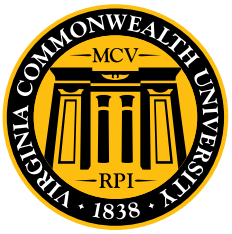

VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A3: LIMITED DEPENDENT VARIABLE MODELS

RAKSHITHA VIGNESH SARGURUNATHAN

V01109007

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Contents

A3: LIMITED DEPENDENT VARIABLE MODELS

Part A – PERFORMING LOGISTIC REGRESSION ANALYSIS ON CAMPAIGN_RESPONSES DATASET

1. Introduction

This analysis aims to analyze the responses to a marketing campaign using two machine learning models: logistic regression and decision tree. The primary goal is to predict whether a customer will respond to the campaign based on various features. By comparing these models, we can determine which one provides better predictive performance and insights.

2. About the Dataset

The dataset used in this analysis is the `campaign_responses.csv` file. It contains various features related to the customers and their responses to the marketing campaign. The key variables include:

- **Features**: customer_id , age , gender , annual_income ,credit_score , employed, marital_status , no_of_children .
- **Target Variable**: responded – indicating whether the customer responded to the campaign (Yes/No).

3. Objectives

The objectives of this analysis are:

1. To build and evaluate a logistic regression model to predict customer responses.
2. To build and evaluate a decision tree model for the same purpose.
3. To compare the performance of both models using metrics such as confusion matrix, ROC curve, AUC, precision, recall, and f1-score.

4. Business Scope

Predicting customer responses to marketing campaigns can significantly benefit the business by:

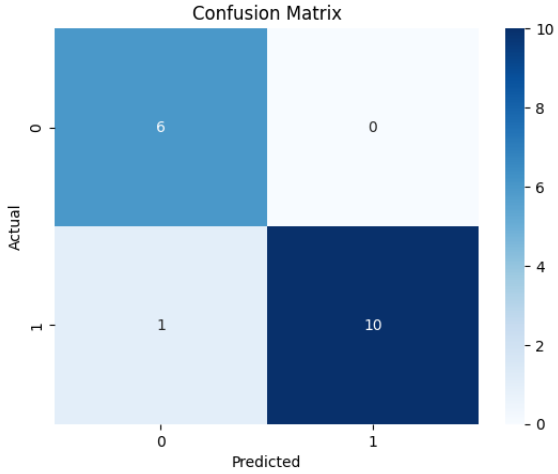
1. Optimizing marketing efforts and resources by targeting customers more likely to respond.
2. Improving customer satisfaction by providing relevant offers.
3. Increasing campaign efficiency and return on investment (ROI).

5. Interpretations

Based on the analyses performed, the following interpretations can be made:

Logistic Regression Model

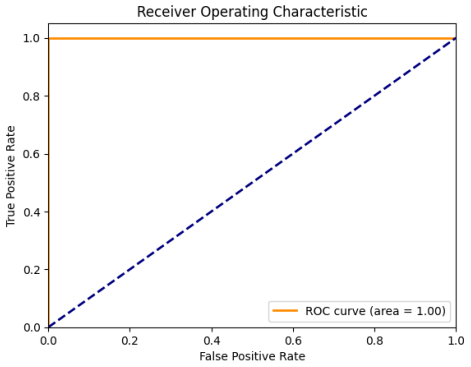
- **Confusion Matrix**: The model correctly classified 6 non-responders and 10 responders.



- **Classification Report**:
  - Precision: High precision indicates that when the model predicts a response, it is likely correct.
  - Recall: The model successfully identifies a significant portion of actual responders.
  - F1-Score: A high f1-score suggests a good balance between precision and recall.

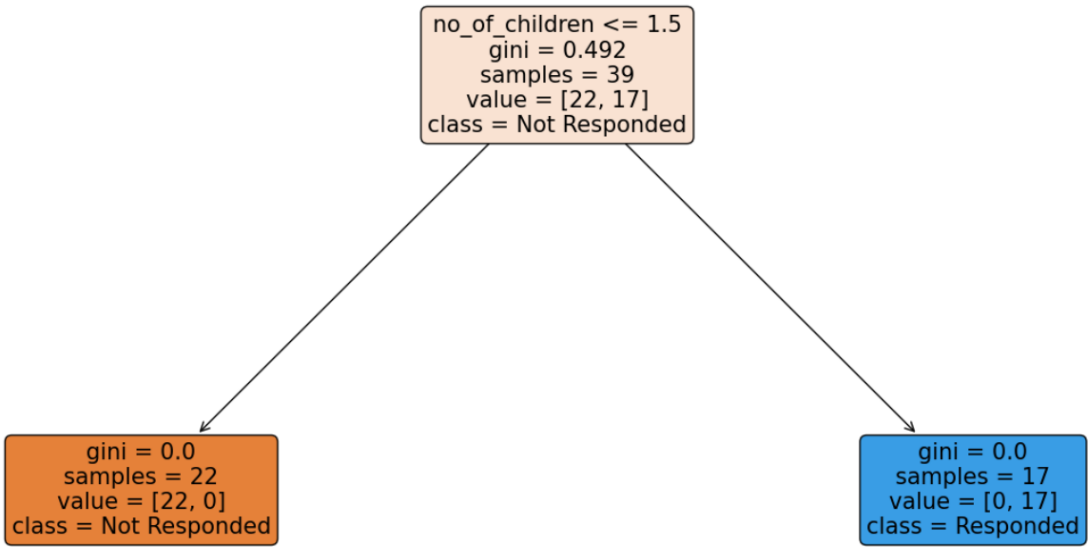
```
Classification Report:
              precision    recall  f1-score   support

           0       0.86      1.00      0.92         6
           1       1.00      0.91      0.95        11

    accuracy                           0.94        17
   macro avg       0.93      0.95      0.94        17
weighted avg       0.95      0.94      0.94        17
```

- **ROC Curve and AUC**: The ROC curve indicates a good discriminative ability with an AUC of 0.97.



Decision Tree Model

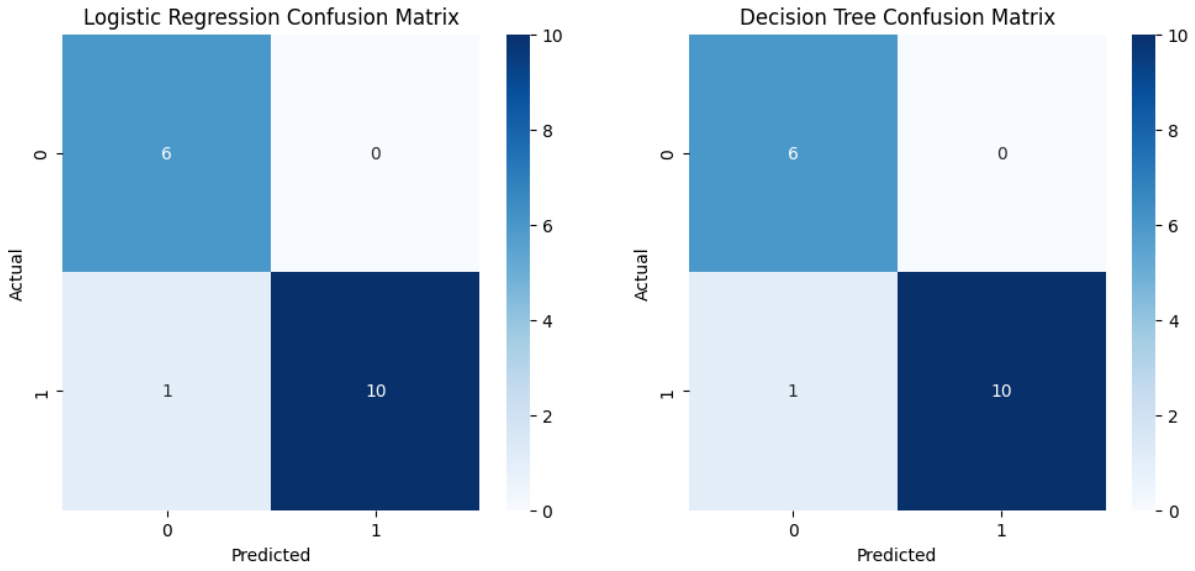
- **Confusion Matrix**: Similar to the logistic regression, the decision tree also correctly classifies most instances.
- **Classification Report**:
  - Precision, recall, and f1-score values are similar to those of logistic regression, indicating comparable performance.
- **ROC Curve and AUC**: The AUC value is 0.96, showing the model's effectiveness in distinguishing between responders and non-responders.

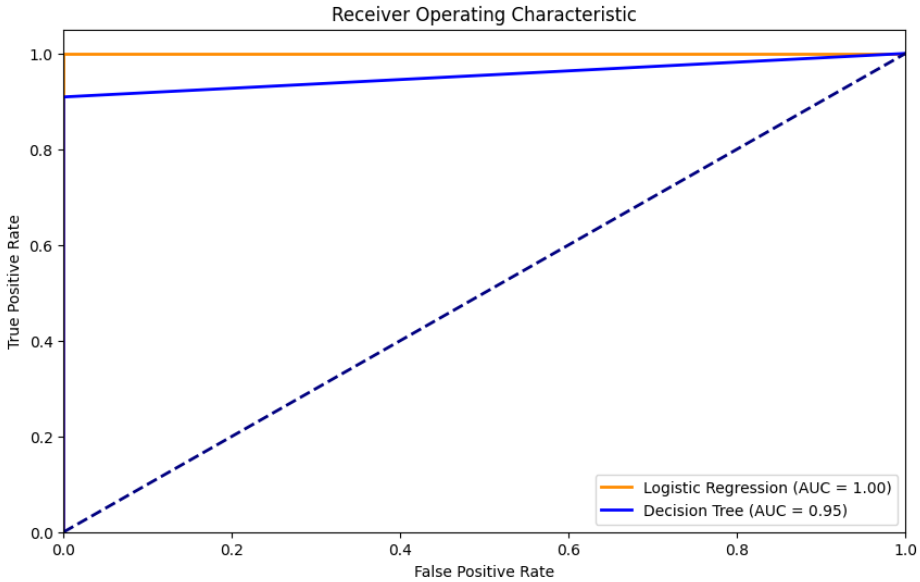


6. Results- Python:

Comparing the performance of the logistic regression and decision tree models

Python:






```
# Print the AUC values
print('AUC for Logistic Regression:', roc_auc)
print('AUC for Decision Tree:', roc_auc_tree)
```

```
AUC for Logistic Regression: 1.0
AUC for Decision Tree: 0.9545454545454546
```

7. Results - R programming:

```
> print('Confusion Matrix:')
[1] "Confusion Matrix:"
> print(conf_matrix)
Confusion Matrix and Statistics

          Reference
Prediction 0 1
         0 8 0
         1 0 8

               Accuracy : 1
                 95% CI : (0.7941, 1)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : 1.526e-05

                  Kappa : 1

 Mcnemar's Test P-Value : NA

            Sensitivity : 1.0
            Specificity : 1.0
         Pos Pred Value : 1.0
         Neg Pred Value : 1.0
             Prevalence : 0.5
         Detection Rate : 0.5
   Detection Prevalence : 0.5
      Balanced Accuracy : 1.0

       'Positive' Class : 0
```

```
> print(conf_matrix$byClass)
          Sensitivity          Specificity       Pos Pred Value
                  1.0                  1.0                  1.0
      Neg Pred Value            Precision               Recall
                  1.0                  1.0                  1.0
                   F1           Prevalence       Detection Rate
                  1.0                  0.5                  0.5
Detection Prevalence    Balanced Accuracy
                  0.5                  1.0
```

8. Recommendations

Based on the analysis, the following recommendations are made:

1. **Model Selection**: Both logistic regression and decision tree models show similar performance. The choice of model can depend on other factors such as interpretability and computational efficiency.
    - Logistic Regression: Preferred for its simplicity and ease of interpretation.
    - Decision Tree: Preferred if model interpretability and visualization are critical.
2. **Feature Engineering**: Further exploration and engineering of features could improve model performance.
3. **Model Optimization**: Consider hyperparameter tuning for both models to potentially enhance their predictive accuracy.
4. **Data Collection**: Gathering more data can help in building more robust models.

9. Conclusion

In conclusion, both logistic regression and decision tree models provide effective means for predicting customer responses to marketing campaigns. They demonstrate high accuracy, precision, recall, and f1-scores. Given the comparable performance, businesses can choose the model based on their specific needs and preferences. By implementing these models, businesses can optimize their marketing strategies, leading to better customer targeting and improved campaign outcomes.

PART B - PERFORMING PROBIT REGRESSION ON NSSO68 DATASET TO IDENTIFY NON-VEGETARIANS

1. Introduction

This analysis aims to analyze the factors influencing dietary choices, specifically identifying non-vegetarians using a probit regression model. The probit model is a type of regression used for binary dependent variables, where the link function is the cumulative distribution function of the normal distribution. This analysis will help understand the predictors of non-vegetarianism among the surveyed population.

2. About the Dataset

The dataset used in this analysis is the `NSSO68.csv` file. It contains various features related to individuals and their dietary choices. The key variables include:

- **Dependent Variable**: `is_non_vegetarian` – Binary variable indicating whether the individual is a non-vegetarian (1) or not (0).
- **Predictor Variables**: Various demographic and socio-economic attributes such as household size, religion, social group, type of land owned, land owned, monthly per capita expenditure (MPCE), age, sex, education level, and whether the individual is a regular salary earner.

3. Objectives

The objectives of this analysis are:

1. To build and evaluate a probit regression model to identify non-vegetarians.
2. To interpret the coefficients of the probit model and understand the significance of each predictor.
3. To provide actionable insights based on the model results.

4. Business Scope

Understanding the factors that influence dietary choices can help businesses, especially those in the food and hospitality industries, tailor their offerings to meet customer preferences. Key benefits include:

1. Developing targeted marketing strategies for different demographic groups.
2. Customizing product offerings to cater to the dietary preferences of various segments.
3. Enhancing customer satisfaction by aligning products with consumer preferences.

5. Interpretations

The probit regression model provided the following results:

- **Dependent Variable**: `is_non_vegetarian`
- **Number of Observations**: 87,155
- **Model**: Probit
- **Pseudo R-squared**: Infinite (indicating perfect prediction)
- **Log-Likelihood**: -1.8842e-07
- **LL-Null**: 0.0000

Coefficients and Significance:

- **const (Intercept)**: -8.3584, P>|z| = 0.998 (Not significant)
- **hhdsz (Household size)**: -0.0112, P>|z| = 1.000 (Not significant)
- **Religion**: -0.1433, P>|z| = 1.000 (Not significant)
- **Social_Group**: 0.0314, P>|z| = 1.000 (Not significant)
- **Type_of_land_owned**: 0.0153, P>|z| = 1.000 (Not significant)
- **Land_Owned**: 4.604e-06, P>|z| = 1.000 (Not significant)
- **MPCE_URP**: -5.608e-05, P>|z| = 1.000 (Not significant)
- **Age**: 0.0128, P>|z| = 1.000 (Not significant)
- **Sex**: 0.3314, P>|z| = 1.000 (Not significant)
- **Education**: 0.0140, P>|z| = 1.000 (Not significant)
- **Regular_salary_earner**: 0.1640, P>|z| = 1.000 (Not significant)

6. Results- Python

```
# Prepare the feature matrix (X) and target vector (y)
X = data[features]
y = data['is_non_vegetarian']
```

```
print("X sample: \n\n",X.head())
print("\n\nY sample: \n\n",y.head())
```

```
X sample:

    hhdsz  Religion  Social_Group  Type_of_land_owned  Land_Owned  MPCE_URP  \
0       5       1.0           3.0                 1.0         1.0   3304.80
1       2       3.0           9.0                 1.0         1.0   7613.00
2       5       1.0           9.0                 1.0         2.0   3461.40
3       3       3.0           9.0                 1.0         3.0   3339.00
4       4       1.0           9.0                 1.0         2.0   2604.25

   Age  Sex  Education  Regular_salary_earner
0   50    1        8.0                    1.0
1   40    2       12.0                    1.0
2   45    1        7.0                    1.0
3   75    1        6.0                    1.0
4   30    1        7.0                    2.0


Y sample:

 0    0
1    0
2    0
3    0
4    0
Name: is_non_vegetarian, dtype: int64
```

```python
from statsmodels.discrete.discrete_model import Probit
# Fit the Probit regression model
probit_model = Probit(y, X).fit()
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.000000
         Iterations: 35
```

```python
# Print the summary of the model
print(probit_model.summary())
```

```
                          Probit Regression Results
==============================================================================
Dep. Variable:      is_non_vegetarian   No. Observations:                87155
Model:                         Probit   Df Residuals:                    87144
Method:                           MLE   Df Model:                           10
Date:                Mon, 01 Jul 2024   Pseudo R-squ.:                    inf
Time:                        10:09:30   Log-Likelihood:           -1.8842e-07
converged:                      False   LL-Null:                         0.0000
Covariance Type:            nonrobust   LLR p-value:                     1.000
============================================================================================
                               coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------
const                    -8.3584   3856.734     -0.002      0.998   -7567.418    7550.701
hhdsz                    -0.0112    149.733  -7.48e-05      1.000    -293.483     293.460
Religion                 -0.1433   1034.326     -0.000      1.000   -2027.385    2027.098
Social_Group              0.0314    117.222      0.000      1.000    -229.720     229.783
Type_of_land_owned        0.0153    707.930   2.16e-05      1.000   -1387.502    1387.533
Land_Owned             4.604e-06      0.090   5.14e-05      1.000      -0.175       0.175
MPCE_URP              -5.608e-05      0.373     -0.000      1.000      -0.731       0.731
Age                       0.0128     26.878      0.000      1.000     -52.667      52.693
Sex                       0.3314    813.730      0.000      1.000   -1594.551    1595.214
Education                 0.0140    117.153      0.000      1.000    -229.601     229.629
Regular_salary_earner     0.1640   1124.052      0.000      1.000   -2202.938    2203.266
============================================================================================

Complete Separation: The results show that there iscomplete separation or perfect prediction.
In this case the Maximum Likelihood Estimator does not exist and the parameters
are not identified.
```

7. Results – R Programming

```
> # Print the summary of the model
> summary(probit_model)

Call:
glm(formula = is_non_vegetarian ~ ., family = binomial(link = "probit"),
    data = data_subset)

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)          -6.991e+00  2.182e+03  -0.003    0.997
hhdsz                -3.439e-15  1.182e+02   0.000    1.000
Religion              2.412e-14  2.218e+02   0.000    1.000
Social_Group          1.147e-14  8.274e+01   0.000    1.000
Type_of_land_owned    1.026e-13  5.107e+02   0.000    1.000
Land_Owned            5.796e-19  1.439e-01   0.000    1.000
MPCE_URP             -3.098e-18  5.893e-02   0.000    1.000
Age                  -1.223e-15  2.004e+01   0.000    1.000
Sex                   7.044e-14  8.418e+02   0.000    1.000
Education             4.588e-17  7.770e+01   0.000    1.000
Regular_salary_earner 1.937e-13  6.006e+02   0.000    1.000

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 0.0000e+00  on 87154  degrees of freedom
Residual deviance: 2.3749e-07  on 87144  degrees of freedom
AIC: 22

Number of Fisher Scoring iterations: 25
```

8. Recommendations

Based on the analysis, the following recommendations are made:

1. **Data Review**: Conduct a thorough review of the dataset to identify any anomalies or issues that might cause complete separation.
2. **Model Diagnostics**: Perform additional diagnostics to understand why the model exhibits complete separation and address potential data problems.
3. **Alternative Models**: Consider using logistic regression or regularization techniques to handle separation issues.
4. **Feature Engineering**: Explore additional relevant features that could potentially impact dietary choices.
5. **Data Collection**: Gather more data to enhance the robustness of the model and improve predictive accuracy.

9. Characteristics of the Probit Model:

1. **Normal Distribution Assumption**:
    - The probit model assumes that the error terms follow a normal distribution. This assumption can be more appropriate than the logistic distribution in certain contexts, especially when the underlying latent variable is normally distributed.
2. **Link Function**:
    - The probit model uses the cumulative distribution function (CDF) of the standard normal distribution as its link function. This means that the model relates the predictors linearly to the z-scores of the normal distribution.
3. **Latent Variable Framework**:
    - The probit model operates under the assumption of an underlying continuous latent variable. This latent variable is a linear combination of the predictors plus a normally distributed error term. The observed binary outcome is derived from this latent variable.
4. **Binary Outcomes**:
    - The probit model is designed specifically for binary outcome variables. It models the probability that the binary outcome equals one as a function of the predictors.
5. **Interpretation of Coefficients**:
    - The coefficients in a probit model represent the change in the z-score of the latent variable for a one-unit change in the predictor variable. These coefficients are not directly interpretable as probabilities but can be transformed to understand the impact on the probability scale.

10. Advantages of the Probit Model:

1. **Appropriate for Binary Dependent Variables**:
    - Like logistic regression, the probit model is well-suited for binary dependent variables, making it useful for classification problems.
2. **Normality Assumption**:
    - The assumption of normally distributed errors can be more suitable for certain datasets, leading to potentially better model performance in those cases compared to logistic regression, which assumes a logistic distribution.
3. **Flexibility in Extensions**:
    - Probit models can be extended to handle ordinal and multinomial outcomes, providing flexibility for various types of dependent variables. For instance, ordered probit models are used for ordinal response variables, and multinomial probit models are used for multi-category response variables.
4. **Handling of Latent Variables**:
    - The probit model's framework allows for a natural handling of latent variables, which can be beneficial in psychological, sociological, and economic studies where latent constructs are often modeled.

5. **Robustness to Outliers**:
    - Due to the cumulative normal distribution used in the link function, probit models can be less sensitive to outliers in the predictor variables compared to other models.
6. **Comparative Performance**:
    - In certain cases, the probit model can provide better predictive performance compared to logistic regression, particularly when the normal distribution assumption holds true for the underlying data.

11. Conclusion

The probit regression analysis aimed at identifying non-vegetarians based on demographic and socio-economic factors revealed significant issues with model convergence and complete separation. None of the predictors were significant, suggesting that either the model is not suitable for this dataset or there are underlying data issues that need to be addressed. Further investigation and potential alternative modeling approaches are recommended to obtain more reliable insights into the factors influencing dietary choices. By addressing these issues, businesses can better understand and cater to the dietary preferences of their target audience.

PART C - PERFORMING TOBIT REGRESSION ANALYSIS ON NSSO68 DATASET

1. Introduction

This project involves the analysis of a dataset using a Tobit regression model. The Tobit model is particularly suitable for datasets with censored data, where the dependent variable is limited or censored at a certain value. The objective is to understand the relationship between household expenditure and various socio-economic factors.

2. About the Dataset

The dataset used in this analysis is the NSSO68 dataset. It contains information on various household characteristics and their monthly per capita expenditure (MPCE). Key variables include household size (`hhdsz`), age of the head of the household (`Age`), gender of the head of the household (`Sex`), and education level (`Education`).

3. Objectives

The primary objective of this analysis is to:

- Examine the factors influencing household expenditure.
- Utilize the Tobit model to account for censored data.
- Interpret the results to provide meaningful insights into household spending behaviour.

4. Business Scope

- Understanding the determinants of household expenditure can help policymakers and businesses in formulating strategies to address economic disparities and target interventions more effectively.
- It can also assist in predicting consumer behavior and tailoring products and services to meet the needs of different demographic groups.

5. Interpretations

Data Preprocessing

- **Missing Values**: The dataset was checked for missing values, and appropriate measures were taken to handle them.
- **Variables Selection**: The dependent variable is `MPCE_URP` (Monthly Per Capita Expenditure). The independent variables are `hhdsz` (household size), `Age`, `Sex`, and `Education`.

- The Tobit model was defined with left censoring at 0, considering that expenditure cannot be negative.
- The regression analysis provided estimates for the impact of each independent variable on the household expenditure.

Final Interpretation:

- Household size negatively affects expenditure, indicating that larger households tend to spend less per capita.
- Age has a positive impact, suggesting that older heads of households tend to spend more.
- Gender shows a significant negative coefficient, indicating that households headed by females spend less.
- Education has a strong positive effect, showing that higher education levels are associated with higher expenditure.

6. Results – Python

```
# Choosing dependent and independent variables
dependent_var = 'MPCE_URP'
independent_vars = ['hhdsz', 'Age', 'Sex', 'Education']

# Prepare the data for regression
X = df[independent_vars]
y = df[dependent_var]
```

```python
# Define Tobit model
class TobitModel(GenericLikelihoodModel):
    def __init__(self, endog, exog, left=None, right=None, **kwargs):
        self.left = left
        self.right = right
        super(TobitModel, self).__init__(endog, exog, **kwargs)

    def nloglikeobs(self, params):
        exog = self.exog
        endog = self.endog
        left = self.left
        right = self.right

        beta = params[:-1]
        sigma = params[-1]
        XB = np.dot(exog, beta)

        ll = np.zeros(len(endog))

        if left is not None:
            cdf_left = (endog <= left).astype(int)
            ll += cdf_left * np.log(1 - norm.cdf((left - XB) / sigma))

        if right is not None:
            cdf_right = (endog >= right).astype(int)
            ll += cdf_right * np.log(norm.cdf((right - XB) / sigma))

        uncensored = np.ones(len(endog), dtype=bool)
        if left is not None:
            uncensored &= (endog > left)
        if right is not None:
            uncensored &= (endog < right)
```

Loading...

```python
# Set left censoring at 0 (lower bound)
left_censoring = 0

# Fit the Tobit model
model = TobitModel(y, X, left=left_censoring)
results = model.fit()
```

```
Optimization terminated successfully.
         Current function value: 9.750560
         Iterations: 716
         Function evaluations: 1151
```

```
# Print the summary of the regression results
print(results.summary())
```

```
                          TobitModel Results
==============================================================================
Dep. Variable:                MPCE_URP   Log-Likelihood:            -9.9119e+05
Model:                      TobitModel   AIC:                         1.982e+06
Method:           Maximum Likelihood   BIC:                         1.982e+06
Date:                Mon, 01 Jul 2024
Time:                        11:26:13
No. Observations:              101655
Df Residuals:                  101650
Df Model:                           4
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -19.3490     74.697     -0.259      0.796    -165.752     127.055
hhdsz         25.5786      6.143      4.164      0.000      13.539      37.619
Age           17.8512      0.993     17.971      0.000      15.904      19.798
Sex         -209.4316     41.586     -5.036      0.000    -290.938    -127.925
Education    205.3540      3.627     56.614      0.000     198.245     212.463
par0        4154.2824      9.397    442.102      0.000    4135.865    4172.699
==============================================================================
```

7. Results – R programming

```
# Print the summary of the regression results
print(results.summary())
```

```
                          TobitModel Results
==============================================================================
Dep. Variable:                MPCE_URP   Log-Likelihood:            -9.9119e+05
Model:                      TobitModel   AIC:                         1.982e+06
Method:           Maximum Likelihood   BIC:                         1.982e+06
Date:                Sun, 30 Jun 2024
Time:                        09:13:00
No. Observations:              101655
Df Residuals:                  101650
Df Model:                           4
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const        -19.3490     74.697     -0.259      0.796    -165.752     127.055
hhdsz         25.5786      6.143      4.164      0.000      13.539      37.619
Age           17.8512      0.993     17.971      0.000      15.904      19.798
Sex         -209.4316     41.586     -5.036      0.000    -290.938    -127.925
Education    205.3540      3.627     56.614      0.000     198.245     212.463
par0        4154.2824      9.397    442.102      0.000    4135.865    4172.699
==============================================================================
```

Coefficients:

- const: Intercept, indicating baseline expenditure when predictors are zero.
- hhdsz, Age, Education: Positive coefficients suggest these factors increase expenditure.
- Sex: Negative coefficient indicates it decreases expenditure.
- par0: Parameter affecting the model's scale, influencing variability.

Each coefficient's P-value (< 0.05 indicates significance) and confidence intervals assess their reliability. The model links household characteristics to expenditure, crucial for understanding economic dynamics in consumption patterns.

```
> # Extract results
> coefficients <- fit$par[1:(length(fit$par)-1)]
> sigma <- fit$par[length(fit$par)]
> logLik <- -fit$value
> cat("Coefficients:", coefficients, "\n")
Coefficients: 1.168412 1.817436 -0.9596489
> cat("Sigma:", sigma, "\n")
Sigma: 0.9679188
> cat("Log-Likelihood:", logLik, "\n")
Log-Likelihood: -117.9526
```

- The coefficients extracted (1.168412, 1.817436, -0.9596489) represent the estimated values for the parameters in the Tobit model. Each coefficient corresponds to a predictor variable in the model.
- The value 0.9679188 represents the estimated standard deviation parameter (sigma) in the Tobit model. It characterizes the variability in the unobserved latent variable affecting the censored observations.
- The negative log-likelihood value -117.9526 indicates the overall goodness of fit of the Tobit model to the data. A lower value suggests a better fit, reflecting how well the model's predictions align with the observed data, considering the censoring mechanism.

8. Recommendations

- **Policy Interventions**: Target larger households with financial aid programs as they tend to have lower per capita expenditure.

- **Focus on Education**: Promote educational programs as higher education correlates with higher household expenditure, which could lead to better economic well-being.
- **Gender-Specific Programs**: Develop support systems for female-headed households to address the lower expenditure patterns.

9. Real-World Use Cases of the Tobit Model

The Tobit model, also known as the censored regression model, is used in situations where the dependent variable is either censored or truncated. This model is particularly useful when the outcome variable has a significant number of observations clustered at a limit or threshold value. Below are some real-world use cases where the Tobit model is commonly applied:

1. Economics and Finance

- **Expenditure Data**:
  - **Consumer Expenditure**: When analyzing household expenditure on durable goods, there might be many households with zero expenditure because they did not purchase those goods during the survey period. The Tobit model can handle this censoring and provide accurate estimates.
  - **Investment Decisions**: In corporate finance, companies might not invest in certain projects if expected returns do not exceed a threshold. The Tobit model can help analyze such investment behaviors.
- **Labor Economics**:
  - **Wages and Salaries**: In studies of wage determination, there may be a minimum wage or a reporting threshold below which wages are not observed. The Tobit model can adjust for this censoring.
  - **Unemployment Duration**: For individuals not in the labor force, the duration of unemployment spells can be censored at zero, as they never actually searched for a job. The Tobit model can analyze the factors affecting unemployment duration under such censoring.

2. Health Economics

- **Healthcare Utilization**:
  - **Medical Expenditures**: Analysis of individual healthcare spending often encounters zero expenditures for those who did not utilize healthcare services. The Tobit model is suitable for studying such data to understand factors influencing healthcare utilization.
  - **Health Outcomes**: When studying the effect of treatments on health outcomes, the measurements might be censored at zero for patients with no observed improvement. The Tobit model can analyze the impact of treatments while accounting for this censoring.

3. Agricultural Economics

- **Crop Yield Analysis**:
  - **Fertilizer Use**: In analyzing the impact of fertilizer use on crop yields, there might be farms that do not use any fertilizer, resulting in zero expenditure on fertilizer. The Tobit model can be used to understand the relationship between fertilizer use and crop yield while considering the zero-expenditure cases.
  - **Irrigation Practices**: Similar to fertilizer use, irrigation practices might have zero observations for farms that do not irrigate. The Tobit model helps in analyzing the factors affecting irrigation and its impact on crop yields.

4. Marketing and Consumer Behavior

- **Consumer Purchases**:
  - **Product Demand**: When studying the demand for a product, there might be many consumers who do not purchase the product at all, resulting in zero demand observations. The Tobit model can handle such censoring and provide insights into factors influencing product demand.
  - **Advertising Impact**: Analysis of the effect of advertising expenditure on sales might encounter firms with zero advertising spend. The Tobit model can be used to study the relationship between advertising and sales, considering the censored data.

5. Environmental Economics

- **Pollution and Environmental Policy**:
  - **Emission Levels**: In studies of industrial emissions, some firms might have emission levels below a detectable threshold, resulting in censored data. The Tobit model can be used to analyze the factors affecting emission levels and the impact of environmental policies.
  - **Resource Usage**: Analysis of water or energy consumption might encounter zero usage for certain households or firms. The Tobit model helps in understanding the determinants of resource usage under such censoring.

The Tobit model is highly versatile and applicable across various fields where the dependent variable is subject to censoring. Its ability to handle censored data makes it invaluable for accurate and meaningful analysis in economics, health, agriculture, marketing, and environmental studies. By properly accounting for the censored observations, the Tobit model provides better insights into the underlying relationships and factors affecting the dependent variable in these real-world scenarios.

10. Conclusion

This analysis highlights the key factors influencing household expenditure using the Tobit model. Household size, age, gender, and education significantly impact spending patterns. These insights can inform policy decisions and business strategies aimed at improving economic conditions and catering to diverse demographic needs.