

# Phil/LPS 31 Introduction to Inductive Logic

## Lecture 19

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# Topics

- ▶ Relative Risk
- ▶ Odds Ratio
- ▶ Simpson's Paradox

# Measures of Association in contingency tables

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# Measures of Association in contingency tables

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- ▶ In this lecture we want to learn how to use data in contingency tables to quantify the association between the dependent and independent variables.
- ▶ Some interesting puzzles such as the Simpson's paradox arise in the analysis of contingency tables. Such paradoxes emphasize further the need for control of extraneous confounding variables in making causal inferences.

# Contingency Tables

- ▶ A contingency table is a rectangular table that cross-classifies categorical variables  $X$  and  $Y$ . If we let  $r$  denote the number of categories of  $X$  (the rows) and  $c$  denote the number of categories of  $Y$  (the columns); a contingency table has cells that display the  $r \times c$  possible combinations of outcomes.

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- ▶ A table that cross-classifies two variables is called a **two-way contingency table**; one that cross-classifies three variables is called a **three-way contingency table**, and so forth.
- ▶ In two-way tables, usually the column variable  $Y$  is a **response variable** and the other row variable  $X$  is an **explanatory variable**



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- ▶ For the conditional distribution we are usually interested in the conditional probabilities of  $Y$ , given  $X$  at each value or level of  $X$ .
- ▶ **Note:** When the rows of a contingency table refer to different groups, the sample sizes for those groups are often fixed by the sampling design. An example is a randomized experiment to compare a new drug to placebo in treating some illness, in which half the sample is randomly allocated to each of two treatments. When the marginal totals for  $X$  are fixed rather than random, a joint distribution for  $X$  and  $Y$  is not meaningful, but conditional distributions for  $Y$  (given  $X$ ) are.

# Contingency Tables

- Recall the cross-classification table of belief in afterlife by gender in Homework 5.

Gender	Belief in Afterlife		Total
	Yes	No or Undecided	
Females	1230	357	1587
Males	859	413	1272
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  - (1) the joint probability distribution of the data;
  - (2) the marginal probability distributions for  $Y$ ;
  - (3) the conditional distributions of belief in afterlife, given gender.



## Relative Risk

The following table comes from the Physicians' Health Study, which was a five-year randomized study investigating whether regular intake of aspirin reduces the chance of myocardial infarction (heart attacks). Every other day, the male physicians participating in the study took either one aspirin tablet or a placebo. The study was blind – the physicians in the study did not know which type of pill they were taking.

Group	Myocardial Infarction		Total
	Yes	No	
Placebo	189	10845	11034
Aspirin	104	10933	11037

## Relative Risk

- ▶ Since the study is a randomized control study, **relative risk** is a useful descriptive measure of the effect of aspirin in reducing the risk of heart attacks. For  $2 \times 2$  tables, the relative risk for  $E$ ,  $RR(E)$ , is given by:

$$RR(E) = \frac{\text{Proportion in Group 1 with Outcome } E}{\text{Proportion in Group 2 with Outcome } E}$$

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  - ▶ Let  $E$  be an incident of myocardial infarction (i.e., heart attack) and  $E^c$  an no incident of myocardial infarction. Find  $RR(E)$  for physicians who took the placebo compared to those who took aspirin. Interpret the result.

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  - ▶ Is  $RR(E) = RR(E^c)$ ?

## Odds Ratio

The following table comes from one of the first studies of the association between lung cancer and smoking, based on data from 20 hospitals in London, England, in 1920. At the time, many medical scientists thought that the increased rates of lung cancer in London mainly reflected the increasingly severe air pollution due to the burning of coal (and, thus, the frequent “London fog”) before the Clean Air Act of 1956. However, the epidemiologist Richard Doll and statistician Austin Bradford Hill thought that smoking could be a culprit. In their study, patients admitted to the hospital with lung cancer in the preceding year were queried about their smoking behavior. Patients were defined as smokers if they had smoked at least one cigarette a day for at least a year. For each patient admitted, they recorded the smoking behavior of a noncancer patient at the same hospital of the same gender and within the same 5-year grouping on age. The 709 cases in the first column are those having lung cancer and the 709 controls in the second column are those not having it.

# Odds Ratio

- ▶ Here is the table.

Smoker	Lung Cancer	
	Cases	Controls
Yes	688	650
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- ▶ This is a case-control study because the study begins with the absence or presence of an outcome (here lung cancer) and then **looks backward in time** to try to detect possible causes or risk factors.



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- ▶ Normally, whether lung cancer occurs is a response variable and smoking behavior is an explanatory variable. smoking behavior. Here when we assess the relative risk of lung cancer by comparing smokers with nonsmokers the proportions refer to the conditional distribution of lung cancer, given smoking behavior.

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- ▶ In contrast, case-control studies provide proportions in **the reverse direction**. Here we're interested in the conditional distribution of smoking behavior, given lung cancer status.
- ▶ We shall see that Odds Ratio (**unlike relative risk**) can be usefully used to quantify this reverse direction of association in  $2 \times 2$  table.

# Odds Ratio

- ▶ In  $2 \times 2$  tables the **odds ratio**,  $\theta$  is the appropriate measure of association for detecting possible risk factors in a **case-control study**.

$$\theta = \frac{\text{Odds of outcome E for those in Group 1}}{\text{Odds of outcome E for those in Group 2}} = \frac{\frac{P_1(E)}{1-P_1(E)}}{\frac{P_2(E)}{1-P_2(E)}}$$

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- ▶ Because  $\theta = \frac{n_{11}n_{22}}{n_{12}n_{21}}$  some authors use the term odds ratio interchangeably with the **cross-product ratio**.

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- ▶ For instance, when  $\theta = 4$ , the odds of outcome  $E$  in Group 1 are four times the odds of outcome  $E$  in Group 2.
- ▶ Values of  $\theta$  farther from 1 in a given direction represent a stronger association. An odds ratio of 4 is farther from independence than an odds ratio of 2, and an odds ratio of 0.25 is farther from independence than an odds ratio of 0.50.

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- ▶ The odds ratio is the same when we treat the columns as the response variable and the rows as the explanatory variable, or the rows as the response variable and the columns as the explanatory variable.
- ▶ Because of this symmetry, interpretations can use the direction of interest, even though the study was retrospective.

# Odds Ratio

- ▶ Consider the smoking data from earlier.

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- ▶ Calculate the odds ratio of the association between smoking and incidence of lung cancer. Interpret.

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- ▶ When we add control variables like  $Z$  we get a three-way contingency table.

# Partial Tables, Marginal Tables and Simpson's Paradox

- ▶ Three way contingency tables lead to **two-way partial tables**, which cross-classify  $X$  and  $Y$  at separate categories or levels of  $Z$ . A two-way partial table controls for the effect of  $Z$  by holding its value constant.

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- ▶ The associations in partial tables are called **conditional associations** because they show the association between  $X$  and  $Y$  **conditional** on  $Z$  being constant, i.e., controlling for  $Z$ .

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- ▶ The association in the marginal table is called the **marginal association** between  $X$  and  $Y$ .
- ▶ **Simpson's Paradox** arises whenever **the direction** of conditional association between  $X$  and  $Y$  is different from **the direction** of marginal association between  $X$  and  $Y$ .



## Simpson's Paradox: First Illustration

- ▶ If a major league batter gets  $f = 152$  hits in  $n = 500$  official **at bats**(AB) during the season, then the relative frequency  $f/n = 0.304$  is an estimate of his probability of getting a hit and is called his **batting average for that season**.

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- ▶ Question: Is it possible for batter A to have a higher average than batter B during each season of their careers yet, at the end of their careers, batter B has a better batting average than batter A?
- ▶ You might say, “Obviously, no!” But wait. . . “Obviousness is. . .”

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- ▶ Consider the following data on the batting average between two players  $A$  and  $B$ .

Season	Player A			Player B		
	At Bat	Hits	Average	At Bat	Hits	Average
1	500	126	0.252	300	75	0.250
2	300	90	0.300	500	145	0.290
Totals	800	216	0.270	800	220	0.275

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- ▶ Controlling for season (or conditional on the season played), Player A has a higher batting average than Player B. However, marginally, Player B has a higher batting average than Player A. This is Simpson's Paradox.

## Simpson's Paradox: Second Illustration

- ▶ The following  $2 \times 2 \times 2$  contingency table is from an article that studied the effects of racial characteristics on whether subjects convicted of homicides receive the death penalty. The 674 subjects were the defendants in indictments involving cases with multiple murders, in Florida during a 12-year period. The variables are  $Y$  = death penalty verdict,  $X$  = race of defendant, and  $Z$  = race of victims. The question of interest was **to study the association between a defendant's race and whether they received the death penalty verdict, controlling for the victims' race.**

## Simpson's Paradox: Second Illustration

- Here is the table.

Victims' Race	Defendant's Race	Death Penalty	
		Yes	No
White	White	53	414
	Black	11	37
Black	White	0	16
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- ▶ Exercise.
  - ▶ Write down the marginal table for the association between the defendant's race and whether they received the death penalty verdict. Calculate the odds ratio. This is called the **marginal odds ratio**. Interpret it.

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- ▶ Exercise.
  - ▶ Write down the marginal table for the association between the defendant's race and whether they received the death penalty verdict. Calculate the odds ratio. This is called the **marginal odds ratio**. Interpret it.
  - ▶ Write down the partial table if the victim's race is white and calculate the odds ratio. This is called a **conditional odds ratio**. Interpret it.

## Simpson's Paradox: Second Illustration Cont'd.

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## Simpson's Paradox: Second Illustration Cont'd.

- ▶ Exercise (Cont'd.)
  - ▶ Write down the partial table if the victim's race as black and calculate the odds ratio. This is also called a **conditional odds ratio** Interpret it.
  - ▶ Compare the direction of conditional association to the direction of marginal association, is this Simpson's Paradox?

# Conditional Independence

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- ▶ To check for **conditional independence** between  $X$  and  $Y$  given  $Z$ , check that **all** the conditional odds ratios between  $X$  and  $Y$  at each level of  $Z$  are equal 1.
- ▶ In general, conditional independence of  $X$  and  $Y$ , given  $Z$ , does not imply marginal independence of  $X$  and  $Y$ .