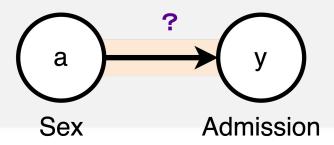
# Sex Bias in Graduate Admissions: Data from Berkeley

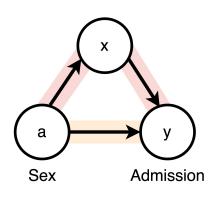
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### Bias vs. Discrimination

**Bias** is a pattern of association between a particular decision and a particular sex of applicant, of sufficient strength to make us confident that it is unlikely to be the result of chance alone.

**Discrimination** is the exercise of decision influenced by the sex of the applicant when that is immaterial to the qualifications for entry.





### **Background**

- UC-Berkeley 1973 Fall Grad School Admission
  - 12763 completed applications
  - Sex (F/M), Department (101), Admission Outcome (Yes/No)
- Sex Bias?
  - **44%** of the male applicants got admitted (8442 total)
  - **35%** of the female applicants got admitted (4321 total)
- Men and women applicants should have equal chances of admission to the university.

Applicants	81	Outo	Difference			
	Observed				Expected	
	Admit	Deny	Admit	Deny	Admit	Deny
Men	3738	4704	3460.7	4981.3	277.3	- 277.3
Women	1494	2827	1771.3	2549.7	<b>— 277.3</b>	277.3



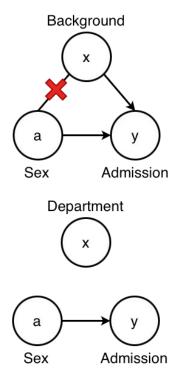
### **Discrimination Against Women?**

#### **Assumption 1: Exchangeability**

Male and female applicants <u>do not differ in intelligence</u>, <u>skill, qualifications, promise</u>, or other attribute that impacted the admission decision.

# Assumption 2: Department Not A Mediator Or Confounder

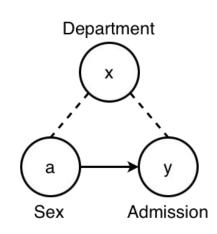
The sex ratios of applicants to the various <u>fields of</u> <u>graduate study</u> are <u>not importantly associated with any</u> <u>other factors in admission</u>.





### When Examining By Departments...

- Individual department did not show consistent bias against women.
- Excluding 16 that either had no women applicants (positivity) or denied admission to no applicants of either sex (no association between a, y).
- From remaining 85:
  - 4 show significant bias against women
  - 6 departments show bias against men.

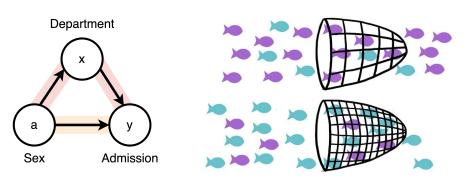


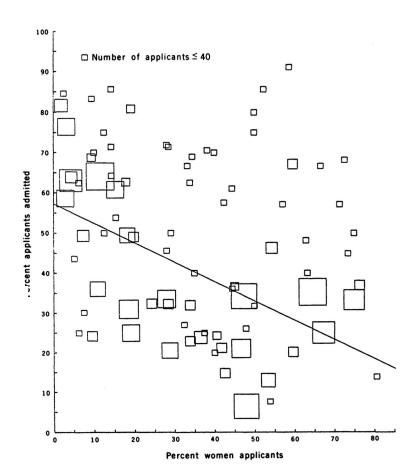


### Why? Simpson's Paradox

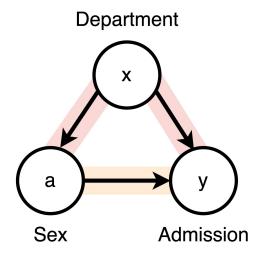
- Women are accepted at equal/higher rate in most individuals departments.
- Men are accepted at an overall higher rate in the university.

Women tend to apply to departments that are hard to get into.



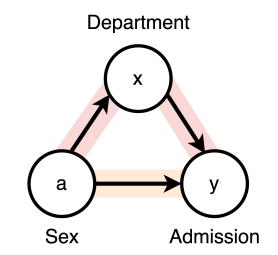


## **Causal Graph**



**Case 1**: x is an unobserved confounder

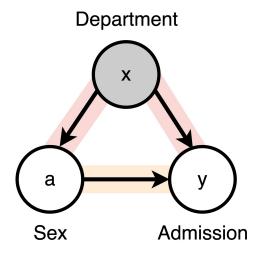
a ← x → y is an open, non-causal path Spurious correlation (Backdoor)



Case 2: x is an unobserved mediator

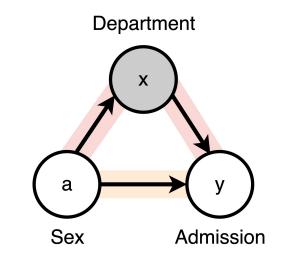
a → x → y is an open, causal path Statistical relation = Total causal relation

## **Causal Graph**



**Case 3**: x is an observed confounder

a ← x → y is closed Statistical relation = Causal relation



Case 4: x is an observed mediator

a → x → y is closed Statistical relation = Direct causal relation

### Adjusted Approach: Pooling

- Recalculating the expected admission
  - Take into account of individual department admission rate
- For each department
  - Pooled by the department admission rate instead of university admission rate
- Sum the expected number of admissions across departments
- Evidence of Bias In Favor of Women

Expected female admittees	1432.9
Observed female admittees	1493.0
Difference $(O-E)$	60.1



### Example

#### **Originally:**

Applicants		Outo	Difference			
	Observed				Expected	
	Admit	Deny	Admit	Deny	Admit	Deny
		Departm	ent of machis	matics		
Men	200	200	200	200	0	0
Women	100	100	100	100	0	0
		Departme	ent of social v	varfare		
Men	50	100	50	100	0	0
Women	150	300	150	300	0	0
			Totals			
Men	250	300	229.2	320.8	20.8	- 20.8
Women	250	400	270.8	379.2	<b>- 20.8</b>	20.8

- Overall Admit Rate: (250 + 250)/(250 + 300 + 250 + 400) = 0.417
- Then, the number of expected female admittees,  $E_f$ : (250+400)\*0.417=270.8
- $O_f E_f = -20.8$

#### **After Pooling:**

- Machismatics Admit Rate:
- (200 + 100)/(200 + 200 + 100 + 100) = 0.5
- Social Warfare Admit Rate:
- (50+150)/(50+100+150+300) = 0.333
- $E_f$ :

$$(100 + 100) * 0.5 + (150 + 300) * 0.333 = 250$$

$$- O_f - E_f = 0$$



### Pooling - Department as a Mediator

Treating Department as the mediator,

$$P(y|Do(a = female)) = \sum_{x} P(y|a = female, x)P(x|a = female)$$

Let the number of female applicants be  $N_f$ . The expected count of female admittees (no bias):

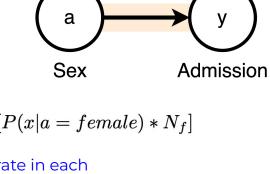
$$E_f = P(y|Do(a = female)) * N_f$$

$$= \left[\sum_{x} P(y|a = female, x)P(x|a = female)\right] * N_f$$

$$=\sum_{x}P(y|a=female,x)\left[P(x|a=female)*N_{f}\right]=\sum_{x}P(y|x)\left[P(x|a=female)*N_{f}\right]$$

admit rate for females number of females applying in each department to each department

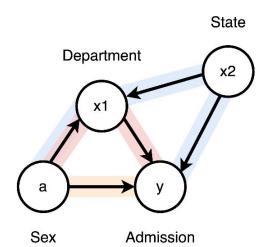
admit rate in each department (if no bias)



Department

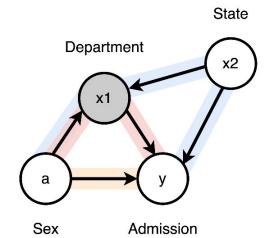


## Kruskal's Argument



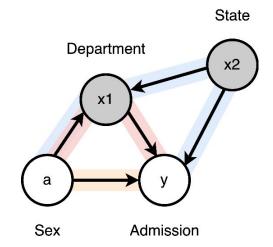
x1 unobserved x2 unobserved

 $a \rightarrow y = Open$   $a \rightarrow x1 \rightarrow y = Open$  $a \rightarrow x1 \leftarrow x2 \rightarrow y = Closed$ 



x1 observed x2 unobserved

$$a \rightarrow y = Open$$
  
 $a \rightarrow x1 \rightarrow y = Closed$   
 $a \rightarrow x1 \leftarrow x2 \rightarrow y = Open$ 



x1 observed x2 observed

$$a \rightarrow y = Open$$

$$a \rightarrow x1 \rightarrow y = Closed$$

$$a \rightarrow x1 \leftarrow x2 \rightarrow y = Closed$$

### **Conclusions**

#### **Simpson's Paradox Case Study**

- Aggregate data suggests bias against female applicants, that reverses when data is disaggregated by departments.
- Simpson's Paradox is not solely tied to confounding variables.

#### **Causal Effect Calculation**

- Causal effect calculation largely depends on assumptions about the data generation process. For example, the department can act as a mediator or a confounder.
- The inferences must be accompanied by our assumptions about the data. For example, we must assume that we measured all confounders.

### **Analysis Replication**

https://colab.research.google.com/drive/1ACD6BNw1AMArVXj MEtghoA2-Ap1HvilO?usp=sharing



### References

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# Thank You

Open to questions!