



[Course](#) > [Unit 4 Hypothesis testing](#) > [Discrete Distributions](#) > [Lecture 15: Goodness of Fit Test for 5. Maximum Likelihood Estimator for the Categorical Distribution](#)

## 5. Maximum Likelihood Estimator for the Categorical Distribution

**Video note:** The following video derives the maximum likelihood estimator  $\hat{p}$  of a categorical statistical model. Note that we have seen this previously in [Lecture 10](#) and in [Recitation 6](#).

The maximum likelihood estimator will form the basis of goodness of fit testing for discrete distributions.

### MLE for the Categorical Distribution

## Multinomial likelihood

$K = \# \text{ of modalities}$

► Likelihood of the model:



$X \sim \text{Multinomial}(\underbrace{p_1, \dots, p_K}_{\vec{p}})$

$$L_n(X_1, \dots, X_n, \mathbf{p}) = p_1^{N_1} p_2^{N_2} \dots p_K^{N_K},$$

where  $N_i = \#\{i = 1, \dots, n : X_i = a_i\}$ .

► Let  $\hat{\mathbf{p}}$  be the MLE:

$$\hat{p}_j = \frac{N_j}{n}, \quad j = 1, \dots, K.$$

⚠  $\hat{\mathbf{p}}$  maximizes  $\log L_n(X_1, \dots, X_n, \mathbf{p})$  under the constraint

► 9:15 / 9:15

► 1.50x



### Video

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## Concept Check: Examples of the Categorical Distribution

2/2 points (graded)

Consider the distribution  $\text{Ber}(0.25)$ . Consider the categorical statistical model  $(\{a_1, \dots, a_K\}, \{\mathbf{P}_{\mathbf{p}}\})$  for this Bernoulli distribution.

If we let  $a_1 = 1$  and  $a_2 = 0$ , then this corresponds to a categorical distribution  $\mathbf{P}_{\mathbf{p}}$  with parameter vector  $\mathbf{p}$  given by...

☐ 0.25

☐ 0.75

☒  $[0.25 \ 0.75]^T$

☐  $[0.75 \ 0.25]^T$



Let  $a_i = i$  for  $i = 1, \dots, K$ . The uniform distribution on  $E = \{1, 2, \dots, K\}$  can be expressed as a categorical distribution  $\mathbf{P}_{\mathbf{p}}$  for some choice of parameter  $\mathbf{p}$ .

What is  $\sum_{i=1}^K p_i^2$ ?

✓ Answer: 1/K

STANDARD NOTATION

**Solution:**

Let  $X \sim \text{Ber}(0.25)$ . Observe that

$$p_1 = P(X = a_1) = P(X = 1) = 0.25$$

and

$$p_2 = P(X = a_2) = P(X = 0) = 0.75.$$

Hence,  $\mathbf{p} = [0.25 \ 0.75]^T$ .

**Remark:** Observe that  $\text{Ber}(p)$  has a one-dimensional parameter and  $\mathbf{P}_{\mathbf{p}}$  for this example involves a parameter that is two-dimensional, but such that the second parameter depends on the first one ( $p_1 = 1 - p_2$ ). In general, the categorical distribution for  $\mathbf{p} \in \Delta_K$  involves a  $K$ -dimensional parameter, but the last parameter  $p_K$ , for example, is redundant because  $p_K = 1 - \sum_{i=1}^{K-1} p_i$ . Even though  $\mathbf{p}$  is  $K$ -dimensional, the categorical distribution has only  $K - 1$  degrees of freedom. This will make our analysis more challenging: the extra constraint on the parameter  $\sum_{i=1}^K p_i = 1$  implies that the Fisher information for the model as specified **does not exist**. Hence, we cannot apply Wald's test directly.

For the second question, by definition, the uniform distribution weighs all elements in  $\{1, \dots, K\}$  equally. Let  $\mathbf{P}$  denote the parameter vector of the uniform distribution on  $\{1, 2, \dots, K\}$ . Then

$$p_i = P(X = i) = \frac{1}{K}.$$

Thus,

$$\sum_{i=1}^K p_i^2 = \sum_{i=1}^K \frac{1}{K^2} = \frac{1}{K}.$$

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You have used 1 of 2 attempts

**i** Answers are displayed within the problem

## Likelihood for a Categorical Distribution

3/3 points (graded)

Suppose that  $K = 3$ , and let  $E = \{1, 2, 3\}$ . Let  $X_1, \dots, X_n \stackrel{iid}{\sim} \mathbf{P}_{\mathbf{p}}$  for some unknown  $\mathbf{p} \in \Delta_3$ . Let  $f_{\mathbf{p}}$  denote the pmf of  $\mathbf{P}_{\mathbf{p}}$  and recall that the likelihood is defined to be

$$L_n(X_1, \dots, X_n, \mathbf{p}) = \prod_{i=1}^n f_{\mathbf{p}}(X_i).$$

Here we let the sample size be  $n = 12$ , and you observe the sample  $\mathbf{x} = x_1, \dots, x_{12}$  given by

$$\mathbf{x} = 1, 3, 1, 2, 2, 2, 1, 1, 3, 1, 1, 2, .$$

The likelihood for this data set can be expressed as  $L_{12}(\mathbf{x}, \mathbf{p}) = p_1^A p_2^B p_3^C$ .

Fill in the values of  $A$ ,  $B$ , and  $C$  below.

$A =$    Answer: 6  $B =$    Answer: 4  $C =$    Answer: 2

**Solution:**

Since  $K = 3$  and  $E = \{1, 2, 3\}$ ,

$$f_{\mathbf{p}}(i) = p_i, \quad i = 1, 2, 3.$$

Next,

$$L_n(X_1, \dots, X_n, \mathbf{p}) = \prod_{i=1}^n f_{\mathbf{p}}(X_i) = p_1^{N_1} p_2^{N_2} p_3^{N_3}$$

where

$N_i$  = number of times  $i$  appears in  $(X_1, \dots, X_n)$ ,  $i = 1, 2, 3$ .

In the data set above, 1 appears 6 times, 2 appears 4 times, and 3 appears 2 times. Thus,  $A = N_1 = 6$ ,  $B = N_2 = 4$ , and  $C = N_3 = 2$ .

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You have used 1 of 2 attempts

**i** Answers are displayed within the problem

## Maximum Likelihood Estimator for Categorical Distribution

3/3 points (graded)

As above, under the statistical model  $(\{1, 2, 3\}, \{\mathbf{P}_{\mathbf{p}}\}_{\mathbf{p} \in \Delta_3})$ , we have

$$L_{12}(\mathbf{x}, \mathbf{p}) = p_1^A p_2^B p_3^C$$

where

$$\mathbf{x} = 1, 3, 1, 2, 2, 2, 1, 1, 3, 1, 1, 2.$$

In the previous problem, you found the specific values for  $A$ ,  $B$ , and  $C$ .

Recall that the MLE is given by

$$\hat{\mathbf{p}}_n^{MLE} = \operatorname{argmax}_{\mathbf{p} \in \Delta_3} \log L_n(X_1, \dots, X_n, \mathbf{p}).$$

By the theory of Lagrange multipliers, one can show that the maximum occurs at the point  $\mathbf{p}$  such that there exists  $\lambda \neq 0$  so that

$$\nabla \log L_n(X_1, \dots, X_n, \mathbf{p}) = \lambda \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

(The gradient above is taken with respect to the parameter  $\mathbf{p}$ .)

Using this result and the previous problem, what is the estimate  $\hat{\mathbf{p}}_{12}^{MLE}$  for  $\mathbf{p}$  given the data set  $\mathbf{x}$ ?

$(\hat{\mathbf{p}}_{12}^{MLE})_1 =$   ✓ Answer: 1/2
 $(\hat{\mathbf{p}}_{12}^{MLE})_2 =$   ✓ Answer: 1/3
 $(\hat{\mathbf{p}}_{12}^{MLE})_3 =$   ✓

Answer: 1/6

**Solution:**

In the previous problem, we saw that  $A = 6$ ,  $B = 4$ , and  $C = 2$ . Thus

$$\log L_n(\mathbf{x}, \mathbf{p}) = 6 \log p_1 + 4 \log p_2 + 2 \log p_3.$$

Hence,

$$\nabla \log L_n(\mathbf{x}, \mathbf{p}) = \begin{bmatrix} \frac{6}{p_1} \\ \frac{4}{p_2} \\ \frac{2}{p_3} \end{bmatrix}.$$

Applying the Lagrange multipliers, we have

$$\begin{bmatrix} \frac{6}{p_1} \\ \frac{4}{p_2} \\ \frac{2}{p_3} \end{bmatrix} = \lambda \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

Therefore,

$$p_1 = \frac{6}{\lambda}, p_2 = \frac{4}{\lambda}, p_3 = \frac{2}{\lambda}.$$

By the constraint  $p_1 + p_2 + p_3 = 1$ , we see that

$$\lambda = 6 + 4 + 2 = 12.$$

Therefore,

$$\hat{\mathbf{p}}_{12}^{MLE} = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{3} \\ \frac{1}{6} \end{bmatrix}.$$

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You have used 1 of 2 attempts

**i** Answers are displayed within the problem

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