a-b-testing-ad-campaigns

May 13, 2024

Kindle Ad Campaigns

Campaign AKIN9326 focuses on promoting the long-term benefits of reading in one's professional life and emphasizes how Kindle can facilitate reading.

Campaign AKIN8012 aims to instill fear in people's minds about the potential negative impact on their professional career if they don't read regularly.

GOAL/OBJECTIVE

Conversions serve as a key metric for evaluating the effectiveness of each ad campaign in driving user engagement and sales.

A higher conversion rate suggests that more users took the desired action, such as purchasing a Kindle, in response to the ad campaign.

Comparing the cost per conversion between the two campaigns can provide insights into the efficiency of acquiring new customers.

Analyzing the Click Through Rate (CTR) helps assess the relevance and appeal of each ad, potentially influencing conversion rates.

The number of ad clicks is another factor to consider, as it may correlate with higher conversion rates if the ad content resonates with users.

Efforts should be made to optimize ad expenditure while maximizing conversions to achieve the best return on investment.

Preference is given to ad campaigns with higher values of Total Conversions and Total Approved Conversions, indicating successful customer acquisition.

[8]:
```
#loading packages

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import plotly.express as px
import optuna
import matplotlib.pyplot as plt
import math

from colorama import Fore, Style, init;
# Import necessary libraries
```

```
from IPython.display import display, HTML
from scipy.stats import skew  # Import the skew function
# Import Plotly.go
import plotly.graph_objects as go
# import Subplots
from plotly.subplots import make_subplots

palette = ['#422057FF', '#fafa00']
color_palette = sns.color_palette(palette)
# Remove Warnings
import warnings
warnings.filterwarnings("ignore")
# Set the option to display all columns
pd.set_option('display.max_columns', None)
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
```

Loading the Dataset

[9]:
```
df = pd.read_excel("kindle AB testing dataset.xlsx")
```

[10]:
```
def print_boxed_blue_heading(heading):
    gradient = [Fore.RED, Fore.YELLOW, Fore.GREEN, Fore.CYAN, Fore.BLUE, Fore.
↪MAGENTA]
    print("\n" + "=" * (len(heading) + 4))
    words = heading.split()
    for i, word in enumerate(words):
        if i == len(words) - 1:
            print(f"| {gradient[len(word) % len(gradient)] + word + Style.
↪RESET_ALL} |")
        else:
            print(f"| {gradient[len(word) % len(gradient)] + word + Style.
↪RESET_ALL}", end=" ")
    print("=" * (len(heading) + 4))

def print_error(message):
    raise ValueError(message)

def D_O(train_df):
    try:

        # Display head of the training dataset nicely
        print_boxed_blue_heading("The Head Of Dataset is:")
```

```
    display(HTML(train_df.head(5).to_html(index=False).replace('<table border="1" class="dataframe">', '<table style="border: 2px solid blue;">').replace('<td>', '<td style="color: skyblue;">')))
    print('\n')

    # Display tail of the training dataset nicely
    print_boxed_blue_heading("The Tail Of Dataset is:")
    display(HTML(train_df.tail(5).to_html(index=False).replace('<table border="1" class="dataframe">', '<table style="border: 2px solid blue;">').replace('<td>', '<td style="color: skyblue;">')))
    print('\n')

    print_boxed_blue_heading("Shape Data:")
    print(f'The Shape of the Data is {train_df.shape} |')
    print(f'- 1.The No of Rows is {train_df.shape[0]} |')
    print(f'- 2.The No of Cols is {train_df.shape[1]}|')

    print('\n')

    print_boxed_blue_heading("Info Of Train Data:")
    train_df.info()

    # Describe both numerical and categorical data
    print_boxed_blue_heading("Numerical Summary of Data:")
    print(f"\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}The Numerical Summary of Data is:{Style.RESET_ALL}")
    display(train_df.describe().style.set_caption("Data Summary").set_table_styles([{'selector': 'caption', 'props': [('color', 'skyblue')]}]))

    Cat_cols_train = [col for col in train_df.columns if train_df[col].dtype == 'O']
    print_boxed_blue_heading("Categorical Columns of Data:")
    print(f'\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}The Categorical Columns of Data are :{Style.RESET_ALL} {Cat_cols_train}')

    N_cols_train = [col for col in train_df.columns if train_df[col].dtype == 'float']
    print_boxed_blue_heading("Numerical Columns of Data:")
    print(f'\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}The Numerical Columns of Data are :{Style.RESET_ALL} {N_cols_train}\n')

    print_boxed_blue_heading("Null Values in Data:")
    print(f'\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}The Null Values of Data are:{Style.RESET_ALL}\n{train_df.isnull().sum()}')

    print_boxed_blue_heading("Duplicates Check in Data:")
```

```
        if train_df.duplicated().any():
            print(f'\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}Duplicates exist in the␣
↪dataset.{Style.RESET_ALL}')
        else:
            print(f'\n{Style.BRIGHT + Fore.LIGHTBLUE_EX}No duplicates found in␣
↪the dataset.{Style.RESET_ALL}')

        print('\n' + "=" * 100 + '\n')


    except Exception as e:
        print_error
```

[11]:
```
D_O(df)
```

```
===========================
| The | Head | Of | Dataset | is: |
===========================

<IPython.core.display.HTML object>




===========================
| The | Tail | Of | Dataset | is: |
===========================

<IPython.core.display.HTML object>




===============
| Shape | Data: |
===============
The Shape of the Data is (1250, 10) |
- 1.The No of Rows is 1250 |
- 2.The No of Cols is 10|




=======================
| Info | Of | Train | Data: |
=======================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1250 entries, 0 to 1249
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype
```

```
---  ------                 --------------  -----
 0   ad_id                  1250 non-null   int64
 1   campaign_id            1250 non-null   object
 2   age                    1250 non-null   object
 3   gender                 1250 non-null   object
 4   interest               1250 non-null   object
 5   Impressions            1250 non-null   int64
 6   Clicks                 1250 non-null   int64
 7   Spent                  1250 non-null   float64
 8   Total_Conversion       1250 non-null   int64
 9   Approved_Conversion    1250 non-null   int64
dtypes: float64(1), int64(5), object(4)
memory usage: 97.8+ KB

==============================
| Numerical | Summary | of | Data: |
==============================

The Numerical Summary of Data is:

<pandas.io.formats.style.Styler at 0x2bf3333aa90>


================================
| Categorical | Columns | of | Data: |
================================

The Categorical Columns of Data are : ['campaign_id', 'age',
'gender', 'interest']

==============================
| Numerical | Columns | of | Data: |
==============================

The Numerical Columns of Data are : ['Spent']


========================
| Null | Values | in | Data: |
========================

The Null Values of Data are:
ad_id                  0
campaign_id            0
age                    0
gender                 0
interest               0
Impressions            0
Clicks                 0
```

```
Spent                  0
Total_Conversion       0
Approved_Conversion    0
dtype: int64

=============================
| Duplicates | Check | in | Data: |
=============================

Duplicates exist in the dataset.

================================================================================
====================
```

[12]:

```
#drop_duplicates
df.drop_duplicates(keep='first',inplace=True)
```

[13]:

```
cat_columns = df.select_dtypes(include=['object'])

#calculate the frequency of category columns
frequency_counts = {}

for column in cat_columns:
    frequency_counts[column] = df[column].value_counts()


# print the frequency counts for each categorical column
for column, counts in frequency_counts.items():
    print_boxed_blue_heading(f"Frequency counts for {column}:")
    print(counts)
    print()
```

```
=====================================
| Frequency | counts | for | campaign_id: |
=====================================
campaign_id
AKIN9326    626
AKIN8012    554
Name: count, dtype: int64


=============================
| Frequency | counts | for | age: |
=============================
```

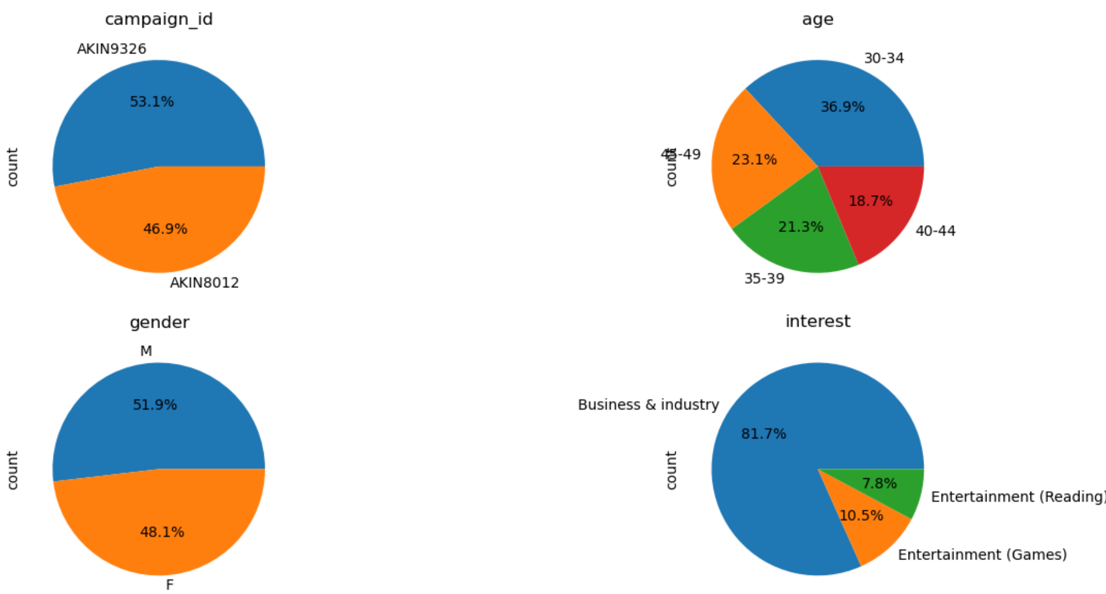
```
age
30-34    436
45-49    272
35-39    251
40-44    221
Name: count, dtype: int64


================================
| Frequency | counts | for | gender: |
================================
gender
M    612
F    568
Name: count, dtype: int64


==================================
| Frequency | counts | for | interest: |
==================================
interest
Business & industry         964
Entertainment (Games)       124
Entertainment (Reading)      92
Name: count, dtype: int64
```

[14]:
```python
cat_columns
```

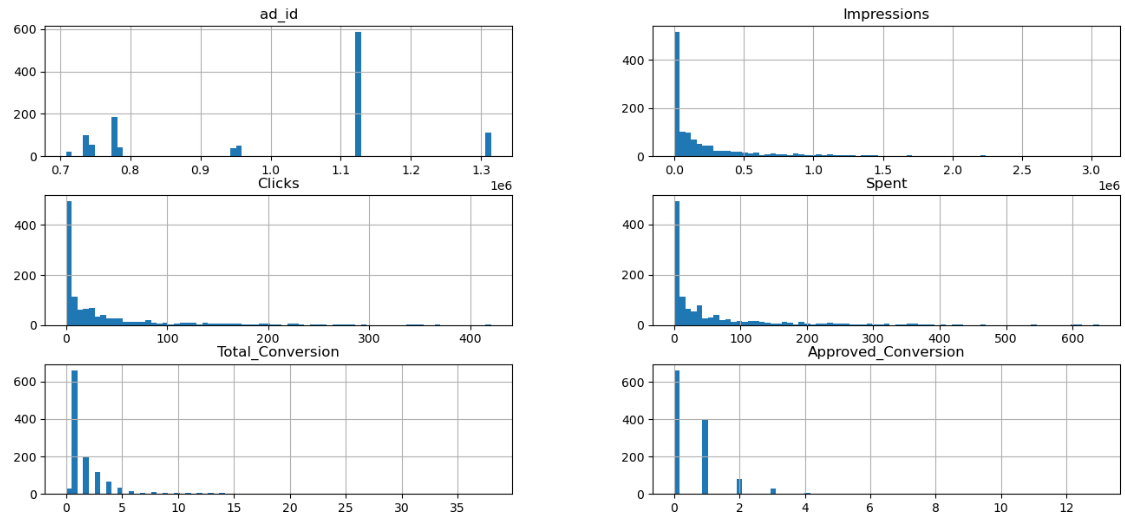
[14]:
```
     campaign_id    age gender                 interest
0       AKIN9326  30-34      M      Business & industry
1       AKIN9326  30-34      M      Business & industry
2       AKIN9326  30-34      M      Business & industry
3       AKIN9326  30-34      M      Business & industry
4       AKIN9326  30-34      M      Business & industry
…            …      …      …                        …
1245    AKIN8012  30-34      M  Entertainment (Reading)
1246    AKIN8012  30-34      M      Business & industry
1247    AKIN8012  40-44      F  Entertainment (Reading)
1248    AKIN8012  30-34      F      Business & industry
1249    AKIN8012  35-39      M      Business & industry

[1180 rows x 4 columns]
```

[15]:
```python
cat_columns = ['campaign_id','age','gender','interest']

#calculate  the number of rows and columns based on the number of categotical␣
↪columns and suplots
```

```
num_cols = 2
num_rows = (len(cat_columns) + num_cols - 1) // num_cols

#create a figure and a set of subplots
fig,axes = plt.subplots(num_rows, num_cols, figsize=(15, 3 * num_rows))

#iterate through each categorical column and plot a pie chart
for i, col in enumerate(cat_columns):
    ax = axes[i // num_cols, i %  num_cols] #select the subplot based on the␣
↪index
    df[col].value_counts().plot.pie(ax=ax,autopct='%1.1f%%')
    ax.set_title(col)

for j in range(len(cat_columns),num_rows *num_cols):
    axes.flatten()[j].axis('off')

#adjust the spacing
plt.tight_layout()
```



[16]:
```
#data distributions for numeric columns
df.hist(bins=75,figsize=(16,7))

plt.show()
```



[17]:

```
#chi-squre test - testing the significant difference in unique instances of the␣
↪two campaigns
from scipy.stats import chi2_contingency

#create a contingency
contingency_table = pd.crosstab(index = df['campaign_id'],columns='count')

#perform the chi-square test
chi1,p_value,_,_ = chi2_contingency(contingency_table)

#print the results
print_boxed_blue_heading(f"Chi-Square Statistic {chi1}")
print_boxed_blue_heading(f"P-Value: {p_value}")

#determine significance level
alpha = 0.05
if p_value <= alpha:
    print_boxed_blue_heading(f"There is significant difference between the␣
↪categories in the Campaign ID")
else:
    print_boxed_blue_heading(f"There is no significance differencebetwwen the␣
↪categories in the Campaign ID")
```

```
============================
| Chi-Square | Statistic | 0.0 |
============================

================
```

```
| P-Value: | 1.0 |
================
```

```
================================================================================
| There | is | no | significance |
differencebetwwen | the | categories | in |
the | Campaign | ID |
================================================================================
```

#

Feature Engineering

0.1 Adding other columns based on the columns we have

Adding cick through rate CTR = (clicks/impressions)

[18]:
```
#calculate CTR, handling the division by zero
df['CTR'] = np.where((df['Clicks'] == 0) | (df['Impressions'] == 0), np.
 ↪nan,(df['Clicks']/df['Impressions']) * 100)

df.head(10)
```

[18]:
```
      ad_id campaign_id    age gender            interest  Impressions  \
0   1121121    AKIN9326  30-34      M  Business & industry       323899
1   1121091    AKIN9326  30-34      M  Business & industry      1194718
2   1121092    AKIN9326  30-34      M  Business & industry       637648
3   1121094    AKIN9326  30-34      M  Business & industry        24362
4   1121095    AKIN9326  30-34      M  Business & industry       459690
5   1121096    AKIN9326  30-34      M  Business & industry       750060
6   1121097    AKIN9326  30-34      M  Business & industry        30068
7   1121098    AKIN9326  30-34      M  Business & industry      1267550
8   1121100    AKIN9326  30-34      M  Business & industry      3052003
9   1121101    AKIN9326  30-34      M  Business & industry        29945

   Clicks       Spent  Total_Conversion  Approved_Conversion       CTR
0      46   78.920000                 5                    1  0.014202
1     141  254.049996                 3                    1  0.011802
2      67  122.400000                 3                    0  0.010507
3       0    0.000000                 1                    1       NaN
4      50   86.330001                 3                    2  0.010877
5      86  161.909999                 2                    1  0.011466
6       1    1.820000                 1                    0  0.003326
7     123  236.769999                 4                    1  0.009704
8     340  639.949998                 5                    1  0.011140
9       1    1.590000                 2                    1  0.003339
```

0.1.1 Conversion Rate

[19]:
```
df['Conversion Rate'] = np.where((df['Approved_Conversion'] == 0) |
↪(df['Total_Conversion'] == 0), np.nan,(df['Approved_Conversion']/
↪df['Total_Conversion']) * 100)

df.head(10)
```

[19]:
```
     ad_id campaign_id    age gender             interest  Impressions  \
0  1121121    AKIN9326  30-34      M  Business & industry       323899
1  1121091    AKIN9326  30-34      M  Business & industry      1194718
2  1121092    AKIN9326  30-34      M  Business & industry       637648
3  1121094    AKIN9326  30-34      M  Business & industry        24362
4  1121095    AKIN9326  30-34      M  Business & industry       459690
5  1121096    AKIN9326  30-34      M  Business & industry       750060
6  1121097    AKIN9326  30-34      M  Business & industry        30068
7  1121098    AKIN9326  30-34      M  Business & industry      1267550
8  1121100    AKIN9326  30-34      M  Business & industry      3052003
9  1121101    AKIN9326  30-34      M  Business & industry        29945

   Clicks       Spent  Total_Conversion  Approved_Conversion       CTR  \
0      46   78.920000                 5                    1  0.014202
1     141  254.049996                 3                    1  0.011802
2      67  122.400000                 3                    0  0.010507
3       0    0.000000                 1                    1       NaN
4      50   86.330001                 3                    2  0.010877
5      86  161.909999                 2                    1  0.011466
6       1    1.820000                 1                    0  0.003326
7     123  236.769999                 4                    1  0.009704
8     340  639.949998                 5                    1  0.011140
9       1    1.590000                 2                    1  0.003339

   Conversion Rate
0        20.000000
1        33.333333
2              NaN
3       100.000000
4        66.666667
5        50.000000
6              NaN
7        25.000000
8        20.000000
9        50.000000
```

0.1.2 Cost per Conversion

[20]:
```
df['Cost Per Conversion']  = np.where((df['Spent'] == 0) |␣
↪(df['Approved_Conversion'] == 0), np.nan,(df['Spent']/
↪df['Approved_Conversion']) * 100)

df.head()
```

[20]:
```
     ad_id campaign_id    age gender             interest  Impressions  \
0  1121121    AKIN9326  30-34      M  Business & industry       323899
1  1121091    AKIN9326  30-34      M  Business & industry      1194718
2  1121092    AKIN9326  30-34      M  Business & industry       637648
3  1121094    AKIN9326  30-34      M  Business & industry        24362
4  1121095    AKIN9326  30-34      M  Business & industry       459690

   Clicks       Spent  Total_Conversion  Approved_Conversion       CTR  \
0      46   78.920000                 5                    1  0.014202
1     141  254.049996                 3                    1  0.011802
2      67  122.400000                 3                    0  0.010507
3       0    0.000000                 1                    1       NaN
4      50   86.330001                 3                    2  0.010877

   Conversion Rate  Cost Per Conversion
0        20.000000          7892.000020
1        33.333333         25404.999600
2              NaN                  NaN
3       100.000000                  NaN
4        66.666667          4316.500056
```

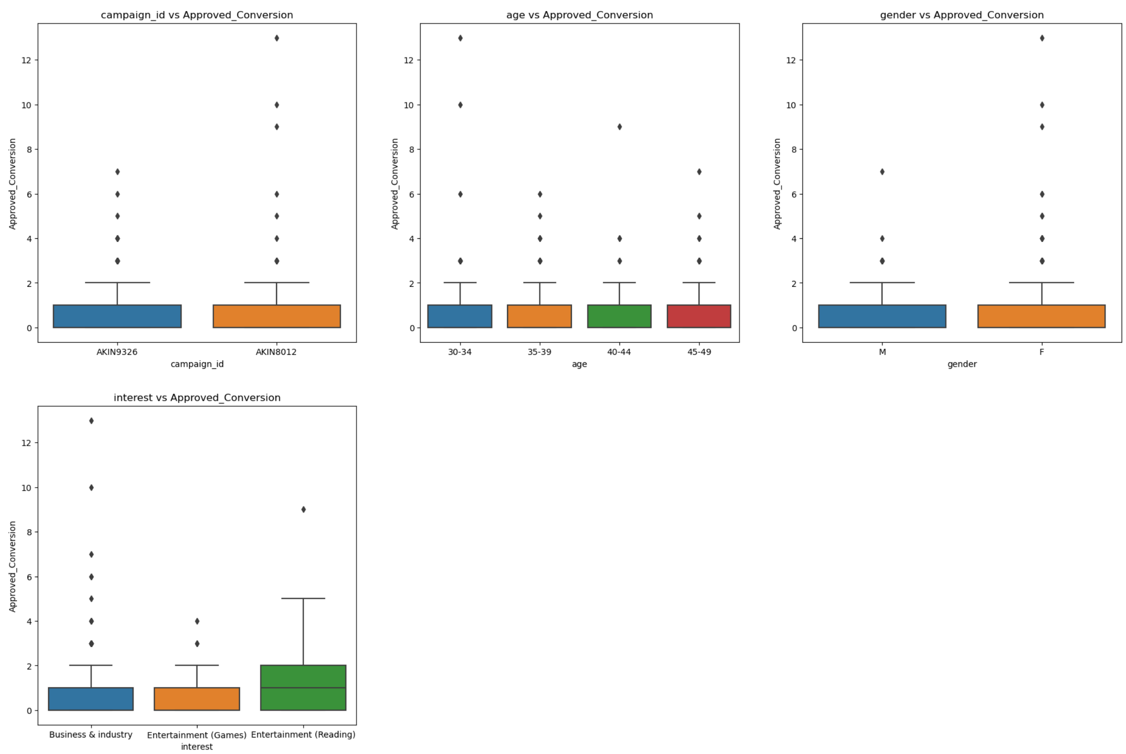
[ ]:
```

```

#

EDA

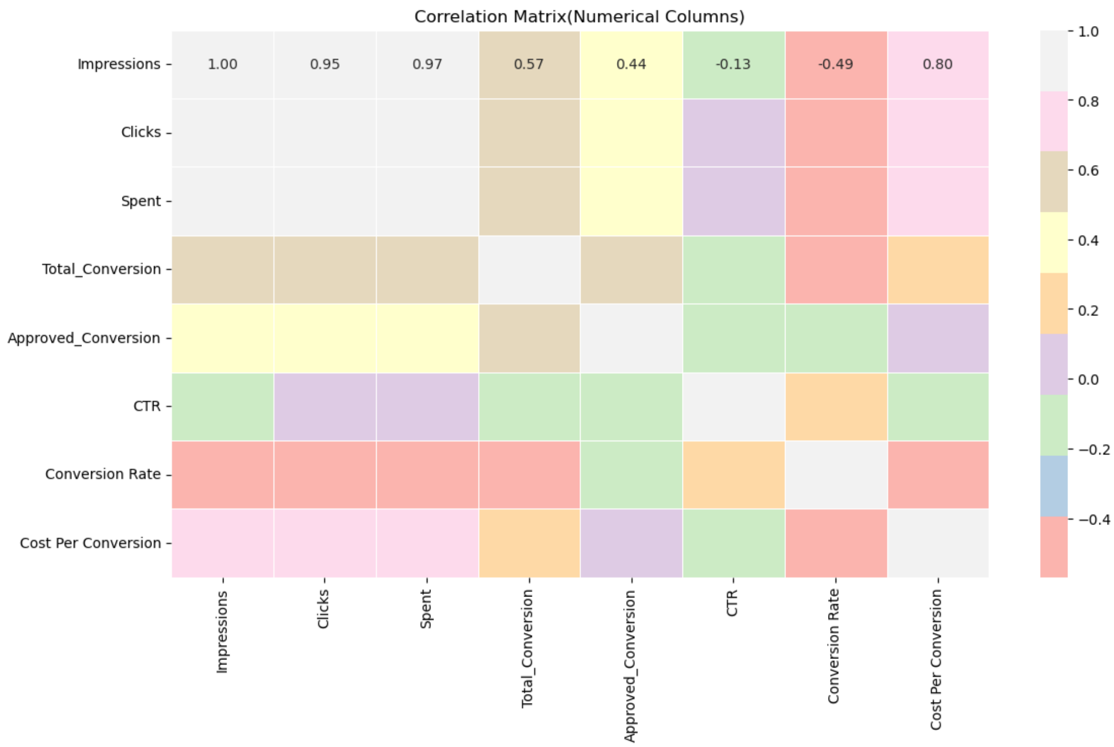
[21]:
```
#BOX PLOT
#set the figure size for the plots
plt.figure(figsize=(23,15))

#select categorical columns excluding 'Product ID' from the dataframe.
categorical_columns = [col for col in df.select_dtypes('object').columns if col␣
↪!= 'ad_id']

#loop through each categorical column plotting
for i ,col in enumerate(categorical_columns):
    #create subplots with 2 rows,3 columns
    plt.subplot(2,3,i+1)
```

```
    #create a boxplot with x-axis as the current categorical columns and y-axis as Approved Conversions
    sns.boxplot(x=df[col],y=df['Approved_Conversion'])

    #set the title of the subplot to show the current categorical column and Approved Conversion
    plt.title(f'{col} vs Approved_Conversion')
```



1 Correlation Matrix

[22]:
```
#select categorical columns excluding 'Product ID' from the dataframe.
numerical_columns = [col for col in df.select_dtypes('number').columns if col != 'ad_id']

correlation_matrix = df[numerical_columns].corr()

#plot the correlation matrix as a heatmap
plt.figure(figsize=(13,7))
sns.heatmap(correlation_matrix,annot=True,cmap='Pastel1',fmt=".2f",linewidth=.5)
plt.title("Correlation Matrix(Numerical Columns)")
plt.show()
```



2 Perfomance

Campaign ID

The higher your conversion rate, the more effective your ad campaign

A higher cost per conversion clearly indicates that obtaining your real customer is getting expensive

A higher CTR is a good indication that users find your ads and listings helpful and relevant.

The higher the ad clicks, the more successful the ad.

Prefer less expenditure.

Total Conversions and Total Approved Conversions high values preferred.

[23]:
```
campaign_type = df.groupby(['campaign_id']).agg(
    {'Impressions': 'sum','Clicks':'sum','Spent':'sum','Total_Conversion':
 ↪'sum','Approved_Conversion':'sum',
    'CTR':'mean','Conversion Rate':'mean','Cost Per Conversion':'mean'}).
 ↪reset_index()

campaign_type.columns = ['Campaign ID','Total AD Impressions','Total Ad␣
 ↪Clicks','Total Ad Expenditure',
```

```
                          'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate']

campaign_type
```

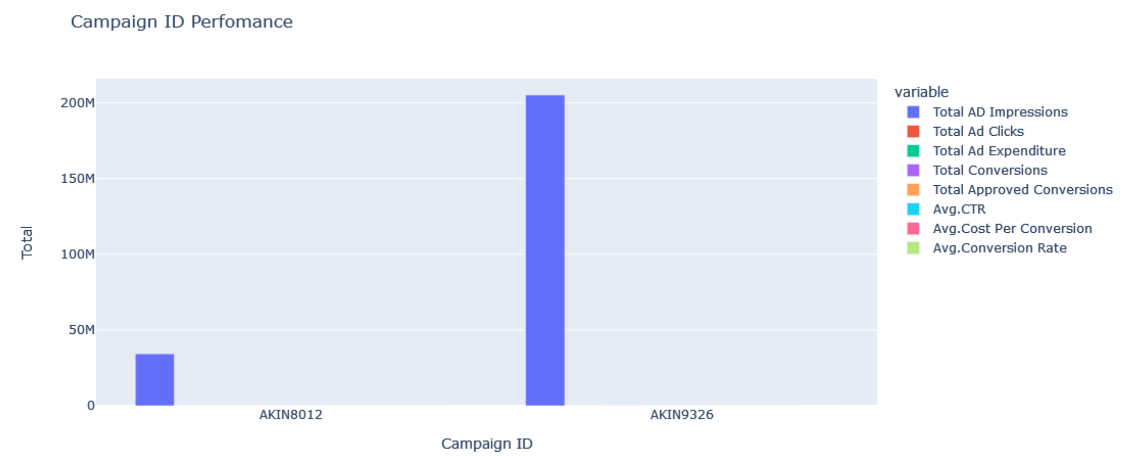
[23]:
```
  Campaign ID  Total AD Impressions  Total Ad Clicks  Total Ad Expenditure  \
0    AKIN8012              34295216             6617           9827.529982
1    AKIN9326             205147615            36114          55741.069959

   Total Conversions  Total Approved Conversions   Avg.CTR  \
0                891                         290  0.024578
1               1810                         437  0.016535

   Avg.Cost Per Conversion  Avg.Conversion Rate
0                84.391655          2203.466059
1                58.355654          8251.197851
```

Insights

Campaign ID AKIN9326 ranks top in Total Ad Clicks, Total Ad Expenditure, Total Conversions, and Total Approved Conversions.

Campaign ID AKIN8012 has the highest Click Through Rate and a lower cost per conversion,conversion rate, cost per conversion.

[24]:
```
#plotting a grouped bar graph
fig = px.bar(campaign_type,x='Campaign ID',y=['Total AD Impressions','Total Ad␣
↪Clicks','Total Ad Expenditure',
                          'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate'],
              labels={'value':'Total'}, title='Campaign ID␣
↪Perfomance',barmode='group')

#update layout to vary length and width
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```

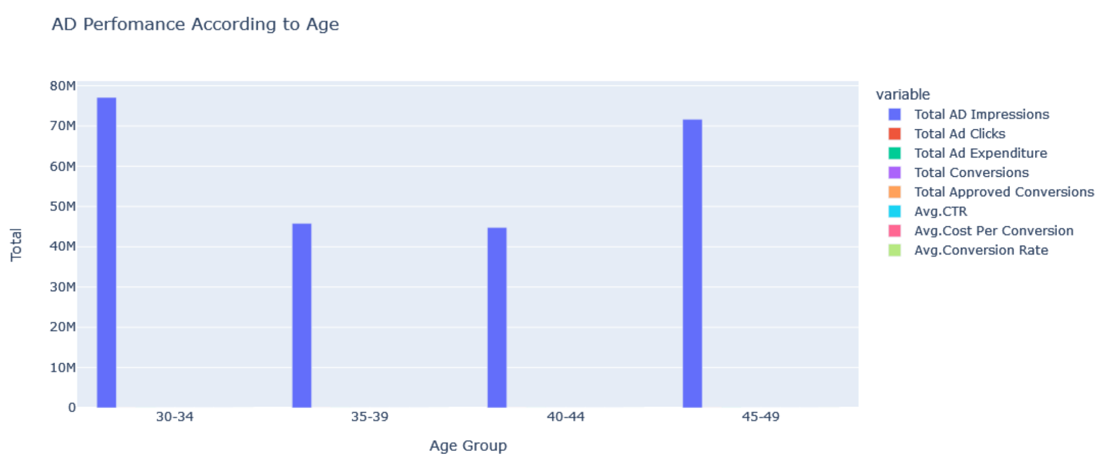


[25]:
```
Age = df.groupby(['age']).agg({'Impressions': 'sum','Clicks':'sum','Spent':
↪'sum','Total_Conversion':'sum','Approved_Conversion':'sum',
   'CTR':'mean','Conversion Rate':'mean','Cost Per Conversion':'mean'}).
↪reset_index()

#rename columns for clarity
Age.columns = ['Age Group','Total AD Impressions','Total Ad Clicks','Total Ad␣
↪Expenditure',
                        'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate']

Age
```

[25]:
```
  Age Group  Total AD Impressions  Total Ad Clicks  Total Ad Expenditure  \
0     30-34              77091917            10876          17355.079984
1     35-39              45843178             7635          11992.739993
2     40-44              44823435             8675          12989.919975
3     45-49              71684301            15545          23230.859989

   Total Conversions  Total Approved Conversions   Avg.CTR  \
0                938                         267  0.015509
1                523                         162  0.018504
2                543                         129  0.022154
3                697                         169  0.023566

   Avg.Cost Per Conversion  Avg.Conversion Rate
0                76.548502          4927.393599
1                70.408083          4784.319513
2                67.177986          6114.763582
```

```
3                  59.467182          9189.741118
```

[26]:
```
#plotting a grouped bar graph
fig = px.bar(Age,x='Age Group',y=['Total AD Impressions','Total Ad␣
↪Clicks','Total Ad Expenditure',
                        'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate'],
             labels={'value':'Total'}, title='AD Perfomance According to␣
↪Age',barmode='group')

#update layout to vary length and width
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```



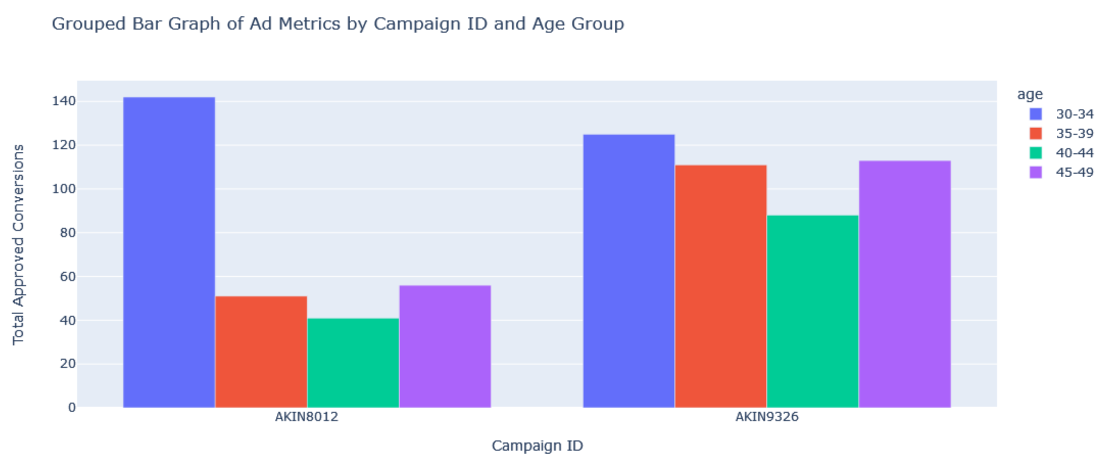
2.0.1 Total Approved Conversions with Age Group

[27]:
```
#grouping  the data by Camapign ID and Age Group then aggregating the desired ␣
↪metrics
campaign_age = df.groupby(['campaign_id','age']).agg({'Approved_Conversion':
↪'sum'}).reset_index()

#renaming the aggregated columns
campaign_age.columns = ['Campaign ID','age','Total Approved Conversions']

#display
campaign_age
```

[27]:

	Campaign ID	age	Total Approved Conversions
0	AKIN8012	30-34	142
1	AKIN8012	35-39	51
2	AKIN8012	40-44	41
3	AKIN8012	45-49	56
4	AKIN9326	30-34	125
5	AKIN9326	35-39	111
6	AKIN9326	40-44	88
7	AKIN9326	45-49	113

[28]:
```
#plotting a grouped bar graph
fig = px.bar(campaign_age,x='Campaign ID',y='Total Approved␣
↪Conversions',color='age',labels={'value':'Total'}, title='Grouped Bar Graph␣
↪of Ad Metrics by Campaign ID and Age Group',barmode='group')

#update layout to vary length and width
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```



Insights

AKIN8012 performs better for age group 30-34

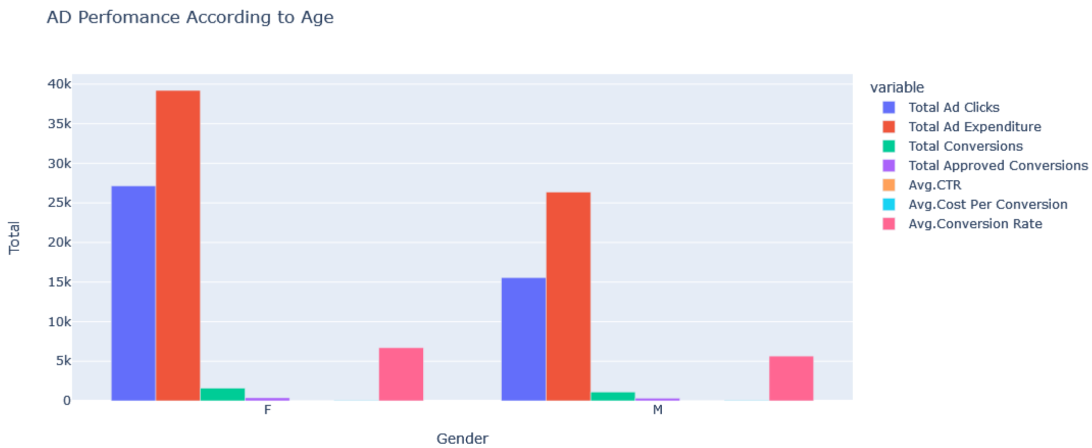
AKIN9326 performs better for age groups 35-39, 40-44, 45-49

2.0.2 Gender

[29]:
```
Gender = df.groupby(['gender']).agg({'Impressions': 'sum','Clicks':
↪'sum','Spent':'sum','Total_Conversion':'sum','Approved_Conversion':'sum',
   'CTR':'mean','Conversion Rate':'mean','Cost Per Conversion':'mean'}).
↪reset_index()

#rename columns for clarity
Gender.columns = ['Gender','Total AD Impressions','Total Ad Clicks','Total Ad␣
↪Expenditure',
                        'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate']

Gender
```

[29]:
```
  Gender  Total AD Impressions  Total Ad Clicks  Total Ad Expenditure  \
0      F             131664114            27154          39208.259947
1      M             107778717            15577          26360.339995

   Total Conversions  Total Approved Conversions   Avg.CTR  \
0               1584                         387  0.022629
1               1117                         340  0.016532

   Avg.Cost Per Conversion  Avg.Conversion Rate
0                64.642286          6712.272689
1                74.027968          5660.949842
```

[30]:
```
#plotting a grouped bar graph
fig = px.bar(Gender,x='Gender',y=['Total Ad Clicks','Total Ad Expenditure',
                        'Total Conversions','Total Approved Conversions','Avg.
↪CTR','Avg.Cost Per Conversion','Avg.Conversion Rate'],
             labels={'value':'Total'}, title='AD Perfomance According to␣
↪Age',barmode='group')

#update layout to vary length and width
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```



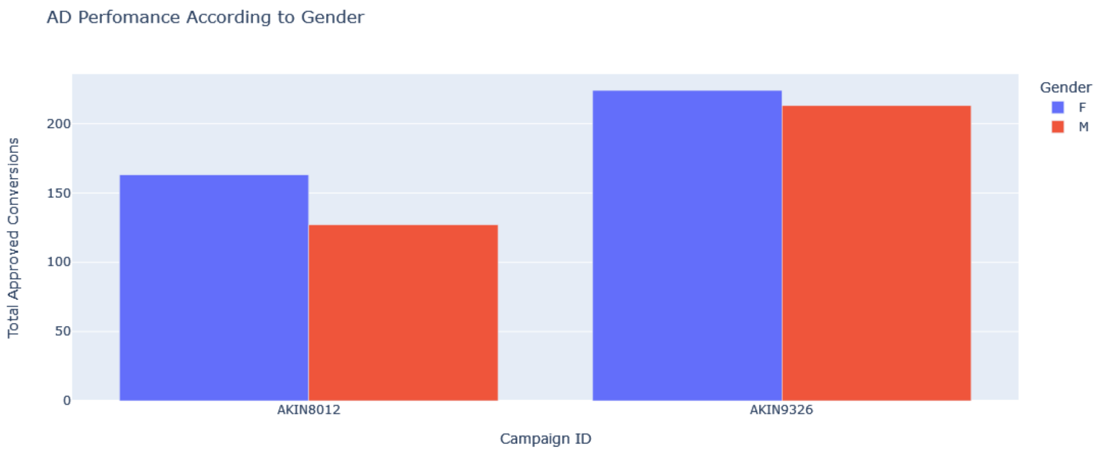
2.0.3 Total Approved Conversions with Gender

[31]:
```
#grouping  the data by Camapign ID and Age Group then aggregating the desired ␣
↪metrics
Gender = df.groupby(['gender','campaign_id']).agg({'Approved_Conversion':
↪'sum'}).reset_index()

#renaming the aggregated columns
Gender.columns = ['Gender','Campaign ID','Total Approved Conversions']

#display
Gender
```

[31]:

	Gender	Campaign ID	Total Approved Conversions
0	F	AKIN8012	163
1	F	AKIN9326	224
2	M	AKIN8012	127
3	M	AKIN9326	213

[32]:
```
#plotting a grouped bar graph
fig = px.bar(Gender,x='Campaign ID',y='Total Approved␣
↪Conversions',color='Gender',labels={'value':'Total'}, title='AD Perfomance␣
↪According to Gender',barmode='group')

#update layout to vary length and width
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```



Insights

AKIN8012 performs poor with 163 F and 127 M Conversions

AKIN9326 performs better with 224 F and 213 M Conversions

2.0.4 Total Approved Conversions on Audience Interest

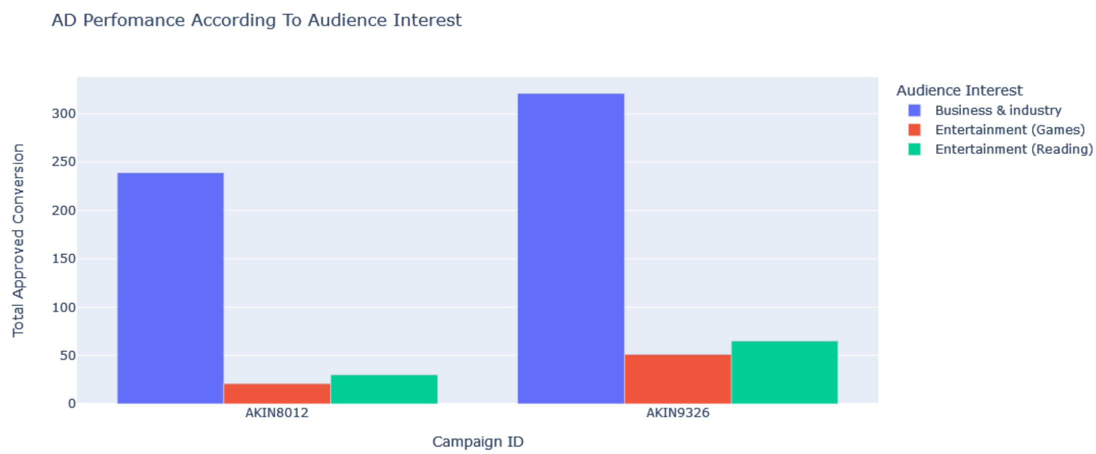
[33]:
```
campaign_audience = df.groupby(['campaign_id','interest']).
↪agg({'Approved_Conversion':'sum'}).reset_index()

#rename columns
campaign_audience.columns = ['Campaign ID','Audience Interest','Total Approved␣
↪Conversion']

campaign_audience
```

[33]:

	Campaign ID	Audience Interest	Total Approved Conversion
0	AKIN8012	Business & industry	239
1	AKIN8012	Entertainment (Games)	21
2	AKIN8012	Entertainment (Reading)	30
3	AKIN9326	Business & industry	321
4	AKIN9326	Entertainment (Games)	51
5	AKIN9326	Entertainment (Reading)	65

[34]:
```
#plotting a grouped bar graph
fig = px.bar(campaign_audience,x='Campaign ID',y='Total Approved␣
↪Conversion',color='Audience Interest',labels={'value':'Total'}, title='AD␣
↪Perfomance According To Audience Interest',barmode='group')

#update layout to vary length and width
```

```
fig.update_layout(width=1000,height=500,bargap=0.2)

fig.show()
```



Insights(Total Approved Conversions)

AKIN9326 performs better for all audience of interest

2.0.5 Cost Effective Campaign

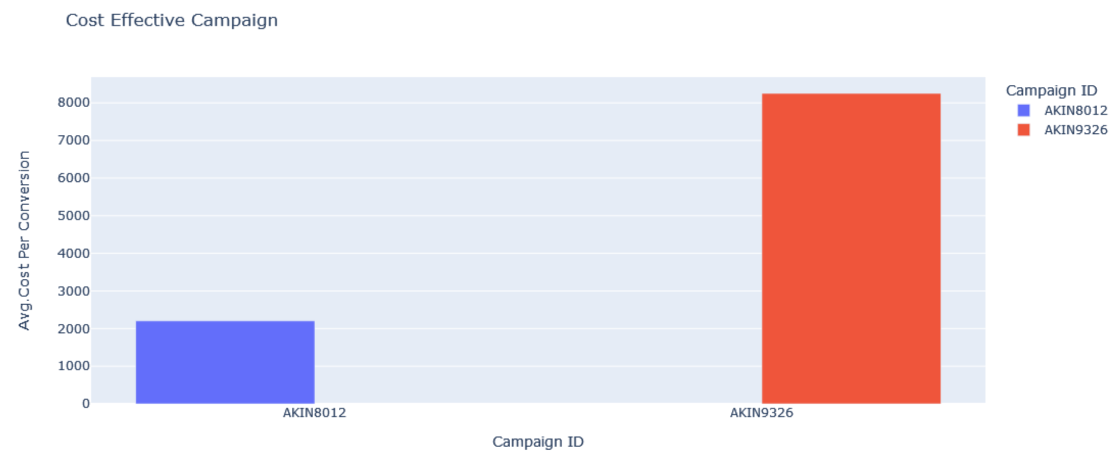
[35]:
```
campaign_type = df.groupby(['campaign_id']).agg({'Cost Per Conversion':'mean'}).
    ↪reset_index()

#rename
campaign_type.columns = ['Campaign ID','Avg.Cost Per Conversion']

campaign_type
```

[35]:

	Campaign ID	Avg.Cost Per Conversion
0	AKIN8012	2203.466059
1	AKIN9326	8251.197851

[36]:
```
#plotting a grouped bar graph
fig = px.bar(campaign_type,x='Campaign ID',y='Avg.Cost Per␣
    ↪Conversion',color='Campaign ID',labels={'value':'Total'}, title='Cost␣
    ↪Effective Campaign',barmode='group')

#update layout to vary length and width
fig.update_layout(width=800,height=500,bargap=0.2)
```

```
fig.show()
```



Insights(Total Approved Conversions)

AKIN9326 is the most Cost Effective Campaign

Conclusion

Was our objective met?

The best campaign was AKIN9326. It performed better in Age group, Audience Interest Category, and Gender It however had the highest cot per conversion.(It was more expensive than AKIN 8012)