

# STATS 111/202

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## Lecture 5: Confounding and effect modifiers, MH-test, BD-test

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# Three-way tables (cont'd)



2.7

# Recall confounders vs effect modifiers

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## Confounders

- **Masks** the true relationship between the explanatory variable and the outcome.
- Wholly or partially accounts for the observed effect of the explanatory variable on the outcome. Can lead to inaccurate conclusions

## Effect modifiers

- **Alters** the relationship between the explanatory variable and the outcome.
- Natural behavior we want to understand. Different groups may have different outcomes when effect modification is present.

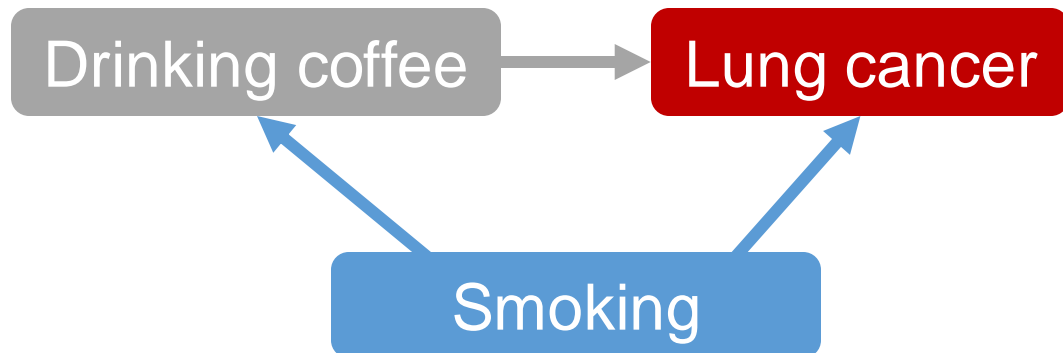
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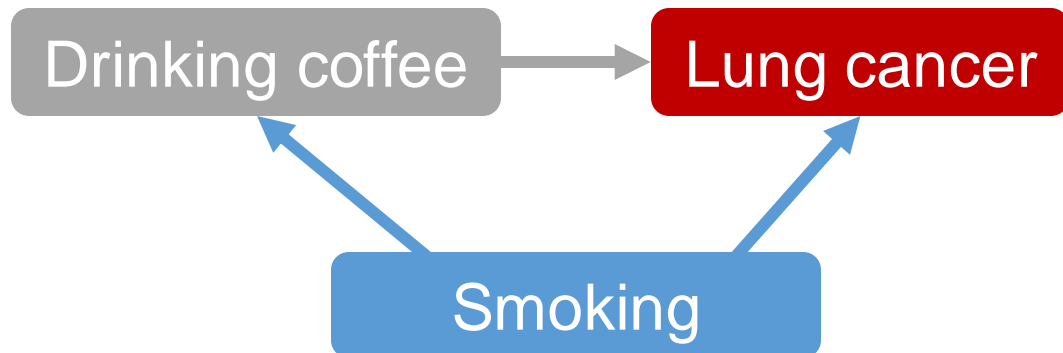
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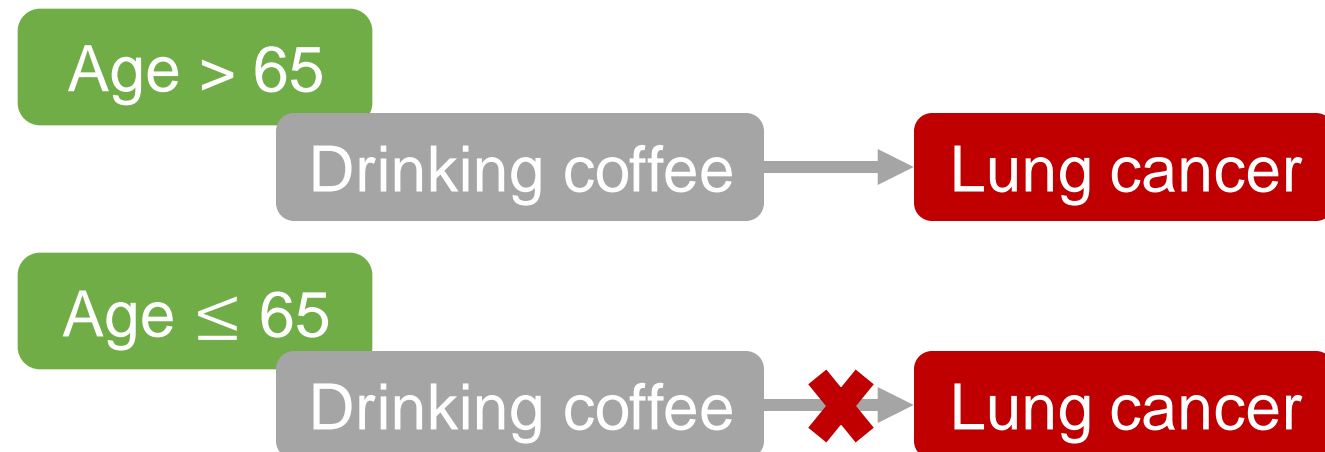
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# Recall confounders vs effect modifiers

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## Confounders

- A third variable  $W$ , may cause a spurious association between  $X$  and  $Y$  or even mask an effect taking place

## Effect modifiers

- The association between  $X$  and  $Y$  varies at different levels of  $W$

## Possible confounder example



## Possible effect modifier example





# Overview

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Assume we have a three-way table, which is really a two-way tables over levels of a third variable  $W$ .

- **Check confounding**
  - Combine tables to check for association between  $X$  and  $W$
  - Combine tables to check for association between  $Y$  and  $W$
  - Can use a chi-squared test for independence

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If we are worried about confounding, how can we see if there is an association between  $X$  and  $Y$  while controlling for  $W$ ?

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- **Check for effect modification**
  - Use original tables to compute and test the association between  $X$  and  $Y$  over all levels of  $W$

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How can we test whether these associations are similar enough?

# Mantel-Haenszel test

Goal: test whether X and Y are independent at each level of W

- Let W have  $k = 1, 2, \dots, K$  many levels ( $K \geq 2$ )
- Consider X and Y taking on 2 levels at each level of W
- Then we have K of these tables

	Y=0	Y=1	Total
X=0	$n_{11k}$	$n_{12k}$	$n_{1.k}$
X=1	$n_{21k}$	$n_{22k}$	$n_{2.k}$
Total	$n_{.1k}$	$n_{.2k}$	$n_{..k}$

Below the table, there are labels for the row and column totals:  $n_{1.k}$ ,  $n_{2.k}$ ,  $n_{.1k}$ ,  $n_{.2k}$ , and  $n_{..k}$ .

- Let's condition on the column and row totals (these are fixed)
- Then only a single cell in the 2x2 table can vary, say  $n_{11k}$

K tables total

$H_0$ : X and Y are independent at each level of W

$H_a$ : X and Y are dependent at at least one level of W

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Under the null,  $n_{11k}$  follows a Hypergeometric distribution with parameters  $(n_{..k}, n_{.1k}, n_{1.k})$

# Recall: Hypergeometric distribution

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Say we have  $N$  objects/trials with  $K$  successes. What if we randomly select (without replacement)  $n$  of them?

- Three important parameters:  $N$ ,  $K$ , and  $n$
- Let  $X$  be the number of successes from the  $n$  draws
  - $X$  can take on values (i.e., has support)  $\{\max(0, n + K - N), \dots, \min(n, K)\}$
- The probability mass function is:
  - $$f(x) = P(X = x) = \frac{\binom{K}{x} \binom{N-K}{n-x}}{\binom{N}{n}}$$

# Mantel-Haenszel test

Under the null,  $n_{11k}$  follows a Hypergeometric distribution with parameters  $(n_{..k}, n_{.1k}, n_{1.k})$

- Then under the null where X and Y are independent across all levels of W
  - $E(n_{11k}) = \frac{n_{1.k}n_{.1k}}{n_{..k}}$
  - $Var(n_{11k}) = \frac{n_{1.k}n_{2.k}n_{.1k}n_{.2k}}{n_{..k}^2(n_{..k}-1)}$
- And the MH test statistic follows:

$$MH = \frac{\left(\sum_{k=1}^K (n_{11k} - E(n_{11k}))\right)^2}{\sum_{k=1}^K Var(n_{11k})}$$

	Y=0	Y=1	Total
X=0	$n_{11k}$	$n_{12k}$	$n_{1.k}$
X=1	$n_{21k}$	$n_{22k}$	$n_{2.k}$
Total	$n_{.1k}$	$n_{.2k}$	$n_{..k}$

This follows an approximate chi-squared distribution with 1 degree of freedom



# Mantel-Haenszel test

- Under the null, the odds ratio in each level of W will be equal (and each is equal to 1). We can combine across levels of W to form a **single common odds ratio**
- Then the MH estimator of a common odds ratio in a 2x2xK table is given by:

$$\widehat{OR}_{MH} = \frac{\sum_{k=1}^K (n_{22k} n_{11k} / n_{..k})}{\sum_{k=1}^K (n_{21k} n_{12k} / n_{..k})}$$

	Y=0	Y=1	Total
X=0	$n_{11k}$	$n_{12k}$	$n_{1.k}$
X=1	$n_{21k}$	$n_{22k}$	$n_{2.k}$
Total	$n_{.1k}$	$n_{.2k}$	$n_{..k}$

- The MH common odds ratio is the odds ratio for Y = 1 comparing X = 1 to X = 0 **while accounting or controlling for W (a potential confounder)**

# MH common odds ratio intuition

- What happened to our odds ratio?

	Y=1	Y=0	Total
X=1	$n_{11k}$	$n_{12k}$	$n_{1.k}$
X=0	$n_{21k}$	$n_{22k}$	$n_{2.k}$
Total	$n_{.1k}$	$n_{.2k}$	$n_{..k}$

$$\widehat{OR}_{MH} = \frac{\sum_{k=1}^K (n_{22k} n_{11k} / n_{..k})}{\sum_{k=1}^K (n_{21k} n_{12k} / n_{..k})}.$$

$$OR = \frac{p_1 / (1-p_1)}{p_0 / (1-p_0)} = \frac{\left( \frac{n_{11k}}{n_{1 \cdot k}} \right) / \left( \frac{n_{12k}}{n_{1 \cdot k}} \right)}{\left( \frac{n_{21k}}{n_{2 \cdot k}} \right) / \left( \frac{n_{22k}}{n_{2 \cdot k}} \right)}$$

$$= \frac{\left( \frac{n_{11k}}{n_{1 \cdot k}} \right) \left( \frac{n_{22k}}{n_{2 \cdot k}} \right)}{\left( \frac{n_{21k}}{n_{2 \cdot k}} \right) \left( \frac{n_{12k}}{n_{1 \cdot k}} \right)}$$

$$= \frac{\frac{n_{11k} n_{22k}}{n_{1 \cdot k} n_{2 \cdot k}}}{\frac{n_{21k} n_{12k}}{n_{2 \cdot k} n_{1 \cdot k}}}$$

$$= \frac{n_{11k} n_{22k}}{n_{21k} n_{12k}}$$

$$OR = \frac{P_1 / (1 - P_1)}{P_0 / (1 - P_0)} = \frac{\left( \frac{n_{11k}}{n_{1 \cdot k}} \right) / \left( \frac{n_{12k}}{n_{1 \cdot k}} \right)}{\left( \frac{n_{21k}}{n_{2 \cdot k}} \right) / \left( \frac{n_{22k}}{n_{2 \cdot k}} \right)}$$

$$= \frac{\left( \frac{n_{11k}}{n_{1 \cdot k}} \right) \left( \frac{n_{22k}}{n_{2 \cdot k}} \right)}{\left( \frac{n_{21k}}{n_{2 \cdot k}} \right) \left( \frac{n_{12k}}{n_{1 \cdot k}} \right)}$$

$$= \frac{\frac{n_{11k} n_{22k}}{n_{1 \cdot k} n_{2 \cdot k}}}{\frac{n_{21k} n_{12k}}{n_{2 \cdot k} n_{1 \cdot k}}}$$

$$= \frac{n_{11k} n_{22k}}{n_{21k} n_{12k}}$$

$$\widehat{OR}_{MH} = \frac{\sum_{k=1}^K (n_{22k} n_{11k} / n_{..k})}{\sum_{k=1}^K (n_{21k} n_{12k} / n_{..k})}$$

So we're just taking the weighted sum of the numerator and denominator (adjusting for the number of samples in each level of W)

# Mantel-Haenszel test

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- Then formally, the null hypothesis for the MH test is  $H_0 : OR_{MH} = 1$
- The alternative can follow  $H_\alpha : OR_{MH} \neq 1$  or  $H_\alpha : OR_{MH} > 1$  or  $H_\alpha : OR_{MH} < 1$
- This is testing for independence between X and Y while adjusting or controlling for W (a possible confounder)

# Breslow-Day test

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- Now if we want to directly test for a homogenous association, meaning the relationship between X and Y conditioned on W is the same across all levels of W, we would use the BD test
- $H_0: OR_1 = OR_2 = \dots = OR_K$  vs  $H_a: OR_i \neq OR_j$  for at least one  $i \neq j$
- The B-D test statistic: 
$$BD = \sum_{i,j,k} \frac{(n_{ijk} - \hat{\mu}_{ijk})^2}{\hat{\mu}_{ijk}}$$
  - Where  $n_{ijk}$  is the observed count in the ij-th cell in the k-th table
  - $\hat{\mu}_{ijk}$  is the expected count in the ij-th cell in the k-th table under the null that all odds ratios are the same
- This test statistic follows a chi-squared distribution with K-1 degrees of freedom

# MH and BD Test Example

