Technical Report

Predictive Analysis – Turtle Games

Kuok Tou Leong

1) Background of the Business

Turtle Games, a global game manufacturer and retailer, offers a diverse product range. The company collects sales and customer review data to improve sales performance by analysing customer trends. This report evaluates customer engagement with loyalty points, customer segmentation for marketing, and the use of customer reviews to inform campaigns. This analysis will help Turtle Games refine their marketing strategies and enhance customer retention.

2) Analytical approach

The turtle_reviews dataset was imported into Python for initial cleaning and exploration. Descriptive statistics and metadata analysis revealed central tendencies, dispersion, and distribution of the data. Unnecessary columns ("language", "platform") were removed to improve clarity. Missing value handling ensured data consistency.(A)

Linear regression explored relationships between loyalty points (dependent variable) and factors like age, income, and spending habits (independent variables). This analysis produced regression models with coefficients, standard errors, and predicted values. Scatterplots and regression plots visualised these relationships.(B)

A decision tree regressor was developed for enhanced predictive modelling. Metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared were evaluated. Pruning techniques simplified the decision tree and improved interpretability.(C)

Scatterplots investigated the relationship between remuneration and spending score, identifying potential correlations and customer groups. The Silhouette and Elbow methods determined the optimal number of clusters for k-means analysis, revealing distinct customer segments within the data.(D)

Natural Language Processing (NLP) techniques analysed textual data from reviews and summaries. Tokenisation enabled the creation of word clouds to visualise word frequency and importance. Sentiment analysis using histograms assessed sentiment polarity, highlighting positive and negative sentiments.(E)

Finally, the dataset was imported into R for further summarisation. Exploratory data analysis employed histograms, boxplots, and scatterplots to visualise data distributions and relationships. Normality checks using Q-Q plots, Shapiro-Wilk tests, and measures of skewness and kurtosis ensured data suitability for linear regression models used to predict loyalty points.(F)

3) Visualisation and insights

In Figure 1, spending score 50 appeared most frequently among all scores. Figure 2, depicted as a box plot, provided detailed insights into the distribution of spending scores. The lower quartile (Q1 = 32) indicates that 25% of scores are below this value, while the median and mean (both 50) signify central tendency. The upper quartile (Q3 = 73) shows that 75% of scores fall below this threshold, illustrating the dataset's spread and variability.(F)

Figure 3 illustrated a decision tree with the spending score at the root node, indicating its central importance as a primary driver that strongly influences other variables in the analysis.(C)

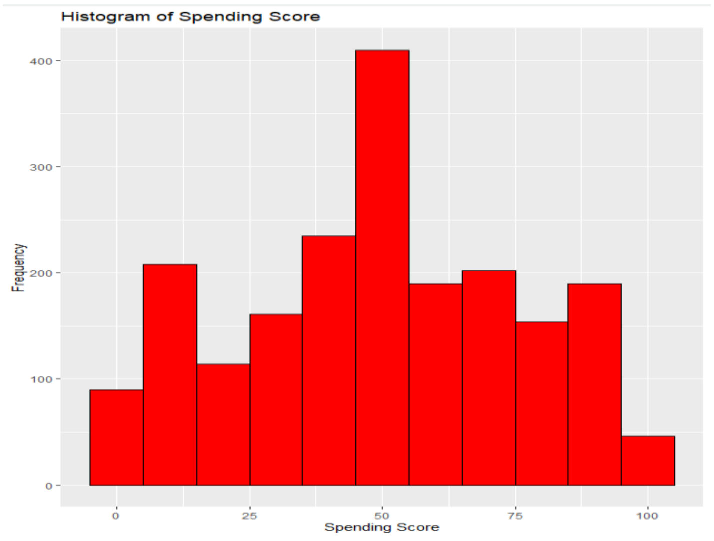


Figure 1Histogram of Spending Score

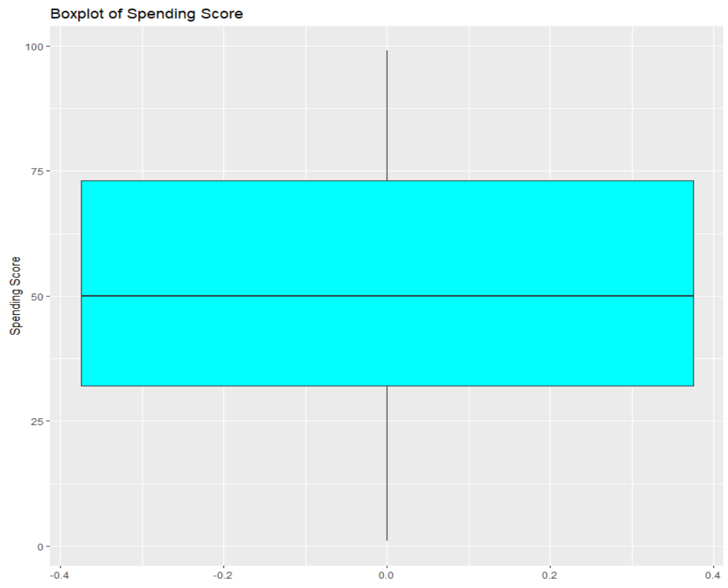


Figure 2 Boxplot of Spending Score

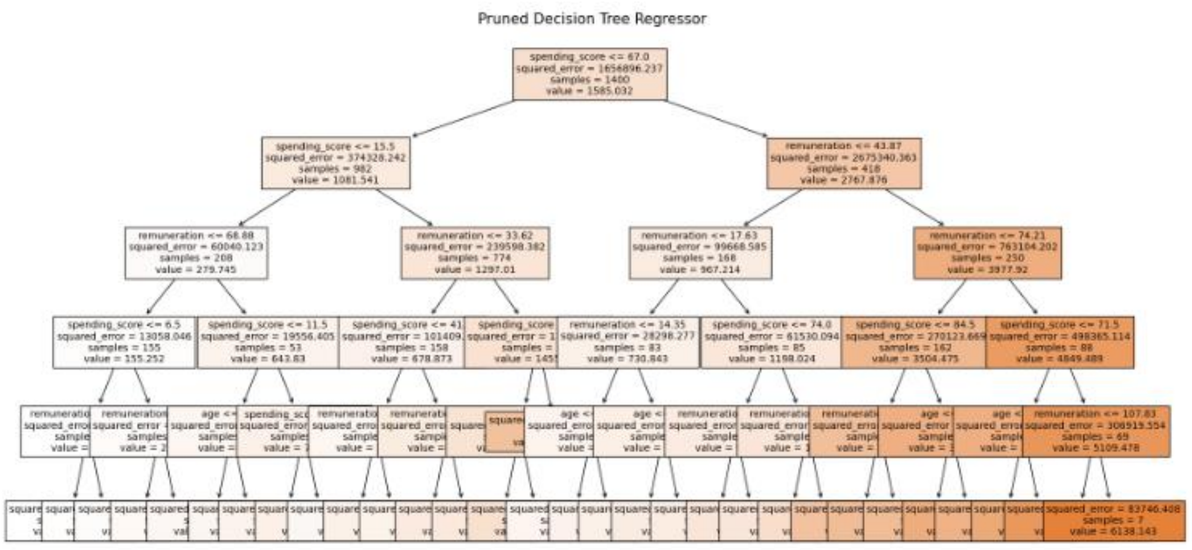


Figure 3 Decision Tree

In Figure 5, the age group 35-45 appeared most frequently compared to other age groups. Figure 4's box plot for Age shows quartile values (Q1 = 29, median = 38, Q3 = 49), with outliers beyond this range.(F)

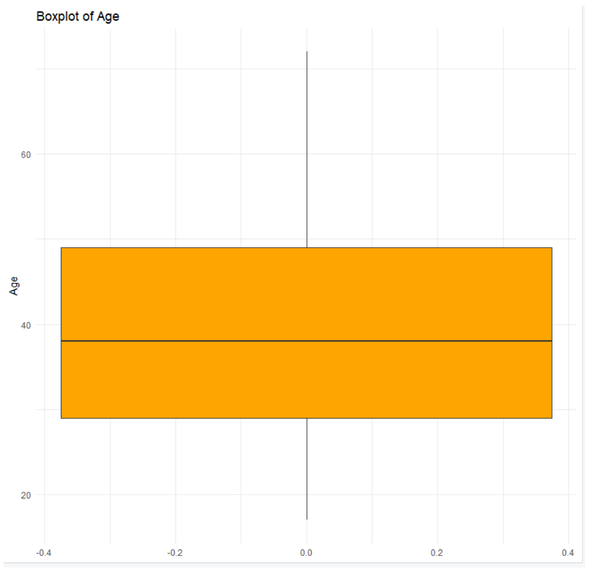


Figure 4 Boxplot of Age

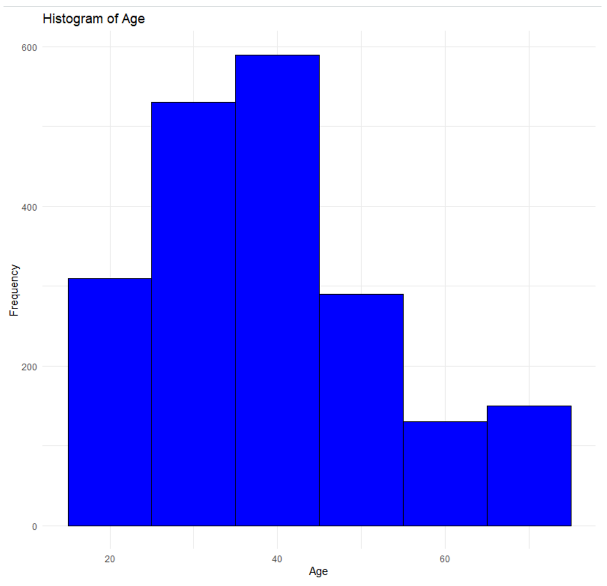


Figure 5 Histogram of Age

In Figure 6, the remuneration of 35-45K had the highest frequency compared to others. Figure 7 illustrates that the dataset has a first quartile (Q1) of 30.34k, a median of 47.15k, a mean of 48.08, and a third quartile (Q3) of 63.96k.(F)

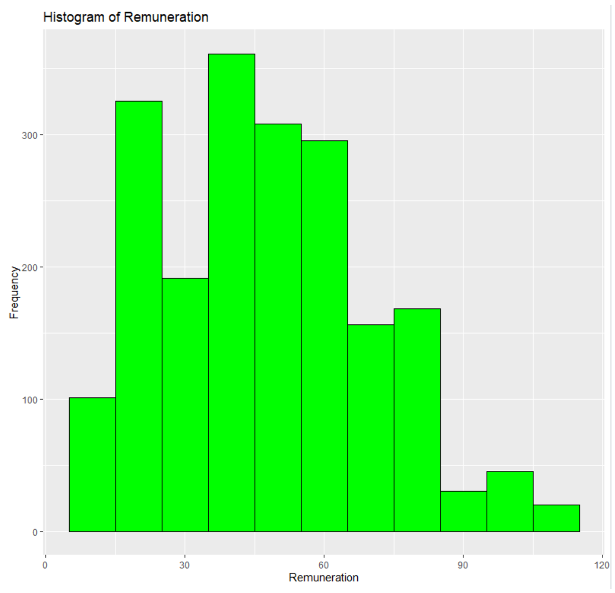


Figure 6 Histogram of Remuneration

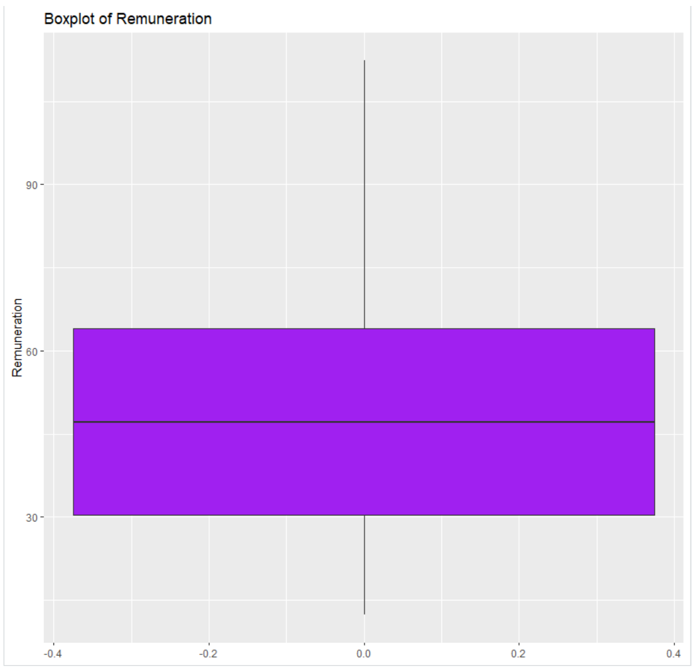
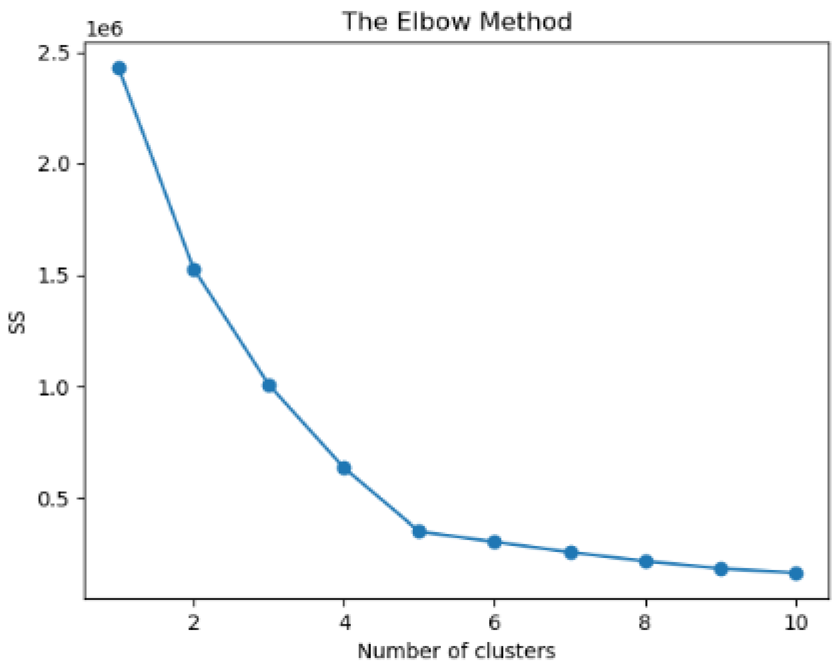
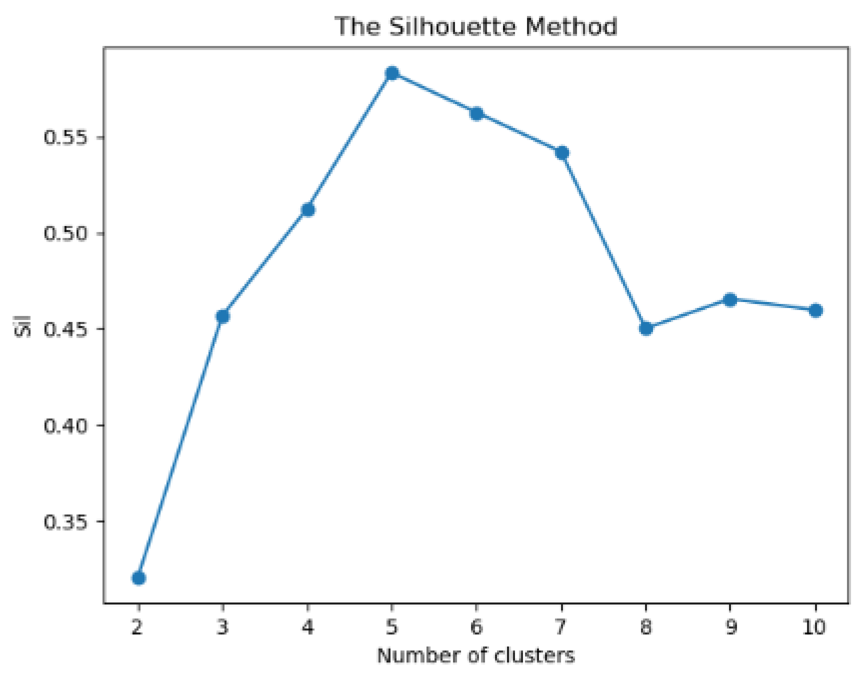
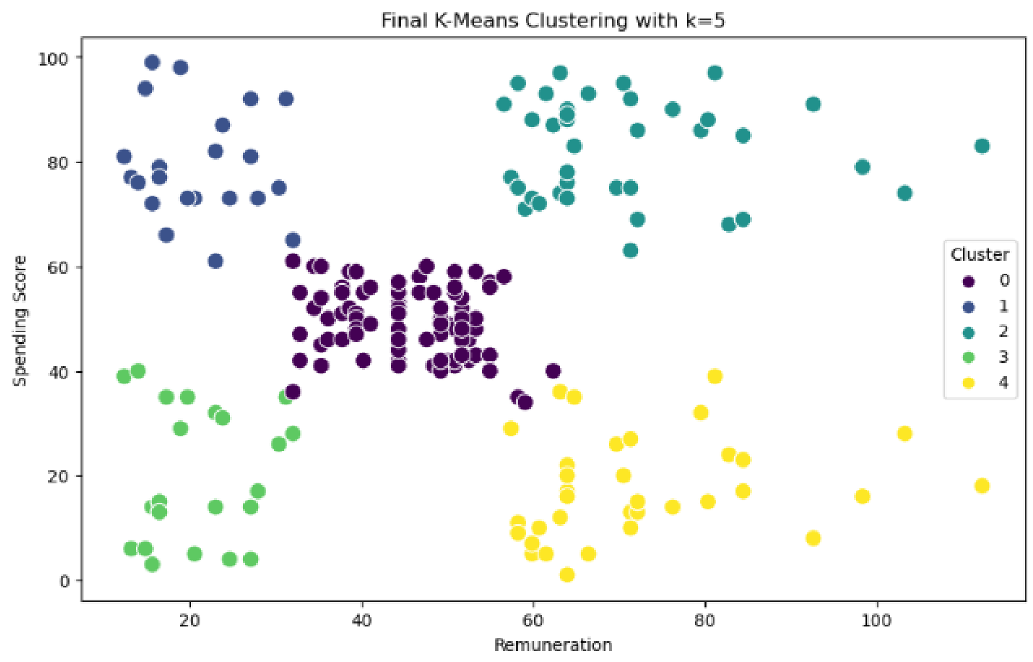


Figure 7 Boxplot of Remuneration

Customer data was segmented using k-means clustering with k = 5, determined as optimal through the Elbow and Silhouette methods. Each cluster reveals distinct customer behaviours, guiding tailored marketing strategies.







- Cluster 0 (774 members): Medium remuneration and medium spending score customers.
- Cluster 1 (269 members): Low remuneration but high spending score customers.
- Cluster 2 (356 members): High remuneration and high spending score customers.
- Cluster 3 (271 members): Low remuneration and low spending score customers.
- Cluster 4 (330 members): High remuneration but low spending score customers.

These clusters provide insights into customer spending patterns and preferences, enabling businesses to refine marketing approaches depending on their marketing goal.(D)

The most common words in reviews are game appear 1706 times and stars appear 439 times in summaries. While 'game', 'fun' and 'great' appear top 5 in both columns.

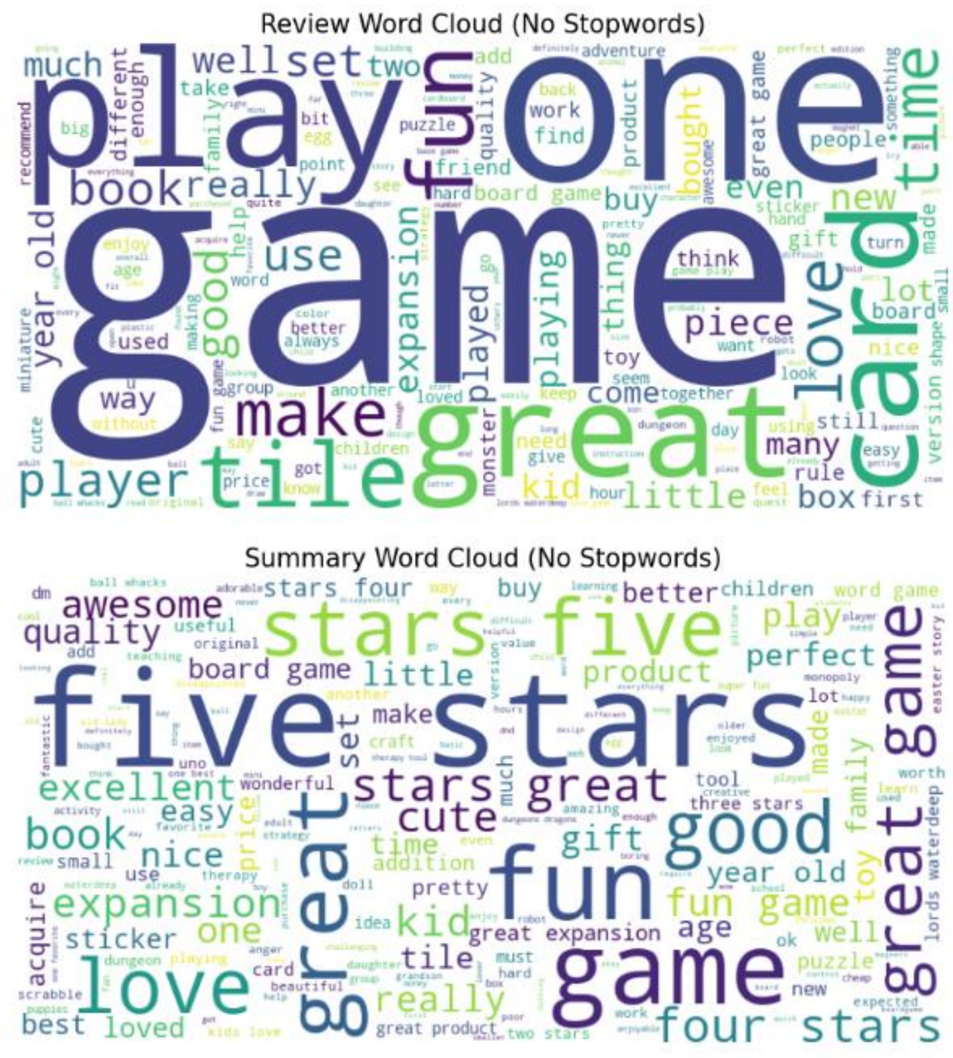


Figure 8 Word Clouds for Most Common Words in Reviews and Summaries

The overall polarity for reviews and summaries is generally neutral to positive, as shown in Figure 9. Summary polarity most frequently occurs at 0.0, while review polarity peaks between 0 and 0.25.(E)

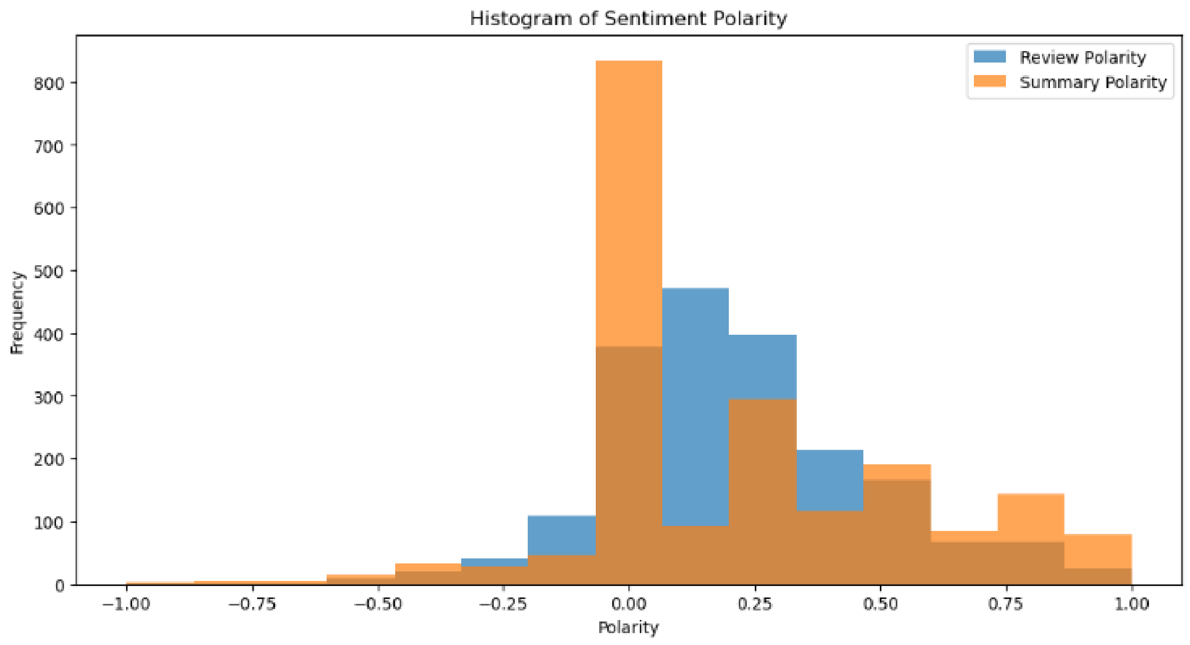


Figure 9 Histogram of sentiment Polarity

4) Patterns and Predictions

Figure 10's box plot illustrates Loyalty Points with quartile values (Q1 = 772, median = 1276, Q3 = 1751) and outliers beyond this range. Figure 11's analysis reveals a non-normal distribution ($p < 2.2e-16$), positive skewness (1.46), and higher kurtosis (4.71), indicating a right-skewed distribution with heavier tails. This means more extreme value exist on both ends which can impact the reliability of the models.

Due to the non-normality of the loyalty points data, linear regression or decision tree might not be suitable for accurate predictions.Therefore, descriptive statistics can't be used to provide insights.

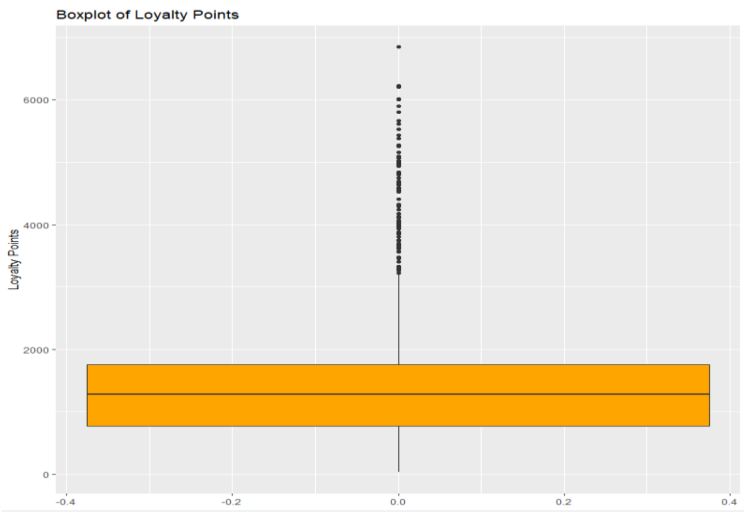


Figure 10 Boxplot of Loyalty Points

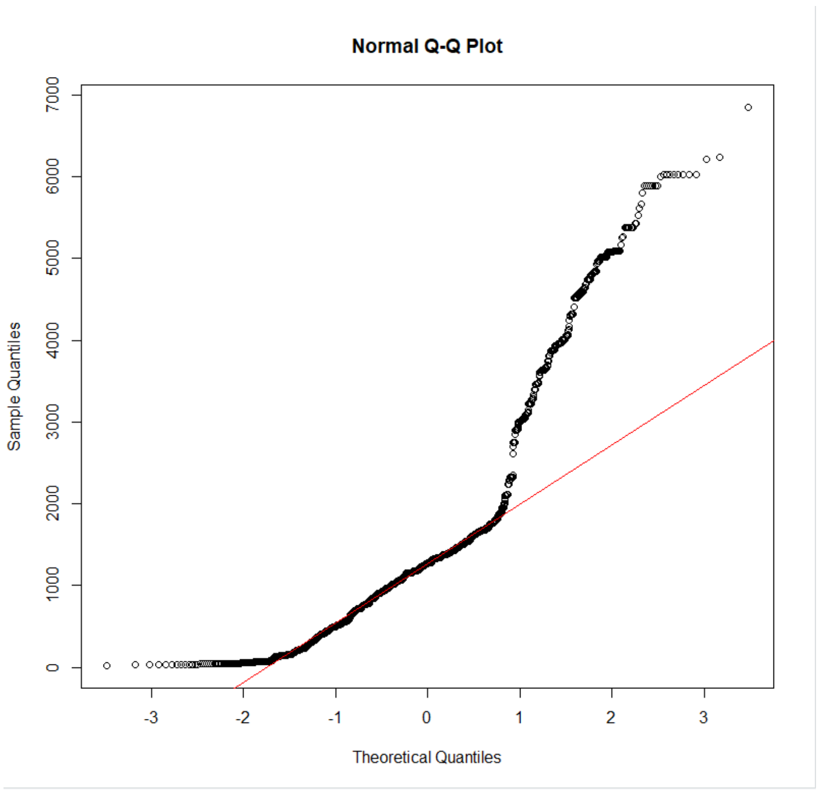


Figure 11 Quantile-Quantile Plot of Loyalty Points

Figure 12's regression model shows that age has minimal impact on loyalty points, as indicated by the extremely low R-squared value of 0.0018. The coefficient for age is -4.0128, suggesting that each additional year of age predicts a decrease of approximately 4.01 loyalty points. However, given the very low R-squared value, this inverse relationship is weak and not practically significant.(A)

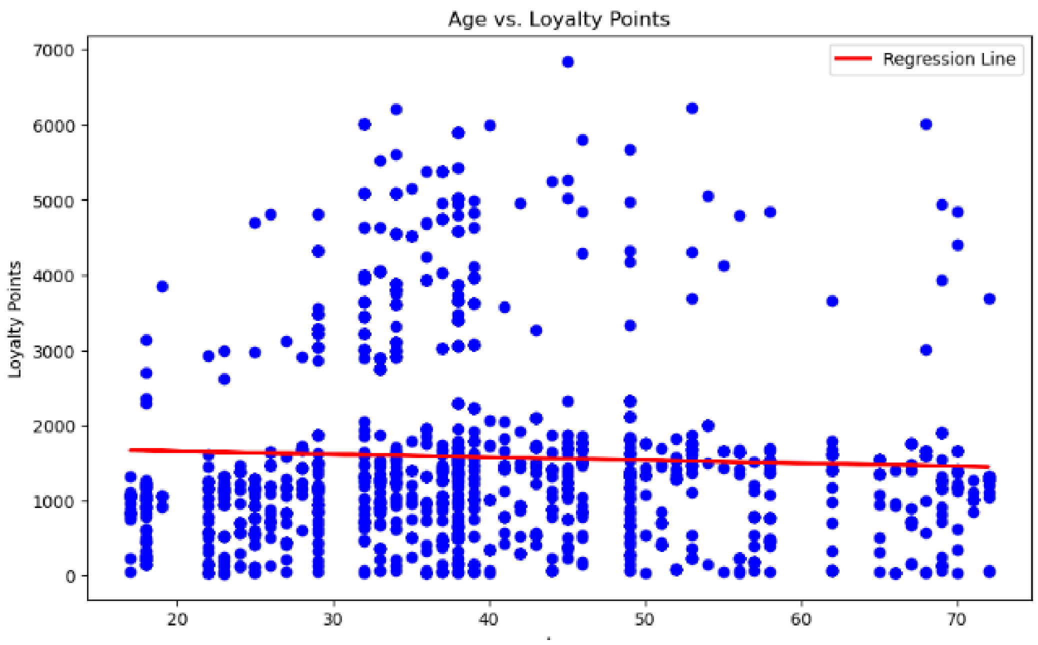


Figure 12 Relationship between Age and Loyalty Points

Figure 13's regression model shows that remuneration has a positive correlation with loyalty points, with an R-squared value of 0.3795. The coefficient for remuneration is 34.19, indicating that for each unit increase in remuneration, the model predicts an increase of approximately 34.19 loyalty points. The positive sign suggests a direct relationship between remuneration and loyalty points.(A)

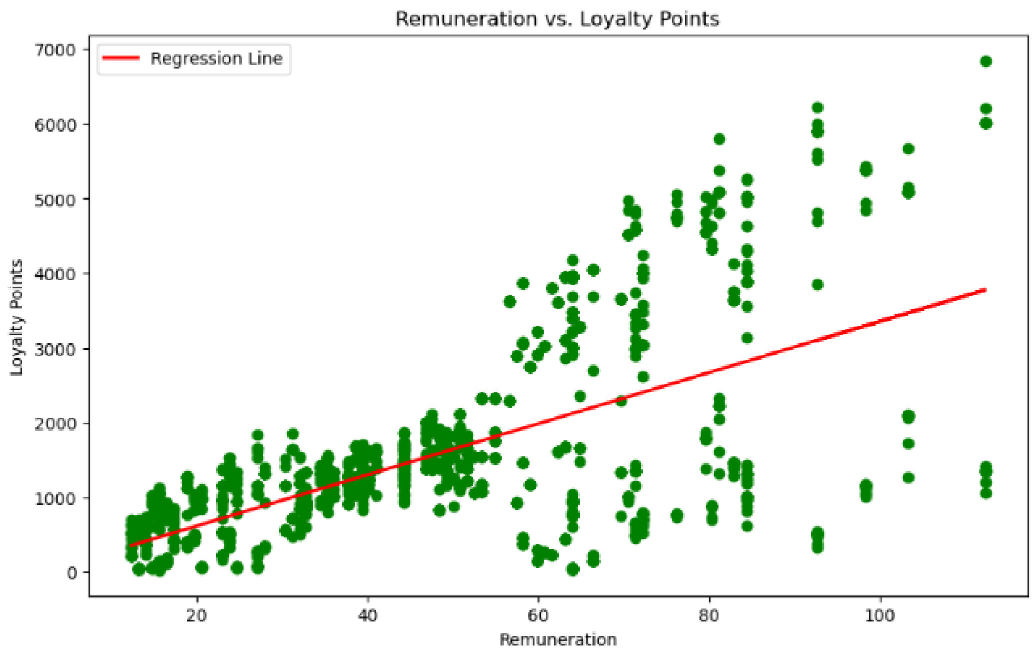


Figure 13 Relationship between Remuneration and Loyalty Points

Figure 14's regression model shows that the spending score has a positive correlation with loyalty points, with an R-squared value of 0.4520. The coefficient for the spending score is 33.06, indicating that for each unit increase in the spending score, the model predicts an increase of approximately 33.06 loyalty points.(A)

Customers can accumulate more loyalty points either by increasing remuneration or spending score.

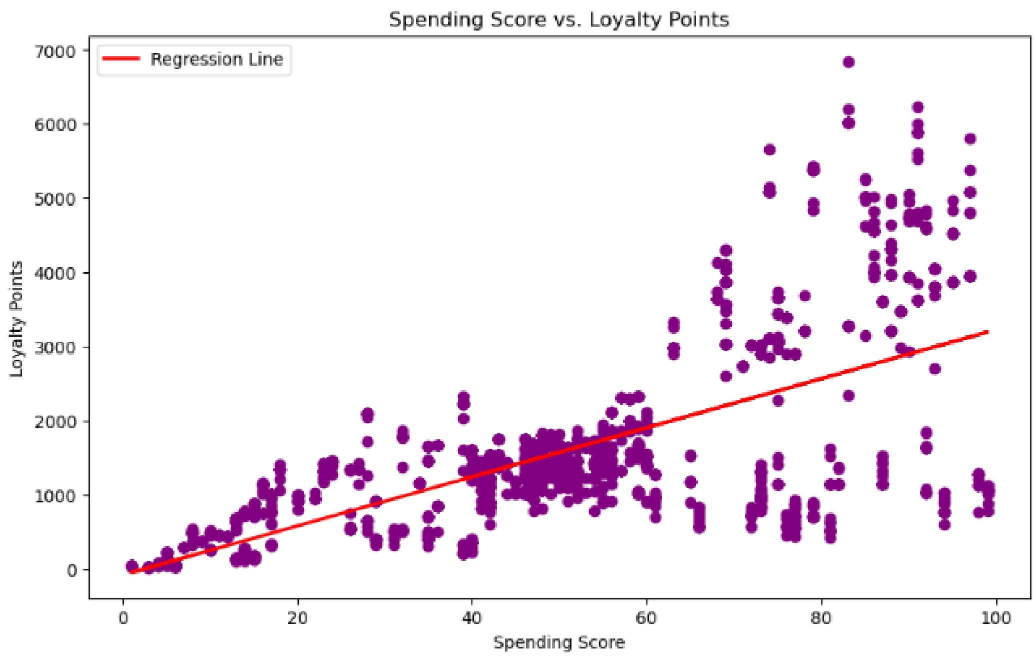


Figure 14 Relationship between Spending Score and Loyalty Points

5) Recommendation

Turtle Games can tailor marketing strategies based on cluster characteristics to optimise loyalty programs and drive business growth effectively.

Turtle Games utilise insights from common words found in reviews and summaries, like "Game," "Great," "Fun," "Stars," and "Five," combined with NLP analysis of customer feedback, to refine marketing strategies effectively and enhance customer satisfaction.

Appendices

A) Import Data in Python and sense-checking code

```
# Import all the necessary packages.
import numpy as np
import pandas as pd
import statsmodels.api as sm
import statsmodels.stats.api as sms
import sklearn
import matplotlib.pyplot as plt

from sklearn import linear_model
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from statsmodels.formula.api import ols

import warnings
warnings.filterwarnings('ignore')
```

```
# Import the data set.
turtle_reviews = pd.read_csv('turtle_reviews.csv')

# View the DataFrame.
turtle_reviews.head()
```

	gender	age	remuneration (k£)	spending_score (1-100)	loyalty_points	education	language	platform	product	review	summary
0	Male	18	12.30	39	210	graduate	EN	Web	453	When it comes to a DM's screen, the space on t...	The fact that 50% of this space is wasted on a...
1	Male	23	12.30	81	524	graduate	EN	Web	466	An Open Letter to GaleForce9*:\n\nYour unpaint...	Another worthless Dungeon Master's screen from...
2	Female	22	13.12	6	40	graduate	EN	Web	254	Nice art, nice printing. Why two panels are f...	pretty, but also pretty useless
3	Female	25	13.12	77	562	graduate	EN	Web	263	Amazing buy! Bought it as a gift for our new d...	Five Stars
4	Female	33	13.94	40	366	graduate	EN	Web	291	As my review of GF9's previous screens these w...	Money trap

```
# View the metadata.
turtle_reviews.info()

# Generate descriptive statistics summary
turtle_reviews.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 11 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   gender                  2000 non-null   object 
 1   age                     2000 non-null   int64  
 2   remuneration (k£)       2000 non-null   float64
 3   spending_score (1-100)  2000 non-null   int64  
 4   loyalty_points          2000 non-null   int64  
 5   education               2000 non-null   object 
 6   language                2000 non-null   object 
 7   platform                2000 non-null   object 
 8   product                 2000 non-null   int64  
 9   review                  2000 non-null   object 
 10  summary                 2000 non-null   object 
dtypes: float64(1), int64(4), object(6)
memory usage: 172.0+ KB
```

	age	remuneration (k£)	spending_score (1-100)	loyalty_points	product
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	39.495000	48.079060	50.000000	1578.032000	4320.521500
std	13.573212	23.123984	26.094702	1283.239705	3148.938839
min	17.000000	12.300000	1.000000	25.000000	107.000000
25%	29.000000	30.340000	32.000000	772.000000	1589.250000
50%	38.000000	47.150000	50.000000	1276.000000	3624.000000
75%	49.000000	63.960000	73.000000	1751.250000	6654.000000
max	72.000000	112.340000	99.000000	6847.000000	11086.000000

Data cleaning in Python

```
# Check for missing values
missing_values = turtle_reviews.isnull().sum()
print("Missing values in each column:\n", missing_values)
```

```
Missing values in each column:
 gender                  0
age                     0
remuneration (k£)       0
spending_score (1-100)  0
loyalty_points          0
education               0
language                0
platform                0
product                 0
review                  0
summary                 0
dtype: int64
```

```
# Check column names before dropping
print(turtle_reviews.columns.tolist())  # View list of columns
```

```
['gender', 'age', 'remuneration (k£)', 'spending_score (1-100)', 'loyalty_points', 'education', 'language', 'platform', 'produc
t', 'review', 'summary']
```

```
# Remove redundant columns
turtle_reviews.drop(columns=['language', 'platform'], inplace=True)
```

```
# Rename columns
turtle_reviews.rename(columns={
    'remuneration (k£)': 'remuneration',
    'spending_score (1-100)': 'spending_score'
}, inplace=True)

# Save the cleaned DataFrame as a new CSV file in the current directory
cleaned_file_path = 'cleaned_turtle_reviews.csv'
turtle_reviews.to_csv(cleaned_file_path, index=False)
cleaned_reviews = pd.read_csv(cleaned_file_path)
```

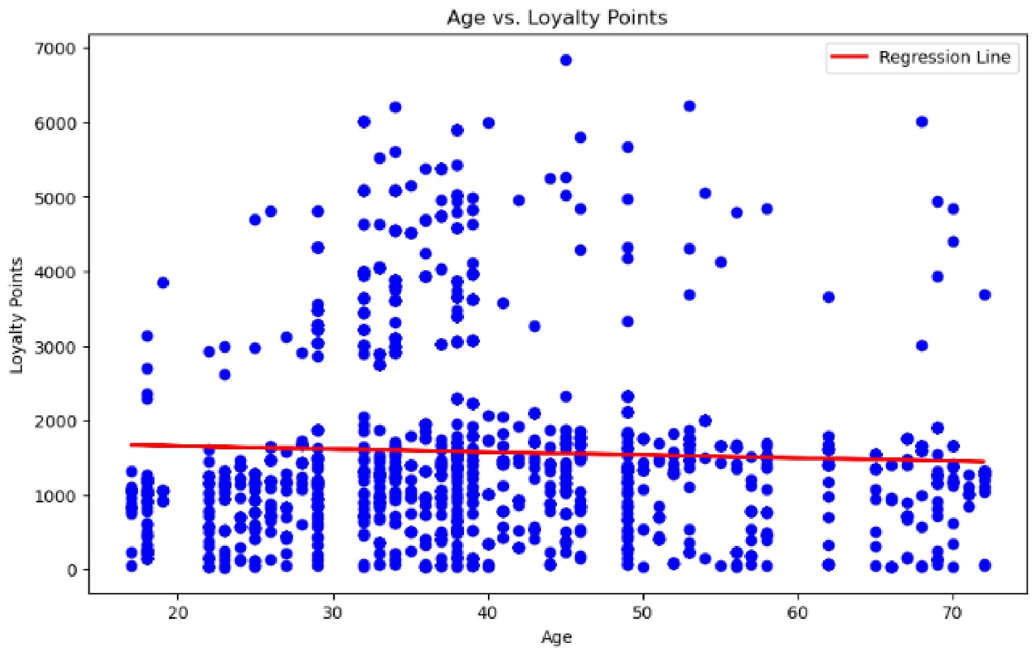
```
cleaned_info = cleaned_reviews.info()
cleaned_head = cleaned_reviews.head()
print(cleaned_info)
print(cleaned_head)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   gender          2000 non-null   object 
 1   age             2000 non-null   int64  
 2   remuneration    2000 non-null   float64
 3   spending_score  2000 non-null   int64  
 4   loyalty_points  2000 non-null   int64  
 5   education       2000 non-null   object 
 6   product         2000 non-null   int64  
 7   review          2000 non-null   object 
 8   summary         2000 non-null   object 
dtypes: float64(1), int64(4), object(4)
memory usage: 140.8+ KB
None
   gender  age  remuneration  spending_score  loyalty_points education  \
0    Male   18         12.30              39             210  graduate   
1    Male   23         12.30              81             524  graduate   
2  Female   22         13.12               6              40  graduate   
3  Female   25         13.12              77             562  graduate   
4  Female   33         13.94              40             366  graduate   

   product                                             review  \
0      453  When it comes to a DM's screen, the space on t...   
1      466  An Open Letter to GaleForce9*:\n\nYour unpaint...   
2      254  Nice art, nice printing.  Why two panels are f...   
3      263  Amazing buy! Bought it as a gift for our new d...   
4      291  As my review of GF9's previous screens these w...   

                                             summary  
0  The fact that 50% of this space is wasted on a...  
1  Another worthless Dungeon Master's screen from...  
2                     pretty, but also pretty useless  
3                                          Five Stars  
4                                          Money trap  
```

B) Finding relationships between independent variable and the dependent variable.

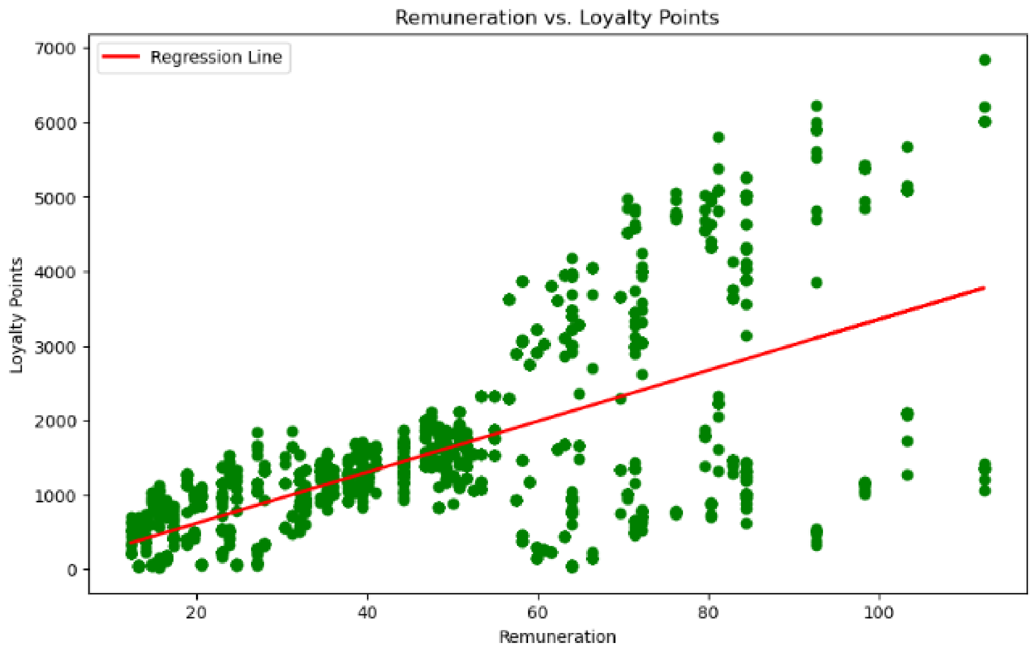
```
# Define the independent variables (age) and the dependent variable (loyalty_points)
X_age = cleaned_reviews[['age']]
y = cleaned_reviews['loyalty_points']


# Create the linear regression model
model = LinearRegression()
model.fit(cleaned_reviews[['age']], y)

# Call the predictions for X (array).
y_pred_age = model.predict(X_age)

# Extract the estimated parameters, standard errors, and predicted values
print("R-squared: ", model.score(X_age,y))
print("Intercept: ", model.intercept_)
print("coefficients: ", model.coef_)

# Plotting remuneration vs. loyalty_points
plt.figure(figsize=(10, 6))
plt.scatter(cleaned_reviews['age'], y, color='blue')
plt.plot(cleaned_reviews['age'], y_pred_age, color='red', linewidth=2, label='Regression Line')
plt.title('Age vs. Loyalty Points')
plt.xlabel('Age')
plt.ylabel('Loyalty Points')
plt.legend()
plt.show()
```

```
R-squared:  0.0018015480437203468
Intercept:  1736.517739399063
coefficients:  [-4.01280515]
```



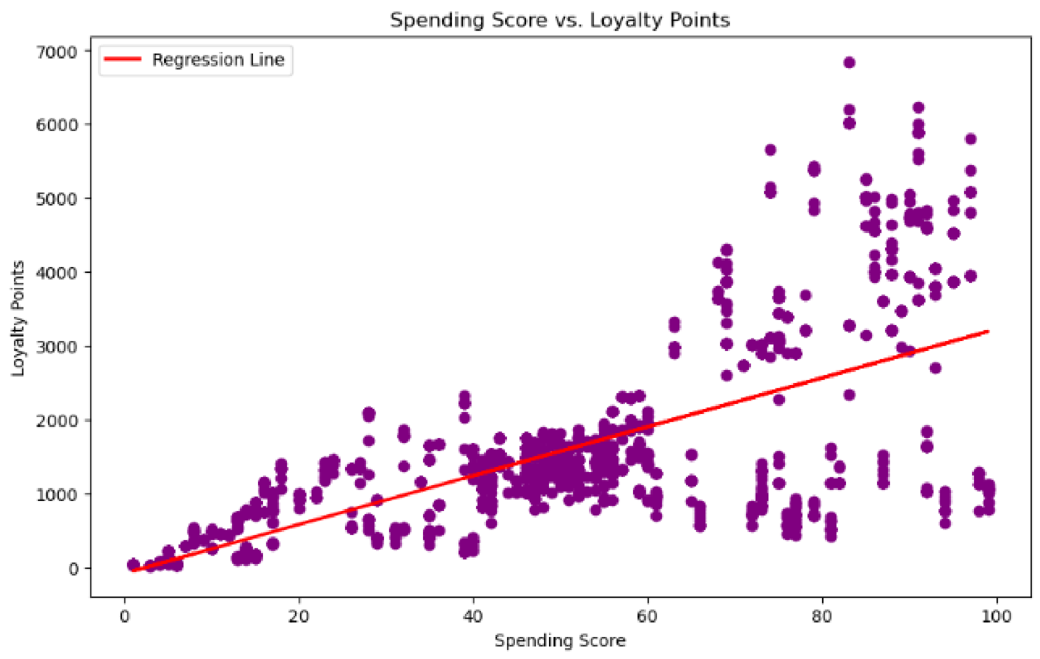
```
# Define the independent variables (remuneration) and the dependent variable (loyalty_points)
X_remuneration = cleaned_reviews[['remuneration']]
y = cleaned_reviews['loyalty_points']


# Create the linear regression model
model = LinearRegression()
model.fit(cleaned_reviews[['remuneration']], y)

# Call the predictions for X (array).
y_pred_remuneration = model.predict(X_remuneration)

# Extract the estimated parameters, standard errors, and predicted values
print("R-squared: ", model.score(X_remuneration,y))
print("Intercept: ", model.intercept_)
print("coefficients: ", model.coef_)

# Plotting remuneration vs. loyalty_points
plt.figure(figsize=(10, 6))
plt.scatter(cleaned_reviews['remuneration'], y, color='green')
plt.plot(cleaned_reviews['remuneration'], y_pred_remuneration, color='red', linewidth=2, label='Regression Line')
plt.title('Remuneration vs. Loyalty Points')
plt.xlabel('Remuneration')
plt.ylabel('Loyalty Points')
plt.legend()
plt.show()
```

```
R-squared:  0.3795357732793634
Intercept:  -65.68651279500409
coefficients:  [34.18782549]
```

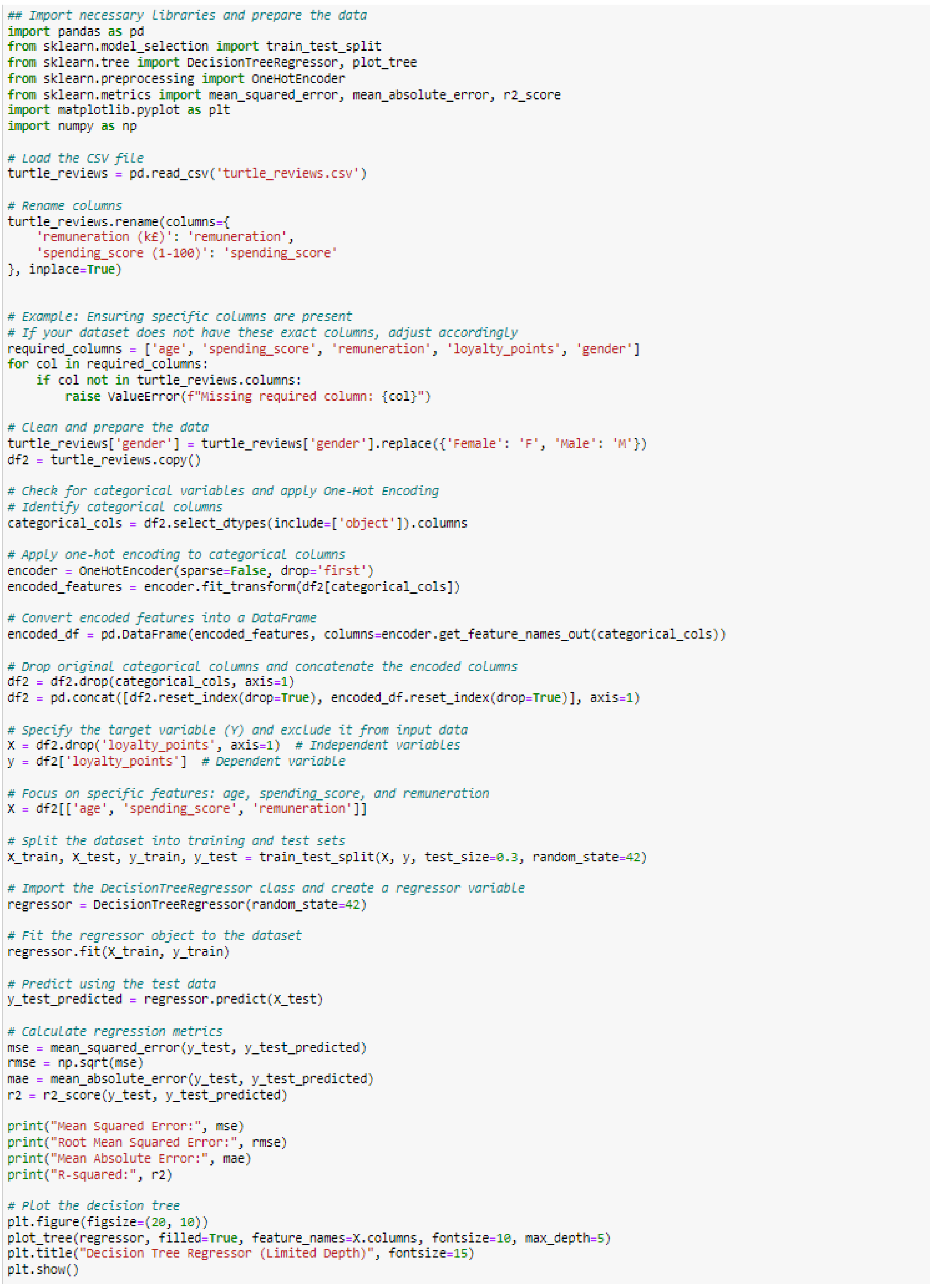


```
# Define the independent variables (spending_score) and the dependent variable (loyalty_points)
X_spending_score = cleaned_reviews[['spending_score']]
y = cleaned_reviews['loyalty_points']


# Create the linear regression model
model = LinearRegression()
model.fit(cleaned_reviews[['spending_score']], y)

# Call the predictions for X (array).
y_pred_spending_score = model.predict(X_spending_score)

# Extract the estimated parameters, standard errors, and predicted values
print("R-squared: ", model.score(X_spending_score,y))
print("Intercept: ", model.intercept_)
print("coefficients: ", model.coef_)

# Plotting spending_score vs. loyalty_points
plt.figure(figsize=(10, 6))
plt.scatter(cleaned_reviews['spending_score'], y, color='purple')
plt.plot(cleaned_reviews['spending_score'], y_pred_spending_score, color='red', linewidth=2, label='Regression Line')
plt.title('Spending Score vs. Loyalty Points')
plt.xlabel('Spending Score')
plt.ylabel('Loyalty Points')
plt.legend()
plt.show()
```

```
R-squared:  0.4520008865838909
Intercept:  -75.05266293364707
coefficients:  [33.06169326]
```



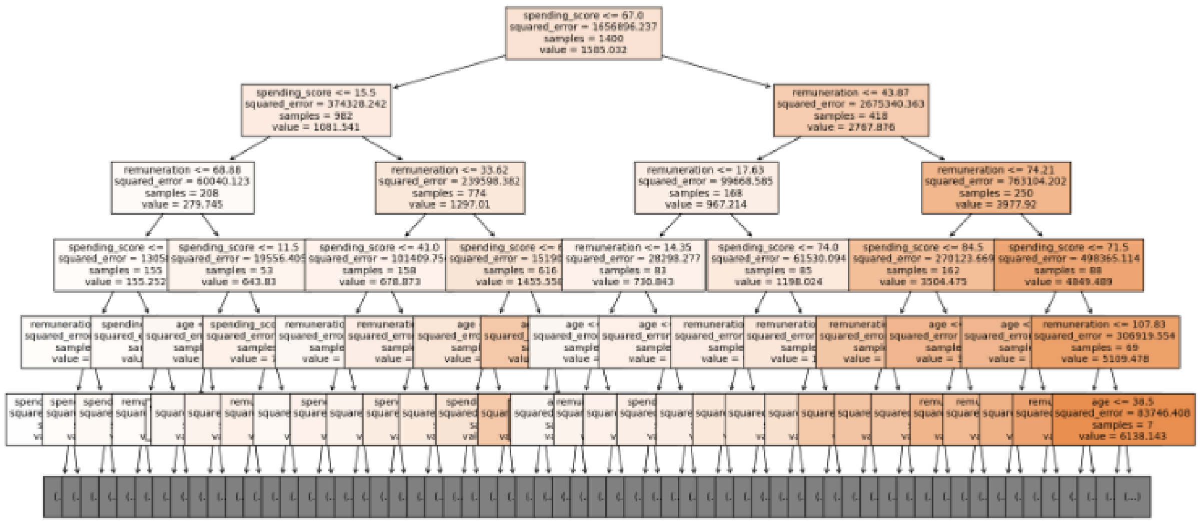
C) Decision Tree regressor



```python
## Import necessary libraries and prepare the data
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
import numpy as np

# Load the CSV file
turtle_reviews = pd.read_csv('turtle_reviews.csv')

# Rename columns
turtle_reviews.rename(columns={
    'remuneration (k£)': 'remuneration',
    'spending_score (1-100)': 'spending_score'
}, inplace=True)


# Example: Ensuring specific columns are present
# If your dataset does not have these exact columns, adjust accordingly
required_columns = ['age', 'spending_score', 'remuneration', 'loyalty_points', 'gender']
for col in required_columns:
    if col not in turtle_reviews.columns:
        raise ValueError(f"Missing required column: {col}")

# Clean and prepare the data
turtle_reviews['gender'] = turtle_reviews['gender'].replace({'Female': 'F', 'Male': 'M'})
df2 = turtle_reviews.copy()

# Check for categorical variables and apply One-Hot Encoding
# Identify categorical columns
categorical_cols = df2.select_dtypes(include=['object']).columns

# Apply one-hot encoding to categorical columns
encoder = OneHotEncoder(sparse=False, drop='first')
encoded_features = encoder.fit_transform(df2[categorical_cols])

# Convert encoded features into a DataFrame
encoded_df = pd.DataFrame(encoded_features, columns=encoder.get_feature_names_out(categorical_cols))

# Drop original categorical columns and concatenate the encoded columns
df2 = df2.drop(categorical_cols, axis=1)
df2 = pd.concat([df2.reset_index(drop=True), encoded_df.reset_index(drop=True)], axis=1)

# Specify the target variable (Y) and exclude it from input data
X = df2.drop('loyalty_points', axis=1)  # Independent variables
y = df2['loyalty_points']  # Dependent variable

# Focus on specific features: age, spending_score, and remuneration
X = df2[['age', 'spending_score', 'remuneration']]

# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Import the DecisionTreeRegressor class and create a regressor variable
regressor = DecisionTreeRegressor(random_state=42)

# Fit the regressor object to the dataset
regressor.fit(X_train, y_train)

# Predict using the test data
y_test_predicted = regressor.predict(X_test)

# Calculate regression metrics
mse = mean_squared_error(y_test, y_test_predicted)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_test_predicted)
r2 = r2_score(y_test, y_test_predicted)

print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)

# Plot the decision tree
plt.figure(figsize=(20, 10))
plot_tree(regressor, filled=True, feature_names=X.columns, fontsize=10, max_depth=5)
plt.title("Decision Tree Regressor (Limited Depth)", fontsize=15)
plt.show()
```

```
Mean Squared Error: 6390.448333333334
Root Mean Squared Error: 79.94027979268857
Mean Absolute Error: 26.171666666666667
R-squared: 0.9960547843086969
```

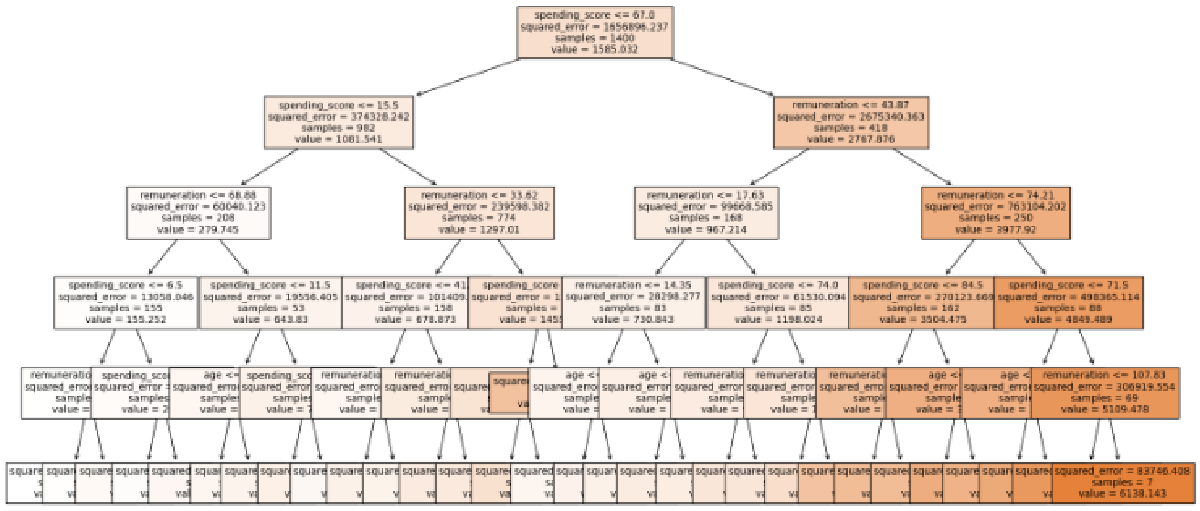
Decision Tree Regressor (Limited Depth)



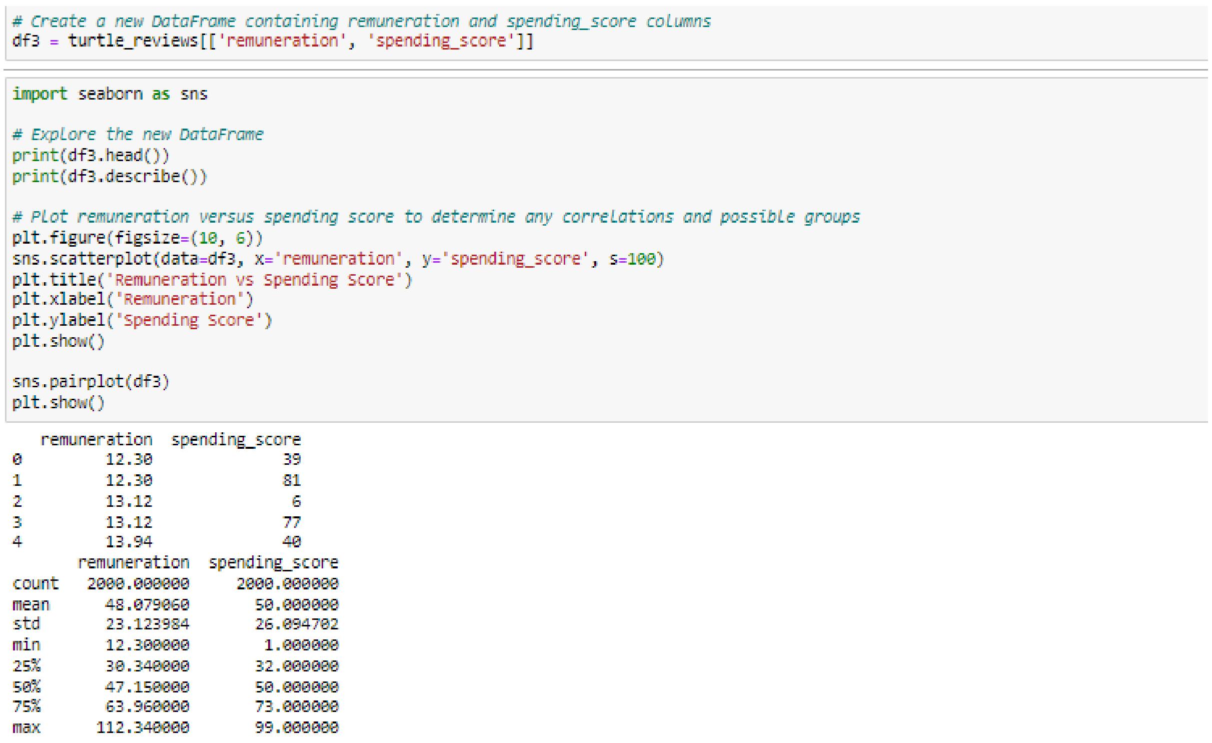
```python
# Prune the tree and re-evaluate
regressor_pruned = DecisionTreeRegressor(random_state=42, max_depth=5, min_samples_split=5, min_samples_leaf=5)
regressor_pruned.fit(X_train, y_train)
y_test_predicted_pruned = regressor_pruned.predict(X_test)

# Evaluate the pruned model
mse_pruned = mean_squared_error(y_test, y_test_predicted_pruned)
rmse_pruned = np.sqrt(mse_pruned)
mae_pruned = mean_absolute_error(y_test, y_test_predicted_pruned)
r2_pruned = r2_score(y_test, y_test_predicted_pruned)

print("Pruned Mean Squared Error:", mse_pruned)
print("Pruned Root Mean Squared Error:", rmse_pruned)
print("Pruned Mean Absolute Error:", mae_pruned)
print("Pruned R-squared:", r2_pruned)

# Plot the pruned decision tree
plt.figure(figsize=(20, 10))
plot_tree(regressor_pruned, filled=True, feature_names=X.columns, fontsize=10)
plt.title("Pruned Decision Tree Regressor", fontsize=15)
plt.show()
```

```
Pruned Mean Squared Error: 70229.10691738166
Pruned Root Mean Squared Error: 265.0077487874301
Pruned Mean Absolute Error: 177.2664367154586
Pruned R-squared: 0.9566432650505238
```

Pruned Decision Tree Regressor



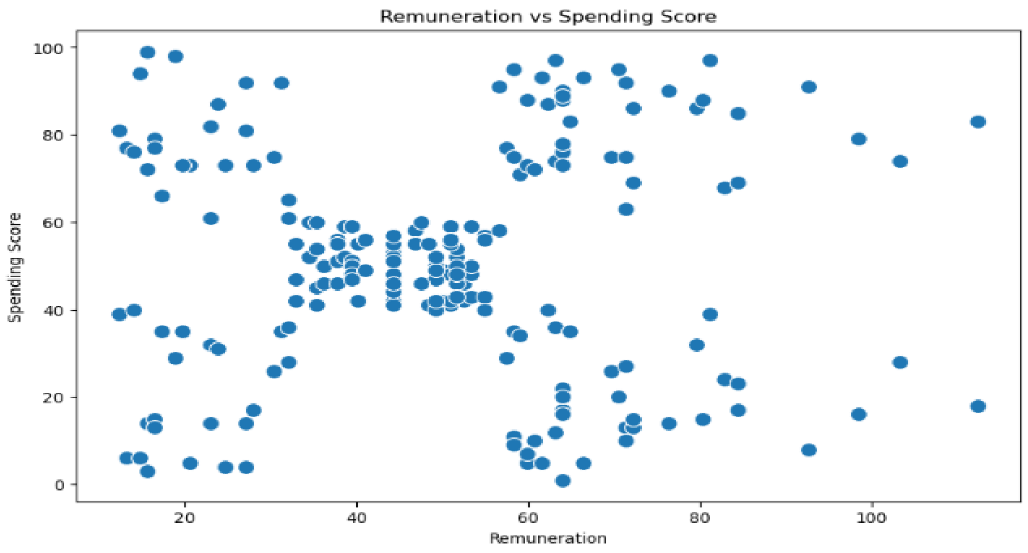
D) the remuneration versus spending score scatterplot

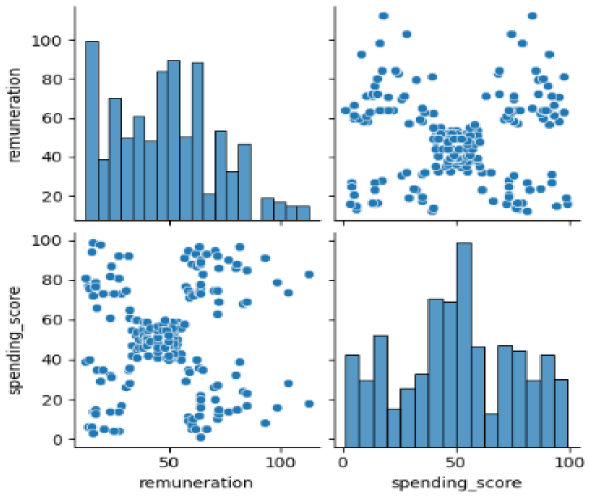


```
# Create a new DataFrame containing remuneration and spending_score columns
df3 = turtle_reviews[['remuneration', 'spending_score']]
```

```
import seaborn as sns

# Explore the new DataFrame
print(df3.head())
print(df3.describe())

# Plot remuneration versus spending score to determine any correlations and possible groups
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df3, x='remuneration', y='spending_score', s=100)
plt.title('Remuneration vs Spending Score')
plt.xlabel('Remuneration')
plt.ylabel('Spending Score')
plt.show()

sns.pairplot(df3)
plt.show()
```

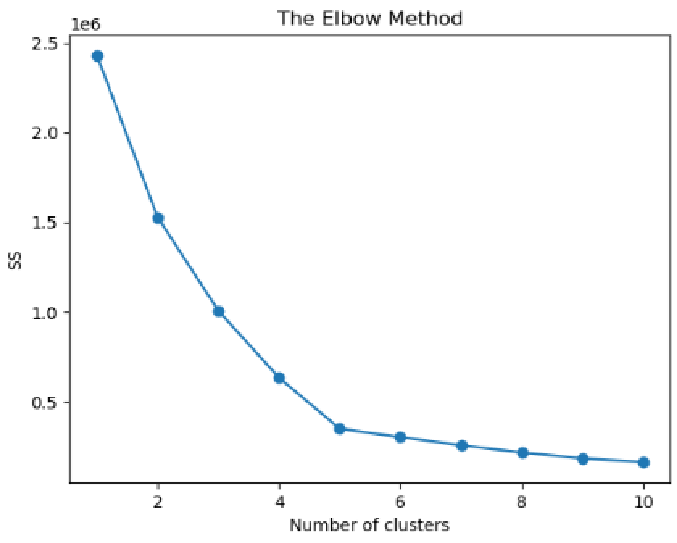
```
   remuneration  spending_score
0         12.30              39
1         12.30              81
2         13.12               6
3         13.12              77
4         13.94              40
       remuneration  spending_score
count   2000.000000     2000.000000
mean      48.079060       50.000000
std       23.123984       26.094702
min       12.300000        1.000000
25%       30.340000       32.000000
50%       47.150000       50.000000
75%       63.960000       73.000000
max      112.340000       99.000000
```



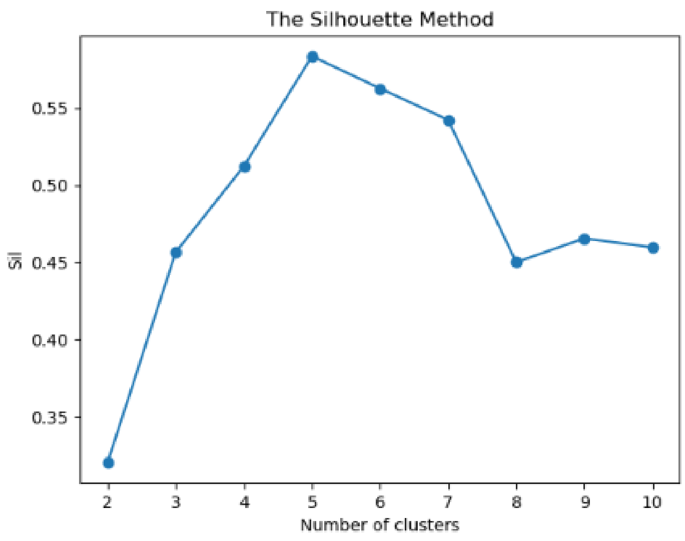


The Elbow and Silhouette method and final k model

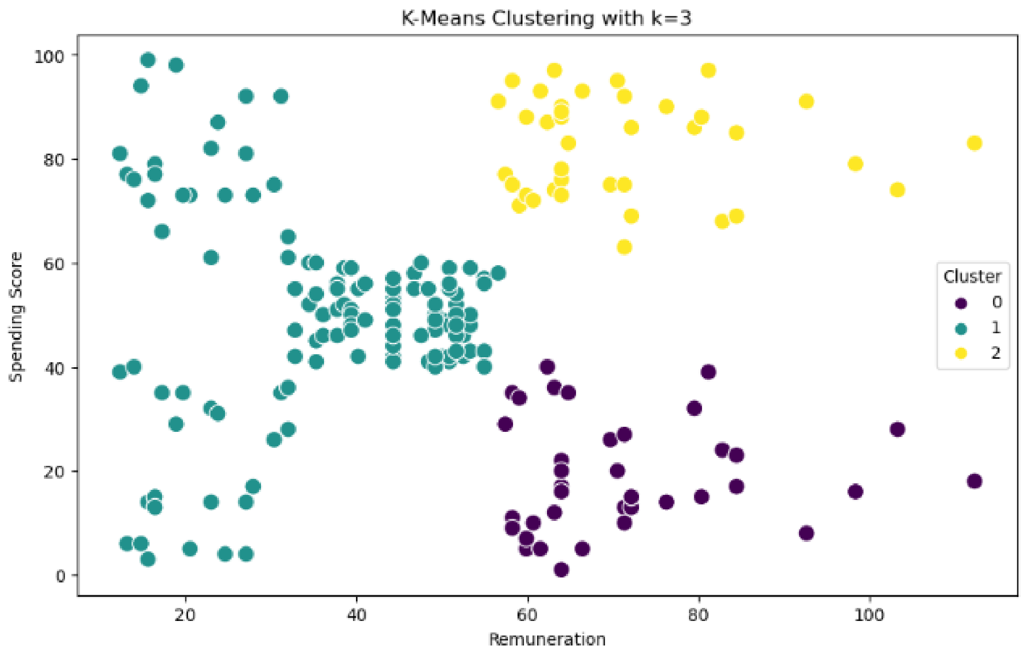
```
# Elbow Method
from sklearn.cluster import KMeans

# Elbow chart for us to decide on the number of optimal clusters.
ss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i,
                    init = 'k-means++',
                    max_iter = 500,
                    n_init = 10,
                    random_state = 42)
    kmeans.fit(df3)
    ss.append(kmeans.inertia_)

plt.plot(range(1, 11),
         ss,
         marker='o')

plt.title("The Elbow Method")
plt.xlabel("Number of clusters")
plt.ylabel("SS")

plt.show()
```

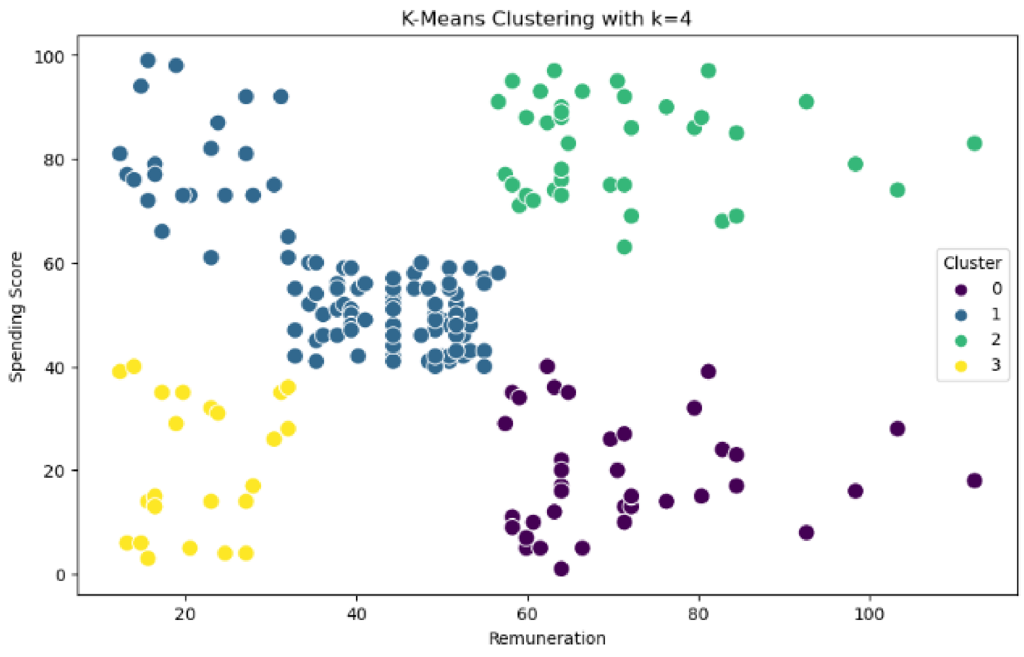


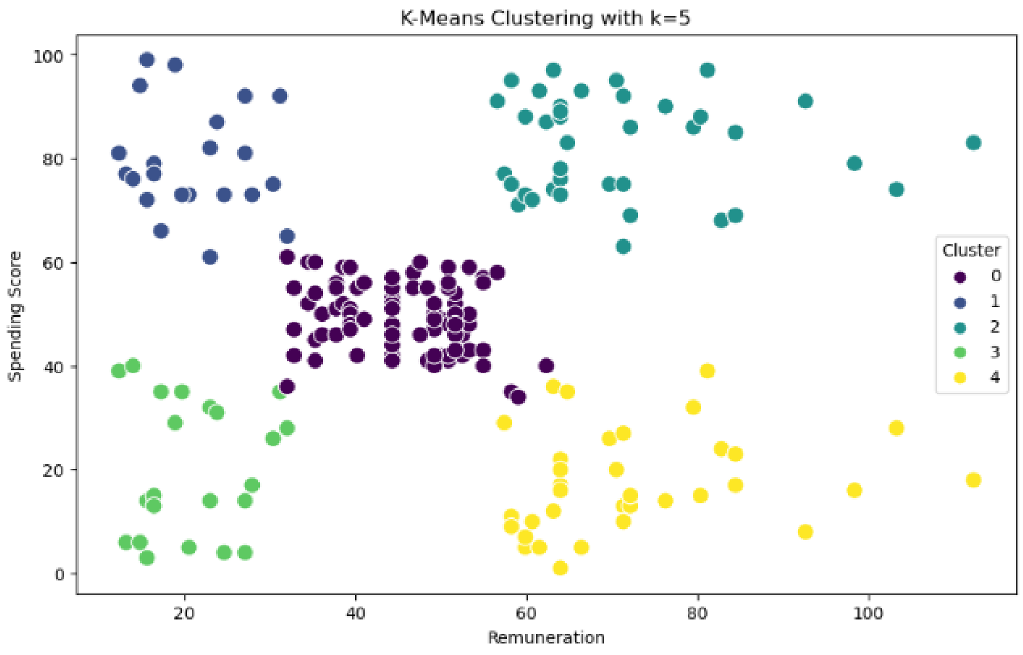
```
# Silhouette Method
from sklearn.metrics import silhouette_score

# Find the range of clusters to be used using silhouette method.
sil = []
kmax = 10

for k in range(2, kmax+1):
    kmeans_s = KMeans(n_clusters = k).fit(df3)
    labels = kmeans_s.labels_
    sil.append(silhouette_score(df3,
                                labels,
                                metric = 'euclidean'))

# Plot the silhouette method.
plt.plot(range(2, kmax+1),
         sil,
         marker='o')

plt.title("The Silhouette Method")
plt.xlabel("Number of clusters")
plt.ylabel("Sil")

plt.show()
```



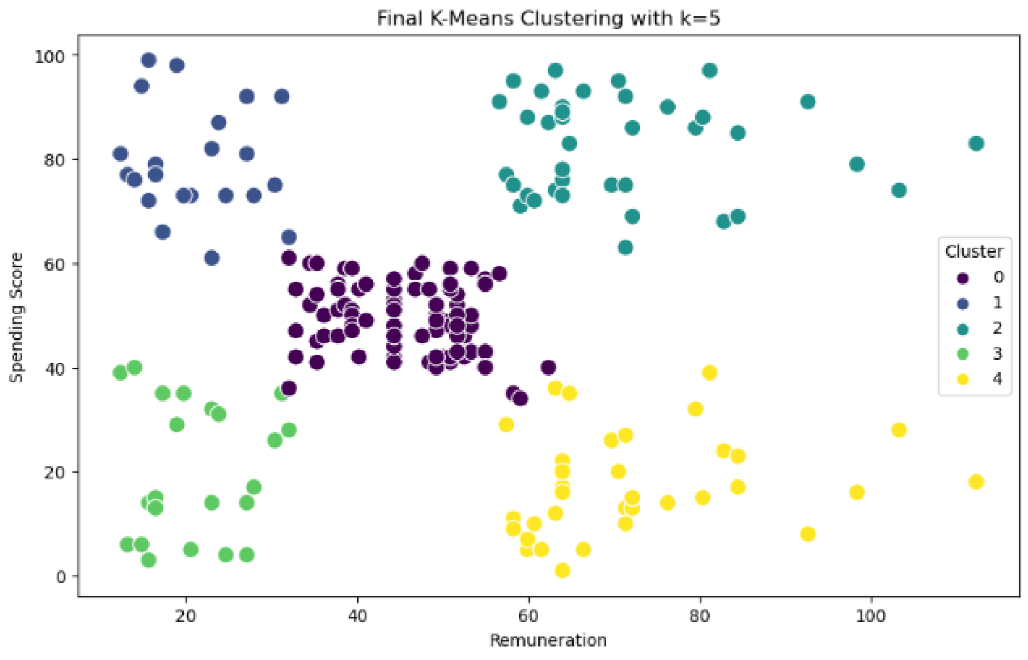
```python
# Based on the Elbow and Silhouette methods, evaluate k=3, k=4, and k=5
k_values = [3, 4, 5]
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(df3)
    df3[f'cluster_{k}'] = kmeans.labels_

    plt.figure(figsize=(10, 6))
    sns.scatterplot(data=df3, x='remuneration', y='spending_score', hue=f'cluster_{k}', palette='viridis', s=100)
    plt.title(f'K-Means Clustering with k={k}')
    plt.xlabel('Remuneration')
    plt.ylabel('Spending Score')
    plt.legend(title='Cluster')
    plt.show()
```






K-Means Clustering with k=5
Spending Score
Remuneration
Cluster
0
1
2
3
4

```
# Fit the final model using k=4
final_k = 5
final_kmeans = KMeans(n_clusters=final_k, random_state=42)
final_kmeans.fit(df3[['remuneration', 'spending_score']])
df3['final_cluster'] = final_kmeans.labels_

# Plot the final clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df3, x='remuneration', y='spending_score', hue='final_cluster', palette='viridis', s=100)
plt.title(f'Final K-Means Clustering with k={final_k}')
plt.xlabel('Remuneration')
plt.ylabel('Spending Score')
plt.legend(title='Cluster')
plt.show()

# Check the number of observations per predicted class
print(df3['final_cluster'].value_counts())
```



```
final_cluster
0    774
2    356
4    330
3    271
1    269
Name: count, dtype: int64
```

```
# Calculate the average remuneration and spending score
mean_remuneration = df3['remuneration'].mean()
mean_spending_score = df3['spending_score'].mean()

print(f"Mean Remuneration: {mean_remuneration}")
print(f"Mean Spending Score: {mean_spending_score}")

# Define the medium range around these averages
std_remuneration = df3['remuneration'].std()
std_spending_score = df3['spending_score'].std()

medium_remuneration_range = (mean_remuneration - std_remuneration, mean_remuneration + std_remuneration)
medium_spending_score_range = (mean_spending_score - std_spending_score, mean_spending_score + std_spending_score)

print(f"Medium Remuneration Range: {medium_remuneration_range}")
print(f"Medium Spending Score Range: {medium_spending_score_range}")

# Describe the groups identified
cluster_centers = final_kmeans.cluster_centers_
print(f'Cluster Centers:\n {cluster_centers}')

# Comment on the relative sizes of the groups
group_sizes = df3['final_cluster'].value_counts()
print(f'Group Sizes:\n {group_sizes}')

# Suggest specific actions per group or suggest groups that should be targeted
for i in range(final_k):
    cluster_remuneration, cluster_spending_score = cluster_centers[i]

    print(f'Cluster {i} has {group_sizes[i]} members. Centroid: {cluster_centers[i]}')

    if (medium_remuneration_range[0] <= cluster_remuneration <= medium_remuneration_range[1] and
        medium_spending_score_range[0] <= cluster_spending_score <= medium_spending_score_range[1]):
        print(f'Cluster {i} consists of medium remuneration and medium spending score customers. Consider offering balanced valu
    elif cluster_remuneration > mean_remuneration and cluster_spending_score > mean_spending_score:
        print(f'Cluster {i} consists of high remuneration and high spending score customers. Consider offering premium loyalty p
    elif cluster_remuneration < mean_remuneration and cluster_spending_score > mean_spending_score:
        print(f'Cluster {i} consists of low remuneration but high spending score customers. Consider offering discounts and prom
    elif cluster_remuneration > mean_remuneration and cluster_spending_score < mean_spending_score:
        print(f'Cluster {i} consists of high remuneration but low spending score customers. Consider offering incentives to incr
    else:
        print(f'Cluster {i} consists of low remuneration and low spending score customers. Consider offering budget-friendly opt
```

```
Mean Remuneration: 48.07906
Mean Spending Score: 50.0
Medium Remuneration Range: (24.95507554997869, 71.20304445002131)
Medium Spending Score Range: (23.905298109896584, 76.09470189010341)
Cluster Centers:
 [[44.41878553 49.52971576]
 [20.3536803  79.41635688]
 [73.2402809  82.00842697]
 [20.42435424 19.76383764]
 [74.83121212 17.42424242]]
Group Sizes:
 final_cluster
0    774
2    356
4    330
3    271
1    269
Name: count, dtype: int64
Cluster 0 has 774 members. Centroid: [44.41878553 49.52971576]
Cluster 0 consists of medium remuneration and medium spending score customers. Consider offering balanced value programs.

Cluster 1 has 269 members. Centroid: [20.3536803  79.41635688]
Cluster 1 consists of low remuneration but high spending score customers. Consider offering discounts and promotions.

Cluster 2 has 356 members. Centroid: [73.2402809  82.00842697]
Cluster 2 consists of high remuneration and high spending score customers. Consider offering premium loyalty programs.

Cluster 3 has 271 members. Centroid: [20.42435424 19.76383764]
Cluster 3 consists of low remuneration and low spending score customers. Consider offering budget-friendly options and rewards.

Cluster 4 has 330 members. Centroid: [74.83121212 17.42424242]
Cluster 4 consists of high remuneration but low spending score customers. Consider offering incentives to increase spending.
```

E) NLP

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from nltk.corpus import stopwords, words
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
import string
from wordcloud import WordCloud
from textblob import TextBlob
```

```python
df = turtle_reviews.copy()

# Display the first few rows of the dataframe
df.head()
```

	gender	age	remuneration	spending_score	loyalty_points	education	language	platform	product	review	summary
0	M	18	12.30	39	210	graduate	EN	Web	453	When it comes to a DM's screen, the space on t...	The fact that 50% of this space is wasted on a...
1	M	23	12.30	81	524	graduate	EN	Web	466	An Open Letter to GaleForce9*:\n\nYour unpaint...	Another worthless Dungeon Master's screen from...
2	F	22	13.12	6	40	graduate	EN	Web	254	Nice art, nice printing. Why two panels are f...	pretty, but also pretty useless
3	F	25	13.12	77	562	graduate	EN	Web	263	Amazing buy! Bought it as a gift for our new d...	Five Stars
4	F	33	13.94	40	366	graduate	EN	Web	291	As my review of GF9's previous screens these w...	Money trap

```python
# Retain only the review and summary columns
df = df[['review', 'summary']]

# Check for missing values
missing_values = df.isnull().sum()
print(f'Missing Values:\n{missing_values}')
```

```
Missing Values:
review     0
summary    0
dtype: int64
```

```python
# Convert text to lowercase
df['review'] = df['review'].str.lower()
df['summary'] = df['summary'].str.lower()

# Replace punctuation
df['review'] = df['review'].str.replace('[{}]'.format(string.punctuation), ' ', regex=True)
df['summary'] = df['summary'].str.replace('[{}]'.format(string.punctuation), ' ', regex=True)

# Drop duplicates
df = df.drop_duplicates(subset=['review', 'summary'])

# Display the updated dataframe
df.head()
```

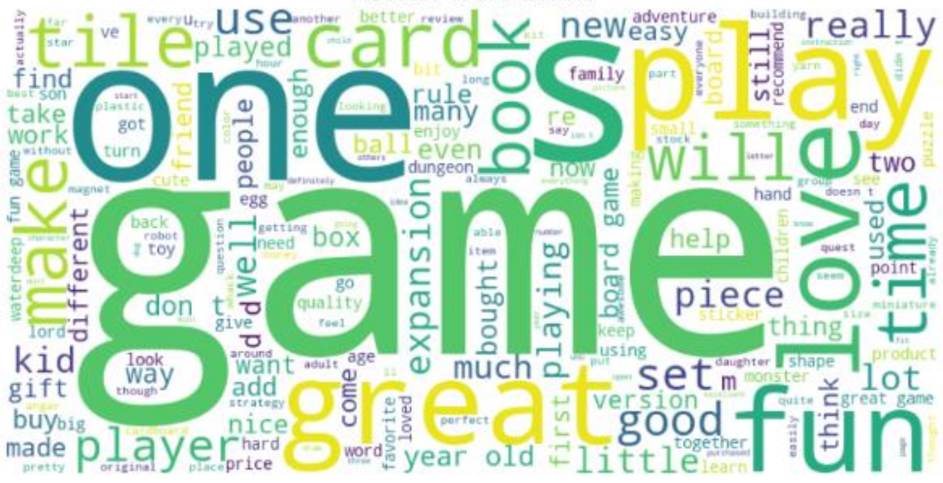
	review	summary
0	when it comes to a dm s screen the space on t...	the fact that 50 of this space is wasted on a...
1	an open letter to galeforce9 \n\nyour unpaint...	another worthless dungeon master s screen from...
2	nice art nice printing why two panels are f...	pretty but also pretty useless
3	amazing buy bought it as a gift for our new d...	five stars
4	as my review of gf9 s previous screens these w...	money trap

```python
# Create a copy of the dataframe
df_copy = df.copy()

# Tokenize the columns
df_copy['review_tokens'] = df_copy['review'].apply(word_tokenize)
df_copy['summary_tokens'] = df_copy['summary'].apply(word_tokenize)

# Display the updated dataframe
df_copy.head()
```

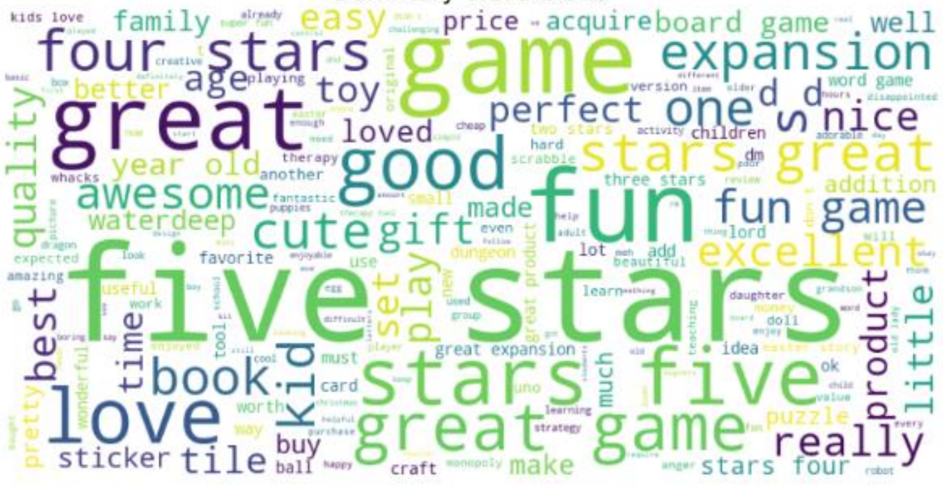
	review	summary	review_tokens	summary_tokens
0	when it comes to a dm s screen the space on t...	the fact that 50 of this space is wasted on a...	[when, it, comes, to, a, dm, s, screen, the, s...	[the, fact, that, 50, of, this, space, is, was...
1	an open letter to galeforce9 \n\nyour unpaint...	another worthless dungeon master s screen from...	[an, open, letter, to, galeforce9, your, unpai...	[another, worthless, dungeon, master, s, scree...
2	nice art nice printing why two panels are f...	pretty but also pretty useless	[nice, art, nice, printing, why, two, panels, ...	[pretty, but, also, pretty, useless]
3	amazing buy bought it as a gift for our new d...	five stars	[amazing, buy, bought, it, as, a, gift, for, o...	[five, stars]
4	as my review of gf9 s previous screens these w...	money trap	[as, my, review, of, gf9, s, previous, screens...	[money, trap]

```python
# Function to generate and plot a word cloud
def plot_word_cloud(text, title):
    wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(title, fontsize=15)
    plt.axis('off')
    plt.show()

# Join the tokens for word cloud generation
review_text = ' '.join(df_copy['review_tokens'].apply(lambda x: ' '.join(x)))
summary_text = ' '.join(df_copy['summary_tokens'].apply(lambda x: ' '.join(x)))

# Plot word clouds
plot_word_cloud(review_text, 'Review Word Cloud')
plot_word_cloud(summary_text, 'Summary Word Cloud')
```

Review Word Cloud

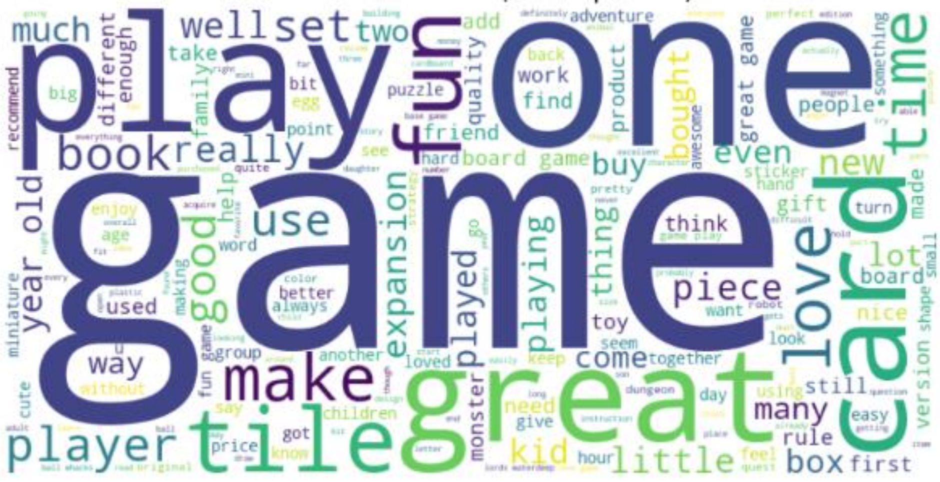


Summary Word Cloud

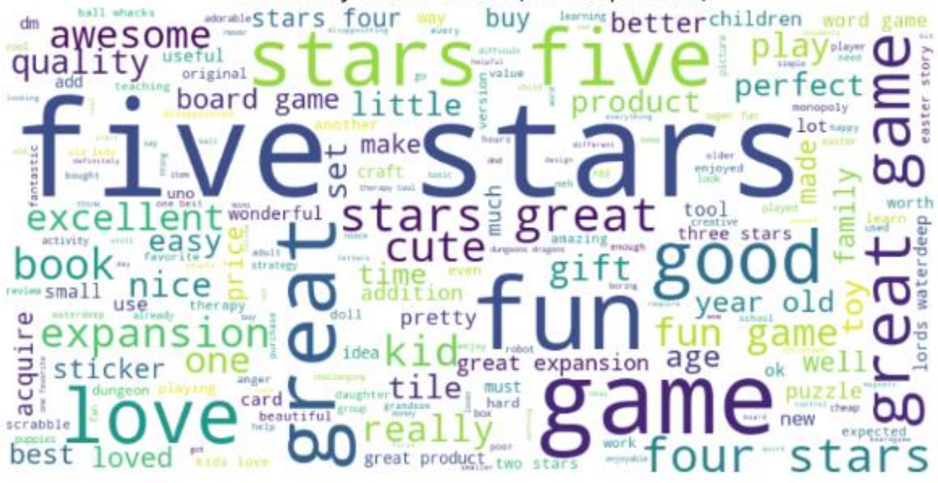


```
stop_words = set(stopwords.words('english'))

# Function to remove stopwords
def remove_stopwords(tokens):
    return [word for word in tokens if word not in stop_words and word.isalpha()]

# Remove stopwords
df_copy['review_tokens'] = df_copy['review_tokens'].apply(remove_stopwords)
df_copy['summary_tokens'] = df_copy['summary_tokens'].apply(remove_stopwords)

# Join the tokens for word cloud generation
review_text_no_stop = ' '.join(df_copy['review_tokens'].apply(lambda x: ' '.join(x)))
summary_text_no_stop = ' '.join(df_copy['summary_tokens'].apply(lambda x: ' '.join(x)))

# Plot word clouds without stopwords
plot_word_cloud(review_text_no_stop, 'Review Word Cloud (No Stopwords)')
plot_word_cloud(summary_text_no_stop, 'Summary Word Cloud (No Stopwords)')
```

Review Word Cloud (No Stopwords)



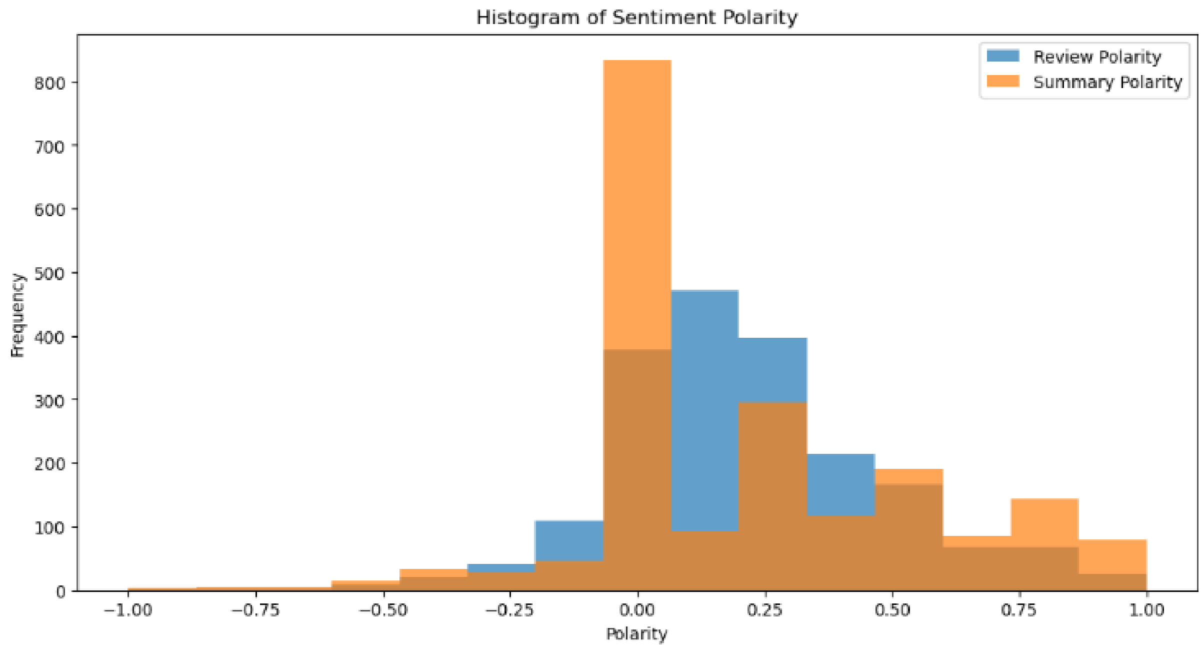
Summary Word Cloud (No Stopwords)

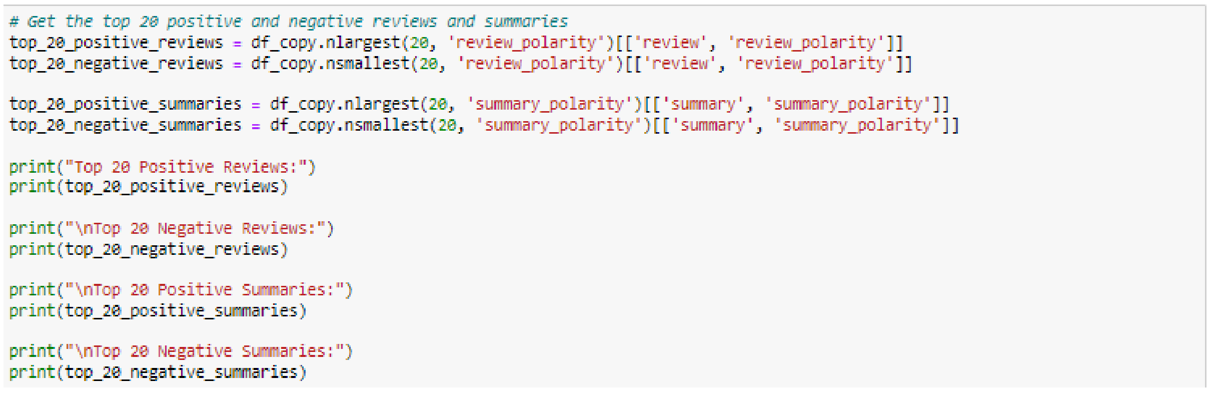


```
def get_common_words(tokens):
    # Flatten the list of token lists into a single list of tokens
    all_words = [word for sublist in tokens for word in sublist]
    # Convert the list of tokens into a single space-separated string, then split into individual words
    freq_dist = pd.Series(all_words).value_counts().head(15)
    return freq_dist

# Get the 15 most common words
common_review_words = get_common_words(df_copy['review_tokens'])
common_summary_words = get_common_words(df_copy['summary_tokens'])

print(f'15 Most Common Words in Reviews:\n{common_review_words}')
print(f'15 Most Common Words in Summaries:\n{common_summary_words}')
```

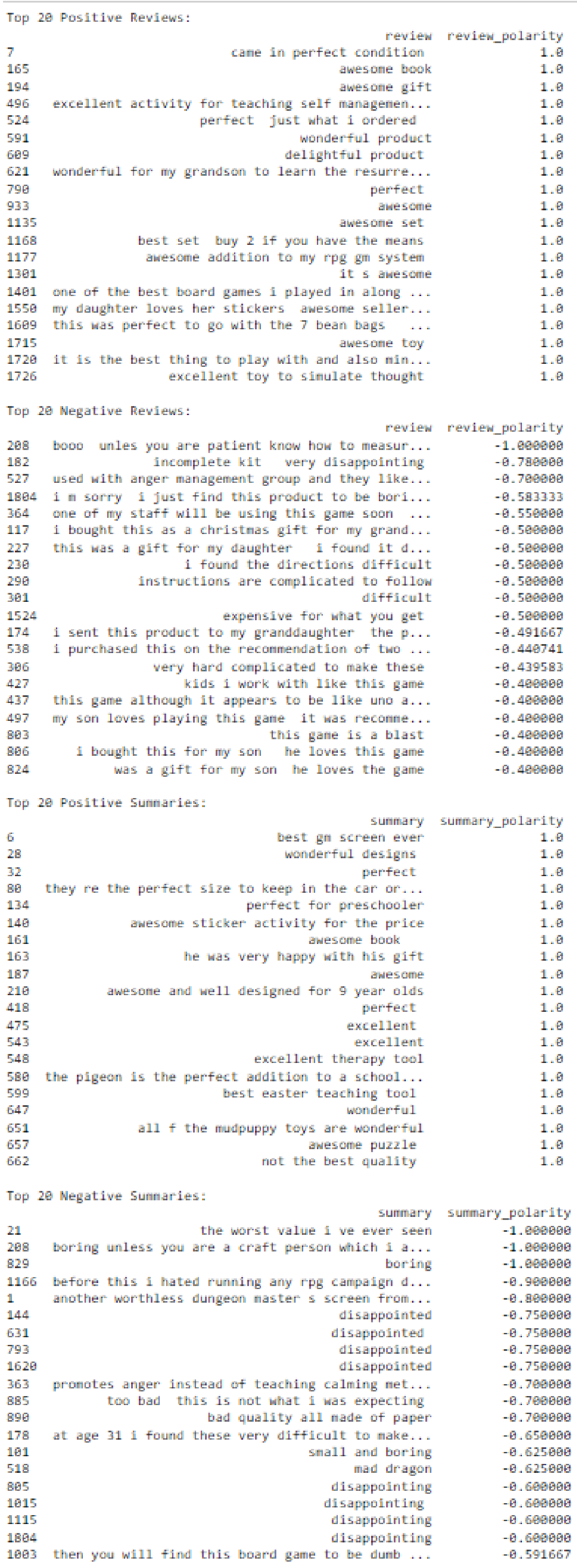
```
15 Most Common Words in Reviews:
game      1706
great      587
fun        558
one        540
play       509
like       421
love       325
get        320
really     319
cards      306
tiles      300
time       297
good       292
would      283
book       278
Name: count, dtype: int64
15 Most Common Words in Summaries:
stars        439
five         354
game         319
great        296
fun          218
love          93
good          93
four          58
like          54
expansion     53
kids          51
cute          45
book          43
one           39
old           37
Name: count, dtype: int64
```

```python
# Function to calculate polarity of text in a column
def get_polarity(column):
    return column.apply(lambda x: TextBlob(x).sentiment.polarity)

# Calculate polarity for reviews and summaries
df_copy['review_polarity'] = get_polarity(df_copy['review'])
df_copy['summary_polarity'] = get_polarity(df_copy['summary'])

# Plot histograms
plt.figure(figsize=(12, 6))
plt.hist(df_copy['review_polarity'], bins=15, alpha=0.7, label='Review Polarity')
plt.hist(df_copy['summary_polarity'], bins=15, alpha=0.7, label='Summary Polarity')
plt.title('Histogram of Sentiment Polarity')
plt.xlabel('Polarity')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```





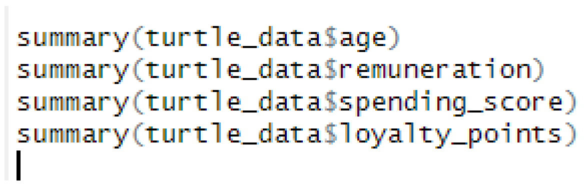
```python
# Get the top 20 positive and negative reviews and summaries
top_20_positive_reviews = df_copy.nlargest(20, 'review_polarity')[['review', 'review_polarity']]
top_20_negative_reviews = df_copy.nsmallest(20, 'review_polarity')[['review', 'review_polarity']]

top_20_positive_summaries = df_copy.nlargest(20, 'summary_polarity')[['summary', 'summary_polarity']]
top_20_negative_summaries = df_copy.nsmallest(20, 'summary_polarity')[['summary', 'summary_polarity']]

print("Top 20 Positive Reviews:")
print(top_20_positive_reviews)

print("\nTop 20 Negative Reviews:")
print(top_20_negative_reviews)

print("\nTop 20 Positive Summaries:")
print(top_20_positive_summaries)

print("\nTop 20 Negative Summaries:")
print(top_20_negative_summaries)
```



```
Top 20 Positive Reviews:
                                                  review  review_polarity
7                           came in perfect condition              1.0
165                                      awesome book              1.0
194                                      awesome gift              1.0
496   excellent activity for teaching self managemen...              1.0
524                         perfect  just what i ordered              1.0
591                                  wonderful product              1.0
609                                 delightful product              1.0
621   wonderful for my grandson to learn the resurre...              1.0
790                                           perfect              1.0
933                                           awesome              1.0
1135                                      awesome set              1.0
1168              best set  buy 2 if you have the means              1.0
1177              awesome addition to my rpg gm system              1.0
1301                                     it s awesome              1.0
1401  one of the best board games i played in along ...              1.0
1550  my daughter loves her stickers  awesome seller...              1.0
1609  this was perfect to go with the 7 bean bags   ...              1.0
1715                                      awesome toy              1.0
1720  it is the best thing to play with and also min...              1.0
1726                  excellent toy to simulate thought              1.0

Top 20 Negative Reviews:
                                                  review  review_polarity
208   booo  unles you are patient know how to measur...        -1.000000
182                 incomplete kit   very disappointing        -0.780000
527   used with anger management group and they like...        -0.700000
1804  i m sorry  i just find this product to be bori...        -0.583333
364   one of my staff will be using this game soon  ...        -0.550000
117   i bought this as a christmas gift for my grand...        -0.500000
227   this was a gift for my daughter   i found it d...        -0.500000
230                    i found the directions difficult        -0.500000
290              instructions are complicated to follow        -0.500000
301                                          difficult        -0.500000
1524                          expensive for what you get        -0.500000
174   i sent this product to my granddaughter  the p...        -0.491667
538   i purchased this on the recommendation of two ...        -0.440741
306                 very hard complicated to make these        -0.439583
427                     kids i work with like this game        -0.400000
437   this game although it appears to be like uno a...        -0.400000
497   my son loves playing this game  it was recomme...        -0.400000
803                               this game is a blast        -0.400000
806      i bought this for my son   he loves this game        -0.400000
824           was a gift for my son  he loves the game        -0.400000

Top 20 Positive Summaries:
                                                 summary  summary_polarity
6                                 best gm screen ever               1.0
28                                  wonderful designs               1.0
32                                            perfect               1.0
80   they re the perfect size to keep in the car or...               1.0
134                             perfect for preschooler               1.0
140              awesome sticker activity for the price               1.0
161                                      awesome book               1.0
163                         he was very happy with his gift               1.0
187                                          awesome               1.0
210           awesome and well designed for 9 year olds               1.0
418                                           perfect               1.0
475                                         excellent               1.0
543                                         excellent               1.0
548                            excellent therapy tool               1.0
580  the pigeon is the perfect addition to a school...               1.0
599                              best easter teaching tool               1.0
647                                         wonderful               1.0
651              all f the mudpuppy toys are wonderful               1.0
657                                    awesome puzzle               1.0
662                                not the best quality               1.0

Top 20 Negative Summaries:
                                                  summary  summary_polarity
21                          the worst value i ve ever seen         -1.000000
208   boring unless you are a craft person which i a...         -1.000000
829                                              boring         -1.000000
1166  before this i hated running any rpg campaign d...         -0.900000
1     another worthless dungeon master s screen from...         -0.800000
144                                        disappointed         -0.750000
631                                       disappointed         -0.750000
793                                        disappointed         -0.750000
1620                                       disappointed         -0.750000
363   promotes anger instead of teaching calming met...         -0.700000
885          too bad  this is not what i was expecting         -0.700000
890                        bad quality all made of paper         -0.700000
178   at age 31 i found these very difficult to make...         -0.650000
101                                     small and boring         -0.625000
518                                          mad dragon         -0.625000
805                                       disappointing         -0.600000
1015                                      disappointing         -0.600000
1115                                      disappointing         -0.600000
1804                                      disappointing         -0.600000
1003  then you will find this board game to be dumb ...         -0.591667
```

F) Importing data in R and review the detail of the dataset

```r
# Import the data
turtle_data <- read.csv("new_turtle_reviews.csv", header=T)

# View the head of the data
head(turtle_data)


# Viewing the structure and summary of the data
str(turtle_data)
summary(turtle_data)

# Check for any missing values
sum(is.na(turtle_data))

# Histogram to view the distribution of age
ggplot(turtle_data, aes(x = age)) +
  geom_histogram(binwidth = 10, fill = "blue", color = "black") +
  labs(title = "Histogram of Age", x = "Age", y = "Frequency") +
  theme_minimal()

# Boxplot to view the distribution of age
ggplot(turtle_data, aes(y = age)) +
  geom_boxplot(fill = "orange") +
  labs(title = "Boxplot of Age", y = "Age") +
  theme_minimal()

# Exploratory data analysis using histograms and boxplots
# Histogram to view the distribution of loyalty_points
ggplot(turtle_data, aes(x = loyalty_points)) +
  geom_histogram(binwidth = 10, fill = "blue", color = "black") +
  labs(title = "Histogram of Loyalty Points", x = "Loyalty Points", y = "Frequency") +
  theme_minimal()

# Boxplot to view the distribution of loyalty_points
ggplot(turtle_data, aes(y = loyalty_points)) +
  geom_boxplot(fill = "orange") +
  labs(title = "Boxplot of Loyalty Points", y = "Loyalty Points")

# Histogram to view the distribution of remuneration
ggplot(turtle_data, aes(x = remuneration)) +
  geom_histogram(binwidth = 10, fill = "green", color = "black") +
  labs(title = "Histogram of Remuneration", x = "Remuneration", y = "Frequency")

# Boxplot to view the distribution of remuneration
ggplot(turtle_data, aes(y = remuneration)) +
  geom_boxplot(fill = "purple") +
  labs(title = "Boxplot of Remuneration", y = "Remuneration")

# Histogram to view the distribution of spending_score
ggplot(turtle_data, aes(x = spending_score)) +
  geom_histogram(binwidth = 10, fill = "red", color = "black") +
  labs(title = "Histogram of Spending Score", x = "Spending Score", y = "Frequency")

# Boxplot to view the distribution of spending_score
ggplot(turtle_data, aes(y = spending_score)) +
  geom_boxplot(fill = "cyan") +
  labs(title = "Boxplot of Spending Score", y = "Spending Score")


# Scatterplot to see the relationship between remuneration and loyalty_points
ggplot(turtle_data, aes(x = remuneration, y = loyalty_points)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Loyalty Points vs Remuneration", x = "Remuneration", y = "Loyalty Points")

# Scatterplot to see the relationship between spending_score and loyalty_points
ggplot(turtle_data, aes(x = spending_score, y = loyalty_points)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Loyalty Points vs Spending Score", x = "Spending Score", y = "Loyalty Points")

# Scatterplot to see the relationship between age and loyalty_points
ggplot(turtle_data, aes(x = age, y = loyalty_points)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Loyalty Points vs Age", x = "Age", y = "Loyalty Points")
```



```
summary(turtle_data$age)
summary(turtle_data$remuneration)
summary(turtle_data$spending_score)
summary(turtle_data$loyalty_points)
```

```
# 3. Determine if data is normally distributed

# Measure normality in Age values.
# Q-Q plot:
qqnorm(turtle_data$age)
# Add a reference line:
qqline(turtle_data$age, col='red')


# Shapiro-Wilk test:
shapiro.test((turtle_data$age))
# Our p-value is <0.05,so the data is not normally distributed.


# Now we can check for skewness.
skewness(turtle_data$age)
# Our output suggests a positive skewness. right_skewed


#Check for kurtosis.
kurtosis(turtle_data$age)
# Our kurtosis value is less than 3, suggesting our data is platykurtic.






# Measure normality in Remuneration values.
# Q-Q plot:
qqnorm(turtle_data$remuneration)
# Add a reference line:
qqline(turtle_data$remuneration, col='red')


# Shapiro-Wilk test:
shapiro.test((turtle_data$remuneration))
# Our p-value is <0.05,so the data is not normally distributed.


# Now we can check for skewness.
skewness(turtle_data$remuneration)
# Our output suggests a positive skewness. right_skewed


#Check for kurtosis.
kurtosis(turtle_data$remuneration)
# Our kurtosis value is less than 3, suggesting our data is platykurtic.





# Measure normality in Spending_score values.
# Q-Q plot:
qqnorm(turtle_data$spending_score)
# Add a reference line:
qqline(turtle_data$spending_score, col='red')


# Shapiro-Wilk test:
shapiro.test((turtle_data$spending_score))
# Our p-value is <0.05,so the data is not normally distributed.


# Now we can check for skewness.
skewness(turtle_data$spending_score)
# Our output suggests a negative skewness. nearly-symmetric


#Check for kurtosis.
kurtosis(turtle_data$spending_score)
# Our kurtosis value is less than 3, suggesting our data is platykurtic.
# Measure normality in Loyalty_points values.
# Q-Q plot:
qqnorm(turtle_data$loyalty_points)
# Add a reference line:
qqline(turtle_data$loyalty_points, col='red')


# Shapiro-Wilk test:
shapiro.test((turtle_data$loyalty_points))
# Our p-value is <0.05,so the data is not normally distributed.


# Now we can check for skewness.
skewness(turtle_data$loyalty_points)
# Our output suggests a positive skewness. right-skewed


#Check for kurtosis.
kurtosis(turtle_data$loyalty_points)
# Our kurtosis value is higher than 3, suggesting our data is not platykurtic.




# Check correlation between BMI and age using Pearson's correlation.
cor(turtle_data$loyalty_points, turtle_data$age)
cor(turtle_data$loyalty_points, turtle_data$remuneration)
cor(turtle_data$loyalty_points, turtle_data$spending_score)


# Create the multiple linear regression model
model <- lm(loyalty_points ~ remuneration + spending_score + age, data = turtle_data)

# Summary of the model
summary(model)


par(mfrow = c(2, 2))
plot(model)

# Calculate VIF for the model
vif_values <- vif(model)
print(vif_values)
```