# DO ANALYTICS DRIVE BETTER DECISIONS?

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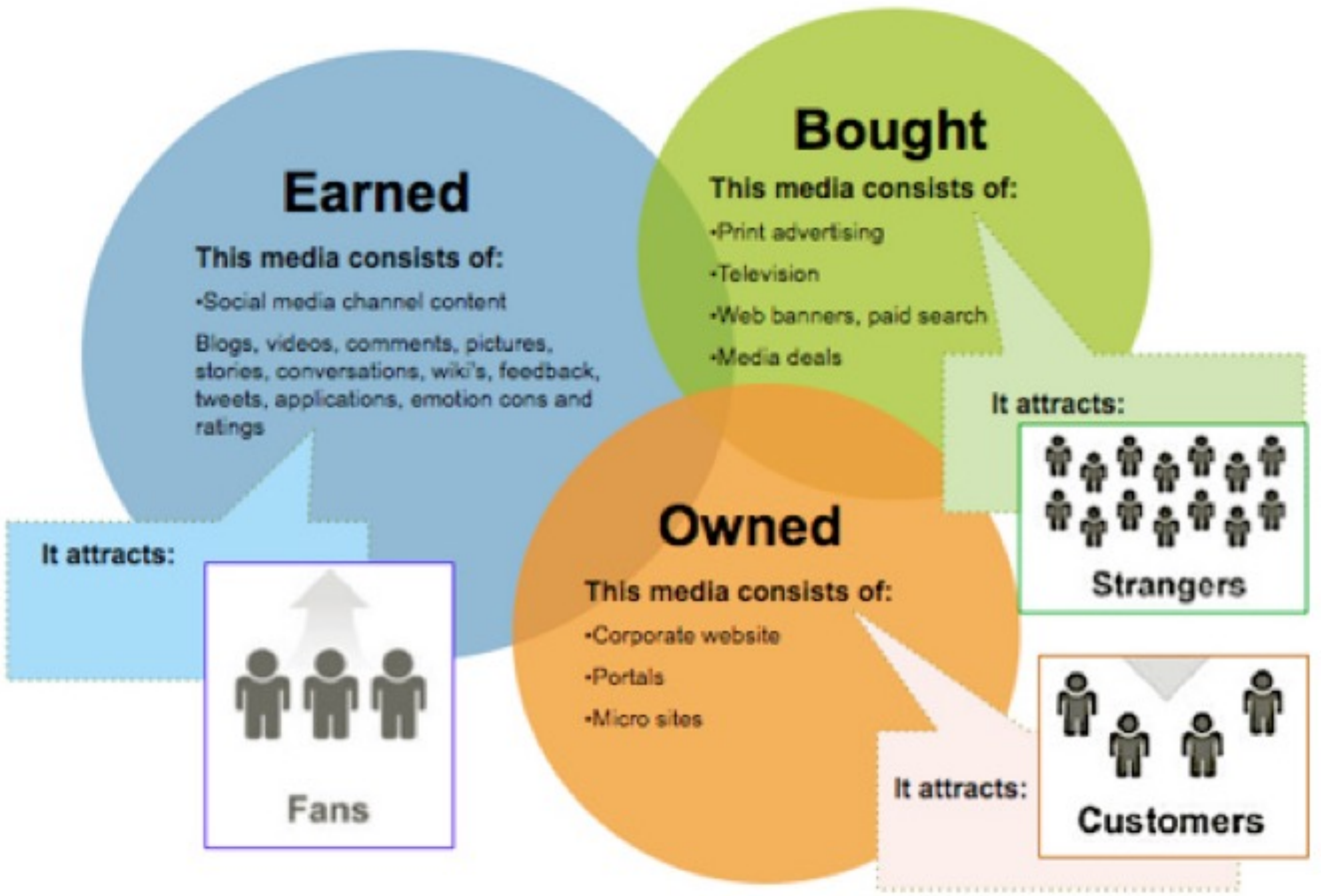
# WE OFTEN WANT ANSWERS TO THESE QUESTIONS

# IS MY ADVERTISING WORKING?

MILLION DOLLAR QUESTION

# WHERE SHOULD WE FOCUS?

## TWO MILLION DOLLAR QUESTION



# HOW TO MAKE IT BETTER?

THREE MILLION DOLLAR QUESTION

# OUR PRIMARY GOAL IS NOT TO ANSWER

- Is this result statistically significant?
- What is the confidence interval for this estimate?
- What is the p-value?
- Is it using deep learning? Is it Bayesian? What about AI?

# TO MAKE GOOD DECISIONS, WE NEED

- Data
- Analysis to generate insights
- Translating insights to decisions/actions

# OFTEN ASSUME THAT

- Collecting more data improves analytics
- Better (precise/accurate/causal) analytics improves decisions
- Better decisions result in higher firm profit

# THE RESEARCH DOES NOT SUPPORT THAT

## Misleading “Data science” leads to big losses

**eBay estimate down from 4000% to -60% ROI**
(Blake et al., ECA 2015)

**Last-touch attribution can lower profit**
(Berman, MKSC 2018)

## Advertising effects small and hard to measure

**Gigantic experiments can’t say if online ads are effective**
(Lewis & Rao, QJE 2015)

**Online & TV campaigns have modest effects**
(Johnson et al., 2017, Shapiro et al., ECA 2021)

## A/B tests are not a panacea

**A/B test often find small non-significant effects**
(Azevedo et al., JPE 2020, Berman & Van den Bulte, MGSC forthcoming)

# BIG QUESTIONS

## 01

How is the data generated?

## 02

What type of analysis are we conducting?

## 03

How to translate metrics into decisions?

# EXAMPLE

# "TASKABELLA"

| | | |
|---|---|---|
| Retargeting campaign using RocketFuel | Sells handbags<br><br>Margin of $40 | Ad cost<br><br>$9 CPM |
| 14,843<br><br>bags purchased | 14,597,182<br><br>ads shown | What is the ROI? |



Source: Katona and Sarvary, "Rocket Fuel: Measuring the Effectiveness of Online Advertising"

# NAÏVE ROI

ROI  = (Revenue – Cost) / Cost

Revenue:
14,843 * $40 = $593,720

Cost:
14,597,182 * $9 / 1000 = $131,375

ROI: 352%

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# SOMETHING SMELLS FISHY

Analysis only looks at people that have seen ads.

Perhaps those that didn't see ads would have bought as well?

Should compare to the ***counterfactual*** – the result of ***not*** running the campaign.

Control group – a group of people which will not be exposed.
Will serve to measure the counterfactual.

# ANOTHER BIG EXAMPLE: EBAY BRANDED ADVERTISING

- eBay was spending tens of millions of dollars a year on branded keyword search advertising.
- ROI estimates of 600% to 4000%.

# WHAT CAN WE DO?

# A FRAMEWORK FOR DECISION MAKING WITH DATA

1. What decision are we trying to make?
2. What KPI should be maximized and how?
3. How should we compute this KPI?
4. What data do we have, and does it correctly lead to the KPI?

# EXERCISE – BIDDING IN AD AUCTIONS

## A daily campaign report looks something like this

| Day | Bid ($) | QS | Avg. Rank | CPC ($) | Impressions | Clicks | Sales ($) |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 8 | 1.2 | 0.78 | 1800 | 88 | 58.08 |
| 2 | 0.9 | 8 | 1.3 | 0.75 | 1300 | 54 | 37.26 |
| 3 | 0.8 | 8 | 2.1 | 0.6 | 2000 | 32 | 29.76 |
| 4 | 0.7 | 8 | 2.3 | 0.58 | 1600 | 21 | 20.79 |
| 5 | 0.6 | 8 | 2.6 | 0.57 | 1200 | 12 | 12.96 |

1. Which metric would you choose to follow (and why) on a Google campaign among:

   Clicks, Impressions, ROI, Profit, CTR, Rank, Sales, CPC

2. Download the data from https://upenn.box.com/v/MSI-Accelerator
3. Calculate:
   i. The Cost for each bid.
   ii. The Profit for each bid.
   iii. The ROI for each day.
4. What is the optimal bid you will choose going forward?

# DISCUSSION

# INSIGHTS FROM BID OPTIMIZATION

- ROI does not always equal Profit.
- Sometimes the data might mislead us to focus on the wrong metric.
- Need to carefully think – why do people see more ads, who are these people, and are these the ones we would like to show ads to.

# EMPIRICAL METHODS THAT HELP TO ENSURE CAUSALITY

- Observational (Quasi-Experimental) Studies:
  - Focus on analysis stage.
  - Well crafted control group.
  - Careful analysis: diff-in-diff (DiD), regression discontinuity, instrumental variables.
- Experimental (A/B Testing):
  - Focus on design/data collection stage.
  - Control group through randomization.
  - Simpler analysis

## RANDOMIZED EXPERIMENTS

## A/B TESTS

The analysis compares averages:

Average(Seen ads) – Average(Didn't see ads)

- If people who see ads buy anyway, we will overestimate the ROI
- Causal testing uses ad allocation independent of the decision to buy

# TASKABELA EXAMPLE PLACEBO VS. NON-PLACEBO

- We compare the conversion rates between the test and control groups:

| Row Labels | Count of converted | Average of converted | Sum of converted |
|---|---|---|---|
| 0 | 23524 | 0.017854106 | 420 |
| 1 | 564577 | 0.02554656 | 14423 |
| **Grand Total** | **588101** | **0.025238862** | **14843** |

- Incremental Revenue:

  564,577*(0.0255-0.0178)*$40 = $173890

- ROI: 32.3%

# PRINCIPLES (I)

*Always* have a control group.

The decision of who is in the control cannot depend on past history, on ad exposure, on ad prices etc.

## PRINCIPLES (II)

Good control groups:

- Geographic areas which are similar (one control, one exposed).
- A/B test randomization.
- Placebo ads.
- Ghost ads (a Google technique).
- Random holdouts.

Not so good control groups:

- People included in the campaign vs. not-included.
- People targeted by an algorithm vs. not targeted.

# CHALLENGES AND SOLUTIONS (I)

Not always possible to run an experiment.

- Next best: Quasi-experiments, causal inference on observational data, matching, geographic splitting etc.

Experiments are expensive (control costs money)

- Next best: use an adaptive experiment that takes profit into account.

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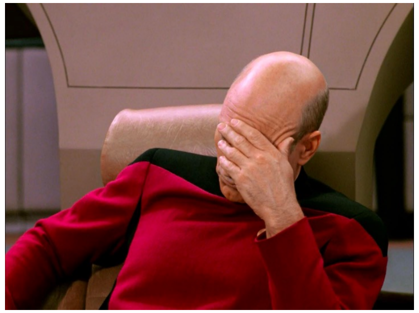
# CHALLENGES AND SOLUTIONS (II)

Need huge control groups

- Next best: Test & Roll (Feit & Berman 2019) – to maximize profit, no need for big control group: www.testandroll.com

My competitor shows better ROI without causal testing

- Next best:



or ¯_(ツ)_/¯

# CONCLUSION

- Causal inference is making its way into online advertising.
- Challenges abound, because ***advertising effects are small***, take time to appear, and there are ***so many*** technologies.
- Next big question (in academic research) is decision making – how to optimize advertising.
- When comparing advertising technologies, make sure to compare apples to apples.
- Comparing over different populations makes the conclusions moot – always have a control group, but make sure it makes sense.

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# THANK YOU

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