Vidio 4: HYPOTHESIS TESTING AND CAUSAL INFERENCE

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introduction

- vidio link
- today we are going to discuss the relationship between hypotshsi testing and casual INFERENCE

free throw example

- player trying to shoot free throws, when he plays away people taunt him
- altnerative: at home free throw percentage highter than at away
- null: they are the samell
- test stat: free throw percentage at home − free throw percentage away
- found p-value$\leq \alpha$
- what does this mean?
- it means if we define two random variables: free throw outcome $\tilde{y}$ and fans taunting $\tilde{t}$
- we can say according to the data $P_{\tilde{y}|\tilde{t}}$(made — taunted)) $>$ $P_{\tilde{y}|\tilde{t}}$(made — taunted))
- note **this does not mean that taunting causes his free throw % to decrease**
- that is a causal INFERENCE question, which may have confounding factors that we have not controlled for.
- confounding factors are systematic differences that prevent us from getting an arcuate view of the casual relationship

evaluating nba players example

- our goal was to evaluate the impact of a player on a team preformance
- our test stat was the mean difference in points when that player played versus did not play
- we conducted a permutation test with the bonferroni correction to account for testing many players
- we say that there were 8 players with statistically signefgence p values
- what does this mean? we ar epretty sure that the condtional mean of the point difference with this player was higher than the condtional mean with out this player
- **this is again not a casual statement**
- one player who was statistically significant only played 24 out out 300 games over 4 years
- does this mean he was helping his team play? **no he was a worse player so he was only put in to games where they were already winning. that does not mean that he caused the win, instead he was playing because they were winning**

casual inference

- to identify a casual effect, out come and treatment must be independent
- how can we achieve this? **via randomization**
- with out randomization it is super hard to assign a casual effect

vaccine example

- treatment group 20,000 patients 0.03% precedence of covid
- control group 20,000 patients 0.74% precedence of covid
- we can apply a two sample z test t
- null hypothesis all data are iid bernoulili wth perameter θ
- test stat infection rate with vaccine - fection rate without vaccine
- causal inference and hypothesis testig have complementary roles
- the hypothesis test tells us we are not seeing random flucuations in the data, there is a difference, it does not say if there is a casual effect unless we have randomized assignment to each group

ab testing

- goal compare two groups A/B when designing a product
- users are randomly assigned to each option, because they are randomly assigned so any real differences between the two groups are casual
- then hypothesis testing is applied to determine wether differences between the two groups are statistically signefgence

obama

- goal determine if an immage or vedio is more effective at getting people to sign up
- metric sign up rate
- immages 9% sign up
- vedio : 6.66%
- crucially this was done with random assignment
- we can run a two sample t test on this and see that this is a very small p-value
- the difference reveals a causal effect due to randomization
- does this imply practical signefgence? ie is the effect we are picking up on actually important? not necessarily