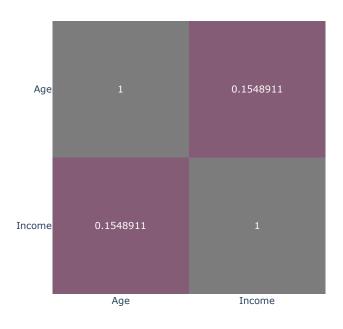
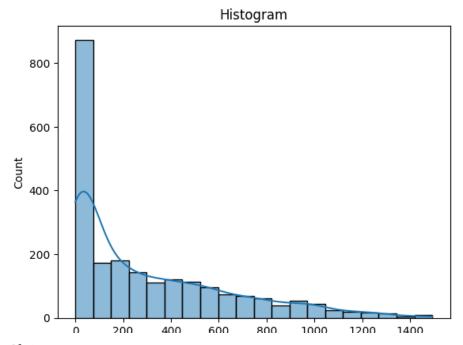
```
# Load necessary libraries
import pandas as pd
import numpy as np
import plotly.express as px
# Load the dataset
data = pd.read_excel('/content/marketing_campaign_final.xlsx')
# Explore and preprocess data (handle missing values, outliers, encoding, etc.)
# Example preprocessing steps:
# data.info() # Check data types and missing values
# data.describe() # Summary statistics
# Handle missing values: data.fillna(), data.dropna()
# Encode categorical variables: pd.get_dummies(), LabelEncoder, etc.
from sklearn.preprocessing import LabelEncoder
# Assuming 'df' is your DataFrame and 'column_name' is the column you want to encode
# Create a LabelEncoder instance
label_encoder = LabelEncoder()
# Fit and transform the column to convert labels to numeric values
data['Education'] = label_encoder.fit_transform(data['Education'])
# Create a LabelEncoder instance
label_encoder = LabelEncoder()
# Fit and transform the column to convert labels to numeric values
data['Marital Status'] = label_encoder.fit_transform(data['Marital Status'])
data.drop(columns=['Dt_Customer'], axis=1, inplace=True)
data.fillna(0, inplace=True)
# Split the data into features (X) and target variable (y)
X = data.drop('Teenhome', axis=1) # Features
y = data['Teenhome'] # Target variable
print(data.head())
          ID Year Birth Education Marital Status
                                                    Income Kidhome
     0 5524
                   1957
                                 2
                                                 4 58138.0
     1 2174
                   1954
                                                 4 46344.0
                                                                              1
     2 4141
                   1965
                                 2
                                                 5 71613.0
                                                                              0
                   1984
                                 2
                                                  5 26646.0
                                                                   1
                                                                             0
     3 6182
     4 5324
                   1981
                                 4
                                                  3 58293.0
        Recency MntWines MntFruits ... NumWebVisitsMonth AcceptedCmp3
                                 88 ...
     0
             58
                     635
                                                          7
                                                                        0
                                  1 ...
                                                          5
                                                                        0
     1
             38
                      11
                                                                        0
     2
             26
                      426
                                 49 ...
                                                          4
             26
                                  4 ...
                                                          6
                                                                        0
     3
                      11
     4
             94
                      173
                                 43
                                                                         0
        AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2
                                                              Complain \
     a
                                0
                                              0
                  0
                                0
                                              0
                                                            0
                                                                      0
     1
     2
                                0
                                              0
                                                            0
                                                                      0
                  0
                                0
     3
                  0
                                                             0
                                                                      0
                     Z_Revenue Response
        Z_CostContact
     0
                   3
                             11
                                        1
     1
                   3
                             11
                                        0
                                        0
```

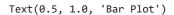
Correlation Between Age and Income

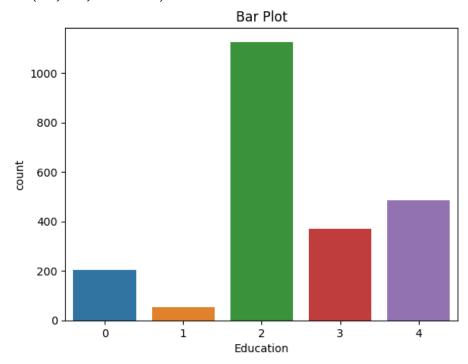


```
Kidhome Countplot.
                                                                      Teenhome Countplot.
                                                      1000
       1000
       800
                                                     600
                                                       400
                                                       200
       200
## Children feature creation
data['Children'] = data['Kidhome'] + data['Teenhome']
def has_chid_or_no(x):
    if x > 0:
        return "Has child"
    else :
        return "no child"
data['Has_child'] = data["Children"].apply(has_chid_or_no)
data['Has_child'].value_counts()
     Has child
                   1602
     no child
                    638
     Name: Has_child, dtype: int64
## drop outliers
data = data.loc[(data["Income"] <= 200000)]</pre>
## reset index after drop outliers
data.reset_index(drop=True, inplace=True)
print(f'Shape After Drop Outliers : {data.shape}')
print(f'Statistics Info. about Income : \n{data["Income"].describe()}')
     Shape After Drop Outliers: (2239, 32)
     Statistics Info. about Income :
     count
                2239.000000
               51412.792765
     mean
               22069.582225
     std
                    0.000000
     min
     25%
               34716.000000
               51039.000000
     50%
     75%
               68277.500000
     max
              162397.000000
     Name: Income, dtype: float64
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
# Load the dataset
data = pd.read_excel('/content/marketing_campaign_final.xlsx')
# Example visualizations
# Histogram
sns.histplot(data['MntWines'], bins=20, kde=True)
plt.title('Histogram')
plt.show()
```



Bar Plot
sns.countplot(x='Education', data=data)
plt.title('Bar Plot')

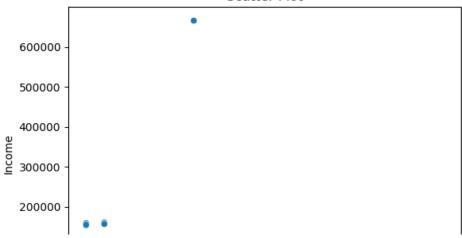




Scatter Plot
sns.scatterplot(x='NumWebVisitsMonth', y='Income', data=data)
plt.title('Scatter Plot')

Text(0.5, 1.0, 'Scatter Plot')

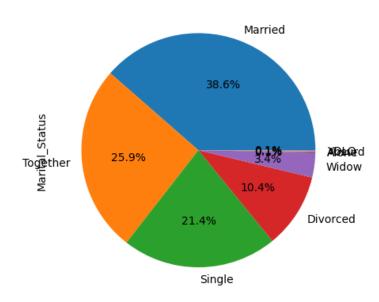




Pie Chart
data['Marital_Status'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title('Pie Chart')

Text(0.5, 1.0, 'Pie Chart')

Pie Chart

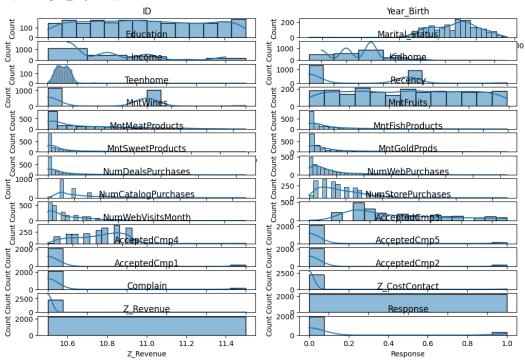


```
# Histograms for each column in the dataset
data.drop('Dt_Customer', axis=1, inplace=True) # axis=1 indicates column-wise operation

plt.figure(figsize=(12, 8))
num_columns = len(data.columns)
for i, column in enumerate(data.columns):
    plt.subplot((num_columns // 2) + (num_columns % 2), 2, i + 1)
    sns.histplot(data[column], kde=True)
    plt.title(column)

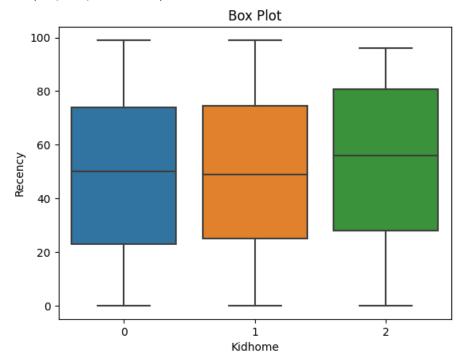
plt.tight_layout()
plt.show()
```

<ipython-input-54-27df3b85dbc4>:10: UserWarning: Tight layout not applied. tight_layout
plt.tight_layout()



Box Plot (Interquartile Range)
sns.boxplot(x='Kidhome', y='Recency', data=data)
plt.title('Box Plot')

Text(0.5, 1.0, 'Box Plot')



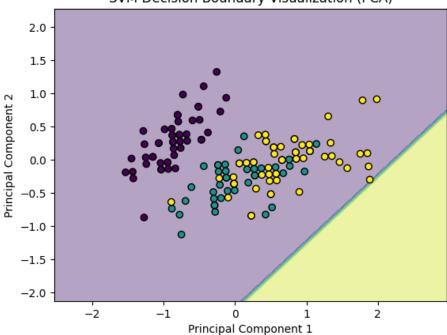
```
# Check the first few rows of the DataFrame
print(data.head())
# List all columns in the DataFrame
print(data.columns)
# Check the shape of the DataFrame
print(data.shape)
          ID Year Birth
                           Education Marital_Status
                                                        Income Kidhome
                                                                           Teenhome \
     0 5524
                     1957 Graduation
                                               Single 58138.0
                                                                        0
                                                                                   0
     1
        2174
                     1954
                           Graduation
                                               Single 46344.0
                                                                        1
                                                                                   1
                     1965
                           Graduation
                                              Together
                                                        71613.0
                                                                        0
                                                                                   0
     2
        4141
        6182
                     1984
                           Graduation
                                             Together
                                                        26646.0
                                                                        1
                                                                                   0
     4 5324
                     1981
                                   PhD
                                              Married 58293.0
        Recency
                 MntWines
                            MntFruits
                                             NumWebVisitsMonth
                                                                 AcceptedCmp3 \
                                        . . .
     0
             58
                       635
                                    88
                                        . . .
                                                              7
                                                                             0
              38
                        11
                                                              5
     1
                                    1
                                        ...
                                                                             0
     2
             26
                       426
                                    49 ...
                                                              4
                                                                             0
     3
             26
                        11
                                    4 ...
                                                              6
                                                                             0
     4
             94
                       173
                                    43
                                                               5
                                                                             0
                                       . . .
        AcceptedCmp4 AcceptedCmp5 AcceptedCmp1 AcceptedCmp2
                                                                   Complain \
     0
                                   0
                                                  0
     1
                    0
                                   0
                                                  0
                                                                 0
                                                                           0
                                   0
                                                  0
                                                                 0
                                                                           0
     2
                    0
     3
                    0
                                   0
                                                  0
                                                                 0
                                                                           0
                    0
                                   0
                                                                 0
                                                                           0
     4
                                                  a
        Z_CostContact Z_Revenue Response
     0
                     3
                               11
                                           1
                     3
                                           0
     1
                               11
                     3
                               11
                                           0
     2
     3
                     3
                                11
                                           0
     4
                     3
                                11
                                           0
     [5 rows x 28 columns]
     Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
             'Teenhome', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
             'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
            'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth', 'AcceptedCmp3',
             'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1', 'AcceptedCmp2',
             'Complain', 'Z_CostContact', 'Z_Revenue', 'Response'],
           dtype='object')
     (2240, 28)
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegressionCV
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X test scaled = scaler.transform(X test)
# Using L1 regularization
logreg = LogisticRegression(max_iter=10000, solver='saga', penalty='l1' , tol=1e-3)
logreg.fit(X_train, y_train)
# Predict on the test set
predictions = logreg.predict(X_test)
# Evaluate the model
accuracy = logreg.score(X_test, y_test)
accuracy_percentage = accuracy * 100
print(f"Accuracy: {accuracy_percentage:.2f}%")
     Accuracy: 86.00%
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris # Using Iris dataset as an example
# Load the dataset (replace this with your dataset)
data = load_iris()
X = data.data # Features
y = data.target # Target
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Logistic Regression model
logreg = LogisticRegression(max_iter=1000 , solver='saga', penalty='11' , tol=1e-3) # You can specify other paramete
# Fit the model on the training data
logreg.fit(X_train, y_train)
# Predict on the test set
predictions = logreg.predict(X_test)
# Evaluate the model
accuracy = logreg.score(X_test, y_test)
print(f"Accuracy: {accuracy:.2f}")
     Accuracy: 1.00
```

```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.datasets import load iris # Using Iris dataset as an example
# Load the dataset (replace this with your dataset)
data = load iris()
X = data.data # Features
y = data.target # Target
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Support Vector Classifier
svm = SVC(kernel='rbf') # You can specify other parameters like kernel, C, gamma, etc.
# Fit the model on the training data
svm.fit(X_train, y_train)
# Predict on the test set
predictions = svm.predict(X_test)
# Evaluate the model
accuracy = svm.score(X_test, y_test)
accuracy_percentage = accuracy * 100
print(f"Accuracy: {accuracy_percentage:.2f}%")
     Accuracy: 100.00%
from sklearn.decomposition import PCA
from sklearn.svm import SVC
# Load the dataset (replace this with your dataset)
data = load_iris()
X = data.data[:, :2] # Considering only the first two features for visualization purposes
y = data.target
# Initialize the SVM classifier
svm = SVC(kernel='linear') # You can use different kernels
# Fit the SVM on the data
svm.fit(X, y)
# Use PCA to reduce dimensions for visualization (for plotting purposes)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Create a meshgrid to plot decision boundary
x_{min}, x_{max} = X_{pca}[:, 0].min() - 1, <math>X_{pca}[:, 0].max() + 1
y_{min}, y_{max} = X_{pca}[:, 1].min() - 1, <math>X_{pca}[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
# Get predictions for meshgrid points
Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
# Plot decision boundary
plt.contourf(xx, yy, Z, alpha=0.4)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, edgecolor='k')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('SVM Decision Boundary Visualization (PCA)')
plt.show()
```

Accuracy: 100.00

SVM Decision Boundary Visualization (PCA)



```
from sklearn.tree import DecisionTreeClassifier
 # Using Iris dataset as an example
# Load the dataset (replace this with your dataset)
data = load_iris()
X = data.data # Features
y = data.target # Target
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Decision Tree Classifier
clf = DecisionTreeClassifier(max_depth=3, random_state=42) # You can specify other parameters like max_depth, criter
# Fit the model on the training data
clf.fit(X_train, y_train)
# Predict on the test set
predictions = clf.predict(X_test)
# Evaluate the model
accuracy = clf.score(X_test, y_test)
accuracy_percentage=accuracy*100
print(f"Accuracy: {accuracy_percentage:.2f}")
```

```
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt

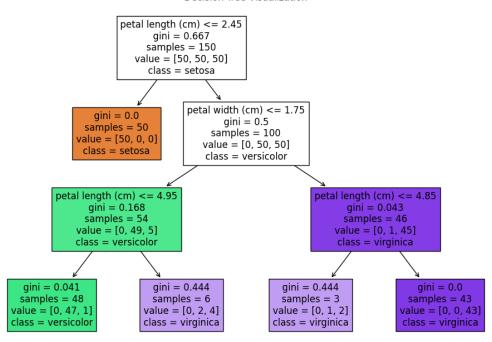
# Load the dataset (replace this with your dataset)
data = load_iris()
X = data.data  # Features
y = data.target  # Target

# Initialize the Decision Tree Classifier
clf = DecisionTreeClassifier(max_depth=3, random_state=42)  # You can specify other parameters like max_depth, criter

# Fit the model on the entire dataset (for demonstration purposes)
clf.fit(X, y)

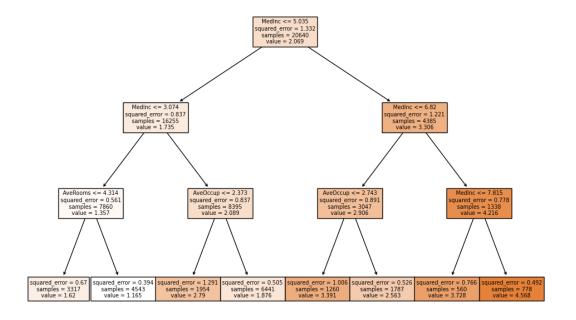
# Plot the Decision Tree
plt.figure(figsize=(12, 8))
plot_tree(clf, filled=True, feature_names=data.feature_names, class_names=data.target_names)
plt.title("Decision Tree Visualization")
plt.show()
```

Decision Tree Visualization



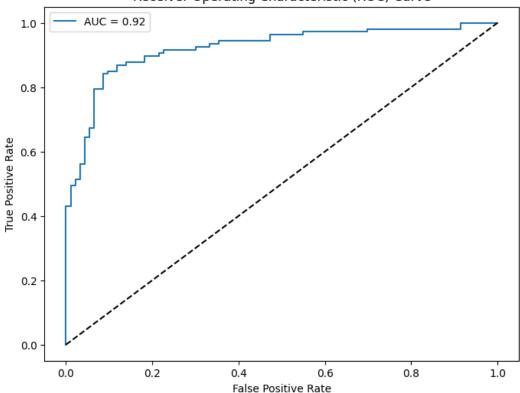
```
from sklearn.datasets import fetch_california_housing
from sklearn.tree import DecisionTreeRegressor, plot_tree
import matplotlib.pyplot as plt
# Load the California housing dataset
data = fetch california housing()
X = data.data # Features
y = data.target # Target (continuous variable for regression)
# Initialize the CART Regressor
regressor = DecisionTreeRegressor(max_depth=3, random_state=42) # You can specify other parameters like max_depth, c
# Fit the model on the entire dataset (for demonstration purposes)
regressor.fit(X, y)
# Plot the CART Decision Tree for regression
plt.figure(figsize=(12, 8))
plot_tree(regressor, filled=True, feature_names=data.feature_names)
plt.title("CART Decision Tree Visualization (Regression)")
plt.show()
```

CART Decision Tree Visualization (Regression)



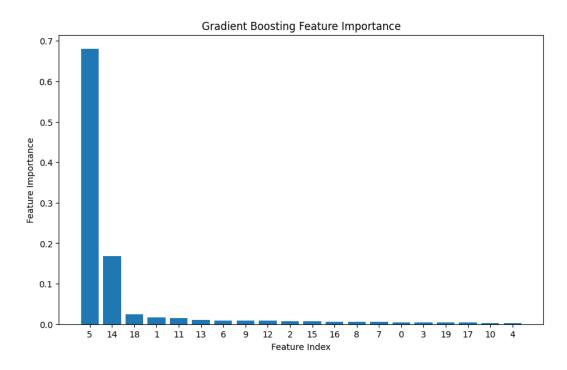
```
from sklearn.datasets import make_classification
from sklearn.metrics import roc_curve, roc_auc_score
# Generate synthetic data for demonstration purposes
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2, random_state=42)
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Logistic Regression model
model = LogisticRegression()
# Fit the model on the training data
model.fit(X_train, y_train)
# Predict probabilities for the test set
y_prob = model.predict_proba(X_test)[:, 1]
# Calculate ROC curve and AUC score
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
auc = roc_auc_score(y_test, y_prob)
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {auc:.2f}')
plt.plot([0, 1], [0, 1], 'k--') # Diagonal line representing random guessing
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```





```
# Generate synthetic data for demonstration purposes
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2, random_state=42)
# Split the data into training and test sets
X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
# Initialize the Random Forest Classifier
rf = RandomForestClassifier(n estimators=100, random state=42) # You can specify other parameters like max depth, et
# Fit the model on the training data
rf.fit(X_train, y_train)
# Predict on the test set
predictions = rf.predict(X test)
# Evaluate accuracy
accuracy = accuracy_score(y_test, predictions)
accuracy_percentage = accuracy*100
print(f"Random Forest Accuracy: {accuracy_percentage:.2f}%")
     Random Forest Accuracy: 90.00%
from sklearn.datasets import make_classification
from sklearn.ensemble import GradientBoostingClassifier
# Generate synthetic data for demonstration purposes
X, y = make classification(n samples=1000, n features=20, n classes=2, random state=42)
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Gradient Boosting Classifier
gb = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, random_state=42) # You can specify other parame
# Fit the model on the training data
gb.fit(X_train, y_train)
# Predict on the test set
predictions = gb.predict(X_test)
# Evaluate accuracy
accuracy = accuracy_score(y_test, predictions)
accuracy_percentage = accuracy*100;
print(f"Gradient Boosting Accuracy: {accuracy_percentage:.2f}%")
     Gradient Boosting Accuracy: 91.00%
```

```
# Generate synthetic data for demonstration purposes
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2, random_state=42)
# Initialize the Gradient Boosting Classifier
gb = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, random_state=42)
gb.fit(X, y)
# Get feature importances
feature_importance = gb.feature_importances_
# Sort feature importances in descending order
indices = feature_importance.argsort()[::-1]
# Plot feature importances
plt.figure(figsize=(10, 6))
plt.title("Gradient Boosting Feature Importance")
plt.bar(range(X.shape[1]), feature_importance[indices], align="center")
plt.xticks(range(X.shape[1]), indices)
plt.xlabel("Feature Index")
plt.ylabel("Feature Importance")
plt.show()
```



```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import load_iris # Using Iris dataset as an example
# Load the dataset (replace this with your dataset)
data = load iris()
X = data.data # Features
y = data.target # Target
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the Random Forest Classifier
rf = RandomForestClassifier(n estimators=100, random state=42) # You can specify other parameters like n estimators,
# Fit the model on the training data
rf.fit(X_train, y_train)
# Predict on the test set
predictions = rf.predict(X_test)
# Evaluate the model
accuracy = rf.score(X_test, y_test)
accuracy_percentage = accuracy * 100
print(f"Accuracy: {accuracy_percentage:.2f}%")
           Accuracy: 100.00%
# Create NumPy arrays from the columns
recency = np.array(data['Recency'])
kidhome = np.array(data['Kidhome'])
# Compute Pearson correlation coefficient using NumPy
correlation_matrix = np.corrcoef(recency, kidhome)
# Extract the correlation coefficient
correlation = correlation_matrix[0, 1]
print(f"Pearson Correlation for recency and kidhome: {correlation}")
           Pearson Correlation for recency and kidhome: -1.2819751242557092e-17
print(data.columns)
           Index(['ID', 'Year Birth', 'Education', 'Marital Status', 'Income', 'Kidhome',
                           'Teenhome', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
                          'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
                          \verb|'NumDealsPurchases', \verb|'NumWebPurchases', \verb|'NumCatalogPurchases', 
                          'NumStorePurchases', 'NumWebVisitsMonth', 'AcceptedCmp3',
                          'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1', 'AcceptedCmp2',
                           'Complain', 'Z_CostContact', 'Z_Revenue', 'Response'],
                        dtype='object')
# Basic filter method: Filtering rows based on a condition
# For example, filtering rows where 'Column_A' values are greater than 50
filtered_df = data[data['Recency'] > 98]
# Display the filtered DataFrame
print("\nFiltered DataFrame:")
print(filtered_df)
```

Filtered DataFrame:

1.00								Ontal Odo.ip	yiib Colub	oratory	
		ID	Year_B			Marital_S			Kidhome	\	
38		8595 1973		Graduation		Widow		0			
192		7829 1900		2n Cycle		Divorced		1			
208		868 1966		Graduation		Married		0			
444		2106		1974	2n Cycle		rried		0		
491		22		1976	Graduation		orced		1		
606		7232		1973	Graduation		Widow		0		
685 700		10142 9977		1976 1973	PhD Graduation		orced orced		0		
725		7212		1966	Graduation		rried		0		
103		5263		1977	2n Cycle		rried		1		
117		3363 1974			2n Cycle		Married		0		
147		4070 1969		PhD	Married			0			
154		528 1978			Graduation	Married			0		
168		7947 1969			Graduation	Married			1		
186				1976	Graduation	Together			0		
182				1962	Graduation	Together			0		
189				1974	Graduation				0		
		_, .,			0. 4444.220.		8	0572510			
		Teenho	me Rec	ency	MntWines	MntFruits		NumWebVis	itsMonth	\	
38			1	99	55	0	• • •		5		
192			0	99	15	6	• • •		5		
208			1	99	54	0	• • •		6		
444			0	99	0	6	• • •		8		
491			0	99	185	2	• • •		8		
606			1	99	55	0	• • •		5		
685			1	99	372	18	• • •		4		
700			1	99	321	11	• • •		4		
725			1	99	54	0	• • •		6		
103			0	99	5	10	• • •		8		
117			0	99	0	6	• • •		8		
147			2	99	169	24	• • •		7		
154			0	99	267	38	• • •		3		
168			1 1	99	24 452	0	• • •		5 3		
186			1	99	453 262	38 17	• • •		4		
182 189			0	99 99	362 273	86	• • •		1		
103	94		0	99	2/3	00	• • •		1		
		Accept	edCmp3	Acce	ptedCmp4 A	cceptedCmp!	5 Ac	ceptedCmp1	Accepte	dCmp2	١
38			0		0		0	0		0	
192	2		0		0		0	0		0	
208	8		0		0	(0	0		0	
444	4		0		0	(0	0		0	
491	1		0		0		0	0		0	
606	6		0		0		0	0		0	
685	5		0		0	(0	0		0	
700	0		0		0		0	0		0	
725	5		0		0	(0	0		0	
103			0		0	(0	0		0	
117			0		0	(0	0		0	
147	73	0		1	:	1			0		
154			0		0	(0	0		0	
168			0		0		0	0		0	
186			0		0		0	0		0	
182			0		0		0	1		0	
120	94		а		а		а	a		а	

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.

[#] Assuming 'X' contains your features and 'y' contains the target variable