VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A3b: Limited Dependent Variable Models:

Probit Regression Analysis

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CONTENTS

Introduction

This report's goal is to use information from the 68th round of the National Sample Survey Office (NSSO) to discover variables related to eating practices that are not vegetarian. The purpose of this analysis is to comprehend how socioeconomic and demographic factors affect dietary preferences, particularly the probability that a person will not follow a vegetarian diet.
A probit regression model is used to do this. The probit model offers a strong framework for evaluating the likelihood of an event occurring based on several predictor variables, making it a good fit for binary outcome variables. The event of interest in this case is whether or not a person is not vegetarian.

Objectives :

- Identify factors influencing non-vegetarian dietary habits
- Apply probit regression to model and analyze the probability of individuals being non-vegetarian
- Provide insights for public health and policy interventions
- Evaluate model performance and applicability
- Educate stakeholders and decision makers
- Contribute to scientific understanding
- Provide recommendations for future research and data collection

Business Significance :

There are important economic ramifications from the study on utilizing probit regression to identify non-vegetarians in the "NSSO68.csv" dataset, especially in the fields of consumer behavior, nutrition, and health. It offers market segmentation and consumer information, allowing companies to customize their marketing plans and create goods that cater exclusively to non-vegetarian customers. Public health policymakers can utilize this information to create focused initiatives geared at lowering health disparities and improving nutritional outcomes, while health professionals and nutritionists can use it to provide individualized dietary advice and interventions.
By aligning product offers and marketing messages with non-vegetarian preferences, company

strategy modifications, risk management, and competitive advantage can all contribute to strategic decision-making. Customizing goods and services to fulfill the demands of particular clients boosts client happiness and loyalty, which may lead to an increase in market share and profitability.

Opportunities for research and development come from creating novel ingredients or formulations, encouraging innovation in food technology, and learning about customer preferences for non-vegetarian diets. Research institutes, corporations, and public health organizations can work together to investigate new developments in eating practices.

Since knowledge of consumer preferences for non-vegetarian diets can inform sustainable practices in agriculture, food production, and resource management, ethical and social responsibility are also significant components of the report. Companies can significantly impact community well-being and public health results by coordinating their CSR programs with nutrition and health goals. The report's overall significance stems from its capacity to offer practical insights into consumer behavior concerning non-vegetarian dietary habits, augmenting market responsiveness, refining product offerings, and advancing societal well-being via strategic initiatives and well-informed decision-making.

Results and Interpretation using R

- **Create a binary variable for non-vegetarian status using dplyr pipeline, selecting relevant variables for the probit model and handling missing values**

```
> # Create a binary variable for non-vegetarian status using dplyr pipelin
e
> data <- data %>%
+   mutate(non_veg = case_when(
+     eggsno_q > 0 ~ 1,
+     fishprawn_q > 0 ~ 1,
+     goatmeat_q > 0 ~ 1,
+     beef_q > 0 ~ 1,
+     pork_q > 0 ~ 1,
+     chicken_q > 0 ~ 1,
+     othrbirds_q > 0 ~ 1,
+     TRUE ~ 0
+   ))
> # Select relevant variables for the probit model and handle missing valu
es
> data_clean <- data %>%
+   select(non_veg, Age, Sex, hhdsz, Religion, Education, MPCE_URP, state,
State_Region) %>%
+   filter_all(all_vars(!is.na(.)))
```

Interpretation:

Categorical data on food consumption can be converted into a binary indication that is appropriate for modeling dietary patterns by introducing the non_veg variable. Making sure that only complete and appropriate data are used for further analysis involves handling missing values and choosing pertinent variables. Code readability and repeatability are guaranteed and efficient data processing is facilitated by the usage of the dplyr pipeline (%>%). Using programs like glm or brglm, you can fit a probit model after preparing the data as instructed. Based on the chosen variables, this model will assist us in analyzing the factors impacting eating habits of non-vegetarians.

- **Converting categorical variables to factors and fitting the probit regression model using the glm function**

```
# Convert categorical variables to factors
> data_clean <- data_clean %>%
+   mutate(
+     Sex = as.factor(Sex),
+     Religion = as.factor(Religion),
+     state = as.factor(state),
+     State_Region = as.factor(State_Region)
```

```
+   )
# Fit the probit regression model using the glm function
> probit_model <- glm(non_veg ~ Age + Sex + hhdsz + Religion + Educatio
n + MPCE_URP + state + State_Region,
+                     data = data_clean, family = binomial(link = "prob
it"))
# Summarize the model
> summary(probit_model)

Call:
glm(formula = non_veg ~ Age + Sex + hhdsz + Religion + Education +
    MPCE_URP + state + State_Region, family = binomial(link = "probit")
,
    data = data_clean)

Coefficients: (34 not defined because of singularities)
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -2.014e-02  5.345e-02  -0.377 0.706315
Age             -4.831e-03  3.843e-04 -12.569  < 2e-16 ***
Sex2            -2.399e-01  1.623e-02 -14.780  < 2e-16 ***
hhdsz            7.275e-02  2.428e-03  29.968  < 2e-16 ***
Religion2        1.278e+00  2.139e-02  59.745  < 2e-16 ***
Religion3        5.379e-01  3.750e-02  14.342  < 2e-16 ***
Religion4       -7.938e-02  4.141e-02  -1.917 0.055227 .
Religion5       -1.985e+00  1.450e-01 -13.691  < 2e-16 ***
Religion6        8.171e-01  6.216e-02  13.145  < 2e-16 ***
Religion7       -4.675e-01  7.802e-01  -0.599 0.549079
Religion9        3.624e-01  8.478e-02   4.274 1.92e-05 ***
Education       -3.436e-02  1.450e-03 -23.702  < 2e-16 ***
MPCE_URP         3.411e-06  1.590e-06   2.145 0.031958 *
state2           2.444e-01  6.288e-02   3.886 0.000102 ***
state3          -7.275e-01  6.359e-02 -11.441  < 2e-16 ***
state4          -2.332e-01  8.912e-02  -2.617 0.008875 **
state5           2.412e-01  5.704e-02   4.228 2.36e-05 ***
state6          -1.437e+00  8.070e-02 -17.803  < 2e-16 ***
state7           2.996e-02  6.392e-02   0.469 0.639273
state8          -1.085e+00  7.148e-02 -15.181  < 2e-16 ***
state9          -5.993e-01  5.658e-02 -10.593  < 2e-16 ***
state10          3.362e-01  5.673e-02   5.927 3.08e-09 ***
state11          1.067e+00  7.711e-02  13.840  < 2e-16 ***
state12          1.706e+00  8.343e-02  20.455  < 2e-16 ***
state13          2.587e+00  2.334e-01  11.083  < 2e-16 ***
state14          1.473e+00  1.087e-01  13.554  < 2e-16 ***
state15          2.480e+00  1.732e-01  14.318  < 2e-16 ***
state16          2.179e+00  8.154e-02  26.720  < 2e-16 ***
state17          1.765e+00  1.007e-01  17.536  < 2e-16 ***
state18          1.934e+00  1.102e-01  17.546  < 2e-16 ***
state19          1.993e+00  8.729e-02  22.825  < 2e-16 ***
state20          5.885e-01  6.028e-02   9.763  < 2e-16 ***
state21          1.321e+00  6.704e-02  19.710  < 2e-16 ***
state22          6.486e-01  8.419e-02   7.704 1.32e-14 ***
state23         -6.435e-01  7.334e-02  -8.775  < 2e-16 ***
state24         -1.121e+00  7.212e-02 -15.540  < 2e-16 ***
state25          1.248e+00  1.505e-01   8.292  < 2e-16 ***
state26          1.416e-01  1.040e-01   1.362 0.173237
state27          6.161e-01  7.809e-02   7.889 3.05e-15 ***
state28          1.055e+00  6.507e-02  16.208  < 2e-16 ***
state29         -7.753e-02  5.725e-02  -1.354 0.175618
state30          1.445e+00  9.717e-02  14.869  < 2e-16 ***
state31          6.500e-01  1.611e-01   4.034 5.49e-05 ***
```

```
state32          1.468e+00  6.087e-02  24.113  < 2e-16 ***
state33          1.011e+00  5.980e-02  16.914  < 2e-16 ***
state34          1.376e+00  8.348e-02  16.477  < 2e-16 ***
state35          1.655e+00  9.827e-02  16.841  < 2e-16 ***
State_Region12  -5.617e-02  7.013e-02  -0.801 0.423194
State_Region13   1.218e+00  1.060e-01  11.489  < 2e-16 ***
State_Region14   1.263e+00  2.763e-01   4.572 4.84e-06 ***
State_Region21  -2.533e-01  5.669e-02  -4.468 7.89e-06 ***
State_Region22          NA         NA      NA       NA
State_Region31   2.654e-01  5.112e-02   5.191 2.09e-07 ***
State_Region32          NA         NA      NA       NA
State_Region41          NA         NA      NA       NA
State_Region51          NA         NA      NA       NA
State_Region61   7.027e-01  7.396e-02   9.502  < 2e-16 ***
State_Region62          NA         NA      NA       NA
State_Region71          NA         NA      NA       NA
State_Region81  -2.246e-01  8.054e-02  -2.788 0.005297 **
State_Region82   1.821e-01  6.605e-02   2.757 0.005827 **
State_Region83   4.674e-01  8.365e-02   5.587 2.31e-08 ***
State_Region84   3.237e-01  8.299e-02   3.900 9.61e-05 ***
State_Region85          NA         NA      NA       NA
State_Region91   2.146e-01  4.788e-02   4.482 7.41e-06 ***
State_Region92   1.821e-01  4.729e-02   3.851 0.000117 ***
State_Region93   3.665e-01  3.700e-02   9.905  < 2e-16 ***
State_Region94   4.826e-01  6.152e-02   7.844 4.36e-15 ***
State_Region95          NA         NA      NA       NA
State_Region101  4.630e-01  4.158e-02  11.135  < 2e-16 ***
State_Region102         NA         NA      NA       NA
State_Region111         NA         NA      NA       NA
State_Region121         NA         NA      NA       NA
State_Region131         NA         NA      NA       NA
State_Region141  9.655e-01  1.281e-01   7.534 4.92e-14 ***
State_Region142         NA         NA      NA       NA
State_Region151         NA         NA      NA       NA
State_Region161         NA         NA      NA       NA
State_Region171         NA         NA      NA       NA
State_Region181 -1.643e-01  1.233e-01  -1.333 0.182630
State_Region182  5.136e-02  1.281e-01   0.401 0.688446
State_Region183 -1.294e-01  1.423e-01  -0.910 0.362876
State_Region184         NA         NA      NA       NA
State_Region191  1.529e-01  1.365e-01   1.120 0.262770
State_Region192  2.235e-02  1.043e-01   0.214 0.830275
State_Region193 -4.395e-01  8.618e-02  -5.100 3.39e-07 ***
State_Region194 -4.057e-01  9.002e-02  -4.507 6.56e-06 ***
State_Region195         NA         NA      NA       NA
State_Region201  1.666e-01  5.562e-02   2.995 0.002746 **
State_Region202         NA         NA      NA       NA
State_Region211  2.074e-01  6.710e-02   3.091 0.001996 **
State_Region212 -2.204e-01  6.158e-02  -3.579 0.000345 ***
State_Region213         NA         NA      NA       NA
State_Region221  5.665e-01  1.217e-01   4.657 3.21e-06 ***
State_Region222 -3.483e-01  7.650e-02  -4.553 5.28e-06 ***
State_Region223         NA         NA      NA       NA
State_Region231  4.890e-01  7.022e-02   6.964 3.31e-12 ***
State_Region232  6.899e-02  7.628e-02   0.905 0.365707
State_Region233  1.990e-01  6.907e-02   2.881 0.003967 **
State_Region234  5.052e-01  7.142e-02   7.073 1.51e-12 ***
State_Region235  6.281e-01  7.759e-02   8.096 5.69e-16 ***
State_Region236         NA         NA      NA       NA
State_Region241  8.386e-01  6.565e-02  12.773  < 2e-16 ***
```

```
State_Region242  2.406e-01  7.264e-02   3.313 0.000925 ***
State_Region243  2.411e-01  1.113e-01   2.166 0.030322 *
State_Region244  7.419e-02  1.652e-01   0.449 0.653290
State_Region245         NA         NA      NA       NA
State_Region251         NA         NA      NA       NA
State_Region261         NA         NA      NA       NA
State_Region271  5.074e-02  6.919e-02   0.733 0.463298
State_Region272 -1.506e-01  6.843e-02  -2.201 0.027721 *
State_Region273 -5.623e-01  7.456e-02  -7.541 4.65e-14 ***
State_Region274 -7.695e-01  7.119e-02 -10.809  < 2e-16 ***
State_Region275 -5.138e-01  7.121e-02  -7.215 5.38e-13 ***
State_Region276         NA         NA      NA       NA
State_Region281  3.281e-01  6.164e-02   5.323 1.02e-07 ***
State_Region282  1.084e-01  6.213e-02   1.745 0.081044 .
State_Region283  2.982e-01  5.974e-02   4.993 5.96e-07 ***
State_Region284  6.408e-01  7.566e-02   8.469  < 2e-16 ***
State_Region285         NA         NA      NA       NA
State_Region291  9.428e-01  8.122e-02  11.608  < 2e-16 ***
State_Region292  1.203e+00  8.058e-02  14.927  < 2e-16 ***
State_Region293  7.774e-01  4.751e-02  16.363  < 2e-16 ***
State_Region294         NA         NA      NA       NA
State_Region301         NA         NA      NA       NA
State_Region311         NA         NA      NA       NA
State_Region321  8.915e-02  6.154e-02   1.449 0.147432
State_Region322         NA         NA      NA       NA
State_Region331  1.110e-01  4.908e-02   2.262 0.023711 *
State_Region332  7.012e-02  5.534e-02   1.267 0.205176
State_Region333  3.248e-01  5.302e-02   6.125 9.08e-10 ***
State_Region334         NA         NA      NA       NA
State_Region341         NA         NA      NA       NA
State_Region351         NA         NA      NA       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 128251  on 101651  degrees of freedom
Residual deviance:  83536  on 101552  degrees of freedom
AIC: 83736

Number of Fisher Scoring iterations: 7
```

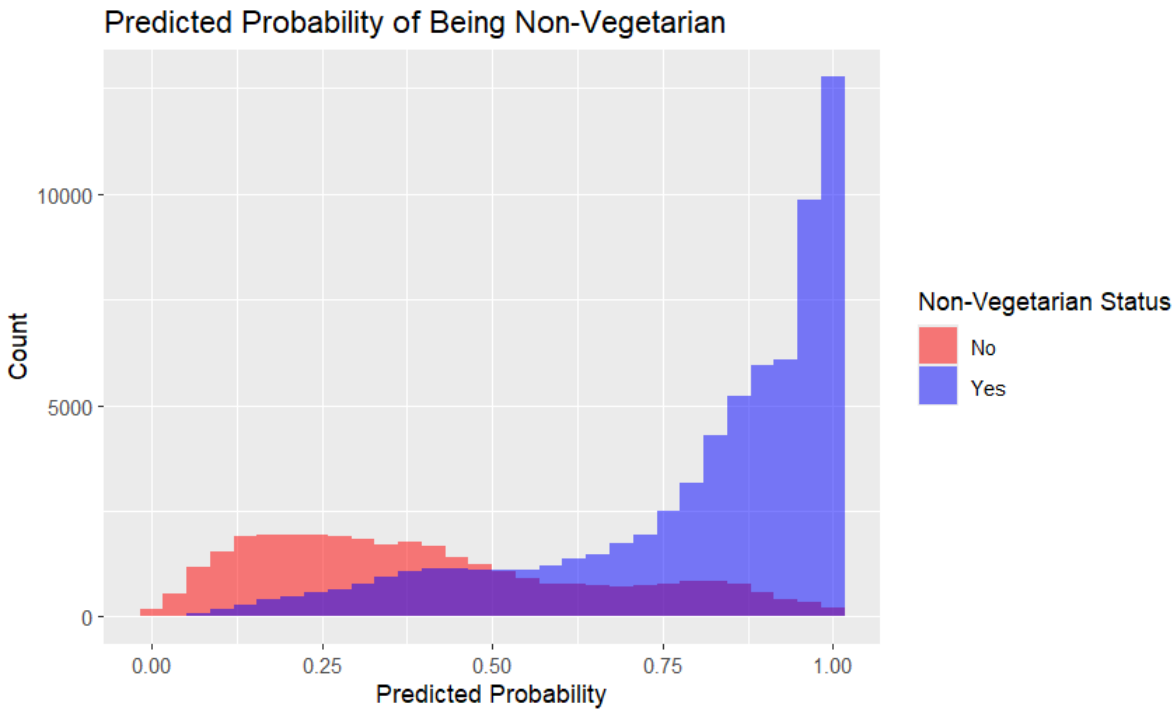
Interpretation:

The results of the probit regression model offer important information on the variables affecti ng a person's dietary status if they are not vegetarian. The estimated log-odds of not becoming a vegetarian when all other variables are zero are represented by the intercept. When other fac tors are taken into account, there is no indication of a non-vegetarian baseline in this instance ($p = 0.706$), which suggests that it is not statistically significant. The log-odds of not being ve getarian rise by -0.0048 ($p < 0.001$) for each unit increase in age. This implies that the likeliho od of non-vegetarianism is higher among younger people. In comparison to females (coded as 1), males (coded as 2) have a lower log-odds of being non-vegetarian by -0.2399 ($p < 0.001$).

The log-odds of not being a vegetarian rise by 0.0728 ($p < 0.001$) for every unit increase in household size. Higher education levels result in a -0.0344 ($p < 0.001$) drop in the log-odds of not becoming a vegetarian. The log-odds of not being vegetarian rise by 0.00000341 ($p = 0.032$) for every unit increase in MPCE_URP, which is apparently an indicator of economic status. Different geographic regions are represented by State and State_Region. According to a reference state or region, each level shows how living in a particular state or region influences the log-odds of not becoming a vegetarian. The model is compared to an intercept-only model (a model without any predictors) using the deviance goodness-of-fit test. Better model fit is indicated by a lower null deviation. The fitted model and the saturated model (perfect fit) are compared using residual deviance. A smaller residual deviation indicates that the model fits the data better. AIC is applied while choosing a model. A better trade-off between model complexity and goodness of fit is indicated by lower AIC values. A thorough grasp of the ways in which demographic, socioeconomic, and geographic factors affect the probability of not becoming a vegetarian is provided by this probit regression model. It highlights the major factors (MPCE_URP) that influence dietary patterns, including age, sex, family size, religion, education, and economic position. These data can be used by companies, legislators, and medical experts to create customized plans, focus interventions, and encourage healthier eating habits across various demographic groups.

- **Make predictions and visualize the results**

```
# Make predictions
> data_clean <- data_clean %>%
+   mutate(predicted_prob = predict(probit_model, type = "response"))
> # Visualize the results
> ggplot(data_clean, aes(x = predicted_prob, fill = as.factor(non_veg))
) +
+   geom_histogram(position = "identity", alpha = 0.5, bins = 30) +
+   labs(title = "Predicted Probability of Being Non-Vegetarian", x = "
Predicted Probability", y = "Count") +
+   scale_fill_manual(values = c("1" = "blue", "0" = "red"), name = "No
n-Vegetarian Status", labels = c("No", "Yes"))
```



Interpretation:

Based on the traits that the model was able to capture, the predicted probabilities show how li kely it was that a certain person would not be vegetarian. The expected probabilities are binne d by the histogram. The expected probability values are plotted on the x-axis. The number of people falling into each anticipated probability category is displayed on the y-axis. Blue is the color of non-vegetarians (non_veg = 1). Red is assigned to vegetarians (non_veg = 0). As per the histogram, the majority of them do not follow a vegetarian diet.

Results and Interpretation using Python

- **Fitting the probit regression model**

```
# Add a constant term for the intercept
# Define dependent variable (y) and independent variables (X)
y = df1['NV']
X = df1[['HH_type', 'Religion', 'Social_Group', 'Regular_salary_earner',
         'Possess_ration_card', 'Sex', 'Age', 'Marital_Status', 'Educatio
n',
         'Meals_At_Home', 'Region', 'hhdsz', 'NIC_2008', 'NCO_2004']]

# Assuming X is your DataFrame containing the independent variables
X['Social_Group'] = X['Social_Group'].astype('category')
X['Regular_salary_earner'] = X['Regular_salary_earner'].astype('category')
X['HH_type'] = X['HH_type'].astype('category')
X['Possess_ration_card'] = X['Possess_ration_card'].astype('category')
X['Sex'] = X['Sex'].astype('category')
X['Marital_Status'] = X['Marital_Status'].astype('category')
X['Education'] = X['Education'].astype('category')
X['Region'] = X['Region'].astype('category')

X= sm.add_constant(X)

# Fit the probit regression model
probit_model = Probit(y, X).fit()

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

```
Optimization terminated successfully.
         Current function value: 0.589533
         Iterations 5
                          Probit Regression Results
==============================================================================
Dep. Variable:                     NV   No. Observations:                93096
Model:                         Probit   Df Residuals:                    93081
Method:                           MLE   Df Model:                           14
Date:                Wed, 03 Jul 2024   Pseudo R-squ.:                 0.05196
Time:                        23:36:13   Log-Likelihood:                -54883.
converged:                       True   LL-Null:                       -57891.
Covariance Type:            nonrobust   LLR p-value:                     0.000
=====================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
const             0.0501      0.056      0.902      0.367      -0.059       0.159
HH_type           0.0174      0.004      4.677      0.000       0.010       0.025
Religion          0.1878      0.005     37.169      0.000       0.178       0.198
Social_           0.0464      0.001    -32.205      0.000      -0.049      -0.044
Group
Regular_          -0.0321     0.011     -2.904      0.004      -0.054      -0.010
_salary
_earner
Possess           0.0222      0.012      1.897      0.058      -0.001       0.045
_ration
```

```
_card
Sex     -0.0262      0.020     -1.305      0.192      -0.065       0.013
Age     -0.0020      0.000     -5.265      0.000      -0.003      -0.001
Marital-0.0228       0.016     -1.438      0.150      -0.054       0.008
_Status
Educati-0.0127       0.001     -8.534      0.000      -0.016      -0.010
Meals_   0.0103      0.000     36.460      0.000       0.010       0.011
At_Home
Region -0.0789       0.003    -23.916      0.000      -0.085      -0.072
hhdsz   -0.0070      0.002     -3.342      0.001      -0.011      -0.003
NIC_    2.4e-06   1.81e-07     13.247      0.000    2.05e-06    2.76e-06
2008
NCO_ 6.919e-05    2.17e-05      3.196      0.001    2.68e-05       0.000
2004
==============================================================================
```

Interpretation:

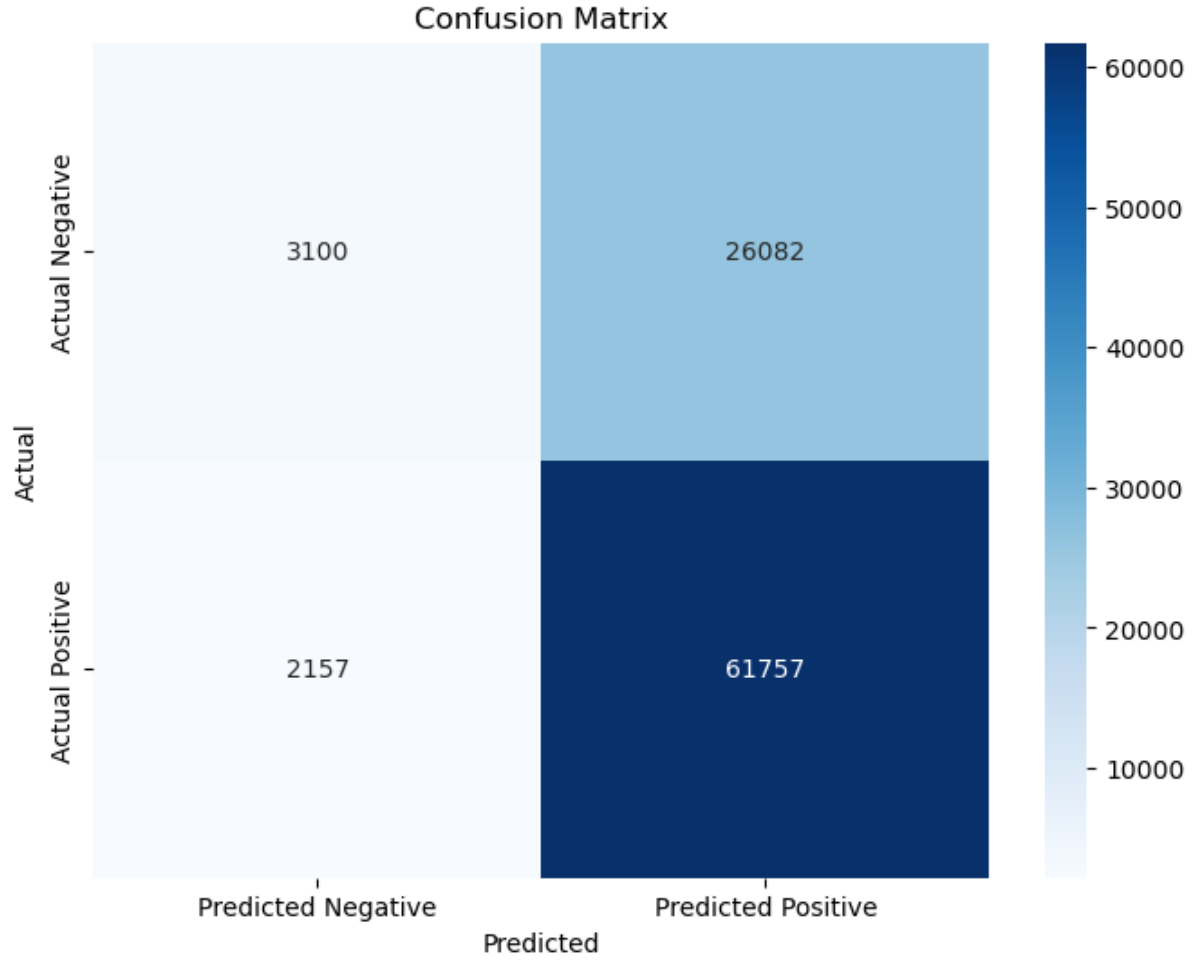
In order to predict non-vegetarian status, the study evaluated 93,096 observations and employed a Probit regression model. With a pseudo-R-squared of 0.05196 and a log-likelihood of -57,891, the model fit was -54,883. When all other variables were held constant, the coefficients showed the estimated impact of an independent variable on the likelihood of not becoming a vegetarian. When all independent factors were zero, the baseline probability of not being a vegetarian was 0.0501. With p-values less than 0.05, HH_type, Religion, Social_Group, Age, Education, Meals_At_Home, Region, hhdsz, NIC_2008, and NCO_2004 appear to have a significant effect on the likelihood of not being a vegetarian. Though more barely, regular_salary_earner also had a considerable impact on the likelihood. One illustration of the findings is that, when all else is equal, a one-year rise in age reduces the log odds of not being a vegetarian by 0.0020. People who belong to specific social groupings (represented by Social_Group) are 0.0464 more likely than people in the reference group to be non-vegetarians by log odds. Understanding the determinants of dietary choices within the examined population is aided by the results, which shed light on the factors influencing non-vegetarian status and assist quantify the direction and intensity of these associations.

- Printing confusion matrix and ROC curve for Logistic Regression

```
# Predict probabilities
predicted_probs = probit_model.predict(X)

# Convert probabilities to binary predictions using a threshold of 0.5
predicted_classes = (predicted_probs > 0.5).astype(int)

# Confusion Matrix
```

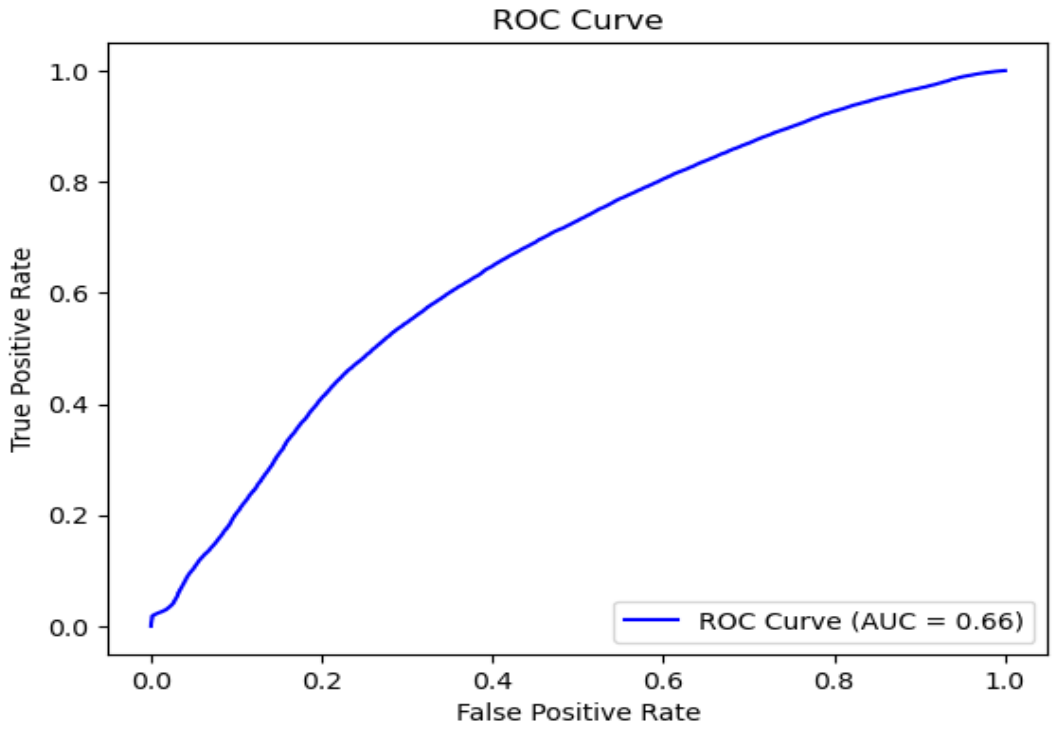
```
conf_matrix = confusion_matrix(y, predicted_classes)
conf_matrix_df = pd.DataFrame(conf_matrix, index=['Actual Negative', 'Actual
Positive'], columns=['Predicted Negative', 'Predicted Positive'])
print("Confusion Matrix:\n", conf_matrix_df)

# Plotting the Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_df, annot=True, fmt='d', cmap='Blues')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()
```

```
Confusion Matrix:
                  Predicted Negative  Predicted Positive
Actual Negative                3100               26082
Actual Positive                2157               61757
```




```
# ROC curve and AUC value
fpr, tpr, _ = roc_curve(y, predicted_probs)
auc_value = roc_auc_score(y, predicted_probs)
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC = {auc_value:.2f})')
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
print(f"AUC: {auc_value}")

# Accuracy, Precision, Recall, F1 Score
accuracy = accuracy_score(y, predicted_classes)
precision = precision_score(y, predicted_classes)
recall = recall_score(y, predicted_classes)
f1 = f1_score(y, predicted_classes)

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
```




```
AUC: 0.6624909652546589
Accuracy: 0.6966679556586749
Precision: 0.7030703901456073
Recall: 0.9662515254873737
F1 Score: 0.8139147166777593
```

Interpretation:

Evaluation measures and a confusion matrix were used to assess the probit regression model's performance. With an AUC of 0.66 suggesting a reasonable level of accuracy, the model demonstrated a moderate degree of discrimination skill in differentiating between non-vegetarians and vegetarians. 69.7% of the model's predictions were accurate, yielding an accuracy of 0.697. The accuracy rate of 70.3% was achieved in predicting the non-vegetarian status with a precision of 0.703. With a recall of 0.966, 96.6% of real non-vegetarians were identified accurately. With an F1 score of 0.814, recall and precision were well-balanced. Based on the given features, the model demonstrated a rather decent capacity to predict the non-vegetarian status with a high recall and reasonable precision. Nonetheless, the moderate AUC indicates that the discriminatory power of the model could be strengthened. The model's accuracy in categorizing vegetarians and non-vegetarians is broken down in depth in the confusion matrix. Enhancements or modifications to the model can concentrate on raising overall predicted accuracy and AUC.

Recommendations

After analysis, the probit regression model's strong points were found to be its moderate AUC and good recall for predicting non-vegetarian status. The model's overall capacity to discriminate may be strengthened, though. With a 70.3% accuracy rate in predicting non-vegetarian status, the model accurately predicts 69.7% of cases. It includes 96.6 percent of real non-vegetarians. The F1 score indicates strong overall performance by offering a balanced evaluation of recall and precision.

The distribution of true positives, false positives, false negatives, and false negatives is shown by the confusion matrix analysis, which sheds light on the model's advantages and disadvantages. We talk about the ROC curve and AUC, where 0.66 denotes a modest degree of discrimination skill.

To increase the discriminatory power of the model, it is suggested to investigate new characteristics or improve current ones. One can assess several criteria for binary classification in order to maximize the trade-off between recall and precision. Refinement procedures for models can involve feature engineering, regularization methods, or investigating alternative modeling algorithms such as gradient boosting or random forests.

The study concludes by summarizing the results and highlighting the applicability of the

model's ability to forecast non-vegetarian status. A summary of the model's present applicability and prospective future prospects for raising its predicted accuracy and dependability is provided at the end.

R Codes

```
# Load necessary libraries
library(readr)
library(dplyr)
library(ggplot2)
library(magrittr)

# Read the dataset
data <- read_csv("C:\\Users\\sayas\\OneDrive\\New folder\\python projects\\NSSO68.csv")

# Create a binary variable for non-vegetarian status using dplyr pipeline
data <- data %>%
  mutate(non_veg = case_when(
    eggsno_q > 0 ~ 1,
    fishprawn_q > 0 ~ 1,
    goatmeat_q > 0 ~ 1,
    beef_q > 0 ~ 1,
    pork_q > 0 ~ 1,
    chicken_q > 0 ~ 1,
    othrbirds_q > 0 ~ 1,
    TRUE ~ 0
  ))

# Select relevant variables for the probit model and handle missing values
data_clean <- data %>%
```

```
  select(non_veg, Age, Sex, hhdsz, Religion, Education, MPCE_URP, state, State_Region
) %>%
  filter_all(all_vars(!is.na(.)))

# Convert categorical variables to factors
data_clean <- data_clean %>%
  mutate(
    Sex = as.factor(Sex),
    Religion = as.factor(Religion),
    state = as.factor(state),
    State_Region = as.factor(State_Region)
  )

# Fit the probit regression model using the glm function
probit_model <- glm(non_veg ~ Age + Sex + hhdsz + Religion + Education + MPCE_UR
P + state + State_Region,
                    data = data_clean, family = binomial(link = "probit"))

# Summarize the model
summary(probit_model)

# Make predictions
data_clean <- data_clean %>%
  mutate(predicted_prob = predict(probit_model, type = "response"))

# Visualize the results
ggplot(data_clean, aes(x = predicted_prob, fill = as.factor(non_veg))) +
  geom_histogram(position = "identity", alpha = 0.5, bins = 30) +
  labs(title = "Predicted Probability of Being Non-Vegetarian", x = "Predicted Probabili
ty", y = "Count") +
  scale_fill_manual(values = c("1" = "blue", "0" = "red"), name = "Non-Vegetarian Sta
tus", labels = c("No", "Yes"))

# Save the plot
```

ggsave("predicted_probabilities.png", width = 8, height = 6)

Python Codes

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.discrete.discrete_model import Probit
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, accuracy_score, pr
ecision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns
import os

os.chdir("C:\\Users\\sayas\\OneDrive\\New folder\\python projects")

# Load the dataset
data = pd.read_csv('NSSO68.csv', encoding='Latin-1', low_memory=False)

# Display basic information about the dataset
print(data.info())
# Display first few rows to understand the data
print(data.head())

# Create a new feature called NV
data['NV'] = data[['eggsno_q', 'fishprawn_q', 'goatmeat_q', 'beef_q', 'pork_q', 'chicken_q', 'oth
rbirds_q']].sum(axis=1).apply(lambda x: 1 if x > 0 else 0)
data.shape
df= data.copy()
df.dropna(how= 'all',inplace=True)
df1 = df[['NV','HH_type', 'Religion', 'Social_Group', 'Regular_salary_earner',
        'Possess_ration_card', 'Sex', 'Age', 'Marital_Status', 'Education',
        'Meals_At_Home', 'Region', 'hhdsz', 'NIC_2008', 'NCO_2004']]
```

```
df1.dropna(how='any',inplace=True)
df1

# Add a constant term for the intercept
# Define dependent variable (y) and independent variables (X)
y = df1['NV']
X = df1[['HH_type', 'Religion', 'Social_Group', 'Regular_salary_earner',
        'Possess_ration_card', 'Sex', 'Age', 'Marital_Status', 'Education',
        'Meals_At_Home', 'Region', 'hhdsz', 'NIC_2008', 'NCO_2004']]

# Assuming X is your DataFrame containing the independent variables
X['Social_Group'] = X['Social_Group'].astype('category')
X['Regular_salary_earner'] = X['Regular_salary_earner'].astype('category')
X['HH_type'] = X['HH_type'].astype('category')
X['Possess_ration_card'] = X['Possess_ration_card'].astype('category')
X['Sex'] = X['Sex'].astype('category')
X['Marital_Status'] = X['Marital_Status'].astype('category')
X['Education'] = X['Education'].astype('category')
X['Region'] = X['Region'].astype('category')

X= sm.add_constant(X)

# Fit the probit regression model
probit_model = Probit(y, X).fit()

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

# Predict probabilities
predicted_probs = probit_model.predict(X)

# Convert probabilities to binary predictions using a threshold of 0.5
predicted_classes = (predicted_probs > 0.5).astype(int)
# Confusion Matrix
```

```
conf_matrix = confusion_matrix(y, predicted_classes)
conf_matrix_df = pd.DataFrame(conf_matrix, index=['Actual Negative', 'Actual Positive'], co
lumns=['Predicted Negative', 'Predicted Positive'])
print("Confusion Matrix:\n", conf_matrix_df)

# Plotting the Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_df, annot=True, fmt='d', cmap='Blues')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()

# ROC curve and AUC value
fpr, tpr, _ = roc_curve(y, predicted_probs)
auc_value = roc_auc_score(y, predicted_probs)
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC = {auc_value:.2f})')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
print(f"AUC: {auc_value}")

# Accuracy, Precision, Recall, F1 Score
accuracy = accuracy_score(y, predicted_classes)
precision = precision_score(y, predicted_classes)
recall = recall_score(y, predicted_classes)
f1 = f1_score(y, predicted_classes)

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
```

References

1. www.github.com
2. www.geeksforgeeks.com
3. www.datacamp.com