

# Day 12

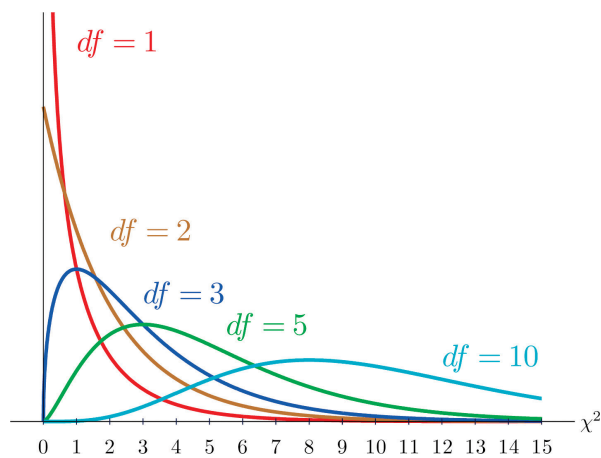
## Outline

1. Computing p-values with software using  $\chi^2$  distribution
2. Test of independence
3. Measures of association between two categorical variables

## Computing P-Value

Given  $\chi^2$

P-Value is always above or equal to degrees of freedom.



p \_\_\_\_

- interval values  $\rightarrow$  probability

q \_\_\_\_

- probability  $\rightarrow$  values

P-Values = probability of getting our data or data that “disagree” as much or more with our model, if model is correct.

```
arbitrary_val <- 4.8  
pchisq(arbitrary_val, df = 5, lower.tail = FALSE)
```

## Test of Independence

What I'm recording: two categorical variables

What I want to know: whether a suspected association between the variables will hold when generalized to the population.

## Test of Homogeneity

What I'm recording: 1 categorical variable in samples from multiple populations

What I want to know: Is the variable's distribution the same in all populations?

**Both tests use data summarised in two-way tables**

We use Fisher's significance testing approach.

Test of independence: we model assuming that the two variables are not actually associated

$H_0$

- [Variable 1] does not affect [Variable 2]
  - [Variable 1] and [Variable 2] are independent/not associated/ not related

Testing of homogeneity: we model assuming the distribution is the same in every population

- $H_0$ : the distribution of [variable] is the same in [list of population]

More simply put:  $H_a$ : not  $H_0$

In test of homogeneity, we consider "population" to be an explanatory variable & run a test of independence

Observed counts = number in sample of each cell of table.

### Example (Book Example 9.12)

	Low Salt	High Salt	Total
<u>CVD</u>			200
<u>NO CVD</u>			2215
Total	1169	1246	2415

Figure 1: Base Table

Estimated probability of Cardiovascular Disease(CVD) =  $\frac{200}{2415}$

If independent (according to chart):

- $P(\text{CVD} \mid \text{low salt}) = 1169 \times \frac{200}{2415} = 96.81$
- $P(\text{CVD} \mid \text{high salt}) = 1246 \times \frac{200}{2415} = 103.19$
- $P(\text{NO CVD} \mid \text{low salt}) = 1169 \times \frac{2215}{2415} = 1072.19$
- $P(\text{NO CVD} \mid \text{high salt}) = 1246 \times \frac{2215}{2415} = 1142.81$

## Pearson Residuals

$\frac{O-E}{\sqrt{E}} \rightarrow$  for each cell

Contribution of a cell to  $\chi^2$ :  $\text{residual}^2 = \frac{(O-E)^2}{E}$

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

- $P(\text{CVD} \mid \text{low salt}) = \frac{88-96.81}{\sqrt{96.81}} = -0.895$
- $P(\text{CVD} \mid \text{high salt}) = \frac{112-103.19}{\sqrt{103.19}} = 0.867$
- $P(\text{NO CVD} \mid \text{low salt}) = \frac{1081-1072.19}{\sqrt{1072.19}} = 0.269$
- $P(\text{NO CVD} \mid \text{high salt}) = \frac{1134-1142.81}{\sqrt{1142.81}} = -0.261$

$$\chi^2 = (-0.895)^2 + (0.867)^2 + (0.269)^2 + (-0.261)^2 = 1.69$$

*finish second chart from picture*

## To get a P-Value

- Option 1: Our  $\chi^2_{\text{observed}}$  value comes from a  $\chi^2$  distribution with degrees of freedom. Find  $P(\chi^2 \geq \chi^2_{\text{observed}})$
- Option 2: Simulate a bunch of samples assuming independence, then find proportion of simulated  $\chi^2$  statistic  $\geq \chi^2_{\text{observed}}$

Fisher:  $\text{df (degrees of freedom)} = (r - 1)(c - 1)$

- r: rows
- c: columns

“Sample size assumptions” method (2) always works but different people can get different values.

Method 1 always gives some value, but that value can be inaccurate at small sample sizes.

When all expected counts  $\geq 5$ , use method 1.

When any expected count  $< 5$ , use method 2.

Alternate method when **n** is really small: Fisher’s exact test

Condition on marginal totals being fixed, get a test statistic with hypergeometric distribution.

P-Value =  $P(\chi^2 \geq 1.69)$  from  $\chi^2$  distribution with 1 degree of freedom = 0.193

Not on test but may show up in context:

### 3 “Measures of association” between categorical variables

1. Difference in proportions

- Population:  $P_1 - P_2$
- Samples:  $\hat{P}_1 - \hat{P}_2$

2. Relative risk (RR)

- Population :  $\frac{P_1}{P_2}$