Test Task for Data Science [Stirring Minds]

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Problem Statement

The file KAG_conversion_data.csv (found in the above link) contains 1143 observations in 11 variables. This satisfies the constraint in our assignment having over a thousand observations with at least ten attributes.

Business Questions

1. How to optimize the social ad campaigns for the highest conversion rate possible? (Attain best Reach to Conversion ratios/Click to Conversion ratios)
2. Finding the perfect target demographics with the appropriate click through rates
3. Understanding the ideal turnaround/decision making time per age group to convert and re-target future social campaigns
4. Comparing the individual campaign performance so the best creative/campaign can be run again with adjusted audiences.

Context

Cluster Analysis for Ad Conversions Data

Data

The data used in this project is from an anonymous organisation's social media ad campaign. The data file can be downloaded from here. The file conversion_data.csv contains 1143 observations in 11 variables. Below are the descriptions of the variables.

1. ad_id: an unique ID for each ad.
2. xyz_campaign_id: an ID associated with each ad campaign of XYZ company.
3. fb_campaign_id: an ID associated with how Facebook tracks each campaign.
4. age: age of the person to whom the ad is shown.
5. gender: gender of the person to whim the add is shown
6. interest: a code specifying the category to which the person's interest belongs (interests are as mentioned in the person's Facebook public profile).

7. Impressions: the number of times the ad was shown.
8. Clicks: number of clicks on for that ad.
9. Spent: Amount paid by company xyz to Facebook, to show that ad.
10. Total conversion: Total number of people who enquired about the product after seeing the ad.
11. Approved conversion: Total number of people who bought the product after seeing the ad.

Aim : To optimize Sales conversion and predict future sales

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing Dataset

In [2]:
```
df = pd.read_csv('KAG_conversion_data.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	ad_id	xyz_campaign_id	fb_campaign_id	age	gender	interest	Impressions	Clicks	Spent	T
0	708746	916	103916	30-34	M	15	7350	1	1.43	
1	708749	916	103917	30-34	M	16	17861	2	1.82	
2	708771	916	103920	30-34	M	20	693	0	0.00	
3	708815	916	103928	30-34	M	28	4259	1	1.25	
4	708818	916	103928	30-34	M	28	4133	1	1.29	

Checking Null Values

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1143 entries, 0 to 1142
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ad_id                1143 non-null   int64  
 1   xyz_campaign_id      1143 non-null   int64  
 2   fb_campaign_id       1143 non-null   int64  
 3   age                  1143 non-null   object 
 4   gender               1143 non-null   object 
 5   interest             1143 non-null   int64  
 6   Impressions          1143 non-null   int64  
 7   Clicks               1143 non-null   int64  
 8   Spent                1143 non-null   float64
 9   Total_Conversion     1143 non-null   int64  
 10  Approved_Conversion  1143 non-null   int64  
dtypes: float64(1), int64(8), object(2)
memory usage: 98.4+ KB
```

EDA

In [5]:
```
df.shape
```

Out[5]:
```
(1143, 11)
```

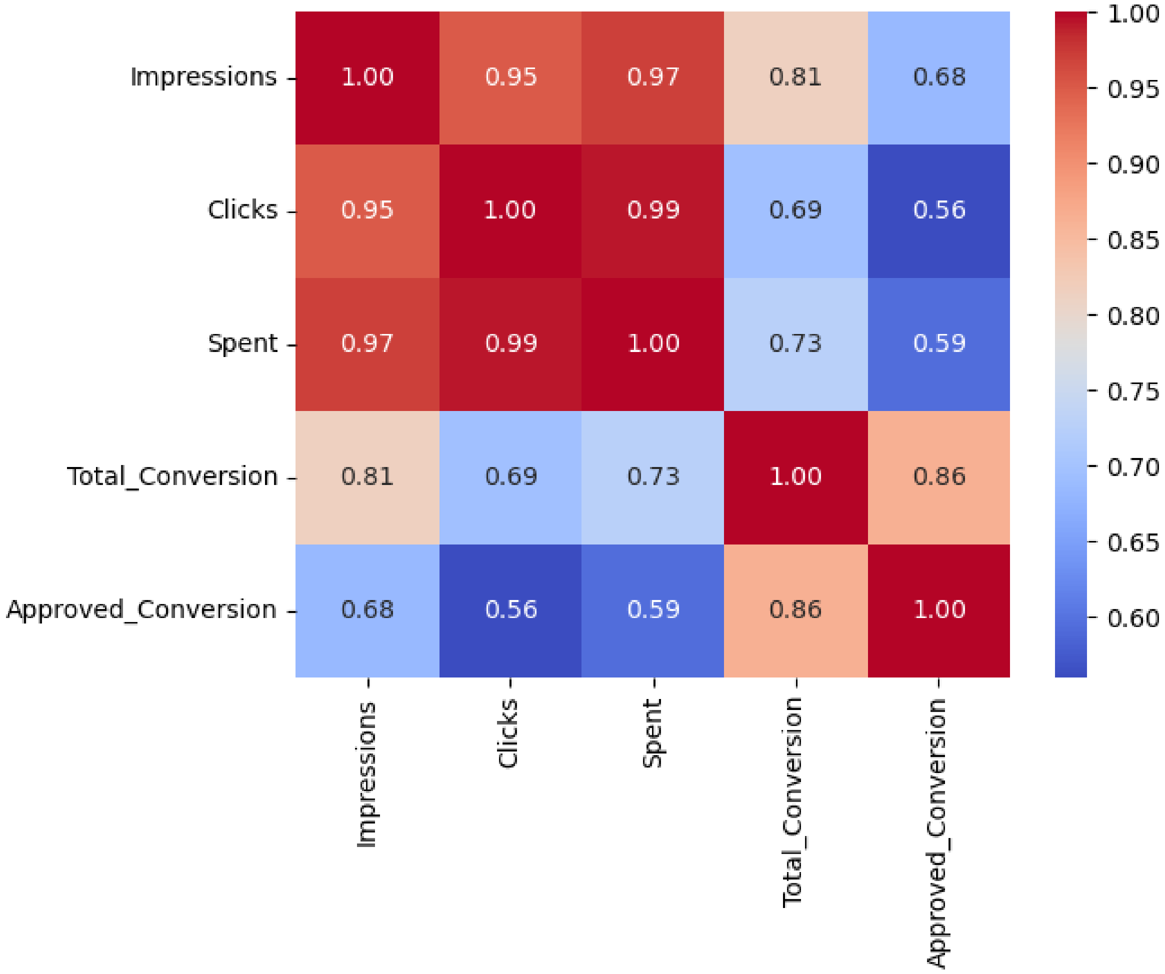
In [6]:
```
df.describe()
```

Out[6]:

	ad_id	xyz_campaign_id	fb_campaign_id	interest	Impressions	Clicks	
count	1.143000e+03	1143.000000	1143.000000	1143.000000	1.143000e+03	1143.000000	1
mean	9.872611e+05	1067.382327	133783.989501	32.766404	1.867321e+05	33.390201	
std	1.939928e+05	121.629393	20500.308622	26.952131	3.127622e+05	56.892438	
min	7.087460e+05	916.000000	103916.000000	2.000000	8.700000e+01	0.000000	
25%	7.776325e+05	936.000000	115716.000000	16.000000	6.503500e+03	1.000000	
50%	1.121185e+06	1178.000000	144549.000000	25.000000	5.150900e+04	8.000000	
75%	1.121804e+06	1178.000000	144657.500000	31.000000	2.217690e+05	37.500000	
max	1.314415e+06	1178.000000	179982.000000	114.000000	3.052003e+06	421.000000	

Correlation Matrix

In [7]:
```
g = sns.heatmap(df[["Impressions", "Clicks", "Spent", "Total_Conversion", "Approve
```



Observation

"Approved_Conversion" is
more related to ["Impressions", "Total_Conversion"]
than ["Clicks", "Spent"]

Campaigns based distribution

In [8]:
```
df["xyz_campaign_id"].unique()
```

Out[8]:
```
array([ 916,  936, 1178], dtype=int64)
```

Replacing Campaign ID

In [9]:
```
df["xyz_campaign_id"].replace({916 : "campaign_a", 936 : "campaign_b", 1178 : "cam
```

In [10]:
```
df.head()
```

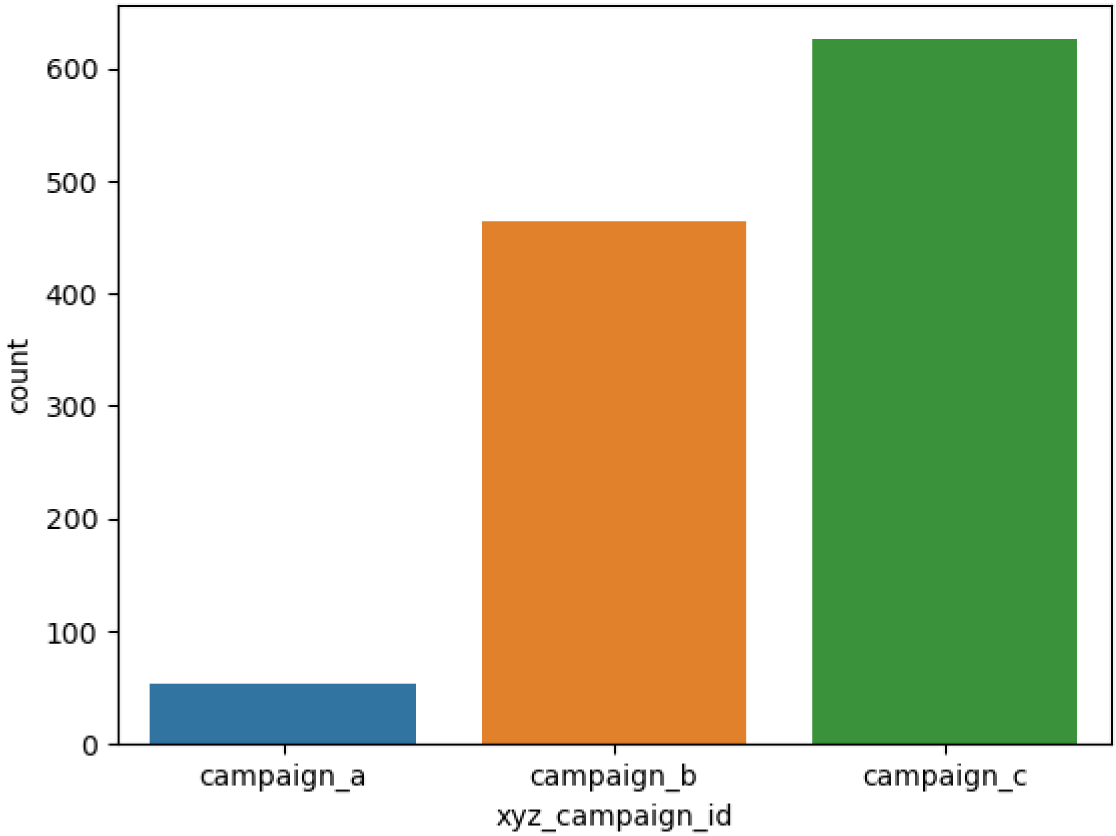
Out[10]:

	ad_id	xyz_campaign_id	fb_campaign_id	age	gender	interest	Impressions	Clicks	Spent	T
0	708746	campaign_a	103916	30-34	M	15	7350	1	1.43	
1	708749	campaign_a	103917	30-34	M	16	17861	2	1.82	
2	708771	campaign_a	103920	30-34	M	20	693	0	0.00	
3	708815	campaign_a	103928	30-34	M	28	4259	1	1.25	
4	708818	campaign_a	103928	30-34	M	28	4133	1	1.29	

In [11]:

```
sns.countplot(x = 'xyz_campaign_id', data = df)
```

Out[11]: <Axes: xlabel='xyz_campaign_id', ylabel='count'>

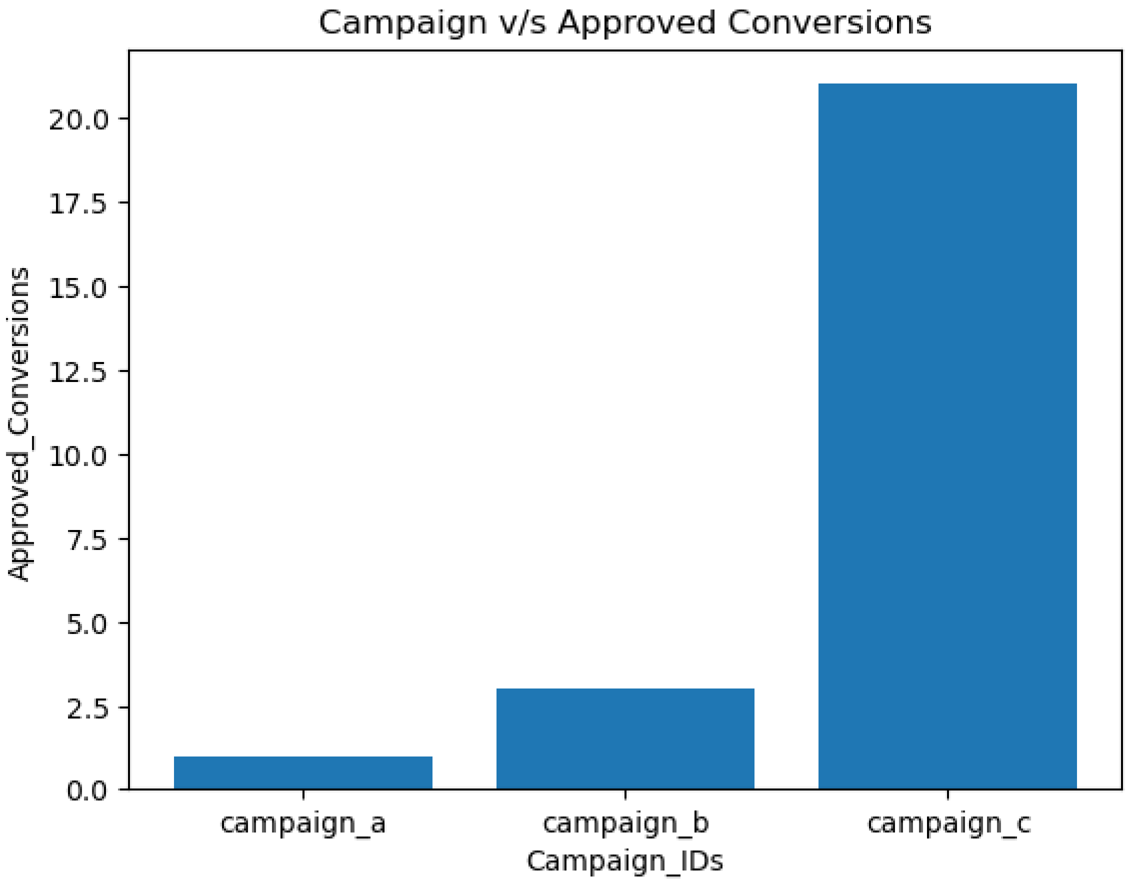


This shows Campaign_C has most number of ads

In [12]:

```
plt.bar(df["xyz_campaign_id"], df["Approved_Conversion"])
plt.xlabel("Campaign_IDs")
plt.ylabel("Approved_Conversions")
plt.title("Campaign v/s Approved Conversions")
```

Out[12]: Text(0.5, 1.0, 'Campaign v/s Approved Conversions')

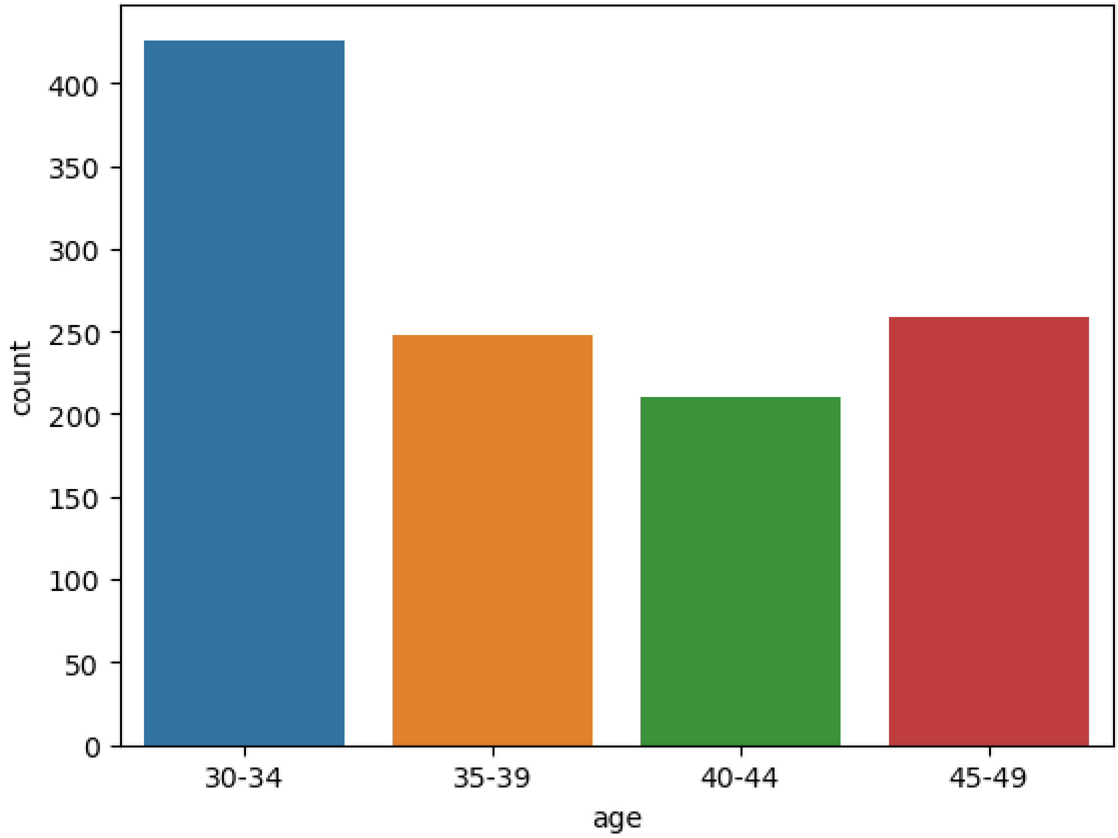


It also clears that Campaign_C has more number of Approved Conversions than other Campaigns

Age based distribution

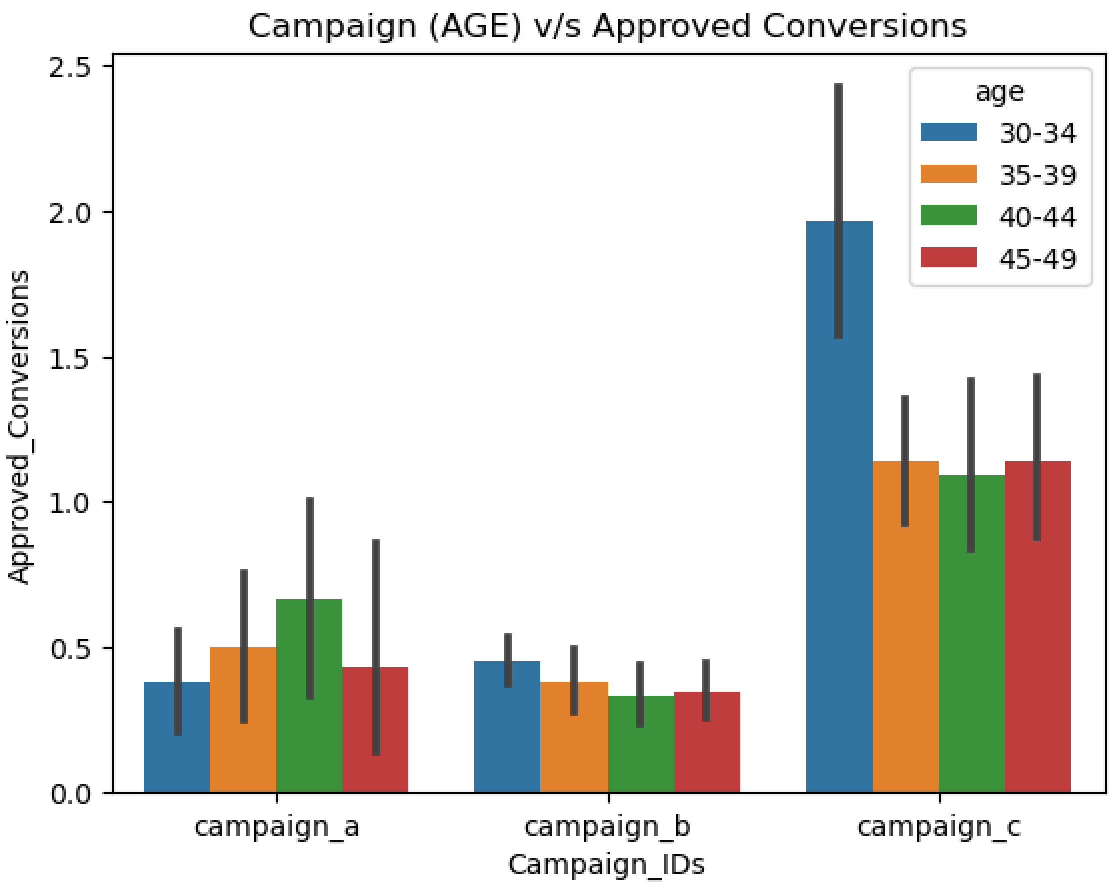
In [13]:
```
sns.countplot(x = 'age', data = df)
```

Out[13]:
```
<Axes: xlabel='age', ylabel='count'>
```



In [14]:
```
sns.barplot(x = df["xyz_campaign_id"], y = df["Approved_Conversion"], hue = df["ag
plt.xlabel("Campaign_IDs")
plt.ylabel("Approved_Conversions")
plt.title("Campaign (AGE) v/s Approved Conversions")
```

Out[14]: `Text(0.5, 1.0, 'Campaign (AGE) v/s Approved Conversions')`



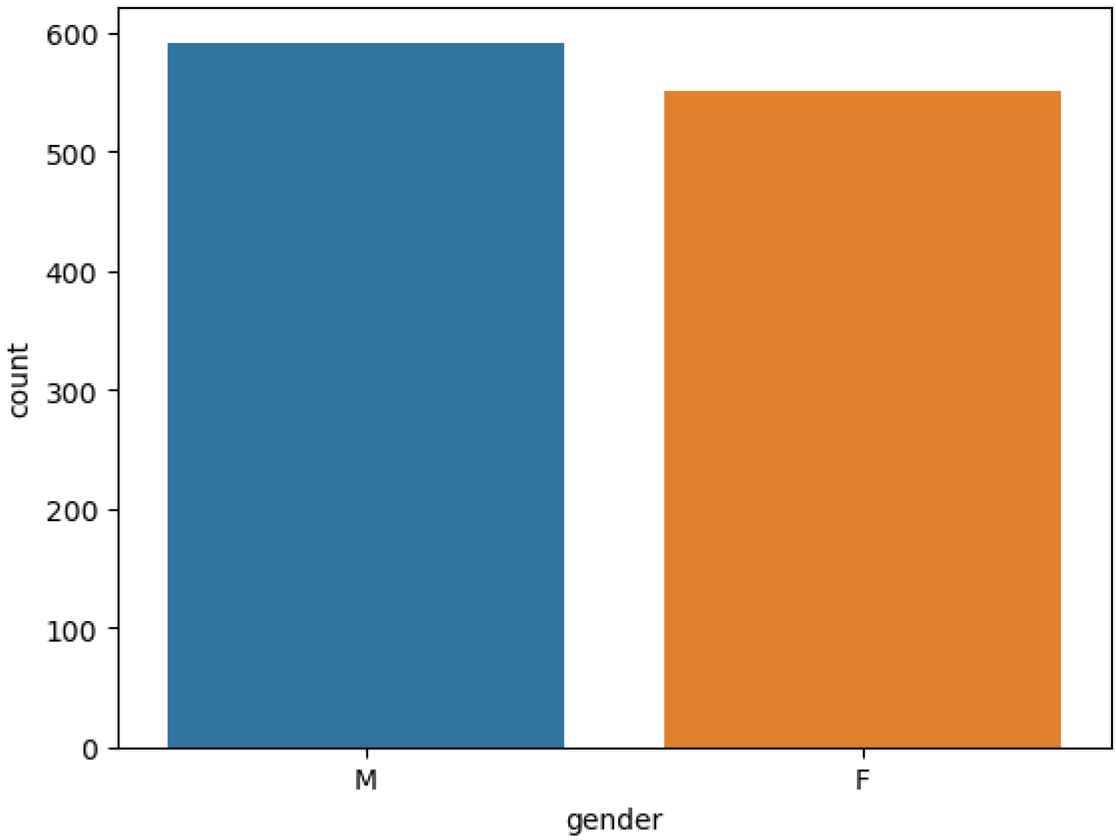
Campaign_b and Campaign_c : 30-34 shows most interest

Campaign_a : 40-44 shows most interest

Gender based distribution

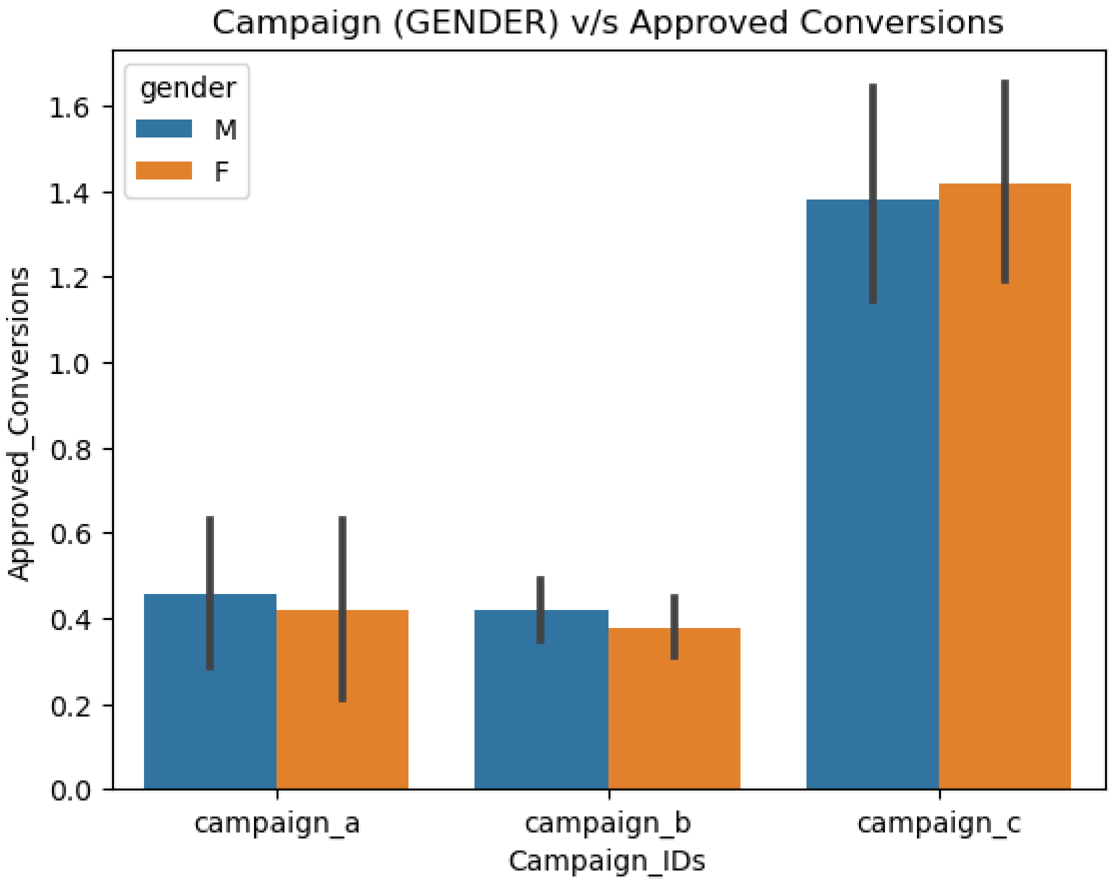
In [15]:
```
sns.countplot(x = 'gender', data = df)
```

Out[15]:
```
<Axes: xlabel='gender', ylabel='count'>
```



In [16]:
```
sns.barplot(x = df["xyz_campaign_id"], y = df["Approved_Conversion"], hue = df["ge
plt.xlabel("Campaign_IDs")
plt.ylabel("Approved_Conversions")
plt.title("Campaign (GENDER) v/s Approved Conversions")
```

Out[16]:
```
Text(0.5, 1.0, 'Campaign (GENDER) v/s Approved Conversions')
```

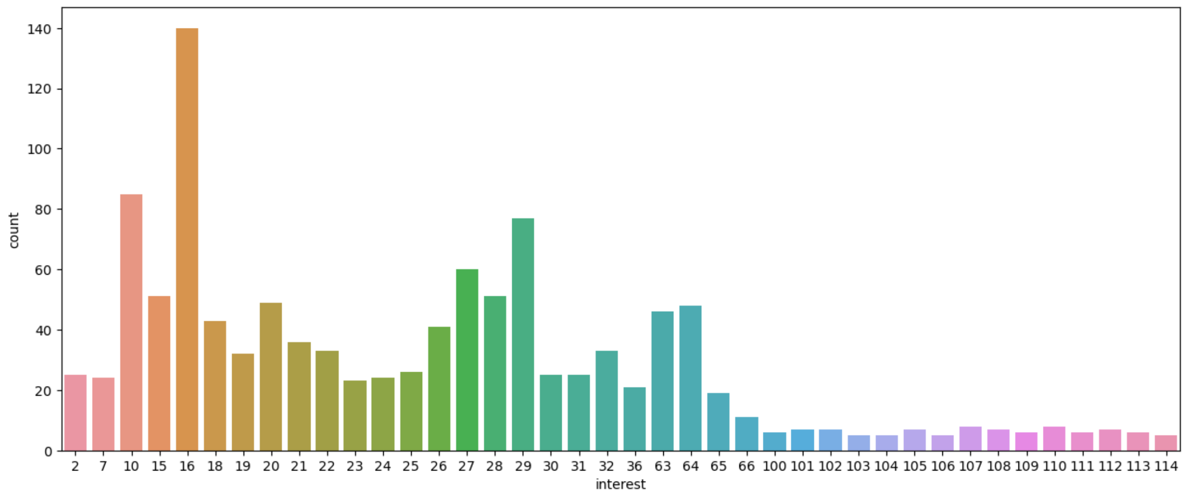


Both Gender Shows Similar Interests

Interest based distribution

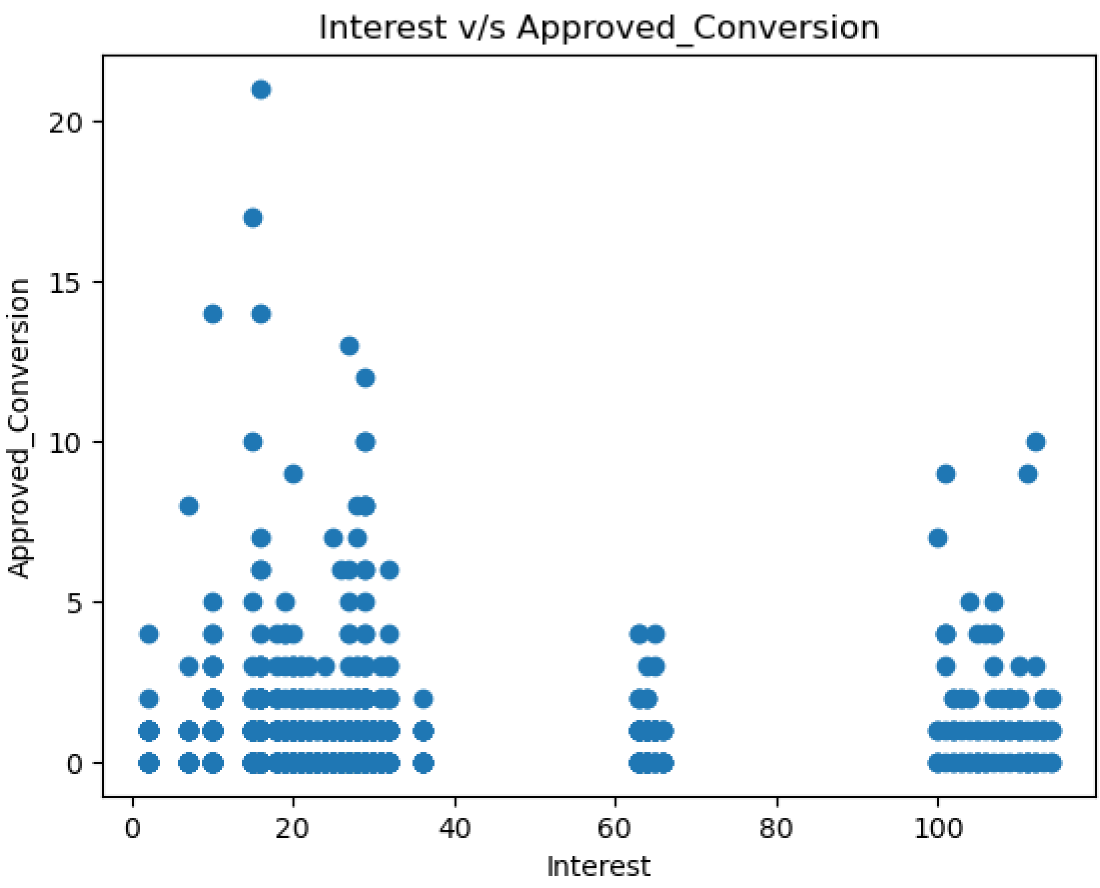
In [17]:
```
fig_dims = (15,6)
fig, ax = plt.subplots(figsize = fig_dims)
sns.countplot(x = 'interest', data = df)
```

Out[17]: `<Axes: xlabel='interest', ylabel='count'>`



In [18]:
```
plt.scatter(df['interest'], df['Approved_Conversion'])
plt.title("Interest v/s Approved_Conversion")
plt.xlabel('Interest')
plt.ylabel('Approved_Conversion')
```

Out[18]: `Text(0, 0.5, 'Approved_Conversion')`

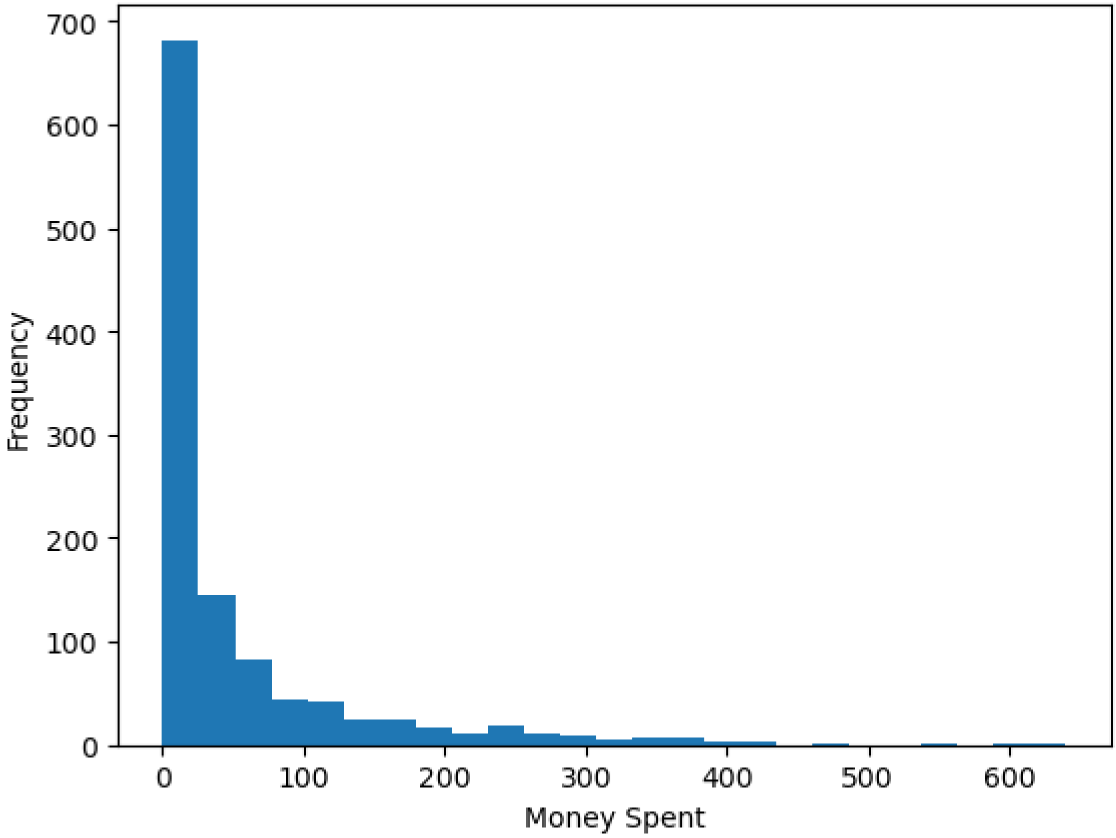


Although the count of interest after 100 is less,there is a rise of users after 100 who actually bought the product. Rest of the distribution is according to what was expected.

Spent based distribution

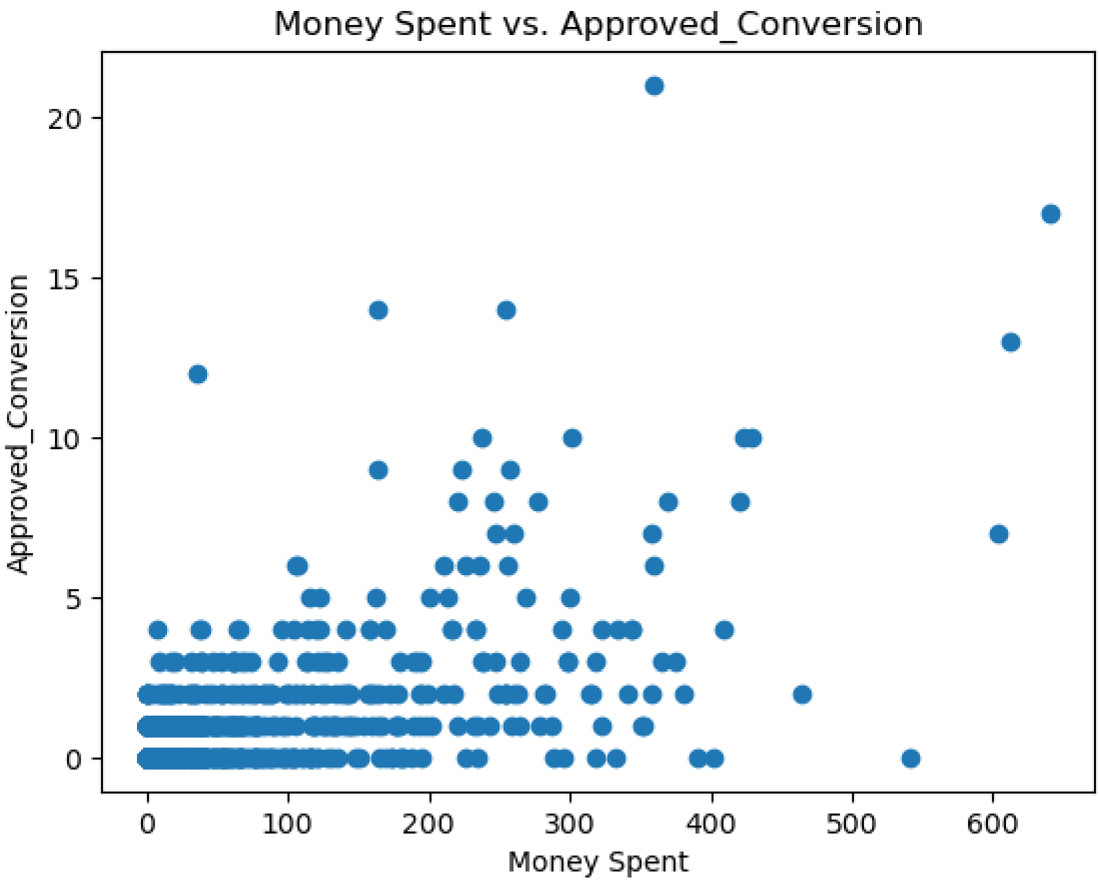
In [19]:
```
plt.hist(df["Spent"], bins = 25)
plt.xlabel("Money Spent")
plt.ylabel("Frequency")
```

Out[19]:
```
Text(0, 0.5, 'Frequency')
```



In [20]:
```
plt.scatter(df["Spent"], df["Approved_Conversion"])
plt.title("Money Spent vs. Approved_Conversion")
plt.xlabel("Money Spent")
plt.ylabel("Approved_Conversion")
```

Out[20]:
```
Text(0, 0.5, 'Approved_Conversion')
```

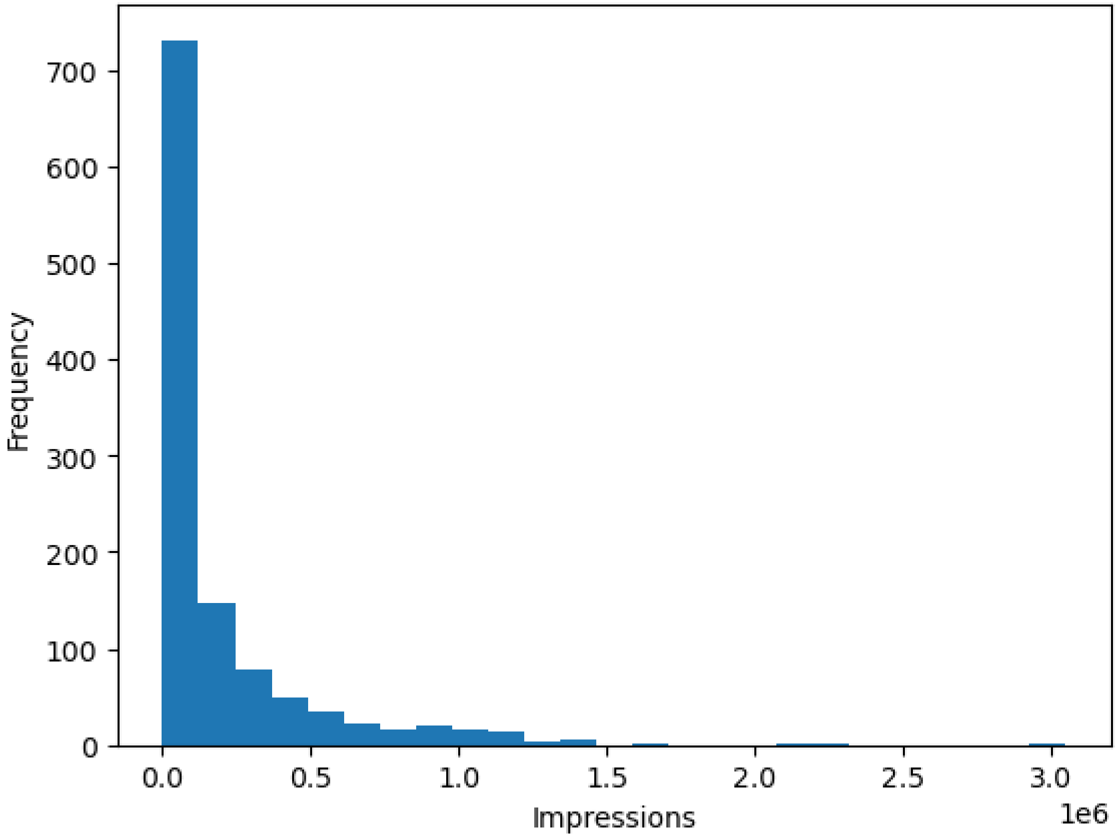


It can be observed that, as the amount of money spent is increased, number of products bought increased

Impressions based distribution

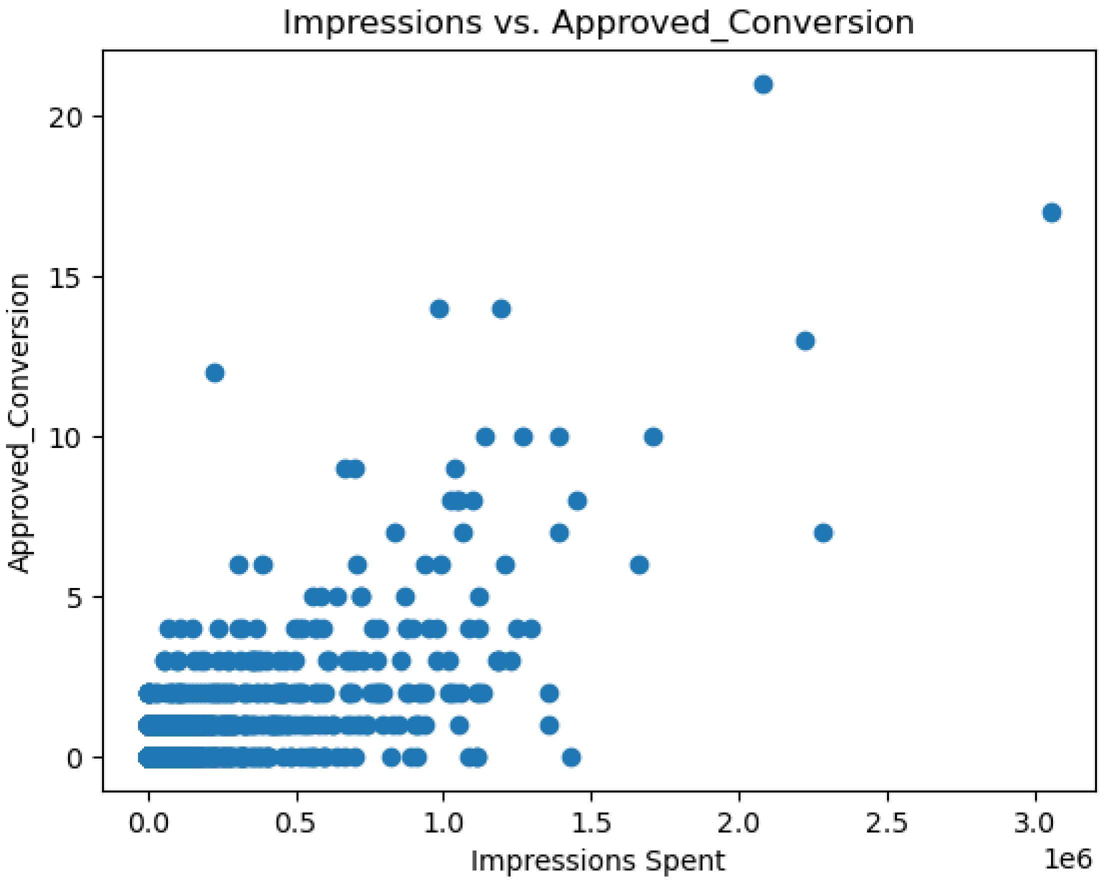
In [21]:
```
plt.hist(df['Impressions'], bins = 25)
plt.xlabel("Impressions")
plt.ylabel("Frequency")
```

Out[21]: Text(0, 0.5, 'Frequency')



In [22]:
```
plt.scatter(df["Impressions"], df["Approved_Conversion"])
plt.title("Impressions vs. Approved_Conversion")
plt.xlabel("Impressions Spent")
plt.ylabel("Approved_Conversion")
```

Out[22]: Text(0, 0.5, 'Approved_Conversion')



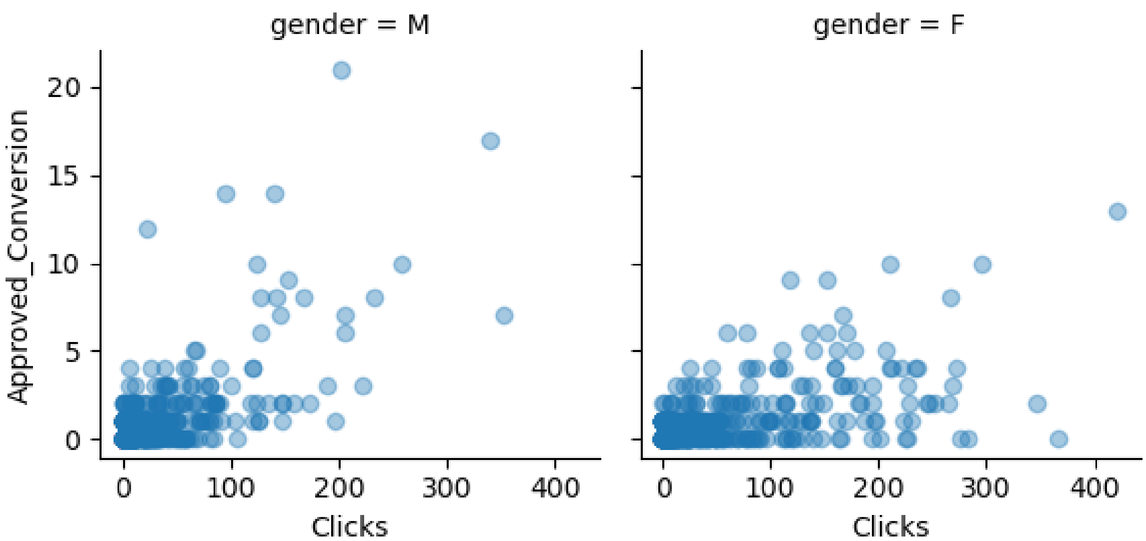
It can be observed that, there is a sudden rise in Approved_conversions after a certain point in Impressions

People who actually bought the product

1. After Clicking the ad

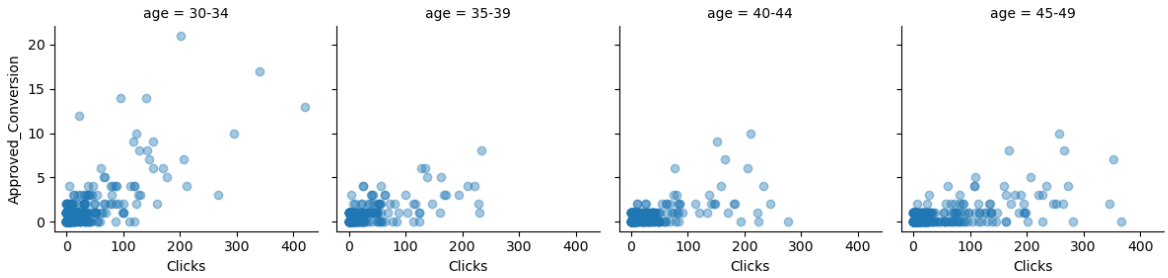
In [23]:
```
g = sns.FacetGrid(df, col="gender")
g.map(plt.scatter, "Clicks", "Approved_Conversion", alpha=.4)
g.add_legend()
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x1bd7225c410>



It seems men tend to click more than women but women buy more products than men after clicking the add.

In [24]:
```
g = sns.FacetGrid(df, col="age")
g.map(plt.scatter, "Clicks", "Approved_Conversion", alpha=.4)
g.add_legend();
```

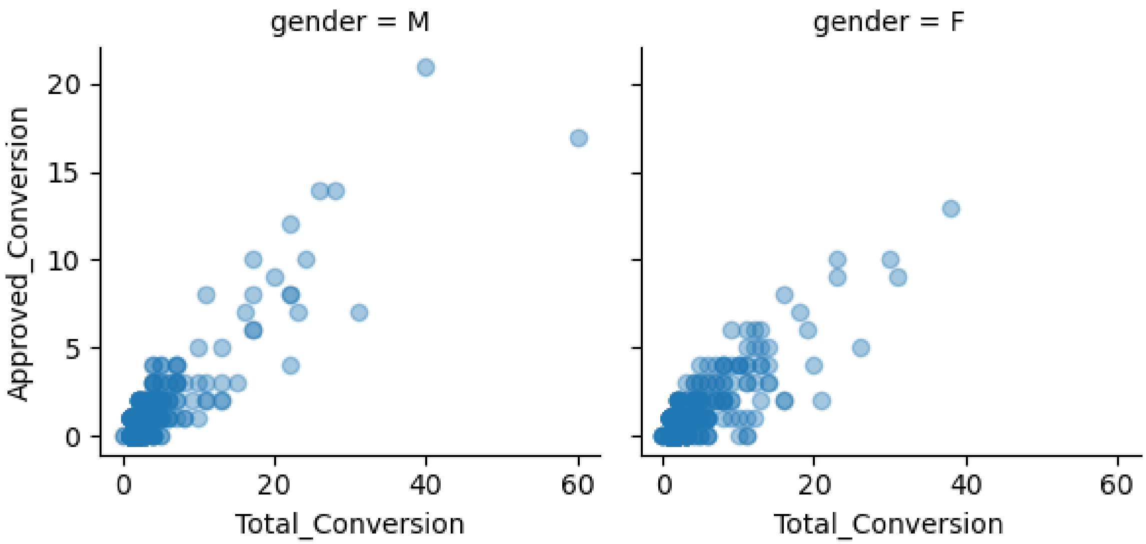


People in age group 30-34 has more tendency to buy product after clicking the add.

2. After Enquiring the product

In [25]:
```
g = sns.FacetGrid(df, col="gender")
g.map(plt.scatter, "Total_Conversion", "Approved_Conversion", alpha=.4)
g.add_legend()
```

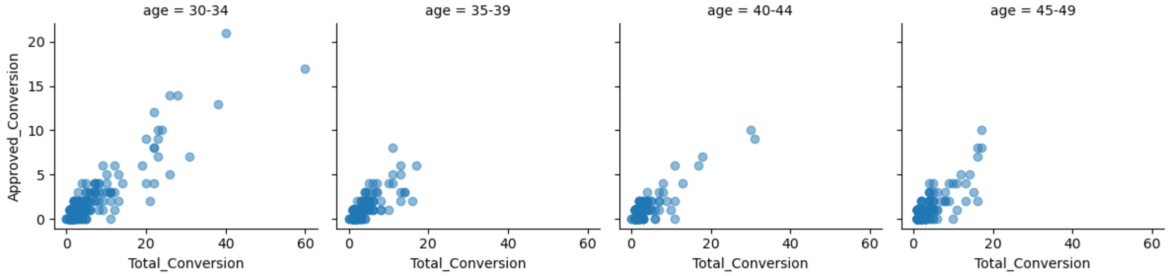
Out[25]:
```
<seaborn.axisgrid.FacetGrid at 0x1bd723864d0>
```



It seems women buys more products than men after enquiring the product. However men tends to enquire more about the product.

In [26]:
```
g = sns.FacetGrid(df, col="age")
g.map(plt.scatter, "Total_Conversion", "Approved_Conversion",alpha=.5)
g.add_legend()
```

Out[26]:
```
<seaborn.axisgrid.FacetGrid at 0x1bd72995790>
```



It seems people in age group 30-34 are more likely to buy the product after enquiring the product.

Zooming into Campaign C

In [27]:
```
a=[]
b=[]
c=[]
for i,j,k in zip(df.xyz_campaign_id, df.fb_campaign_id, df.Approved_Conversion):
    if i=="campaign_c":
      a.append(i),b.append(j),c.append(k)
```

In [28]:
```
d={'campaign_name':a, 'fb_campaign_id':b, 'Approved_Conversion':c}
campaign_c=pd.DataFrame(d)
campaign_c.head()
```

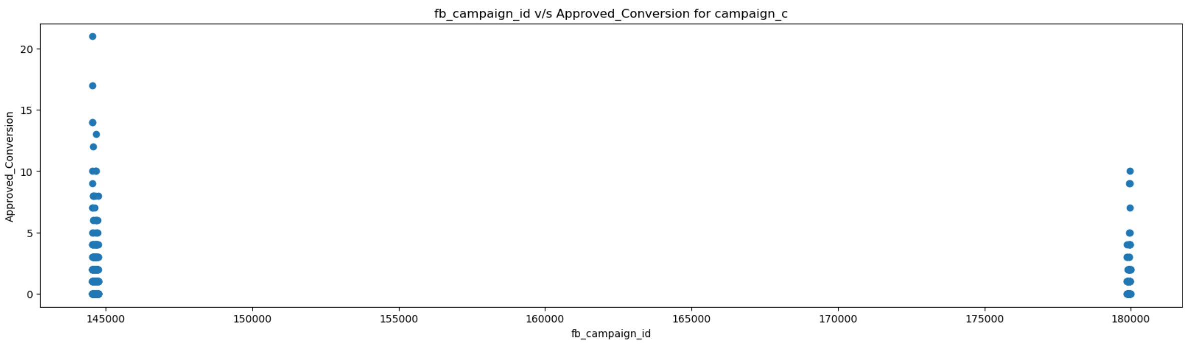
Out[28]:

	campaign_name	fb_campaign_id	Approved_Conversion
0	campaign_c	144531	14
1	campaign_c	144531	5
2	campaign_c	144531	1
3	campaign_c	144531	2
4	campaign_c	144531	2

Distribution of fb_campaign_id with Approved_Conversion for campaign_c

In [29]:
```
plt.figure(figsize=(20,5))
plt.scatter(campaign_c["fb_campaign_id"], campaign_c["Approved_Conversion"])
plt.title("fb_campaign_id v/s Approved_Conversion for campaign_c")
plt.xlabel("fb_campaign_id")
plt.ylabel("Approved_Conversion")
```

Out[29]: Text(0, 0.5, 'Approved_Conversion')



We can see fb_campaign_ids around 145000 have more Approved_Conversion than around 180000 for campaign_c

Summary

- **campaign_a : 916**
- **campaign_b : 936**
- **campaign_c : 1178**

Correlations :

"Approved_Conversion" is more related to ["Impressions", "Total_Conversion"]
than ["Clicks", "Spent"]

Campaign_C:

1. campaign_c has most number of ads.
2. compaign_c has better Approved_conversion count, i.e. most people bought products in campaign_c.

Age_Group:

1. In campaign_c and campaign_b, the age group of 30-34 shows more interest, whereas in campaign_a the age group of 40-44 shows more interest.

Campaign_C:

1. campaign_c has most number of ads.
2. compaign_c has better Approved_conversion count, i.e. most people bought products in campaign_c.

Gender:

1. Both the genders shows similar interests in all three campaigns.

Interest:

1. Although the count of interest after 100 is less,there is a rise of users after 100 who actually bought the product. Rest of the distribution is according to what was expected.

Money Spent:

1. campaign_c has most number of ads.

2. compaign_c has better Approved_conversion count, i.e. most people bought products in campaign_c.

Product bought after clicking the ad:

1. It seems men tend to click more than women but women buy more products than men after clicking the add.
2. People in age group 30-34 has more tendency to buy product after clicking the add.

Product bought after enquiring the ad:

1. It seems women buys more products than men after enquiring the product. However men tends to enquire more about the product.
2. It seems people in age group 30-34 are more likely to buy the product after enquiring the product.

Instructive_conclusion:

1. For campaign_c, fb_campaign_ids around 145000 have more Approved_Conversion than around 180000

Business Questions

1. How to optimize the social ad campaigns for the highest conversion rate possible? (Attain best Reach to Conversion ratios/Click to Conversion ratios)

Since highest conversion rate was attained in campaign_c, we can consider the factors contributed in this campaign:

- The number of ad counts should be more for better reach.
- The age group of 30-34 should be the main aim.
- People with interest types after 100 should be given more attention
- More the number of times the add is shown i.e. "impression", more approved_conversion rate is achieved.

2. Finding the perfect target demographics with the appropriate click through rates

- Women tend to buy the product more often after clicking the ad than men.
- Also the age group 30 to 34 buy the product more often after clicking the ad

3. Understanding the ideal turnaround/decision making time per age group to convert and re-target future social campaigns

- Age group 30-34 tend to take less decision making time followed by 35 to 39 and 40-44.
- Age group 45-49 take the most time to decide.

4. Comparing the individual campaign performance so the best creative/campaign can be run again with adjusted audiences.

- Clearly campaign_c wins the battle due to highest approved_conversion rate.
- Also campaign_a does pretty well , considering the number of ads it involves. With less no of ads, it has managed to peform better than campaign_b with large no of ads.