Microsoft

Causal Inference with EconML

An Introduction

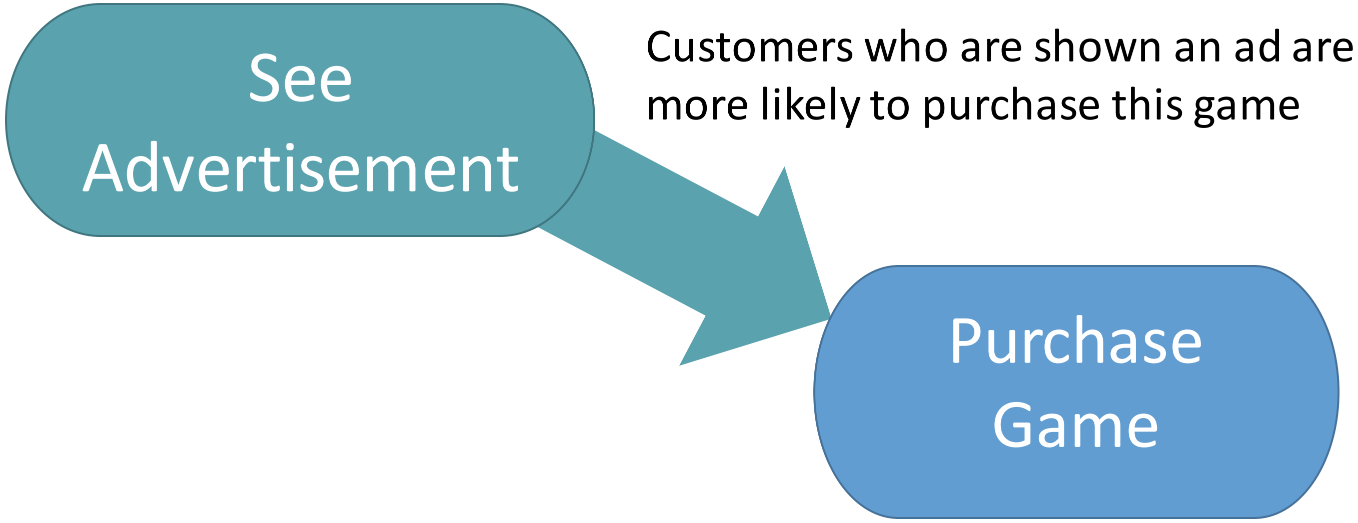
Data-Driven Decision Making

- **Forecasting problems** use past data to predict future outcomes in the current state of the world
  - How many people will buy a video game next month?
- **Causal problems** ask what would happen if some policy changes
  - How many more people will buy the game if we show them an advertisement?
- These two families of questions require different approaches to data analysis

Correlation Patterns vs. Causal Pathways

Correlation between Ads and Purchases

Most current machine learning tools uncover the correlation patterns between a **treatment** like seeing an advertisement and an **outcome**, like purchasing a game.

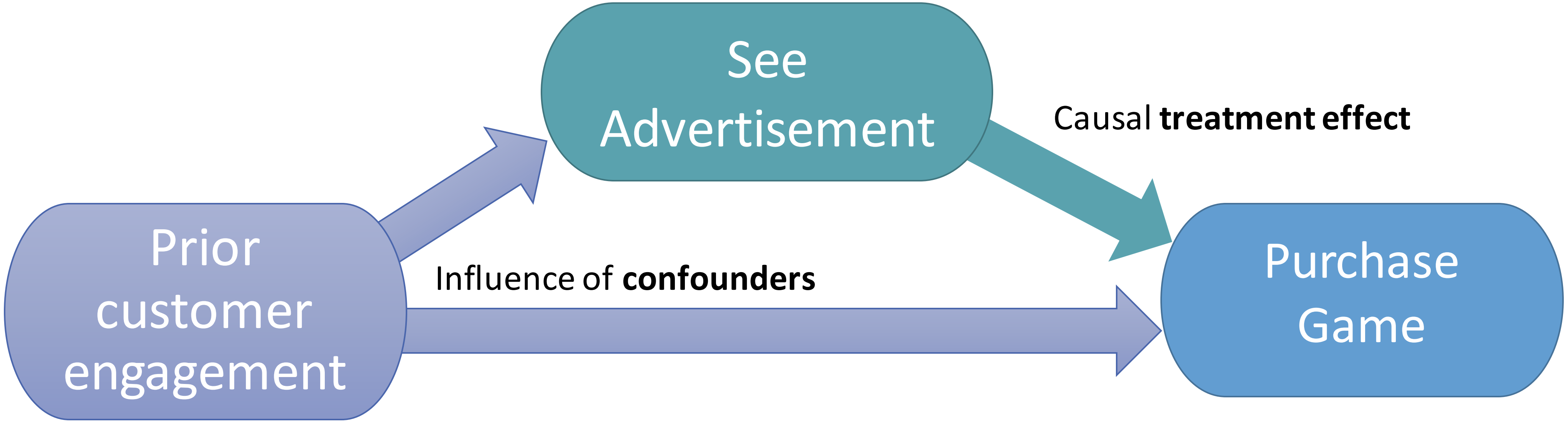


Customers who are shown an ad are 40% more likely to purchase this game

Uncovering Causal Pathways

This correlation pattern combines multiple causal pathways

1. The **treatment** may have a direct causal effect on the **outcome**, for example an informative ad makes potential customers more excited about a new game.
2. **Confounding features** may influence both the probability of treatment and the outcome, creating additional non-causal correlation. For example, engaged existing customers are more likely to be strategically targeted for ads and more likely, even without the ad, to buy new games.



Forecasting vs Causal Problems

- **Forecasting:** if you want to predict which customers will purchase the game, any observed correlation with other behaviors and customer features is useful

- **Causal:** if you want to estimate the treatment effect of the ad, observed correlations can be misleading

People + AI for Causal Inference

- **Causal modeling tools** like the ones in EconML can separate each causal pathway to measure just the treatment effect of interest.

- However, all causal inference also requires **human judgement** to frame the causal question and identify likely confounders.

Tools for Causal Inference

Framing a Question

- The first step in any causal analysis is posing a clear question
  - What **treatment** am I interested in?
  - What **outcome** do I want to consider?
  - What **confounders** might be correlated with both my outcome and my treatment?

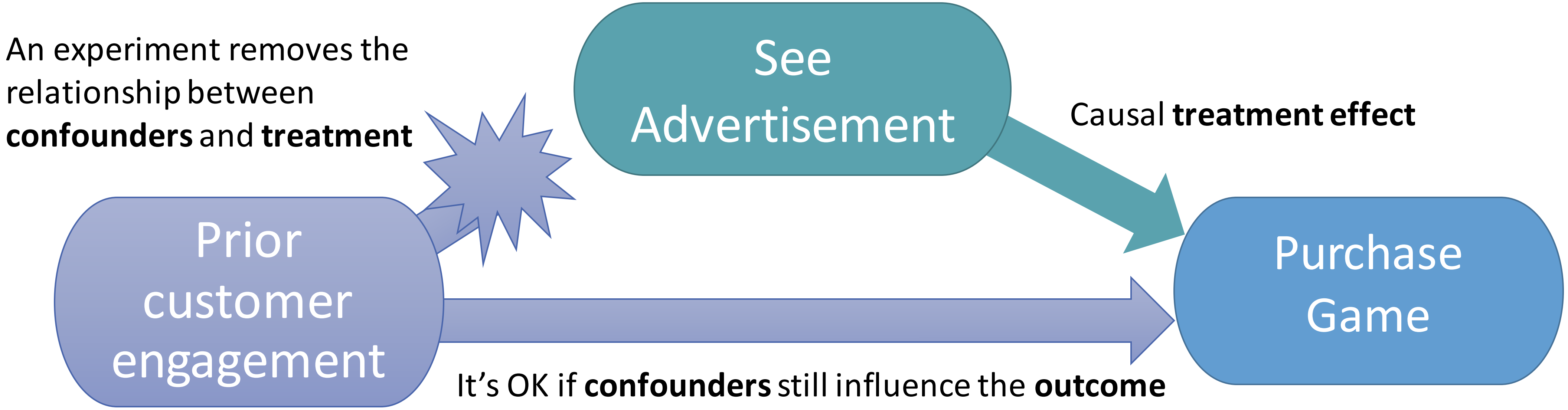
- Even if you cannot measure all confounders, it's important to name them so you can choose an appropriate estimation strategy

Language of Causal Inference

VIDEO GAME EXAMPLE	
Outcome (Y)	Probability of buying a specific new game
Treatment (T)	Seeing an advertisement
Confounders (W)	Current gaming habits, past purchases, customer location, platform

Method 1: Randomized Experiments

- The gold standard approach to answering causal questions is to run an experiment that randomly assigns the treatment to some customers.
- Randomization eliminates any relationship between the confounders and the probability of treatment, so any differences between treated and untreated customers can only reflect the causal treatment effect



Random Assignment

- Pros:
  - Gold standard for isolating causal effect
  - Don’t need to measure or even name confounding variables

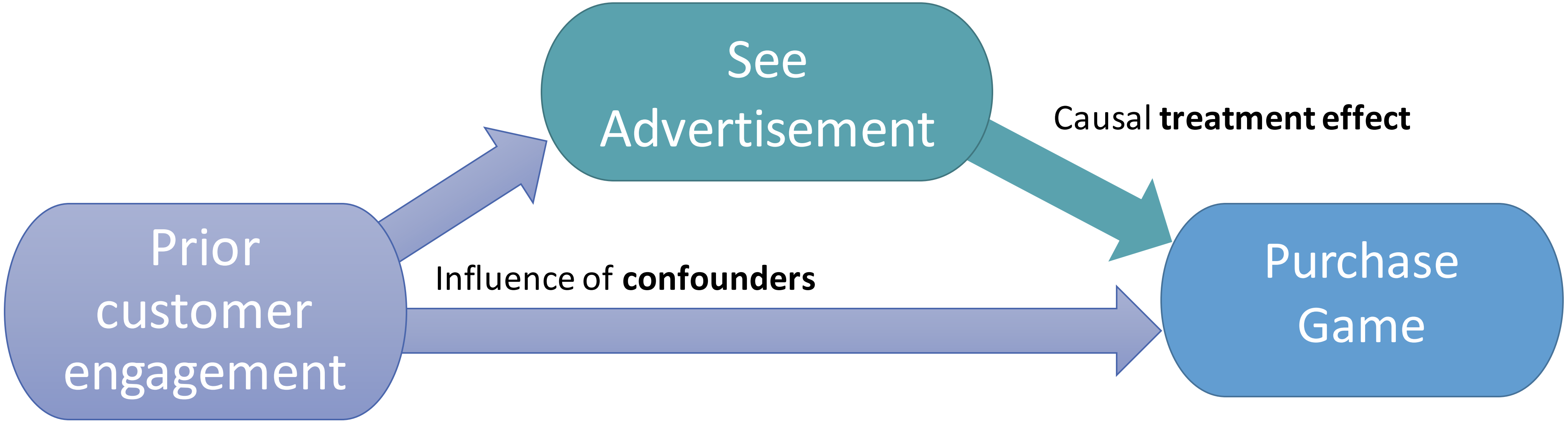
- Cons
  - For some treatments experiments are impossible or cost prohibitive
  - In experiments, some users may not comply with their assignment
    - Customer offered a small discount may visit site repeatedly until offered a large discount
    - Customer encouraged to join a loyalty program may still not join

How EconML Helps with Random Assignment

- Heterogeneous treatments: EconML estimates how the *response* to the treatment varies for users with different attributes
  - Any of our Estimation Methods that assume unconfoundedness can also estimate heterogeneous effects from experimental data
  - See the Customer Segmentation use case for an example of interpreting individualized treatment responses
- Compliance: EconML's instrumental variable tools can correct estimates from experiments with imperfect compliance
  - See our Recommendation A/B Testing use case for an example of correcting experiments for compliance

Method 2: Measure Confounders

- If you can plausibly measure all confounding influences, carefully designed statistical models can separately estimate each causal path in the graph: the effect of confounders on the treatment and the outcome, and the causal effect of the treatment on the outcome.
- This case of full observability is known as **unconfoundedness**



Observed Confounder Estimation

- Pros
  - Identifies causal effects from observational data
  - Does not require either an experiment or an instrument
- Cons
  - Requires naming and measuring all confounders (or proxies for confounders)

How EconML Helps with Observed Confounders

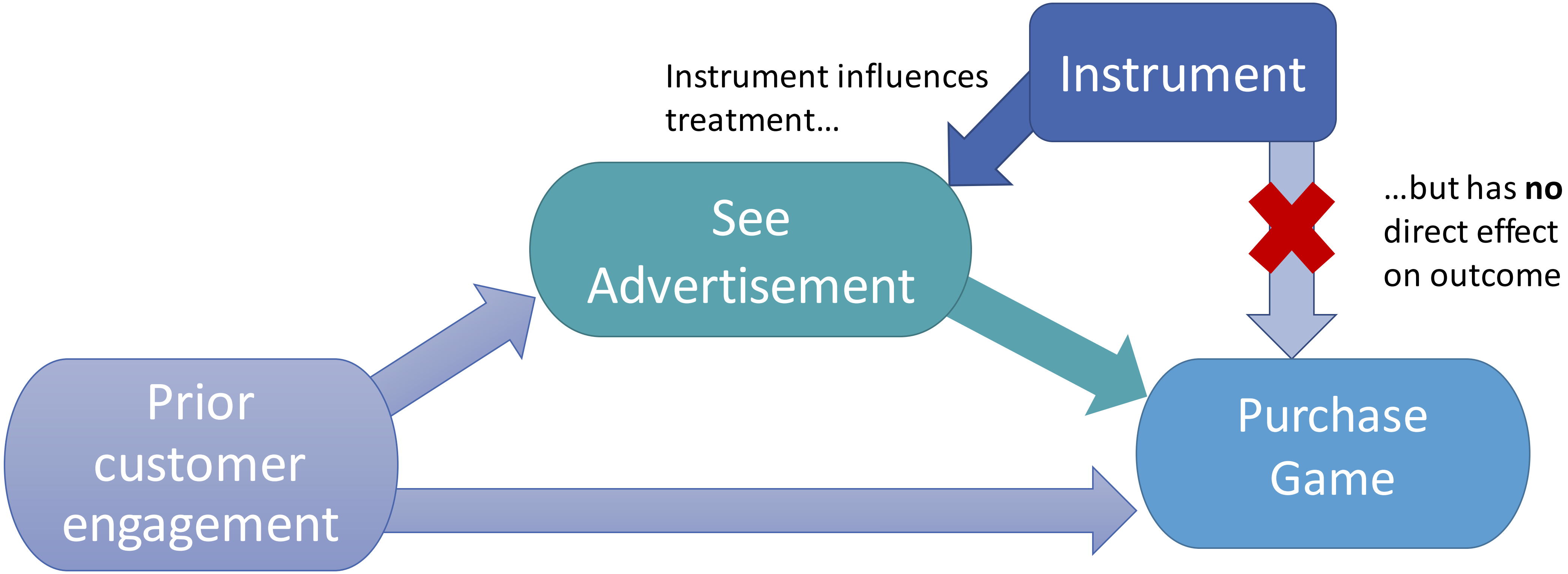
- Multiple ML steps within each causal model automatically estimate flexible relationships between variables
  - This flexibility makes the unconfoundedness assumption more plausible than traditional economic causal models
- Estimate heterogeneous treatment effects and consider multiple continuous or discrete treatments
  - See the Customer Segmentation use case for an example of interpreting individualized treatment responses
  - See the Attribution use case for an example of estimating the conditional effects of multiple treatments

Method 3: Instrumental Variables

- Sometimes you can't randomize your treatment, but you can discover randomization that happened naturally or in a related context
- Instrumental Variables (IV) estimation isolates the variation in your treatment that was generated by this random **instrument**
- **This method is effective even in cases where you have important confounders that you cannot measure**

Method 3: Instrumental Variables

- Under the assumption that the instrument has no direct effect on the outcome, any correlation between the instrument and the outcome can only reflect a causal path **through** the treatment



Finding a Good Instrument

IV estimation requires finding an instrument that

1. Has a strong direct effect on the treatment
2. Only correlates with the outcome through the treatment (in other words, the instrument is not correlated with any *unobserved* confounders and has no direct effect on the outcome. Correlation with observed confounders is OK.)

- Common sources of good instruments
  - Randomized experiments that are related (though perhaps not directed) to the treatment
  - Arbitrary assignment to one of many intermediaries (judges in research on sentencing, doctors for disability insurance approval, sales managers for discounts)

IV Example 2: Effect of Discounts

- A 3D printing company wants to know the value for future sales of offering discounts to business customers
- Larger companies are more likely to get offered discounts (and more likely to purchase more in general), but some account managers are particularly likely to grant discounts.
- There are many account managers and assignment to accounts is somewhat arbitrary

CUSTOMER RETENTION	
Outcome (Y)	Customer revenue over the next year
Treatment (T)	Offered discount on new products
Instrument (Z)	Account manager assigned to each customer
Confounders (W)	Current customer size, customer growth potential

IV Example 1: Customer Retention

- Trials of different installation methods for a new app create variation across users in time to a successful installation.
- Random assignment to different installation methods (plausibly uncorrelated with future loyalty) is a good instrument for exploring the effect of time to install.

CUSTOMER RETENTION	
Outcome (Y)	Times a customer uses an app in the 2 months after installation
Treatment (T)	Time to successfully install app
Instrument (Z)	Randomly assigned installation method
Confounders (W)	General technical skills, initial enthusiasm for the new app

Instrumental Variables Estimation

- Pros
  - Identifies causal effects from observational data
  - Does not require measuring all confounders, though you should name the confounders in order to recognize a good instrument

- Cons
  - Good instruments can be hard to find.
  - If the first requirement for an instrument is barely satisfied (instrument has a weak relationship with treatment) IV estimates can be more biased than approaches using measured confounders.

How EconML Helps with IV

- EconML's instrumental variable estimators automatically model relationships between the instrument, the treatment, and the outcome conditioning flexibly on other observed confounders.

- Unlike traditional economic IV methods, EconML estimators allow for individualized estimates of the responsiveness to the instrument (correcting for selection into being treated) and for responsiveness to the treatment.