# Scream, Shout, and yelp: for Causal Inference

PH252: Causal Inference

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### Presentation Overview

- 1. Scientific Question
- 2. Causal model
- 3. Causal question
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- 6. Identifying our parameter
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# Scientific Question

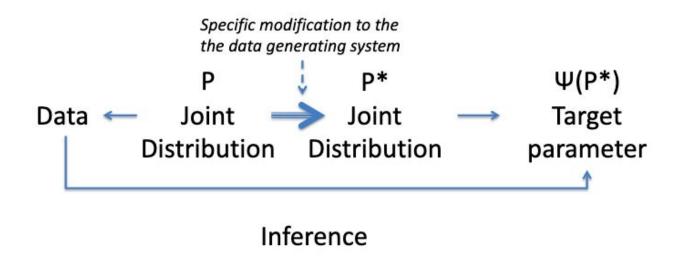
Do Yelp reviews influence restaurant closure?



# Causal Model

```
W_{age} = f_{age}(W_{type}, W_{chain}, U_{W_{age}})
   W_{type} = f_{type}(W_{chain}, U_{W_{type}})
W_{reviews} = f_{reviews}(W_{age}, W_{type}, W_{chain}, U_{W_{reviews}})
                                                                                                        UWage
                                                                                                                        Uwreviews
                                                                                                                                           UWchain
                                                                                       UWtype
  W_{chain} = f_{chain}(U_{W_{chain}})
          A = f_A(W, U_A)
          Y = f_Y(W, A, U_Y)
                                                                                      W_{type}
                                                                                                         Wage
                                                                                                                         W<sub>reviews</sub>
                                                                                                                                             W<sub>chain</sub>
                                                                         UΑ
                                                                                                                                  Yopen 2019
                                                                                    A_{\text{star review (>= 3.5)}}
```

# From Statistical to Causal Analysis



# **Causal Question**

**Question**: What is the effect of average Yelp review on two-year survival in Las Vegas restaurants?

Intervention variable: threshold of 3.5 stars



#### Counterfactuals:

- Y<sub>1</sub>: Restaurant survival at year 2 having received an average Yelp rating above or equal to 3.5 stars
- Y<sub>0</sub>: Restaurant survival at year 2 having received an average Yelp rating below 3.5 stars

### Our Parameter

Target Causal Parameter: Average treatment effect

The difference in counterfactual probability of 2 year survival had all restaurants received an average Yelp rating above or equal to 3.5 stars and the counterfactual probability of 2 year survival had all restaurants received an average Yelp rating below 3.5 stars:

$$\Psi^F = E_{U,X}[Y_1] - E_{U,X}[Y_0] = P_{U,X}(Y_1 = 1) - P_{U,X}(Y_0 = 1)$$

### Observed Data and Link to Causal Model

 We assume our observed data were generated by sampling 3,644 i.i.d. times from a data generating process compatible with our causal model

$$O = (W_{age}, W_{type}, W_{reviews}, W_{chain}, A, Y) \sim \mathbb{P}_0$$

- The distribution of U and the structural equations F identify the distribution of X, and thus, the observed data
- This is the link between the causal model and the statistical model
- Statistical model is non-parametric

### Data

- Our datasets
  - 2017 Yelp challenge dataset
  - 2019 Yelp challenge dataset
- Our columns
  - Stars above 3.5 on Yelp
  - Open > 2,606 days
  - Review count > 65 reviews
  - American restaurant (Yes/no)
  - Chain restaurant (Yes/no)



Table 1. Characteristics of 3,644 Las Vegas restaurants reviewed on Yelp by survival status in 2019.

Variable n (%)	Closed in 2019 248 (7)	Open in 2019 3396 (93)	p-value
90000 00 0000	240 (1)	3330 (33)	8 888
Number of stars			0.00
< 3.5	58 (4.3)	1298 (95.7)	
$\geq 3.5$	190 (8.3)	2098 (91.7)	
Days open			0.00
$\leq 2606$	158 (8.7)	1664 (91.3)	
> 2606	90 (4.9)	1732 (95.1)	
Number of reviews			0.55
$\leq 65$	129(7.1)	1695 (92.9)	
> 65	119 (6.5)	1701 (93.5)	
American restaurant			0.19
No	187(7.2)	2423 (92.8)	
Yes	61 (5.9)	973 (94.1)	
Chain restaurant		2	0.00
No	209 (8.9)	2151 (91.1)	
Yes	39 (3.0)	1245 (97.0)	

Values are N (%).

Fisher's exact test was used for categorical variables.

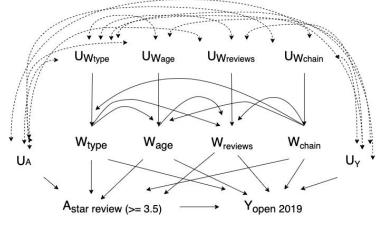
Median values were selected as cut-off points.

# Identifiability

**Positivity assumption:** Met in theory and practice (more on this later)

**Backdoor criterion:** Not satisfied due to lack of independence

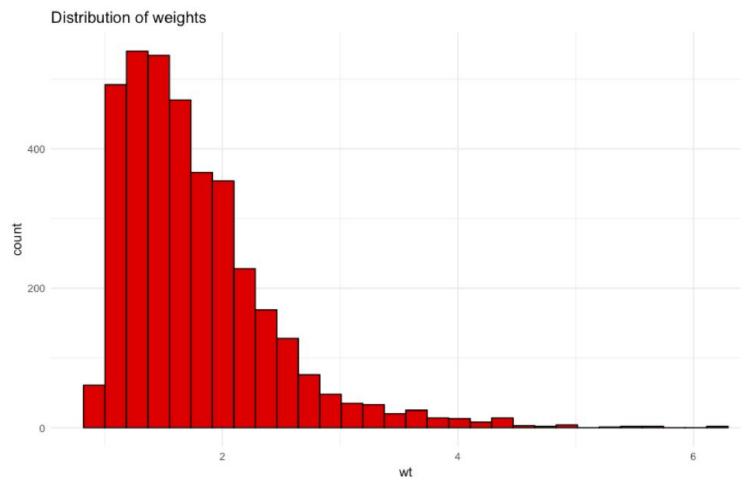
assumptions.



# Positivity assumption

Positivity assumption: Met in theory and (informally) in practice

- P(A=a|W=w) is defined for all possible values (a,w) -- no zero cells
- Each treatment of interest occurs with some positive probability for each possible covariate history (though some have less variation than others)



**Figure 1**. Distribution of weights used in IPTW estimation

# Modeling

#### **Working SCM:**

- Augment SCM with additional assumptions to continue analysis
- Working SCM assumes independence of exogenous variables

#### **Estimand:**

$$\Psi(P_0) = E_W[E_0[Y|A=1, W] - E_0[Y|A=0, W]]$$

$$= E_W[Pr_0[Y=1|A=1, W] - Pr_0[Y=1|A=0, W]]$$

# **Estimation**

Table 2. Results obtained for each estimation method

Method	*Resulting value $\Psi(P_0)$
Simple Substitution	-0.024
IPTW	-0.011
Stabilized IPTW	-0.028
TMLE	-0.027
TMLE: Asymptotic Variance	0.316
TMLE: 95% CI / p-value	(-0.045, -0.008) / p-value = 0.004

<sup>\*</sup>The average effect of having a Yelp review score above or equal to 3.5 stars on the probability of two-year restaurant survival in Las Vegas.

# Non-parametric Bootstrap

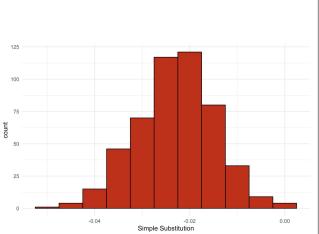


Figure 2. Bootstrapped distribution of simple substitution estimator

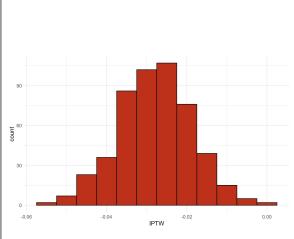


Figure 3. Bootstrapped distribution of s-IPTW estimator

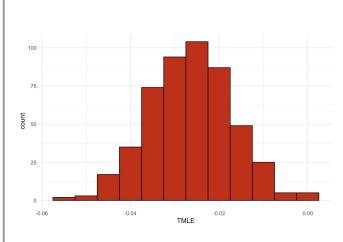
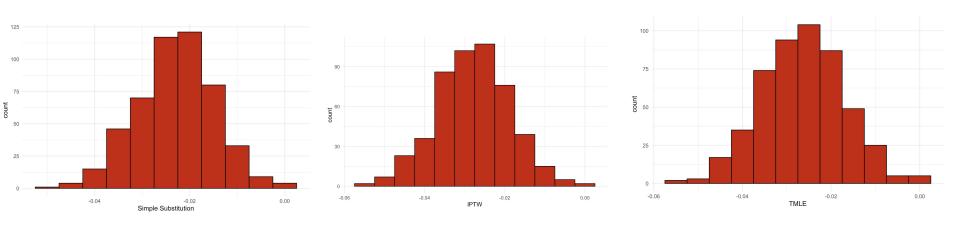


Figure 4. Bootstrapped distribution of TMLE estimator

B = 500 bootstraps



# Non-parametric Bootstrap

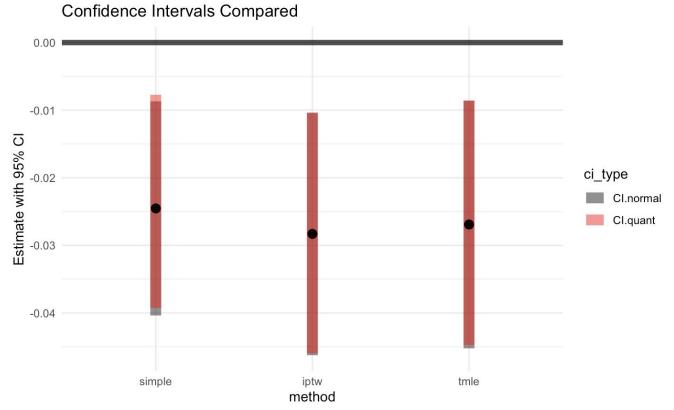


Figure 5. Bootstrap CI coverage for the three methods

# Non-parametric Bootstrap

Table 3. Confidence intervals obtained for each bootstrap

Method	Normal-based confidence interval	Quantile confidence interval
Simple Substitution	(-0.0404, -0.0087)	(-0.0393, -0.0077)
Stabilized IPTW	(-0.0462, -0.0104)	(-0.0460, -0.0105)
TMLE	(-0.0452, -0.0086)	(-0.0447, -0.0086)

# Statistical Interpretation

- The average effect of having a Yelp review score above or equal to 3.5 stars on the probability of two-year restaurant survival in Las Vegas is about -0.028 according to TMLE methods.
- After controlling for baseline covariates, the marginal difference in the probability of survival among restaurants with a Yelp review score above or equal to 3.5 stars and Yelp review score less than 3.5 stars was -0.028.
- Bootstrap CIs (testing the hypothesis that the effect is 0) do not contain 0.

# Causal Interpretation

- If causal model + convenience assumptions are true, then:
  - Under the causal assumptions, the probability of survival is 2.8% lower if the restaurant had a Yelp review score above or equal to 3.5.
- Convenience assumptions were made

# Limitations

- Treated all variables as binary
  - Above/below median is not informative for covariates with wide ranges
- Removed certain covariates (loss of information)
- Using a working model
  - Exogeneous variables have some sort of dependence structure
  - We ignored this
  - We made some convenience assumptions (no unmeasured confounding)
- Quality of data
  - Not collecting all the data we can (unmeasured covariates)
- Data is spatial
- Reviews may not be representative of restaurant quality

### Conclusion

- We expected that having 3.5 stars or more on Yelp would help 2-year-survival.
- We don't think that our results are representative of the truth because:
  - We did not mine the data to incorporate spatial aspects
  - We removed a lot of information by using binary variables only
- The assumptions we had to make were too extreme for the problem at hand

### **Future Work**

- Extend to continuous and spatial covariates
- Better understand the system that governs restaurant closure in order to make less assumptions and work with more variables
- How would our estimators vary if we chose another city?
- What would it mean to intervene on Yelp reviews in the real world?
  - Ex: Incentivize 5-star Yelp reviews with discounts



### Team contributions

- Asem Berkalieva:
  - Sections 3, 5; Data preparation; Bootstrap; Interpretation
- Philippe Boileau:
  - Sections 1, 2, 6, 7; SuperLearner estimation (G-comp, IPTW, stabilized IPTW, TMLE); Interpretation
- Edie Espejo:
  - Sections 4; Data preparation; G-comp formula and TMLE estimation;
     Bootstrap; Interpretation
- Naomi Wilcox:
  - Sections 5; Practical positivity assumption analysis; Interpretation;
     DAG; Table 1

#### Limitations

#### **Good Practice**

- -Get more data
- -Do the best job you can with data you have, and understand limitations
- Formal Causal Framework:
- -Which data and/or how to change design
- -What additional assumptions are needed: "convenience assumptions"?
- -Estimand that comes closest to answering our question with the data we have
- •Use lack of identifiability to inform interpretation and future studies