Business Problem

As a marketing agency, our primary objective is to maximize the return on investment (ROI) for o clients' advertising campaigns. We have conducted two ad campaigns, one on Facebook and the on AdWords, and we need to determine which platform yields better results in terms of clicks, conversions, and overall cost-effectiveness. By identifying the most effective platform, we can all our resources more efficiently and optimize our advertising strategies to deliver better outcomes clients.

Research Question

Which ad platform is more effective in terms of conversions, clicks, and overall co effectiveness?

Importing Libraries

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import coint
import warnings
warnings.filterwarnings('ignore')
```

Data Description

The dataset comprises a collection of data comparing the performance of two separate ad campa[...]
conducted throughout the year 2019. Specifically, the data covers a Facebook Ad campaign and [...]
AdWords Ad campaign. For each day of the year 2019, there is a corresponding row in the datas[...]
resulting in a total of 365 lines of campaign data to analyze. The dataset includes various perform[...]
metrics for each ad campaign, providing insights into their effectiveness and efficiency over time.

Key features included in the dataset are as follows:

- Date: The date corresponding to each row of campaign data, ranging from January 1st, 201[...]
  December 31st, 2019.
- Ad Views: The number of times the ad was viewed.
- Ad Clicks: The number of clicks received on the ad.
- Ad Conversions: The number of conversions resulting from the ad.
- Cost per Ad: The cost associated with running the Facebook ad campaign.
- Click-Through Rate (CTR): The ratio of clicks to views, indicating the effectiveness of the ad [...]
  generating clicks.
- Conversion Rate: The ratio of conversions to clicks, reflecting the effectiveness of the ad in [...]
  desired actions.
- Cost per Click (CPC): The average cost incurred per click on the ad.

```
In [ ]: # loading the dataset
        df = pd.read_csv('/content/drive/MyDrive/DATASETS/ABmarketing_campaign.csv
```

```
In [ ]: from google.colab import drive
        drive.mount('/content/drive')
```

        Drive already mounted at /content/drive; to attempt to forcibly remount, call
        drive.mount("/content/drive", force_remount=True).

```
In [ ]: # data overview
        df.head()
```

Out[ ]:

	Date	Facebook Ad Campaign	Facebook Ad Views	Facebook Ad Clicks	Facebook Ad Conversions	Cost per Facebook Ad	Facebook Click-Through Rate (Clicks / View)	Fac Conv (Conver
0	1/1/2019	FB_Jan19	2116	18	8	$126	0.83%	[...]
1	1/2/2019	FB_Jan19	3106	36	12	$104	1.15%	[...]
2	1/3/2019	FB_Jan19	3105	26	8	$102	0.84%	[...]
3	1/4/2019	FB_Jan19	1107	27	9	$71	2.45%	[...]
4	1/5/2019	FB_Jan19	1317	15	7	$78	1.10%	[...]

```
In [ ]: # rows and columns count of the dataset
        df.shape
```

```
Out[ ]:  (365, 17)
```

```
In [ ]:  # datatypes of the columns
         df.dtypes
```

```
Out[ ]:  Date                                                object
         Facebook Ad Campaign                                object
         Facebook Ad Views                                    int64
         Facebook Ad Clicks                                   int64
         Facebook Ad Conversions                              int64
         Cost per Facebook Ad                                object
         Facebook Click-Through Rate (Clicks / View)         object
         Facebook Conversion Rate (Conversions / Clicks)     object
         Facebook Cost per Click (Ad Cost / Clicks)          object
         AdWords Ad Campaign                                 object
         AdWords Ad Views                                     int64
         AdWords Ad Clicks                                    int64
         AdWords Ad Conversions                               int64
         Cost per AdWords Ad                                 object
         AdWords Click-Through Rate (Clicks / View)          object
         AdWords Conversion Rate (Conversions / Click)       object
         AdWords Cost per Click (Ad Cost / Clicks)           object
         dtype: object
```

```
In [ ]:  # converting date to datetime
         df['Date'] = pd.to_datetime(df['Date'])
```

```
In [ ]:  # descriptive stats of the campaigns
         df.describe()
```

Out[ ]:

|	Date	Facebook Ad Views	Facebook Ad Clicks	Facebook Ad Conversions	AdWords Ad Views	AdWords Ad Clicks	AdWo Conve
count	365	365.000000	365.000000	365.000000	365.00000	365.000000	365.
mean	2019-07-02 00:00:00	2179.687671	44.049315	11.742466	4717.19726	60.383562	5.
min	2019-01-01 00:00:00	1050.000000	15.000000	5.000000	3714.00000	31.000000	3.
25%	2019-04-02 00:00:00	1656.000000	35.000000	10.000000	4247.00000	49.000000	5.
50%	2019-07-02 00:00:00	2202.000000	43.000000	12.000000	4711.00000	60.000000	6.
75%	2019-10-01 00:00:00	2717.000000	54.000000	13.000000	5190.00000	73.000000	7.
max	2019-12-31 00:00:00	3320.000000	73.000000	19.000000	5760.00000	89.000000	9.
std	NaN	618.074639	12.140559	2.924786	561.11406	14.368225	1.

Comparing Campaigns performance

```python
# Plot distribution of clicks and conversions
plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
plt.title('Facebook Ad Clicks')
sns.histplot(df['Facebook Ad Clicks'], bins=7, edgecolor='k', kde=True)
plt.subplot(1, 2, 2)
plt.title('Facebook Ad Conversions')
sns.histplot(df['Facebook Ad Conversions'], bins=7, edgecolor='k', kde=Tru
plt.show()

plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
plt.title('AdWords Ad Clicks')
sns.histplot(df['AdWords Ad Clicks'], bins=7, edgecolor='k', kde=True)
plt.subplot(1, 2, 2)
plt.title('AdWords Ad Conversions')
sns.histplot(df['AdWords Ad Conversions'], bins=7, edgecolor='k', kde=True
plt.show()
```
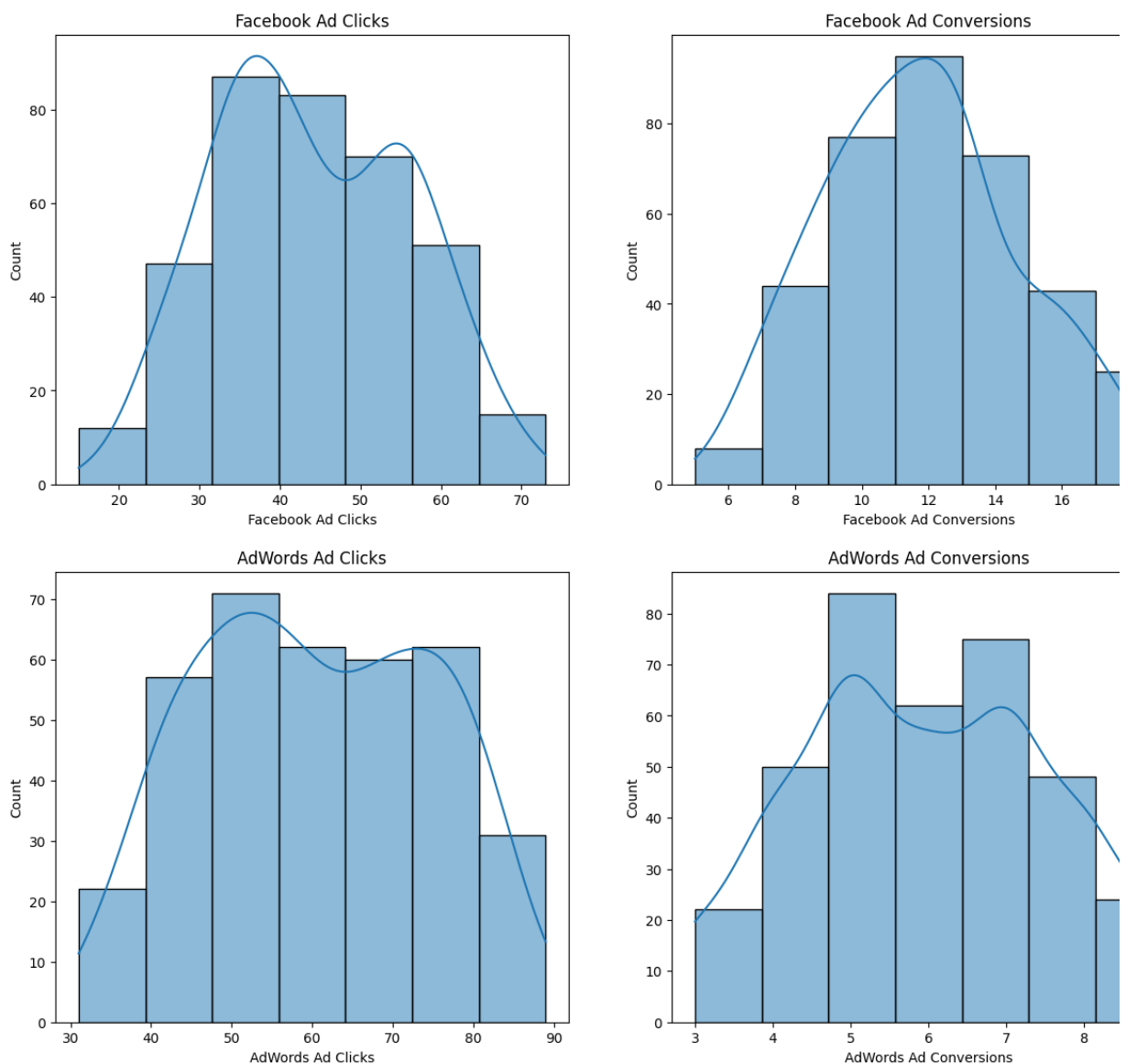

All the histogram are showing somewhat symmetrical shape. This symmetrical shape suggests th
number of clicks and conversions is relatively evenly distributed. In other words, there are not ma
clicks or conversions that are outliers on either the high or low end.

How frequently do we observe days with high numbers of conversions compared days with low numbers of conversions?

```
In [ ]: # creating function to calculate the category for the conversions
        def create_conversion_category(conversion_col):
            category = []
            for conversion in df[conversion_col]:
                if conversion < 6:
                    category.append('less than 6')
                elif 6 <= conversion < 11:
                    category.append('6 - 10')
                elif 11 <= conversion < 16:
                    category.append('10 - 15')
                else:
                    category.append('more than 15')
            return category

        # applying function of different campaign's conversions
        df['Facebook Conversion Category'] = create_conversion_category('Facebook
        df['AdWords Conversion Category'] = create_conversion_category('AdWords A
```

```
In [ ]: df[['Facebook Ad Conversions','Facebook Conversion Category','AdWords Ad (
```

Out[ ]:

	Facebook Ad Conversions	Facebook Conversion Category	AdWords Ad Conversions	AdWords Con Ca
0	8	6 - 10	5	les
1	12	10 - 15	6	
2	8	6 - 10	4	les
3	9	6 - 10	5	les
4	7	6 - 10	7	

```
In [ ]: df['Facebook Conversion Category'].value_counts()
```

```
Out[ ]: Facebook Conversion Category
        10 - 15         189
        6 - 10          128
        more than 15     47
        less than 6       1
        Name: count, dtype: int64
```

```
In [ ]: facebook = pd.DataFrame(df['Facebook Conversion Category'].value_counts()
        facebook
```

Out[ ]:

	Category	count
0	10 - 15	189
1	6 - 10	128
2	more than 15	47
3	less than 6	1

```
In [ ]: df['AdWords Conversion Category'].value_counts()
```

```
Out[ ]:  AdWords Conversion Category
         6 - 10         209
         less than 6    156
         Name: count, dtype: int64
```

```
In [ ]:  adwords = pd.DataFrame(df['AdWords Conversion Category'].value_counts()).
         adwords
```

Out[ ]:

	Category	count
0	6 - 10	209
1	less than 6	156

```
In [ ]:  category_df = pd.merge(facebook, adwords, on = 'Category', how = 'outer')
         category_df
```

Out[ ]:

	Category	count_x	count_y
0	10 - 15	189	0.0
1	6 - 10	128	209.0
2	more than 15	47	0.0
3	less than 6	1	156.0

```
In [ ]:  category_df = category_df.iloc[[3,1,0,2]]
         category_df
```

Out[ ]:

	Category	count_x	count_y
3	less than 6	1	156.0
1	6 - 10	128	209.0
0	10 - 15	189	0.0
2	more than 15	47	0.0

```
In [ ]:  X_axis = np.arange(len(category_df))
         X_axis
```

```
Out[ ]:  array([0, 1, 2, 3])
```

```
In [ ]:  # Bar chart to compare conversion categories
         plt.figure(figsize=(15, 6))
         plt.bar(X_axis - 0.2, category_df['count_x'], 0.4, label='Facebook', colo
         plt.bar(X_axis + 0.2, category_df['count_y'], 0.4, label='AdWords', color=
         plt.xticks(X_axis, category_df['Category'])
         plt.xlabel("Conversion Category")
         plt.ylabel("Number of Days")
         plt.title("Frequency of Daily Conversions by Conversion Categories", fonts
         plt.legend(fontsize=15)
         plt.show()
```

Frequency of Daily Conversions by Conversion Categories
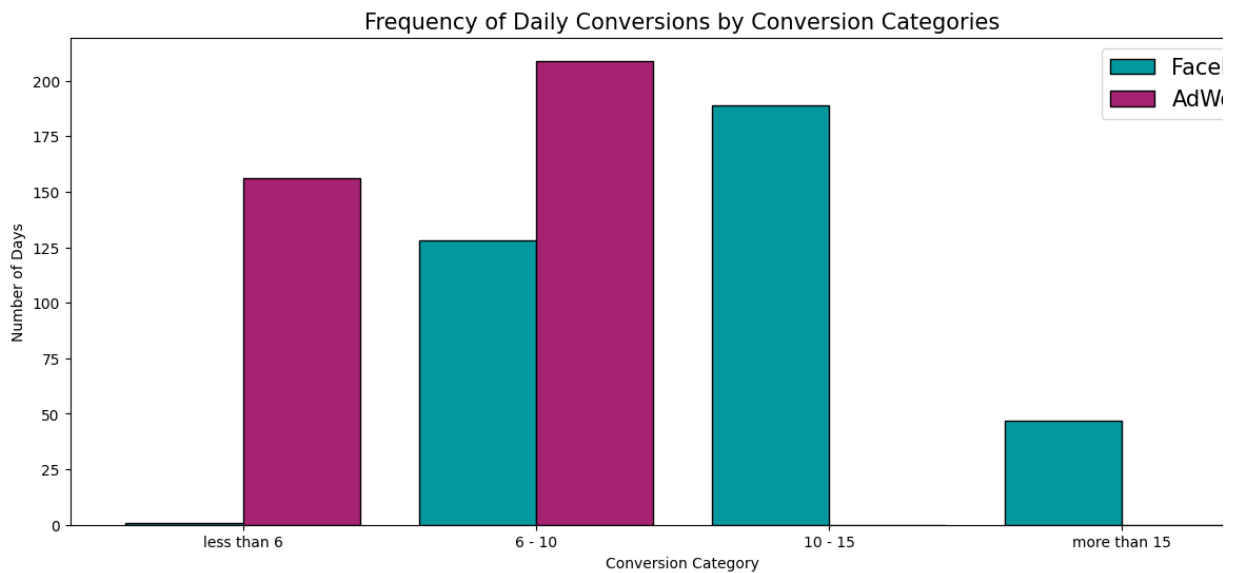
- The data suggests Facebook had more frequent higher conversion days than AdWords, whi
  had very low conversion rates (less than 6) or moderate ones (6 - 10).
- There is a significant variance in the number of high-conversion days between two different
  campaigns.
- The absence of any days with conversions between 10 - 15 and more than 15 in AdWords in
  a need to review what strategies were changed or what external factors could have influence
  numbers.

Do more clicks on the ad really lead to more sales?

```
In [ ]: plt.figure(figsize=(15,6))
        plt.subplot(1,2,1)
        plt.title('Facebook')
        sns.scatterplot(x = df['Facebook Ad Clicks'],y = df['Facebook Ad Conversi
        plt.xlabel('Clicks')
        plt.ylabel('Conversions')
        plt.subplot(1,2,2)
        plt.title('AdWords')
        sns.scatterplot(x = df['AdWords Ad Clicks'],y = df['AdWords Ad Conversions
        plt.xlabel('Clicks')
        plt.ylabel('Conversions')
        plt.show()
```
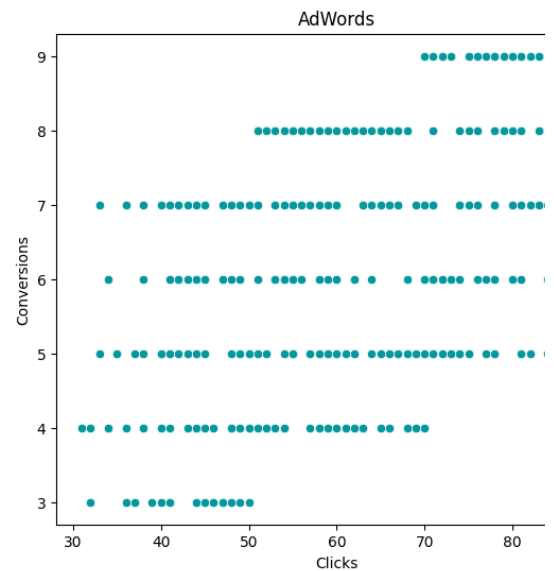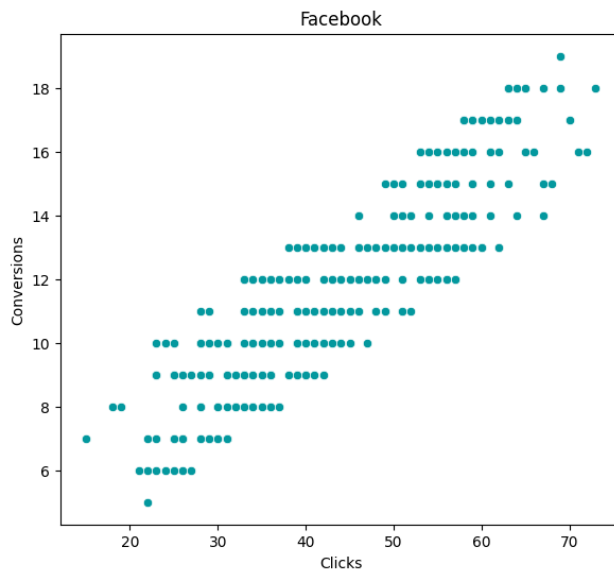
```
In [ ]:  facebook_corr = df[['Facebook Ad Conversions','Facebook Ad Clicks']].corr
         facebook_corr
```

Out[ ]:

	Facebook Ad Conversions	Facebook Ad Clicks
Facebook Ad Conversions	1.000000	0.873775
Facebook Ad Clicks	0.873775	1.000000

```
In [ ]:  adwords_corr = df[['AdWords Ad Conversions','AdWords Ad Clicks']].corr()
         adwords_corr
```

Out[ ]:

	AdWords Ad Conversions	AdWords Ad Clicks
AdWords Ad Conversions	1.000000	0.447993
AdWords Ad Clicks	0.447993	1.000000

```
In [ ]:  # Correlation calculation
         facebook_corr = df[['Facebook Ad Conversions', 'Facebook Ad Clicks']].cor
         adwords_corr = df[['AdWords Ad Conversions', 'AdWords Ad Clicks']].corr()
         corr_results = {
             'Facebook': round(facebook_corr.values[0, 1], 2),
             'AdWords': round(adwords_corr.values[0, 1], 2)
         }

         print('Correlation Coeff \n--------------')
         print('Facebook :',round(facebook_corr.values[0,1],2))
         print('AdWords : ',round(adwords_corr.values[0,1],2))

         Correlation Coeff
         --------------
         Facebook : 0.87
         AdWords :  0.45
```

- A correlation coefficient of 0.87 indicates a strong positive linear relationship between clicks Facebook ads and sales. This suggests that as the number of clicks on Facebook ads increa sales tend to increase as well.
- This strong correlation suggests that Facebook ads are highly effective in driving sales, as a portion of the variation in sales can be explained by the variation in clicks on Facebook ads.
- The strong correlation between clicks on Facebook ads and sales suggests that Facebook advertising is highly effective in driving sales for the business. Increasing investment in Face ads or optimizing their performance could potentially lead to even higher sales.
- A correlation coefficient of 0.45 indicates a moderate positive linear relationship between clic AdWords ads and sales. While there is still a positive relationship, it is not as strong as with Facebook ads.
- The moderate correlation between clicks on AdWords ads and sales indicates that while AdV advertising does contribute to sales, its effectiveness may be influenced by other factors. Fu analysis is needed to identify these factors and optimize AdWords campaigns accordingly.

Hypothesis Testing

Hypothesis: Advertising on Facebook will result in a greater number of conversions compared t advertising on AdWords.

Null Hypothesis (H0): There is no difference in the number of conversions between Facebook a AdWords, or the number of conversions from AdWords is greater than or equal to those from Fac

H0: μ_Facebook ≤ μ_AdWords

Alternate Hypothesis (H1): The number of conversions from Facebook is greater than the num conversions from AdWords.

H1: μ_Facebook > μ_AdWords

```
In [ ]:  print('Mean Conversion \n--------------')
         print('Facebook :', round(df['Facebook Ad Conversions'].mean(),2))
         print('AdWords :', round(df['AdWords Ad Conversions'].mean(),2))

         t_stats, p_value = st.ttest_ind(a = df['Facebook Ad Conversions'], b = df
         print('\nT statistic', t_stats, '\np-value',p_value)

         # comparing the p value with the significance of 5% or 0.05
         if p_value < 0.05:
             print("\np-value is less than significance value, Reject the null hyp
         else:
             print("\np-value is greater than significance value, Accept the null l
```

```
Mean Conversion
--------------
Facebook : 11.74
AdWords : 5.98

T statistic 32.88402060758184
p-value 9.348918164530465e-134

p-value is less than significance value, Reject the null hypothesis
```

- The mean number of conversions from Facebook ads (11.74) is substantially higher than the number of conversions from AdWords ads (5.98). This suggests that, on average, Facebook advertising is more effective in generating conversions compared to AdWords advertising.
- The T statistic (32.88) is a measure of the difference between the means of the two groups relative to the variation within the groups. A larger T statistic indicates a greater difference between the means of the two groups.
- The p-value (9.35e-134) is extremely small, indicating strong evidence against the null hypothesis.
- The results strongly support the alternate hypothesis, indicating that the number of conversions from Facebook advertising is indeed greater than the number of conversions from AdWords advertising.
- Facebook advertising appears to be a more effective channel for generating conversions compared to AdWords advertising, based on the sample data analyzed.
- Given the significant difference in conversion rates between Facebook and AdWords, consider reallocating resources towards Facebook advertising efforts. This could involve increasing ad spend, expanding targeting efforts, or experimenting with different ad formats to capitalize on the platform's effectiveness in driving conversions.

Regression Analysis

What will happen when I do go with the Facebook Ad? How many facebook ad conversions can I expect given a certain number of facebook ad clicks?

```python
In [ ]: # independent variable
        X = df[['Facebook Ad Clicks']]

        # dependent variable
        y = df[['Facebook Ad Conversions']]

        # initializing and fitting Linear Regression model
        reg_model = LinearRegression()
        reg_model.fit(X,y)
        prediction = reg_model.predict(X)

        # model evaluation
        r2 = r2_score(y, prediction)*100
        mse = mean_squared_error(y, prediction)
        print('Accuracy (R2 Score):',round(r2,2),'%')
        print('Mean Squared Error:', round(mse,2))

        Accuracy (R2 Score): 76.35 %
        Mean Squared Error: 2.02
```
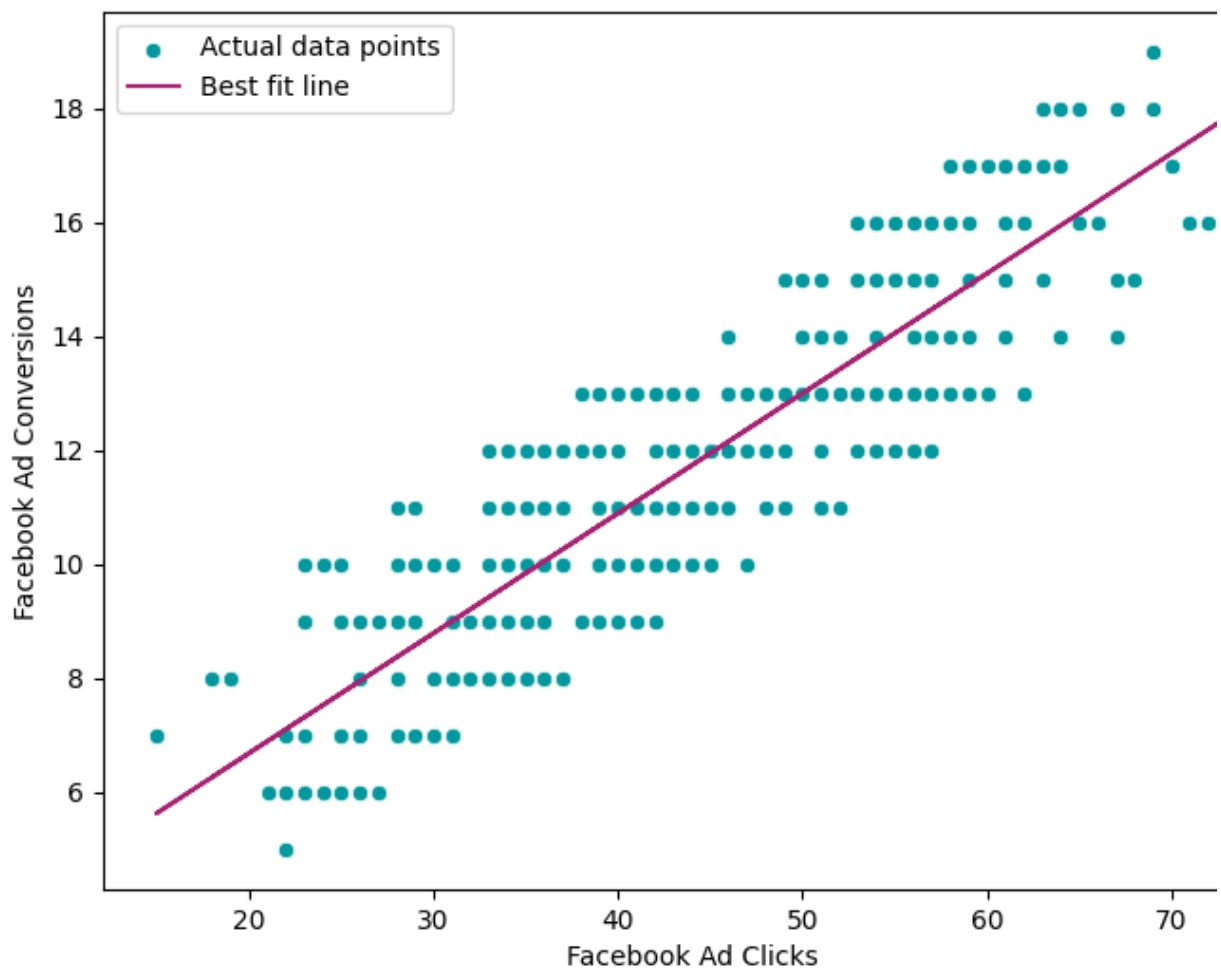
```
In [ ]: # Plotting linear regression
        plt.figure(figsize=(8, 6))
        sns.scatterplot(x=df['Facebook Ad Clicks'], y=df['Facebook Ad Conversions
        plt.plot(df['Facebook Ad Clicks'], prediction, color='#A62372', label='Bes
        plt.legend()
        plt.show()
```



```
In [ ]: print(f'For {50} Clicks, Expected Conversion : {round(reg_model.predict([
        print(f'For {80} Clicks, Expected Conversion : {round(reg_model.predict([

        For 50 Clicks, Expected Conversion : 13.0
        For 80 Clicks, Expected Conversion : 19.31
```

- The model has a reasonably good predictive power, with an R2 score of 76.35%. This sugge
  it can effectively predict Facebook ad conversions based on the number of Facebook ad clic
- With the insights provided by the Linear Regression model, businesses can make informed
  decisions about resource allocation, budget planning, and campaign optimization.
- For instance, knowing the expected number of Facebook ad conversions based on a certain
  of Facebook ad clicks can help in setting realistic campaign goals, optimizing ad spend, and
  assessing the ROI of Facebook advertising efforts.

Analyzing Facebook Campaign metrics over tir

```python
In [ ]: def safe_float_conversion(value):
            if isinstance(value, str):
                # Strip unwanted characters and convert
                return float(value.strip('%$'))
            return value  # If already a float, just return it

        # Apply this function to your DataFrame
        df['Facebook Click-Through Rate (Clicks / View)'] = df['Facebook Click-Th
        df['Facebook Conversion Rate (Conversions / Clicks)'] = df['Facebook Conve
        df['Facebook Cost per Click (Ad Cost / Clicks)'] = df['Facebook Cost per (
        df['Cost per Facebook Ad'] = df['Cost per Facebook Ad'].apply(lambda x: sa
```

```python
In [ ]: # filtering for facebook campaign
        df = df[['Date','Facebook Ad Views',
                'Facebook Ad Clicks', 'Facebook Ad Conversions', 'Cost per Faceboo
                'Facebook Click-Through Rate (Clicks / View)',
                'Facebook Conversion Rate (Conversions / Clicks)',
                'Facebook Cost per Click (Ad Cost / Clicks)']]

        df.head()
```

Out[ ]:

|	Date	Facebook Ad Views	Facebook Ad Clicks	Facebook Ad Conversions	Cost per Facebook Ad	Facebook Click-Through Rate (Clicks / View)	Facebook Conversion Rate (Conversions / Clicks)	F
0	2019-01-01	2116	18	8	126.0	0.83	42.73	
1	2019-01-02	3106	36	12	104.0	1.15	34.04	
2	2019-01-03	3105	26	8	102.0	0.84	31.45	
3	2019-01-04	1107	27	9	71.0	2.45	34.76	
4	2019-01-05	1317	15	7	78.0	1.10	47.59	

At what times of the month or days of the week do we observe the conversions?

```python
In [ ]: # extracting month and week day from the date column
        df['month'] = df['Date'].dt.month
        df['week'] = df['Date'].dt.weekday
```

```python
In [ ]: plt.figure(figsize=(8,5))
        plt.title('Weekly Conversions')
        weekly_conversion = df.groupby('week')[['Facebook Ad Conversions']].sum()
        week_names= ['Sunday','Monday','Tuesday','Wednesday','Thursday','Friday',
        plt.bar(week_names, weekly_conversion['Facebook Ad Conversions'], color =
        plt.show()
```

Weekly Conversions
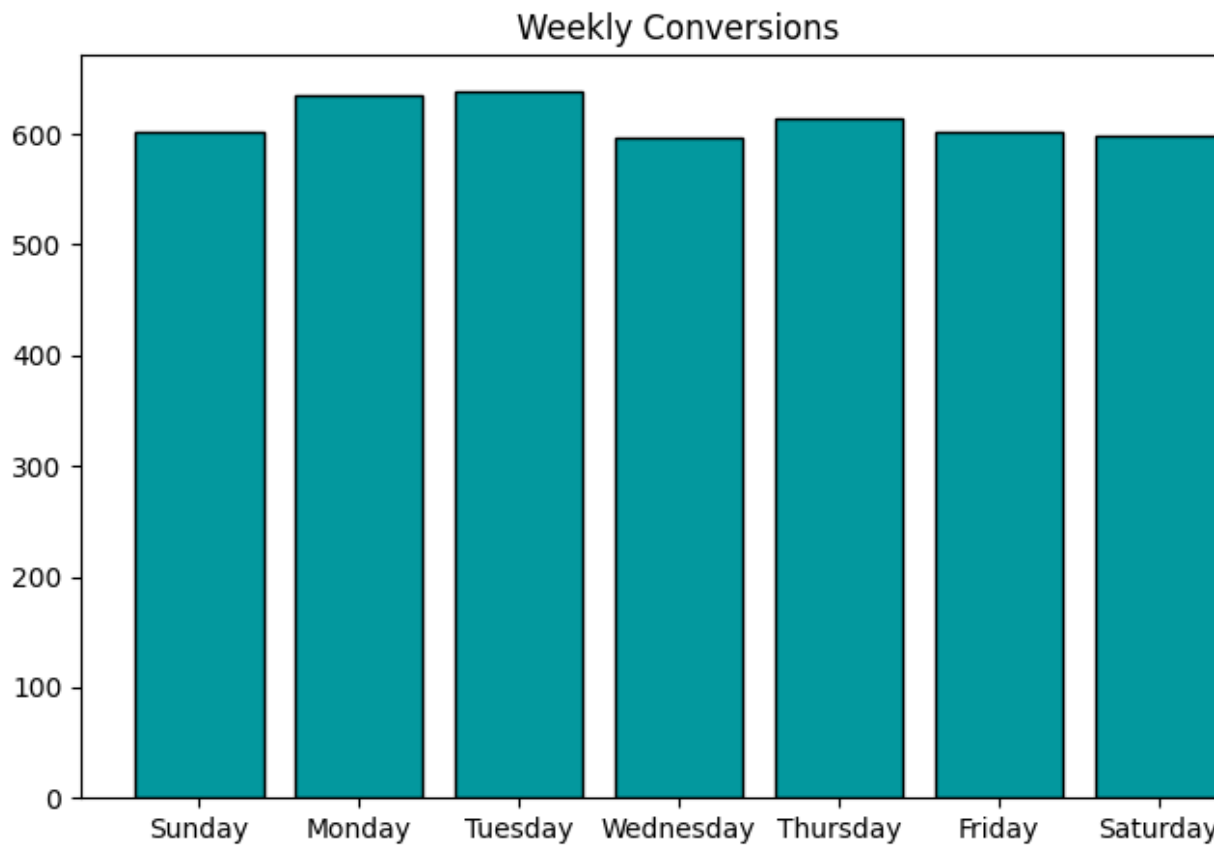

```
In [ ]: plt.figure(figsize=(8,5))
        plt.title('Monthly Conversions')
        monthly_conversion = df.groupby('month')[['Facebook Ad Conversions']].sum
        month_names = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct
        plt.plot(month_names, monthly_conversion['Facebook Ad Conversions'],'-o',
        plt.show()
```
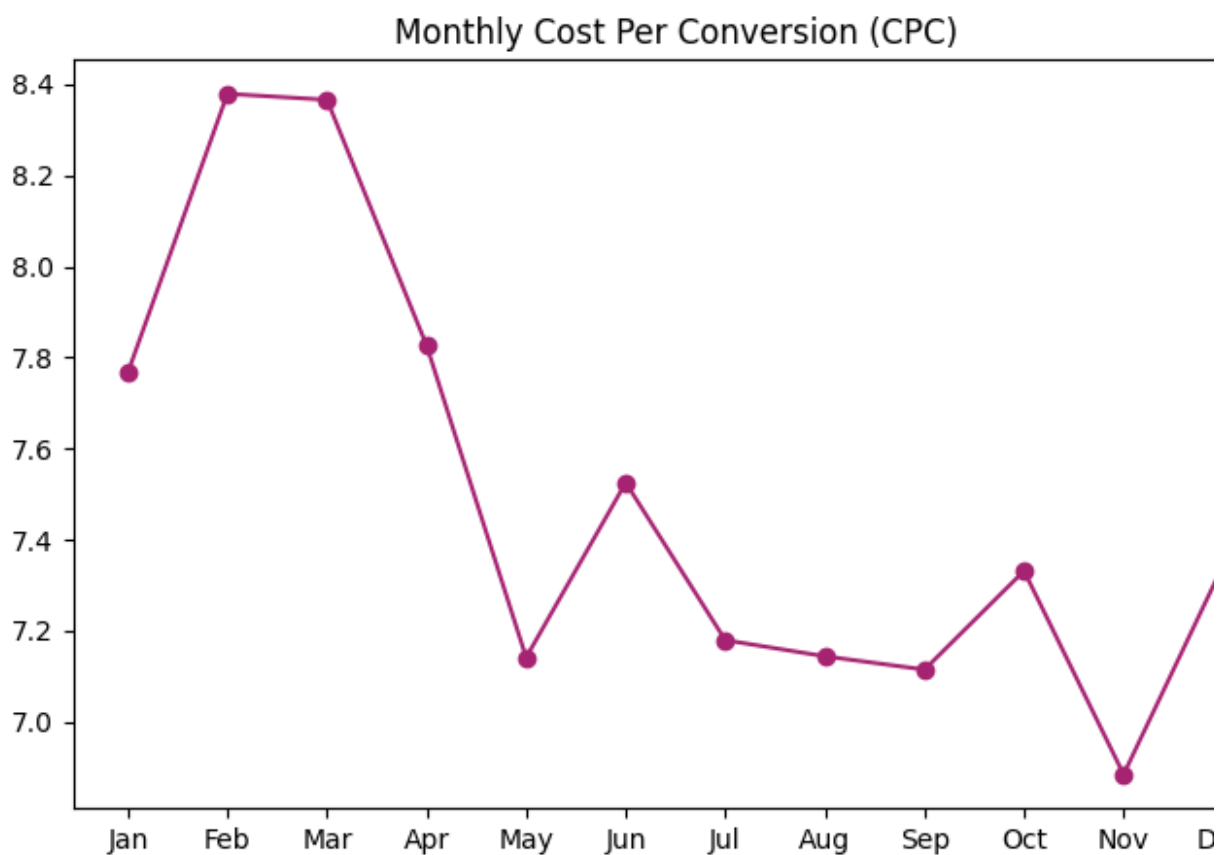
Monthly Conversions
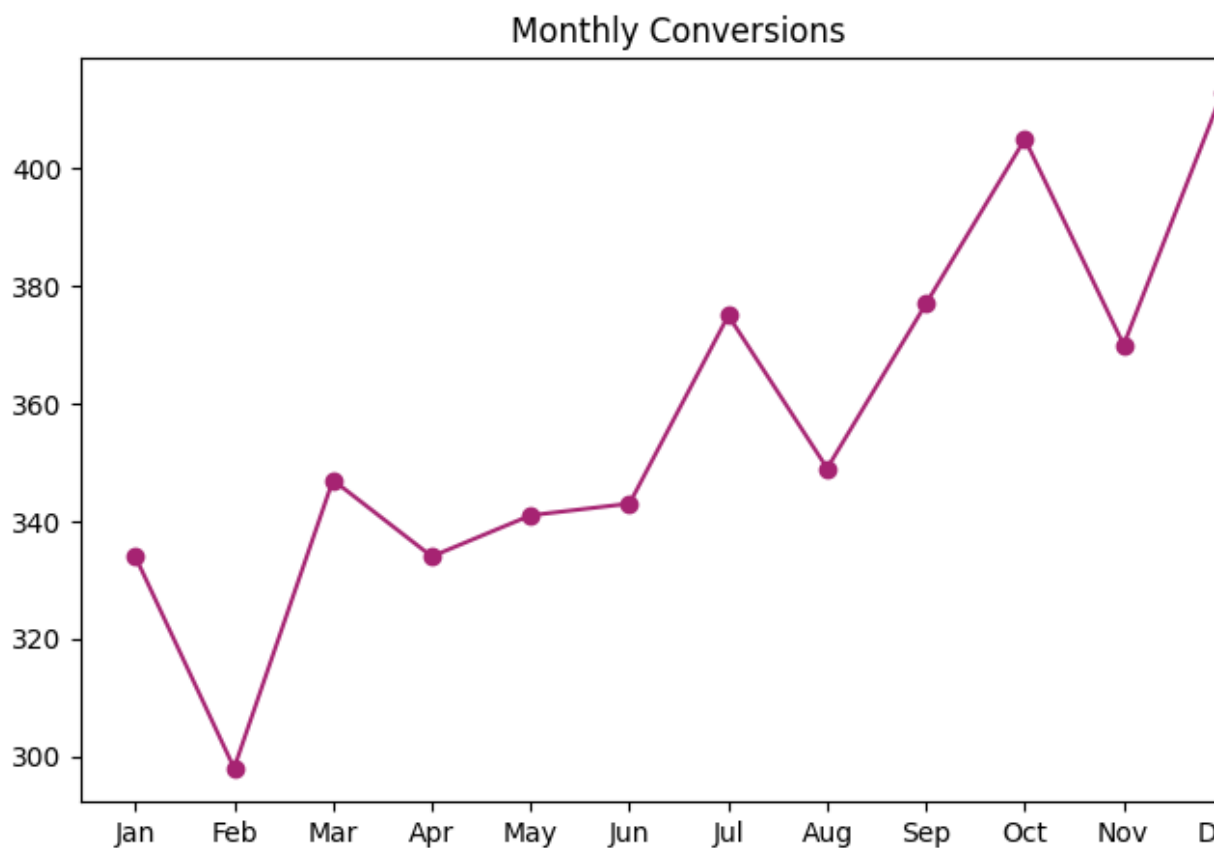
- Across the weekdays over a year, the total number of conversions remains relatively consist indicating a consistent level of engagement throughout the week. However, Mondays and Tu consistently exhibit the highest conversion rates compared to other days, suggesting that the beginning of the workweek sees heightened user engagement or responsiveness to marketi efforts.
- Examining the monthly trend in conversions reveals an overall upward trajectory, indicating a general increase in conversions over time. However, certain months stand out with variation conversion rates. February, April, May, June, August, and November experience a decline in conversions compared to neighboring months. These periods of decreased conversion rates be influenced by factors such as seasonal fluctuations, changes in consumer behavior, or adjustments in marketing strategies.

How does the Cost Per Conversion (CPC) trend over time?

Cost Per Conversion (CPC): This metric is used to evaluate the cost effectiveness and profitabilit online advertising campaign. This metric helps marketers understand how much they are spendir obtain each conversion, allowing them to optimize their spending and targeting strategies effectiv

```
In [ ]:  plt.figure(figsize=(8,5))
         plt.title('Monthly Cost Per Conversion (CPC)')
         monthly_df = df.groupby('month')[['Facebook Ad Conversions','Cost per Face
         monthly_df['Cost per Conversion'] = monthly_df['Cost per Facebook Ad']/mor
         plt.plot(month_names, monthly_df['Cost per Conversion'],'-o', color = '#A(
         plt.show()
```


Monthly Cost Per Conversion (CPC)

- The CPC trend over the 12-month period shows some fluctuations but overall maintains a re stable range.
- May and November have the lowest CPC values, indicating potentially more cost-effective advertising or higher conversion rates during these periods.
- February has the highest CPC value, suggesting that advertising costs may be relatively hig during this month compared to others.
- Lower CPC values in certain months (e.g., May and November) could indicate periods of hig advertising effectiveness or more favorable market conditions.
- Consider allocating more advertising budget to months with historically lower CPC values (e and November) to maximize ROI.

Is there a long-term equilibrium relationship between advertising spend and conv rates that suggests a stable, proportional impact of budget changes on conversio over time?

```
In [ ]: score, p_value, _ = coint(df['Cost per Facebook Ad'], df['Facebook Ad Conv
        print('Cointegration test score:', score)
        print('P-value:', p_value)
        if p_value < 0.05:
            print("\np-value is less than significance value, Reject the null hypo
        else:
            print("\np-value is greater than significance value, Accept the null I

        Cointegration test score: -14.755428385103219
        P-value: 2.1337375979061323e-26

        p-value is less than significance value, Reject the null hypothesis
```

- Since the p-value is significantly lower than the chosen significance level, we reject the null hypothesis. This indicates that there is a long-term equilibrium relationship between advertis spend (cost) and conversions.

- Businesses can use this understanding of the stable relationship between cost and conversi optimize their advertising strategies. By investing in campaigns that demonstrate a strong re investment (ROI) and adjusting spending based on performance, companies can maximize conversions while minimizing costs.