# Multinomial Regression (Module -10)

**Instructions**

Please share your answers filled inline in the word document. Submit Python code and R code files wherever applicable.

Please ensure you update all the details:

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**Topic: Multinomial Regression.**

1. **Business Problem**
   1. **Objective**
   2. **Constraints (if any)**
2. **Work on each feature of the dataset to create a data dictionary as displayed in the below image:**



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**2.1 Make a table as shown above and provide information about the features such as its Data type and its relevance to the model building, if not relevant provide reasons and provide description of the feature.**

**Using R and Python codes perform:**

1. **Data Pre-processing**

**3.1 Data Cleaning, Feature Engineering, etc.**

**3.2 Outlier Imputation**

1. **Exploratory Data Analysis (EDA):**
   1. **Summary**
   2. **Univariate analysis**
   3. **Bivariate analysis**
2. **Model Building**
   1. **Build the model on the scaled data (try multiple options)**
   2. **Perform Multinomial Regression Modl.**
   3. **Train and Test the data and compare accuracies by Confusion Matrix, plot ROC AUC curve.**

**5.4 Briefly explain the model output in the documentation.**

1. **Share the benefits/impact of the solution - how or in what way the business (client) gets benefit from the solution provided.**

# Note:

The assignment should be submitted in the following format:

* R code
* Python code
* Code Modularization should be maintained
* Documentation of the model building (elaborating on steps mentioned above)

**Problem Statement:**

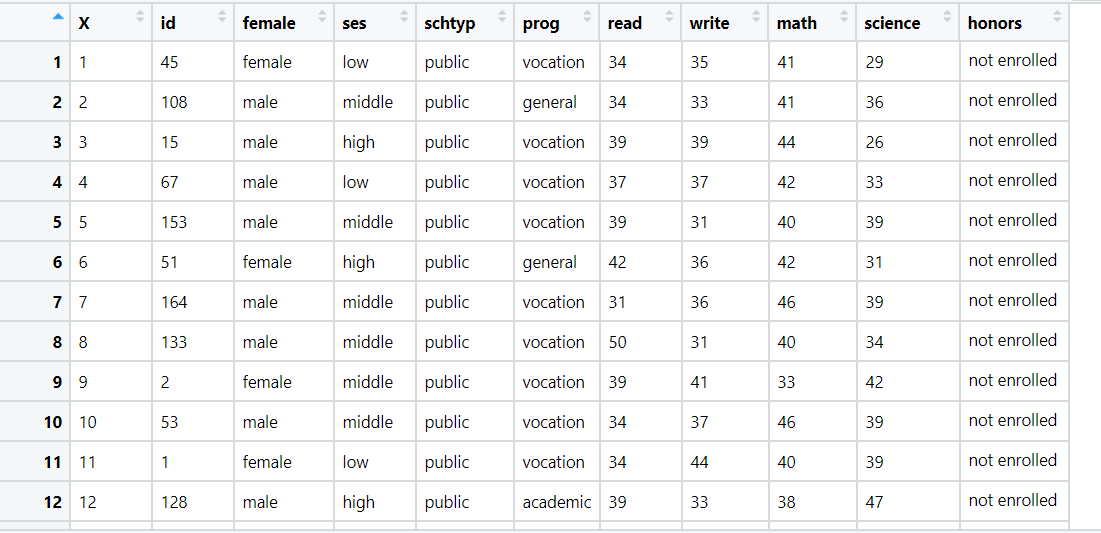
A University would like to effectively classify their student based on the Program they are enrolled into, perform multinomial regression on the given dataset and provide insights in the documentation.

**prog**: is a categorical variable indicating what type of program a student is in: “General” (1), “Academic” (2), or “Vocational” (3)

**Ses**: is a categorical variable indicating someone’s socioeconomic class: “Low” (1), “Middle” (2), and “High” (3)

**read, write, math, science** are their scores on different tests

**honors**: Whether they have enrolled or not



**Objective:** Maximize the accuracy in predicting outcome that related between explanatory variables.

**Constraints:** Imposes too much constraint on the relative preferences between the different alternatives.

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature Name** | **Description** | **Type** | **Relevance** |
| id | Student ID | Nominal | Irrelevant, does not provide useful information. |
| female | Gender of student | Ordinal | Relevant, Provides useful information. |
| ses | Socio economic class | Ordinal | Relevant, Provides useful information. |
| schtyp | School type | Nominal | Irrelevant, does not provide useful information. |
| prog | Type of program student enrolled into | Ordinal | Relevant, Provides useful information |
| Read | Read score | Discrete | Relevant, Provides useful information |
| Write | Write score | Discrete | Relevant, Provides useful information |
| Math | Math score | Discrete | Relevant, Provides useful information |
| Science | Science score | Discrete | Relevant, Provides useful information |
| honors | Result (Selected or Not) | Ordinal | Relevant, Provides useful information |

**Problem statement:**

You work for a consumer finance company which specializes in lending various types of loans to urban customers. When the company receives a loan application, the company has to make a decision for loan approval based on the applicant’s profile. Two types of risks are associated with the bank’s decision:

• If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company

• If the applicant is not likely to repay the loan, i.e. he/she is likely to default, then approving the loan may lead to a financial loss for the company

The data given below contains the information about past loan applicants and whether they ‘defaulted’ or not. The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc.

In this case study, you will use EDA to understand how consumer attributes and loan attributes influence the tendency of default.

When a person applies for a loan, there are two types of decisions that could be taken by the company:

1. Loan accepted: If the company approves the loan, there are 3 possible scenarios described below:

o Fully paid: Applicant has fully paid the loan (the principal and the interest rate)

o Current: Applicant is in the process of paying the instalments, i.e. the tenure of the loan is not yet completed. These candidates are not labelled as 'defaulted'.

o Charged-off: Applicant has not paid the instalments in due time for a long period of time, i.e. he/she has defaulted on the loan

2. Loan rejected: The company had rejected the loan (because the candidate does not meet their requirements etc.). Since the loan was rejected, there is no transactional history of those applicants with the company and so this data is not available with the company (and thus in this dataset)

This company is the largest online loan marketplace, facilitating personal loans, business loans, and financing of medical procedures. Borrowers can easily access lower interest rate loans through an online interface.

Like most other lending companies, lending loans to ‘risky’ applicants is the largest source of financial loss (called credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed. In other words, borrowers who default cause the largest amount of loss to the lenders. In this case, the customers labelled as 'charged-off' are the 'defaulters'.

If one is able to identify these risky loan applicants, then such loans can be reduced thereby cutting down the amount of credit loss.

In other words, the company wants to understand the driving factors (or driver variables) behind loan default, i.e. the variables which are strong indicators of default. The company can utilize this knowledge for its portfolio and risk assessment.

Perform Multinomial regression on the dataset in which loan\_status is the output (Y) variable and it has three levels in it.

A screenshot of a cell phone

Description automatically generated

**Objective:** Maximize the accuracy in predicting outcome that related between explanatory variables.

**Constraints:** Imposes too much constraint on the relative preferences between the different alternatives.

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature Name** | **Description** | **Type** | **Relevance** |
| id | Customer ID | Nominal | Irrelevant, does not provide useful information. |
| member\_id | Customer’s member ID | Nominal | Irrelevant, does not provide useful information. |
| loan\_amnt | Loan amount requested for sanction | Continuous | Relevant, Provides useful information. |
| funded\_amnt | Sanctioned loan amount. | Continuous. | Relevant, Provides useful information. |
| funded\_amnt\_inv | Sanctioned loan amount invested. | Continuous. | Relevant, Provides useful information. |
| term | Time for return of term. | Discrete | Relevant, Provides useful information. |
| int\_rate | Rate of interest | Continuous. | Relevant, Provides useful information. |
| installment | Installment per month | Continuous. | Relevant, Provides useful information. |
| grade | Grade for customer given by bank | Ordinal | Relevant, Provides useful information. |
| sub\_grade | Secondary grade | Ordinal | Relevant, Provides useful information. |
| emp\_title | Profile of customer | Nominal | Irrelevant, does not provide useful information |
| emp\_length | Experience | Discrete | Irrelevant, does not provide useful information |
| home\_ownership | House information | Nominal | Relevant, Provides useful information. |
| annual\_inc | Annual income of customer | Continuous | Relevant, Provides useful information. |
| verification\_status | Status of application | Ordinal | Relevant, Provides useful information. |
| issue\_d | Application issue date | Nominal | Irrelevant, does not provide useful information |
| loan\_status | Status of loan application | Ordinal | Relevant, Provides useful information. (also, a response variable) |
| url | URL of customer information | Nominal | Irrelevant, does not provide useful information |
| desc | Description of purpose for which loan applied. | Nominal | Irrelevant, does not provide useful information |
| title | Title of description which loan applied. | Nominal | Irrelevant, does not provide useful information |
| zip\_code | Zip code of customer | Nominal | Irrelevant, does not provide useful information |
| addr\_state | State address of customer | Nominal | Irrelevant, does not provide useful information |

