

Math 362: Mathematical Statistics II

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Chapter 10. Goodness-of-fit Tests

§ 10.1 Introduction

§ 10.2 The Multinomial Distribution

§ 10.3 Goodness-of-Fit Tests: All Parameters Known

§ 10.4 Goodness-of-Fit Tests: Parameters Unknown

§ 10.5 Contingency Tables

Plan

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Statistics is the grammar of science.

(Karl Pearson)

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2. English mathematician and biostatistician.
3. He has been credited with establishing the discipline of mathematical statistics
4. Method of moments; p-Value; Chi-square test; Foundations of statistical hypothesis testing theory; principle component analysis ...



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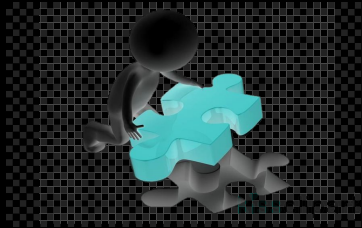
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Pearson's chi-squared test
in one shot



$$\chi^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}} \sim \text{Chi Square of } df$$

df = numer of classes – number of estimated parameters – 1

All expected ≥ 5

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Def. Suppose one does an experiment of extracting n balls of t different colors from a jar, replacing the extracted ball after each draw. Balls from the same color are equivalent. Denote the variable which is the number of extracted balls of color i ($i = 1, \dots, t$) as X_i , and denote as p_i the probability that a given extraction will be in color i . The probability distribution function of the vector (X_1, \dots, X_t) is called the **multinomial distribution**, which is equal to

$$\begin{aligned} p_{X_1, \dots, X_t}(k_1, \dots, k_t) &= \mathbb{P}(X_1 = k_1, \dots, X_t = k_t) \\ &= \binom{n}{k_1, \dots, k_t} p_1^{k_1} \dots p_t^{k_t} \end{aligned}$$

where $k_i \in \{0, 1, \dots, n\}$, $1 \leq i \leq t$, $\sum_{i=1}^t k_i = n$, and $p_1 + \dots + p_t = 1$.

Thm Suppose (X_1, \dots, X_t) follows the multinomial distribution with parameters n and (p_1, \dots, p_t) with $p_i \geq 0$ and $\sum_i p_i = 1$. Then

1. $X_i \sim \text{Binomial}(n, p_i)$ and hence

$$\mathbb{E}[X_i] = np_i$$

$$\text{Var}(X_i) = np_i(1 - p_i)$$

2. $\text{Cov}(X_i, X_j) = -np_i p_j, i \neq j.$ (negative correlated)

3. $M_{X_1, \dots, X_t}(s_1, \dots, s_t) = (p_1 e^{s_1} + \dots + p_t e^{s_t})^n.$

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3. $M_{X_1, \dots, X_t}(s_1, \dots, s_t) = (p_1 e^{s_1} + \dots + p_t e^{s_t})^n.$

Proof

(3)

$$\begin{aligned}M_{X_1, \dots, X_t}(s_1, \dots, s_t) &= \mathbb{E} \left[e^{X_1 s_1 + \dots + X_t s_t} \right] \\&= \sum_{\substack{k_1, \dots, k_t=0 \\ k_1 + \dots + k_t = n}}^n \binom{n}{k_1, \dots, k_t} p_1^{k_1} \dots p_t^{k_t} e^{k_1 s_1 + \dots + k_t s_t} \\&= \sum_{\substack{k_1, \dots, k_t=0 \\ k_1 + \dots + k_t = n}}^n \binom{n}{k_1, \dots, k_t} (p_1 e^{s_1})^{k_1} \dots (p_t e^{s_t})^{k_t} \\&= (p_1 e^{s_1} + \dots + p_t e^{s_t})^n\end{aligned}$$

(1) To find $M_{X_i}(s_i)$, we simply set $s_j \equiv 0$ for $j \neq i$. Hence

$$M_{X_i}(s_i) = \underbrace{(p_1 + \dots + p_{i-1} + p_{i+1} + \dots + p_t + p_i e^{s_i})}_{=1-p_i}^n \implies X_i \sim \text{Binomial}(n, p_i)$$

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(2) Set $M := M_{X_1, \dots, X_t}(s_1, \dots, s_t)$. Then for $i \neq j$,

$$\frac{\partial M}{\partial s_i} = n (p_1 e^{s_1} + \dots + p_i e^{s_i})^{n-1} p_i e^{s_i}$$

$$\frac{\partial^2 M}{\partial s_i \partial s_j} = n(n-1) (p_1 e^{s_1} + \dots + p_i e^{s_i})^{n-2} p_i e^{s_i} p_j e^{s_j}$$

↓

$$\mathbb{E}[X_i X_j] = \left. \frac{\partial^2 M}{\partial s_i \partial s_j} \right|_{s_1 = \dots = s_t = 0} = n(n-1)(p_1 + \dots + p_i)^{n-2} p_i p_j = n(n-1)p_i p_j$$

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$$\begin{aligned} \text{Cov}(X_i, X_j) &= \mathbb{E}[X_i X_j] - \mathbb{E}[X_i] \mathbb{E}[X_j] \\ &= n(n-1)p_i p_j - np_i \times np_j \\ &= -np_i p_j \end{aligned}$$

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□

From a continuous pdf to a multinomial distribution:

E.g. Let Y_i be a random sample of size n from $f_Y(y) = 6y(1 - y)$, $y \in [0, 1]$.

Define

$$X_i = \begin{cases} 1 & Y_i \in [0, 0.25) \\ 2 & Y_i \in [0.25, 0.5) \\ 3 & Y_i \in [0.5, 0.75) \\ 4 & Y_i \in [0.75, 1) \end{cases}$$

Find the distribution of (X_1, \dots, X_n) .

Sol. (X_1, X_2, X_3, X_4) follows multinomial distribution with parameters (p_1, p_2, p_3, p_4) where

$$p_1 = \int_0^{\frac{1}{4}} 6y(1 - y)dy = \dots = \frac{5}{32},$$

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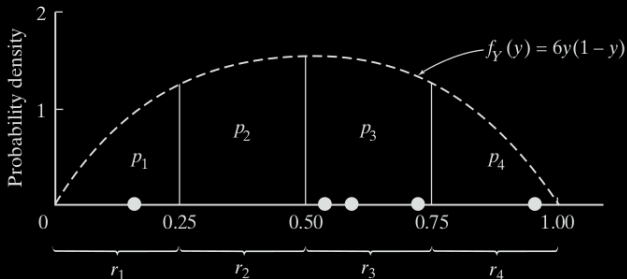
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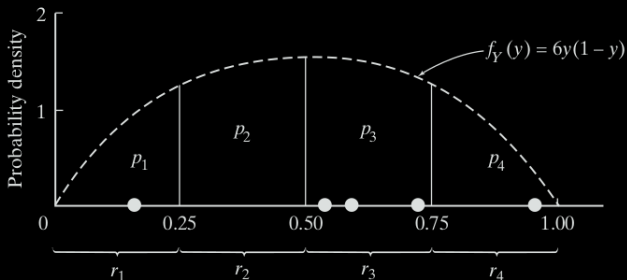
and by symmetry,

$$p_4 = p_1 = \frac{5}{32} \quad \text{and} \quad p_2 = p_3 = \frac{1}{2} (1 - p_1 - p_4) = \frac{11}{32}.$$

□

Remark In this way, we transform the outcomes, any values between $[0, 1]$, into **categorical data**. This chapter is about

Analysis of Categorical Data



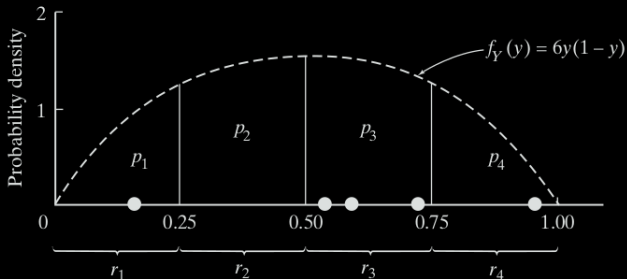
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Rationale

! We want to test if the c.d.f. $F_Y(\cdot)$ is given by the true c.d.f. $F_0(\cdot)$, i.e.,

$$H_0 : F_Y(y) = F_0(y) \quad v.s. \quad H_1 : F_Y(y) \neq F_0(y)$$

~ By properly partitioning the domain, the random sample should follow
an induced multinomial distribution.

⇒ Then testing $F_Y(\cdot) = F_0(\cdot)$ reduces to testing the induced multinomial distribution of the following form:

$$H_0 : p_1 = p'_1, \dots, p_n = p'_n$$

v.s.

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How

1. Suppose we are sampling from the c.d.f. $F(y)$
2. Divide the range of the distribution into k mutually exclusive and exhaustive intervals, say I_1, \dots, I_k .
3. Let $\pi_i = \mathbb{P}(X \in I_i)$, $i = 1, \dots, k$.
4. Let O_1, \dots, O_k be the respective observed numbers of the observations X_1, \dots, X_n in the intervals I_1, \dots, I_k .
5. Then $O = (O_1, \dots, O_k) \sim$ multinomial distribution with (π_1, \dots, π_k) , i.e.,

$$\mathbb{P}(O_1 = o_1, \dots, O_k = o_k) = \frac{n!}{\prod_{i=1}^k o_i!} \prod_{i=1}^k \pi_i^{o_i}$$

with $\sum_{i=1}^k \pi_i = 1$, $\sum_{i=1}^k o_i = n$, and

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3. Let $\pi_i = \mathbb{P}(X \in I_i)$, $i = 1, \dots, k$.
4. Let O_1, \dots, O_k be the respective observed numbers of the observations X_1, \dots, X_n in the intervals I_1, \dots, I_k .
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$$\mathbb{P}(O_1 = o_1, \dots, O_k = o_k) = \frac{n!}{\prod_{i=1}^k o_i!} \prod_{i=1}^k \pi_i^{o_i}$$

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6. When $k = 2$, by CLT, as $n \rightarrow \infty$,

$$\begin{aligned} \frac{O_1 - n\pi_1}{\sqrt{n\pi_1(1 - \pi_1)}} &\xrightarrow{d} N(0, 1) \quad \implies \quad \frac{(O_1 - n\pi_1)^2}{n\pi_1(1 - \pi_1)} \xrightarrow{d} \chi_1^2 \\ & \parallel \\ & \frac{(O_1 - n\pi_1)^2}{n\pi_1} + \frac{(O_2 - n\pi_2)^2}{n\pi_2} \\ & \parallel \\ & \frac{(O_1 - \theta_1)^2}{\theta_1} + \frac{(O_2 - \theta_2)^2}{\theta_2} \end{aligned}$$

Hence, as $n \rightarrow \infty$,

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$$\sum_{i=1}^k \frac{(O_i - n\pi_i)^2}{n\pi_i} = \sum_{i=1}^k \frac{(O_i - e_i)^2}{e_i}$$

follows a complicated, but exact, distribution, from which, one can show

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$$D = \sum_{i=1}^k \frac{(O_i - e_i)^2}{e_i} \underset{\text{appr.}}{\sim} \chi_{k-1}^2.$$

Rmk: The above is called Pearson's chi-square test. It is asymptotically equivalent to the generalized likelihood ratio test.

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Alternative: G-test

– the likelihood ratio test for multinomial model

1. Under $H_0 : \pi_i = p_i, i = 1, \dots, k$, the MLE of π_i are

$$\tilde{\pi}_i = p_i = \frac{np_i}{n} = \frac{e_i}{n}, \quad \forall i.$$

2. When there are no constraints, for $i = 1, \dots, k-1$,

$$\frac{\partial}{\partial \pi_i} \ln L(\pi_1, \dots, \pi_{k-1} | o_1, \dots, o_k) = 0, \quad 1 \leq i \leq k-1$$

\Downarrow

$$\frac{o_i}{\hat{\pi}_i} = \frac{o_k}{1 - \hat{\pi}_1 - \dots - \hat{\pi}_{k-1}}, \quad 1 \leq i \leq k-1$$

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$$\hat{\pi}_i = \frac{o_i}{n}, \quad 1 \leq i \leq k.$$

⇒

$$\begin{aligned}\lambda &:= \ln \left(\frac{L(\tilde{\pi}_1, \dots, \tilde{\pi}_{k-1} | \mathbf{o}_1, \dots, \mathbf{o}_k)}{L(\hat{\pi}_1, \dots, \hat{\pi}_{k-1} | \mathbf{o}_1, \dots, \mathbf{o}_k)} \right) = \log \left(\frac{\prod_{i=1}^k \tilde{\pi}_i^{o_i}}{\prod_{i=1}^k \hat{\pi}_i^{o_i}} \right) \\ &= \sum_{i=1}^k o_i \ln \left(\frac{\tilde{\pi}_i}{\hat{\pi}_i} \right) \\ &= \sum_{i=1}^k o_i \ln \left(\frac{\theta_i}{\phi_i} \right)\end{aligned}$$

Critical region: $\lambda < \lambda_* < 0$.

Def.

$$G := -2\lambda = -2 \sum_{i=1}^k o_i \ln \left(\frac{\phi_i}{\theta_i} \right) = 2 \sum_{i=1}^k o_i \ln \left(\frac{\theta_i}{\phi_i} \right)$$

$G \stackrel{\text{approx.}}{\sim} \chi_{k-1}^2$ for large n .

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Relation G-test and Pearson's Chi square test

By second order Taylor expansion around 1,

$$\begin{aligned}G &= -2 \sum_{i=1}^k o_i \ln \left(\frac{e_i}{o_i} \right) \\&\approx -2 \sum_{i=1}^k o_i \left[\left(\frac{e_i}{o_i} - 1 \right) - \frac{1}{2} \left(\frac{e_i}{o_i} - 1 \right)^2 \right] \\&= -2 \sum_{i=1}^k (e_i - o_i) + \sum_{i=1}^k o_i \left(\left(1 - \frac{o_i}{e_i} \right) + \frac{o_i}{e_i} \right) \left(\frac{e_i}{o_i} - 1 \right)^2 \\&= 0 + \sum_{i=1}^n \frac{o_i^2}{e_i} \left(1 - \frac{o_i}{e_i} \right)^3 + \sum_{i=1}^k \frac{(e_i - o_i)^2}{e_i} \\&\approx \sum_{i=1}^k \frac{(e_i - o_i)^2}{e_i} \\&\quad \parallel \\&\quad D\end{aligned}$$

∴ Pearson's Chi-square test is an approximation of G-test.

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\therefore Pearson's Chi-square test is an approximation of G-test.

E.g. 1 *Benford's law*:

Initial digits

Use this law to check whether the bookkeepers have made up entries.

Assume that bookkeepers are not aware of Benford's law.

E.g. 1 *Benford's law*:

Table 10.3.1	
Digit, i	$\log_{10}(i + 1) - \log_{10}(i)$
1	0.301
2	0.176
3	0.125
4	0.097
5	0.079
6	0.067
7	0.058
8	0.051
9	0.046

Initial digits

Digit	Observed, k_i
1	111
2	60
3	46
4	29
5	26
6	22
7	21
8	20
9	20
	<hr/>
	355

Use this law to check whether the bookkeepers have made up entries.

Assume that bookkeepers are not aware of Benford's law.

Sol. The test should be

$$H_0 : p_1 = p_{10}, \dots, p_9 = p_{90}$$

v.s.

$$H_1 : p_i \neq p_{i0} \quad \text{for at least one } i = 1, \dots, 9.$$

Critical region: $(\chi^2_{95,8}, \infty) = (15.507, \infty)$.

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Compute the D and G scores:

Digit	o_i	p_i	e_i	$(o_i - e_i)^2 / e_i$	$2o_i \ln(e_i / o_i)$
1	111	0.301			
2	60	0.176			
3	46	0.125			
4	29	0.097			
5	26	0.079			
6	22	0.067			
7	21	0.058			
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9	20	0.046			
sum	355	1	355	$d = \underline{\hspace{2cm}}$	$g = \underline{\hspace{2cm}}$

Digit	o_i	p_i	e_i	$(o_i - e_i)^2 / e_i$	$2o_i \ln(e_i / o_i)$
1	111	0.301	106.9	0.16	8.449
2	60	0.176	62.5	0.10	-4.860
3	46	0.125	44.4	0.06	3.309
4	29	0.097	34.4	0.86	-9.963
5	26	0.079	28.0	0.15	-3.937
6	22	0.067	23.8	0.13	-3.433
7	21	0.058	20.6	0.01	0.828
8	20	0.051	18.1	0.20	3.982
9	20	0.046	16.3	0.82	8.109
sum	355	1	355	$d = \underline{2.49}$	$g = \underline{2.48}$

Conclusion: Fail to reject.

```

1 > # EX 10.3.2
2 > library(data.table)
3 > mydat <- fread('http://math.emory.edu/~lchen41/teaching/2020_Spring/Case_
  10-3-2.data')
4 trying URL 'http://math.emory.edu/~lchen41/teaching/2020_Spring/Case_10-3-2.
  data'
5 Content type 'unknown' length 153 bytes
6 =====
7 downloaded 153 bytes
8
9 > head(mydat)
10   Digit Oi   Pi
11 1:     1 111 0.301
12 2:     2  60 0.176
13 3:     3  46 0.125
14 4:     4  29 0.097
15 > pi = mydat[,3]
16 > oi = mydat[,2]
17 > n = sum(oi)
18 > ei = n*pi
19 > di = (ei-oi)^2/ei
20 > gi = 2*oi*log(oi/ei)
21 > print(paste("Using Pearson's test, D value is equal to ", round(sum(di),3)))
22 [1] "Using Pearson's test, D value is equal to 2.491"
23 > print(paste("Using the G-test, G value is equal to ", round(sum(gi),3)))
24 [1] "Using the G-test, G value is equal to 2.484"

```

Codes available

http://math.emory.edu/~lchen41/teaching/2020_Spring/Case_10-3-2.R

E.g. 2 Test for randomness

Is the following sample of size 40 from $f_Y(y) = 6y(1 - y)$, $y \in [0, 1]$?

E.g. 2 Test for randomness

Is the following sample of size 40 from $f_Y(y) = 6y(1 - y)$, $y \in [0, 1]$?

0.18	0.06	0.27	0.58	0.98
0.55	0.24	0.58	0.97	0.36
0.48	0.11	0.59	0.15	0.53
0.29	0.46	0.21	0.39	0.89
0.34	0.09	0.64	0.52	0.64
0.71	0.56	0.48	0.44	0.40
0.80	0.83	0.02	0.10	0.51
0.43	0.14	0.74	0.75	0.22

Sol. Test continuous pdf \rightarrow reduce to a set of classes:

$$d = \dots = 1.84.$$

Sol. Test continuous pdf \rightarrow reduce to a set of classes:

Class	Observed Frequency, k_i	P_{i_o}	$40 p_{i_o}$
$0 \leq y < 0.20$	8	0.104	4.16
$0.20 \leq y < 0.40$	8	0.248	9.92
$0.40 \leq y < 0.60$	14	0.296	11.84
$0.60 \leq y < 0.80$	5	0.248	9.92
$0.80 \leq y < 1.00$	5	0.104	4.16

$$d = \dots = 1.84.$$

Sol. Test continuous pdf \rightarrow reduce to a set of classes:

Table 10.3.5			
Class	Observed Frequency, k_i	P_{i_o}	$40 p_{i_o}$
$0 \leq y < 0.20$	8	0.104	4.16
$0.20 \leq y < 0.40$	8	0.248	9.92
$0.40 \leq y < 0.60$	14	0.296	11.84
$0.60 \leq y < 0.80$	5	0.248	9.92
$0.80 \leq y < 1.00$	5	0.104	4.16

Table 10.3.6			
Class	Observed Frequency, k_i	P_{i_o}	$40 p_{i_o}$
$0 \leq y < 0.40$	16	0.352	14.08
$0.40 \leq y < 0.60$	14	0.296	11.84
$0.60 \leq y \leq 1.00$	10	0.352	14.08

$$d = \dots = 1.84.$$

Sol. Test continuous pdf \rightarrow reduce to a set of classes:

Table 10.3.5			
Class	Observed Frequency, k_i	P_{i_o}	$40 p_{i_o}$
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$$d = \dots = 1.84.$$

Critical region: $(\chi_{.95,2}^2, \infty) = (5.992, \infty)$.

Conclusion: Fail to reject.

Sol. Test continuous pdf \rightarrow reduce to a set of classes:

Table 10.3.5			
Class	Observed Frequency, k_i	P_{i_0}	$40 p_{i_0}$
$0 \leq y < 0.20$	8	0.104	4.16
$0.20 \leq y < 0.40$	8	0.248	9.92
$0.40 \leq y < 0.60$	14	0.296	11.84
$0.60 \leq y < 0.80$	5	0.248	9.92
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$$d = \dots = 1.84.$$

Critical region: $(\chi_{.95,2}^2, \infty) = (5.992, \infty)$.

Conclusion: Fail to reject.

```

1 > # Case Study 10.3.2
2 > # Read data from the URL link
3 > library(data.table)
4 > mydat <- fread('http://math.emory.edu/~lchen41/teaching/2020_Spring/EX_
      10-3-1.data')
5 trying URL 'http://math.emory.edu/~lchen41/teaching/2020_Spring/EX_10-3-1.
      data'
6 Content type 'unknown' length 234 bytes
7 =====
8 downloaded 234 bytes
9
10 >d(mydat)
11   Col1 Col2 Col3 Col4 Col5
12 1: 0.18 0.06 0.27 0.58 0.98
13 2: 0.55 0.24 0.58 0.97 0.36
14 3: 0.48 0.11 0.59 0.15 0.53
15 4: 0.29 0.46 0.21 0.39 0.89
16 5: 0.34 0.09 0.64 0.52 0.64
17 6: 0.71 0.56 0.48 0.44 0.40
18 # Conditions for lower bounds
19 > lb=c(0,0.40,0.60)
20 > # Conditions for upper bounds
21 > up=c(0.40,0.60,1.00)
22 > # Store the results in d
23 > oi <- seq(1:length(lb))
24 > pi <- seq(1:length(lb))
25 > integrand <- function(y) {6*y*(1-y)}
26 > for (i in c(1:length(lb))) {
27 +   oi[i] <- table(mydat>=lb[i] & mydat<up[i])[2]
28 +   pi[i] <- integrate(integrand, lb[i], up[i])$value[1]
29 +   print(paste("the", i,"th bin has", oi[i],
30 +     "entries and pi is equal to", pi[i]))
31 + }

```

```

1 [1] "the 1 th bin has 16 entries and pi is equal to 0.352"
2 [1] "the 2 th bin has 14 entries and pi is equal to 0.296"
3 [1] "the 3 th bin has 10 entries and pi is equal to 0.352"
4 > pi <- unlist(pi)
5 > n <- sum(oi)
6 > ei <- n*pi
7 > di <- (ei-oi)^2/ei
8 > gi <- 2*oi*log(oi/ei)
9 > rbind(oi,pi,ei,di,gi)
10      [,1]      [,2]      [,3]
11 oi 16.0000000 14.0000000 10.0000000
12 pi  0.3520000 0.2960000 0.3520000
13 ei 14.0800000 11.8400000 14.0800000
14 di  0.2618182 0.3940541 1.182273
15 gi  4.0906679 4.6920636 -6.843405
16 > print(paste("Using Pearson's test, D value is equal to ",round(sum(
    di),3)))
17 [1] "Using Pearson's test, D value is equal to 1.838"
18 > print(paste("Using the G-test, G value is equal to ", round(sum(gi
    ),3)))
19 [1] "Using the G-test, G value is equal to 1.939"<Paste>

```

http://math.emory.edu/~lchen41/teaching/2020_Spring/EX_10-3-1.R

E.g. 3 Fisher's suspicion on Mendel's experiments on 1866:

$$d = \dots = 0.47$$

$$P\text{-value} = \mathbb{P}(\chi_3^2 \leq 0.47) = 0.0746.$$

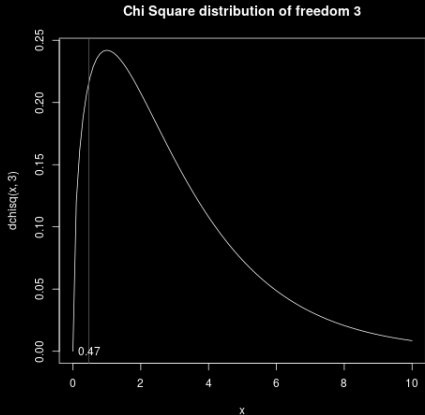
E.g. 3 Fisher's suspicion on Mendel's experiments on 1866:

Phenotype	Obs. Freq.	Mendel's Model	Exp. Freq.
(round, yellow)	315	9/16	312.75
(round, green)	108	3/16	104.25
(angular, yellow)	101	3/16	104.25
(angular, green)	32	1/16	34.75

$$d = \dots = 0.47$$

$$P\text{-value} = \mathbb{P}(\chi_3^2 \leq 0.47) = 0.0746.$$


```
1 > # Case Study 10.3.3
2 > x=seq(0,10,0.1)
3 > plot(x,dchisq(x,3),type = "l")
4 > abline(v=0.47,col = "gray60")
5 > text(0.47,0,"0.47")
6 > title("Chi Square distribution
7 +   of freedom 3")
8 > pchisq(0.47,3)
9 [1] 0.07456892
```



E.g. 2' A second look at the random generator in E.g. 2.

Does it fit the model too well? Find the P -value.

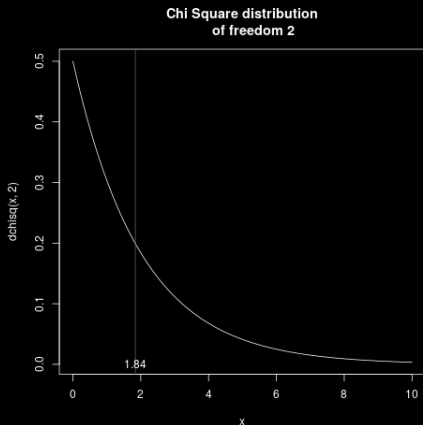
```
1 > # Example 10.3.1
2 > x=seq(0,10,0.1)
3 > plot(x,dchisq(x,2),type = "l")
4 > abline(v=1.84,col = "gray60")
5 > text(1.84,0,"1.84")
6 > title("Chi Square distribution
7 +     of freedom 2")
8 > pchisq(1.84,2)
9 [1] 0.601481
```

P -value = 0.601 \implies No.

E.g. 2' A second look at the random generator in E.g. 2.

Does it fit the model too well? Find the P -value.

```
1 > # Example 10.3.1
2 > x=seq(0,10,0.1)
3 > plot(x,dchisq(x,2),type = "l")
4 > abline(v=1.84,col = "gray60")
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```



P -value = 0.601 \implies No.

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§ 10.2 The Multinomial Distribution

§ 10.3 Goodness-of-Fit Tests: All Parameters Known

§ 10.4 Goodness-of-Fit Tests: Parameters Unknown

§ 10.5 Contingency Tables

Chapter 10. Goodness-of-fit Tests

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p_i are known	p_i are unknown
$D = \sum_{i=1}^t \frac{(X_i - np_i)^2}{np_i}$	$D_1 = \sum_{i=1}^t \frac{(X_i - n\hat{p}_i)^2}{n\hat{p}_i}$
χ^2 with f.d. $t - 1$	χ^2 with f.d. $t - 1 - s$
$d = \sum_{i=1}^t \frac{(k_i - np_{i0})^2}{np_{i0}}$	$d_1 = \sum_{i=1}^t \frac{(k_i - n\hat{p}_{i0})^2}{n\hat{p}_{i0}}$
$np_{i0} \geq 5$	$n\hat{p}_{i0} \geq 5$
$d > \chi_{1-\alpha, t-1}^2$	$d_1 > \chi_{1-\alpha, t-1-s}^2$

† s is the number of unknown parameters.

df = number of classes - 1 - number of unknown parameters.

E.g. 1 Binomial data: 4096 students, each shots basketball 4 times. Let X_i be the number of hits for the i th student.

People believe that X_i should following binomial(4, p), that is, shotting basketball should be something like trying to get red chocolate beans from a jar of beans of two colors.

Find the MLE for p . Use the data to make a conclusion.

Sol. 1) $H_0 : X_i \sim \text{binomial}(4, p)$.

2) Under H_0 , the MLE for p is $p_e = \dots = 0.251$

E.g. 1 Binomial data: 4096 students, each shots basketball 4 times. Let X_i be the number of hits for the i th student.



Number of Hits, i	Obs. Freq., k_i
0	1280
1	1717
2	915
3	167
4	17

People believe that X_i should following binomial(4, p), that is, shotting basketball should be something like trying to get red chocolate beans from a jar of beans of two colors.

Find the MLE for p . Use the data to make a conclusion.

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People believe that X_i should following binomial(4, ρ), that is, shotting basketball should be something like trying to get red chocolate beans from a jar of beans of two colors.

Find the MLE for ρ . Use the data to make a conclusion.

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3) Compute the expected frequencies:

Number of Hits, i	Obs. Freq., k_i	Estimated Exp. Freq., $n \hat{p}_{i_0}$
$r'_i \left\{ \begin{array}{l} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \right.$	1280	1289.1
	1717	1728.0
	915	868.6
	167	194.0
	17	16.3

$$\implies d_1 = \dots = 6.401.$$

4) Critical region: $(\chi_{.95, 5-1-1}^2, +\infty) = (7.815, +\infty)$

5) Conclusion: Fail to reject.

6) Alternatively, P -value = $\mathbb{P}(\chi_3^2 \geq 6.401) = 0.094, \dots$ discuss... \square

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Table 10.4.1		
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E.g. 2 Does the number of death per day follow the Poisson distribution?

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Number of Deaths, i	Obs. Freq., k_i
0	162
1	267
2	271
3	185
4	111
5	61
6	27
7	8
8	3
9	1
10+	0
	<hr/>
	1096

Sol. 1) Let X_i be the number of death in i th day, $1 \leq i \leq 1096$.

2) H_0 : X_i follow $\text{Poisson}(\lambda)$.

3) The MLE for λ is: $\lambda_{\theta} = \dots = 2.157$.

4) Compute the expected frequencies:

Sol. 1) Let X_i be the number of death in i th day, $1 \leq i \leq 1096$.

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4) Compute the expected frequencies:

$$\implies d_1 = \dots = 25.98.$$

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4) Compute the expected frequencies:

Number of Deaths, i	Obs. Freq., k_i	Est. Exp. Freq., $n \hat{p}_{i_e}$
0	162	126.8
1	267	273.5
2	271	294.9
3	185	212.1
4	111	114.3
5	61	49.3
6	27	17.8
7	8	5.5
8	3	1.4
9	1	0.3
10+	0	0.1
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0	162	126.8
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7+	12	7.3
	<u>1096</u>	<u>1096</u>

$$\implies d_1 = \dots = 25.98.$$

5) P -value = $\mathbb{P}(\chi_{1,8-1-1}^2 \geq 25.98) = 0.00022$. Reject!

□

Plan

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§ 10.5 Contingency Tables

E.g. 1 Whether are the two ratings independent?

		Ebert Ratings			Total
		Down	Sideways	Up	
Siskel Ratings	Down	24	8	13	45
	Sideways	8	13	11	32
	Up	10	9	64	83
	Total	<u>42</u>	<u>30</u>	<u>88</u>	<u>160</u>

E.g. 2 Whether is the suicide rate independent of the mobility factor?

Table 10.5.7

City	Suicides per 100,000, x_i	Mobility Index, y_i	City	Suicides per 100,000, x_i	Mobility Index, y_i
New York	19.3	54.3	Washington	22.5	37.1
Chicago	17.0	51.5	Minneapolis	23.8	56.3
Philadelphia	17.5	64.6	New Orleans	17.2	82.9
Detroit	16.5	42.5	Cincinnati	23.9	62.2
Los Angeles	23.8	20.3	Newark	21.4	51.9
Cleveland	20.1	52.2	Kansas City	24.5	49.4
St. Louis	24.8	62.4	Seattle	31.7	30.7
Baltimore	18.0	72.0	Indianapolis	21.0	66.1
Boston	14.8	59.4	Rochester	17.2	68.0
Pittsburgh	14.9	70.0	Jersey City	10.1	56.5
San Francisco	40.0	43.8	Louisville	16.6	78.7
Milwaukee	19.3	66.2	Portland	29.3	33.2
Buffalo	13.8	67.6			

E.g. 2 Whether is the suicide rate independent of the mobility factor?

Table 10.5.7

City	Suicides per 100,000, x_i	Mobility Index, y_i	City	Suicides per 100,000, x_i	Mobility Index, y_i
New York	19.3	54.3	Washington	22.5	37.1
Chicago	17.0	51.5	Minneapolis	23.8	56.3
Philadelphia	17.5	64.6	New Orleans	17.2	82.9
Detroit	16.5	42.5	Cincinnati	23.9	62.2
Los Angeles	23.8	20.3	Newark	21.4	51.9
Cleveland	20.1	52.2	Kansas City	24.5	49.4
St. Louis	24.8	62.4	Seattle	31.7	30.7
Baltimore	18.0	72.0	Indianapolis	21.0	66.1
Boston	14.8	59.4	Rochester	17.2	68.0
Pittsburgh	14.9	70.0	Jersey City	10.1	56.5
San Francisco	40.0	43.8	Louisville	16.6	78.7
Milwaukee	19.3	66.2	Portland	29.3	33.2
Buffalo	13.8	67.6			

$$\bar{x} = 20.8 \quad \text{and} \quad \bar{y} = 56.0$$

Table 10.5.8

		Mobility Index	
		Low (<56.0)	High (\geq 56.0)
Suicide Rate	High (\geq 20.8)	7	4
	Low (<20.8)	3	11

Thm 10.4.1 Suppose that n observations are taken on a sample space partitioned by the events A_1, \dots, A_r and B_1, \dots, B_c .

Let $p_i = \mathbb{P}(A_i)$, $q_j = \mathbb{P}(B_j)$, $p_{ij} = \mathbb{P}(A_i \cap B_j)$.

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$$D_2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(X_{ij} - np_{ij})^2}{np_{ij}} \sim \text{Chi square of f.d. } rc - 1$$

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E.g. 1 Sol: Compute the expected frequencies:

		Ebert Ratings			Total
		Down	Sideways	Up	
Siskel Ratings	Down	24 (11.8)	8 (8.4)	13 (24.8)	45
	Sideways	8 (8.4)	13 (6.0)	11 (17.6)	32
	Up	10 (21.8)	9 (15.6)	64 (45.6)	83
	Total	42	30	88	160

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$$\implies d_2 = \dots = 45.37$$

Critical region is

$$(\chi_{0.99, (3-1) \times (3-1)}^2, +\infty) = (13.277, +\infty)$$

Alternatively P -value = $\mathbb{P}(\chi_4^2 \geq 45.37) = 3.33 \times 10^{-9}$.

Rejection at $\alpha = 0.01$.

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E.g. 2 Sol: Compute the expected frequencies:

		Mobility Index	
		Low (<56.0)	High (\geq 56.0)
Suicide Rate	High (\geq 20.8)	4.4*	6.6
	Low (<20.8)	5.6	8.4

* $\hat{E}(X_{11}) = 4.4$ does not quite satisfy the " $n\hat{p}_i\hat{q}_j \geq 5$ " restriction stated in Theorem 10.5.1, but 4.4 is close enough to 5 to maintain the integrity of the χ^2 approximation.

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Alternatively P -value = $\mathbb{P}(\chi_1^2 \geq 4.57) = 0.033$

Rejection at $\alpha = 0.05$.



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