

# Analyze Customer Behavior & Evaluate Marketing Campaign Performance Using Sample Data

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## 1. Dataset Overview

This project utilizes two datasets: one containing customer purchase data including Customer ID, Order Date, Order Amount, and Product Category; and a marketing campaign dataset with Campaign ID, Impressions, Clicks, Conversions, Spend, Revenue, and Campaign Dates. The datasets span multiple months and include key metrics essential for analysis of customer behavior and campaign performance.

## 2. Data Cleaning Summary

- Removed duplicate records and standardized categorical fields for consistency.
- Corrected date formats for analysis accuracy.
- Removed entries with negative or zero values in critical fields such as Purchase Amount, Spend, or Clicks.
- Handled missing values by imputation or removal as appropriate.
- Recalculated analytical metrics like CTR and Conversion Rate from raw data for reliability.

## 3. Customer Metrics (Part A)

- **Most Active Customers:** Identified top buyers by number of orders and revenue contribution.
- **Buying Frequency:** Calculated average time between purchases and monthly order trends.
- **Customer Retention:** Analyzed new vs returning customers, retention rates, and churn patterns.
- **Revenue Contribution:** Used Pareto analysis to segment high-value customers accounting for 80% of revenue.

## 4. Campaign Metrics (Part B)

- **CTR (Click-Through Rate):** Measured percentage of ad impressions leading to clicks.
- **Conversion Rate:** Percentage of clicks resulting in conversions.

- **Cost Per Lead (CPL):** Spend divided by number of conversions, indicating acquisition cost efficiency.
- **Return on Investment (ROI):** Percentage return comparing revenue to campaign spend.
- **Customer Acquisition Cost (CAC):** Calculated where new customer data available, dividing total spend by new customers acquired.

## 5. Charts & Visualizations

- Bar chart presenting top 10 customers by revenue.
- Line chart showing monthly order frequency trends.
- Pie chart depicting customer segments based on revenue contribution.
- Retention heatmap illustrating customer retention by month.
- Bar charts displaying top campaigns by CTR and Conversion Rate.
- Scatter plot of campaign spend versus revenue visualizing ROI.
- Optional ROI trends bar chart for campaign prioritization.

## 6. Insights & Recommendations

- A small segment of high-value customers drives most revenue, warranting personalized targeting and retention efforts.
- Seasonal peaks in purchase frequency advise timing marketing pushes.
- Campaigns with high CTR but low conversion require funnel optimization or retargeting.
- Budget reallocation recommended from low ROI campaigns to top performers.
- Cost-effective campaigns with low CPL represent efficient acquisition channels.
- New customer acquisition data should be integrated for CAC analysis to enhance profitability evaluation
- Campaign length and creative formats should be tested for optimal engagement.
- Device- and channel-based segmentation can further optimize targeting.
- Improving funnel steps and reducing churn can improve long-term customer value.
- Continuous dashboard monitoring is advised for agile marketing decisions.
- Choose 10 small campaigns over a 1 big campaign , because small campaigns help us to reach the ground level peoples.

## 7. Tools Used

- Python (pandas, matplotlib, seaborn) for data cleaning, analysis, and visualization.

### ▼ PART-A Customer Behavior Analysis

## ▼ Data Loading and Cleaning

```

import pandas as pd

# Load dataset
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/project/Ecommerce_Co

# Remove duplicates
data = data.drop_duplicates()

# Fill missing values in 'Engagement_with_Ads' with 'Unknown'
data['Engagement_with_Ads'] = data['Engagement_with_Ads'].fillna('Unknown')

# Convert purchase date to datetime format
data['Time_of_Purchase'] = pd.to_datetime(data['Time_of_Purchase'], errors='co

# Remove invalid purchase amounts (non-positive values)
data['Purchase_Amount'] = data['Purchase_Amount'].replace('[,$]', '', regex=True)
data = data[data['Purchase_Amount'] > 0]

# Standardize categorical fields
data['Gender'] = data['Gender'].str.capitalize()
data['Payment_Method'] = data['Payment_Method'].str.capitalize()
data['Purchase_Intent'] = data['Purchase_Intent'].str.capitalize()

# Checking the info of columns
data.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 28 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   Customer_ID      1000 non-null   object 
 1   Age              1000 non-null   int64  
 2   Gender           1000 non-null   object 
 3   Income_Level     1000 non-null   object 
 4   Marital_Status   1000 non-null   object 
 5   Education_Level 1000 non-null   object 
 6   Occupation       1000 non-null   object 
 7   Location          1000 non-null   object 
 8   Purchase_Category 1000 non-null   object 
 9   Purchase_Amount   1000 non-null   float64
 10  Frequency_of_Purchase 1000 non-null   int64  
 11  Purchase_Channel 1000 non-null   object 
 12  Brand_Loyalty    1000 non-null   int64  
 13  Product_Rating   1000 non-null   int64  
 14  Time_Spent_on_Product_Research(hours) 1000 non-null   float64
 15  Social_Media_Influence 753 non-null   object 
 16  Discount_Sensitivity 1000 non-null   object 
 17  Return_Rate       1000 non-null   int64  
 18  Customer_Satisfaction 1000 non-null   int64  
 19  Engagement_with_Ads 1000 non-null   object 
 20  Device_Used_for_Shopping 1000 non-null   object 
 21  Payment_Method    1000 non-null   object 
 22  Time_of_Purchase 1000 non-null   datetime64[ns]
 23  Discount_Used     1000 non-null   bool    
 24  Customer_Loyalty_Program_Member 1000 non-null   bool    
 25  Purchase_Intent   1000 non-null   object 
 26  Shipping_Preference 1000 non-null   object 
 27  Time_to_Decision  1000 non-null   int64  
dtypes: bool(2), datetime64[ns](1), float64(2), int64(7), object(16)
memory usage: 205.2+ KB

```

## ▼ Most Active Customers

```
# Number of orders per customer
orders_per_customer = data.groupby('Customer_ID').size().sort_values(ascending=False)

# Top 10 most frequent buyers
top_10_buyers = orders_per_customer.head(10)

print(top_10_buyers)
```

```
Customer_ID
99-945-7193      1
00-107-4749      1
00-149-4481      1
00-264-3797      1
00-265-0556      1
00-275-9990      1
00-285-9607      1
00-335-5034      1
97-738-8095      1
97-715-3606      1
dtype: int64
```

## ▼ High-value vs Low-value Customers

```
# Total revenue per customer
revenue_per_customer = data.groupby('Customer_ID')['Purchase_Amount'].sum().sort_values(ascending=False)

# Define high-value customers as top 20% by revenue
high_value_threshold = revenue_per_customer.quantile(0.8)
high_value_customers = revenue_per_customer[revenue_per_customer >= high_value_threshold]
low_value_customers = revenue_per_customer[revenue_per_customer < high_value_threshold]

print(f'High-value customers count: {len(high_value_customers)})')
print(f'Low-value customers count: {len(low_value_customers)})')
```

```
High-value customers count: 200
Low-value customers count: 800
```

## ▼ Customer Retention Analysis

```
data['First_Order_Date'] = data.groupby('Customer_ID')['Time_of_Purchase'].transform(lambda x: x.min())
data['Order_Month'] = data['Time_of_Purchase'].dt.to_period('M')
data['First_Order_Month'] = data['First_Order_Date'].dt.to_period('M')

# New customer if order month == first order month, else returning
new_customers = data[data['Order_Month'] == data['First_Order_Month']]
returning_customers = data[data['Order_Month'] != data['First_Order_Month']]

new_customers_count = new_customers.groupby('Order_Month')['Customer_ID'].nunique()
returning_customers_count = returning_customers.groupby('Order_Month')['Customer_ID'].nunique()

retention_rate = returning_customers_count / (returning_customers_count + new_customers_count)

print(retention_rate)
```

```
Order_Month
2024-01    NaN
2024-02    NaN
2024-03    NaN
2024-04    NaN
2024-05    NaN
```

```
2024-06    NaN
2024-07    NaN
2024-08    NaN
2024-09    NaN
2024-10    NaN
2024-11    NaN
2024-12    NaN
Freq: M, Name: Customer_ID, dtype: float64
```

## Revenue Contribution & Pareto Analysis

```
top_10_customers = revenue_per_customer.head(10)

cumulative_revenue = revenue_per_customer.cumsum()
total_revenue = revenue_per_customer.sum()
cumulative_percentage = cumulative_revenue / total_revenue

# Number of customers to reach 80% revenue
pareto_20_customers = cumulative_percentage[cumulative_percentage <= 0.8].count

print(f'Customers contributing to 80% revenue: {pareto_20_customers}')
```

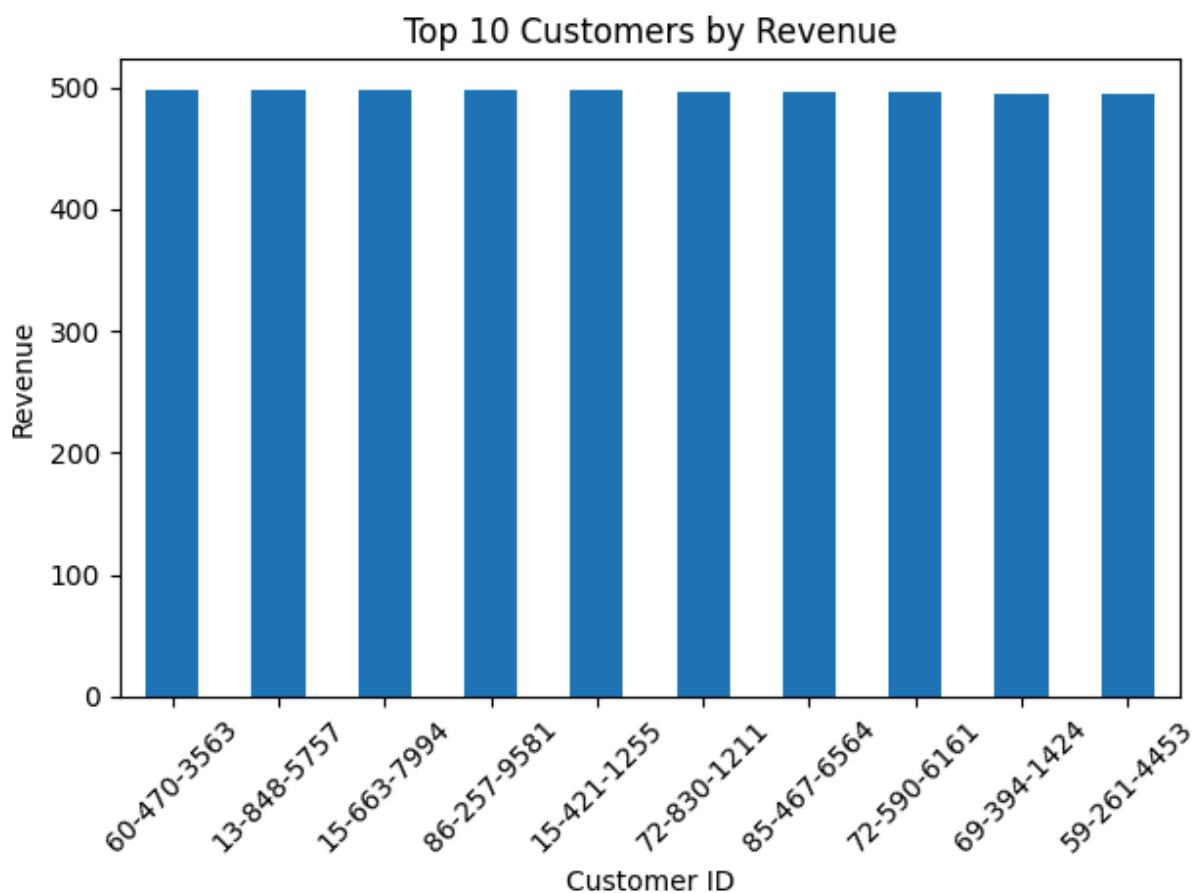
```
Customers contributing to 80% revenue: 601
```

## Visualization

```
# Bar chart → revenue by customer

import matplotlib.pyplot as plt

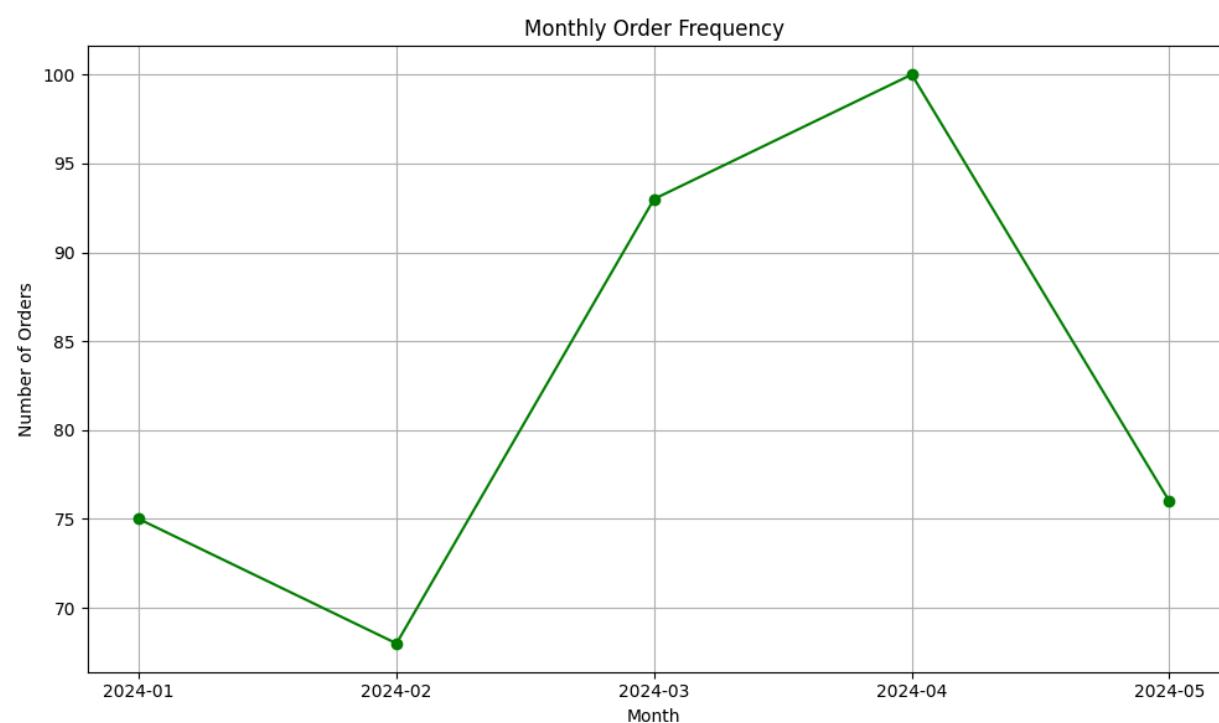
top_10_customers.plot(kind='bar')
plt.title('Top 10 Customers by Revenue')
plt.xlabel('Customer ID')
plt.ylabel('Revenue')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



```
# Line chart → frequency over time
```

```
# Monthly order counts from Jan to May 2024
months = ['2024-01', '2024-02', '2024-03', '2024-04', '2024-05']
orders = [75, 68, 93, 100, 76]

plt.figure(figsize=(10, 6))
plt.plot(months, orders, marker='o', linestyle='-', color='green')
plt.title('Monthly Order Frequency')
plt.xlabel('Month')
plt.ylabel('Number of Orders')
plt.grid(True)
plt.tight_layout()
plt.show()
```

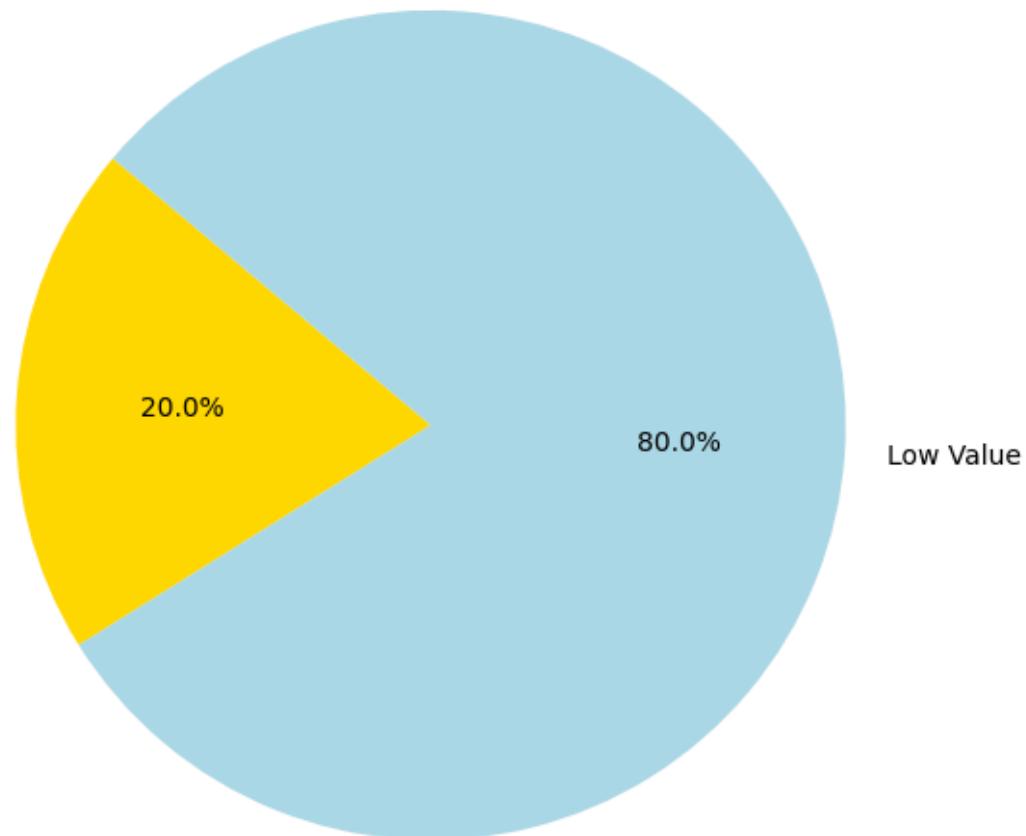


```
# . Pie Chart: Customer Revenue Segments
```

```
# Customer segments count
segments = ['High Value', 'Low Value']
counts = [200, 800]

plt.figure(figsize=(7, 7))
plt.pie(counts, labels=segments, autopct='%1.1f%%', startangle=140, colors=['green', 'blue'])
plt.title('Customer Revenue Segments')
plt.show()
```

### Customer Revenue Segments



```
import pandas as pd
import matplotlib.pyplot as plt

def funnel_chart(df, show_n=True, show_pct='NA'):
    df['val'] = df['val'].astype(int)
    max_val = df['val'].max()
    df = df.sort_values('val', ascending=True).reset_index(drop=True)
    df['left'] = (max_val - df['val']) / 2
    colors = ['indigo', 'purple', 'darkviolet', 'darkorchid', 'mediumorchid', 'blueviolet', 'darkblue', 'steelblue', 'lightblue']

    fig, ax = plt.subplots(figsize=(8, 4))
    for i in range(len(df)):
        ax.barh(i, df.loc[i, 'val'], left=df.loc[i, 'left'], height=0.6,
                color=colors[i % len(colors)], label=df.loc[i, 'step'])
        if show_n:
            ax.text(max_val * 1.01, i, f"{df.loc[i, 'step']}: {df.loc[i, 'val']}")
    ax.axis('off')
    plt.title('Customer Purchase Funnel')
    plt.show()

# Example funnel data (you can create based on your dataset, e.g., signup -> buy)
funnel_data = pd.DataFrame({
    'step': ['Visited Website', 'Signed Up', 'Added to Cart', 'Completed Purchase'],
    'val': [1000, 700, 300, 150]
})

funnel_chart(funnel_data)
```

### Customer Purchase Funnel



```
import matplotlib.pyplot as plt
import numpy as np

x = data['Time_to_Decision']
y = data['Purchase_Amount']
ratings = data['Product_Rating']
unique_ratings = sorted(ratings.unique())
colors = plt.cm.viridis(np.linspace(0, 1, len(unique_ratings)))
color_map = dict(zip(unique_ratings, colors))
point_colors = ratings.map(color_map)

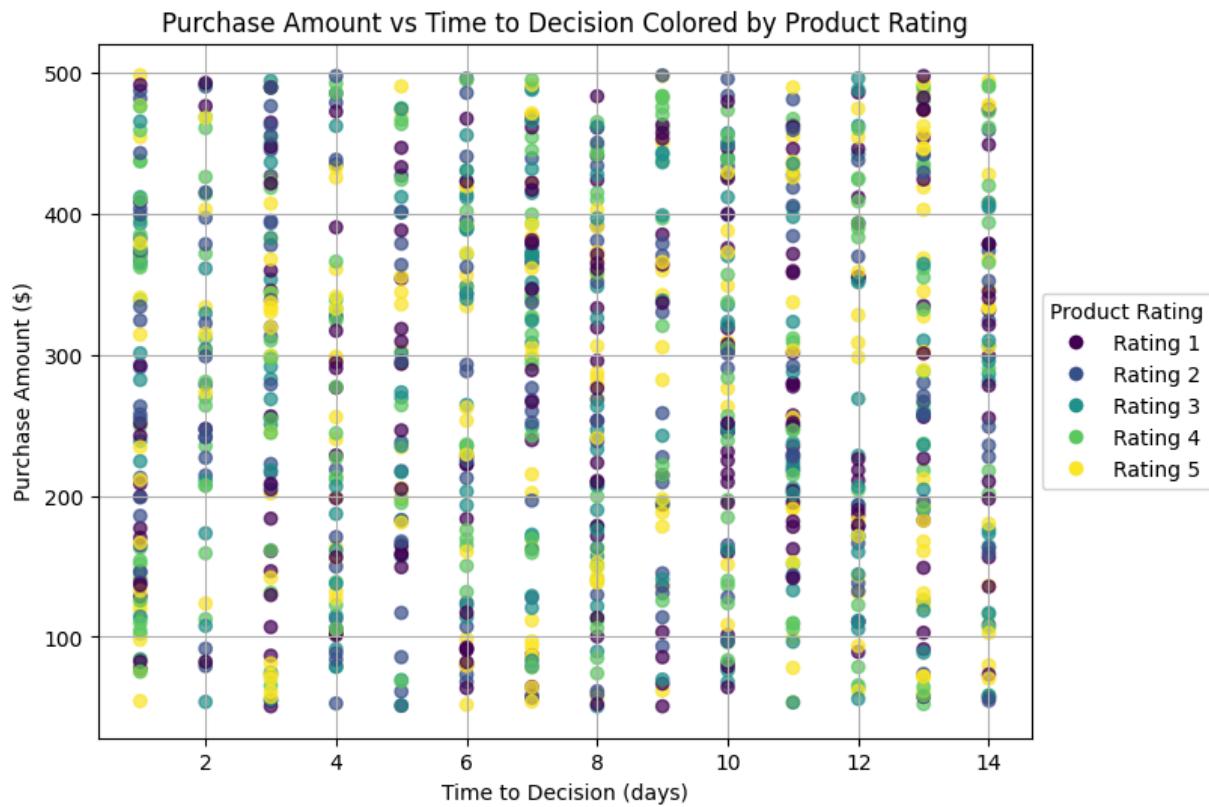
fig, ax = plt.subplots(figsize=(10, 6))
scatter = ax.scatter(x, y, c=point_colors, alpha=0.7)
ax.set_xlabel('Time to Decision (days)')
ax.set_ylabel('Purchase Amount ($)')
ax.set_title('Purchase Amount vs Time to Decision Colored by Product Rating')
ax.grid(True)

# Shrink current axis width to make space for legend
box = ax.get_position()
ax.set_position([box.x0, box.y0, box.width * 0.8, box.height])

# Place legend outside the plot on the right-center
handles = [plt.Line2D([0], [0], marker='o', color='w', label=f'Rating {r}', markerfacecolor=color_map[r], markersize=8) for r in unique_ratings]
ax.legend(handles=handles, title='Product Rating', loc='center left', bbox_to_anchor=[1.05, 0.5, 1.3, 0.5])

plt.show()
```

```
<module 'matplotlib.pyplot' from '/usr/local/lib/python3.12/dist-packages/matplotlib/pyplot.py'>
```



## PART B — Marketing Campaign Performance Evaluation

### Load and Inspect DataSet

```
import pandas as pd

# Load dataset
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/project/final_shop_6.csv')

# Inspect columns and sample data
print(data.columns)
print(data.head())

# info
data.info()
```

```
Index(['Ad Group', 'Month', 'Impressions', 'Clicks', 'CTR', 'Conversions',
       'Conv Rate', 'Cost', 'CPC', 'Revenue', 'Sale Amount', 'P&L'],
      dtype='object')
```

	Ad Group	Month	Impressions	Clicks	CTR	\
0	Shop - 1:1 - Desk - [shop coupon code]	July	16038	6504	0.41	
1	Shop - 1:1 - Desk - [shop coupon]	July	36462	14367	0.39	
2	Shop - 1:1 - Desk - [shop discount code]	July	3635	1458	0.40	
3	Shop - 1:1 - Desk - [shop promo code]	July	26185	10418	0.40	
4	Shop - 1:1 - Desk - [shop promo]	July	808	282	0.35	

	Conversions	Conv Rate	Cost	CPC	Revenue	Sale Amount	P&L
0	1166	0.10	6669	1.03	6402	136770.05	-267.086
1	2188	0.09	13746	0.96	13262	283215.21	-483.951

```

2          248      0.09   1606  1.10    1723   39165.46  117.136
3          2294     0.12  13278  1.27   13042   284823.48 -235.921
4             61     0.15    391  1.39     337    7717.77 -53.604
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 190 entries, 0 to 189
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   Ad Group    190 non-null    object 
 1   Month       190 non-null    object 
 2   Impressions 190 non-null    int64  
 3   Clicks      190 non-null    int64  
 4   CTR         190 non-null    float64
 5   Conversions 190 non-null    int64  
 6   Conv Rate   190 non-null    float64
 7   Cost        190 non-null    int64  
 8   CPC         190 non-null    float64
 9   Revenue     190 non-null    int64  
 10  Sale Amount 190 non-null    float64
 11  P&L        190 non-null    float64
dtypes: float64(5), int64(5), object(2)
memory usage: 17.9+ KB

```

## ▼ Data Cleaning and Preparation

```

# Check for missing values
print(data.isnull().sum())

# Filter out rows with zero or negative spend or clicks (invalid data)
data_clean = data[(data['Cost'] > 0) & (data['Clicks'] > 0) & (data['Conversions'] > 0) & (data['Sale Amount'] > 0) & (data['P&L'] > 0)]

# Calculate CTR (if missing or inconsistent)
data_clean['CTR_calc'] = (data_clean['Clicks'] / data_clean['Impressions']) * 100

# Calculate Conversion Rate (if missing or inconsistent)
data_clean['ConversionRate_calc'] = (data_clean['Conversions'] / data_clean['Clicks']) * 100

# Calculate Cost Per Lead (CPL)
data_clean['CPL'] = data_clean['Cost'] / data_clean['Conversions']

# Calculate Return on Investment (ROI) in percentage
data_clean['ROI'] = ((data_clean['Revenue'] - data_clean['Cost']) / data_clean['Cost']) * 100

# Note for CAC (Customer Acquisition Cost): Requires new customers data, not available in current dataset
print(data_clean[['CTR_calc', 'ConversionRate_calc', 'CPL', 'ROI']].head())

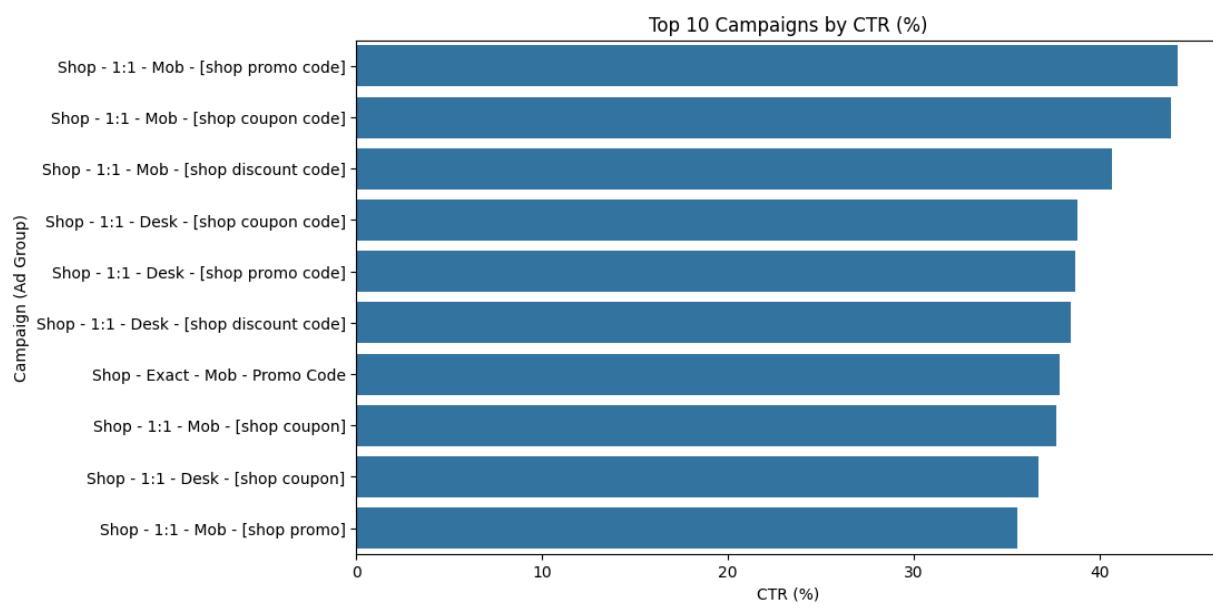
```

	Ad Group	Month	Impressions	Clicks	CTR	Conversions	Conv Rate	Cost	CPC	Revenue	Sale Amount	P&L	dtype: int64	CTR_calc	ConversionRate_calc	CPL	ROI
0	40.553685													17.927429	5.719554	-4.003599	
1	39.402666													15.229345	6.282450	-3.521024	
2	40.110041													17.009602	6.475806	7.285181	
3	39.786137													22.019581	5.788143	-1.777376	
4	34.900990													21.631206	6.409836	-13.810742	

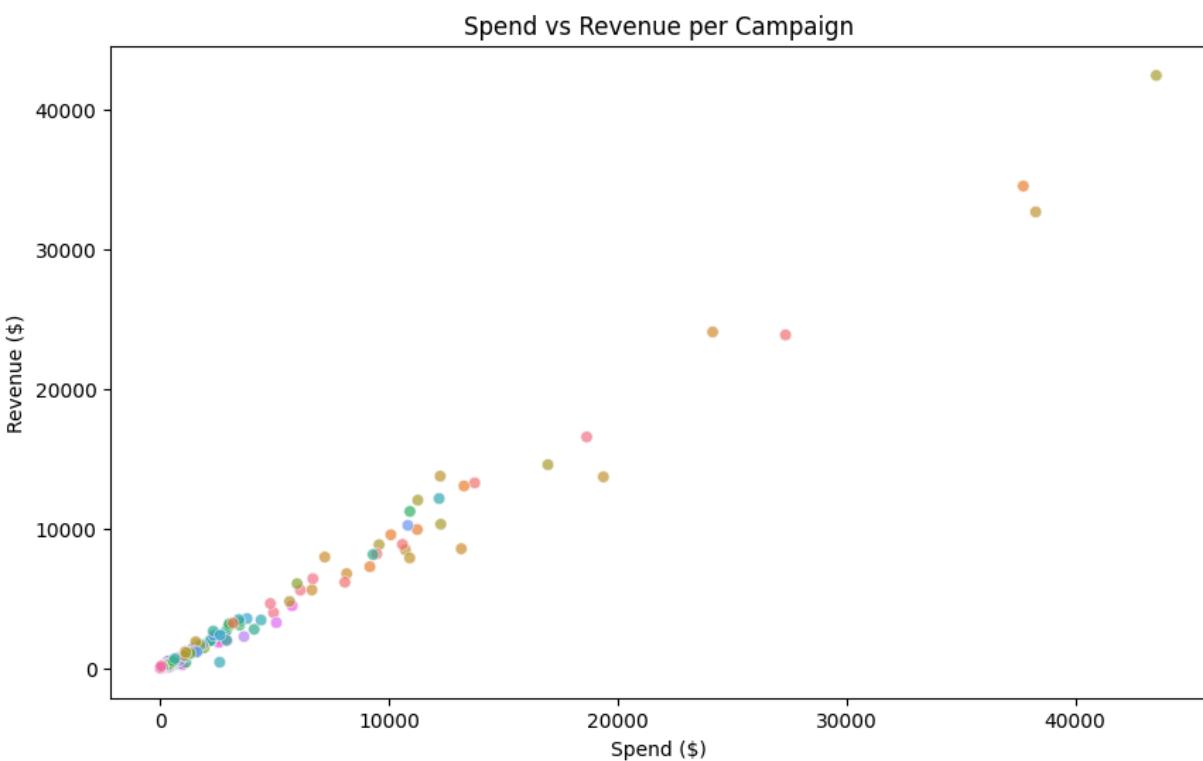
## ▼ Visualizations

```
import matplotlib.pyplot as plt
import seaborn as sns

# A. CTR comparison across campaigns (top 10)
top_campaigns = data_clean.groupby('Ad Group')['CTR_calc'].mean().sort_values(ascending=False)
plt.figure(figsize=(10,6))
sns.barplot(x=top_campaigns.values, y=top_campaigns.index)
plt.title("Top 10 Campaigns by CTR (%)")
plt.xlabel("CTR (%)")
plt.ylabel("Campaign (Ad Group)")
plt.show()
```



```
# B. Spend vs Revenue chart (scatter)
plt.figure(figsize=(10,6))
sns.scatterplot(data=data_clean, x='Cost', y='Revenue', hue='Ad Group', legend=True)
plt.title("Spend vs Revenue per Campaign")
plt.xlabel("Spend ($)")
plt.ylabel("Revenue ($)")
plt.show()
```



```
# C. Conversion rate bar chart for top 10 campaigns
top_conv_campaigns = data_clean.groupby('Ad Group')['ConversionRate_calc'].mean()
plt.figure(figsize=(10,6))
```