

Methods of Applied Statistics I

STA2101H F LEC9101

Week 5

October 8 2020



1. Second syllabus update; Two editions of Faraway
2. In the News: A-levels; Excel; 538
3. Designed Experiments SM 9.1, 9.2; FLM-2 Ch 16, 17; FLM-1 Ch 15, 16
4. Preliminary Analysis – CD Ch. 5
5. (2–3pm) HW1; Reading Statistical Models

Happy Thanksgiving!!!

Monday, Oct 12

No office hours



Syllabus updated Oct 5

STA 2101F: Methods of Applied Statistics I

Week	Date	Methods	References	Computing
1	Sept 10	Review of Linear Regression	SM Ch.8.2.1, 8.3; FLM-2 Ch.2-4; FLM-1 Ch.2-3; CD Ch.1	RStudio and RMarkdown
2	Sept 17	Model Selection Comparing models; factors; model checking; diagnostics; collinearity	SM Ch.8.5,6; FLM Ch.3; FLM-2 14.1, 14.2, 2.11, 2.6; FLM-1 4,13; CD Ch.6	tidyverse
3→HW1	Sept 24	Random and Mixed Effects Models Model selection; Types of studies	SM 8.7.1; FLM-2 Ch.10; FLM-1 Ch.8; CD Ch.1,2	ggplot HW 1 Qs
4←HW1	Oct 1	Designed Experiments Factor variables; Random and Mixed Effects; Principles of Measurement	SM Ch. 9.1,9.2.1; FLM-2 Ch.14-17; FLM-1 Ch.14-16; CD Ch.4	as.factor, is.factor, ggplot, anova, fruitfly data
5	Oct 8	Binary Responses Designed Experiments; Preliminary Analysis	SM Ch.9.1,2; FLM-2 Ch.14, 15 FLM-1 Ch.13, 14; Ch.2 ; CD Ch.5, FLM-2 Ch.5	
6	Oct 15	Logistic Regression	SM 10.6.1; FELM Ch.3	
7→HW2	Oct 22	Generalized Linear Models	FELM Ch.6,7; SM 10.3	

A-level and GCSE results: Pressure mounts on ministers to solve exam crisis

🕒 17 August 2020

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- assignment of final grades in high school, used for university admissions [Introduction](#)
- in the absence of written exams [Full article](#)
- “exam boards would be asking teachers in schools and colleges to submit expected grades and rankings of their students in lieu of exams”
- “These assessments would then go through ‘a process of standardisation using a model’, or algorithm, that Ofqual had developed”
- “Ultimately, when grades were issued on 13 August, some students found the results to be anything but fair, with many receiving lower marks than expected”
- “on 17 August, after student protests, Ofqual abandoned the calculated grades in favour of teacher-assessed grades.”

A-level and GCSE results: Pressure mounts on ministers to solve exam crisis

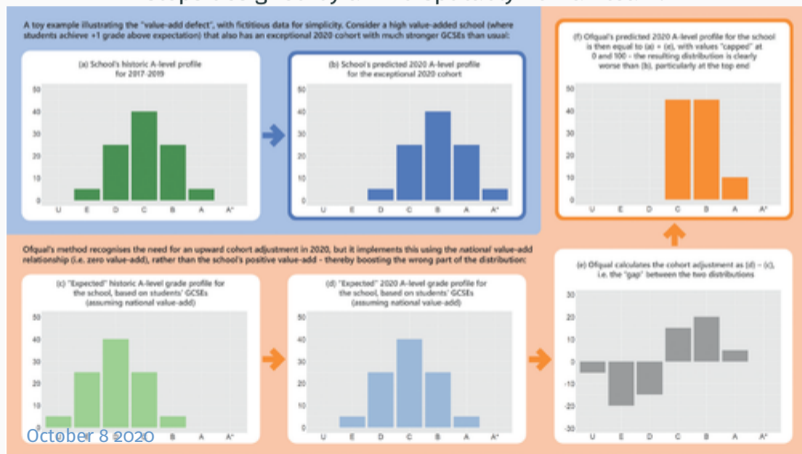
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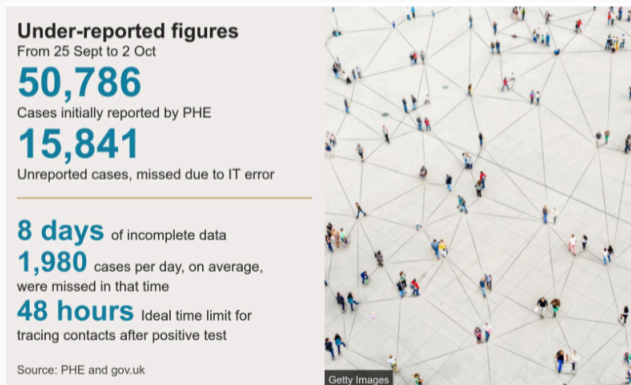
... A-level grades

“the algorithm developed by England’s exam regulator, Ofqual, contained no elements of machine learning, or indeed any artificial intelligence – it was simply a sequence of hand-coded procedural steps designed by an indisputably human team.”



- The health secretary said that a technical glitch that saw nearly 16,000 Covid-19 cases go unreported in England “should never have happened”
- Excess rows in the database ignored by Excel software

BBC News

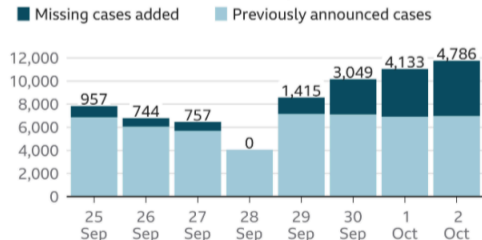


- The health secretary said that a technical glitch that saw nearly 16,000 Covid-19 cases go unreported in England “should never have happened”
- Excess rows in the databased ignored by Excel software

BBC News

Thousands of missing coronavirus cases added after reporting problem

Number of new coronavirus cases by date reported



Source: Gov.uk dashboard, Public Health England

BBC

UPDATED OCT. 7, 2020, AT 11:43 AM

Latest Polls

Updated throughout the day.

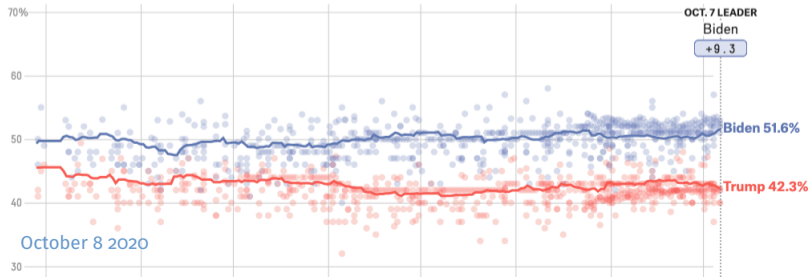
[Polls policy and FAQs](#)



POLL TYPE: STATE: DISTRICT:

Who's ahead in the national polls?

An updating average of 2020 presidential general election polls, accounting for each poll's quality, sample size and recency



Recap of Linear Regression Part 4

- factor variables vs continuous variables
- analysis of variance, F -tests
- fruitfly example: $y_{ij} = \mu + \alpha_i + \beta x_{ij}$

- why use special techniques?
- one-way analysis of variance $y_{ij} = \mu + \alpha_i + \epsilon_{ij}$
 - parameters
 - analysis of variance table
 - partitioning of sums of squares
 - random effects modelling for factor/grouping variable

- principles of measurement
- phases of analysis

CD Ch.1, also Ch.4, p.54,55

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij}, \quad j = 1, \dots, R; i = 1, \dots, T$$

- R observations in each **group**
- groups are defined by a factor variable
 - groups could be treatments, conditions, ... assigned by the investigator
 - groups could be families, litters, classrooms, ... sampled by the investigator
 - groups could be created by insisting that some measured covariate is treated as a factor
- the number of levels in the factor == number of groups
- in a **completely randomized** design, groups are created by random assignment of treatments to experimental units
- parameters α_i can be fixed or random depends on the application
- see FLM-1 13.1,2; FLM-2 14.1,2 for example with one continuous predictor and one two-level factor also HW1 Q3
- fruitflies (last week) on continuous predictor and one 5 level factor FLM-2 14.4; FLM-1 13.3

- two factor variables, **treatment** and **block**
- design: treatments assigned at random **within blocks**
- model:

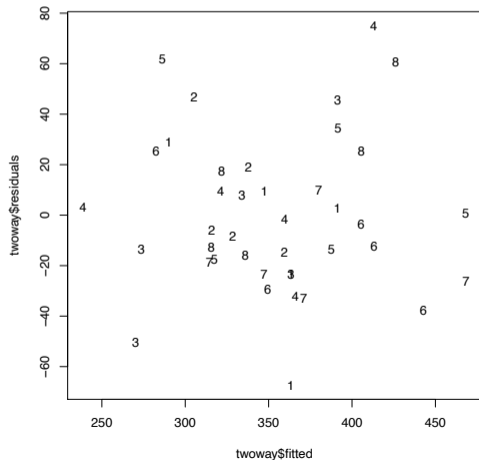
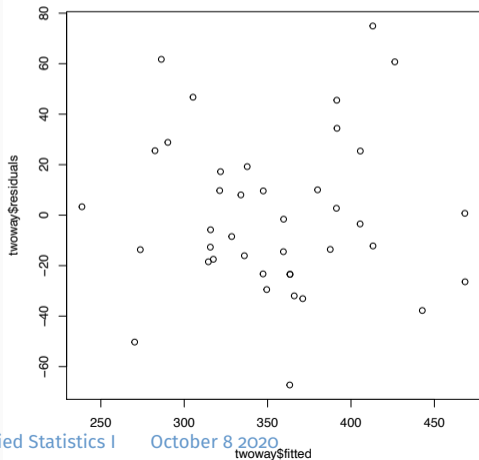
$$y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}, \quad i = 1, \dots, T; j = 1, \dots, R$$

- parameters:
 - $\mu = \mathbb{E}(y_{ij})$ if all $\alpha_i \equiv 0; \beta_j \equiv 0$;
 - α_i is change in $\mathbb{E}(y)$ from μ due to treatment i
 - β_j is change in $\mathbb{E}(y)$ due to effect of block j
 - ϵ_{ij} unexplained variation
- analysis:

$$\begin{aligned} \sum_{ij} (y_{ij} - \bar{y}_{..})^2 &= \sum_{ij} (y_{ij} - \bar{y}_{i.} + \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{.j} - \bar{y}_{..})^2 \\ &= \sum_{ij} (y_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})^2 + \sum_{ij} (\bar{y}_{i.} - \bar{y}_{..})^2 + \sum_{ij} (\bar{y}_{.j} - \bar{y}_{..})^2 \end{aligned}$$



oatvar.Rmd



$$\begin{aligned}\sum_{ij} (y_{ij} - \bar{y}_{..})^2 &= \sum_{ij} (y_{ij} - \bar{y}_{i.} + \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{.j} - \bar{y}_{..})^2 \\ &= \sum_{ij} (y_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..})^2 + \sum_{ij} (\bar{y}_{i.} - \bar{y}_{..})^2 + \sum_{ij} (\bar{y}_{.j} - \bar{y}_{..})^2\end{aligned}$$

Table 9.5 Analysis of variance table for two-way layout model.

Term	df	Sum of squares
Treatments	$T - 1$	$\sum_{t,b} (\bar{y}_{t.} - \bar{y}_{..})^2$
Blocks	$B - 1$	$\sum_{t,b} (\bar{y}_{.b} - \bar{y}_{..})^2$
Residual	$(T - 1)(B - 1)$	$\sum_{t,b} (y_{tb} - \bar{y}_{t.} - \bar{y}_{.b} + \bar{y}_{..})^2$

Analysis of Variance Table

Response: yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
variety	7	77524	11074.8	8.2839	1.804e-05	***
block	4	33396	8348.9	6.2449	0.001008	**
Residuals	28	37433	1336.9			

Residual standard error: 36.56 on 28 degrees of freedom

The interaction between blocks and treatments is used to estimate error. This is sometimes justified by assuming the block effects β_j are random.

Designed Experiments

- Completely randomized design:
 - can be used with more than one factor variable of interest
 - with two or more factors, often of interest to examine main effects and interactions
 - Example SM 9.6 and 8.10
- Randomized block design:
 - can also be used with two or more treatment factors
 - but sometimes it is hard to ensure the blocks are big enough to accommodate all combinations
 - leading to clever incomplete block designs FLM-2 17.2,3; FLM-1 16.2,3; SM 9.2.3 and p.432
 - A randomized block design with just **two** treatments in each block is a **paired comparison** paired t-test

Table 8.10 Poison data (Box and Cox, 1964). Survival times in 10-hour units of animals in a 3×4 factorial experiment with four replicates. The table underneath gives average (standard deviation) for the poison \times treatment combinations.

Treatment	Poison 1	Poison 2	Poison 3
A	0.31, 0.45, 0.46, 0.43	0.36, 0.29, 0.40, 0.23	0.22, 0.21, 0.18, 0.23
B	0.82, 1.10, 0.88, 0.72	0.92, 0.61, 0.49, 1.24	0.30, 0.37, 0.38, 0.29
C	0.43, 0.45, 0.63, 0.76	0.44, 0.35, 0.31, 0.40	0.23, 0.25, 0.24, 0.22
D	0.45, 0.71, 0.66, 0.62	0.56, 1.02, 0.71, 0.38	0.30, 0.36, 0.31, 0.33

Treatment	Poison 1	Poison 2	Poison 3	Average
A	0.41 (0.07)	0.32 (0.08)	0.21 (0.02)	0.31
B	0.88 (0.16)	0.82 (0.34)	0.34 (0.05)	0.68
C	0.57 (0.16)	0.38 (0.06)	0.24 (0.01)	0.39
D	0.61 (0.11)	0.67 (0.27)	0.33 (0.03)	0.53
Average	0.62	0.55	0.28	0.48

Completely Randomized Design with 12 'treatments'
 poison (3 levels) \times Treatment (4 levels), 4 observations for each combination

- Why do we randomize assignment of treatments to units? if we can
- leads to approximate balance on potential confounding variables

- can't we adjust for confounding variables using regression?
- yes, if we know what they are

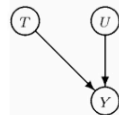
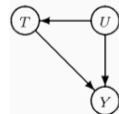
e.g. fruitflies (thorax length)

- can't adjust for unknown confounders

“unknown unknowns”

- depending on the sample size, there's a limit to how many variables can be included in the regression model

- randomization breaks the link from **Unmeasured** to T
e.g. disease severity causal diagram



- comparison of treatments is more **precise** if the units are more homogeneous
- e.g. for agricultural trials, if properties of the soil are similar
- e.g. for clinical trials, if patients have similar levels of important measures, e.g. overall health
- putting experimental units into homogeneous (alike) subgroups before randomizing can give more precise estimates of treatment effects
- compare the two analysis of variance tables for one-way and two-way layouts
- 2-way has separate term for, e.g., blocks so residual SS is smaller
- “Block on what you can measure, randomize over what you can’t measure”

- randomization helps to eliminate **systematic error**
- “distortion in the conclusions arising from irrelevant sources that do not cancel out in the long run”
- treatment differences might be confounded by differences among patients, or by the time of day the treatment is applied, or by spatial differences among plots of land
- for example, units might be treated in space, or in time
- systematic error can arise by the entry of personal judgement into some aspect of the data collection process
- this can often be avoided by randomization and blinding

CD

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9 · Designed Experiments

adjustment for measured covariate

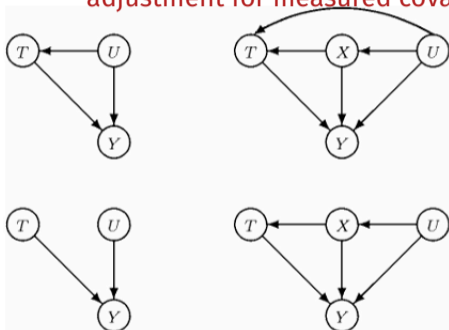


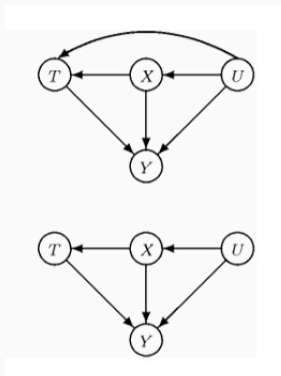
Figure 9.1 Directed acyclic graphs showing consequences of randomization. An arrow from T to Y indicates dependence of Y on T , and so forth. In general both response Y and treatment T may depend on properties U of units (upper left).

Randomization (lower left) makes treatments and units independent, so any observed dependence of Y on T cannot be ascribed to joint dependence on U .

The upper right graph shows the general dependence of Y , T , and covariates X on U .

Randomization makes T and U independent, conditional on X (lower right), so any influence of U on T is mediated through X , for which adjustment is possible in principle. The basic

the control group. The response is to be the blood pressure of an individual measured a fixed time after the drug has first been administered. We calculate the average changes for the treated and control groups, \bar{y}_1 and \bar{y}_0 , observe that $\bar{y}_1 - \bar{y}_0$ is significantly less than zero, and declare that the drug plays an effect in reducing blood pressure. Is this headline news? No!



treatment allocation depends on measured covariate X , similar to blocking
effect of Unmeasured confounder mediated through X