-( + Code )--( + Text )

import numpy as np
import pandas as pd
import matplotlib as plt
import seaborn as sns
import pandas as pd
import scipy.stats as stats

df = pd.read\_csv('campaign - campaign.csv')

## df.head()

₹		ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	 NumCatalogPurcha
	0	1826	1970	Graduation	Divorced	\$84,835.00	0	0	6/16/14	0	189	
	1	1	1961	Graduation	Single	\$57,091.00	0	0	6/15/14	0	464	
	2	10476	1958	Graduation	Married	\$67,267.00	0	1	5/13/14	0	134	
	3	1386	1967	Graduation	Together	\$32,474.00	1	1	5/11/14	0	10	
	4	5371	1989	Graduation	Single	\$21,474.00	1	0	4/8/14	0	6	

5 rows × 27 columns

## df.info()

<<cl>> <class 'pandas.core.frame.DataFrame'>
RangeIndex: 2239 entries, 0 to 2238
Data columns (total 27 columns):

Ducu	COTAINIS (COCAT 27 CO.	-uiiii 13 /	•					
#	Column	Non-N	ull Count	Dtype				
0	ID	2239	non-null	int64				
1	Year_Birth	2239	non-null	int64				
2	Education	2239	non-null	object				
3	Marital_Status	2239	non-null	object				
4	Income	2239	non-null	object				
5	Kidhome	2239	non-null	int64				
6	Teenhome	2239	non-null	int64				
7	Dt_Customer	2239	non-null	object				
8	Recency	2239	non-null	int64				
9	MntWines	2239	non-null	int64				
10	MntFruits	2239	non-null	int64				
11	MntMeatProducts	2239	non-null	int64				
12	MntFishProducts	2239	non-null	int64				
13	MntSweetProducts	2239	non-null	int64				
14	MntGoldProds	2239	non-null	int64				
15	NumDealsPurchases	2239	non-null	int64				
16	NumWebPurchases	2239	non-null	int64				
17	NumCatalogPurchases	2239	non-null	int64				
18	NumStorePurchases	2239	non-null	int64				
19	NumWebVisitsMonth	2239	non-null	int64				
20	AcceptedCmp3	2239	non-null	int64				
21	AcceptedCmp4	2239	non-null	int64				
22	AcceptedCmp5	2239	non-null	int64				
23	AcceptedCmp1	2239	non-null	int64				
24	AcceptedCmp2	2239	non-null	int64				
25	Complain	2239	non-null	int64				
26	Country	2239	non-null	object				
dtypes: int64(22), object(5)								

dtypes: int64(22), object(5)
memory usage: 472.4+ KB

df.isna().sum()

```
\overline{2}
```

```
0
        ID
                     0
     Year_Birth
                     0
     Education
   Marital_Status
                     0
      Income
                     0
     Kidhome
                     0
     Teenhome
                     0
    Dt_Customer
     Recency
                     0
     MntWines
                     0
     MntFruits
                     0
  MntMeatProducts
                     0
  MntFishProducts
 MntSweetProducts
                     0
   MntGoldProds
 NumDealsPurchases
                     0
 NumWebPurchases
                     0
NumCatalogPurchases
 NumStorePurchases
                     0
NumWebVisitsMonth
                    0
   AcceptedCmp3
                     0
   AcceptedCmp4
                     0
   AcceptedCmp5
                     0
   AcceptedCmp1
                     0
   AcceptedCmp2
                     0
     Complain
                     0
                     0
      Country
```

df.describe()

<b>→</b> *		ID	Year_Birth	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	М
	count	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	
	mean	5590.444841	1968.802144	0.443948	0.506476	49.121036	304.067441	26.307727	167.016525	37.538633	
	std	3246.372471	11.985494	0.538390	0.544555	28.963662	336.614830	39.781468	225.743829	54.637617	
	min	0.000000	1893.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	25%	2827.500000	1959.000000	0.000000	0.000000	24.000000	24.000000	1.000000	16.000000	3.000000	
	50%	5455.000000	1970.000000	0.000000	0.000000	49.000000	174.000000	8.000000	67.000000	12.000000	
	75%	8423.500000	1977.000000	1.000000	1.000000	74.000000	504.500000	33.000000	232.000000	50.000000	
	max	11191.000000	1996.000000	2.000000	2.000000	99.000000	1493.000000	199.000000	1725.000000	259.000000	

8 rows × 22 columns

```
numerical_features = ['Year_Birth', 'Recency', 'MntWines', 'MntFruits',
                            'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
                            'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth']
def count_outliers(series):
     Q1 = series.quantile(0.25)
     Q3 = series.quantile(0.75)
     IQR = Q3 - Q1
     lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

```
# Count outliers
    return ((series < lower_bound) | (series > upper_bound)).sum()
# Count outliers in each numerical column
outliers_count = {feature: count_outliers(df[feature]) for feature in numerical_features}
# Display the count of outliers
outliers_count_df = pd.DataFrame.from_dict(outliers_count, orient='index', columns=['Outliers Count'])
print(outliers_count_df)
                          Outliers Count
     Year_Birth
     Recency
                                       a
     MntWines
                                      35
     MntFruits
                                     227
     MntMeatProducts
                                     175
     {\sf MntFishProducts}
                                     223
     MntSweetProducts
     MntGoldProds
                                     207
     NumDealsPurchases
     NumWebPurchases
     NumCatalogPurchases
                                      23
     NumStorePurchases
     NumWebVisitsMonth
                                       8
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # Filter out outliers
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]</pre>
# Remove outliers from each numerical column
for feature in numerical_features:
    df = remove_outliers(df, feature)
# ANOVA Test
# Group data by 'Education' and compute the mean income for each group
import scipy.stats as stats
# ANOVA Test
# Group data by 'Education' and compute the mean income for each group
import scipy.stats as stats
# Convert 'Income' column to numeric, removing '$' and ','
df['Income'] = df['Income'].str.replace('$', '').str.replace(',', '').astype(float)
education_groups = df.groupby('Education')['Income'].apply(list)
# Perform ANOVA test
f_statistic, p_value = stats.f_oneway(*education_groups)
# Display the results
print(f"F-Statistic: {f_statistic}")
print(f"P-Value: {p_value}")
# Interpretation of results
alpha = 0.05 # Significance level
if p_value < alpha:</pre>
    print("Reject the null hypothesis: There is a significant difference in income across education levels.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in income across education levels.")
# Optional: Visualize the income distribution by education level
plt.figure(figsize=(12, 8))
sns.boxplot(x='Education', y='Income', data=df, palette='Set2')
plt.title('Income Distribution by Education Level')
plt.xticks(rotation=45)
education_groups = df.groupby('Education')['Income'].apply(list)
# Perform ANOVA test
f_statistic, p_value = stats.f_oneway(*education_groups)
# Display the results
print(f"F-Statistic: {f_statistic}")
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print("Reject the null hypothesis: There is a significant difference in income across education levels.")
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plt.figure(figsize=(12, 8))
sns.boxplot(x='Education', y='Income', data=df, palette='Set2')
plt.title('Income Distribution by Education Level')
plt.xticks(rotation=45)
F-Statistic: nan
     P-Value: nan
     Fail to reject the null hypothesis: There is no significant difference in income across education levels.
                                                Traceback (most recent call last)
     <ipython-input-20-b17759d7e05c> in <cell line: 28>()
          26
          27 # Optional: Visualize the income distribution by education level
     ---> 28 plt.figure(figsize=(12, 8))
          29 sns.boxplot(x='Education', y='Income', data=df, palette='Set2')
          30 plt.title('Income Distribution by Education Level')
     TypeError: 'module' object is not callable
 Next steps:
              Explain error
# ANOVA Test
\mbox{\#} Group data by 'Education' and compute the mean income for each group
import scipy.stats as stats
import matplotlib.pyplot as plt # Ensure matplotlib.pyplot is imported correctly
# Convert 'Income' to numerical if it's not already
df['Income'] = pd.to_numeric(df['Income'], errors='coerce')
education groups = df.groupby('Education')['Income'].apply(list)
# Perform ANOVA test
f_statistic, p_value = stats.f_oneway(*education_groups)
# Display the results
print(f"F-Statistic: {f_statistic}")
print(f"P-Value: {p_value}")
# Interpretation of results
alpha = 0.05 # Significance level
if p_value < alpha:</pre>
   print("Reject the null hypothesis: There is a significant difference in income across education levels.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in income across education levels.")
# Optional: Visualize the income distribution by education level
plt.figure(figsize=(12, 8)) # Call the figure function from the plt module
import seaborn as sns # Import seaborn for boxplot
\verb|sns.boxplot(x='Education', y='Income', data=df, palette='Set2')|\\
plt.title('Income Distribution by Education Level')
plt.xticks(rotation=45)
```

```
→ F-Statistic: nan
    P-Value: nan
    Fail to reject the null hypothesis: There is no significant difference in income across education levels.
    <ipython-input-22-465985bba4bc>:28: FutureWarning:
    Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set
      sns.boxplot(x='Education', y='Income', data=df, palette='Set2')
    ([0, 1, 2, 3, 4],
[Text(0, 0, 'Graduation'),
      Text(1, 0, 'PhD'),
      Text(2, 0, '2n Cycle'),
      Text(3, 0, 'Master'),
      Text(4, 0, 'Basic')])
                                                      Income Distribution by Education Level
        90000
                                                   0
        80000
        70000
                          8
                                                   0
        60000
        50000
      Income
        40000
        30000
        20000
        10000
                                                                                                   0
                                                                        2n Cycle
                                                  PHO
                                                                       Education
```

```
# Calculate total spending by summing up all spending columns
df['Total_Spending'] = df[['MntWines', 'MntFruits', 'MntMeatProducts',
                             'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']].sum(axis=1)
\ensuremath{\text{\#}} Check the first few rows to verify
print(df[['Income', 'Total_Spending']].head())
\overline{\Sigma}
          Income Total_Spending
         67267.0
                              251
     3
         32474.0
                               11
     4
         21474.0
                               91
         44931.0
     13 26872.0
                                72
import scipy.stats as stats
df['Income'] = pd.to_numeric(df['Income'], errors='coerce')
df['Total_Spending'] = pd.to_numeric(df['Total_Spending'], errors='coerce')
df = df.dropna(subset=['Income', 'Total_Spending'])
# Calculate Pearson correlation coefficient
correlation, p_value = stats.pearsonr(df['Income'], df['Total_Spending'])
print(f"Pearson Correlation Coefficient: {correlation}")
print(f"P-Value: {p_value}")
```

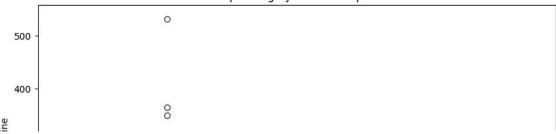
```
# Interpretation
alpha = 0.05
if p_value < alpha:</pre>
    print("There is a significant correlation between income and total spending.")
else:
    print("There is no significant correlation between income and total spending.")
→ Pearson Correlation Coefficient: 0.4726446220666236
     P-Value: 1.6010711861649903e-55
     There is a significant correlation between income and total spending.
# Map marital status to 'In couple' or 'Alone'
df['Relationship_Status'] = df['Marital_Status'].map({
    'Married': 'In couple',
    'Together': 'In couple',
    'Divorced': 'Alone',
    'Single': 'Alone',
    'Absurd': 'Alone',
    'Widow': 'Alone',
    'YOLO': 'Alone'
})
# Check the mapping
print(df[['Marital_Status', 'Relationship_Status']].drop_duplicates())
# Group data by relationship status and calculate mean spending on wine
grouped_data = df.groupby('Relationship_Status')['MntWines']
# Perform independent samples t-test
group_in_couple = grouped_data.get_group('In couple')
group_alone = grouped_data.get_group('Alone')
# Ensure both groups have data
if not group in couple.empty and not group alone.empty:
    t_statistic, p_value = stats.ttest_ind(group_in_couple, group_alone, equal_var=False)
    # Display results
    print(f"T-Statistic: {t_statistic}")
    print(f"P-Value: {p_value}")
    # Interpretation
    alpha = 0.05 # Significance level
    if p_value < alpha:</pre>
       print("Reject the null hypothesis: There is a significant difference in wine spending between couples and individuals living al
    else:
        print("Fail to reject the null hypothesis: There is no significant difference in wine spending between couples and individuals
else:
    print("One or both groups are empty. Check the data and try again.")
# Optional: Visualize the wine spending by relationship status
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
\verb|sns.boxplot(x='Relationship_Status', y='MntWines', data=df)|\\
plt.title('Wine Spending by Relationship Status')
plt.xlabel('Relationship Status')
plt.ylabel('Spending on Wine')
plt.show()
```

```
Marital_Status Relationship_Status
           Married
                              In couple
3
          Together
                              In couple
4
            Single
                                  Alone
17
          Divorced
                                  Alone
28
             Widow
                                  Alone
286
             Alone
                                    NaN
```

T-Statistic: 0.6346714757271168 P-Value: 0.525825023463167

Fail to reject the null hypothesis: There is no significant difference in wine spending between couples and individuals living alon

## Wine Spending by Relationship Status



```
# Calculate the median income
median_income = df['Income'].median()
# Create income brackets
df['Income_Bracket'] = np.where(df['Income'] < median_income, 'Below Median', 'Above Median')</pre>
# Create a column indicating if any campaign was accepted
df['Accepted_Any_Campaign'] = df[['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']].sum(axis=1) > 0
\# Group by income bracket and calculate acceptance rates
acceptance_rates = df.groupby('Income_Bracket')['Accepted_Any_Campaign'].mean()
# Print acceptance rates
print(acceptance rates)
# Perform a Chi-Square Test for independence
contingency_table = pd.crosstab(df['Income_Bracket'], df['Accepted_Any_Campaign'])
chi2_stat, p_value, _, _ = stats.chi2_contingency(contingency_table)
# Display results
print(f"Chi-Square Statistic: {chi2_stat}")
print(f"P-Value: {p_value}")
# Interpretation
alpha = 0.05 # Significance level
if p_value < alpha:</pre>
    print("Reject the null hypothesis: There is a significant difference in campaign acceptance between income brackets.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in campaign acceptance between income brackets.")
→ Income_Bracket
     Above Median
                     0.075510
     Below Median
                     0.078029
     Name: Accepted_Any_Campaign, dtype: float64
     Chi-Square Statistic: 0.0007659611921822663
     P-Value: 0.9779205624803663
     Fail to reject the null hypothesis: There is no significant difference in campaign acceptance between income brackets.
Additional Hypothesis Tests performed
# Correlation analysis for spending on wine vs. number of children
```

```
# Correlation analysis for spending on wine vs. number of children
correlation, p_value = stats.pearsonr(df['Kidhome'], df['MntWines'])
print(f"Pearson Correlation Coefficient: {correlation}")
print(f"P-Value: {p_value}")
```