

# Randomized Experiments and Ad Measurements

Instructor: Davide Proserpio

# A few things

- Wednesday guest speaker: [Yang Wang](#), Principal Economist at Amazon
- A note on participation and attendance

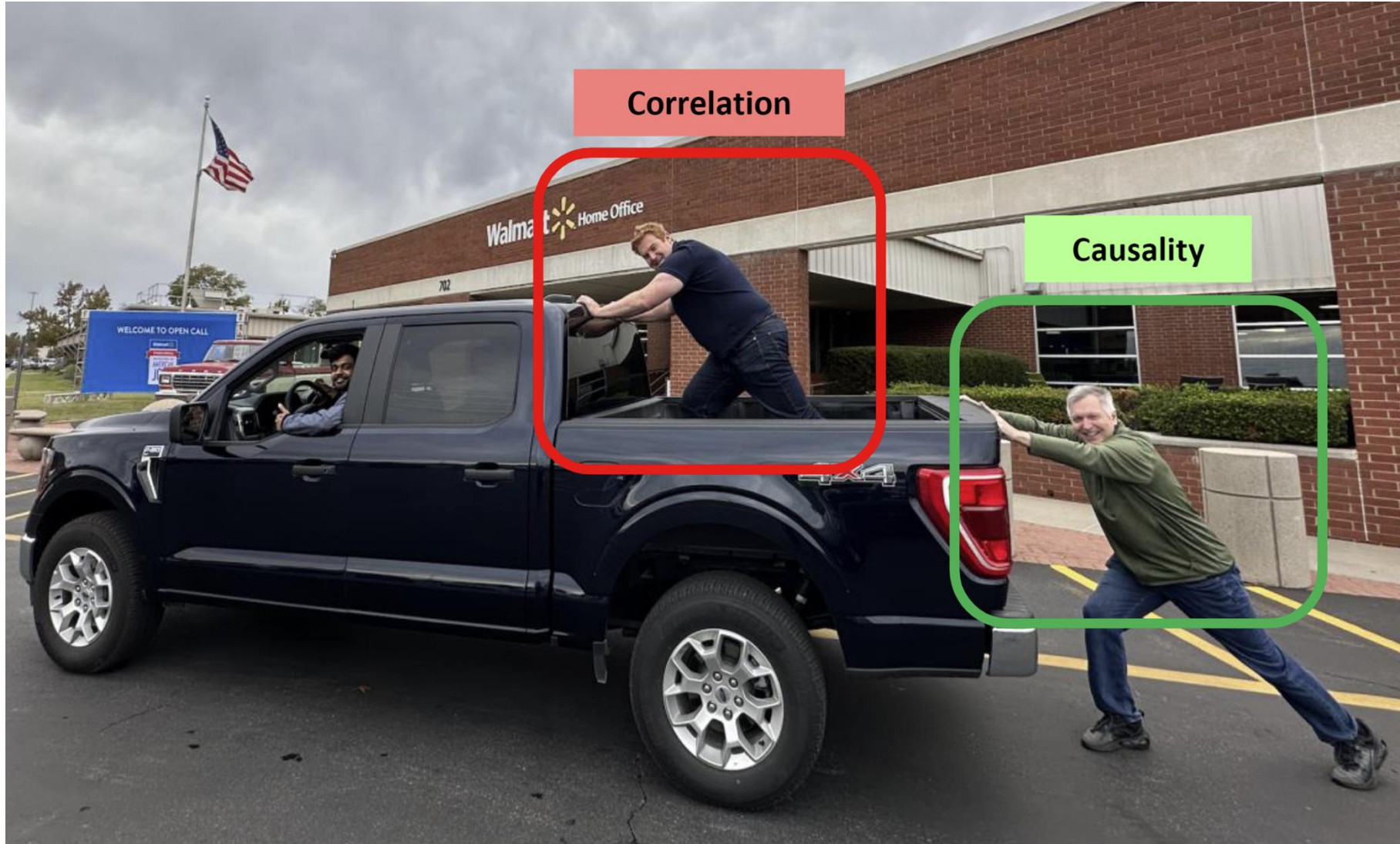
# Why We Run Experiments

- Marketers constantly ask: “*Did my action **cause** a change?*”
- The problem: correlation  $\neq$  causation.

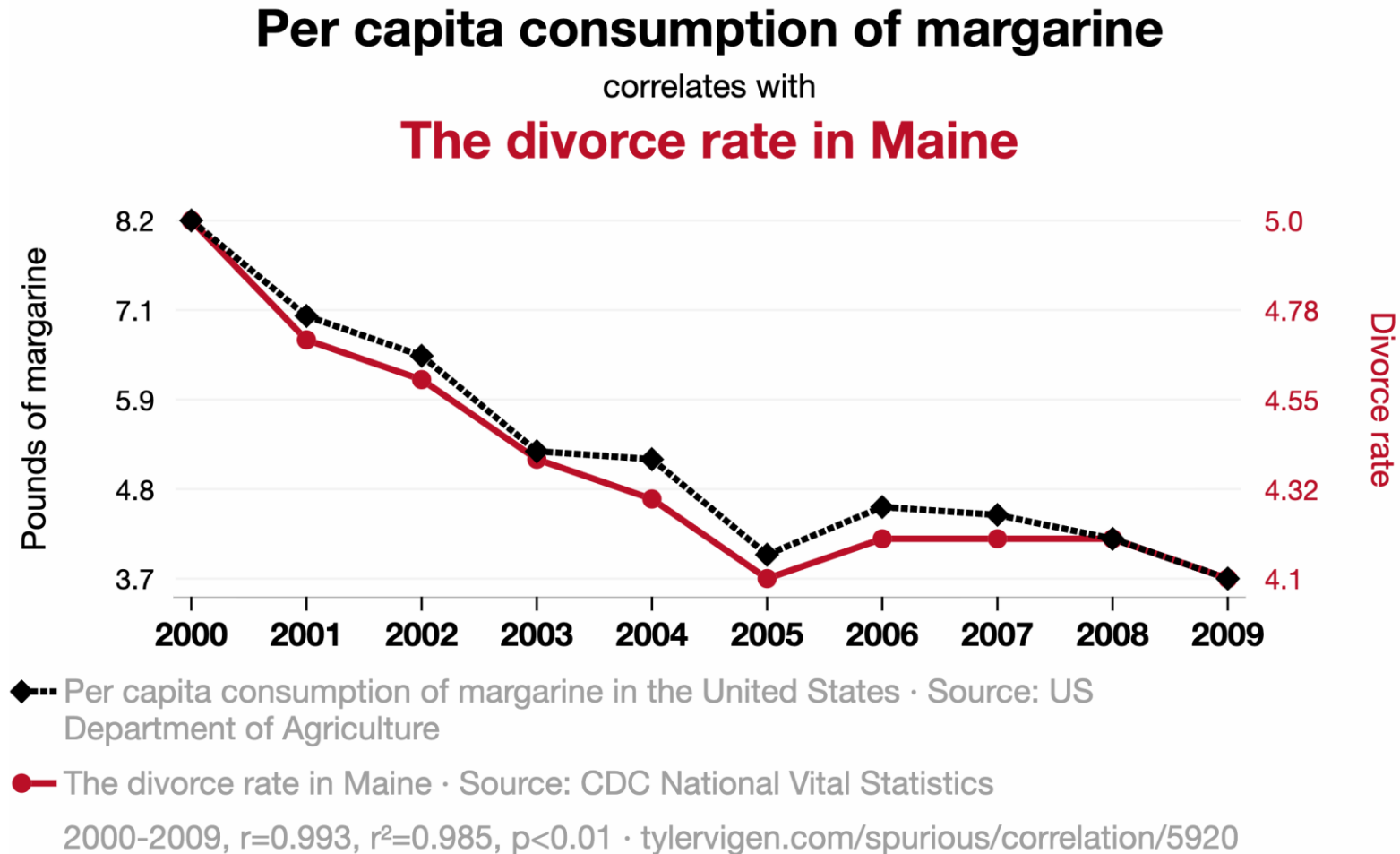
# Why We Run Experiments

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- The problem: correlation  $\neq$  causation.
- In general, what can we learn from a significant correlation?
  - “These two variables likely move together.” Anything more requires assumptions.

# Correlation $\neq$ causation



# Correlation $\neq$ causation



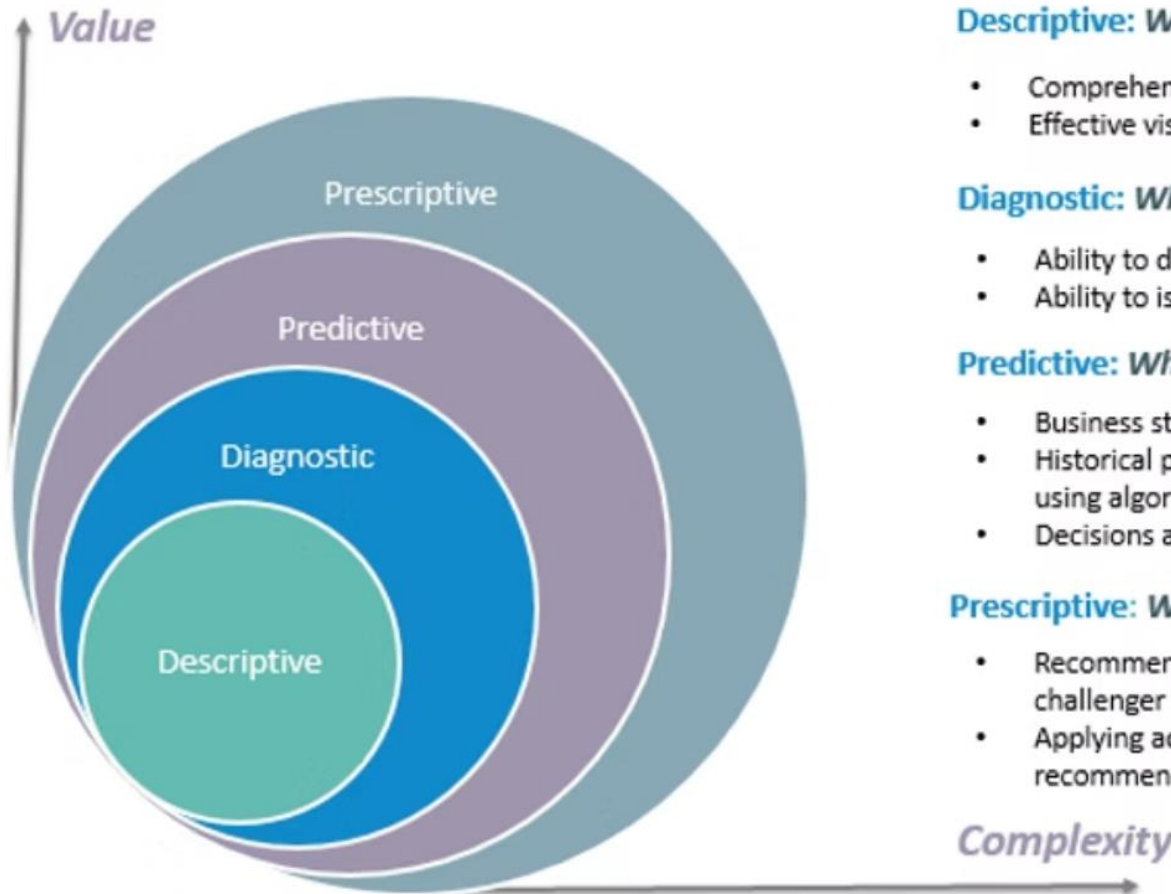
# Correlation $\neq$ causation

## Classic misleading correlations:

- Commuters carrying umbrellas and rain
  - Forward-looking behavior
- Kids receiving tutoring and grades
  - Reverse causality/selection bias
- Ice cream sales and drowning deaths
  - Unobserved confounds

# Why causality matters?

## 4 types of Data Analytics



### What is the data telling you?

#### **Descriptive:** *What's happening in my business?*

- Comprehensive, accurate and live data
- Effective visualisation

#### **Diagnostic:** *Why is it happening?*

- Ability to drill down to the root-cause
- Ability to isolate all confounding information

#### **Predictive:** *What's likely to happen?*

- Business strategies have remained fairly consistent over time
- Historical patterns being used to predict specific outcomes using algorithms
- Decisions are automated using algorithms and technology

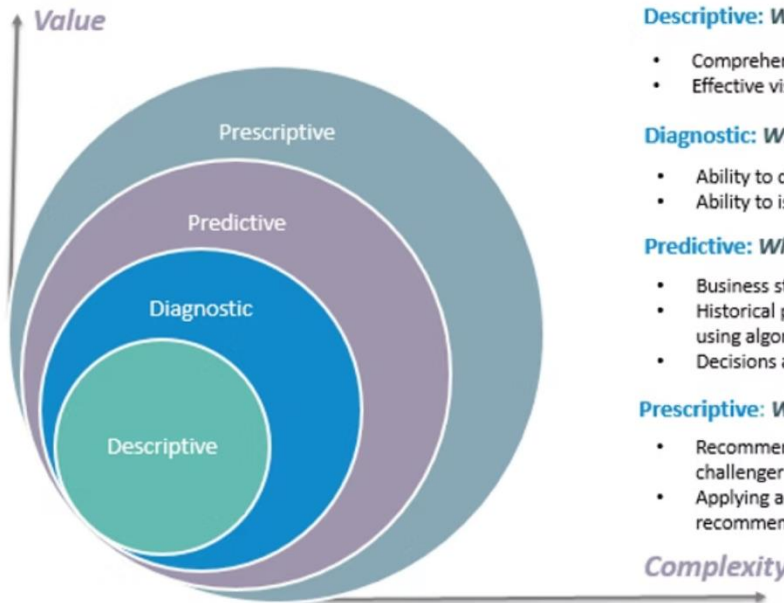
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- Applying advanced analytical techniques to make specific recommendations



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- Correlations are **descriptive** analytics (“facts”)
- Causality matters most for **diagnostic** and **prescriptive** analytics
- Causality can help build predictive models, but correlations suffice most of the time for **predictions**

# Why we need experiments: The Counterfactual Problem

- For each unit, we observe only one outcome:
  - what happened with the treatment, or without, not both.
  - The case we don't observe is called the "counterfactual"
- This is a missing-data problem that we cannot resolve. We only have one reality
  - A significant reason we build models is to compensate for missing data.
- Randomization creates comparable groups → approximates missing world.

# The Logic of an Experiment

- Compare **treated** vs **control** units.
- Everything else held constant through **randomization**.
- Any average difference = **causal effect**.

# Anatomy of a Randomized Experiment

Element	Description
Population	Users, customers, products
Treatment	Message, ad, feature, policy
Randomization	50/50 split or stratified design
Outcome	Click, purchase, satisfaction, etc.

# Randomization in Practice

- Unit of randomization matters:
  - user, session, region, campaign, etc.
- Always check unit **balance**: are treated/control groups similar?
- If not, the experiment may be biased.

# A/B Testing: Experiments in Product and Marketing

- **A/B test** = simplest form of an RCT.
- Test two versions (A and B) differing in *one* element.
- Measure difference in outcomes → decide which performs better.
- Used for web design, pricing, ad creatives, and recommendations.
- [Substack example](#)

# Estimate treatment effect

- Observed differences can arise by chance.
- Use **hypothesis testing** to judge if effect is real.
- Report confidence intervals or p-values.
- Small samples → noisy results.

# Hypothesis testing (a reminder)

- **Setup**

- **Null hypothesis ( $H_0$ ):** The ad / change has *no effect*

$$H_0: \mu_T = \mu_C$$

- **Alternative ( $H_1$ ):** The treatment *changes* the outcome

$$H_1: \mu_T \neq \mu_C$$

- **Logic**

- Compute the **difference in means** between groups.
  - Estimate its **sampling uncertainty** (standard error).
  - Compare to what random chance would produce (p-value).
  - If the difference is unlikely under  $H_0 \rightarrow$  **reject  $H_0$** .



# Common Mistakes in A/B Testing

- Peeking early (stopping when results look good)
- Running time too short → low statistical power
- Multiple tests → false positives
- Spillovers between users
- Focusing on statistical significance, not business value

# Ads Measurements

# Ads Measurements

- **Ad measurement** refers to the set of methods used to **quantify the effect of advertising exposure on desired outcomes** — such as awareness, clicks, conversions, or sales — across channels, audiences, and time.
- Advertising measurement is hard because ad effects depend on ad content, context, timing, targeting, current market conditions, past advertising & past outcomes
- Advertising measurement is expensive, so must *directly* inform firm choices
  - We have to know how measurements will inform next steps, else measurement is wasting money

# What do we measure?

- Often, Return on Ad Spend (ROAS) or Incremental ROAS (iROAS):  
ROAS = (Revenue **attributed** to ads – Ad Spend) / Ad Spend
- ROAS != iROAS because attribution is usually correlational

# Attribution vs. Incrementality

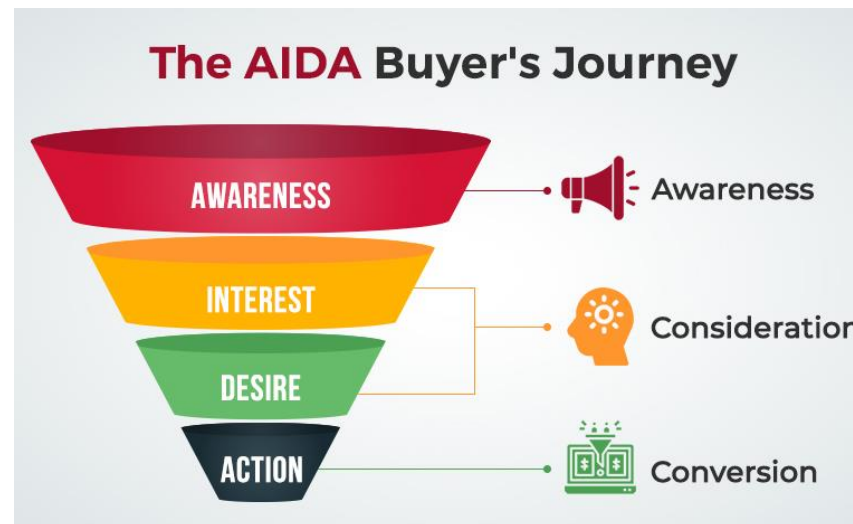
Concept	Main Question	What It Measures	Data Basis	Typical Output	Core Limitation
<b>Attribution</b>	<i>“Which channel, ad, or touchpoint gets credit for the conversion?”</i>	Allocation of credit among exposures	Observational data (click paths, impressions)	% contribution per channel (e.g., search 40%, display 30%, social 30%)	Correlational: cannot tell if ads <i>caused</i> the conversion
<b>Incrementality</b>	<i>“How much of the observed behavior would have happened <b>without</b> the ad?”</i>	True causal lift — incremental effect	Experimental or quasi-experimental data (holdout tests, ghost ads, geo experiments)	Lift %, incremental conversions, iROAS	Requires randomization or strong identification design

# Heuristic Attribution Models

- **Last-touch**: credit to last channel before conversion.
- **First-touch**: credit to first interaction.
- **Linear / Time-decay**: spread credit across touchpoints.
- Easy, but **not causal** → can double-count effects.

# How can we measure ads incrementality?

- RCTs can aid ad measurements
- They are very useful to measure the **incremental (causal) impact** of ads on outcomes.
- Note that it is much easier to measure outcomes for campaigns designed to stimulate **short-run** responses (e.g., sales) rather than **long-run**



# Incrementality Testing in Ads

Run an **ad holdout experiment**:

- Randomly suppress ads for a control group.
- Compare outcomes → estimate incremental lift.



# The “Ghost Ads” Design

- Serve ads as if everyone participated, but only some see them.
- Randomization integrated into ad auction logic.
- Ensures fair control → avoids targeting bias.
- Used by Amazon, Meta, and Google.

# Geo-Split Test

- Randomize ad exposure across markets (cities/regions).
- Measure aggregate lift.
- Useful for TV, brand, or offline campaigns.
- Requires large samples and market comparability.

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# Some firms may be ok with $\text{Cor}(\text{Ad Spend}, \text{Sales})$ , why?

1. Some firms assume that correlations indicate the direction of causal results
  - The guy in the truck bed is pushing forward, right?
  - Biased estimates might lead to unbiased decisions (keyword: "might")
  - But direction is only part of the picture; what about effect size?
2. Estimating causal effects of ads is not always easy
  - Many firms lack expertise, discipline, execution skill
  - Ad/sales tests may be statistically inconclusive, especially if small
  - Tests may be designed without subsequent action in mind, then fail to inform future decisions

# Some firms may be ok with $\text{Cor}(\text{Ad Spend}, \text{Sales})$ , why?

3. Platforms often provide correlational ad/sales estimates
  - Which is larger, correlational or experimental ad effect estimates?
  - Which one might many client marketers prefer?
  - Platform estimates are typically "black box" without neutral auditors
  - Sometimes platforms respond to marketing clients' demand for good numbers
  - Nobody ever got fired for buying [famous platform brand here]"
4. Historically, agencies usually estimated RoAS
  - Agency compensation usually relies on spending, not incremental sales
  - Advertising attribution is all about maximizing credit to ads

# Marketing Mix Models (MMM)

- **Marketing Mix Models** are **statistical models** that estimate how **sales or revenue** respond to **different marketing inputs** over time.
  - However, they often report correlation
- They help answer:
  - “How much does each channel — TV, search, display, email, etc. — contribute to performance?”
- Because correlations are still important and very much used to inform decision, MMMs continue to be very popular

# Marketing Mix Models (MMM)

- [Google Meridian](#)
- [Facebook Robyn](#)

# MMM: Core idea

- Regress **sales** on **spend and other drivers**:

$$\text{Sales}_t = \beta_0 + \beta_1 TV_t + \beta_2 Search_t + \beta_3 Display_t + \dots + \varepsilon_t$$

- The estimated  $\beta$ 's capture the **average (correlational) effect** of each channel.
- **Typical Inputs**
  - Weekly or monthly data
  - Media spend (TV, search, social, radio, etc.)
  - Control variables (seasonality, price, promotions, holidays)
  - Sometimes lagged or decayed ad effects (adstock): the carryover effect of advertising how the *impact* of an ad persists over time even after spending stops.



# What It's Used For

- Estimate **ROI per channel**
- Support **budget allocation** decisions
- Complement experiments when user-level data are unavailable
- Capture **long-term brand effects**

# MMM: Limitations

- Correlation bias — no randomization
- Requires strong modeling assumptions
- Sensitive to multicollinearity among channels
- Slower feedback — often quarterly or annual

# Practical Takeaways

- Randomization = best path to causality.
- Attribution  $\neq$  incrementality — don't confuse credit with causation.
- Experiments should inform budget allocation, not replace it.
- $\text{Cor}(\text{Ad Spend}, \text{Sales})$  are still pretty popular and so are Marketing Mix Models