MBA 753 : Causal Inference Methods for Business Analytics

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08.08.2024

Agenda

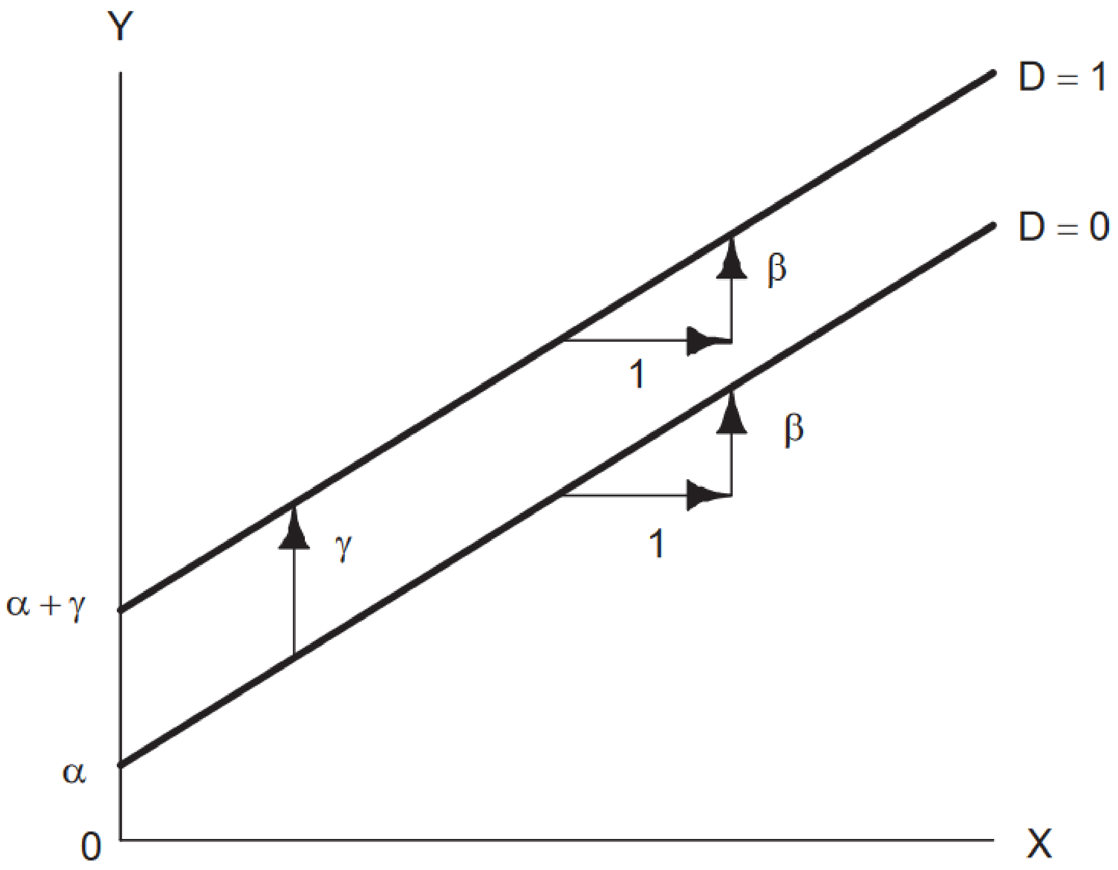
- Categorical predictors and its interpretation
- Interaction effects and its interpretation
- Experiments

Categorical Predictors

$Y = \beta_0 + \beta_1 X + \varepsilon$

Categorical Predictor Variables

- Categorical independent variables can be incorporated into a regression model by converting them into 0/1 ("dummy") variables
  - Involves categorical *X* variable with two levels
  - Assumes only intercept is different
    - Slopes are constant across categories



3 cat → 2 DV

Dummy Regressors

- Dummy regressors are easily extended to explanatory variables with more than two categories
  - A variable with m categories has m – 1 regressors
  - As with the two-category case, one of the categories is a reference group (coded 0 for all dummy regressors)

	D_1	D_2
Blue Collar	1	0
Professional	0	1
White Collar	0	0

Reference group

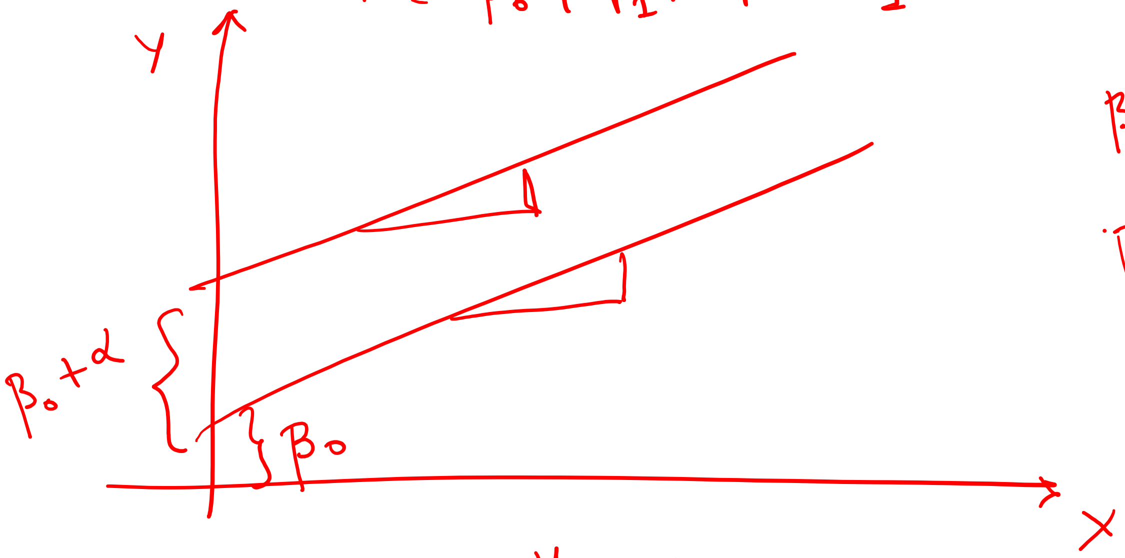
2 cat → 1 dummy var

3 cat → 2 D V

X → D_1 $\quad \underline{Y} = \beta_0 + \beta_1 \underline{X} + \varepsilon$

$\underline{Y} = \beta_0 + \cancel{\beta} \alpha \underline{D_1} + \varepsilon$

$Y = \beta_0 + \beta_1 x + \alpha D_1 + \varepsilon$



$Y = \beta_0 + \alpha D_1 + \varepsilon$

→ $Y = \beta_0 + \underbrace{\alpha_1 D_1 + \alpha_2 D_2} + \varepsilon$

x = C1 $\quad$ x = C2 $\quad$ x = C3

β_0, $\quad \beta_0 + \alpha_1$, $\quad \beta_0 + \alpha_2$

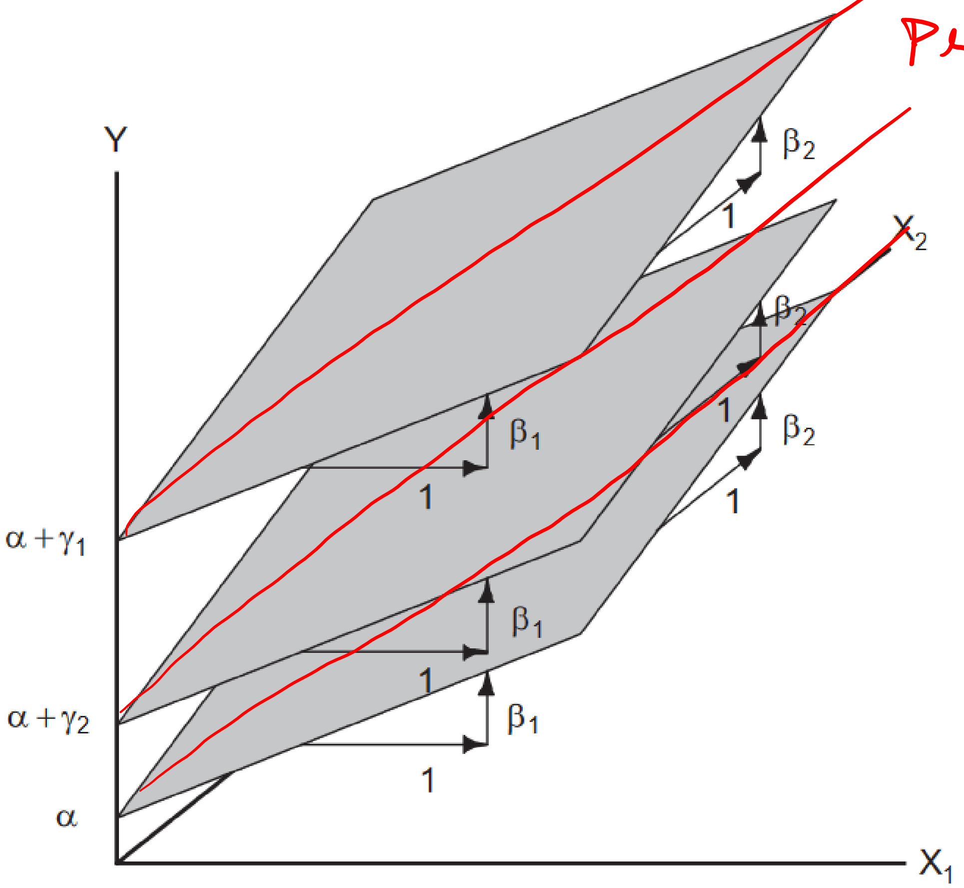
Dummy Regression Model

1 cat

$$Y_i = \alpha + \beta X_i + \underbrace{\gamma_1 D_{i1} + \gamma_2 D_{i2}}_{\text{2 DR}} + \varepsilon_i$$

2 continuous

Pre



- This gives three parallel regression lines

$$\text{Blue Collar: } Y_i = (\alpha + \gamma_1) + \beta X_i + \varepsilon_i$$
$$\text{Professional: } Y_i = (\alpha + \gamma_2) + \beta X_i + \varepsilon_i$$
$$\text{White Collar: } Y_i = \alpha + \beta X_i + \varepsilon_i$$

Interaction Effect and its Interpretation

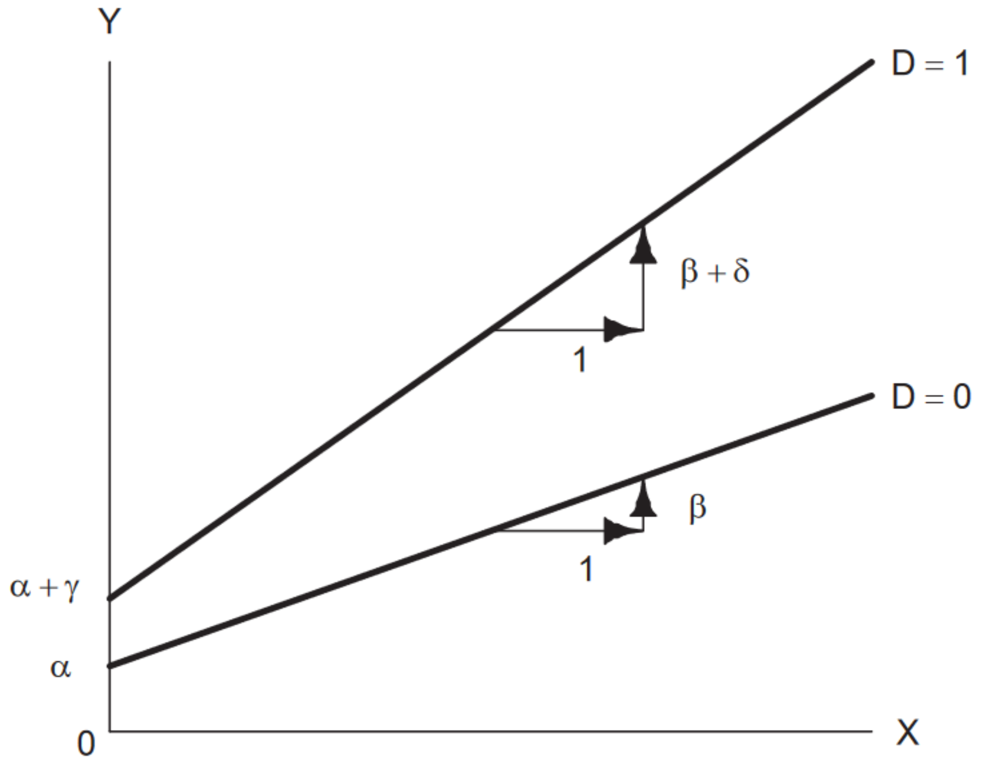
Interaction Effect

- Two predictor variables "interact" when the partial effect of one variable depends on the value of another variable
  - For example, testing whether age effects are different for men (coded 1) and women (coded 0) ← Reference
  - Separate models cannot test for differences among groups
  - Testing for differences in slope

2 Predictor-Age & gender

$$Y_i = \alpha + \beta X_i + \gamma D_i + \delta(X_i D_i) + \varepsilon_i$$

$$\text{income}_i = \alpha + \beta \ \text{age}_i + \gamma \ \text{men}_i + \delta(\text{age}_i \times \text{men}_i) + \varepsilon_i$$



Interaction Interpretation

- When the interaction effect is significant $y = \alpha + \beta X + \gamma D + \delta (X \cdot D) + \varepsilon$
  - The unique partial effects (for example that of age and gender) are no longer interpretable just by themselves

β_1 & β_2 β & γ

- Omitting interaction effects can lead to erroneous conclusions

Causality and Empirical Research

Experiments and Causation

- Cause, Effect, and Causal Relationship
  - Causal relationship exists if
    - Cause preceded the effect
    - Cause was related to the effect – variation in cause related to variation in effect
    - No other plausible alternative explanation

- Experiments can help study causal descriptions and explanations
  - Experiments: a study in which an intervention is deliberately introduced to observe its effects

Types of Experiments

- Randomized experiment: Units are assigned to receive treatment or an alternative condition through a random process
- Quasi experiment: Units are not assigned to conditions randomly
  - Cause is manipulable and occurs before the effect
- Natural experiment: Cause cannot be manipulated
  - Naturally occurring contrasts between treatment and a comparison condition
- Correlational study: Observational study that records size and direction of relationships among variables
  - Structural features of experiments are missing

Regression to Causality

- Regression helps in understanding associations among variables of interest
  - Conditional Expectation Function: $E(Y|X = x) = \beta_0 + \beta_1 X_1 + \ \ldots + \beta_p X_p$
  - Regression is causal if CEF is causal
  - CEF is causal when it describes the differences in average **potential outcomes** for a population

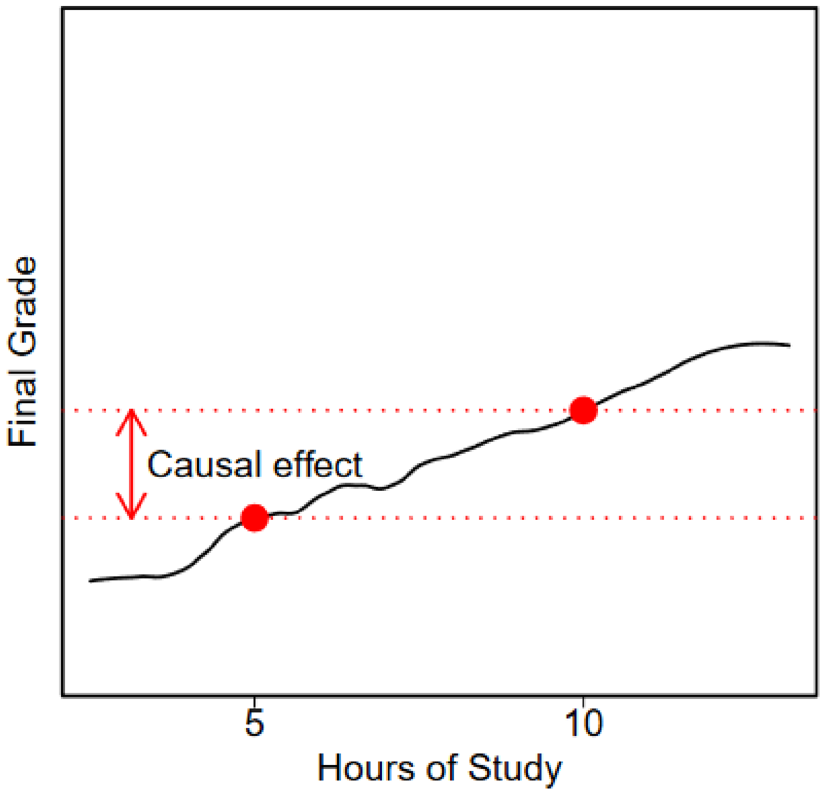
We think of a cause as something that makes a difference, and the difference it makes must be a difference from what would have happened without it.

– David Lewis, Causation, 1973

Potential Outcomes Model

Counterfactuals

- X, is understood to cause Y, if the value for Y would have been different for a different value of X
- Example: Imagine we knew the grade a particular individual would receive for different amounts of study time:
  - Each point on the line represents a potential outcome (the hypothetical outcome associated with each value of our causal factor)
  - Causal effects are defined in terms of **potential outcomes**



Source: Mix Tape by Scott Cunningham

Potential Outcome

- Potential outcome: difference in the outcomes between the two states of the world
  - Actual state where the person did something
  - Counterfactual state where the person did something else

- **Causal inference:** The process of drawing conclusions about features/properties of the full set of **potential outcomes** on the basis of some **observed outcomes.**

Notation and Terminology

- Treatment: Causal variable of interest
  - Defined for binary case, but we can (and will) generalize to continuous treatments

$$D_i: indicator\ of\ treatment$$

$$D_i = \begin{cases} 1\ if\ unit\ i\ received\ the\ treatment \\ 0 \qquad\qquad\qquad\qquad\qquad otherwise \end{cases}$$

- Outcome: Y_i: Observed outcome variable of interest for unit i

Notation and Terminology

- Potential Outcomes
  - potential outcomes are fixed attributes for each i and represent the outcome that would be observed hypothetically if i were treated/untreated

$$Y_i = \begin{cases} Y_{1i} \; if \; D_i = 1 \\ Y_{01} if \; D_i = 0 \end{cases}$$

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}$$

  - $Y_{0i} \; and \; Y_{1i}$ are potential outcomes (counterfactuals)
  - Only one outcome is observed, the other is counterfactual

Notation and Terminology

- Causal Effect
  - For each unit i, the causal effect of the treatment on the outcome is defined as the difference between its two potential outcomes:

  - τ_i is the difference between two hypothetical states of the world
    - One where i receives the treatment
    - One where i does not receive the treatment

  - Fundamental problem of Causal Inference: We cannot observe both potential outcomes (Y_{1i}, Y_{0i}) for the same unit i
    - **How do we calculate $\boldsymbol{\tau_i}$?**

Recap

Summary

- MLR – fitting the best regression space
- Partial effects are estimated assuming ceteris paribus
- A categorical predictor with m groups will have m-1 regressors
- Interaction effects - when effect of one predictor depends on the values of the other

- Objectives achieved:
  - Can understand and interpret "effects" in a MLR model with dummy variables and interactions
  - Can identify different types of experiments

References

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- Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Thank You ☺


SOMEONE SENT ME ANOTHER ANONYMOUS EMAIL WITH A LINK TO AN ARTICLE ABOUT THE WORLD'S WORST BOSSES.
I GET ONE OF THOSE EMAILS EVERY TIME I LEAVE YOUR CUBICLE. DID YOU THINK I WOULDN'T NOTICE THE CORRELATION?
CORRELATION DOES NOT IMPLY CAUSATION.
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