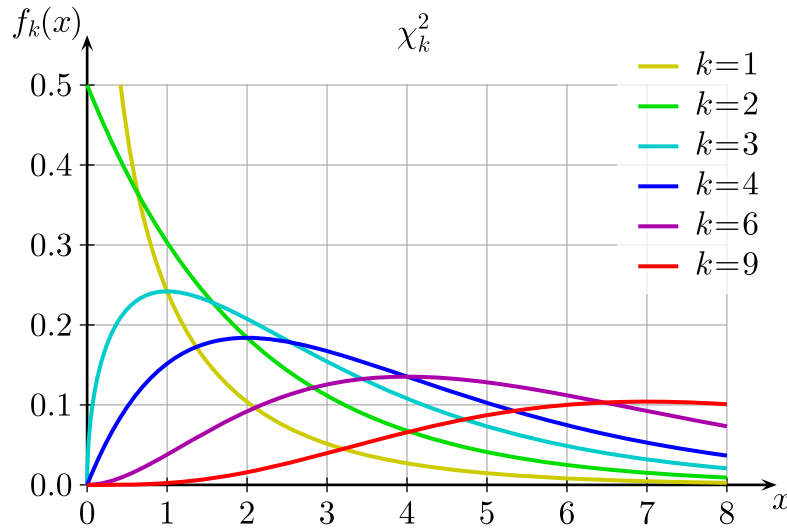


# Chi-Squared $\chi^2$ Tests

## Definition 1.1

A random variable  $X$  is said to follow a  $\chi^2$ -distribution, with degree of freedom  $\nu$ , iff its probability density function is given by

$$f(x) = \begin{cases} \frac{1}{2^{\nu/2}\Gamma(\nu/2)} x^{(\nu/2)-1} e^{-x/2} & \text{if } x > 0, \\ 0 & \text{otherwise.} \end{cases}$$



**Figure 1.1:** Illustration of how the  $\chi^2_{(\nu)}$  distribution looks with increasing degree of freedom  $\nu$ .

## General Information

- Properties of chi-squared distributions.
  - $E(X) = \nu$  and  $\text{Var}(X) = 2\nu$ .
  - The  $\chi^2_{(\nu)}$  distribution tends to a normal distribution as  $\nu \rightarrow \infty$ .
  - Suppose  $Z_i \sim N(0, 1)$  are independent. Then,  $Z_1^2 + \dots + Z_n^2 \sim \chi^2_{(n)}$ .
  - If  $X \sim \chi^2_{(\nu)}$  and  $Y \sim \chi^2_{(v)}$ , then  $X + Y \sim \chi^2_{(\nu+v)}$ .
- A goodness-of-fit test.
  1. Let  $[X \text{ in context}]$ .
  2. 

Test against  $H_0: [X \text{ follows the distribution in context}]$   
 $H_1: [X \text{ does not follows the distribution in context}]$   
 at the  $100\alpha\%$  significance level.
  - 3.

$x$	$x_1$	$x_2$	$\dots$	$x_n$
Observed frequency $f_i$	$f_1$	$f_2$	$\dots$	$f_n$
Expected frequency $e_i$	$e_1$	$e_2$	$\dots$	$e_n$

**Table 1.1:** Observed and expected frequencies for a goodness-of-fit test

4. Under  $H_0$ , the test statistic is

$$\chi^2 = \sum_{i=1}^n \frac{(F_i - E_i)^2}{E_i} \sim \chi^2_{(\nu)}.$$

Here,  $n := \text{\#classes}$  and  $\nu = (\text{\#classes} - \text{\#estimated parameters}) - 1$ .

5. Continue as per usual, calculating the critical region  $\chi^2_{(\nu)} > \chi^2_{(\nu, 1-\alpha)}$  or the  $p$ -value.

#### Note

If  $X$  follows a *discrete* normal distribution, we must state it out in words. We cannot write  $X \sim N(\mu, \sigma^2)$  as this would denote that  $X$  is a *continuous* random variable. But if we really have  $X \sim N(n, p)$  (or  $X \sim B(n, p)$ ,  $X \sim \text{Po}(\lambda)$ , etc), then we can just denote it as such.

#### Note

The expected frequency for each of the  $n$  classes should be at least 5. If it isn't, we need to combine *just enough* adjacent classes, till they do.

#### Example 1.1: #estimated parameters = 0

Given  $X \sim N(0, 1)$  (note how the *population parameters* that define the distribution are *known*), the degree of freedom  $\nu = \text{\#estimated parameters} := n$ .

#### Example 1.2: #estimated parameters = 1

Consider when  $X \sim B(m, p)$ , such that the expected frequency for each of the  $n$  classes is at least 5, but we do not know the exact value of  $p$ . So, we *estimate* it according to the sample given. Then, the degree of freedom is  $\nu = n - 1 - 1 = n - 2$ .

#### Example 1.3: #estimated parameters = 2

Similarly, suppose  $X \sim N(\mu, \sigma^2)$ , such that the expected frequency of each of the  $n$  classes is at least 5, and the true value of  $\mu$  and  $\sigma^2$  are unknown. In this case, the degree of freedom  $\nu = n - 2 - 1 = n - 3$ .

#### G.C. Skills

- To find the value of  $\chi^2_{(\nu, 1-\alpha)}$ , which satisfies  $P(X > \chi^2_{(\nu, 1-\alpha)}) = \alpha$ , we use the table in the [MF26 formula sheet \(Page 9\)](#). Unfortunately, there is no inverse  $\chi^2$  function available.
- For the  $p$ -value:

stat  $\implies$  TESTS  $\implies$  D:  $\chi^2$ GOF-Test...

Tests of independence.

1. Let  $[X \text{ in context}]$ .

2. 

Test	$H_0: [X \text{ in context}]$ is independent of $[Y \text{ in context}]$
against	$H_1: [X \text{ in context}]$ is dependent on $[Y \text{ in context}]$
	at the 100 $\alpha$ % significance level.

3.

		X				Total
		$x_1$	$x_2$	$\cdots$	$x_n$	
Y	$y_1$					$t_{r_1}$
	$y_2$					$t_{r_2}$
	$\vdots$					$\vdots$
	$y_m$					$t_{r_m}$
	Total	$t_{c_1}$	$t_{c_2}$	$\cdots$	$t_{c_n}$	$\sum t_{r_i} + \sum t_{c_i}$

**Table 1.2:** Expected frequencies for a test of independence.

4. Under  $H_0$ , the test statistic is

$$\chi^2 = \sum_{i=1}^n \frac{(F_i - E_i)^2}{E_i} \sim \chi^2_{(\nu)}.$$

Here,  $n := \#cols$  and  $\nu = (\#rows - 1)(\#cols - 1)$ .

5. Continue as per usual, calculating the critical region  $\chi^2_{(\nu)} > \chi^2_{(\nu, 1-\alpha)}$  or the  $p$ -value.

#### G.C. Skills

Key in the matrix of *observed* frequencies (not Table 1.2 of *expected* frequencies):

$$2nd \Rightarrow x^{-1} \Rightarrow EDIT \Rightarrow [A].$$

Then, conduct the test for independence:

$$stat \Rightarrow TESTS \Rightarrow C:\chi^2\text{-Test} \dots$$

# Correlation and Linear Regression

## Note

A good scatter diagram should follow the guidelines below.

- The relative position of each point on the scatter diagram should be clearly shown.
- The range of values for the set of data should be clearly shown by marking out the extreme  $x$  and  $y$  values on the corresponding axis.
- The axes should be labeled clearly with the variables.

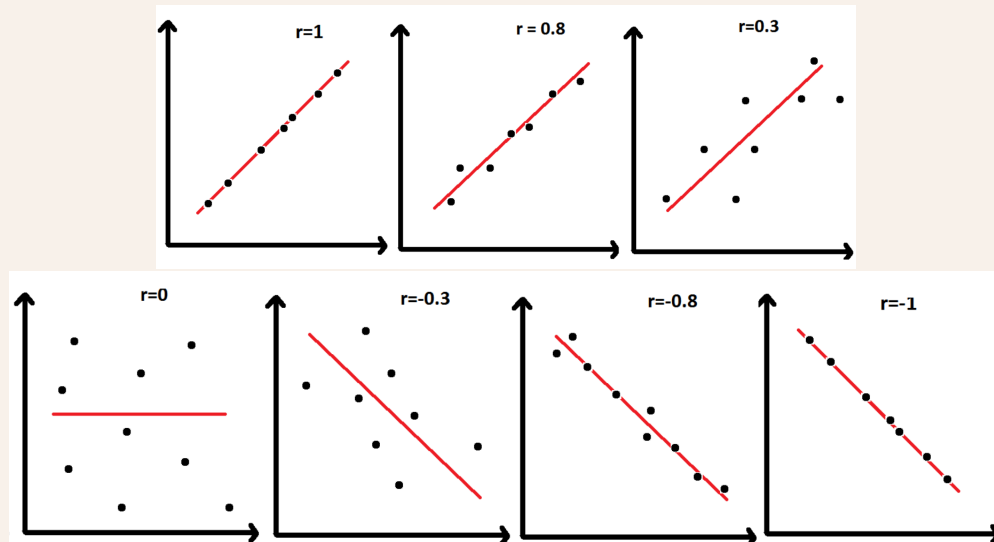
## General Information

- The Product Moment Correlation Coefficient is a measure of the linear correlation between two variables. It is defined by

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sqrt{\left[ \sum x^2 - \frac{(\sum x)^2}{n} \right] \left[ \sum y^2 - \frac{(\sum y)^2}{n} \right]}}$$

which takes on a value from 0 to 1.

- When  $r = 0$ , there is no linear relationship. But, a nonlinear relationship may be present. Additionally, the regression lines are perpendicular.
- The closer the value of  $r$  is to 1 (or -1), the stronger the positive (or negative) linear correlation. Furthermore, the regression lines coincide.



- The regression line of  $y$  on  $x$  minimises the sum of squares deviation (error) in the  $y$ -direction. (i.e. we are assuming  $x$  is the independent variable whose values are known exactly.) It is given by

$$y = \bar{y} + b(x - \bar{x}), \quad \text{where} \quad b = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2} = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}.$$

- The regression lines of  $y$  on  $x$  and  $x$  on  $y$  intersect at  $(\bar{x}, \bar{y})$ .
- Say we are given the value of one variable, and asked to approximate the value of the other variable. Then, we should always use the line of the *dependent* variable on the *independent*.
- Estimations should not be taken for data outside the range of the sample provided, even if the value of  $r$  is close to 1.