

MULTINOMIAL LOGISTIC REGRESSION

Contents

1. Basics of Multinomial Logistic Regression
2. Application areas
3. Statistical Model
4. Case Study
5. Model fitting in R
6. Predicted Probabilities and Classification Table

Multinomial Logistic Regression

DEPENDENT VARIABLE



Nominal

(With more than two mutually exclusive and exhaustive categories)

INDEPENDENT VARIABLE



Categorical or
Continuous

- If there are k categories for the dependent variable then $(k-1)$ logit functions are defined with remaining 1 category as base level.

Application Areas

Industry / Function	Model	Based on Information such as:
Marketing	Buyers' Brand Preference	<ul style="list-style-type: none">• Age, Gender, Payment Mode, Purchase Frequency, Historical purchase details, etc.
Education	Electives Chosen by Students	<ul style="list-style-type: none">• Student Gender, Subjects Chosen at the Current Level, Current Academic Score, etc.
Healthcare	Common painkiller used	<ul style="list-style-type: none">• Demographics, Type of Ailment, socio-economic background, etc.

Statistical Model

- Let Y be the **dependent variable** with 3 categories as A,B,C and X_1, X_2, \dots, X_k are k Independent variables.
- There will be 2 logit functions: one for Y=B versus Y=A and other Y=C versus Y=A Assuming A as the base category.

$$\begin{aligned} g_1(x) &= \text{logit function for } Y=B \text{ versus } Y=A \\ g_1(x) &= \log \left(\frac{P_B}{P_A} \right) \\ &= b_{01} + b_{11}x_1 + b_{21}x_2 + \dots + b_{k1}x_k \end{aligned}$$

where,

$$P_B = P[Y = B | x]$$
$$P_A = P[Y = A | x]$$

$$\begin{aligned} g_2(x) &= \text{logit function for } Y=C \text{ versus } Y=A \\ g_2(x) &= \log \left(\frac{P_C}{P_A} \right) \\ &= b_{02} + b_{12}x_1 + b_{22}x_2 + \dots + b_{k2}x_k \end{aligned}$$

where,

$$P_C = P[Y = C | x]$$

- Parameters of the model are estimated by **Maximum Likelihood Estimation(MLE) Method**



Case Study – High School Program Choice

Background

- At the time of entering high school, students make program choices among **general program**, **vocational program** and **academic program**. Their choice can be modeled using their writing score and their socio-economic status.

Objective

- To model student's choice of programs.

Available Information

- Data source: <https://stats.idre.ucla.edu/>
- Sample size is 200
- **Independent Variables:** Socio-Economic Status (SES) and Writing Score.
- **Dependent Variable:** Program Chosen (General, Vocational or Academic)



Data Snapshot

High School Data

Independent Variables Dependent Variable

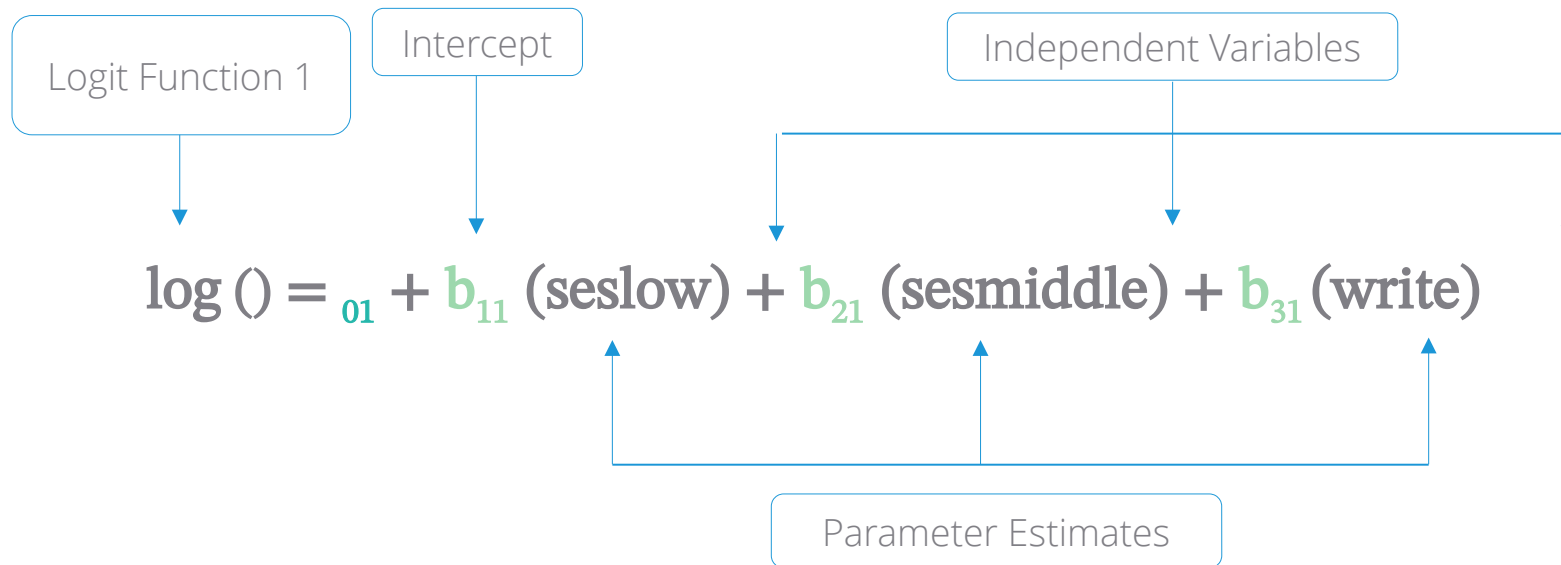
sn	id	ses	write	prog
1	45	low	35	vocation
2	108	middle	33	general

Column	Description	Type	Measurement	Possible Values
sn	serial number	numeric	-	-
id	student id	numeric	-	-
ses	socio-economic status	Categorical	low, middle, high	3
write	writing score of the students	continuous	-	positive value
prog	program chosen by students	categorical	vocational, general, academic	3



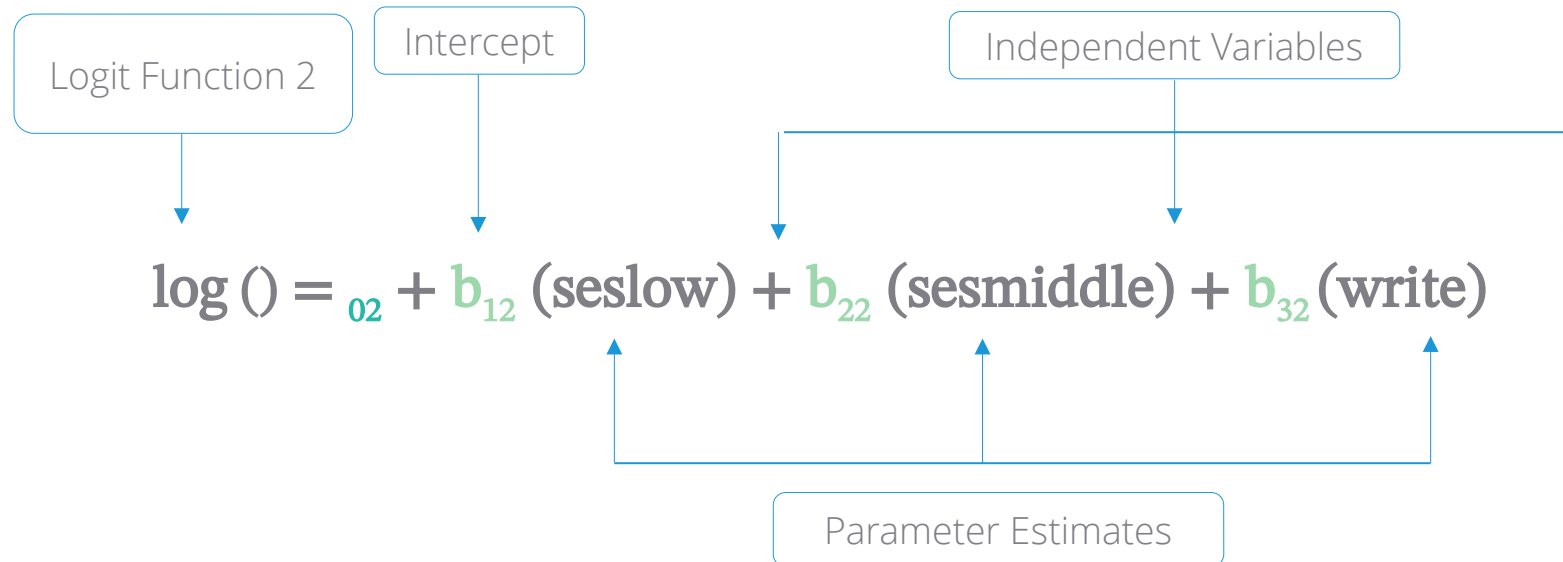
Model for the case study

- There are two categorical variables in the data: 'prog' and 'ses'.
 - For the Dependent variable 'prog', 'academic' is taken as **base category**.
 - For the Independent variable 'ses', 'high' is taken as **base category**.
- Model for the **general vs academic** is given as:



Model for the case study

- Model for the vocational vs academic is given as:



Maximum Likelihood Estimates of Parameters

Coefficients				
	Intercept	seslow	sesmiddle	write
general	1.689478	1.1628411	0.6295638	-0.05793086
vocation	4.235574	0.9827182	1.2740985	-0.11360389
Standard Errors				
	Intercept	seslow	sesmiddle	write
general	1.226939	0.5142211	0.4650289	0.02141101
vocation	1.204690	0.5955688	0.5111119	0.02222000

$$\log () = 1.689478 + 1.1628411(\text{seslow}) + 0.629568(\text{sesmiddle}) + (-0.05793086)(\text{write})$$

Similar to this, there will be another model equation for the category 'vocation' with 'academic' as base category.

Model Fitting in R

#Import the data

```
data<-read.csv("High School Data.csv", header=TRUE)
str(data)
data$prog<-as.factor(data$prog)
```

```
data$prog<-relevel(data$prog, ref="academic")
```

```
# Install and load package 'nnet'.
install.packages("nnet")
library(nnet)
```

- ❑ **relevel()** tells R to re-order levels of a factor so that the level specified by ref is first and the others are moved down. First level is then taken as reference (base) category.

Model Fitting in R

#Run Multinomial Logistic Model

```
choicemodel<-multinom(prog~ses+write,data=data)

m<-summary(choicemodel)
m
```

- ❑ **multinom()** fits a Multinomial Logistic Regression. Dependent variable is followed by '~' and independent variables are separated by plus signs.
- ❑ The output of **multinom()** function does not contain all the parameters required for further testing.
- ❑ In order to be able to extract specific components from the output and perform more actions on them, an object is created from **summary()**.

Model Fitting in R

Output

```
> choicemodel<-multinom(prog~ses+write,data=data)
# weights:  15 (8 variable)
initial value 219.722458
iter  10 value 179.983731
final value 179.981726
converged
> m<-summary(choicemodel)
> m
Call:
multinom(formula = prog ~ ses + write, data = data)

Coefficients:
              (Intercept)      seslow sesmiddle      write
general      1.689478  1.1628411  0.6295638 -0.05793086
vocation     4.235574  0.9827182  1.2740985 -0.11360389

Std. Errors:
              (Intercept)      seslow sesmiddle      write
general      1.226939  0.5142211  0.4650289  0.02141101
vocation     1.204690  0.5955688  0.5111119  0.02222000

Residual Deviance: 359.9635
AIC: 375.9635
```

- Output gives coefficients and standard errors of variables for each logit.

Individual Testing Using Wald's Test

- Individual testing is used for checking significance of each independent variable separately.

Objective	To test the null hypothesis that each variable is insignificant
	<div>Null Hypothesis (H_0): $b_{i1} = 0$ (for 1st logit)</div> <div>Alternate Hypothesis (H_1): $b_{i1} \neq 0$ ((for 1st logit)</div> <div>$i=1,2,...,k$</div>
	<div>Null Hypothesis (H_0): $b_{i2} = 0$ (for 2nd logit)</div> <div>Alternate Hypothesis (H_1): $b_{i2} \neq 0$ (for 2nd logit)</div> <div>$i=1,2,...,k$</div>
Test Statistic	$Z^2 = (b_{i1} / \text{Std. Error of } b_{i1})^2$ Under H_0 , $Z^2 \sim \chi^2_{(1)}$
Decision Criteria	Reject the null hypothesis if p-value < 0.05



Individual Testing- Case study

Table of p-values				
	Intercept	seslow	sesmiddle	write
general	0.1685163893	0.02373673	0.1757949	6.816914e-03
vocational	0.0004382601	0.09893276	0.0126741	3.176088e-07

- p-value for seslow (general), sesmiddle (vocational) and write (general and vocational) < 0.05

Interpretation of Results

Coefficients				
	Intercept	seslow	sesmiddle	write
general	1.689478	1.1628411	0.6295638	-0.05793086
vocational	4.235574	0.9827182	1.2740985	-0.11360389
P-values				
general	0.1685163893	0.02373673	0.1757949	6.816914e-03
vocational	0.0004382601	0.09893276	0.0126741	3.176088e-07

- 'write' is a significant variable. Higher the writing score, less preference to 'general' or 'vocational'(as academic is base category and coefficient sign is negative).
- 'Low' SES category prefer 'general' over 'academic' more than 'high' SES category (as high SES is base category).
- 'middle' SES category prefer 'vocation' over 'academic' more than 'high' SES category.

Individual Testing in R

```
#Individual Testing
```

```
z<-m$coefficients/m$standard.errors
```

```
pvalue <-1-pchisq(z^2,df=1)
```

```
pvalue
```

- ❑ 'z' creates a dataframe of Z values as coefficients divided by standard errors
- ❑ **pchisq()** is used to calculate p-values using square of Z and degrees of freedom as arguments
- ❑ **pvalue** stores table of p-values.

Individual Testing in R

Output:

	(Intercept)	seslow	sesmiddle	write
general	0.1685163893	0.02373673	0.1757949	6.816914e-03
vocation	0.0004382601	0.09893276	0.0126741	3.176088e-07

Interpretation :

- seslow(general), write(general), sesmiddle(vocation), write(vocation) are significant, as p-value < 0.05 .

Classification Table

- **Cross tabulation** of observed values of Y and estimated values of Y is called as Classification Table.
- The predictive success of the logistic regression can be assessed by looking at the classification table

Classification				
Observed	Predicted			
	academic	general	vocation	Percent Correct
academic	92	4	9	87.61%
general	27	7	11	15.56%
vocation	23	4	23	46.00%
Overall Percentage	71.0%	7.5%	21.5%	61.0%

- Table shows that, model is predicting $61\% = (92+7+23)/200$ correctly.

Predicted Probabilities and Classification Table in R

Predicted Probabilities

```
data$predprob<-round(fitted(choicemodel),2)
```

```
head(data)
```

□ **fitted()** generates predicted probabilities for program choice.

Output:

	sn	id	ses	write	prog	predprob.academic	predprob.general	predprob.vocation
1	1	45	low	35	vocation	0.15	0.34	0.51
2	2	108	middle	33	general	0.12	0.18	0.70
3	3	15	high	39	vocation	0.42	0.24	0.34
4	4	67	low	37	vocation	0.17	0.35	0.48
5	5	153	middle	31	vocation	0.10	0.17	0.73
6	6	51	high	36	general	0.35	0.24	0.41

Predicted category is Vocation

Interpretation :

- Predicted probabilities are given for each outcome (academic, general, vocation).
- Category of the maximum of these probabilities is taken as predicted category of that observation



Predicted Probabilities and Classification Table in R

Classification Table

```
expected<-predict(choicemodel,data, type="class")
```

```
ctable<-table(data$prog,expected)
```

```
ctable
```

- ❑ **predict()** returns predicted values.
- ❑ **type="class"** returns a factor of classifications based on the responses (frequency). **type="probs"** returns matrix of probabilities.
- ❑ **table()** function simply gives the true positive and negative rates of the model (in the form of counts), which are key to deciding power of the model.

Output:

	expected		
	academic	general	vocation
academic	92	4	9
general	27	7	11
vocation	23	4	23

Interpretation :

- Classification table of predicted and expected

Quick Recap

In this session, we learned about **Multinomial Logistic Regression** :

Multinomial Logistic Regression

- Dependent variable is nominal with more than two categories and independent variables are categorical or continuous or mix of both.
- Parameters are estimated using MLE.
- If there are k categories for the dependent variable then (k-1) logit functions are defined with remaining 1 category as base level.

Multinomial Logistic regression in R

- **relevel()** used to define base category.
- **nnet()** library required for multinomial regression
- **multinom()** performs multinomial logistic regression
- Use **summary()** function to extract more details from **multinom()** function.



THANK YOU!!