## Chapter 11

## Goodness-of-Fit



The goodness-of-fit test is very old. It was presented by Karl Pearson in 1900. One of the principal goals of a statistician is to associate a probability distribution with a histogram of experimental data. Probability distributions lie in the imaginary world of abstract things like events and sample spaces whereas histograms are constructed from actual measurements. The goodness-of-fit test provides an analytical test for determining if a specified distribution may be ascribed to a population. A $X^{2}$ quantile will serve the purpose of a measuring stick to judge the fit between the histogram and the probability distribution.

Suppose two dice are tossed twenty times and define a random variable, X , which gives the sum of the faces of the two dice. The observed sum of the faces for each toss is listed


Figure 11.1
here:

$$
\begin{array}{lllllllllllllllllll}
2 & 7 & 4 & 9 & 6 & 3 & 8 & 3 & 12 & 4 & 4 & 5 & 7 & 10 & 8 & 3 & 11 & 12 & 4
\end{array} 9
$$

The histogram of the data appears on the left in Figure 11.1. If the two dice are actually fair, then the distribution of X would assume the Triangle distribution like the one shown on the right in Figure 11.1. The histogram bears some resemblance to the Triangle distribution, but the claim that the histogram and the probability distribution form a good fit is questionable simply based on inspection. Suppose that the dice are indeed fair, then the expected number of 2's which would appear from rolling two dice twenty times will be $n p=20 \frac{1}{36}$, and the expected number of 3 's will be $n p=20 \frac{2}{36}$, and so on. These expectations are listed in Table 11.1 in which the observed frequency for each value of X appears on the top line, the expected frequency if the dice were fair, appears in the middle row. The bottom row contains the deviations. If the deviations are small, then for practical purposes, the probability distribution agrees with the histogram.

Table 11.1

| Sum of Faces | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Observed | 1 | 3 | 4 | 1 | 1 | 2 | 2 | 2 |
| Expected | $20\left(\frac{1}{36}\right)$ | $20\left(\frac{2}{36}\right)$ | $20\left(\frac{3}{36}\right)$ | $20\left(\frac{4}{36}\right)$ | $20\left(\frac{5}{36}\right)$ | $20\left(\frac{6}{36}\right)$ | $20\left(\frac{5}{36}\right)$ | $20\left(\frac{4}{36}\right)$ |
| Deviation | .444 | 1.889 | 2.333 | -1.222 | -1.777 | -1.333 | -.778 | -.222 |
| Sum of Faces | 10 | 11 | 12 |  |  |  |  |  |
| Observed | 1 | 1 | 2 |  |  |  |  |  |
| Expected | $20\left(\frac{3}{36}\right)$ | $20\left(\frac{2}{36}\right)$ | $20\left(\frac{1}{36}\right)$ |  |  |  |  |  |
| Deviation | -.667 | -.111 | 1.444 |  |  |  |  |  |

Not surprisingly, the sum of the deviations is equal to zero. In order to eliminate
the effect of negative deviations, they are squared and rather unexpectedly, each squared deviation is divided by the expected value.

Definition 50. $X^{2}=\sum_{i=1}^{n} \frac{\left.\left.\text { (observed }_{i} \text {-expected }\right)_{i}\right)^{2}}{\text { expectede }}$ is called the chi-squared test statistic.
Example 59. Find the chi-squared test statistic for the previous example of throwing two dice twenty times.

$$
\begin{aligned}
& X^{2}=\frac{.444^{2}}{\frac{20}{36}}+\frac{1.889^{2}}{\frac{40}{36}}+\frac{2.333^{2}}{\frac{60}{36}}+\frac{(-1.222)^{2}}{\frac{80}{36}}+\frac{(-1.777)^{2}}{\frac{100}{36}}+\frac{(-1.333)^{2}}{\frac{120}{36}}+\frac{(-.778)^{2}}{\frac{100}{36}}+\frac{(-.222)^{2}}{\frac{80}{36}}+\frac{(-.667)^{2}}{\frac{60}{36}}+ \\
& \frac{(-.111)^{2}}{\frac{40}{36}}+\frac{1.444^{2}}{\frac{10}{36}}=13.44524
\end{aligned}
$$

The $X^{2}$ test statistic gives an indication of the discrepancy in the fit between the histogram and the probability distribution. By comparing it to the $X^{2}$ quantile, the size of the discrepancy will either be too big to support the claim that the probability distribution adequately fits the data or small enough to say that the fit is not bad. If the $X^{2}$ test statistic is too big, then the null hypothesis that the histogram and the probability distribution agree must be rejected. The criterion for rejection is given in the following table.

| $H_{0}$ | Test Statistic | $H_{1}$ | Reject when |
| :--- | :---: | :---: | :---: |
| Population has <br> specified distribu- <br> tion | $X^{2}=\sum_{i=1}^{n} \frac{\left(\text { observed }_{i}-\text { expected }_{i}\right)^{2}}{\text { expected }_{i}}$ | Population does <br> not have specified <br> distribution | $X^{2}>X_{n-1, \alpha}^{2}$ |

A tabulation of $X^{2}$ quantiles is given in Appendix D.
Example 60. Test the hypothesis that the empirical distribution shown by the histogram of the frequency of throwing two dice twenty times is the same as the theoretical distribution at a level of significance of $\alpha=.05$
$X_{11-1, .05}^{2}=18.30$
Does $X^{2}=13.445>18.307$ ? No, cannot reject the null hypothesis that the observed histogram follows the Triangle distribution.

As imperfect as the shape of the histogram appears in relation to the Triangle distribution, the conclusion of the goodness-of-fit test substantiates the claim that the Triangle distribution may be used to account for the experimental outcomes of the actual tossing of two dice. The implication is that the characteristics of the population which are manifested in the experimental results from tossing of two dice not only twenty times but any number of times may be adequately explained by the Triangle distribution. Furthermore, having
successfully made the association between the population which produced the histogram and the sample space consisting of two imaginary fair dice, we may say that the real dice, too, are probably fair. Although we should not say that the goodness-of-fit test proves that the two dice are fair, yet the conclusion of not rejecting the null hypothesis indicates that the dice are probably fair and that the Triangle distribution may adequately describe the population until additional evidence demonstrates otherwise.

### 11.1 Contingency Table

The $X^{2}$ test can be extended from one to two dimensions, for example:
Problem 13. A random sample of 200 married men, all of whom are retired, were classified according to education and to the number of children whom they sired.

|  | Number of Children |  |  |  |
| :--- | ---: | ---: | ---: | ---: |
| Education | $0-1$ | $2-3$ | over 3 | Row Totals |
| Elementary | $14(18.675)$ | $37(39.84)$ | $32(24.495)$ | 83 |
| Secondary | $19(17.55)$ | $42(37.44)$ | $17(23.01)$ | 78 |
| College | $12(8.779)$ | $17(18.72)$ | $10(11.505)$ | 39 |
| Column Totals | 45 | 96 | 59 | 200 |

Definition 51. This table is called a contingency table. An element of it is called a cell.

The numbers written within parentheses are the expected number of occurrences if education and number of children are independent.

## Question 4. Are education and number of children independent events?

Let A be the event of siring 0-1 children. Let B be the event of only getting an elementary school education. If A and B are independent, then $P(A \cap B)=P(A) P(B)$ where $P(A)=\frac{45}{200}$ and $P(B)=\frac{83}{200}$. In the case of independence, what would be the expected number of men who sired 0-1 children but got an elementary school education? $n p=200 P(A \cap B)=200 P(A) P(B)=200 \frac{45}{200} \frac{83}{200}=\frac{45 \times 83}{200}=18.675$. This same number appears in the contingency table within parentheses.

What is the expected number of men who got an elementary education and sired 23 children? Let C be the event of siring 2-3 children. Let B be the event of getting an elementary school education. If C and B are independent, then $n p=200 P(C \cap B)=$ $200 P(C) P(B)=200 \frac{96}{200} \frac{83}{200}=39.84$.

It does not take long to see a pattern emerge from calculating the expected frequencies. We will use the pattern to shorten the computations as is done in our final example. The expected number in the cell for siring 3 or more children with a college education is $\frac{59 \times 39}{200}=11.505$.

The criterion for rejecting the null hypothesis of a contingency table is given below.

| $H_{0}$ | Test Statistic | $H_{1}$ | reject when |
| :--- | :--- | :--- | :--- |
| Rows and columns | $X^{2}=\sum_{i=1}^{n} \frac{\left.\text { observed }_{i}-\text { expected }_{i}\right)^{2}}{\text { expected }_{i}}$ | Not independent | $X^{2}>X_{\nu, \alpha}^{2}$ |
| are Independent |  |  | where $\nu=(r-1)(c-1)$ <br> $\mathrm{r}=$ number of rows <br> $\mathrm{c}=$ number of columns |

Example 61. In our example, $r=3$ and $c=3$; therefore, $\nu=(3-1)(3-1)=4$. Suppose that $\alpha=.05$. The appropriate $X^{2}$ quantile for conducting a goodness-of-fit test is: $X_{4,05}^{2}=9.48$.

$$
X^{2}=\sum_{i=1}^{9} \frac{\left(\text { observed }_{i}-\text { expected }_{i}\right)^{2}}{\text { expected }_{i}}=\frac{(14-18.675)^{2}}{18.675}+\frac{(37-39.84)^{2}}{39.84}+\ldots+\frac{(10-11.505)^{2}}{11.505}=7.4626 .
$$

Is $X^{2}=7.4626>9.48$ ? No. Therefore, we cannot reject the null hypothesis. Hence, based on the data, a man's education and the number of children whom he sires appear to be independent at a level of significance of $\alpha=.05$.

The choice of $\alpha$ has thus far been arbitrary. For sufficiently large $\alpha$ 's, the null hypothesis can be rejected. For sufficiently small $\alpha$ 's, the null hypothesis cannot be rejected. That $\alpha$ which lies exactly at the boundary of admitting a rejection or no rejection is called the $p$ value of the test. It is often published with the results of an analysis for the benefit of the reader. The p value for the above test is $p=P\left(X_{4}^{2}>7.4626\right)=.113$. We used $\alpha=.05$ in conducting the test but since $\alpha<p$, the null hypothesis could not have been rejected. Only when $\alpha$ exceeds .113 will the null hypothesis be rejected.

Example 62. An experiment was conducted to investigate the effect of a vaccination on laboratory animals. Some animals when exposed to the disease contracted it, and some
did not according to whether the animal was inoculated. The developer hopes that the vaccine and the contraction of the disease are not independent. To prove his belief, the null hypothesis was formulated to assume the worst case in that the vaccination and the likelihood of getting a disease are independent in the hope that it will be rejected at a level of significance of .05. A tabulation of the results appears below.

|  | Got the Disease | Did not get the Disease |  |
| :--- | ---: | ---: | :--- |
| Vaccinated | $9(13.84)$ | $42(37.19)$ | 51 |
| Not Vaccinated | $17(12.19)$ | $28(32.81)$ | 45 |
| Column Totals | 26 | 70 | 96 |

1. $\alpha=.05 ; \nu=(r-1)(c-1)=1$.
2. The expected number of cases assuming independence is given in parentheses.
3. $X^{2}=\sum_{i=1}^{4} \frac{\left(\text { observed }_{i}-\text { expected }_{i}\right)^{2}}{\text { expected }_{i}}=\frac{(9-13.84)^{2}}{13.84}+\frac{(42-37.19)^{2}}{37.19}+\frac{(17-12.19)^{2}}{12.19}+\frac{(28-32.81)^{2}}{32.81}=4.918$.
4. $X_{1,05}^{2}=3.48146$.
5. Is $X^{2}=4.918>3.48$ ? Yes. Reject the null hypothesis that the vaccination and contracting the disease are independent. In conclusion, based on the data, it appears that the vaccination prevents the contraction of the disease.

The p value of the test is that $\alpha$ at which the null hypothesis can and cannot be rejected. It is $p=.0266=P\left(X_{1}^{2} \geq 4.918\right)$. For an $\alpha>p$, the null hypothesis will be rejected; for an $\alpha<p$, the null hypothesis cannot be rejected. In other words, suppose $\alpha$ is chosen slightly larger than p , like $\alpha=.0267$, then $X_{1,0267}^{2}=4.910$ and because $4.918>4.910$, the null hypothesis is rejected. Suppose, on the other hand, $\alpha$ is chosen slightly smaller that p, like $\alpha=.0265$, then $X_{1,0265}^{2}=4.923$ and because $4.918 \ngtr 4.923$, the null hypothesis cannot be rejected. The use of the p-value offers a reader a way to judge the proximity of the test statistic to the boundary of the rejection region which the p value marks.

