



CIVIS
ANALYTICS

SHOW ME THE MONEY

Understanding Causality for Ad Attribution

April Chen, Lead Data Scientist, @AprilChenster

John Davis, Senior Data Scientist, @johncdavis_



AGENDA

- Introduction to attribution modeling
- Traditional approaches
- Match attribution
 - Applying methods from statistical inference to measure the *causal* impact of ads
- Case study



MOTIVATION

Organizations spend a lot of money on marketing, but often lack transparency into the impact of their efforts.

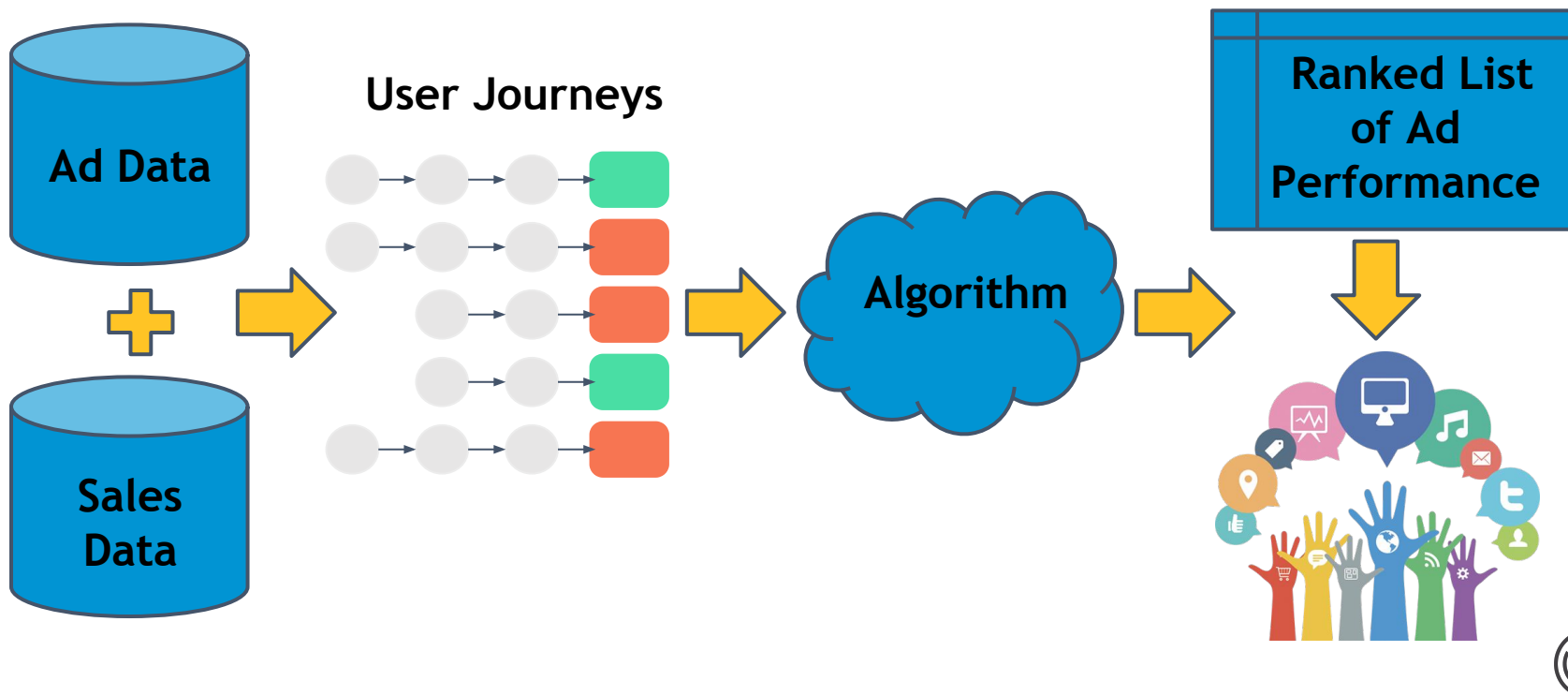
We want to measure the causal effect of advertising on target outcomes to maximize:

- **Sales:** sales of a promoted product or service
- **Awareness:** brand awareness and favorability
- **Engagement:** click-through-rates or signups
- **Political support:** favorability for a political candidate or turnout at the polls



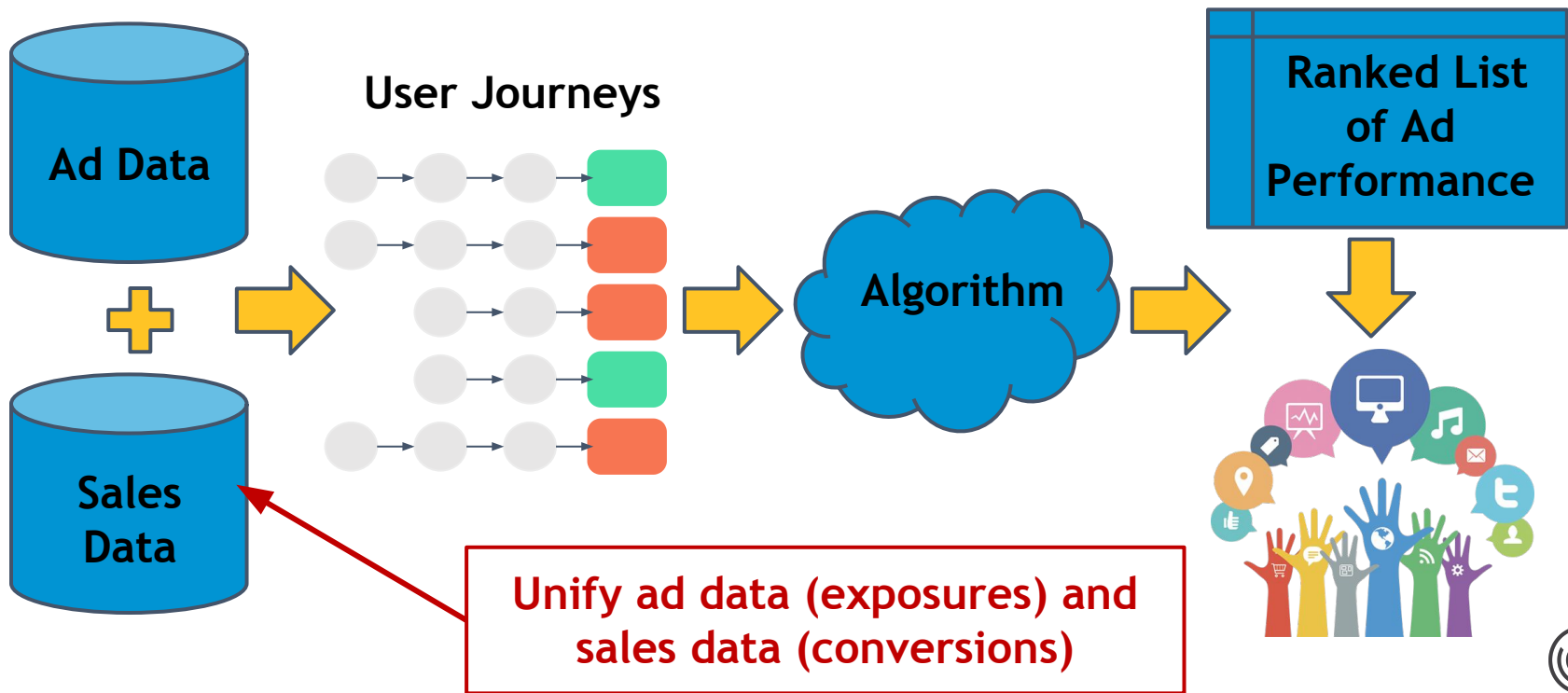
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.



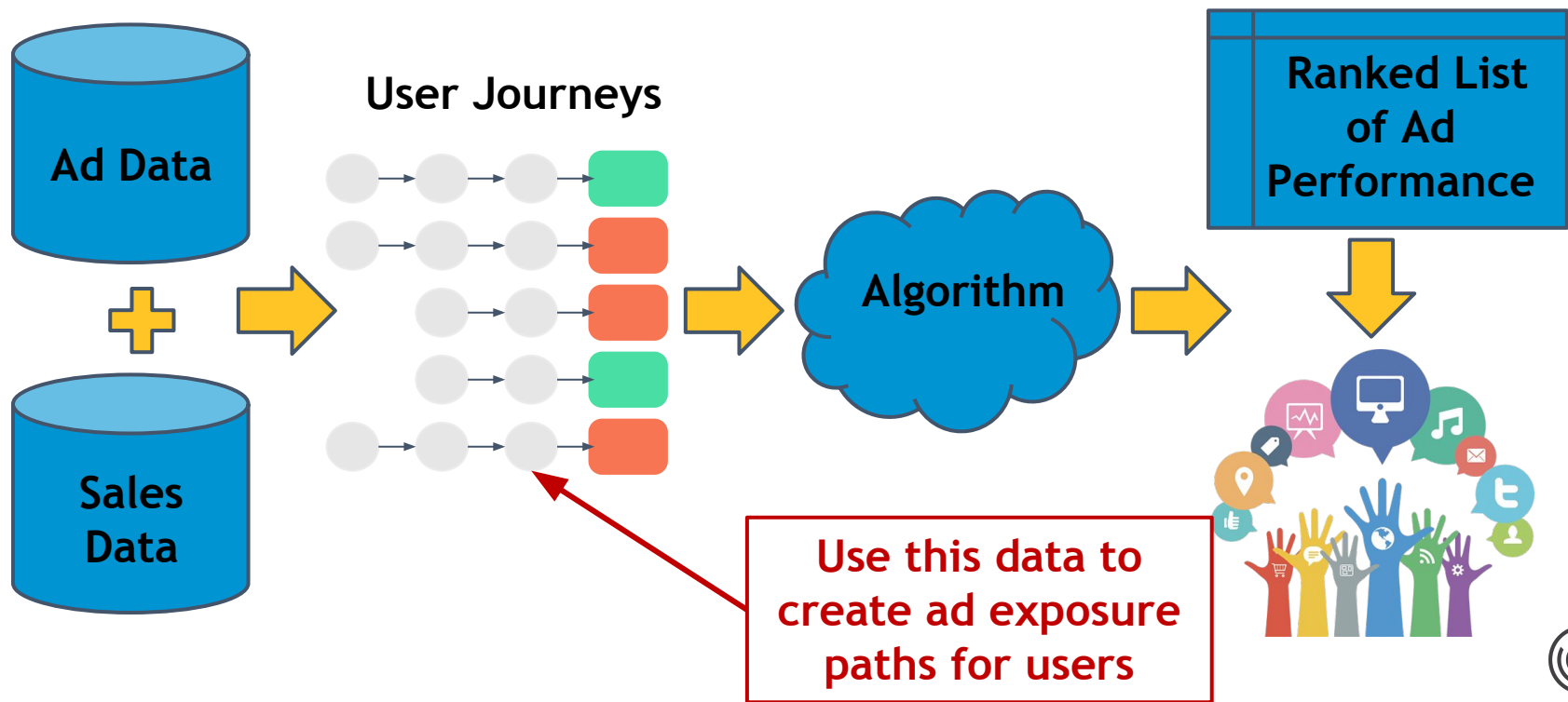
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.



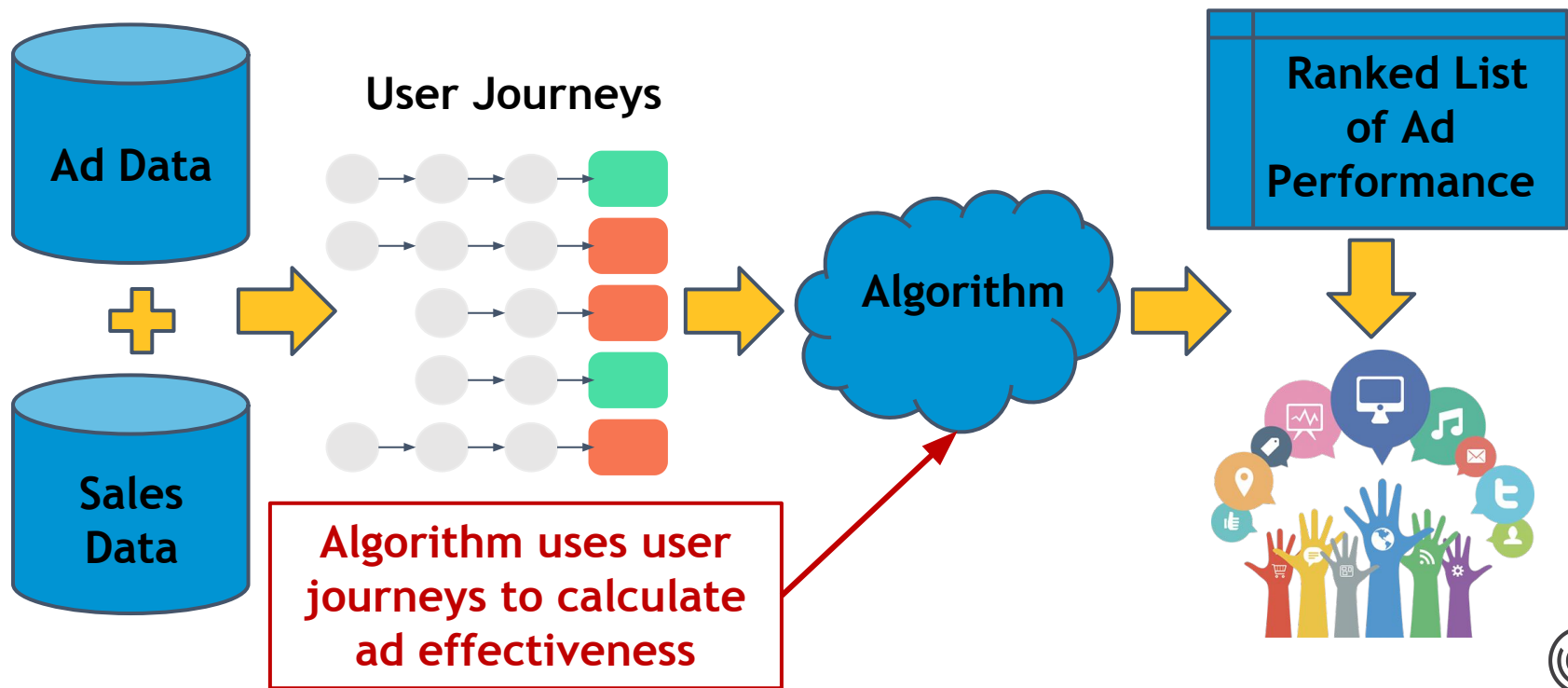
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.



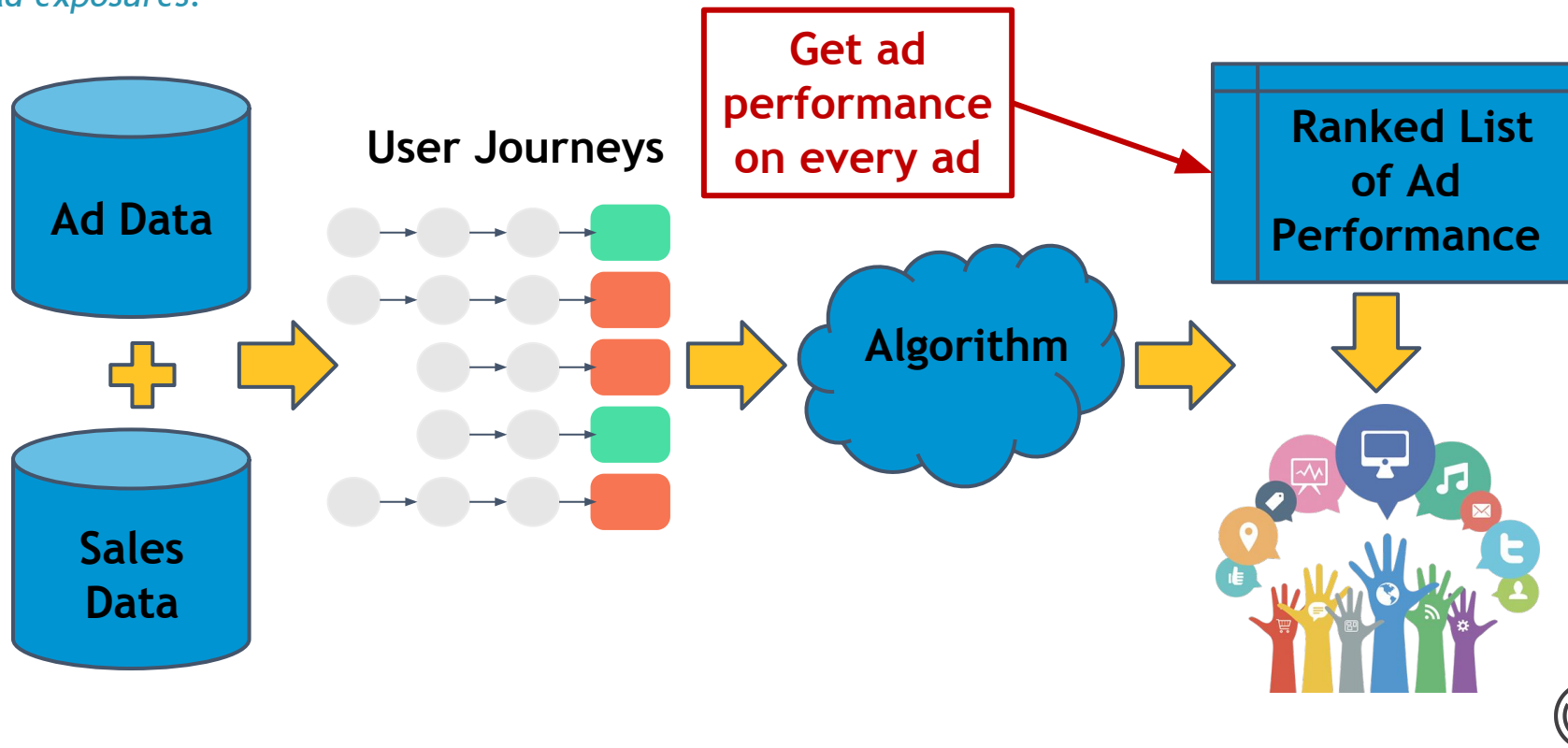
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.



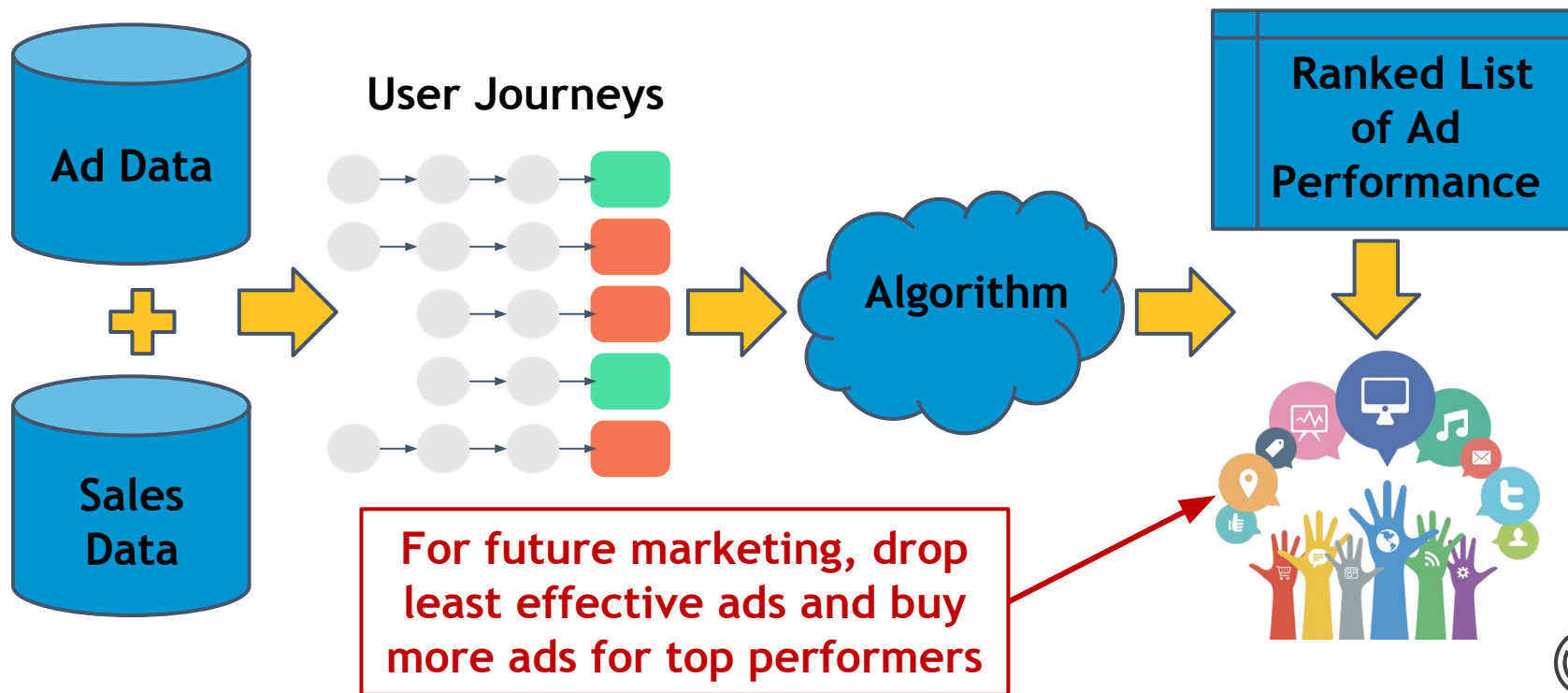
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.



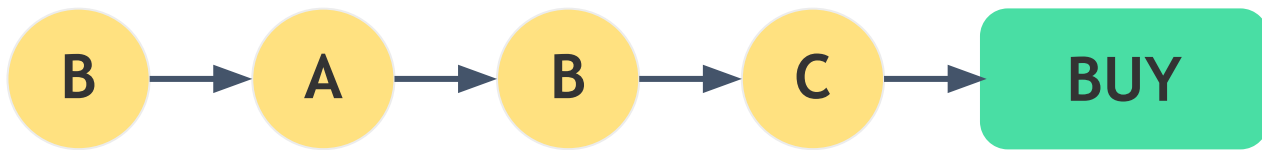
ATTRIBUTION MODELING

A common approach to these problems is attribution modeling, which assigns credit for conversions to ad exposures.

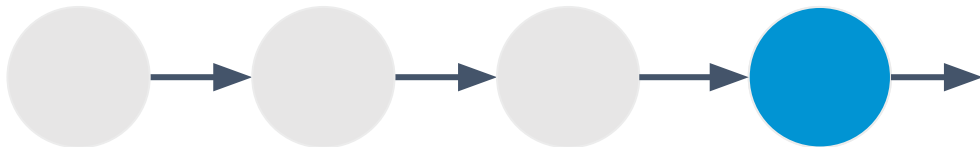


TRADITIONAL ATTRIBUTION: TOUCH MODELS

Let A, B, and C represent different ads. A simple user journey looks like this:

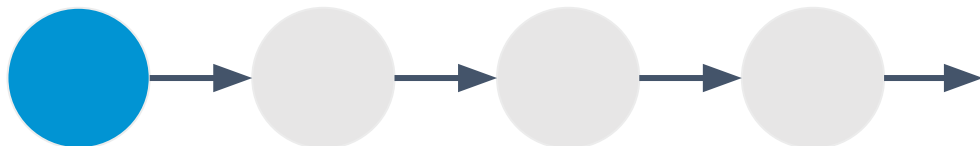


LAST TOUCH



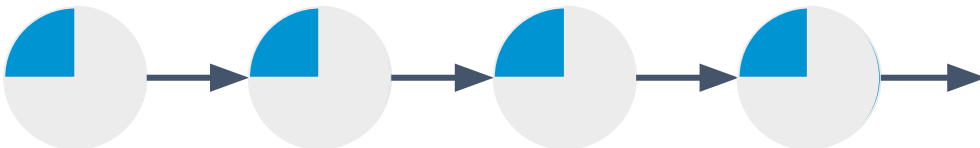
C gets all the credit for the conversion

FIRST TOUCH



B gets all the credit for the conversion

LINEAR TOUCH



B gets 50% of credit,
A gets 25% of credit,
and C gets 25% of credit
for the conversion

Aggregate credit from all user journeys to calculate each ad's effectiveness.



WHY ARE TRADITIONAL APPROACHES PROBLEMATIC?

Touch models make unfounded assumptions about behavior

- ⦿ Assumes that only the first or last ad affects behavior, or that all ad exposures are equal. This is not how people behave in reality.

Touch models result in a self-fulfilling prophecy

- ⦿ Touch models reward high volume campaigns because they are high volume. The effectiveness of an ad should be independent of its volume.

Touch models use the wrong KPI

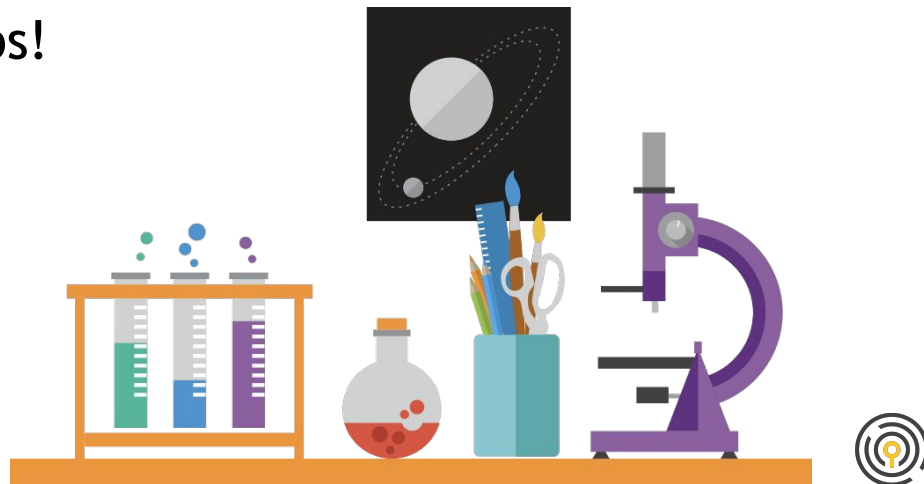
- ⦿ Touch models measure correlation.
- ⦿ Correlation does not imply causation: a touch model may find that a certain ad is associated with conversions, but this doesn't mean the ad caused the conversion.
- ⦿ Attribution models should estimate the causal impact of ads. We can leverage the experimental framework to do this.



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL WORLD*?


Run a Randomized Controlled Trial (RCT)!

Why? Because it's the gold standard for understanding causal relationships!



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL WORLD*?

Run a Randomized Controlled Trial (RCT):



Take a
random
sample of
the
population



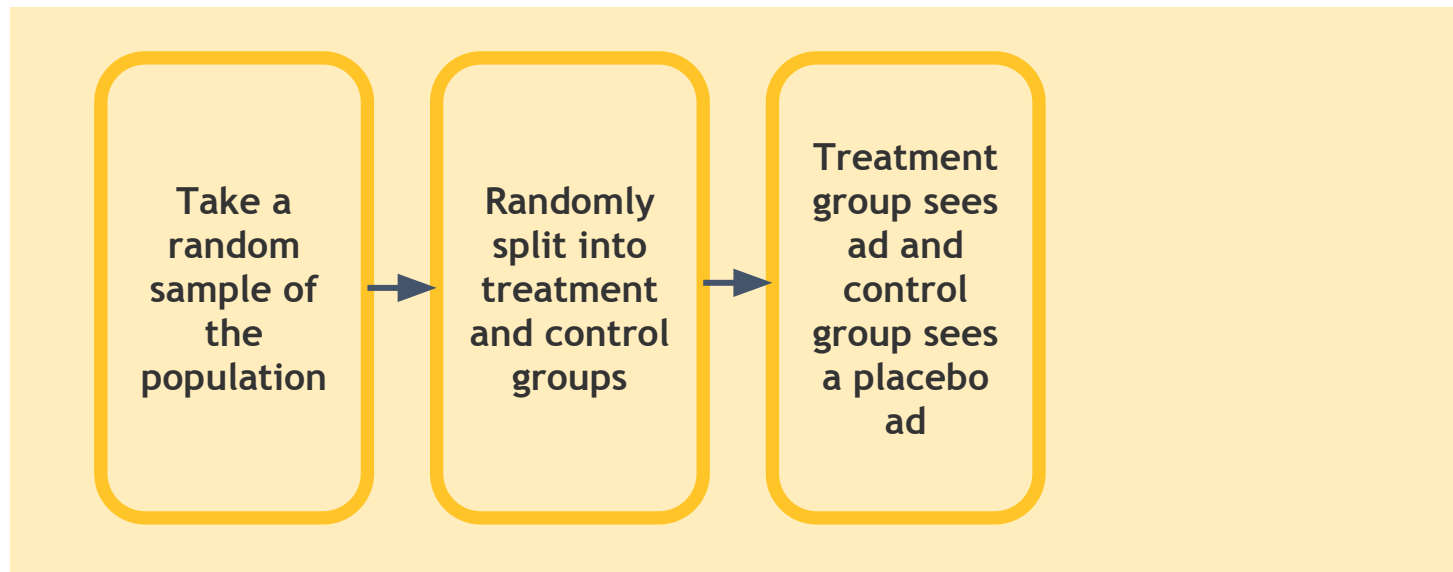
WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL WORLD*?

Run a Randomized Controlled Trial (RCT):



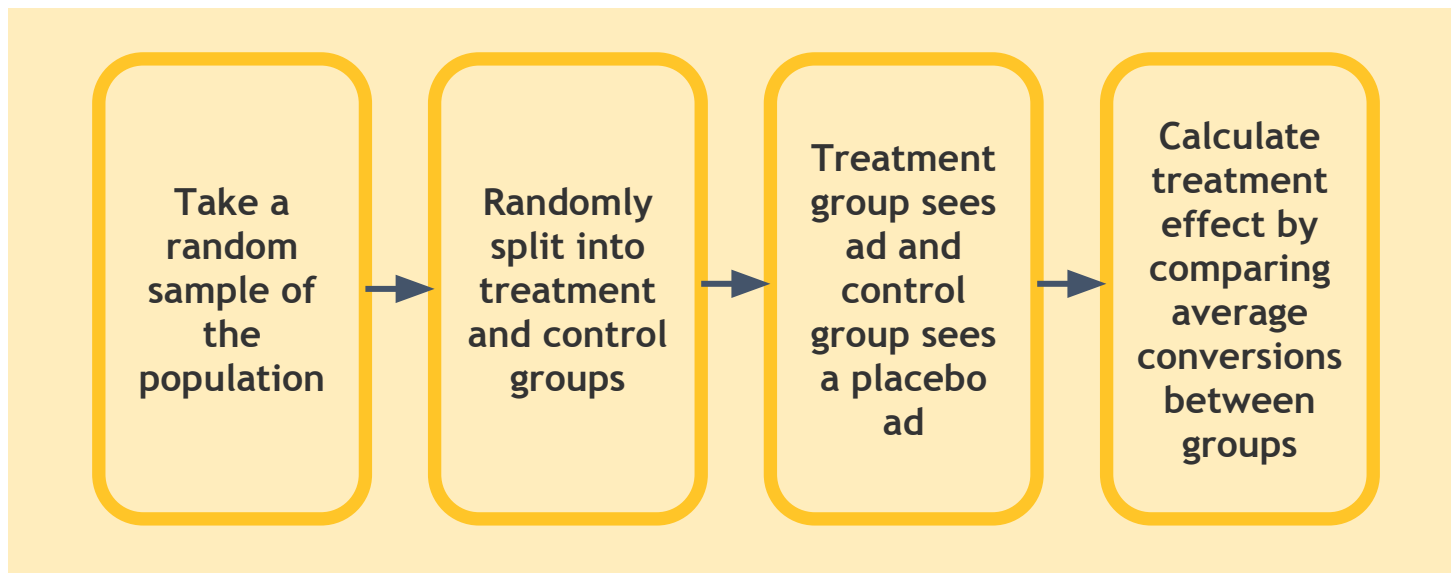
WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL* WORLD?

Run a Randomized Controlled Trial (RCT):



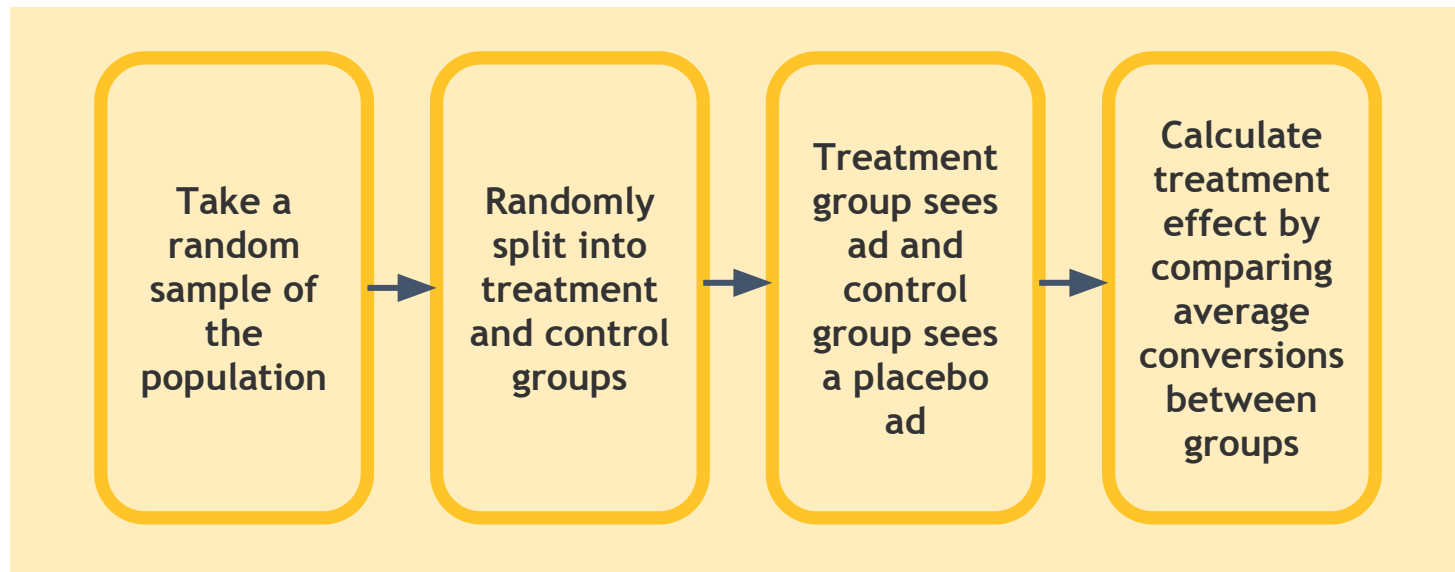
WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL* WORLD?

Run a Randomized Controlled Trial (RCT):



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN AN *IDEAL* WORLD?

Run a Randomized Controlled Trial (RCT):



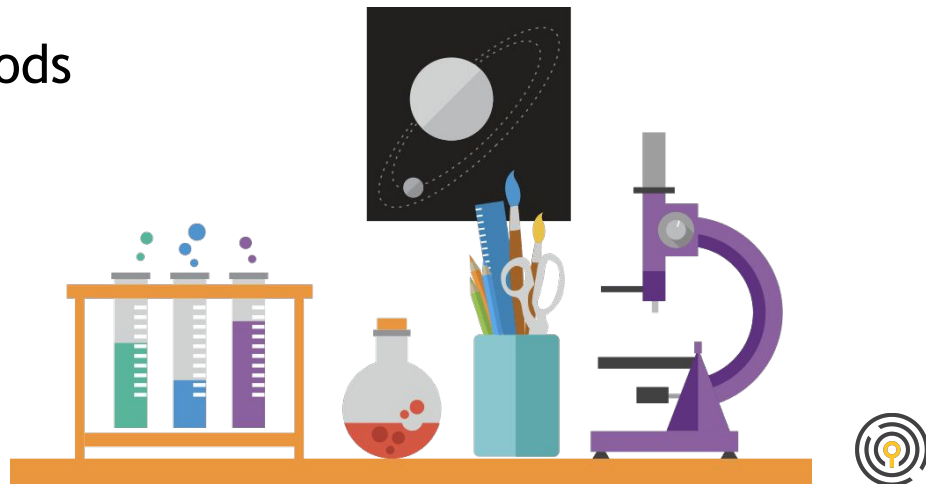
This measures the ***causal effects*** of your ads! Unfortunately, this is expensive, time-consuming, and often infeasible outside of a lab setting.



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN ~~AN IDEAL WORLD?~~ THE REAL WORLD?

**Approximate a Randomized Controlled Trial (RCT)
using observational data!**

How? By applying matching methods
from non-experimental causal
inference!



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN THE *REAL WORLD*?

We will borrow methods from causal inference! Use statistical techniques to mimic an RCT using observational data:

Obtain the
group of
people who
saw the ad -
this is your
pseudo
treatment
group



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN THE *REAL WORLD*?

We will borrow methods from causal inference! Use statistical techniques to mimic an RCT using observational data:

Obtain the group of people who saw the ad - this is your pseudo treatment group



Obtain the group of people who did not see the ad - this is the set of *potential* controls



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN THE *REAL WORLD*?

We will borrow methods from causal inference! Use statistical techniques to mimic an RCT using observational data:

Obtain the group of people who saw the ad - this is your pseudo treatment group



Obtain the group of people who did not see the ad - this is the set of *potential* controls

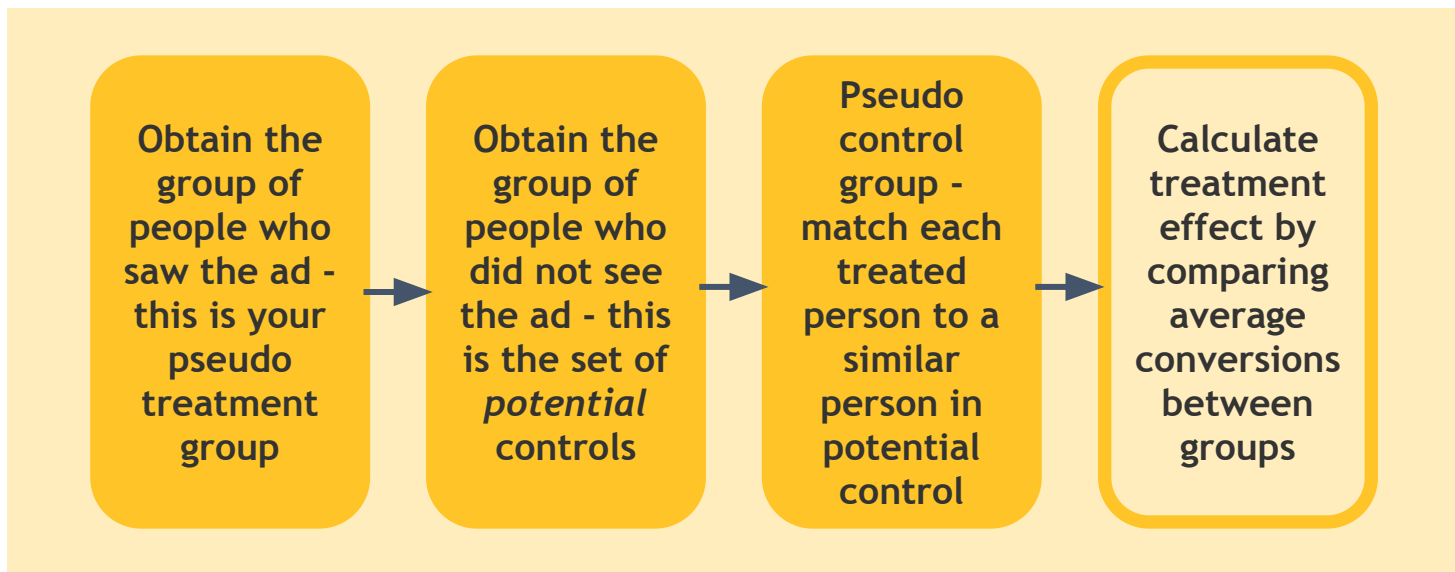


Pseudo control group - match each treated person to a similar person in potential control



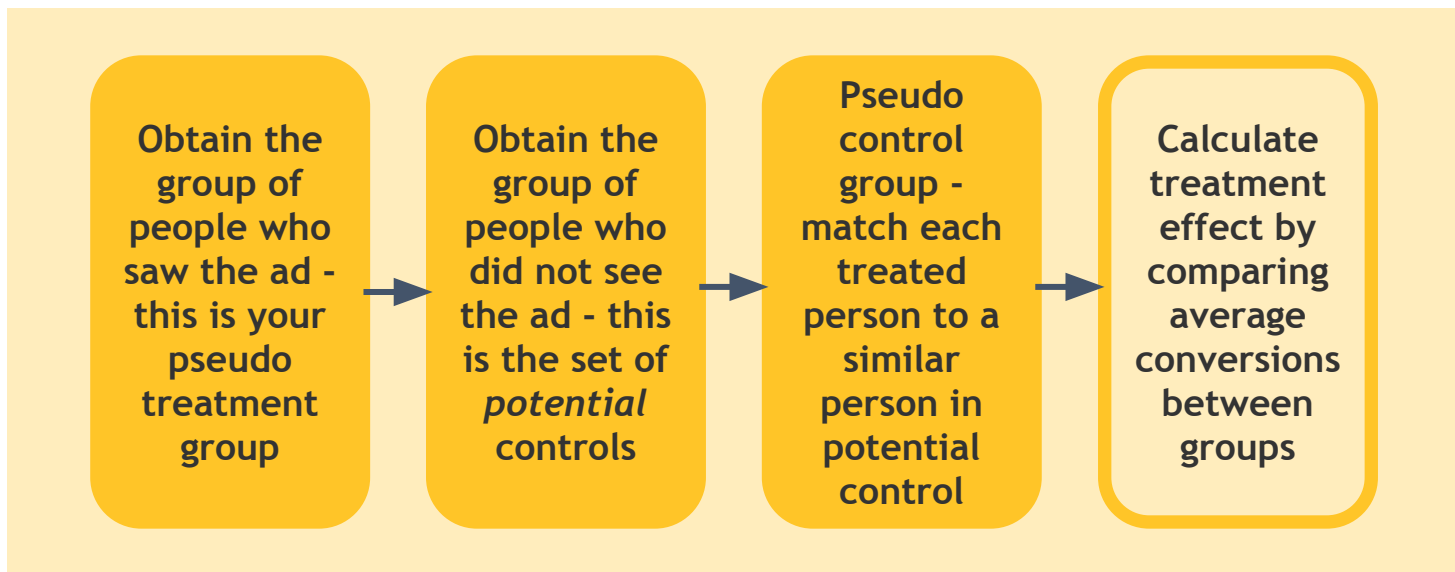
WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN THE *REAL WORLD*?

We will borrow methods from causal inference! Use statistical techniques to mimic an RCT using observational data:



WHAT IS THE IDEAL APPROACH TO MEASURE AD EFFECTIVENESS IN THE *REAL WORLD*?

We will borrow methods from causal inference! Use statistical techniques to mimic an RCT using observational data:



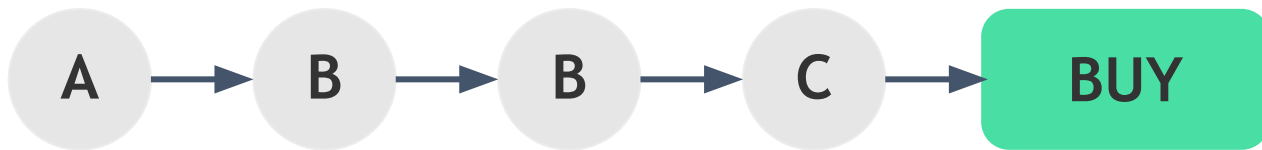
What does this look like in the attribution framework...



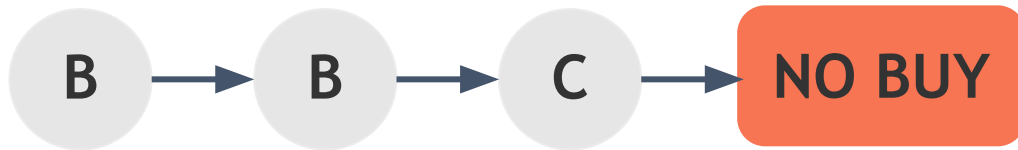
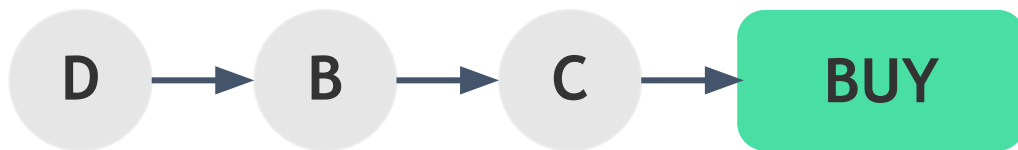
CAUSAL INFERENCE FOR A USER JOURNEY

You are interested in finding the effectiveness of ad A

Treated for ad A



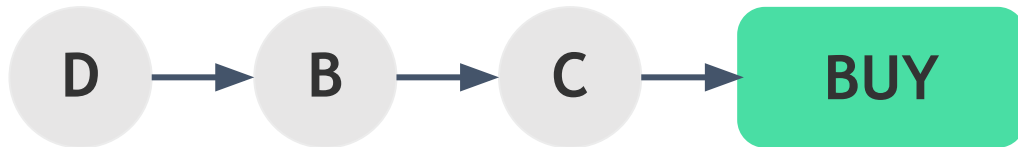
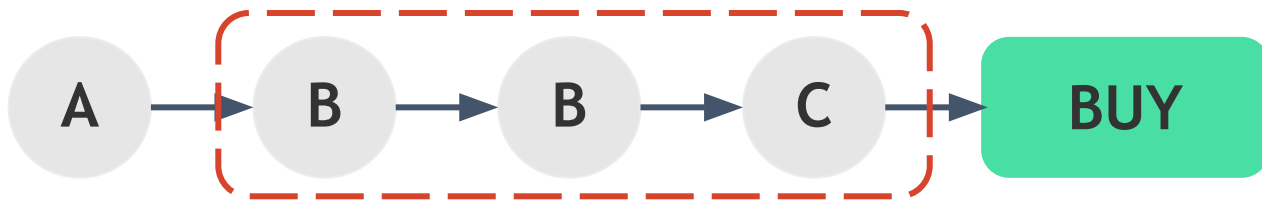
Potential
Controls (not
treated for ad A)



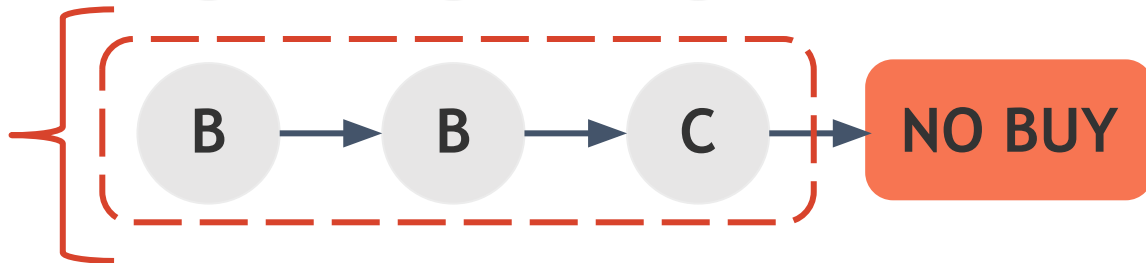
CAUSAL INFERENCE FOR A USER JOURNEY

You are interested in finding the effectiveness of ad A

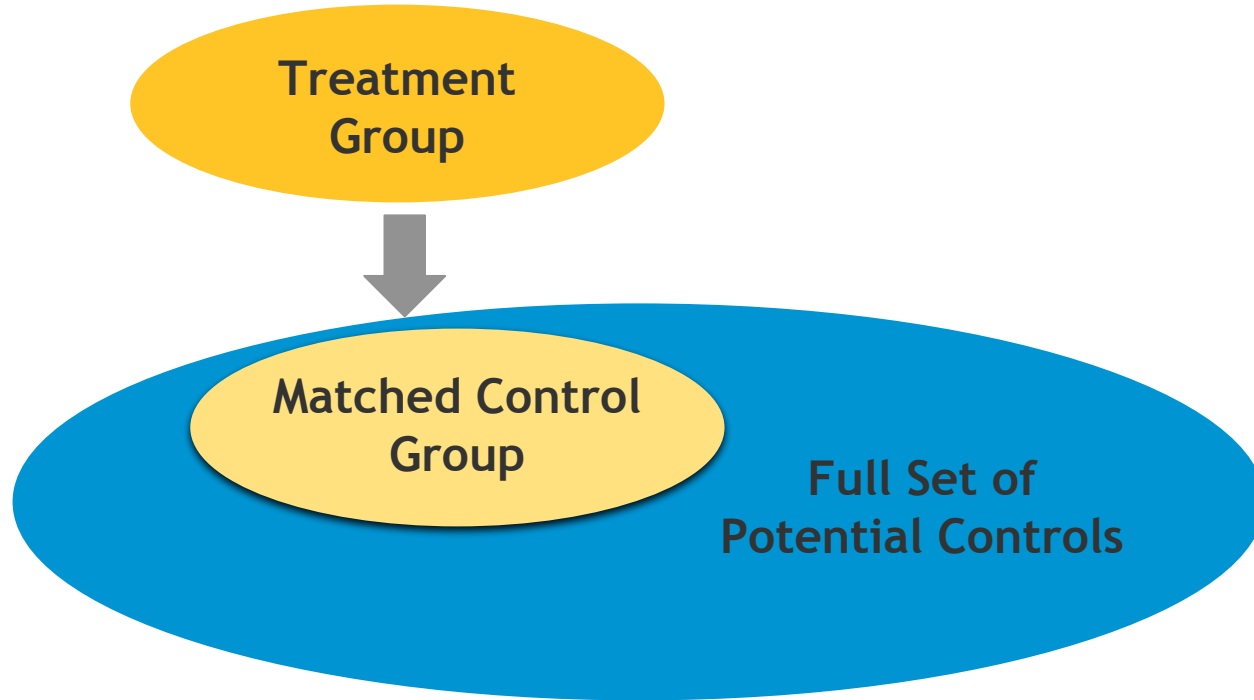
Treated for ad A



Matched Control
(most similar non-A
user journey)



MATCHING CREATES A CONTROL GROUP OF COMPARABLE DATA POINTS



HOW DO WE DO MATCHING?

Every treated person (saw the ad) is matched to a person in the potential control group (did not see the ad) based on their similarity to each other.

How is similarity measured?

- ⦿ Features
 - User journey, i.e. exposure to other ads
 - Ancillary data, e.g. demographic data, historical user activity
- ⦿ Method
 - Calculate the mathematical distance between observations in high dimensional feature space

Essentially, we are isolating the impact of an ad from all other features

- ⦿ Enables us to measure the true impact of an ad in an artificial vacuum



THE CAUSAL INFERENCE FRAMEWORK RESOLVES PROBLEMS INHERENT TO TOUCH MODELS

Touch models make unfounded assumptions about behavior

- ⦿ Matching methods make no assumptions about user behavior.

Touch models result in a self-fulfilling prophecy

- ⦿ Matching ensures that high volume ads are equally represented in treatment and control groups.

Touch models use the wrong KPI

- ⦿ Matching methods measure the causal, rather than the correlative relationship, between ad exposures and outcomes.



CASE STUDY



CASE STUDY



The Challenge

We work with a major advertiser that has a substantial advertising budget. They wanted to quantify how well their digital advertising impacted conversions, as defined by account signups and upgrades. Civis evaluated the impact of their ads and the efficacy of their programmatic tactics.



Our Approach

Our team tackled this attribution challenge by applying matching techniques from statistical inference to mimic randomized controlled trials. Using the results of this analysis, we were able to measure the performance of their digital ad campaigns and quickly see the impact (and sometimes backlash) of their advertising.

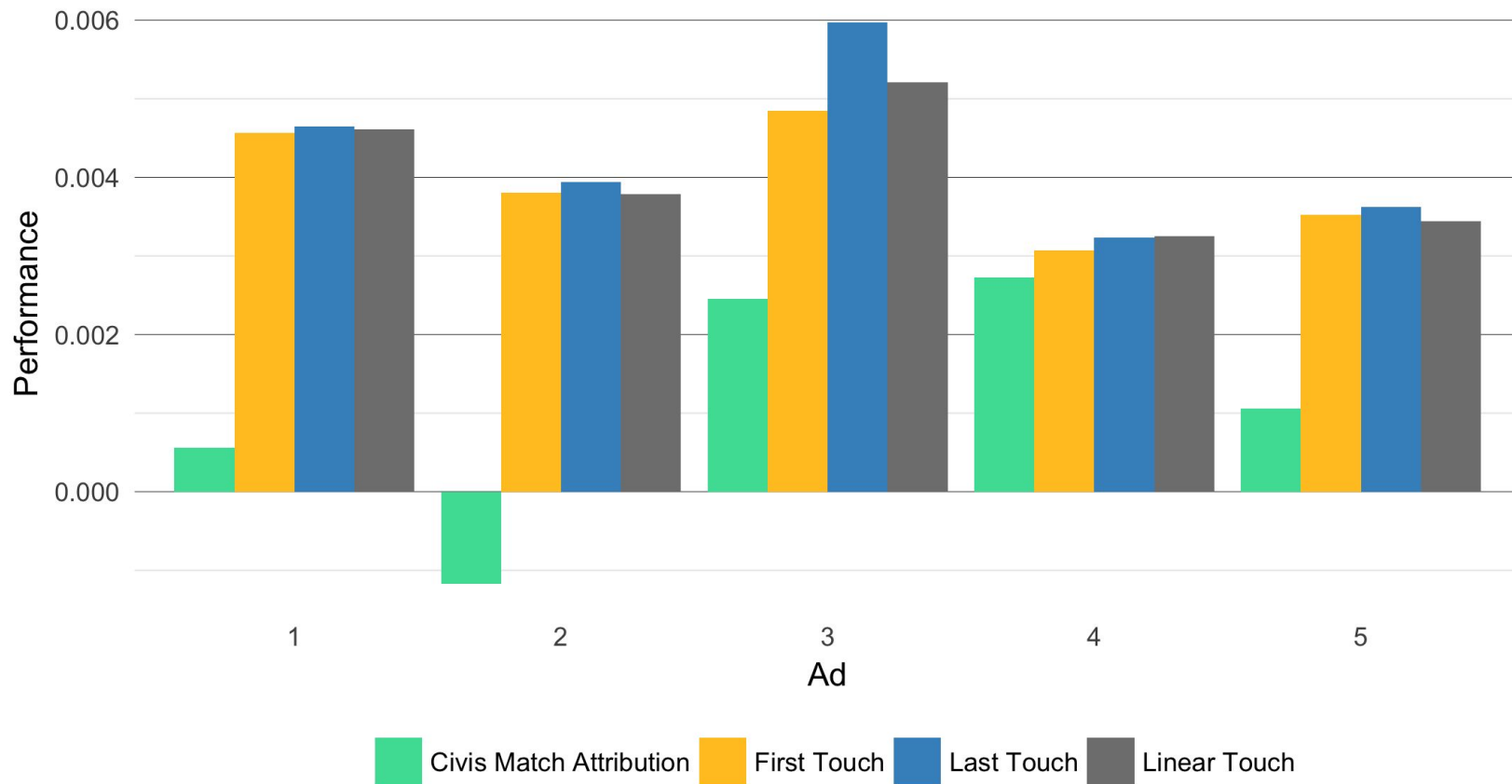


Impact

We can now connect specific marketing events to a customer's transactional behavior to pinpoint whether an ad caused an increase or decrease in conversions, as well as the size of that impact. Our client can now allocate their substantial advertising budget more effectively.

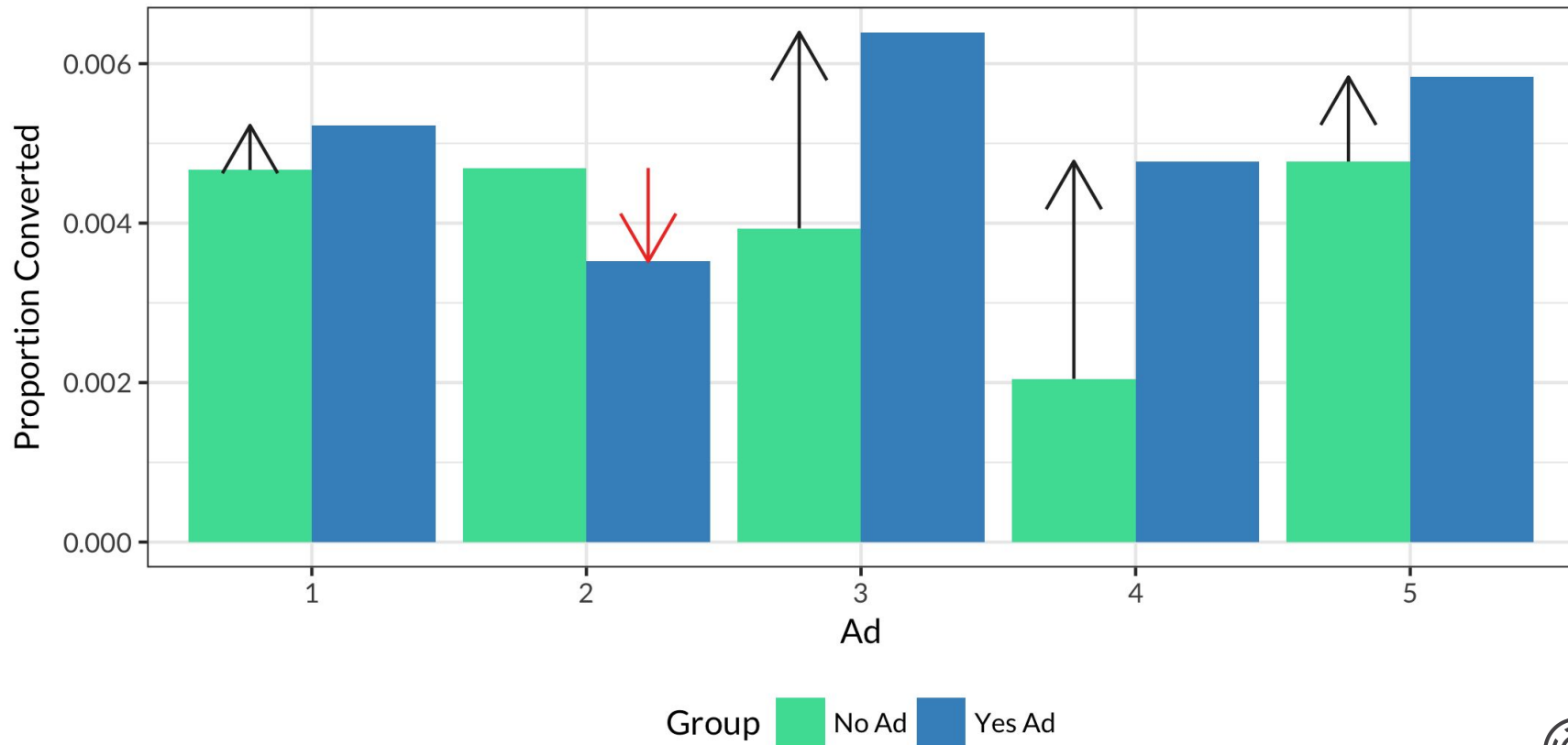


Ad Effectiveness by Ad and Attribution Method



Estimated Incremental Effect of Advertising on Conversion

Civis Match Attribution



MATCHING MEASURES THE OPPORTUNITY COST OF ADVERTISING

In the plot, Civis Match Attribution analyzes the performance of five ads on real client data.

- Matching method estimates the *incremental effect of advertising on conversion*.
- Touch methods only compute lift (the blue bars).
- Basing our decisions on lift leaves money on the table: we would
 - overlook the backlash in ad 2 - spending more money on it would *hurt* conversions;
 - overestimate the impact of ad 5 and spend too much money on it going forward;
 - fail to notice that ad 4 is driving conversions better than ad 3, but at a lower base conversion rate. This is a signal that we should investigate the audience of ad 4 more.

CONCLUSION



CONCLUSION

- ⦿ Attribution modeling ties business outcomes to advertising events
- ⦿ Results of attribution models are used to make decisions about advertising spend
- ⦿ Using touch models for making decisions is problematic:
 - Wrong KPI, can't measure backlash
 - Correlation, not causation
 - Self-fulfilling prophecy, rewards high volume ads

CONCLUSION

- ⦿ Non-experimental causal inference gets us closer to the gold standard of an RCT
 - Captures backlash
 - Estimates a causal effect
 - Adjusts for differences between groups using matching
- ⦿ Better attribution modeling means better decisions about advertising spend!

Thanks!

