Marketing & Data Analysis

Statistical Comparisons

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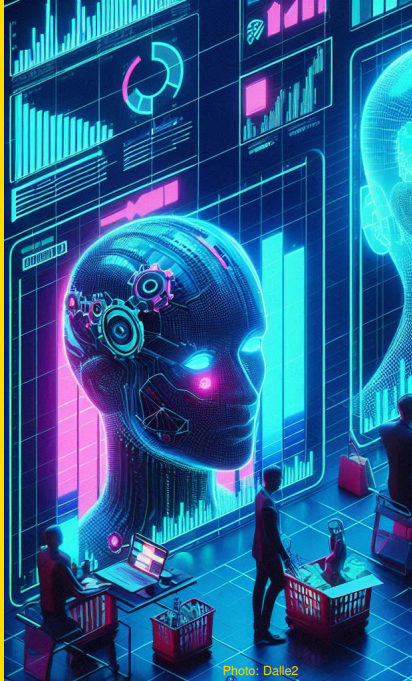

How do we know a campaign worked in social media? (Gordon et al., 2019)

Which is better?

- Randomized control trial (RCT)
- Observational data

RCT Approach (Gordon et al., 2019)

In Facebook (FB) there are three types of people.

- FB doesn't target them and do not see the campaign, but do see other ads (control)
- FB target them but do not see the ad e.g. they didn't log during the period of the campaign (treated unexposed)
- FB target them and see the ad (treated exposed)

RCT Approach (Gordon et al., 2019)

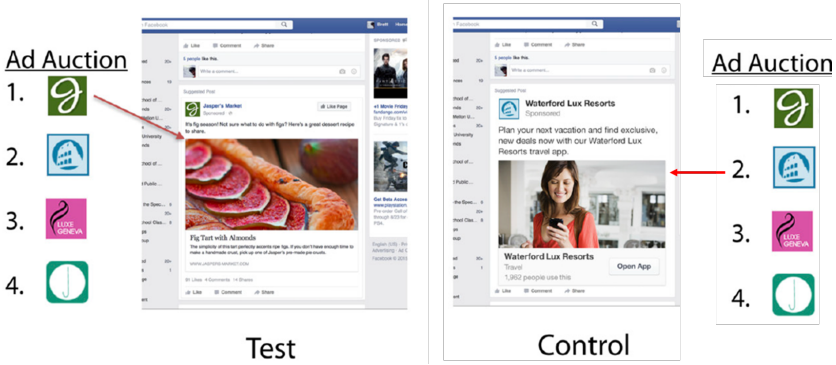

Figure: Design. The control cannot see the test campaign. So if the test campaign wins the auction, it is the 2nd best that actually wins and the user sees that campaign instead of the test campaign

Observational Approach (Gordon et al., 2019)

Usually a regression. For instance

$$Checkout = \beta_0 + \beta_1 Exposure_{add} + \theta Controls$$

There are now techniques to pull causality from these type of regressions. Gordon et al., 2019 use those techniques to compare them with an RCT

Results

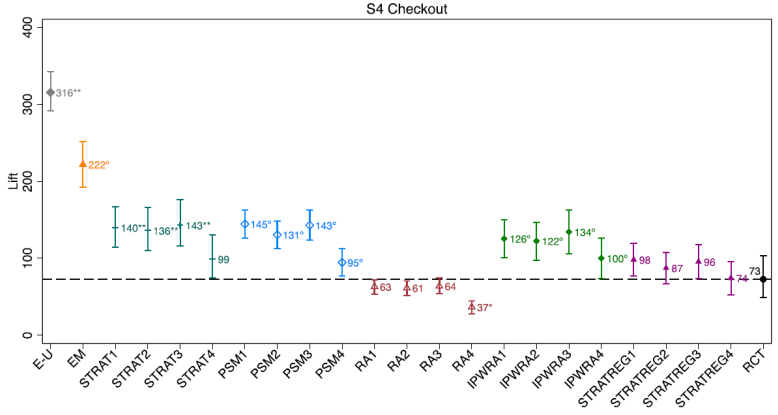

Figure: The RCT effect to the right. The other techniques on the x axis are observational methods. The RCT and observational estimates of campaign exposure efficiency (lift) differ! We need RCTs (assuming it is the true estimate).

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Prediction, Inference, Causality (PIC)

PIC

What does P(Rain|Sun) mean?

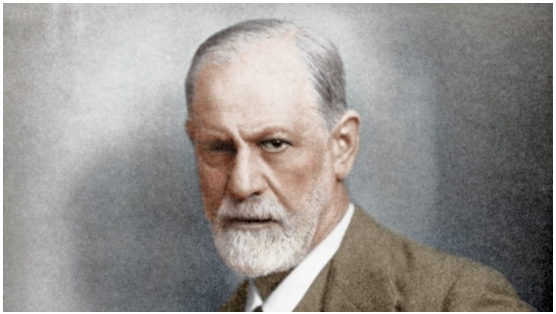
Correlation is causation?

Is conditional probability causality?

For example, if P(Rain|Sun) = 0, is there causality? Does sun causes no rain?

PIC

Do citations depend on prestige or the other way around?



$$Citations = \beta_1 Prestige + \mu$$

PIC

Do grades depend on prestige or the other way around?

$$Notas = \beta_1 Prestige + \mu$$

PIC

Do commissions depend on prestige or the other way around?

$$Comisiones = \beta_1 Prestige + \mu$$

PIC

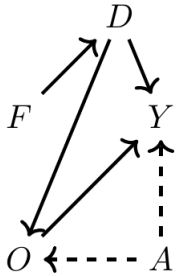
Salary discrimination by gender (Source: Cunningham, 2021)

Google stated that it does not discriminate by gender, once controlling for type of position, hours, and other job characteristics.

But what is the causal model? F: gender; D: Discrimination; Y: income; O: occupation; A: non-observable abilities

PIC

F: gender; D: Discrimination; Y: income; O: occupation; A: non-observable abilities

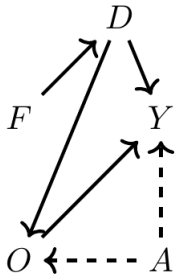


PIC

In the model, discrimination (D) occurs via occupational sorting (O) and that may be affecting (Y).

You have to control for occupation (O) and unobserved skills (A)

Let's look at the code in (Intro_DM_TEC.ipynb; DAG GOOGLE section).



PIC

Without a causal model, Google's occupation control is uninformative. It gives us biased estimators.

The problem of not having clear causal models even leads to paradoxes. Let's look at Simpson's paradox.

PIC

Treatment: paywall or not. Outcome: subscribed or not. Paradox: the group effect is different from the individual (Pearl & Mackenzie, The Book of Why, 2018)

Both	Subscribed	Not subscribed	Total	Ratio
Paywall	20	20	40	**50%**
No paywall	16	24	40	40%
	36	44	80	
Man	Subscribed	Not subscribed	Total	Ratio
Paywall	18	12	30	60%
No paywall	7	3	10	**70%**
	25	15	40	
Woman	Subscribed	Not subscribed	Total	Ratio
Paywall	2	8	10	20%
No paywall	9	21	30	**30%**
	11	29	40	

PIC

A causal understanding solves the paradox.

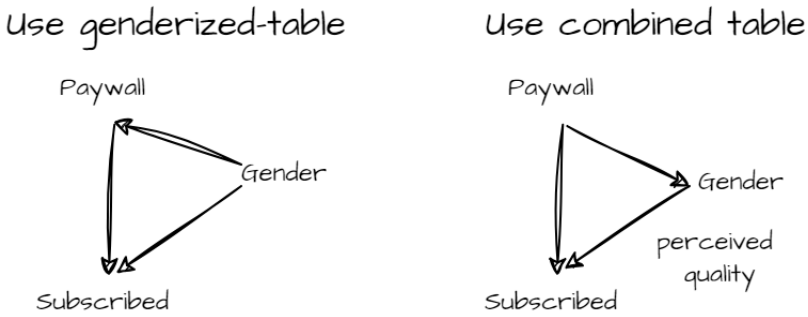


Figure: Both can generate the data. If the experiment was biased and being in a paywall was more likely for, say, men, then use genderized table. But if a paywall affects perceived quality by gender, then combine the table to see the mean effect

(Pearl & Mackenzie, The Book of Why, 2018)

PIC

Another example of the paradox.

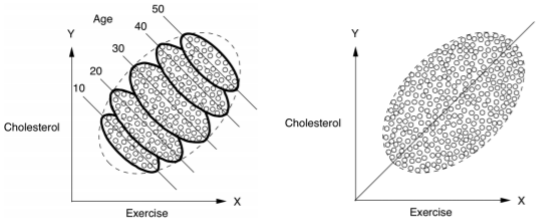


FIGURE 6.6. Simpson's paradox: exercise appears to be beneficial (downward slope) in each age group but harmful (upward slope) in the population as a whole.

(Pearl & Mackenzie, The Book of Why, 2018)

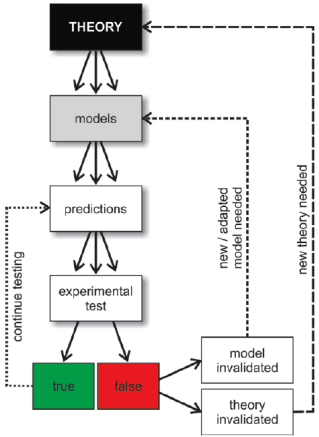
PIC

Another example of the paradox.

Click for thread in X about COVID vaccination

If it does not open or there is no connection, see document X thread by DadosLaplace (Simpsons paradox).pdf

PIC



Blohm et al., 2017

PIC

The Three Layer Causal Hierarchy

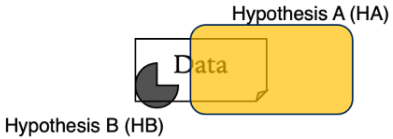
Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in Y?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

Figure 1: The Causal Hierarchy. Questions at level i can only be answered if information from level i or higher is available.

Pearl (2018, https://arxiv.org/pdf/1801.04016.pdf)

Inferential approaches

Two approaches



Approach 1:
max. p(DatalH)
Given HB, the data covers most of HB. Pick HB

Approach 2:
max. p(HlData)
Given the data, HA covers more data. Pick HA

Figure: Maximize probability of data or hypotheses?

Example

1000 of 1150 chili covered lolipops sold in a concert in Mexico City.

Do people in the world love them?

Hypotheses:
* Yes
* No
* Maybe

Figure: What hypothesis max. data prob.? What hypothesis is more likely?

Parametric and non-parametric

- Parametric (most of this course): we assume the data has a distribution with parameters (e.g. $\textit{Mouse Pointer Position} \sim \textit{Normal}(\textit{coord}_{\textit{center}}, 150\textit{px})$)
- Non-parametric: we do not assume the data has a distribution (e.g. sign test for pointer on the left vs right of screen)

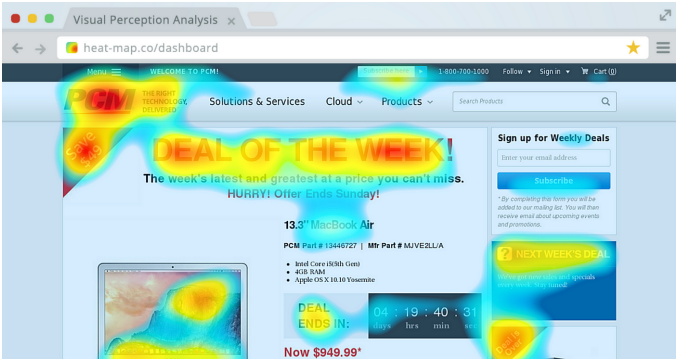


Figure: Source: Jesse Rowe, http://tinyurl.com/keabfe4p

Are weekly sales in our stores larger than the *population* median of 450?

Store	Weekly Sales	Sign (above pop. median = 450)
A	485	+
B	562	+
C	415	-
D	860	+
E	426	-
F	474	+
G	662	+
H	380	-
I	515	+
J	721	+

Anderson, D., Shoesmith, E., Sweeney, D., Anderson, D., & Williams, T. A. (2014). Statistics for business and economics 3e. Cengage Textbooks.

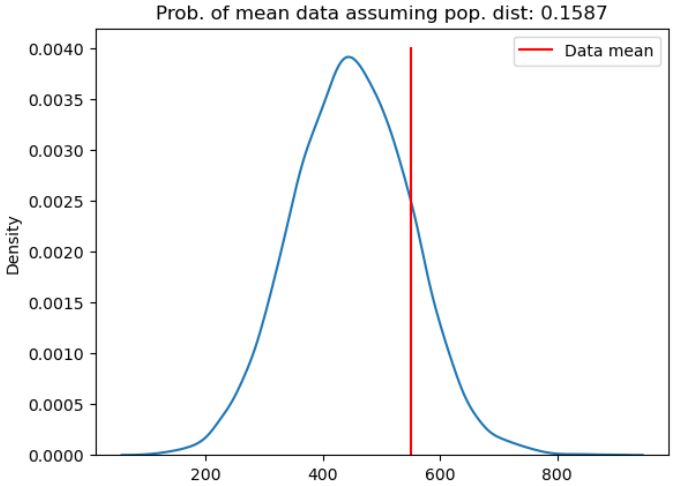
Non-parametric: agnostic on the data distribution

Prob. of positive signs?

Table: Binomial probabilities with n = 10 and p = 0.5

# of plus signs	Probability
0	.0010
1	.0098
2	.0439
3	.1172
4	.2051
5	.2461
6	.2051
7	.1172
8	.0439
9	.0098
10	.0010

Parametric: assume a data distribution



When non-parametric?

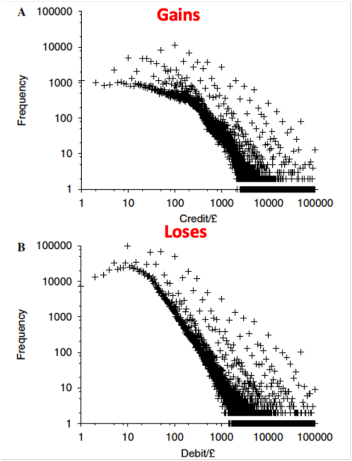
- No a priori knowledge of data distribution
- Data does not follow proposed distributions (e.g. non-normal; strong outliers)
- Categorical or qualitative data (prone to counts or ranks)

Do variables have distributions?

Zipf mystery (video)
here if it doesn't work

Do variables have distributions?

Yes, of course. Decisions by Sampling paper by Stewart et al (2006, 2019)

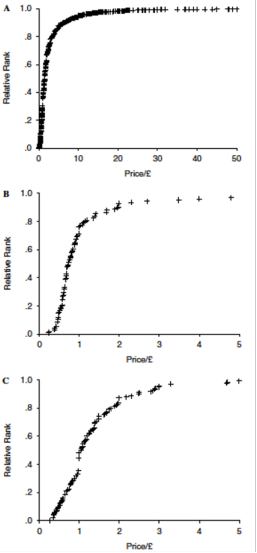


Deposits (gains) and withdrawals (loses) in bank accounts in UK

Power law (e.g. Zipf's law)

Stewart, et al, (2006)

Do variables have prob. distributions?

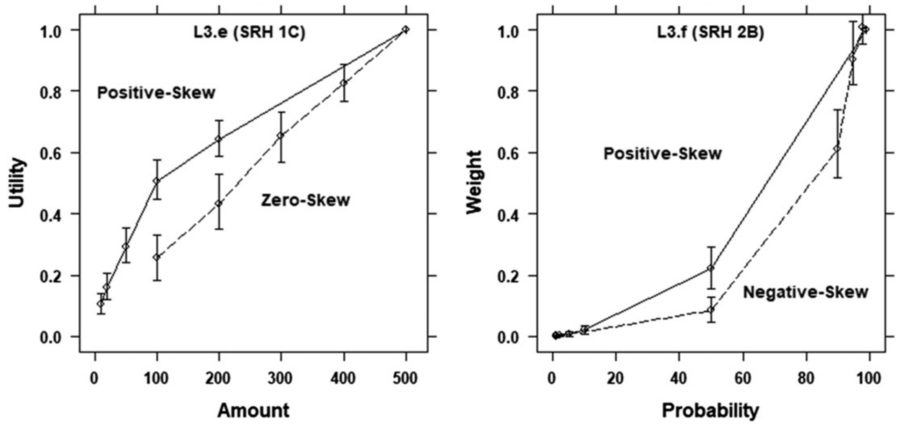


Not just banks

Stewart, et al, (2006)

Do variables have prob. distributions?

And the distributions/contexts change behaviors (utility and probability percepts)?



Alempaki et al., 2019

Do variables have prob. distributions?

Class activity: Benford's Law in first digit of student's documents (also ask friends in Whatsapp or social media) (e.g. ID, credit cards, etc)

Evidence based management

Discuss: evidence-based management and underdetermination of theory by data (UTD)

Let’s go to Python

FMDA_4_Inference.ipynb

References

Alempaki, D., Canic, E., Mullett, T. L., Skylark, W. J., Starmer, C., Stewart, N., & Tufano, F. (2019). Reexamining how utility and weighting functions get their shapes: A quasi-adversarial collaboration providing a new interpretation. *Management Science*, *65*(10), 4841–4862.

Blohm, G., Schrater, P., & Kording, K. (2017). Cosmo 2017. *Cosmo*, *1*(1), 1.

Gordon, B. R., Zettelmeyer, F., Bhargava, N., & Chapsky, D. (2019).A comparison of approaches to advertising measurement: Evidence from big field experiments at facebook. *Marketing Science*, *38*(2), 193–225.