॥वसुधैव कुटुम्बकम्॥

SYMBIOSIS INSTITUTE OF TECHNOLOGY, PUNE

Symbiosis International (Deemed University)

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with 'A' grade (3.58/4) | Awarded Category – I by UGC

Founder: Prof. Dr. S. B. Mujumdar, M. Sc., Ph. D. (Awarded Padma Bhushan and Padma Shri by President of India)

Assignment No. 06	
Subject: Data Science Lab	
Name of Student	**Achyut Shukla**
PRN No.	**20070122005**
Branch	**CS**
Class	**A1**
Academic Year & Semester	2023-24 _ 7th semester
Date	**5th September**
Title of Lab Assignment	**Regression Model Development**

Theory:

- Import a data from web storage.
- Name the dataset and now do Logistic Regression to find out the relationship between variables that are affecting the admission of a student to an institute based on his or her GRE score, GPA obtained, and rank of the student.
- Also check the model is fit or not.
- Use different datasets from an online repository to develop a logistic regression model. Also, check if the model fits or not. Require (foreign), require (MASS). • The logistic regression model predicts the probability of a binary outcome (e.g., admission) based onone or more predictor variables (e.g., GRE score, GPA, rank).
- In the provided dataset, the column names are in lowercase, so the formula is adjusted to admit ~ gre + gpa + rank. The glm function with family = "binomial" is used to fit the logistic regression model inR.

Answer:

Answer:

```
# Load necessary libraries
require(foreign)

require(MASS)


# Import the dataset data <-

read.csv("https://figshare.com/ndownloader/files/34757857")

# Check for missing values print(sum(is.na(data)))

# Handle missing values if any (you can use mean imputation or other methods)
data[is.na(data)] <- mean(data, na.rm = TRUE)


# Display covariance and correlation
print(cov(data)) print(cor(data))

# Check the names of the columns in the dataset
print(names(data))


# Perform logistic regression using the MASS function logit_model <- glm(admit ~ gre +
gpa + rank, data = data, family = "binomial")


# Display the summary of the model
summary(logit_model)


# Check the goodness of fit anova(logit_model,
test="Chisq")


# Plot the graph for the model
 plot(logit_model)
```

Answer:

Part A

```
# Load necessary libraries
require(foreign)
require(MASS)

>

# Import the dataset
```

```
data <- read.csv("https://figshare.com/ndownloader/files/34757857")
>

# Check for missing values

print(sum(is.na(data)))

[1] 0

>

# Handle missing values if any (you can use mean imputation or other methods)
data[is.na(data)] <- mean(data, na.rm = TRUE)

>

# Display covariance and

correlation print(cov(data))

             admit  gre        gpa        rank

admit 0.21723684        9.930075 0.03161078 -0.10675439 gre
          9.93007519 13344.070175 16.89300251 -13.46817043 gpa
          0.03161078 16.893003 0.14483107 -0.02065313 rank -
0.10675439 -13.468170 -0.02065313 0.89200501 print(cor(data))

             admit  gre        gpa        rank

admit 1.0000000 0.1844343 0.17821225 -0.24251318 gre
          0.1844343 1.0000000 0.38426588 -0.12344707 gpa
          0.1782123 0.3842659 1.00000000 -0.05746077

rank -0.2425132 -0.1234471 -0.05746077 1.00000000

>

# Check the names of the columns in the dataset

print(names(data)) [1] "admit"
"gre" "gpa" "rank"

>

# Perform logistic regression using the MASS function

logit_model <- glm(admit ~ gre + gpa + rank, data = data, family = "binomial") >

# Display the summary of the model
summary(logit_model)

Call:

glm(formula = admit ~ gre + gpa + rank, family = "binomial", data = data)


Coefficients:
Estimate Std. Error z value Pr(>|z|)
```

(Intercept) -3.449548 1.132846 -3.045 0.00233 ** gre
0.002294 0.001092 2.101 0.03564 * gpa
0.777014 0.327484 2.373 0.01766 *

rank -0.560031 0.127137 -4.405 1.06e-05 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1) Null deviance: 499.98 on 399 degrees of freedom Residual deviance: 459.44 on 396 degrees of freedom AIC: 467.44

Number of Fisher Scoring iterations: 4

>

# Check the goodness of fit
anova(logit_model, test="Chisq")
Analysis of Deviance Table

Model: binomial, link: logit
Response: admit

Terms added sequentially (first to last)

Df Deviance Resid. Df Resid. Dev Pr(>Chi)

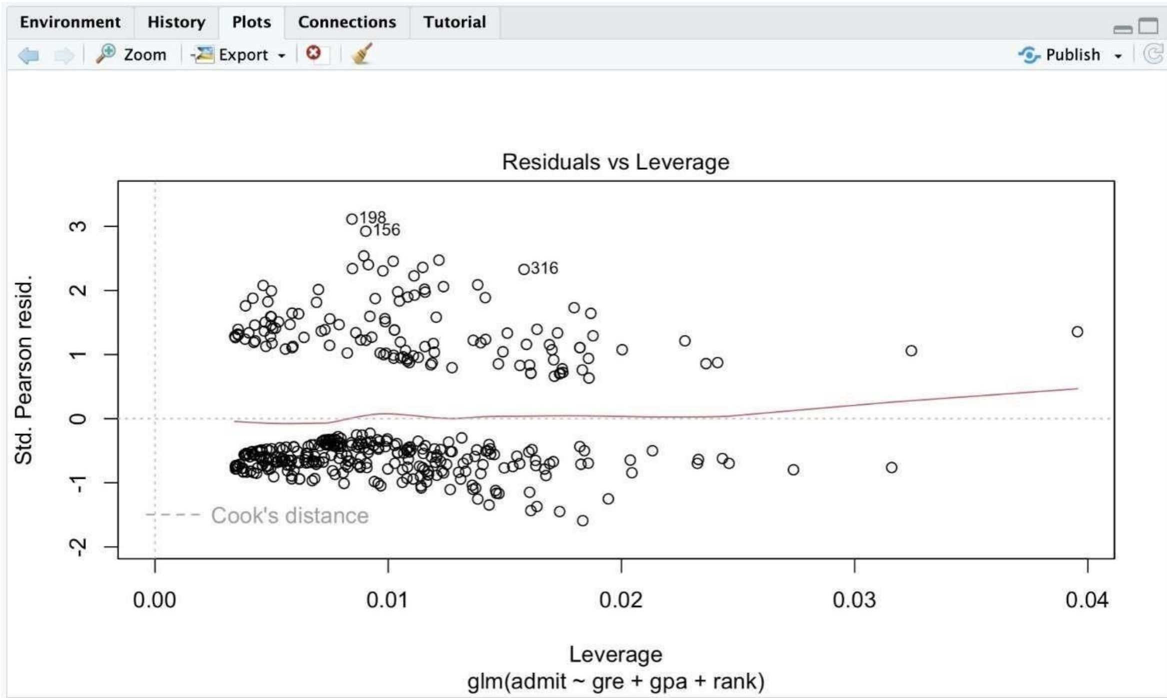
NULL 399 499.98

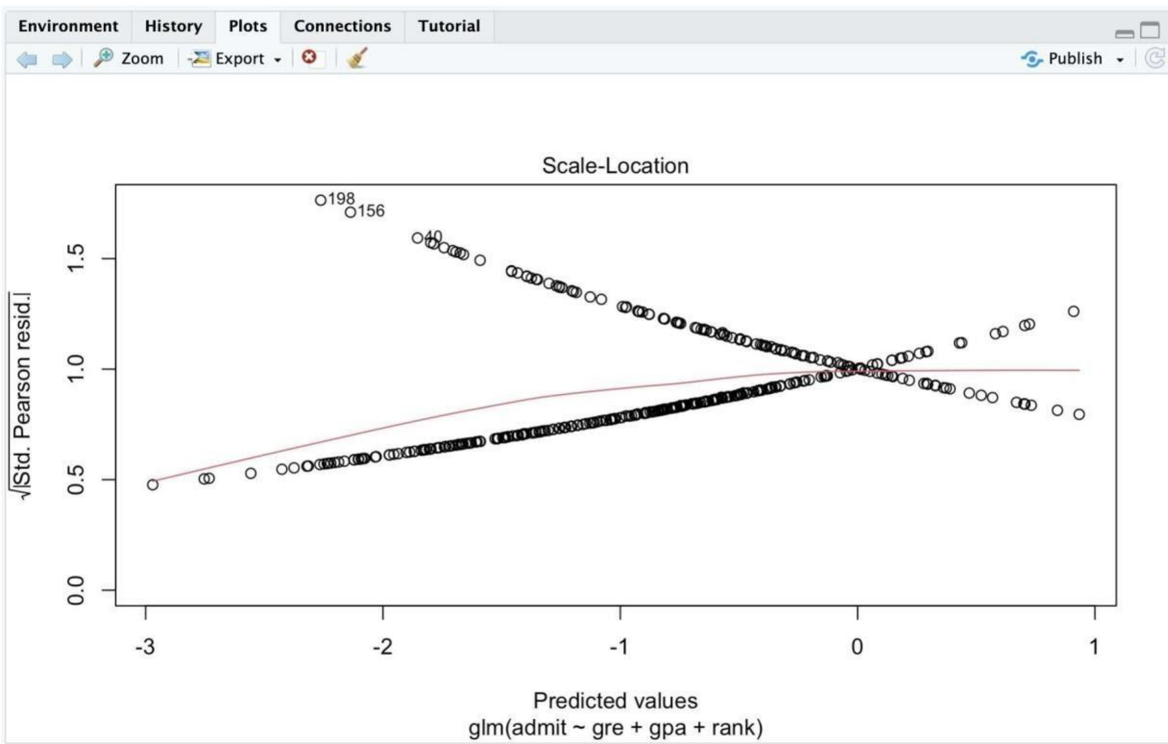
gre 1 13.9204 398 486.06 0.0001907 *** gpa 1
5.7122 397 480.34 0.0168478 * rank 1 20.9022
396 459.44 4.833e-06 ***

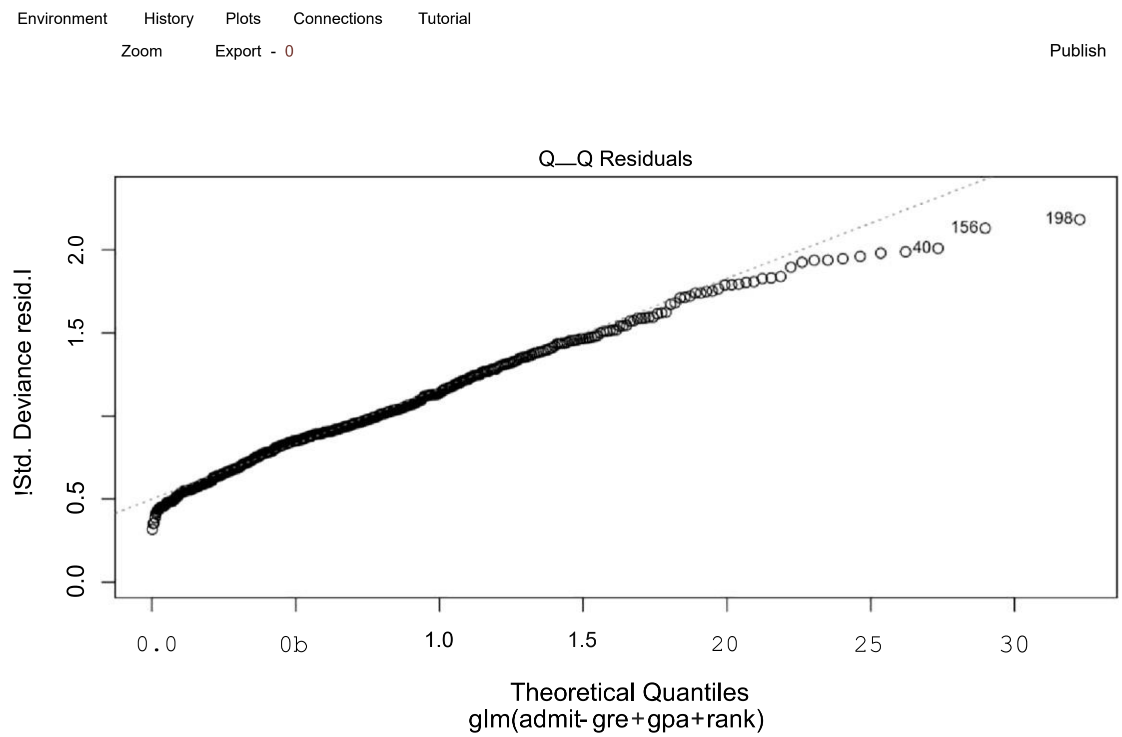
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>

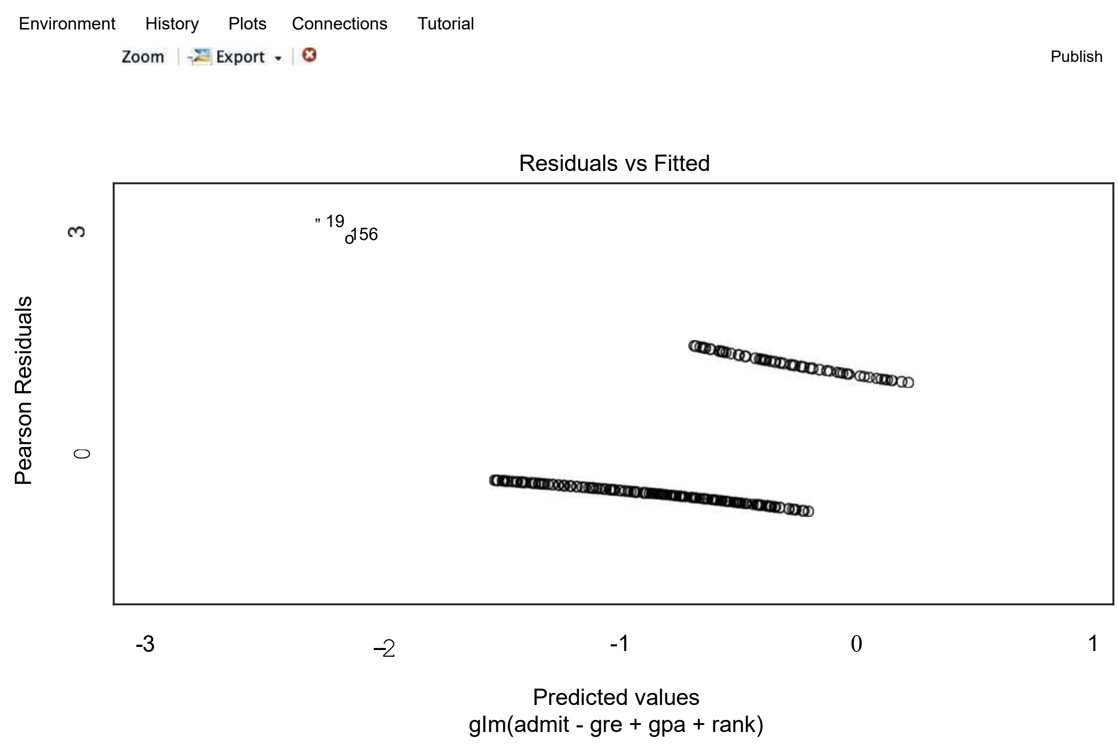
Plot the graph for the model plot(logit_model)

Output:


Environment
History
Plots
Connections
Tutorial
Zoom
Export
Publish
Residuals vs Leverage
198
156
316
Cook's distance
Std. Pearson resid.
Leverage
glm(admit ~ gre + gpa + rank)


Environment
History
Plots
Connections
Tutorial
Zoom
Export
Publish
Scale-Location
198
156
40
√|Std. Pearson resid.|
Predicted values
glm(admit ~ gre + gpa + rank)


Environment History Plots Connections Tutorial
Zoom Export - 0
Publish
Q—Q Residuals
!Std. Deviance resid.I
0.0
0.5
1.5
2.0
0.0
0b
1.0
1.5
20
25
30
198
156
40
Theoretical Quantiles
glm(admit- gre+gpa+rank)


Environment History Plots Connections Tutorial
Zoom Export
Publish
Residuals vs Fitted
Pearson Residuals
3
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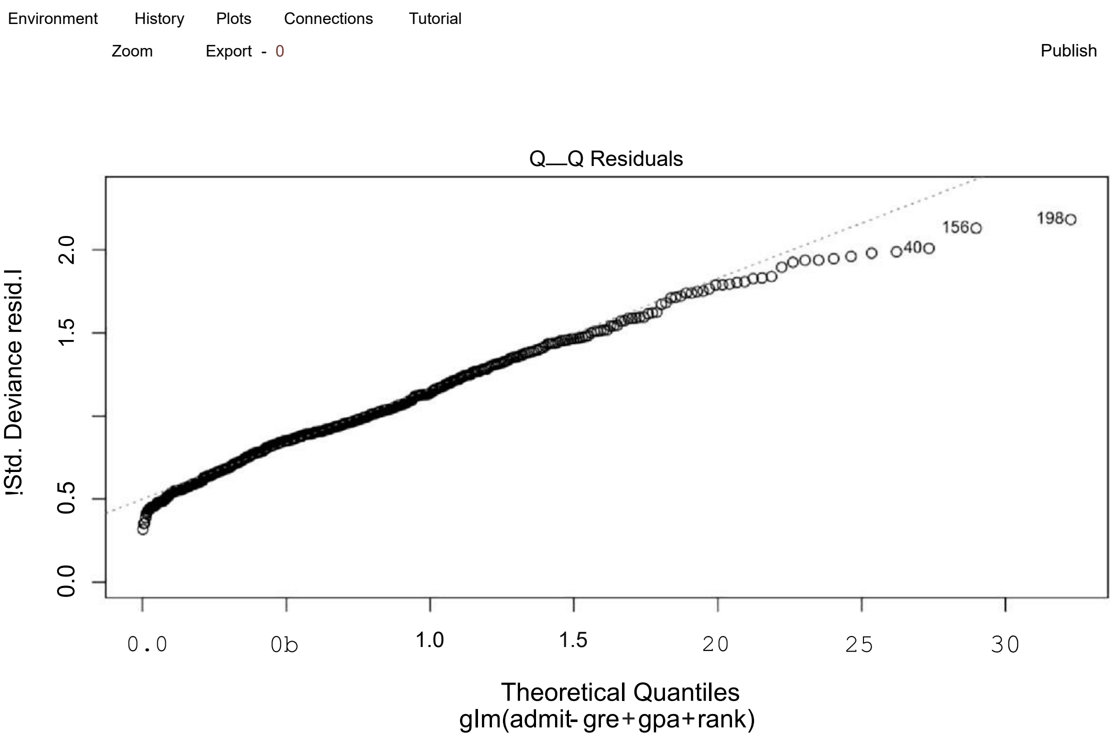
156
-3
-2
-1
0
1
Predicted values
glm(admit - gre + gpa + rank)


Environment
History
Plots
Connections
Tutorial
Zoom
Export
Publish
Q—Q Residuals
!Std. Deviance resid.I
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1.5
2.0
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1.0
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198
156
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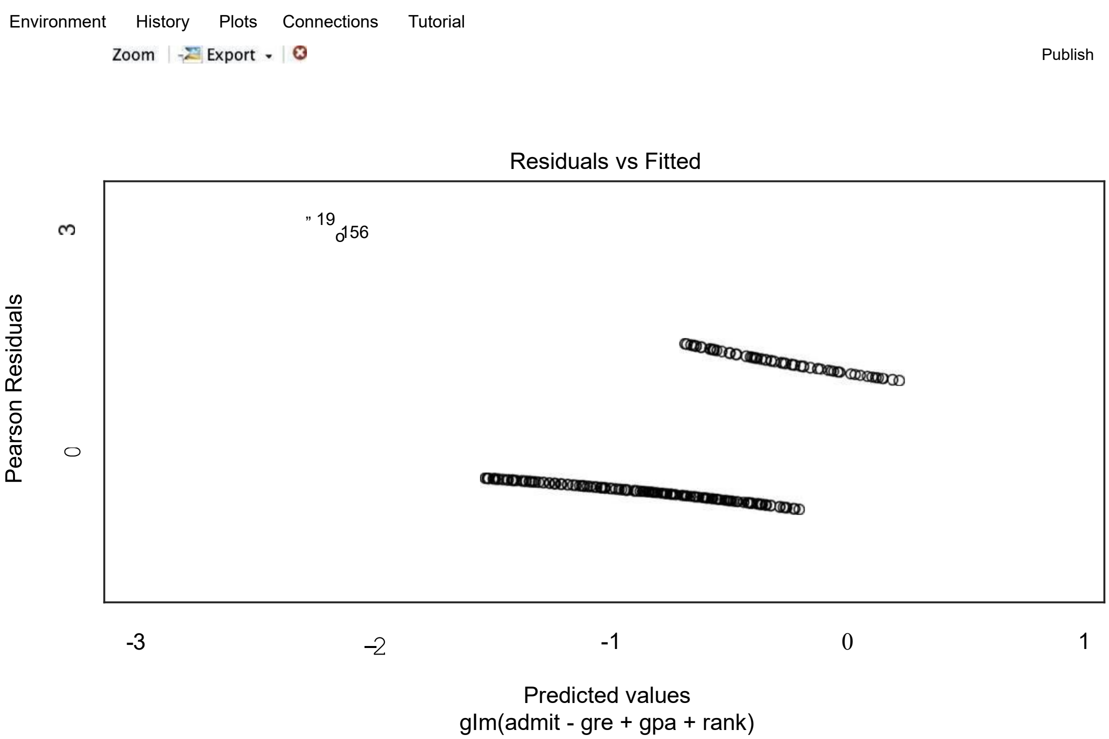
Theoretical Quantiles
glm(admit- gre+gpa+rank)


Environment
History
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Tutorial
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Publish
Residuals vs Fitted
Pearson Residuals
3
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-3
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-1
0
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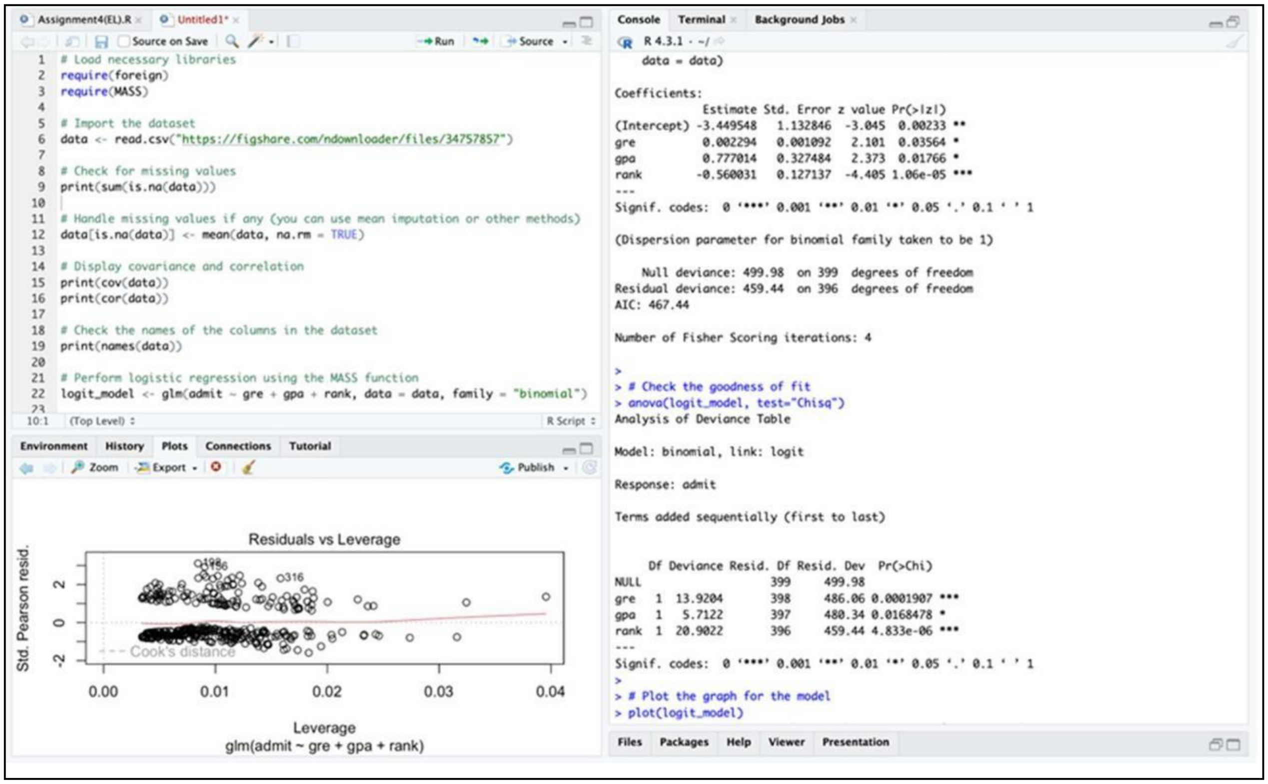
Predicted values
glm(admit - gre + gpa + rank)



Conclusion:

In conclusion, logistic regression is a powerful statistical method used to model and analyze datasets in which the outcome is binary. For the provided dataset, the probability of a student's admission is predicted based on their GRE score, GPA, and rank. Proper understanding and interpretation of the dataset's column names and structure are crucial for accurate model formulation. Using R's glm function with the appropriate formula and family setting ensures a correct fit for the data, enabling meaningful insights and predictions.