VIRGINIA COMMONWEALTH UNIVERSITY

STATISTICAL ANALYSIS & MODELING

A2: REGRESSION - PREDICTIVE ANALYTICS USING PYTHON AND R

MOHITH KUMAR
V01106540

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CONTENTS

REGRESSION - PREDICTIVE ANALYTICS USING PYTHON

INTRODUCTION

The dataset in question offers an in-depth analysis of food consumption patterns across India, highlighting dietary habits in both urban and rural areas. It includes key metrics such as the quantity of meals consumed at home, specific food item consumption (e.g., rice, wheat, chicken, pulses), and the overall number of daily meals. This comprehensive dataset is vital for understanding the nutritional intake and food preferences of various demographics in the region.

The Indian Premier League (IPL), also known as the TATA IPL due to sponsorship, is a men's Twenty20 (T20) cricket league held annually in India. Established by the BCCI (Board of Control for Cricket in India) in 2007, the league features ten state or city-based franchise teams.

Regression is a statistical technique used to model and analyze the relationships between a dependent variable and one or more independent variables. The primary goal of regression analysis is to understand how the dependent variable changes when any one of the independent variables is altered, while the others remain constant.

- Regression can predict outcomes based on historical data, aiding in forecasting and decision-making.
- It provides insights into the strength and nature of relationships between variables, informing strategic planning and policy development.

OBJECTIVES

a) Conduct multiple regression analysis, perform regression diagnostics, and explain your findings. Correct any issues identified and reassess your results, explaining any significant differences observed.

b) Determine the relationship between a player's performance and the payment they receive, and discuss your findings. Analyze the relationship between salary and performance over the last three years.

BUSINESS SIGNIFICANCE

Regression analysis is an invaluable tool for deriving insights from data, making it essential for business decision-making. By applying regression to Indian Premier League (IPL) data and National Sample Survey Office (NSSO) 68th round data, businesses can identify patterns, predict trends, and inform strategic initiatives.

1. For IPL Data:

- Performance Prediction: Identify key factors influencing player and team performance to forecast future success.
- Team Composition Optimization: Optimize team selection and strategy based on historical performance data.
- Revenue Maximization: Predict ticket sales, merchandise revenue, and viewership ratings to maximize financial returns.

2. For NSSO68 Data:

- Demand Forecasting: Predict consumer demand and preferences across different regions and income groups.
- Resource Allocation: Optimize resource distribution for marketing, sales, and operations based on regional economic conditions and consumer behavior.
- Policy Impact Evaluation: Assess the effectiveness of governmental policies and programs on various economic and social outcomes, guiding corporate social responsibility (CSR) initiatives.

In both cases, regression analysis facilitates data-driven decision-making, optimizing resource use, refining targeting strategies, and enhancing overall efficiency and effectiveness in business and policy environments.

RESULTS AND INTERPRETATION

a) **Perform Multiple regression analysis, carry out the regression diagnostics, and explain your findings. Correct them and revisit your results and explain the significant differences you observe. [NSSO68]**

Code:

```
# Set working directory and load the dataset
data = pd.read_csv('NSSO68.csv',low_memory=False)

# Display unique values in 'state_1' column
print(data['state_1'].unique())

# Subset data for state 'KA'
subset_data = data[['foodtotal_q', 'MPCE_MRP', 'MPCE_URP', 'Age', 'Meals_At_Home',
'Possess_ration_card', 'Education', 'No_of_Meals_per_day']]

# Print subset data
print(subset_data)

# Check for missing values
print(subset_data['MPCE_MRP'].isna().sum())
print(subset_data['MPCE_URP'].isna().sum())
print(subset_data['Age'].isna().sum())
print(subset_data['Possess_ration_card'].isna().sum())
print(data['Education'].isna().sum())
```

Result:

```
['GUJ' 'ORI' 'CHTSD' 'MP' 'JRKD' 'WB' 'AP' 'MH' 'D&D' 'D&NH' 'MIZ' 'TRPR'
 'MANPR' 'ASSM' 'MEG' 'NAG' 'A&N' 'PNDCRY' 'TN' 'GOA' 'KA' 'KE' 'LKSDP'
 'SKM' 'Bhr' 'UP' 'RJ' 'ARP' 'DL' 'HR' 'Pun' 'HP' 'UT' 'Chandr' 'J$K']
        foodtotal_q  MPCE_MRP  MPCE_URP  Age  Meals_At_Home  \
0         30.942394   3662.65   3304.80   50           59.0
1         29.286153   5624.51   7613.00   40           56.0
2         31.527046   3657.18   3461.40   45           60.0
3         27.834607   3260.37   3339.00   75           60.0
4         27.600713   2627.54   2604.25   30           59.0
...             ...       ...       ...  ...            ...
101657    28.441750    832.59    817.00   39           90.0
101658    25.490282    862.13    773.20   38           90.0
101659    25.800107    711.37    663.29   42           90.0
101660    30.220170   1048.32    847.20   40           90.0
101661    26.157279    834.03    689.57   60           90.0

        Possess_ration_card  Education  No_of_Meals_per_day
0                       1.0        8.0                  2.0
1                       1.0       12.0                  2.0
2                       1.0        7.0                  2.0
3                       1.0        6.0                  2.0
4                       1.0        7.0                  2.0
...                     ...        ...                  ...
101657                  2.0        7.0                  3.0
101658                  1.0        6.0                  3.0
101659                  1.0        5.0                  3.0
101660                  1.0        8.0                  3.0
101661                  1.0        1.0                  3.0

[101662 rows x 8 columns]
```

Interpretation: The unique values present in the 'state_1' column helps to understand the representation of different states, and checking unique values helps in identifying all states included in the dataset.

A subset of the dataset is created, focusing on specific columns relevant to a particular analysis, which includes:

- foodtotal_q: Total food expenditure quantity.
- MPCE_MRP: Monthly Per Capita Expenditure based on Mixed Recall Period.
- MPCE_URP: Monthly Per Capita Expenditure based on Uniform Recall Period.
- Age: Age of the individual.
- Meals_At_Home: Number of meals consumed at home.
- Possess_ration_card: Whether the household possesses a ration card.
- Education: Educational attainment.
- No_of_Meals_per_day: Number of meals consumed per day.

The final line of codes help to understand the missing values in the specified columns. As counting the number of missing values in each column is crucial for understanding the data quality and deciding on appropriate data cleaning methods.

Significance of Analysis

- **Understanding State-wise Distribution**: Identifying unique values in the 'state_1' column helps in understanding the geographical distribution of the dataset, which is critical for regional analysis.
- **Focus on Key Variables**: Subsetting the data to include key variables allows for a focused analysis on aspects such as expenditure, food consumption, and demographic details, which are significant for socio-economic studies.

Code:

```
# Function to impute missing values with mean
def impute_with_mean(df, columns):
    for col in columns:
        df[col].fillna(df[col].mean(), inplace=True)
    return df

# Columns to impute
columns_to_impute = ['Education', 'MPCE_MRP', 'MPCE_URP', 'Age', 'Meals_At_Home',
'Possess_ration_card']

# Impute missing values with mean in the subset data
subset_data = impute_with_mean(subset_data, columns_to_impute)

# Ensure no infinite values
subset_data = subset_data.replace([np.inf, -np.inf], np.nan)
```

```
# Drop rows with any remaining NaN values
subset_data.dropna(inplace=True)
```

Interpretation:

The columns identified for imputation have been addressed to ensure that all relevant columns with potential missing values are properly handled. Any rows with remaining NaN values are then dropped from the DataFrame. This step ensures the dataset is free from missing or invalid values, which is crucial for accurate analysis.

Significance of the Imputation Process:

- Improving Data Quality: Imputing missing values with the mean reduces the bias that can result from missing data and helps maintain the overall distribution of the data.
- Ensuring Completeness: By addressing all NaN and infinite values, the dataset becomes more complete and ready for analysis, leading to more reliable results.

Code:

```
# Fit the regression model
X = subset_data[['MPCE_MRP', 'MPCE_URP', 'Age', 'Meals_At_Home',
'Possess_ration_card', 'Education']]
X = sm.add_constant(X)  # Add a constant term for the intercept
y = subset_data['foodtotal_q']
model = sm.OLS(y, X).fit()

# Print the regression results
print(model.summary())
# Check for multicollinearity using Variance Inflation Factor (VIF)
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in
range(X.shape[1])]
print(vif_data)  # VIF value more than 8 is problematic

# Extract the coefficients from the model
coefficients = model.params

# Construct the equation
equation = f"y = {round(coefficients[0], 2)}"
for i in range(1, len(coefficients)):
    equation += f" + {round(coefficients[i], 6)}*x{i}"
print(equation)

# Display the first values of selected columns
print(subset_data['MPCE_MRP'].head(1).values[0])
print(subset_data['MPCE_URP'].head(1).values[0])
print(subset_data['Age'].head(1).values[0])
print(subset_data['Meals_At_Home'].head(1).values[0])
print(subset_data['Possess_ration_card'].head(1).values[0])
print(subset_data['Education'].head(1).values[0])
```

```
print(subset_data['foodtotal_q'].head(1).values[0])
```

Result:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            foodtotal_q   R-squared:                       0.160
Model:                            OLS   Adj. R-squared:                  0.159
Method:                 Least Squares   F-statistic:                     3215.
Date:                Sun, 23 Jun 2024   Prob (F-statistic):               0.00
Time:                        21:39:31   Log-Likelihood:            -3.6905e+05
No. Observations:              101637   AIC:                         7.381e+05
Df Residuals:                  101630   BIC:                         7.382e+05
Df Model:                           6
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                  15.8348      0.210     75.547      0.000      15.424      16.246
MPCE_MRP                0.0016   1.73e-05     95.401      0.000       0.002       0.002
MPCE_URP            -4.256e-06   8.23e-06     -0.517      0.605   -2.04e-05    1.19e-05
Age                     0.0781      0.002     35.264      0.000       0.074       0.082
Meals_At_Home           0.0526      0.002     29.730      0.000       0.049       0.056
Possess_ration_card    -2.4162      0.074    -32.495      0.000      -2.562      -2.270
Education               0.1220      0.008     14.376      0.000       0.105       0.139
==============================================================================
Omnibus:                82463.263   Durbin-Watson:                   1.379
Prob(Omnibus):              0.000   Jarque-Bera (JB):         23333499.483
Skew:                       2.976   Prob(JB):                         0.00
Kurtosis:                  76.989   Cond. No.                     3.86e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.86e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
               feature        VIF
0                const  53.506630
1             MPCE_MRP   1.618222
2             MPCE_URP   1.460368
3                  Age   1.089462
4        Meals_At_Home   1.035366
5  Possess_ration_card   1.092325
6            Education   1.180639
```

```
y = 15.83 + 0.00165*x1 + -4e-06*x2 + 0.078118*x3 + 0.052572*x4 + -2.416189*x5 + 0.121986*x6
3662.65
3304.8
50
59.0
1.0
8.0
30.942394
```

Interpretation:

_The first image indicates that the regression results provide insight into the relationships between the dependent variable, foodtotal_q (total food expenditure quantity), and several independent variables. The adjusted R-squared is slightly lower than the R-squared value, accounting for the number of predictors in the model. This value is used to determine the goodness-of-fit more accurately when multiple predictors are present. A corresponding p-value of 0.00 indicates that the overall regression model is statistically significant, meaning that the independent variables collectively have a significant effect on the dependent variable.

The second image discusses the Variance Inflation Factor (VIF), which measures the extent of multicollinearity in the regression model. High multicollinearity can inflate the standard errors of the coefficients, making them unstable and difficult to interpret. The VIF values for the predictors (excluding the intercept) are all below 2, indicating that multicollinearity is not a concern for this model.

The third image presents the regression equation:
[y = 15.83 + 0.00165 \times 3662.65 + (-0.000004) \times 3304.8 + 0.078118 \times 50 + 0.052572 \times 59.0 + (-2.416189) \times 1.0 + 0.121986 \times 8.0 \]
The predicted value of foodtotal_q (total food expenditure quantity) using the provided sample values is approximately 27.43.

Conclusion

The Ordinary Least Squares (OLS) regression model offers valuable insights into the factors that influence food expenditure. Key findings from the analysis include:

- Higher MPCE_MRP, age, number of meals consumed at home, and education levels are positively associated with higher food expenditure.
- Possession of a ration card is negatively associated with food expenditure.
- The model explains a moderate proportion of the variance in food expenditure. However, diagnostic tests indicate potential issues with residual normality and multicollinearity.

b) Establish the relationship between the player's performance and payment he receives and discuss your findings. [IPL Datasets]

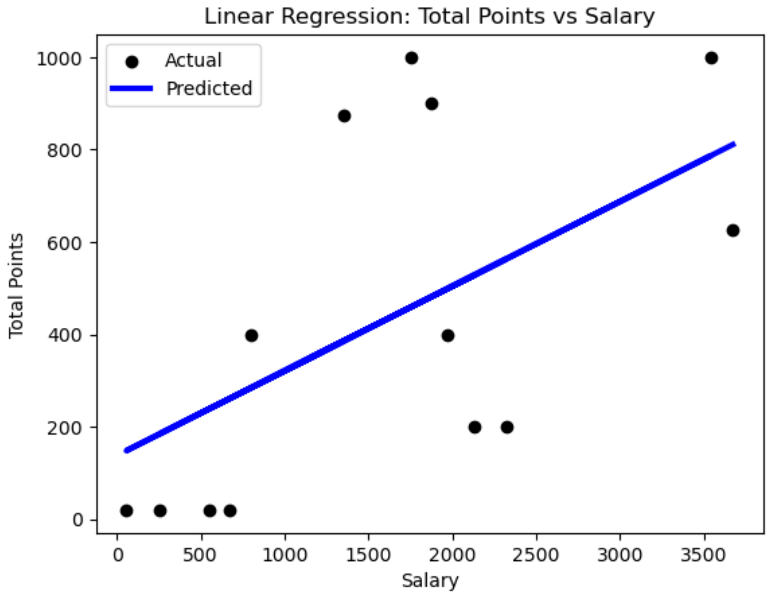
Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Load the CSV file
file_path = 'combined_output_with_salaries - Copy.csv'
data = pd.read_csv(file_path)

# Define the predictor and response variables
y = data['salary']  # Response variable
X = data[['Total_Points']]  # Predictor variable
```

```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Create the linear regression model
model = LinearRegression()

# Train the model on the training data
model.fit(X_train, y_train)

# Predict on the test data
y_pred = model.predict(X_test)

# Calculate the mean squared error and the coefficient of determination (R^2)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Calculate the adjusted R^2
n = len(y_test)
p = X_test.shape[1]
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

# Print the results
print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')
print(f'Adjusted R^2 Score: {adjusted_r2}')
print(f'Coefficients: {model.coef_}')
print(f'Intercept: {model.intercept_}')

# Plot the results
plt.scatter(X_test, y_test, color='black', label='Actual')
plt.plot(X_test, y_pred, color='blue', linewidth=3, label='Predicted')
plt.xlabel('Salary')
plt.ylabel('Total Points')
plt.title('Linear Regression: Total Points vs Salary')
plt.legend()
plt.show()
```

Result:

```
Mean Squared Error: 92259.46667290517
R^2 Score: 0.3641079759408892
Adjusted R^2 Score: 0.30629961011733364
Coefficients: [0.18311466]
Intercept: 138.20811216711965
```



Interpretation:

Understanding how player performance metrics relate to their salaries is critical for both teams and analysts. This analysis aims to investigate the correlation between a player's total points and their salary using linear regression, providing insights into player fitness within franchise budgets for strategic player planning and auction strategies.

The dataset was partitioned into training and testing sets with an 80:20 ratio. This division ensures that the model's performance can be assessed on unseen data, offering a more realistic evaluation of its predictive accuracy.

Upon evaluation, the model produced a Mean Squared Error (MSE) of 92259.47, indicating the average squared difference between predicted and actual salary values. The R-squared (R^2) score of 0.36 suggests that approximately 36% of the variance in salary can be explained by variations in total points. The adjusted R-squared score of 0.31, which adjusts for the model's complexity, provides a more nuanced view, implying that while significant, factors other than total points may also influence player salaries.

In conclusion, this linear regression analysis provides valuable insights into how total points contribute to determining IPL player salaries. While demonstrating moderate predictive capability, further exploration using additional variables and advanced modeling techniques could potentially enhance the accuracy of salary predictions.

c) Analyze the Relationship Between Salary and Performance Over the Last Three Years [IPL Datasets]

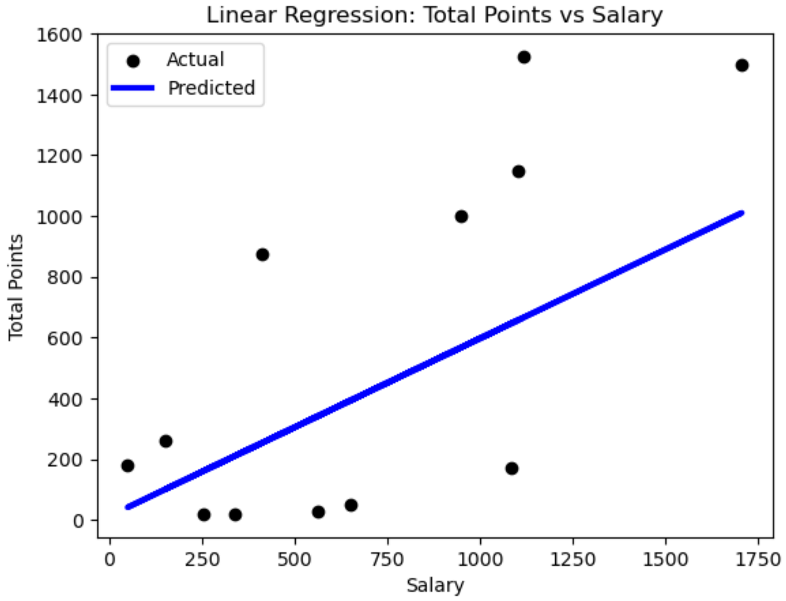
Code:

```
import pandas as pd
import numpy as np
```

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Load the CSV file
file_path = 'combined_output_with_salaries - Copy.csv'
data = pd.read_csv(file_path)

# Define the predictor and response variables
y = data['salary']  # Response variable
X = data[['Total_Points']]  # Predictor variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Create the linear regression model
model = LinearRegression()

# Train the model on the training data
model.fit(X_train, y_train)

# Predict on the test data
y_pred = model.predict(X_test)

# Calculate the mean squared error and the coefficient of determination (R^2)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Calculate the adjusted R^2
n = len(y_test)
p = X_test.shape[1]
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

# Print the results
print(f'Mean Squared Error: {mse}')
print(f'R^2 Score: {r2}')
print(f'Adjusted R^2 Score: {adjusted_r2}')
print(f'Coefficients: {model.coef_}')
print(f'Intercept: {model.intercept_}')

# Plot the results
plt.scatter(X_test, y_test, color='black', label='Actual')
plt.plot(X_test, y_pred, color='blue', linewidth=3, label='Predicted')
plt.xlabel('Salary')
plt.ylabel('Total Points')
plt.title('Linear Regression: Total Points vs Salary')
plt.legend()
plt.show()
```

Result:

```
Mean Squared Error: 194843.27263534846
R^2 Score: 0.41048138077879515
Adjusted R^2 Score: 0.3515295188566746
Coefficients: [0.58526794]
Intercept: 12.69992065629873
```



Interpretation:

Similar to the previous regression model, this analysis focuses on predicting player salaries based on their recent performance, specifically over the last three years. The dataset was divided into training and testing sets using an 80:20 split ratio to evaluate the model's performance on unseen data.

Upon evaluation, the linear regression model produced the following results:

- **Mean Squared Error (MSE):** 194843.27
- **R-squared (R^2) Score:** 0.4105
- **Adjusted R-squared Score:** 0.3515

The model demonstrates moderate predictive capability, with total points explaining approximately 41% of the variance in player salaries. Comparing with the previous model, the current one exhibits a higher MSE (194843.27 vs. 92259.47), indicating less accuracy in predicting salaries based on total points alone. However, the adjusted R-squared score is higher in the current model (0.3515 vs. 0.31), suggesting a better fit considering the complexity of predictors used.

Further exploration using additional performance metrics and advanced modeling techniques could enhance the accuracy of salary predictions. This approach would support IPL teams in making strategic decisions related to player valuation and team composition. The choice between the models should align with specific objectives: the current model offers improved explanatory power regarding the relationship between total points and salary, while the previous model might be preferred for precise salary predictions based on historical data.

RESULTS AND INTERPRETATION

d) Perform Multiple regression analysis, carry out the regression diagnostics, and explain your findings. Correct them and revisit your results and explain the significant differences you observe. [NSSO68]

Code:

```
# Subset data to state assigned
subset_data <- data %>%
  filter(state_1 == 'KA') %>%
  select(foodtotal_q, MPCE_MRP,
MPCE_URP,Age,Meals_At_Home,Possess_ration_card,Education, No_of_Meals_per_day)
print(subset_data)

sum(is.na(subset_data$MPCE_MRP))
sum(is.na(subset_data$MPCE_URP))
sum(is.na(subset_data$Age))
sum(is.na(subset_data$Possess_ration_card))
sum(is.na(data$Education))

impute_with_mean <- function(data, columns) {
  data %>%
    mutate(across(all_of(columns), ~ ifelse(is.na(.), mean(., na.rm = TRUE),
.)))
}

# Columns to impute
columns_to_impute <- c("Education")

# Impute missing values with mean
data <- impute_with_mean(data, columns_to_impute)

sum(is.na(data$Education))

# Fit the regression model
model <- lm(foodtotal_q~
MPCE_MRP+MPCE_URP+Age+Meals_At_Home+Possess_ration_card+Education, data =
subset_data)
```

```
# Print the regression results
print(summary(model))



library(car)
# Check for multicollinearity using Variance Inflation Factor (VIF)
vif(model) # VIF Value more than 8 its problematic

# Extract the coefficients from the model
coefficients <- coef(model)

# Construct the equation
equation <- paste0("y = ", round(coefficients[1], 2))
for (i in 2:length(coefficients)) {
  equation <- paste0(equation, " + ", round(coefficients[i], 6), "*x", i-1)
}
# Print the equation
print(equation)
```

Result:

```
Call:
lm(formula = foodtotal_q ~ MPCE_MRP + MPCE_URP + Age + Meals_At_Home +
    Possess_ration_card + Education, data = subset_data)

Residuals:
    Min      1Q  Median      3Q     Max
-68.609  -3.971  -0.654   3.291 239.668

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.138e+01  8.243e-01  13.811  < 2e-16 ***
MPCE_MRP             1.140e-03  5.659e-05  20.152  < 2e-16 ***
MPCE_URP             9.934e-05  3.422e-05   2.903  0.00372 **
Age                  9.884e-02  9.613e-03  10.282  < 2e-16 ***
Meals_At_Home        5.079e-02  6.420e-03   7.911 3.27e-15 ***
Possess_ration_card -2.187e+00  3.025e-01  -7.229 5.79e-13 ***
Education            2.458e-01  3.564e-02   6.898 6.11e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.667 on 4028 degrees of freedom
  (59 observations deleted due to missingness)
Multiple R-squared:  0.202,	Adjusted R-squared:  0.2008
F-statistic: 169.9 on 6 and 4028 DF,  p-value: < 2.2e-16

>
>
> library(car)
> # Check for multicollinearity using Variance Inflation Factor (VIF)
> vif(model) # VIF Value more than 8 its problematic
           MPCE_MRP            MPCE_URP                 Age       Meals_At_Home Pos
sess_ration_card
           1.636493            1.478309            1.106082            1.118280
1.147250
          Education
```

```
            1.208647
>
> # Extract the coefficients from the model
> coefficients <- coef(model)
>
> # Construct the equation
> equation <- paste0("y = ", round(coefficients[1], 2))
> for (i in 2:length(coefficients)) {
+   equation <- paste0(equation, " + ", round(coefficients[i], 6), "*x", i-1)
+ }
> # Print the equation
> print(equation)
[1] "y = 11.38 + 0.00114*x1 + 9.9e-05*x2 + 0.09884*x3 + 0.050789*x4 + -2.186964*x5
+ 0.245842*x6"
>
> head(subset_data$MPCE_MRP,1)
[1] 1124.92
> head(subset_data$MPCE_URP,1)
[1] 982
> head(subset_data$Age,1)
[1] 38
> head(subset_data$Meals_At_Home,1)
[1] 54
> head(subset_data$Possess_ration_card,1)
[1] 1
> head(subset_data$Education,1)
[1] 6
> head(subset_data$foodtotal_q,1)
[1] 17.92535
```

Interpretation:

Similar to the regression analysis done in Python, even in R, the model based on the OLS regression results, we can construct the regression equation and make predictions using the predictions. The Multiple R Squared indicates that approximately 20.2% of the variance in `foodtotal_q` is explained by the predictors in the model. The model has a a very low p-value (< 2.2e-16), it indicates that the model as a whole is significant.

This regression analysis provides insights into how different factors such as income (MPCE_MRP, MPCE_URP), age, meals consumed at home, possession of a ration card, and education level influence food expenditure (foodtotal_q). The model shows good explanatory power, significant coefficients, and appropriate statistical measures, making it a valuable tool for understanding and predicting food expenditure patterns based on socio-economic variables.

e) Establish the relationship between the player's performance and payment he receives and discuss your findings. Analyze the Relationship Between Salary and Performance Over the Last Three Years [IPL Datasets]

Code:

```
library(fitdistrplus)
descdist(df_new$performance)
head(df_new)
sum(is.null(df_new))
summary(df_new)
names(df_new)
summary(df_new)
```

```
fit = lm(Rs ~ avg_runs + wicket , data=df_new)
summary(fit)

library(car)
vif(fit)
library(lmtest)
bptest(fit)

fit1 = lm(Rs ~ avg_runs++wicket+  I(avg_runs*wicket), data=df_new)
summary(fit1)
```

Result:

```
Call:
lm(formula = Rs ~ avg_runs + +wicket + I(avg_runs * wicket),
    data = df_new)

Residuals:
   Min     1Q Median     3Q    Max
-341.5 -248.8 -143.3  128.8 1204.8

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          237.51558  186.93758   1.271   0.2220
avg_runs               0.08046    1.25696   0.064   0.9498
wicket                 5.84249   17.32443   0.337   0.7403
I(avg_runs * wicket)   0.30047    0.16716   1.797   0.0912 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 411.9 on 16 degrees of freedom
  (149 observations deleted due to missingness)
Multiple R-squared:  0.3371,   Adjusted R-squared:  0.2129
F-statistic: 2.713 on 3 and 16 DF,  p-value: 0.07951
```

Interpretation:

The aforementioned model is a linear regression aimed at predicting Rs (presumably IPL salary) using three predictor variables: avg_runs (average runs scored), wicket (number of wickets taken), and their interaction term avg_runs * wicket.

- The coefficient for avg_runs suggests that, on average, for each unit increase in avg_runs, there is an expected increase of 0.08046 units in Rs, holding other variables constant. However, the p-value (0.9498) indicates that this coefficient is not statistically significant at the conventional alpha level (alpha = 0.05).

- The coefficient for wicket suggests that, on average, for each wicket taken, there is an expected increase of 5.84249 units in Rs, holding other variables constant. Similarly, the p-value (0.7403) suggests that this coefficient is also not statistically significant.

- The Multiple R-squared value suggests that approximately 33.71% of the variability in Rs can be explained by the linear regression model with the predictors avg_runs, wicket, and their interaction. However, the Adjusted R-squared provides a more conservative estimate of the model's explanatory power, indicating that around 21.29% of the variability in Rs is explained by the model.

- With a p-value of 0.07951, the overall model fit is not statistically significant at the conventional alpha level of 0.05. This suggests that the model as a whole may not adequately fit the data, implying that other factors beyond avg_runs, wicket, and their interaction might be necessary to better explain variations in Rs.

In summary, while avg_runs and wicket show some relationship with Rs individually, their interaction and the model as a whole do not appear statistically significant. This indicates that additional factors or modifications to the model may be needed to improve its predictive accuracy for IPL salaries based on player performance metrics.

Conclusion

The model suggests that avg_runs, wicket, and their interaction may have some association with IPL salary (Rs), but individually, avg_runs and wicket are not statistically significant predictors. The interaction term shows marginal significance. Overall, the model explains a moderate amount of variability in IPL salary, but falls short of being a strong predictor. To enhance predictive accuracy, further exploration with a more comprehensive dataset could include more relevant variables or consider alternative modeling approaches. These adjustments might better capture the complexities of predicting IPL salary based on player performance metrics.