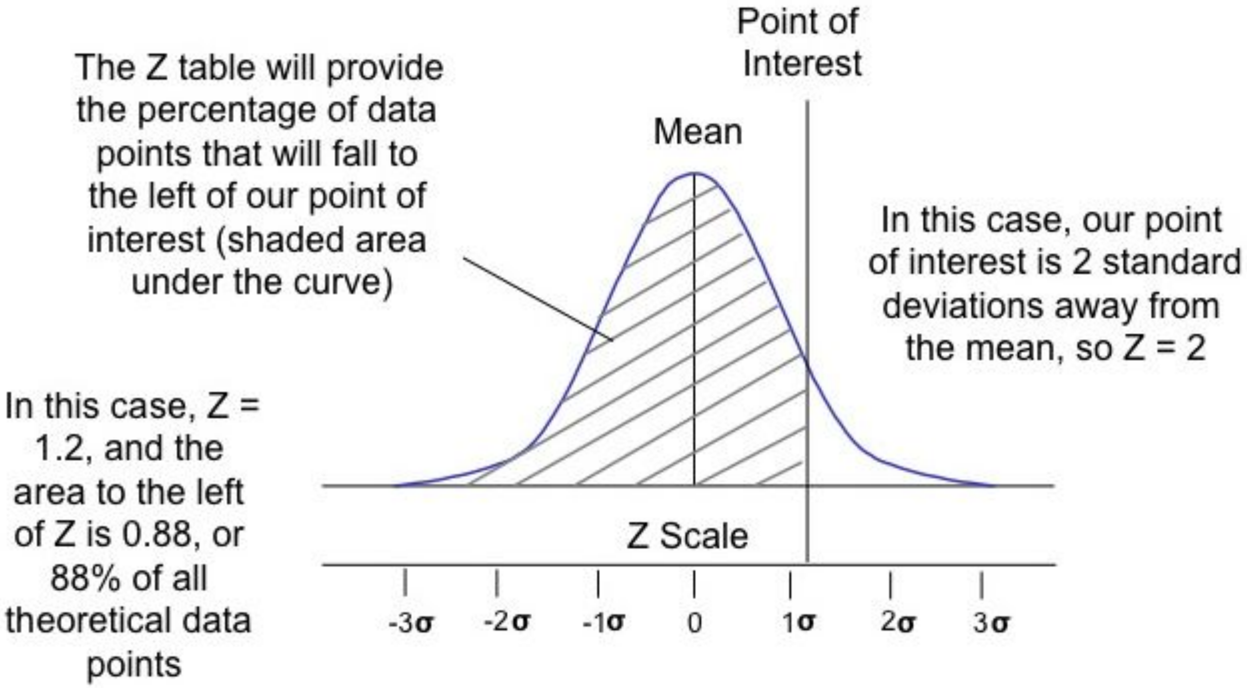
- by formulating it in a way that makes its claims amenable to statistical analysis
  - must explain the data
  - must have a corresponding null hypothesis that can be rejected at a predefined level of confidence

Statistical Proof – cont'd

Z-statistic

$$z = \frac{\bar{X} - \mu}{\sigma}$$

- provides a measure of the likelihood that a data point belongs to a given population



The Null Hypothesis

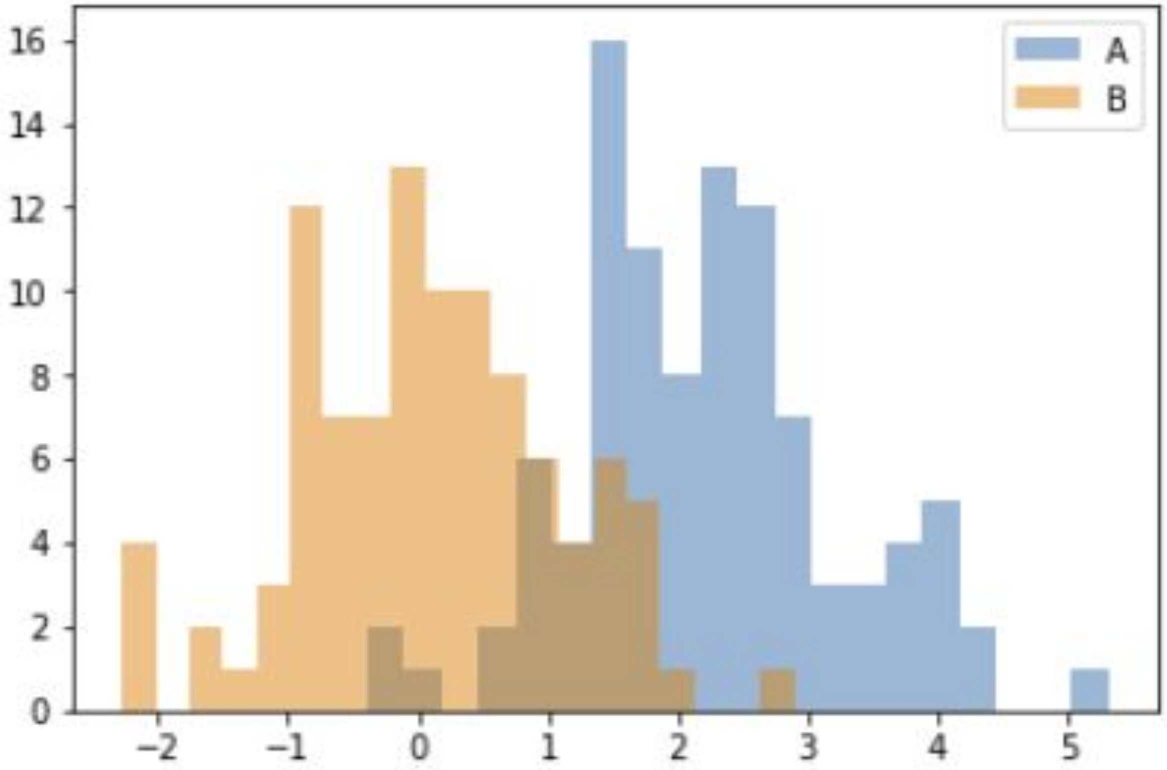
Example:

- dataset comprised of patients' responses to two different therapies:
  - drug A (the old drug, or 'control' treatment)
  - drug B (the new drug, or 'test' treatment).
- we are interested in testing the ***alternative hypothesis*** H_a:
  - A & B deliver significantly different outcomes
- but we do this by assuming (and then trying to reject) the ***null hypothesis*** H_0:
  - there is ***no*** significant difference between A & B
  - the distributions we get from the 'A' data and the 'B' data represent two sample sets from the same 'population'

Testing the Null Hypothesis for Two Samples

Given two samples, A and B

- compute the means X_A, X_B
- compute the variances ${\sigma^2}_A$, ${\sigma^2}_B$
- calculate how close X_A is to X_B given the uncertainty implied by their variances
- calculate the likelihood that this value of our closeness parameter could be obtained at random



The Student's *t*-Test

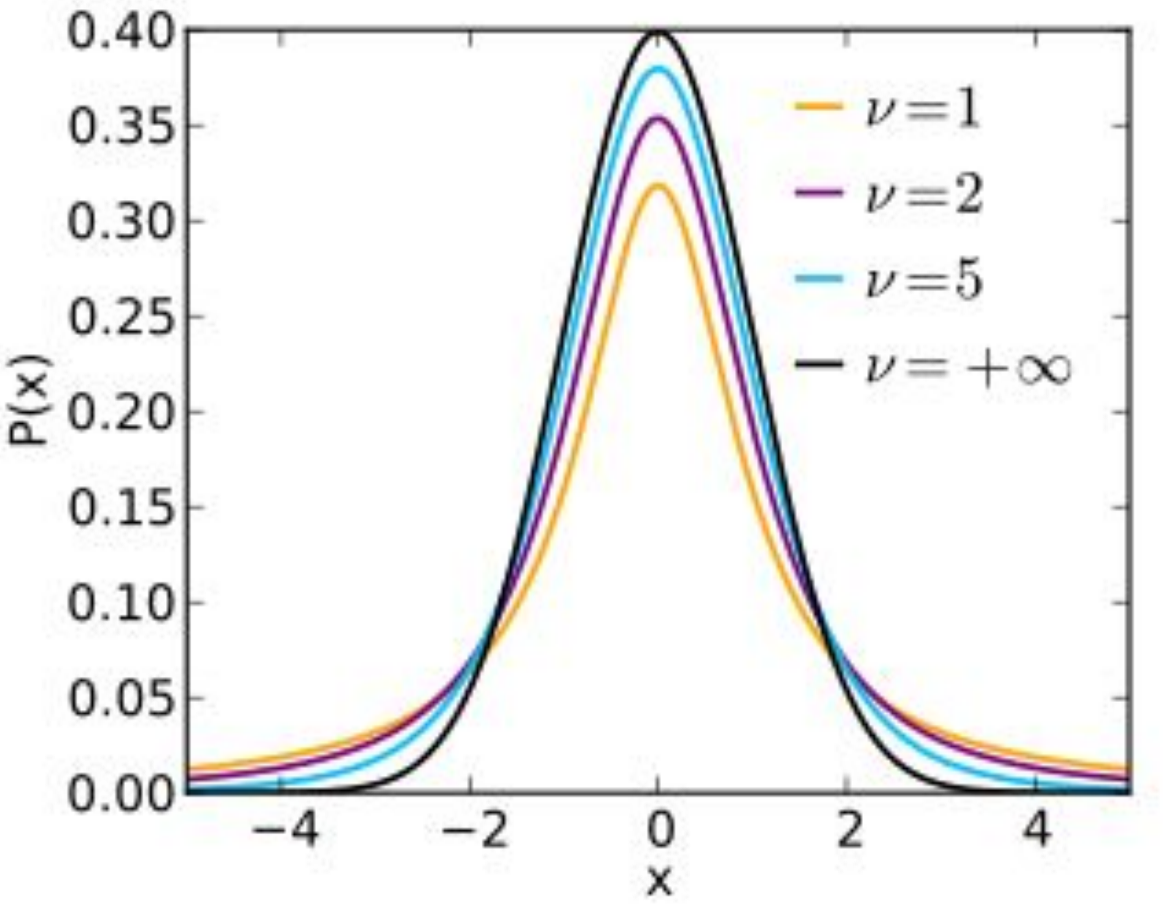
The *t*-statistic for comparing two samples is:

$$t = \frac{\overline{X_1} - \overline{X_2}}{s_{1,2}\sqrt{2/N}}$$

where the *mutual* or *joint* standard deviation is given by:

$$s_{1,2} = \sqrt{\frac{\mathrm{var}(X_1) + \mathrm{var}(X_2)}{2}}$$

The *t*-Distribution



- ν is the number of degrees of freedom
- the distribution narrows (approaches normal distribution) as ν gets larger

Statistical Errors

Type I errors

- false positives (FP)
- we erroneously rejected the null hypothesis

Type II errors

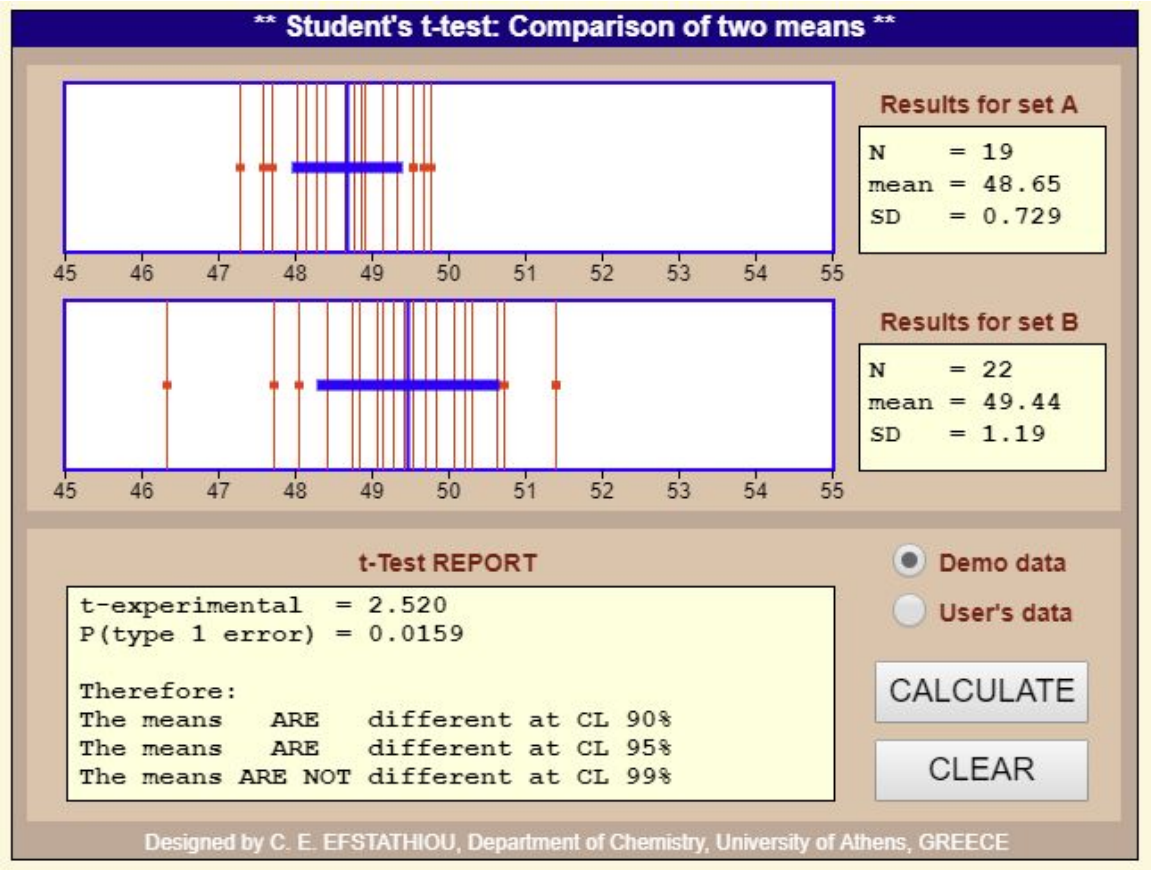
- false negatives (FN)
- we erroneously upheld the null hypothesis

predicted positives PP = TP + FP   predicted negatives PN = TN + FN

actual positives P = TP + FN   actual negatives N = TN + FP

Lab 3.2.2: Statistical Proof

- Purpose:
  - To learn how to use the Student's *t*-test for comparing two samples
- Materials:
  - 'Lab 3.2.2.ipynb'
- Reference:
  - http://195.134.76.37/applets/AppletTtest/Appl_Ttest2.html



Discussion

- Is it sufficient to declare statistical significance at $p < 0.05$?
  - how much confidence is enough?

- Is it okay to mine for significance by testing each variable in turn?
  - how would we control the error estimate in multivariate testing?

- Resources:
  - Statistical Thinking for Managerial Decisions
    https://home.ubalt.edu/ntsbarsh/Business-stat/opre504.htm
  - Statistics: The Art & Science of Learning from Data
    http://www.artofstat.com/webapps.html

ANOVA

Analysis of variance

- generalises *t*-test to >2 samples (groups)
  - more conservative
  - reduces Type I errors
- decomposes data additively
  - compares mean squares, *F*-statistic
  - can test a nested sequence of models
- comprises a suite of methods
  - one-way, two-way, multiple

ANOVA – cont'd

One-way ANOVA

- *F*-statistic:

$$F = \frac{\text{(variance between groups)}}{\text{(variance within groups)}} = \frac{SS_T/(I-1)}{SS_E/(n_T - I)}$$

I = number of groups

n_T = number of subjects

- compare this statistic to *F*-distribution for $I-1, n_T - I$ degrees of freedom
- reject H_0 for $F \geq F_{\text{critical}}$

https://www.marsja.se/four-ways-to-conduct-one-way-anovas-using-python/

Statistical Power

def: the probability that the test correctly rejects the null hypothesis (H_0) when a specific alternative hypothesis (H_1) is true

example

- let A, B be the control & test cohorts:

$$D(N) = \frac{1}{N}\sum_{i=1}^{N} B_i - A_i$$

- define test statistic:

$$T(N) = \frac{D(N) - \mu_D}{\sigma_D / N}, \qquad \mu_D = 0 \quad (H_0)$$

Statistical Power – cont'd

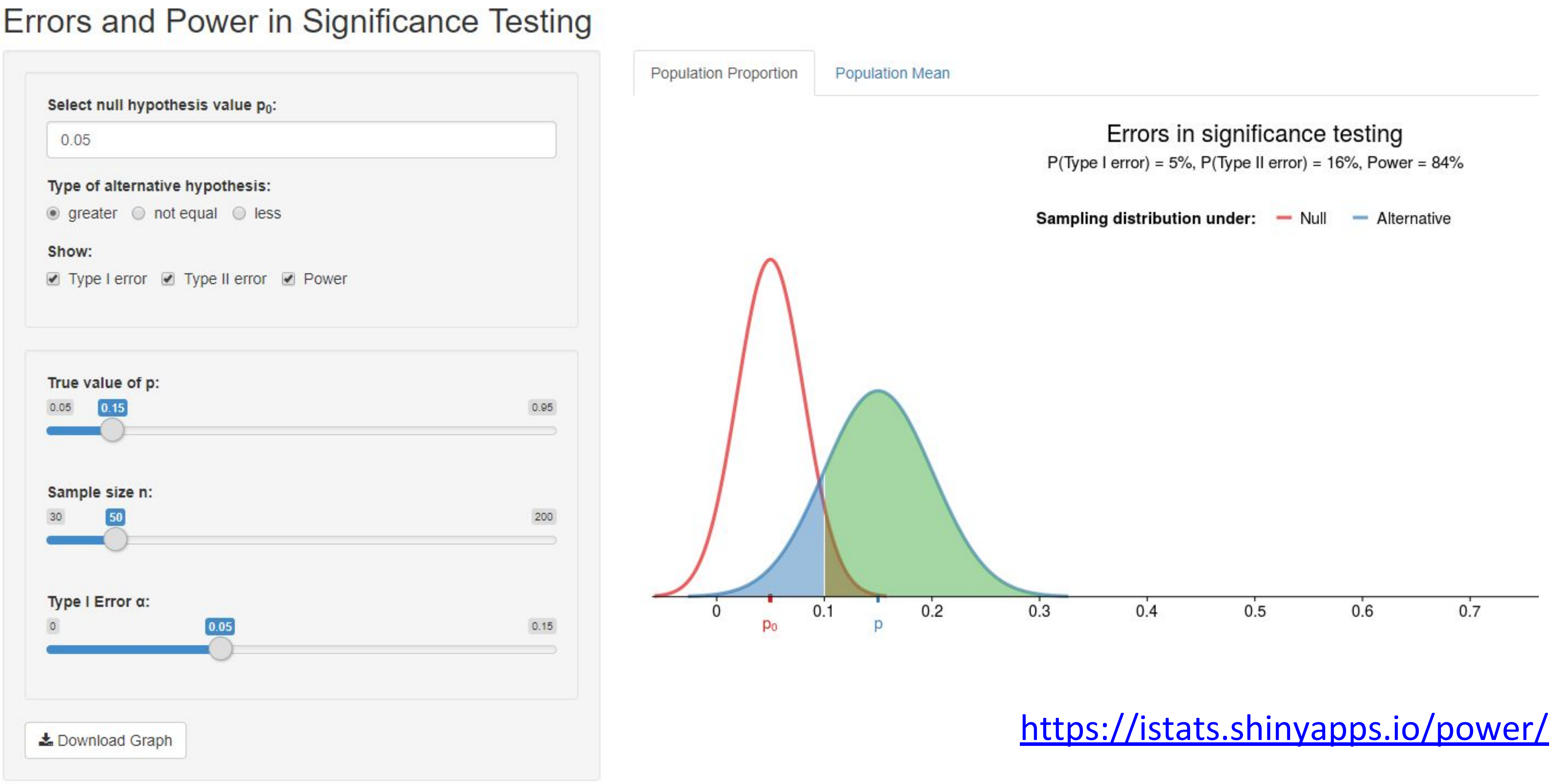
- specify $p < 0.05$ for significance
- from the *t*-distribution, $p = 0.05$ corresponds to $t = 1.64$
- therefore, to reject H_0 we require:

$$T(N) > 1.64$$

- specify power > 0.9 to detect $\mu_D > 1$
- after a few more steps, we obtain this requirement:

$$N > 8.56\ \sigma_D$$

Statistical Power – cont’d



https://istats.shinyapps.io/power/

Controlled Trials

objectives:

- to evaluate an experimental cohort (*test group*) against a baseline (*control group*)
- to measure every factor that has the potential to influence the response variable

challenges / considerations:

- the control group must be representative of the test group in every way except for the influence of the effect that is under test
- if we have limited understanding of the phenomenon, we may neglect important variables
    - *this will lead to experimental bias*
- others?

Randomised Controlled Trials

objective:

- to minimise experimental bias by evenly distributing uncontrolled variables between the study cohorts

challenges / considerations:

- different classes of subjects should be evenly distributed between cohorts
  - e.g. age range, weight range, sex, medical status
  - requires data profiling of subjects prior to commencing experiment
- others?

Blind Randomised Controlled Trials

blind

- subjects do not know if they have been allocated to the test group or the control group

double blind

- experimenters do not know which individuals are test subjects or control subjects
- *only the analysts know!*

A/B Testing

def: a randomized experiment with two variants

examples

- evaluate / compare options for improving performance
  - marketing campaigns
  - website engagement
  - product variants
- conversion rate
  - proportion of sales resulting from all visits
- funnel
  - stages from visit through to conversion

Full Factorial Design

def: an experimental design that tests every combination of factors (categorical features)

- allows interactions between factors to be detected
- produces large experiments
  - if there are k factors, each with l_i levels, the number of combinations to be tested is:

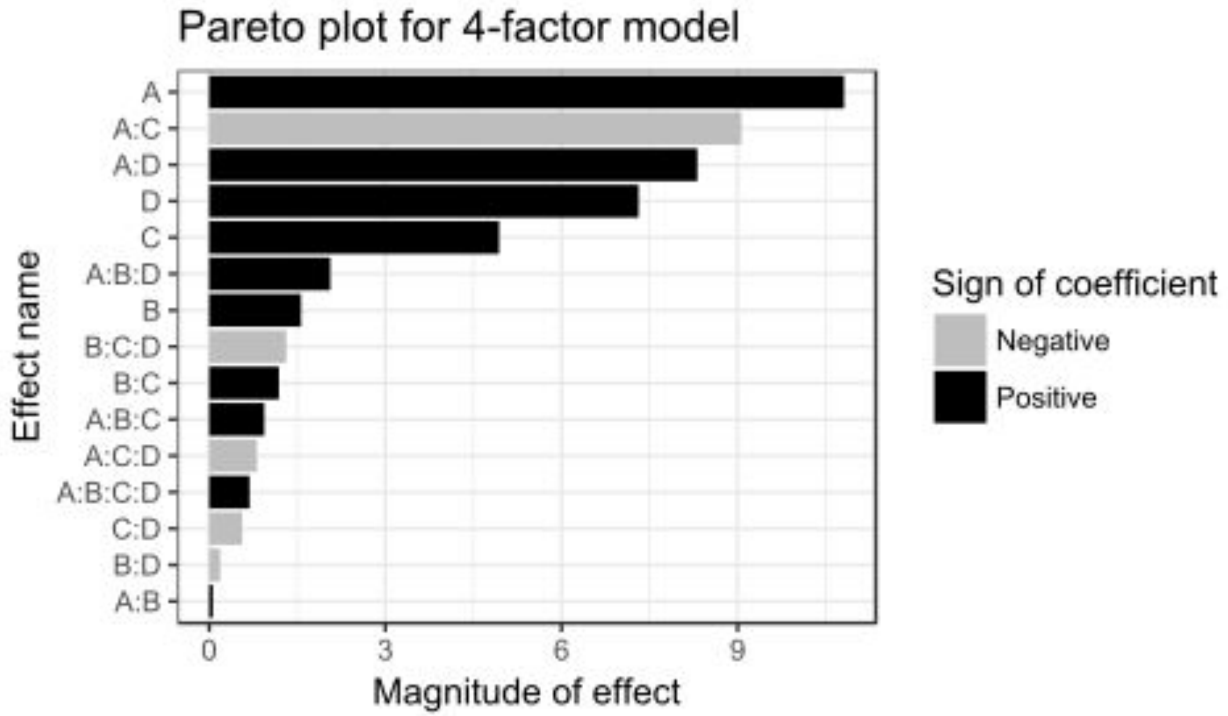
$$N_T = \prod_{i=1}^{k} l_i$$

Full Factorial Design – cont'd

- ***example***
  - a response is tested by varying 4 different factors over 2 levels each
    - number of combinations of factors $= 2 * 2 * 2 * 2 = 16$

ANOVA Results

Coefficients	Estimate	Coefficients	Estimate
Intercept	70.063	A:D	8.313
A	10.813	B:D	−0.188
B	1.563	C:D	−0.563
C	4.938	A:B:C	0.938
D	7.313	A:B:D	2.063
A:B	0.063	A:C:D	−0.813
A:C	−9.063	B:C:D	−1.313
B:C	1.188	A:B:C:D	0.688



Fractional Factorial Design

- reduces the number of combinations to test
- exploits the *sparsity-of-effects principle*:
  - a system is usually dominated by main effects and low-order interactions
  - only a few effects in a factorial experiment will be statistically significant
- levels of some factors are deliberately *confounded* with others to reduce the problem space

  - if there are k factors, each with l levels, and p determines the degree of reduction, the number of combinations to be tested is:

$$N_T = l^{k-p}$$

example

- if $k = 5$, $l = 2$, $p = 2$ only $2^3 = 8$ combinations will be tested instead of $2^5 = 32$

Fractional Factorial Design

- reduces the number of combinations to test
- based on standard designs

example:

- l = 2 levels ('–', '+')
- k = 4 factors
- p = 1

A	B	C	D	Filtration rate
-1	-1	-1	-1	45
1	-1	-1	1	100
-1	1	-1	1	45
1	1	-1	-1	65
-1	-1	1	1	75
1	-1	1	-1	60
-1	1	1	-1	80
1	1	1	1	96

8 tests instead of 16

Factorial Design in Python

- pyDOE (design of experiments)
  - https://pythonhosted.org/pyDOE/factorial.html#factorial
  - https://towardsdatascience.com/design-your-engineering-experiment-plan-with-a-simple-python-command-35a6ba52fa35

fullfact(levels = [2, 3])

```
array([[ 0.,  0.],
       [ 1.,  0.],
       [ 0.,  1.],
       [ 1.,  1.],
       [ 0.,  2.],
       [ 1.,  2.]])
```

ff2n(3)

```
array([[-1., -1., -1.],
       [ 1., -1., -1.],
       [-1.,  1., -1.],
       [ 1.,  1., -1.],
       [-1., -1.,  1.],
       [ 1., -1.,  1.],
       [-1.,  1.,  1.],
       [ 1.,  1.,  1.]])
```

fractfact('a b ab')

```
array([[-1., -1.,  1.],
       [ 1., -1., -1.],
       [-1.,  1., -1.],
       [ 1.,  1.,  1.]])
```

- Nb. pyDOE is not yet available as a package
  - must download code from Github, then python Main.py

Experimental Design for Big Data

- processing time (cost)
  - sample small subsets of the data
    - design the experiment, validate analytic methods before progressing to full dataset
    - for time-dependent data, need to sample many epochs so that periodicity is captured
- the curse of high-dimensionality
  - special methods required when number of features ~ 10^3
    - $O(n^2)$ algorithms too slow
    - exploit sparseness where possible
  - large number of features → many spurious correlations
- *other issues?*

Causation

- Causation vs correlation
- Domain knowledge

Causation vs Correlation

***example*:**

- a study finds that homicide correlates with ice cream consumption
  - what does this mean?

Headline #1: *'Ice Cream Linked to Murder'*

- scientists are desperately trying to discover which brands or flavours of ice cream are driving the murder rate

Headline #2: *'Heat Wave Pushes Murder Rate Up'*

- scientists suspect elevated brain temperatures increase mental instability
- meanwhile, ice cream sales are soaring

Causation vs Correlation – cont'd

1. Install
   - MongoDB Community Server https://www.mongodb.com/download-center#community
   - Neo4j Community Server https://neo4j.com/download-center/#releases

2. Install Python packages:
   - pymongo (conda)
   - neo4j-driver (pip)

Causation vs Correlation – cont'd

A few cups of coffee may lower colon cancer risk

Posted: 01 August 2007 1708 hrs

Photos

TOKYO : Drinking a few cups of coffee a day may lower the risk of advanced colon cancer, at least for women, Japanese researchers said Wednesday.

The study, supported by Japan's health ministry, showed women who drink more than three cups of coffee a day were 56 percent less likely to develop advanced colon cancer than those who drink no coffee at all.

"Drinking coffee sustains the secretion of bile acid and keeps down cholesterol levels, the mechanisms thought to prevent colon cancer," the report said.

But unfortunately the effect was not seen in men, the medical research team said.

Many men smoke and drink alcohol more than women, and those habits probably offset the effect of coffee, the study said.

The research team tracked down about 96,000 people in Japan aged from 40 to 69 between the early 1990s and 2002, of whom 726 men suffered colon cancer.

CancerConsultants.com
oncology resource center

Patient Home · Professional Home · Newsletters · Feedback Survey

Search:
Medline
CancerConsultants.com
Both
Search

Main Menu
Home
Conference Coverage
Current Topics in Oncology
Cancer News
Disease Centers
Physician Resources
About Us

Quick Links
Information by Disease
All
Cancer News

Cancer News: Rectal Cancer: Article

Printable Version

Rectal Cancer News

Coffee Does Not Decrease Risk of Colorectal Cancer

Researchers from the Harvard School of Public Health have reported that, contrary to the results of several previous studies, coffee consumption does not appear to reduce the risk of colorectal cancer. The details of this study were reported in the April 1, 2009 issue of the *International Journal of Cancer*.[1]

Habitual coffee drinking has been associated with a reduced risk of mortality and chronic diseases, including cancer. Current evidence suggests that coffee consumption is associated with a reduced risk of liver, kidney, and to a lesser extent, premenopausal breast cancer and colorectal cancer; coffee consumption has no association with prostate, pancreas, and ovarian cancers.

Some studies have indicated that coffee may have a protective effect against colon cancer; however, researchers continue to evaluate this link in an effort to establish more direct evidence. In order to examine the relationship between coffee consumption and colorectal cancer, researchers from Harvard conducted a review of 12 studies that included 646,848 participants and 5,403 cases of colorectal cancer.

They evaluated high versus low coffee consumption and found no significant effect of coffee consumption on colorectal cancer risk. The review

Causation vs Correlation – cont'd

Simpson's paradox

- a trend appears in different groups of data but disappears or reverses when these groups are combined
  - common in social-science and medical-science statistics

    https://en.wikipedia.org/wiki/Simpson%27s_paradox

- caused by experimental bias

- results in H_0 rejected despite insufficient statistical power
  - difference in means is too small
  - variances are too large
  - number of samples is too small

Can’t we just use ‘common sense’?

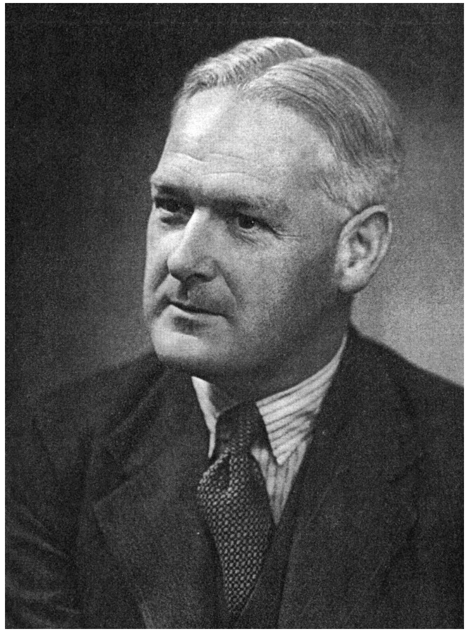
Common sense is the collection of prejudices acquired by age eighteen.

Albert Einstein

Criteria for Evaluating Causation

- Strength of association
- Consistency
- Specificity
- Temporality
- Biological gradient
- Plausibility
- Coherence
- Experiment
- Analogy

> **subject matter expertise + statistics + reasoning**



Bradford Hill

Lab 3.2.3: Statistical Inference

- Purpose:
  - To consolidate the basic concepts of sampling and distributions.

- Materials:
  - ‘Lab 3.2.3.ipynb’

HOMEWORK