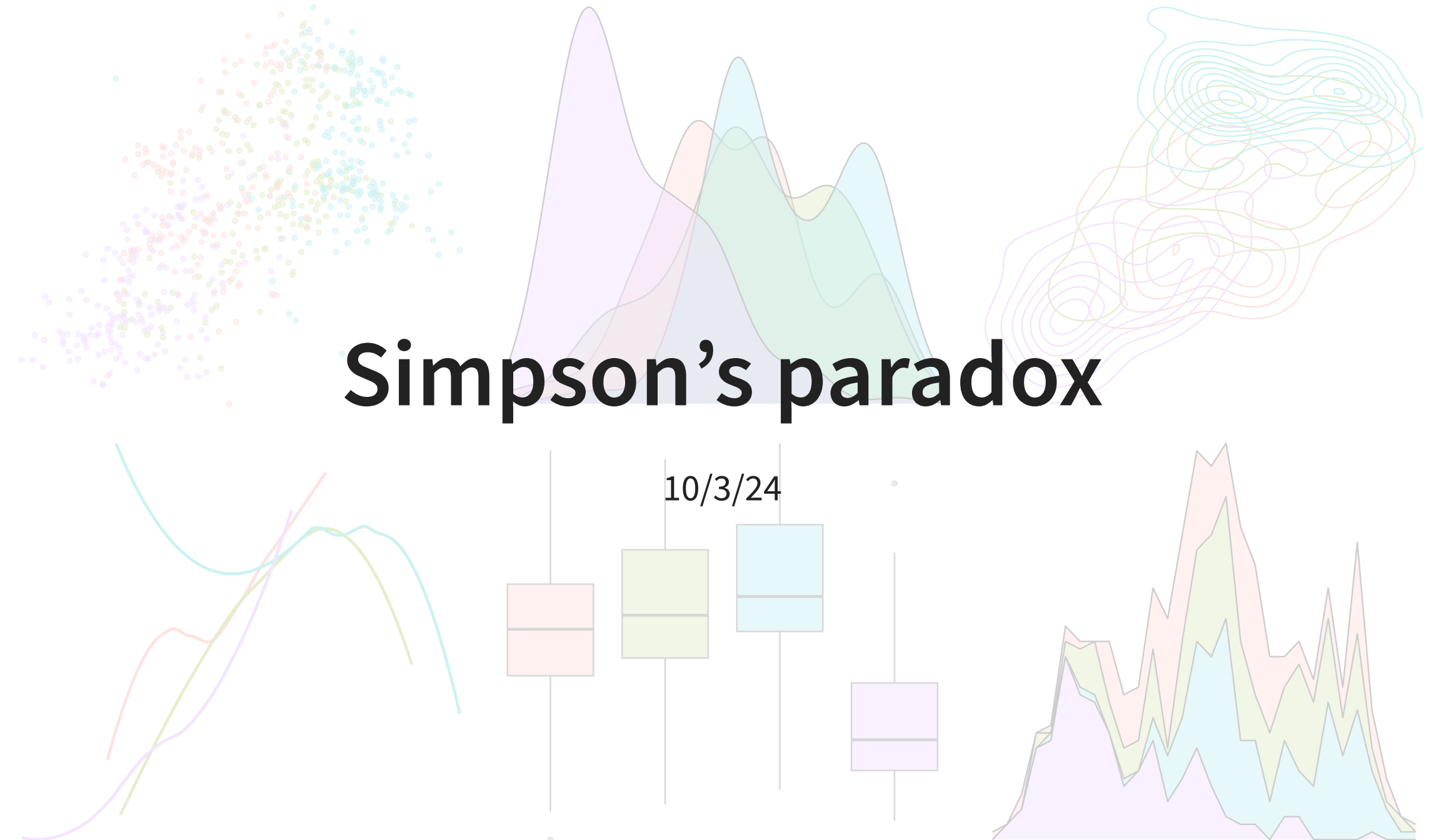


Simpson’s paradox

10/3/24

Brief recap

Study design

- What are the differences between observational studies and experimental studies?
- What is a confounding variable?

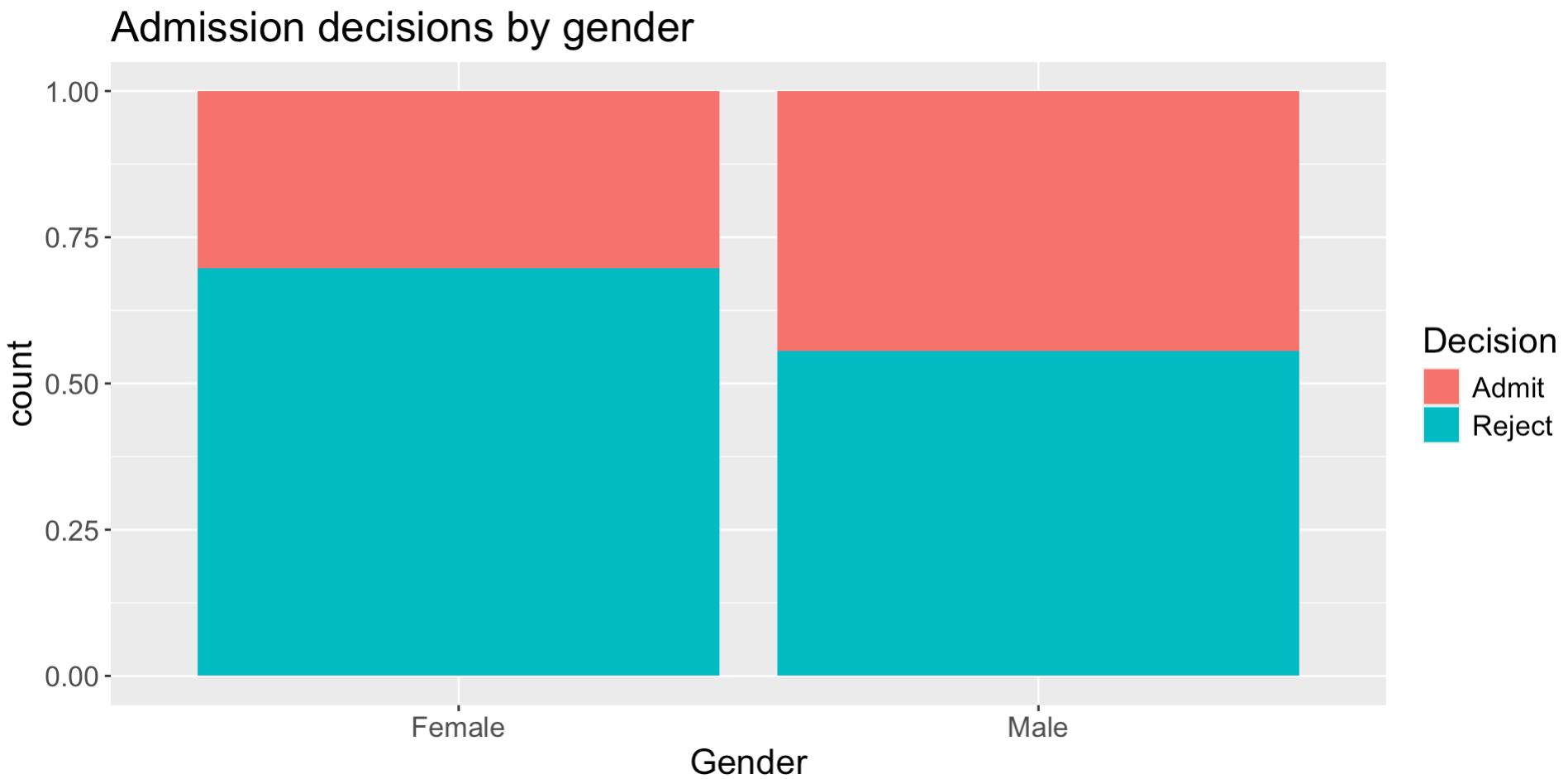
UC Berkeley admissions

Observational study on sex bias based on Fall 1973 admissions data to the graduate program at the University of California, Berkeley

	Admit	Deny	Total
Men	3738	4704	8442
Women	1494	2827	4321
Total	5232	7531	12763

1. What is the probability of admission for a randomly selected applicant?
2. What is the probability of admission among men? Among women?
3. Are the probabilities you found marginal, joint, or conditional probabilities?

Suppose we want to understand the relationship between gender and admission decision. What sort of visualization might be appropriate for representing this data?


Admission decisions by gender
1.00
0.75
0.50
0.25
0.00
count
Female
Male
Gender
Decision
Admit
Reject

Case study

Dive into data

We have more nuanced data about the graduate admissions: we know the department that each person was applied to.

We will consider the six largest departments: A, B, C, D, E, F

- The first six observations in the data frame are as follows:

```
1 head(admissions)
```

```
# A tibble: 6 × 3
  Decision Gender Dept
  <chr>    <chr>  <chr>
1 Admit    Male   B
2 Reject   Female C
3 Admit    Male   C
4 Reject   Female C
5 Admit    Male   A
6 Reject   Male   F
```

- What sort of EDA would be interesting/appropriate for these data?

Frequency tables

Female applicants:

Dept	n
A	108
B	25
C	593
D	375
E	393
F	341

Male applicants:

Dept	n
A	825
B	560
C	325
D	417
E	191
F	373

More-detailed frequency tables

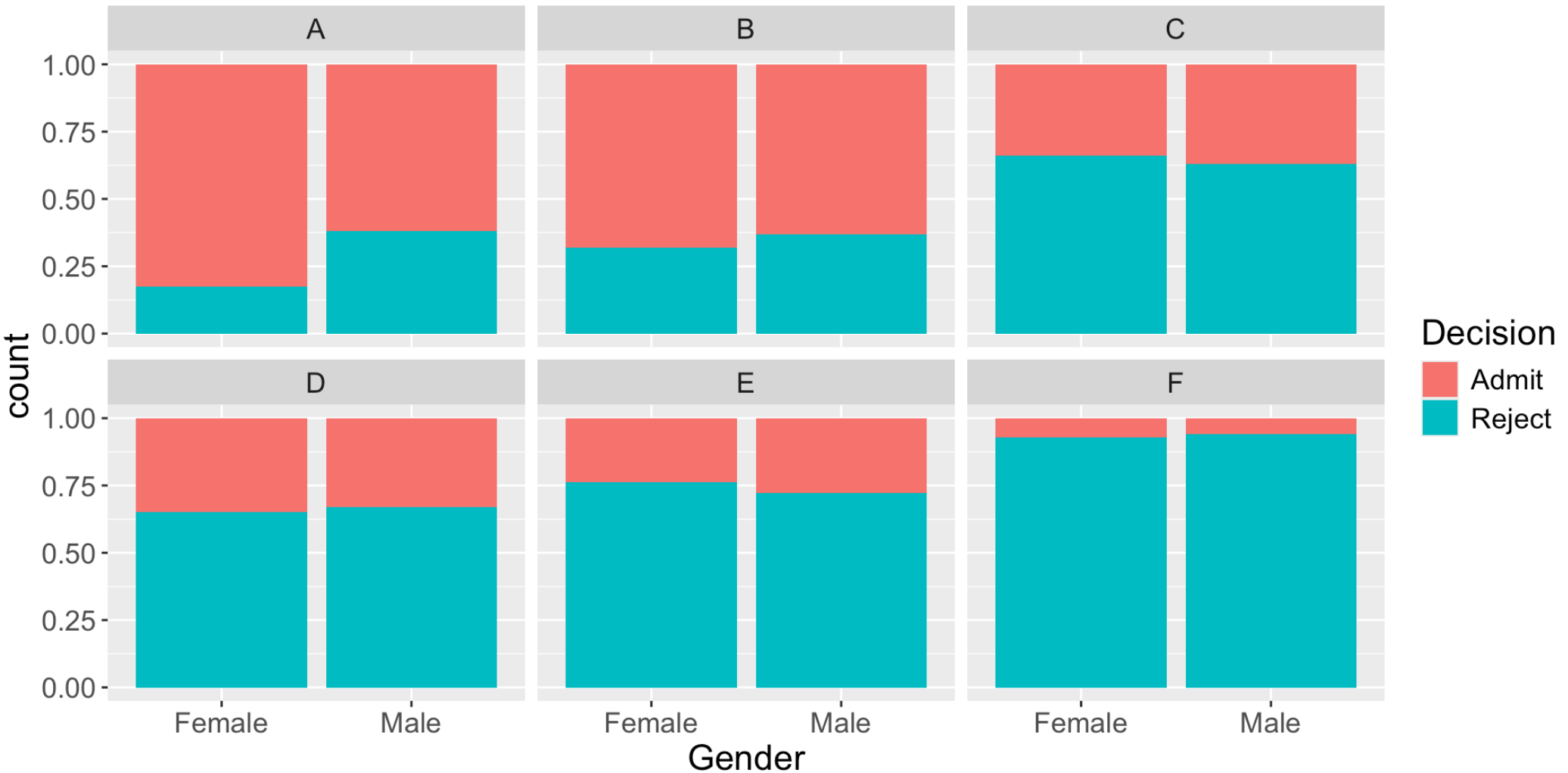
Female applicants:

Dept	Decision	n
A	Admit	89
A	Reject	19
B	Admit	17
B	Reject	8
C	Admit	202
C	Reject	391
D	Admit	131
D	Reject	244
E	Admit	94
E	Reject	299
F	Admit	24
F	Reject	317

Male applicants:

Dept	Decision	n
A	Admit	512
A	Reject	313
B	Admit	353
B	Reject	207
C	Admit	120
C	Reject	205
D	Admit	138
D	Reject	279
E	Admit	53
E	Reject	138
F	Admit	22
F	Reject	351

Visualize


A
B
C
D
E
F
1.00
0.75
0.50
0.25
0.00
count
Female
Male
Gender
Decision
Admit
Reject

Closer look

Dept	Gender	p_admit
A	Female	0.82
A	Male	0.62
B	Female	0.68
B	Male	0.63
C	Female	0.34
C	Male	0.37
D	Female	0.35
D	Male	0.33
E	Female	0.24
E	Male	0.28
F	Female	0.07
F	Male	0.06

- Are all departments uniform in admission rates?
- Do admissions still seem biased against female applicants?

What's going on?

- But wait… didn't we start by noting that men were way more likely to be admitted than women?
- The first two departments (A and B) are easy to get into
  - What percentage of men applied to department A?
  - What percentage of women applied to departments C-F?

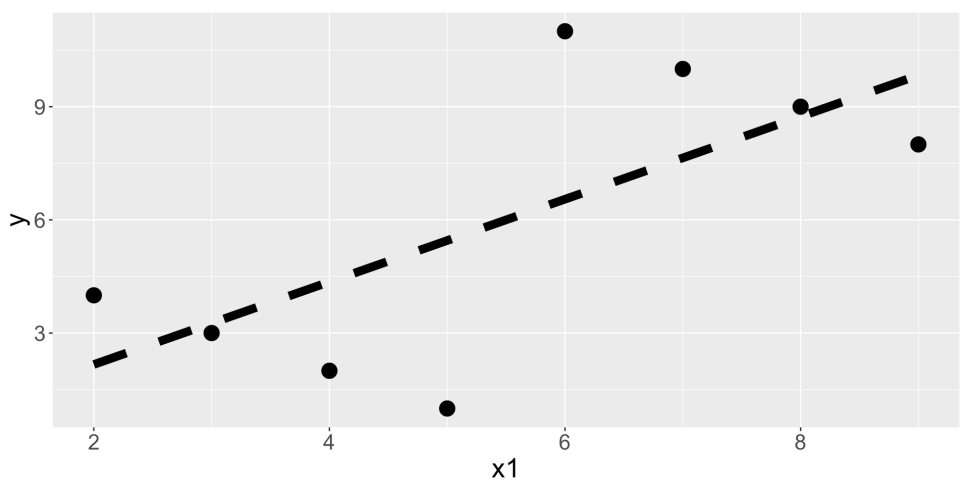
- Following shows for each gender, the proportion of applicants each department received.

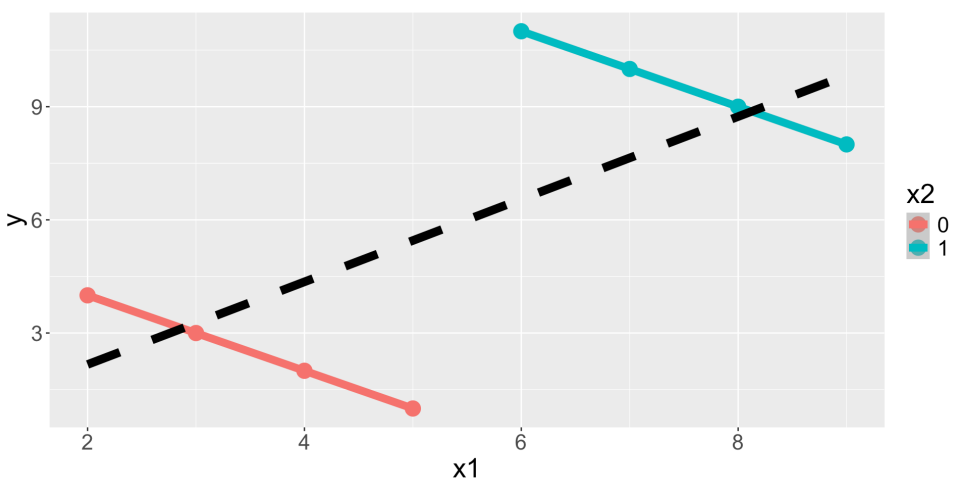
Gender	Dept	prop_apply
Female	A	0.06
Female	B	0.01
Female	C	0.32
Female	D	0.20
Female	E	0.21
Female	F	0.19
Male	A	0.31
Male	B	0.21
Male	C	0.12
Male	D	0.15
Male	E	0.07
Male	F	0.14

Simpson's paradox

The UC Berkeley admissions observational study is an example of **Simpson's paradox**: when omitting one explanatory variable causes the measure/degree of association between another explanatory variable and a response variable to reverse or disappear

- In other words, the inclusion/exclusion of a third variable in the analysis can change the apparent relationship between the other two variables
- What was the confounding variable in UC Berkeley study?





Misc. live code

```
library(readr)
url_file <- "https://raw.githubusercontent.com/midd-stat201-fall2024/midd-stat201-fall2024.github.io/
insurance <- read_csv(url_file)
```

We will return to `insurance` data to learn about:

- Using wrangling to obtain probabilities
- `case_when()` to create more complex categorical variables

Wrangling for probabilities

What is probability that someone is a smoker?

```
insurance |>
  count(smoker) |>
  mutate(prob = n/sum(n)) |>
  select(-n)
```

```
# A tibble: 2 × 2
  smoker  prob
  <chr>  <dbl>
1 no     0.775
2 yes    0.225
```

What is the probability that someone is a smoker, conditioned on sex?

```
insurance |>
  count(smoker, sex) |>
  group_by(sex) |>
  mutate(prob = n/sum(n)) |>
  select(-n)
```

```
# A tibble: 4 × 3
# Groups:   sex [2]
  smoker sex     prob
  <chr>  <chr>  <dbl>
1 no     female 0.837
2 no     male   0.708
3 yes    female 0.163
4 yes    male   0.292
```

More complex categorical variables

Suppose I want to create a new variable representing the categories of BMI, constructed as follows:

- underweight if someone's BMI is less than 18.5
- healthy if BMI is 18.5 to less than 25
- overweight if BMI is 25 to less than 30
- obese if BMI is 30 or greater

```
# option 1 (awful): nested if_else()
insurance |>
  mutate(bmi_cat = if_else(bmi < 18.5, "under",
                           if_else(bmi >= 18.5 & bmi < 25, "healthy",
                                   if_else(...))))
```

case_when()

We will use the `case_when()` function which generalizes `if_else()`. We use the following notation: `<logical condition> ~ <value of variable>`. Different "ifs" are separated by commas, and the logical conditions are checked sequentially.

```
insurance |>
  mutate(bmi_cat = case_when(
    bmi < 18.5 ~ "under",
    bmi >= 18.5 & bmi < 25 ~ "healthy",
    bmi >= 25 & bmi < 30 ~ "over",
    bmi >= 30 ~ "obese"
  )) |>
  select(bmi, bmi_cat) |>
  slice(1:5)
```

```
# A tibble: 5 × 2
    bmi bmi_cat
  <dbl> <chr>
1  27.9 over
2  33.8 obese
3  33   obese
4  22.7 healthy
5  28.9 over
```

```
# The following is also acceptable, but
# relies on sequential ordering:
insurance |>
  mutate(bmi_cat = case_when(
    bmi < 18.5 ~ "under",
    bmi >= 18.5 & bmi < 25 ~ "healthy",
    bmi >= 25 & bmi < 30 ~ "over",
    T ~ "obese"
  )) |>
  select(bmi, bmi_cat) |>
  slice(1:5)
```

```
# A tibble: 5 × 2
    bmi bmi_cat
  <dbl> <chr>
1  27.9 over
2  33.8 obese
3  33   obese
4  22.7 healthy
5  28.9 over
```