

finalLogitModel

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```
library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr   1.5.1
## v ggplot2    3.5.0      v tibble    3.2.1
## v lubridate  1.9.3      v tidyr     1.3.1
## v purrr      1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

library(haven)
library(readxl)
library(MASS)

##
## Attaching package: 'MASS'
##
## The following object is masked from 'package:dplyr':
##
##      select

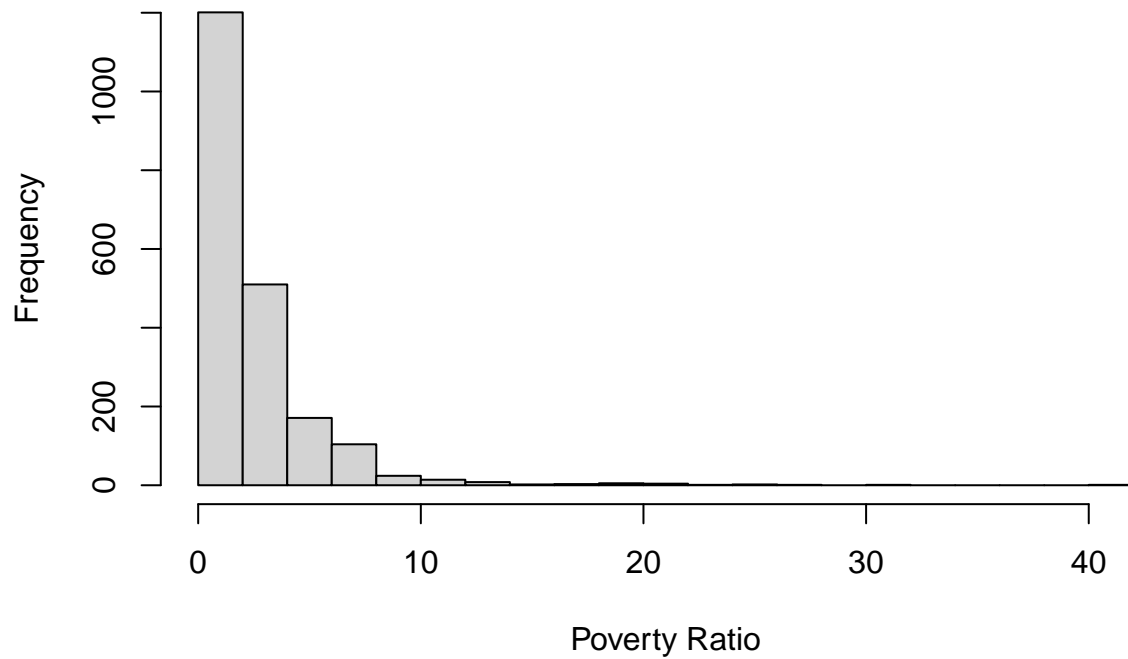
library(ggplot2)

df <- as.data.frame(read_dta("/Users/dominiquebarnes/Desktop/SPR24_Coursework/DATA 2020/FFdata/wave6/FFdata.dta"))
other_var <- read_csv("/Users/dominiquebarnes/Desktop/SPR24_Coursework/DATA 2020/Final_Project/Finances/Finances.csv")
other_df <- as.data.frame(other_var)
# Select Columns
other_var_code <- other_df$Variable
df_select <- df %>% dplyr::select(all_of(other_var_code))

df_filt <- df_select %>%
  filter_all(all_vars(!==9 & . !==8 & . !==7 & . !==5 & . !==4 & . !==3 & . !==2 & . !==1 ))

# cp6povco poverty ratio
poverty_ratio = df_filt$cp6povco
#Histogram
hist(poverty_ratio, breaks = 20, main = "Distribution of Poverty Ratios", xlab = "Poverty Ratio")
```

Distribution of Poverty Ratios

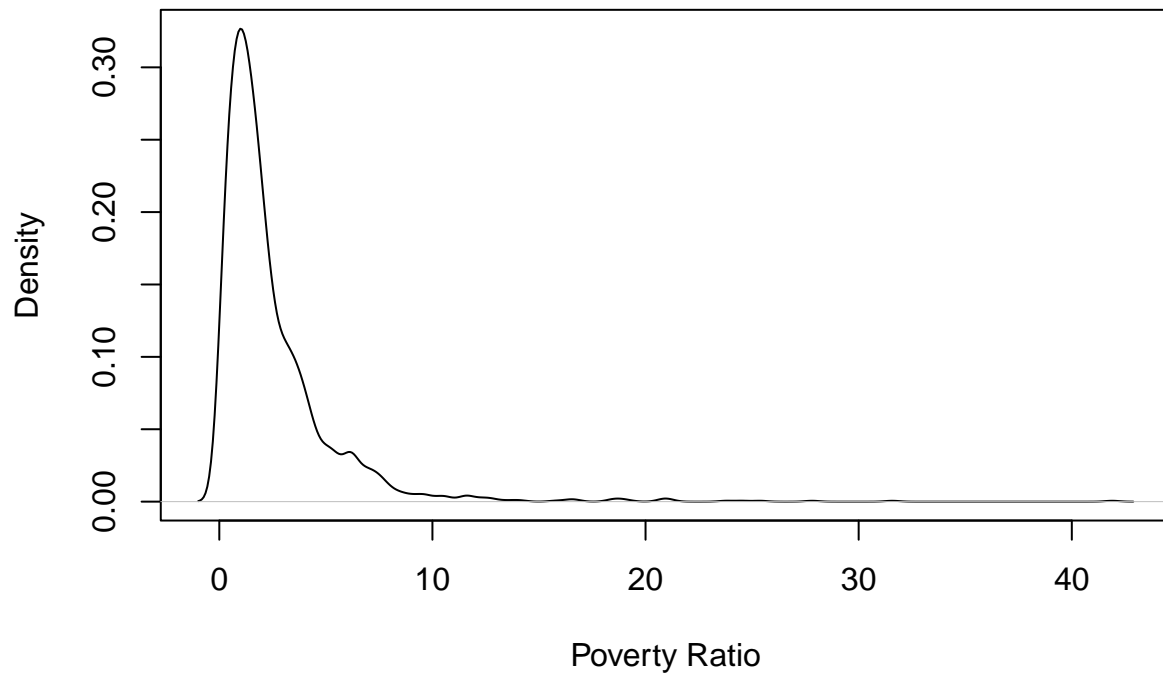


```
#Density Plot
```

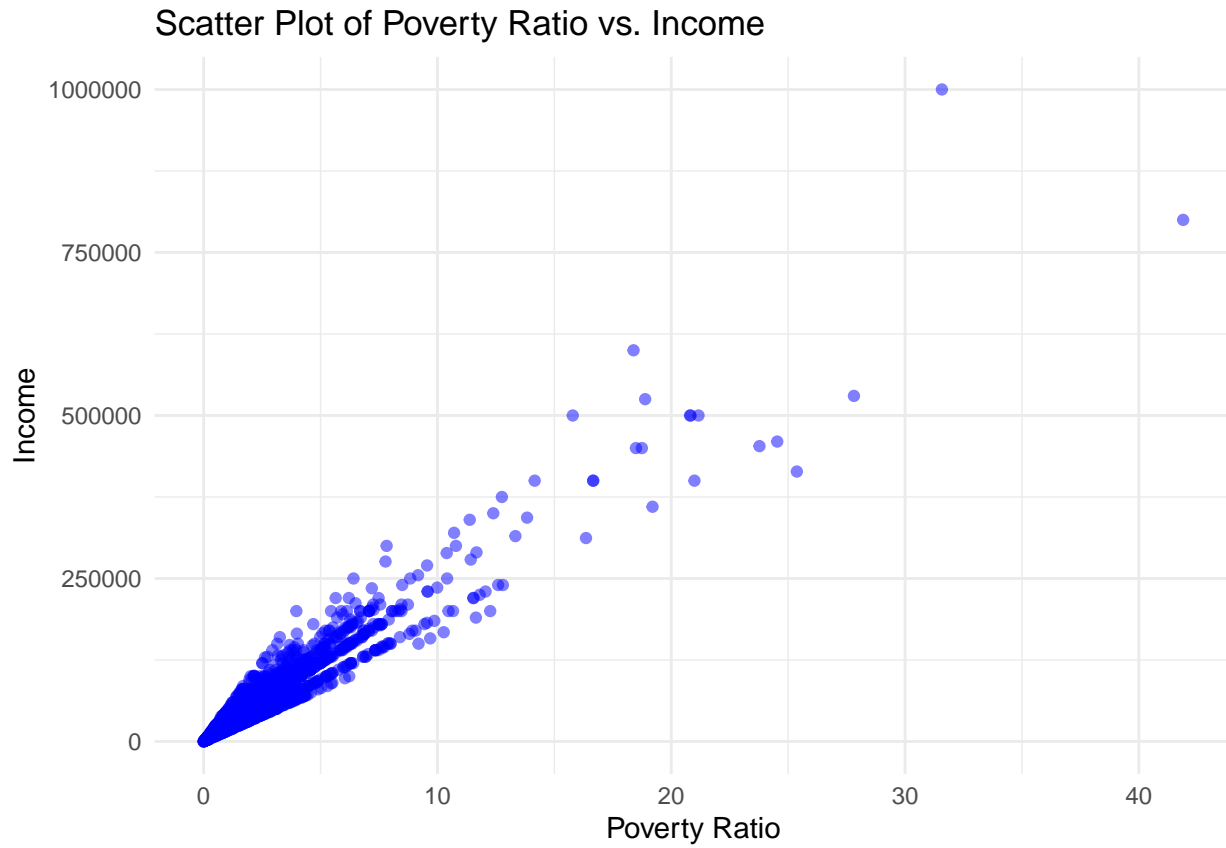
```
# Assuming your poverty ratio variable is named "poverty_ratio"
```

```
plot(density(poverty_ratio), main = "Density Plot of Poverty Ratios", xlab = "Poverty Ratio", ylab = "D
```

Density Plot of Poverty Ratios

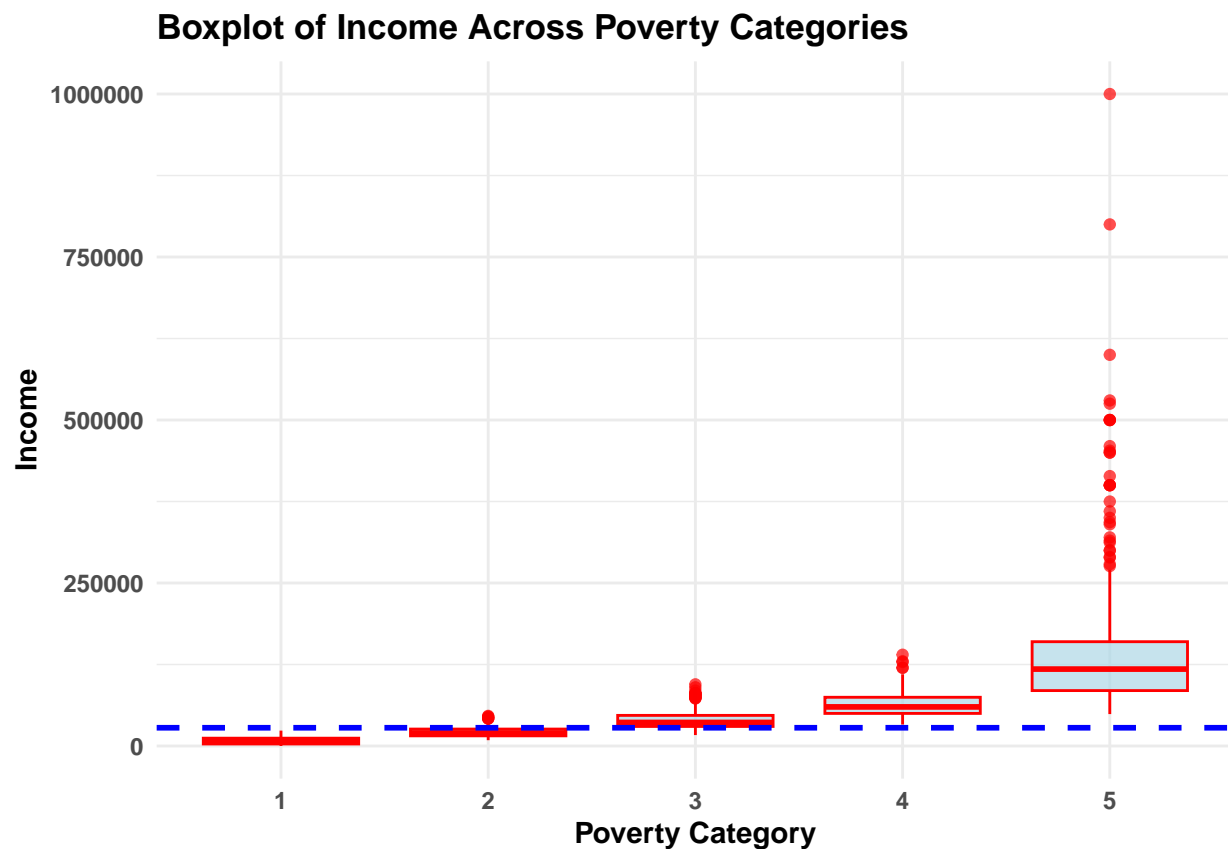


```
# Poverty Ratio v Income
income = df_filt$cp6hhinc
ggplot(df_filt, aes(x = poverty_ratio, y = income)) +
  geom_point(color = 'blue', alpha = 0.5) +
  labs(title = 'Scatter Plot of Poverty Ratio vs. Income',
       x = 'Poverty Ratio',
       y = 'Income') +
  theme_minimal()
```



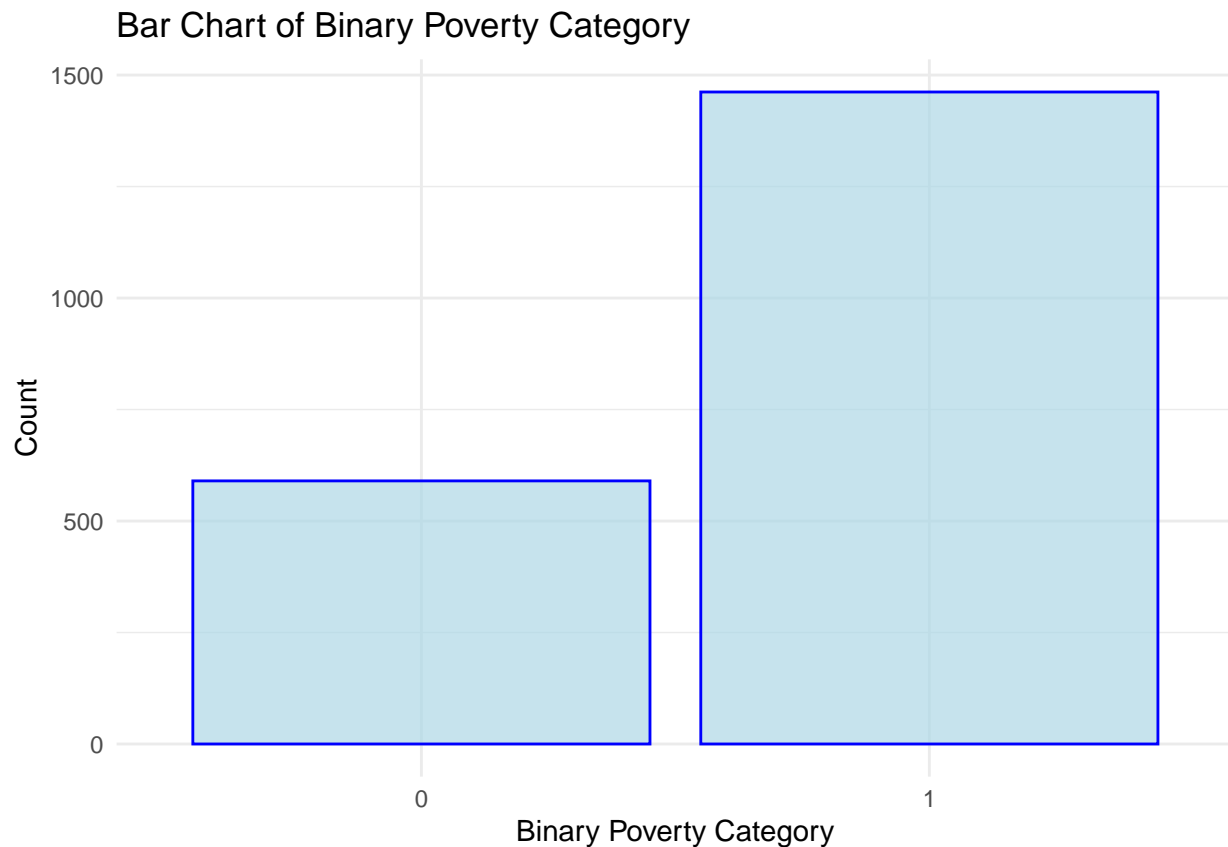
```
# Poverty Cat v Income

ggplot(df_filt, aes(x = factor(cp6povca), y = income)) +
  geom_boxplot(color = 'red', fill = 'lightblue', alpha = 0.7) +
  geom_hline(yintercept = 28000, color = "blue", linetype = "dashed", linewidth = 1) +
  labs(title = 'Boxplot of Income Across Poverty Categories',
       x = 'Poverty Category',
       y = 'Income') +
  theme_minimal()+
  theme(axis.text.x = element_text(face = "bold"),
        axis.text.y = element_text(face = "bold"),
        axis.title = element_text(face = "bold"),
        plot.title = element_text(face = "bold"))
```



```
df_filt$binary_poverty_category <- NA
# Assign 0 to rows where poverty category is below or equal to 2, and 1 otherwise
df_filt$binary_poverty_category[df_filt$cp6povca <= 2] <- 0
df_filt$binary_poverty_category[df_filt$cp6povca > 2] <- 1

ggplot(df_filt, aes(x = factor(binary_poverty_category))) +
  geom_bar(fill = 'lightblue', color = 'blue', alpha = 0.7) +
  labs(title = 'Bar Chart of Binary Poverty Category',
       x = 'Binary Poverty Category',
       y = 'Count') +
  theme_minimal()
```



```

dependent_vars <- c('cp6hhsz', 'p6a3', 'p6a4', 'p6i19', 'p6i20_8', 'p6i21', 'p6j7', 'p6j8', 'p6j9', 'p6j11', 'p6j12', 'p6j13', 'p6j14', 'p6j15', 'p6j16', 'p6j17', 'p6j18', 'p6j19', 'p6j20', 'p6j21', 'p6j22', 'p6j23', 'p6j24', 'p6j25', 'p6j26', 'p6j27', 'p6j28', 'p6j29', 'p6j30', 'p6j31', 'p6j32', 'p6j33', 'p6j34', 'p6j35', 'p6j36', 'p6j37', 'p6j38', 'p6j39', 'p6j40', 'p6j41', 'p6j42', 'p6j43', 'p6j44', 'p6j45', 'p6j46', 'p6j47', 'p6j48', 'p6j49', 'p6j50', 'p6j51', 'p6j52', 'p6j53', 'p6j54', 'p6j55', 'p6j56', 'p6j57', 'p6j58', 'p6j59', 'p6j60', 'p6j61', 'p6j62', 'p6j63', 'p6j64', 'p6j65', 'p6j66', 'p6j67', 'p6j68', 'p6j69', 'p6j70', 'p6j71', 'p6j72', 'p6j73', 'p6j74', 'p6j75', 'p6j76', 'p6j77', 'p6j78', 'p6j79', 'p6j80', 'p6j81', 'p6j82', 'p6j83', 'p6j84', 'p6j85', 'p6j86', 'p6j87', 'p6j88', 'p6j89', 'p6j90', 'p6j91', 'p6j92', 'p6j93', 'p6j94', 'p6j95', 'p6j96', 'p6j97', 'p6j98', 'p6j99', 'p6k19_code_pub', 'p6k36_code_pub')

independent_var <- df_filt$binary_poverty_category

final_df <- df_filt %>% dplyr::select(all_of(dependent_vars))

data <- final_df

binary_vars <- c('p6a4', 'p6i19', 'p6i20_8', 'p6j14', 'p6j15', 'p6j24', 'p6j30', 'p6j33', 'p6j34', 'p6j35', 'p6j36', 'p6j37', 'p6j38', 'p6j39', 'p6j40', 'p6j41', 'p6j42', 'p6j43', 'p6j44', 'p6j45', 'p6j46', 'p6j47', 'p6j48', 'p6j49', 'p6j50', 'p6j51', 'p6j52', 'p6j53', 'p6j54', 'p6j55', 'p6j56', 'p6j57', 'p6j58', 'p6j59', 'p6j60', 'p6j61', 'p6j62', 'p6j63', 'p6j64', 'p6j65', 'p6j66', 'p6j67', 'p6j68', 'p6j69', 'p6j70', 'p6j71', 'p6j72', 'p6j73', 'p6j74', 'p6j75', 'p6j76', 'p6j77', 'p6j78', 'p6j79', 'p6j80', 'p6j81', 'p6j82', 'p6j83', 'p6j84', 'p6j85', 'p6j86', 'p6j87', 'p6j88', 'p6j89', 'p6j90', 'p6j91', 'p6j92', 'p6j93', 'p6j94', 'p6j95', 'p6j96', 'p6j97', 'p6j98', 'p6j99', 'p6k19_code_pub', 'p6k36_code_pub')

#cat_vars <- c('p6k19_code_pub', 'p6k36_code_pub')

cont_vars <- c('cp6hhsz', 'p6a3', 'p6i21', 'p6j7', 'p6j8', 'p6j9', 'p6j11', 'p6j25', 'p6j31', 'p6k34', 'p6k65', 'p6k66', 'p6k67', 'p6k68', 'p6k69', 'p6k70', 'p6k71', 'p6k72', 'p6k73', 'p6k74', 'p6k75', 'p6k76', 'p6k77', 'p6k78', 'p6k79', 'p6k80', 'p6k81', 'p6k82', 'p6k83', 'p6k84', 'p6k85', 'p6k86', 'p6k87', 'p6k88', 'p6k89', 'p6k90', 'p6k91', 'p6k92', 'p6k93', 'p6k94', 'p6k95', 'p6k96', 'p6k97', 'p6k98', 'p6k99')

#One hot encoding Categorical Variables
# Perform one-hot encoding for each categorical variable
#encoded_data <- model.matrix(~ . - 1, data = data[, cat_vars])
# Combine the encoded data with the original data frame
#data <- cbind(data, encoded_data)

#Binary
# Replace 2 with 0 for each binary variable
for (var in binary_vars) {
  data[[var]] <- ifelse(data[[var]] == 2, 0, data[[var]])
}

```

```

data[, cont_vars] <- scale(data[, cont_vars])

# Set the seed for reproducibility
set.seed(123)

# Assuming 'data' is your preprocessed dataset
n <- nrow(data)
train_indices <- sample(1:n, 0.8 * n) # 80% for training
data_train <- data[train_indices, ]
data_test <- data[-train_indices, ]

#Correlation Matrices
correlation_matrix <- cor(data_train[, dependent_vars])
highly_correlated_pairs <- which(correlation_matrix > 0.7 & correlation_matrix != 1, arr.ind = TRUE)

#Remove one variable from each highly correlated pair
vars_to_remove <- rownames(correlation_matrix)[highly_correlated_pairs[, "col"]]
data_train_filtered <- data_train[, !colnames(data_train) %in% vars_to_remove]
data_test_filtered <- data_test[, !colnames(data_test) %in% vars_to_remove]

library(caret)

## Loading required package: lattice
##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
## lift

ctrl <- trainControl(method = "cv", number = 5)
data_train_filtered$binary_poverty_category <- factor(data_train_filtered$binary_poverty_category, levels = c("No", "Yes"))

# Build Logistic Regression Model
model_logit <- train(binary_poverty_category ~ ., data = data_train_filtered, method = "glm", trControl = ctrl)

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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summary(model_logit)

##
## Call:
## NULL
##
## Coefficients:
## Estimate Std. Error z value Pr(>|z|)

```

## (Intercept)	-0.4446363	1.5251369	-0.292	0.770639	
## cp6hhsz	-0.6793373	0.0860925	-7.891	3.00e-15	***
## p6a3	0.0509705	0.0833278	0.612	0.540745	
## p6a4	-0.4202767	0.2476502	-1.697	0.089686	.
## p6i21	0.2132001	0.2134175	0.999	0.317804	
## p6j7	2.4780057	0.4878655	5.079	3.79e-07	***
## p6j11	0.4691230	0.1053989	4.451	8.55e-06	***
## p6j24	-1.7862652	1.9733917	-0.905	0.365373	
## p6j25	-0.0830534	0.0905701	-0.917	0.359139	
## p6j30	-0.9075611	2.6456288	-0.343	0.731567	
## p6j31	0.0826560	0.0926418	0.892	0.372280	
## p6j33	0.4427439	0.1912393	2.315	0.020606	*
## p6j36	-0.4281449	0.1968054	-2.175	0.029595	*
## p6j37	0.0161149	2.4447185	0.007	0.994741	
## p6j38	-0.7026217	2.6064043	-0.270	0.787487	
## p6j39	1.6397589	2.0829802	0.787	0.431154	
## p6j40	-0.2615772	2.3730612	-0.110	0.912229	
## p6j41	0.0779611	2.0421258	0.038	0.969547	
## p6j42	0.1352813	1.8990512	0.071	0.943210	
## p6j43	0.2705381	1.8498161	0.146	0.883723	
## p6j44	2.5629234	1.9490214	1.315	0.188517	
## p6j45	2.3981263	2.9311505	0.818	0.413270	
## p6j46	-3.6337170	2.8683360	-1.267	0.205213	
## p6j47	-3.4381576	2.0271261	-1.696	0.089872	.
## p6k13	0.0845278	0.0410143	2.061	0.039309	*
## p6k69	0.1388736	0.1712816	0.811	0.417486	
## p6k70	0.4656053	0.2028899	2.295	0.021741	*
## p6k71	0.1437858	0.1145834	1.255	0.209531	
## p6k72	1.0780888	0.3416151	3.156	0.001600	**
## p6b31	-0.5656642	0.2218858	-2.549	0.010792	*
## p6e24	0.0198070	0.0311842	0.635	0.525324	
## p6e29	0.3033316	0.0849487	3.571	0.000356	***
## p6f9	-0.0812659	0.0274839	-2.957	0.003108	**
## p6f10	0.2380860	0.1023862	2.325	0.020052	*
## p6j18	-0.1716464	1.5145290	-0.113	0.909766	
## p6j19	0.0859274	0.0856381	1.003	0.315678	
## p6j20	0.0052994	0.2397307	0.022	0.982364	
## p6j21	2.3890647	1.3504761	1.769	0.076885	.
## p6j22	0.0928322	0.0967960	0.959	0.337534	
## p6j23	0.3948067	0.2072518	1.905	0.056785	.
## p6j26	-0.1036160	0.3095420	-0.335	0.737822	
## p6j29	0.0398093	0.0288447	1.380	0.167549	
## p6j32	-0.0291015	0.4199321	-0.069	0.944750	
## p6j48	0.0183444	0.3996101	0.046	0.963385	
## p6j49	-0.0601015	0.4248156	-0.141	0.887493	
## p6j50	0.2754051	0.3312998	0.831	0.405812	
## p6j51	-0.0506869	0.3747205	-0.135	0.892402	
## p6j52	-0.0130880	0.3244407	-0.040	0.967822	
## p6j53	0.0455324	0.3000749	0.152	0.879395	
## p6j54	0.0601113	0.2954242	0.203	0.838764	
## p6j55	0.4440053	0.3095066	1.435	0.151413	
## p6j56	0.5191372	0.4690572	1.107	0.268394	
## p6j57	-0.5703141	0.4684040	-1.218	0.223388	
## p6j58	-0.5096514	0.3227979	-1.579	0.114369	

```

## p6k3_8      0.0155093  0.0298358  0.520 0.603188
## p6k5       -0.9052249  0.2802980 -3.230 0.001240 **
## p6k54      0.3698972  0.1490267  2.482 0.013062 *
## p6k59     -0.3389772  0.1687320 -2.009 0.044540 *
## p6k60      3.0186372  1.6839210  1.793 0.073033 .
## p6k61      0.0001958  0.0001293  1.514 0.130037
## p6k62      0.4035617  0.2710308  1.489 0.136490
## k6e35k     -0.0309731  0.0262160 -1.181 0.237421
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1965.6  on 1640  degrees of freedom
## Residual deviance: 1189.6  on 1579  degrees of freedom
## AIC: 1313.6
##
## Number of Fisher Scoring iterations: 7
#Predictions and Model Eval
predictions_logit <- predict(model_logit, newdata = data_test_filtered, type = "prob")

# Extract predicted probabilities for the positive class
predicted_probs <- predictions_logit[, 2]

# Calculate predictions (convert probabilities to binary predictions)
predicted_class <- ifelse(predicted_probs > 0.5, 1, 0)

# Calculate accuracy
accuracy <- mean(predicted_class == data_test_filtered$binary_poverty_category)
cat("Accuracy:", accuracy, "\n")

## Accuracy: 0.8199513

# Calculate confusion matrix
confusion <- table(predicted_class, data_test_filtered$binary_poverty_category)

# Calculate precision, recall, specificity, and F1 score
TP <- confusion[2, 2]
FP <- confusion[1, 2]
TN <- confusion[1, 1]
FN <- confusion[2, 1]

precision <- TP / (TP + FP)
recall <- TP / (TP + FN)
specificity <- TN / (TN + FP)
f1_score <- 2 * (precision * recall) / (precision + recall)

cat("Precision:", precision, "\n")

## Precision: 0.8865979
cat("Recall:", recall, "\n")

## Recall: 0.8628763

```



```

cat("Specificity:", specificity, "\n")

## Specificity: 0.7053571
cat("F1 Score:", f1_score, "\n")

## F1 Score: 0.8745763
print(confusion)

##
## predicted_class    0    1
##                0  79  33
##                1  41 258
gov_social_aid_vars <- c('p6j36', 'p6j44', 'p6j45', 'p6k70', 'p6b31', 'p6f9', 'p6j20', 'p6j23', 'p6j26', 'p6j29',
gov_social_aid_names <- c('Youth_FreeDinner', 'Moved_Friends', 'Moved_Shelter', 'Loans', 'Medicaid', 'ChildS

# Extract coefficients and standard errors for the variables of interest
coefficients <- summary(model_logit)$coef[, 1]
se <- summary(model_logit)$coef[, 2]

# Create a data frame
df <- data.frame(
  Variables = gov_social_aid_names,
  Estimate = coefficients[gov_social_aid_vars],
  se = se[gov_social_aid_vars]
)

# Calculate confidence intervals
df$lower <- df$Estimate - 1.96 * df$se
df$upper <- df$Estimate + 1.96 * df$se

# Plot
ggplot(df, aes(x = Variables, y = Estimate)) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.5) +
  geom_point() +
  theme_bw() +
  labs(title = "Coefficients of Government and Social Aid", y = "Estimate")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

```

