Notebook

May 4, 2025

[ ]:
```
# Importing libraries

import pandas as pd
import numpy as np
import mysql.connector
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.stats.api as sms
import statsmodels.api as sm
from scipy import stats as st

from dotenv import load_dotenv
import os
#pip install pandas mysql-connector-python
#pip install python-dotenv
```

0.0.1 Importing data

[38]:
```
load_dotenv()

conn = mysql.connector.connect(
    host = 'localhost',
    user = 'root',
    passwd = os.getenv('MYSQL_PASSWORD'),
    database = 'e_master_card'

)
```

[ ]:
```
df_cust = pd.read_sql('select * from customers', conn)
df_trans= pd.read_sql('select * from transactions', conn)
df_credit = pd.read_sql('select * from credit_profiles', conn)
```

```
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2980546640.py:2:
UserWarning: pandas only supports SQLAlchemy connectable (engine/connection) or
database string URI or sqlite3 DBAPI2 connection. Other DBAPI2 objects are not
tested. Please consider using SQLAlchemy.
  df_trans= pd.read_sql('select * from transactions', conn)
```

0.0.2 Customer Table Analysis

[211]:
```python
df_cust.describe()
# findings:
#annual income cannot be 0
# age cannot be 135
```

[211]:
```
           cust_id          age  annual_income
count  1000.000000  1000.000000    1000.000000
mean    500.500000    36.405000  132439.799000
std     288.819436    15.666155  113706.313793
min       1.000000     1.000000       0.000000
25%     250.750000    26.000000   42229.750000
50%     500.500000    32.000000  107275.000000
75%     750.250000    46.000000  189687.500000
max    1000.000000   135.000000  449346.000000
```

0.0.3 Observations:

- Outliers present in data
- For ex: age= 1, 135 not possible

[41]:
```python
df_cust.isna().sum()
```

[41]:
```
cust_id           0
name              0
gender            0
age               0
location          0
occupation        0
annual_income     0
marital_status    0
dtype: int64
```

[43]:
```python
df_cust['annual_income'].value_counts().sort_index(ascending=True)
```

[43]:
```
annual_income
0         50
2          3
20         1
50         6
5175       1
          ..
447655     1
448071     1
448510     1
448699     1
449346     1
```

```
Name: count, Length: 944, dtype: int64
```

- No null values in annual income
- But income cannot be 0, 2,20 replacing annual income of <=50 with median

[55]:
```
df_cust[df_cust['annual_income'] <= 50]
```

[55]:
```
     cust_id               name  gender  age location           occupation  \
14        15      Sanjana Malik  Female   25    Rural               Artist
31        32        Veer Mistry    Male   50     City       Business Owner
82        83  Reyansh Mukherjee    Male   27     City           Freelancer
97        98         Virat Puri    Male   47   Suburb       Business Owner
102      103         Aarav Shah    Male   32     City       Data Scientist
155      156       Kiaan Saxena    Male   24     City  Fullstack Developer
170      171       Advait Verma    Male   52     City       Business Owner
186      187       Samar Sardar    Male   53     City           Consultant
192      193        Ishan Joshi    Male   37   Suburb       Data Scientist
227      228   Advait Mukherjee    Male   48     City       Business Owner
232      233        Aditya Goel    Male   26     City           Freelancer
240      241        Aaryan Bose    Male   24   Suburb           Freelancer
262      263      Vivaan Tandon    Male   53   Suburb       Business Owner
272      273       Kunal Sahani    Male   50   Suburb       Business Owner
275      276        Ananya Bali  Female   47     City           Consultant
312      313       Ritvik Gupta    Male   50     City           Consultant
315      316          Amara Jha  Female   25     City       Data Scientist
316      317      Yuvraj Saxena    Male   47     City           Consultant
333      334       Avani Khanna  Female   29     City       Data Scientist
340      341        Priya Sinha  Female   33    Rural  Fullstack Developer
402      403        Arnav Singh    Male   60     City       Business Owner
404      405     Arnav Banerjee    Male   26     City       Data Scientist
409      410         Kiaan Jain    Male   45    Rural           Consultant
440      441         Rudra Bose    Male   36   Suburb       Data Scientist
446      447      Aahan Gambhir    Male   60     City       Business Owner
449      450      Anika Rathod  Female   24   Suburb  Fullstack Developer
461      462         Kunal Nair    Male   33     City       Data Scientist
474      475        Neha Verma  Female   28     City       Data Scientist
502      503        Samar Dewan    Male   38   Suburb       Data Scientist
508      509         Advait Das    Male   55     City       Business Owner
516      517     Rehan Kulkarni    Male   29    Rural  Fullstack Developer
530      531          Aarya Ver    Male   32     City       Business Owner
536      537       Ritvik Patil    Male   33     City       Data Scientist
543      544       Advait Batra    Male   54     City           Consultant
592      593       Priya Gandhi  Female   32     City       Business Owner
599      600      Ishan Goswami  Female   38     City           Consultant
603      604     Kunal Malhotra    Male   25   Suburb  Fullstack Developer
608      609     Kriti Lalwani  Female   25     City       Data Scientist
633      634       Rudra Mehtani    Male   26     City       Data Scientist
634      635        Anaya Dutta  Female   21     City           Freelancer
```

644	645	Dhruv Das	Male	64	City	Business Owner
648	649	Kunal Rathore	Male	41	City	Consultant
650	651	Gauri Mittal	Female	47	Rural	Consultant
664	665	Ayush Khanna	Male	32	Rural	Fullstack Developer
681	682	Arya Jaiswal	Male	37	Suburb	Data Scientist
686	687	Vihaan Jaiswal	Male	40	City	Business Owner
688	689	Dhruv Dewan	Male	26	City	Artist
693	694	Aditi Mehrotra	Female	37	Suburb	Data Scientist
694	695	Rohan Mehta	Male	28	City	Data Scientist
696	697	Ishan Negi	Male	47	City	Consultant
744	745	Swara Kaul	Female	39	City	Data Scientist
784	785	Rohan Jain	Male	27	City	Data Scientist
788	789	Vihaan Singhal	Male	20	City	Fullstack Developer
791	792	Sara Mhatre	Female	38	City	Data Scientist
817	818	Akshay Mehrotra	Male	47	City	Consultant
932	933	Avinash Tiwari	Male	35	City	Data Scientist
955	956	Aahan Gandhi	Male	39	Suburb	Business Owner
956	957	Priya Malik	Female	24	City	Artist
995	996	Manya Vasudeva	Female	26	City	Freelancer
998	999	Amara Rathore	Female	47	City	Business Owner

	annual_income	marital_status
14	0	Married
31	50	Married
82	0	Single
97	0	Married
102	0	Married
155	0	Married
170	0	Single
186	0	Single
192	0	Married
227	0	Married
232	0	Married
240	0	Married
262	50	Married
272	0	Married
275	0	Single
312	0	Married
315	0	Married
316	50	Married
333	50	Married
340	50	Married
402	0	Married
404	0	Single
409	0	Married
440	0	Married
446	0	Married

```
449               0       Married
461               0       Married
474               0        Single
502               0        Single
508               0       Married
516               0        Single
530               0       Married
536               0       Married
543               2       Married
592              50       Married
599               0        Single
603               0       Married
608               0        Single
633               2       Married
634               0       Married
644               0        Single
648               0       Married
650               0       Married
664               0       Married
681               0       Married
686               2       Married
688               0       Married
693               0       Married
694               0       Married
696              20       Married
744               0       Married
784               0        Single
788               0        Single
791               0        Single
817               0        Single
932               0       Married
955               0       Married
956               0       Married
995               0       Married
998               0       Married
```

0.0.4 Replacing income according to occupation median

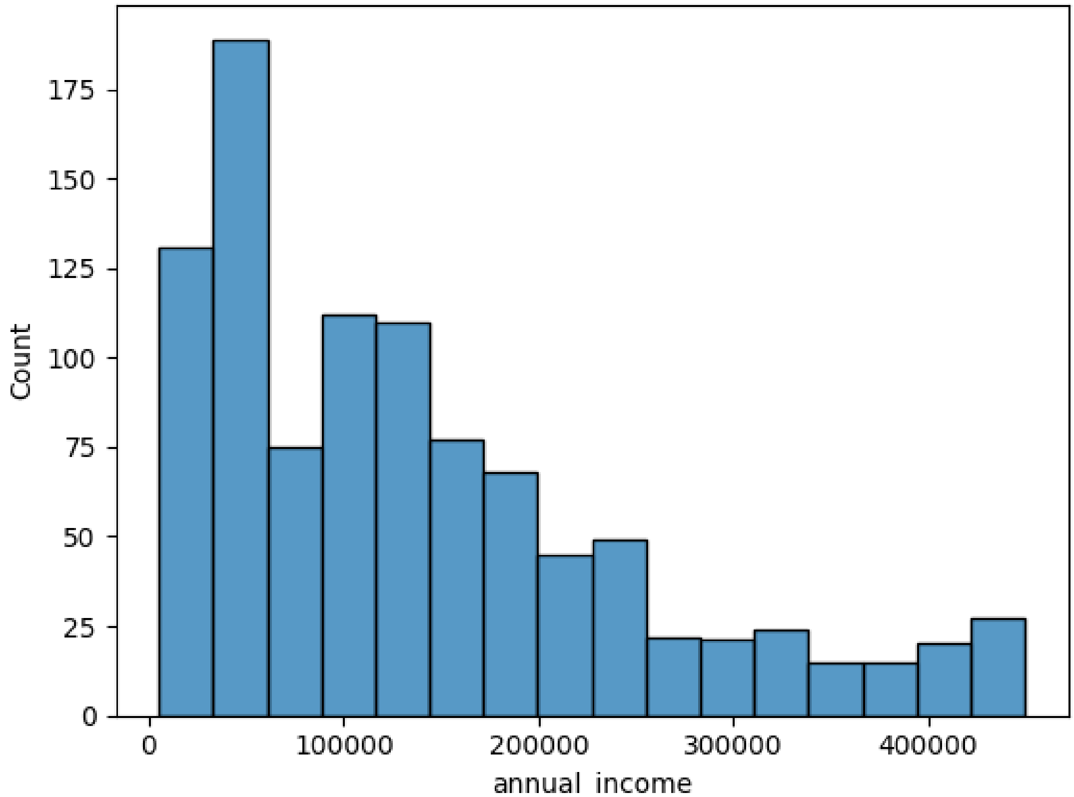
[233]:

```
median_incomes = df_cust.
 ↪groupby(['occupation'],as_index=False)['annual_income'].median().rename( \
  columns= {'annual_income':'median_income'}
)

df_cust = df_cust.merge(median_incomes,on='occupation',how='left')

df_cust['annual_income'] = df_cust.apply(lambda x: x['median_income'] \
  if x['annual_income'] <= 50 else x['annual_income'],axis=1)
```

```
df_cust = df_cust.drop(columns='median_income')
```

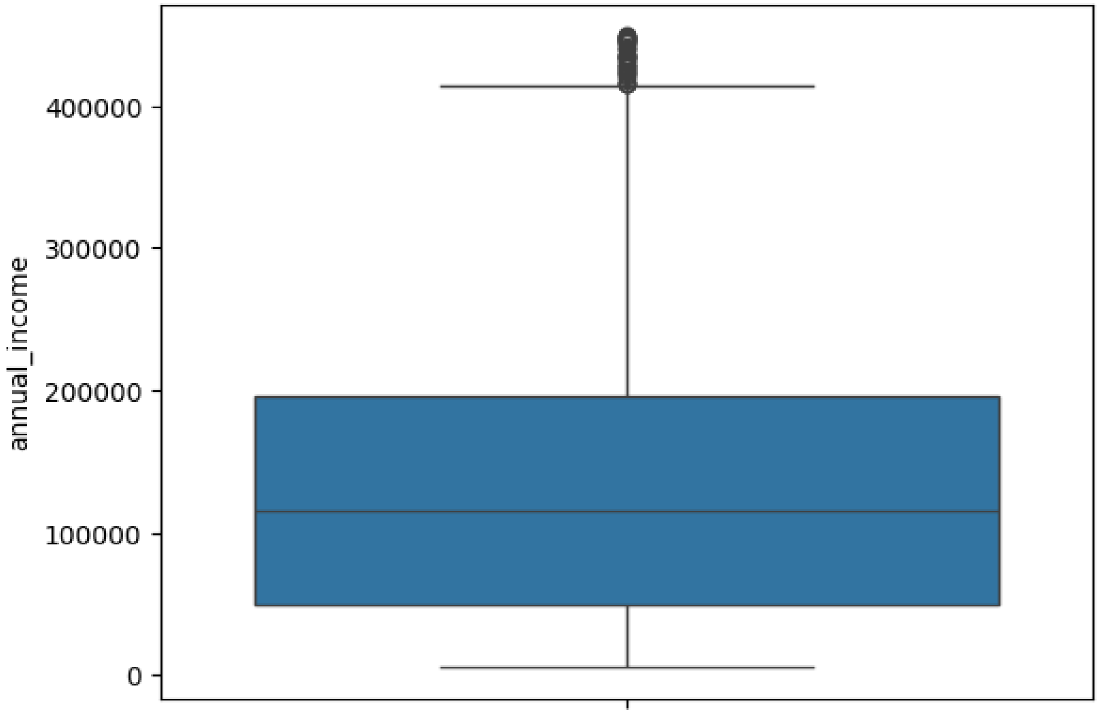
[66]:
```
sns.histplot(df_cust['annual_income'])
```

[66]: <Axes: xlabel='annual_income', ylabel='Count'>



[70]:
```
sns.boxplot(df_cust['annual_income'])
```

[70]: <Axes: ylabel='annual_income'>

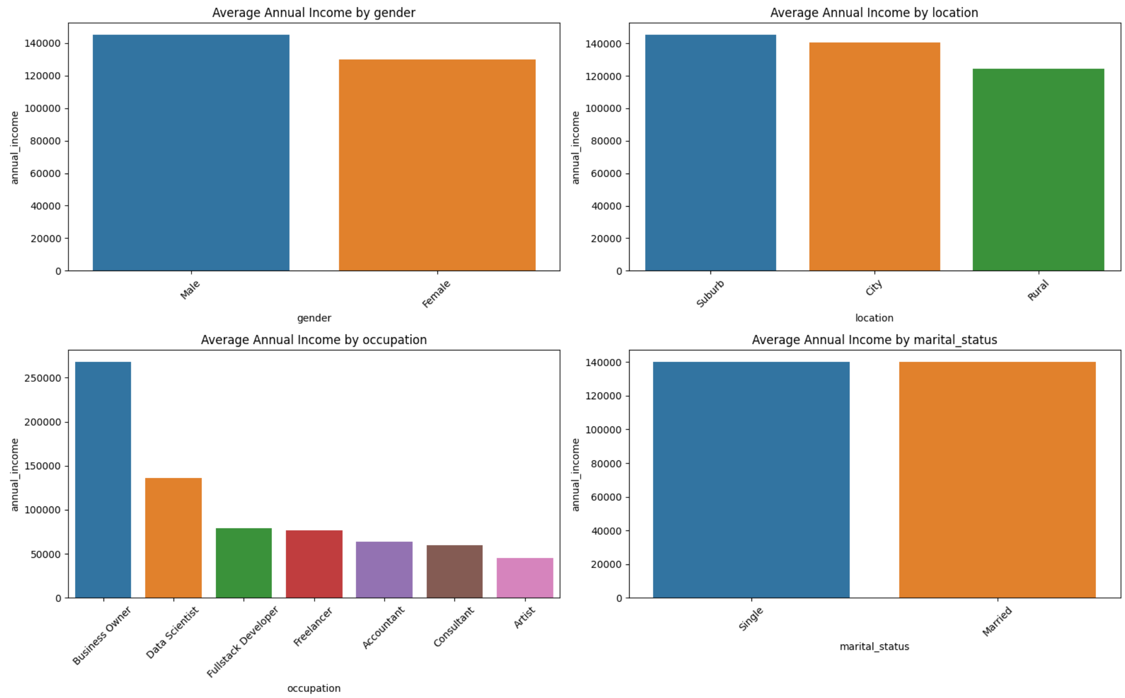


0.0.5 Category wise annual income

[84]:
```
cat_cols = ['gender','location','occupation','marital_status']
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(16, 10))  # 2x2 grid for 4␣
↪plots
axes = axes.flatten()  # flatten 2D array of axes into 1D for easy indexing

for idx, col in enumerate(cat_cols):
    mean_incomes = df_cust.groupby(col, as_index=False)['annual_income'].mean()
    mean_incomes = mean_incomes.sort_values('annual_income', ascending=False)

    sns.barplot(data=mean_incomes, x=col, y='annual_income', palette='tab10',␣
↪ax=axes[idx])
    axes[idx].set_title(f'Average Annual Income by {col}')
    axes[idx].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```

```
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2079269613.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
```

```
effect.

  sns.barplot(data=mean_incomes, x=col, y='annual_income', palette='tab10',
ax=axes[idx])
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2079269613.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_incomes, x=col, y='annual_income', palette='tab10',
ax=axes[idx])
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2079269613.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_incomes, x=col, y='annual_income', palette='tab10',
ax=axes[idx])
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2079269613.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_incomes, x=col, y='annual_income', palette='tab10',
ax=axes[idx])
```



- We can see annual income of business owners is high, followed by Data Scientists

0.0.6 Outlier treatment of age

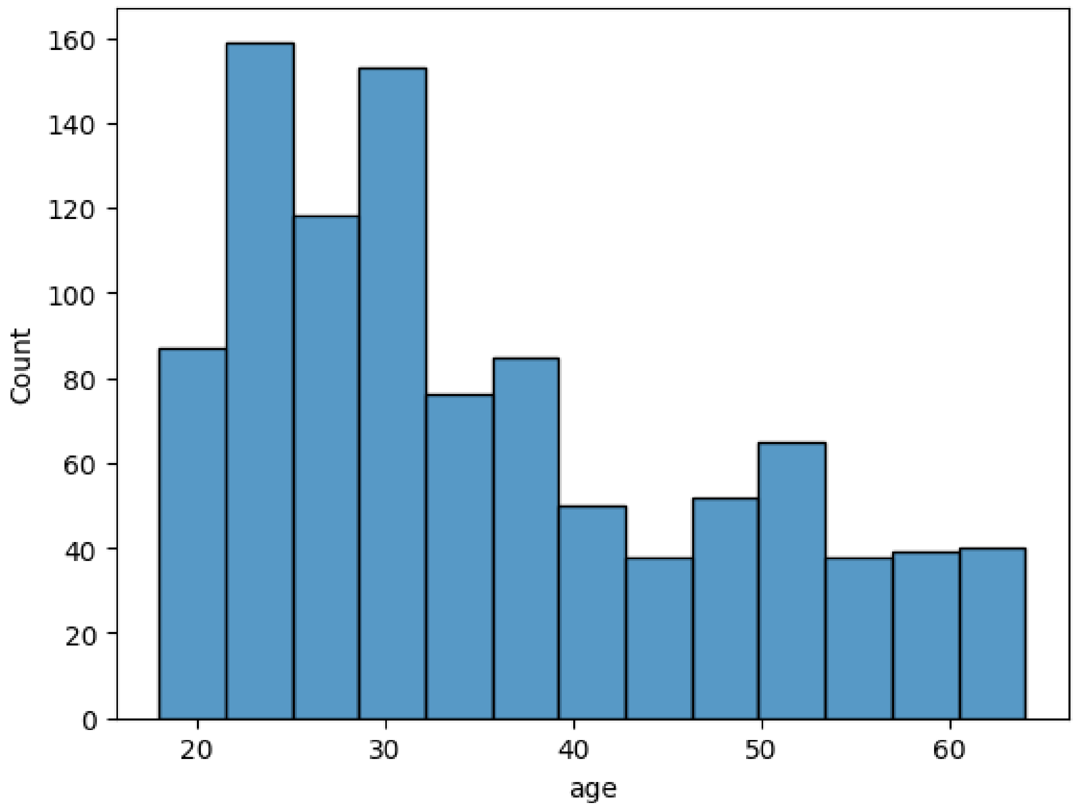
- only keeping age between 15 and 80

[234]:
```
df_cust = df_cust[(df_cust['age'] >= 15) & (df_cust['age'] <=80)]
```

[235]:
```
median_age = df_cust.groupby(['occupation'],as_index=False)['age'].median().
↪rename( \
  columns= {'age':'median_age'}
)

df_cust = df_cust.merge(median_age,on='occupation',how='left')

df_cust['age'] = df_cust.apply(lambda x: x['median_age'] \
  if (x['age'] < 15) | (x['age'] > 80) else x['age'],axis=1)

df_cust = df_cust.drop(columns='median_age')
```

[114]:
```
sns.histplot(df_cust['age'])
```

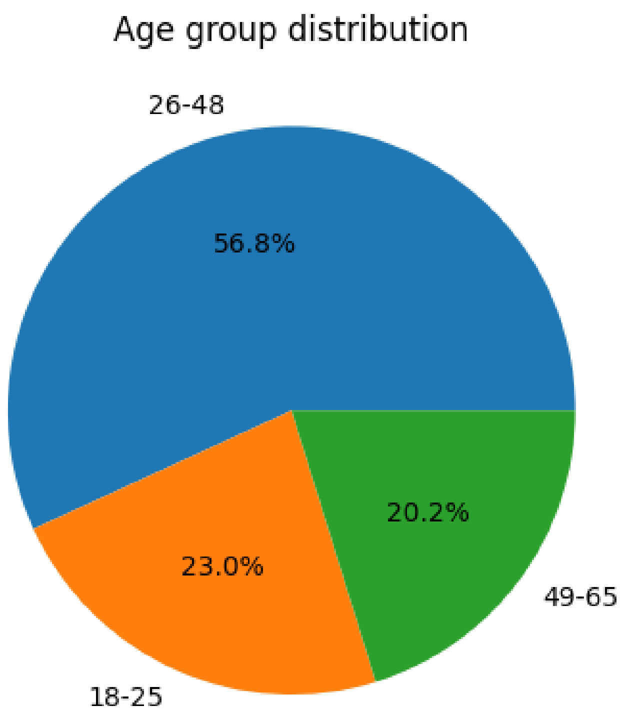
[114]: <Axes: xlabel='age', ylabel='Count'>



0.0.7 Visualization

[236]:
```
df_cust['age_group'] = df_cust.apply(lambda x: '18-25' if (x['age'] >18) &␣
↪(x['age'] <=25) \
                                    else '26-48' if (x['age'] > 25) &␣
↪(x['age'] <=48) \
                                    else '49-65',axis=1 \
                                    )
```

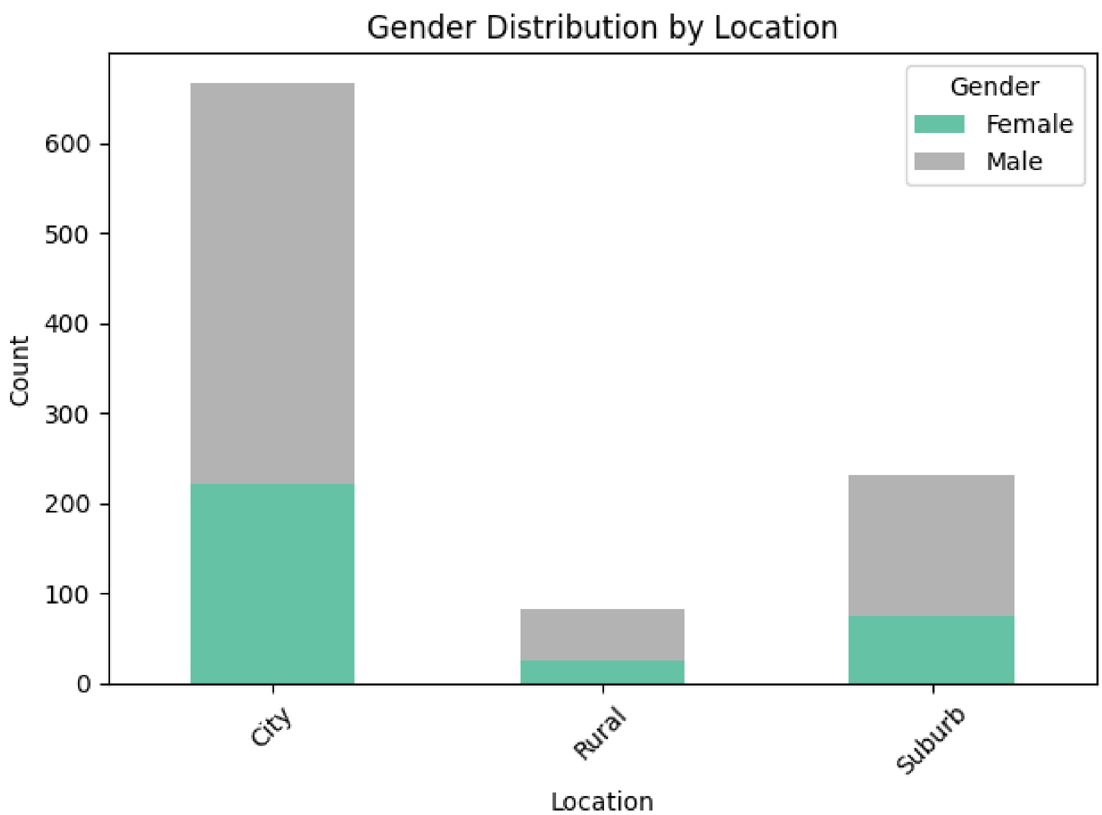
[237]:
```
plt.pie(df_cust['age_group'].value_counts(),
        labels=df_cust['age_group'].value_counts().index,
        autopct='%1.1f%%')
plt.title('Age group distribution')
plt.show()
```



0.0.8 We can see age group 26-48 spend most

0.0.9 Location wise gender distribution

[238]:
```
grouped = df_cust.groupby(['location','gender']).size().unstack()
grouped.plot(kind='bar', stacked=True, colormap='Set2')

plt.title('Gender Distribution by Location')
plt.xlabel('Location')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Gender')
plt.tight_layout()
plt.show()
```



0.0.10 Credit score table

[239]:
```
df_credit[df_credit['cust_id'].duplicated(keep=False)]
```

[239]:
```
     cust_id  credit_score  credit_utilisation  outstanding_debt  \
516      517           308                 NaN               NaN
517      517           308            0.113860              33.0
569      569           344                 NaN               NaN
570      569           344            0.112599              37.0
607      606           734                 NaN               NaN
608      606           734            0.193418            4392.0
664      662           442                 NaN               NaN
665      662           442            0.856039             266.0

     credit_inquiries_last_6_months  credit_limit
516                             NaN           NaN
517                             3.0         500.0
569                             NaN           NaN
570                             0.0         500.0
607                             NaN           NaN
608                             1.0       40000.0
```

```
664                            NaN          NaN
665                            2.0        500.0
```

[ ]:
```
# Dropping some duplicates
df_credit = df_credit.drop_duplicates(subset='cust_id',keep='last')
```

[242]:
```
df_credit.isna().sum()
```

[242]:
```
cust_id                          0
credit_score                     0
credit_utilisation               0
outstanding_debt                 0
credit_inquiries_last_6_months   0
credit_limit                    65
dtype: int64
```

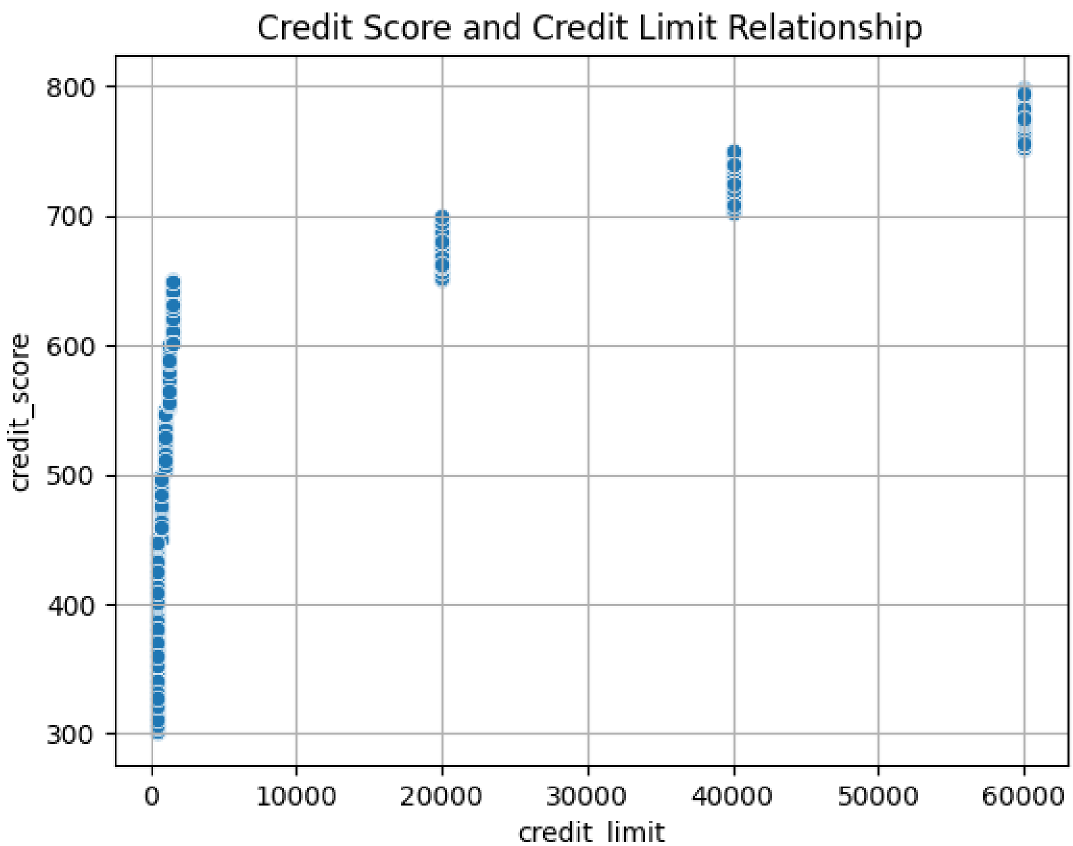
[ ]:
```

```

[173]:
```
df_credit[pd.isna(df_credit['credit_limit'])]
# using credit limit to fill nan values for creditlimit,
# bcz as credit score increase credit limit increase
```

[173]:
```
     cust_id  credit_score  credit_utilisation  outstanding_debt  \
10        11           679            0.557450            9187.0
35        36           790            0.112535            4261.0
37        38           514            0.296971             238.0
45        46           761            0.596041           24234.0
64        65           734            0.473715           13631.0
..       …             …                 …                 …
912      909           479            0.487555             320.0
931      928           311            0.832244             316.0
948      945           526            0.272734             227.0
954      951           513            0.175914             131.0
957      954           783            0.867421           46451.0

     credit_inquiries_last_6_months  credit_limit
10                              2.0           NaN
35                              1.0           NaN
37                              2.0           NaN
45                              2.0           NaN
64                              0.0           NaN
..                              …            …
912                             3.0           NaN
931                             2.0           NaN
948                             1.0           NaN
954                             3.0           NaN
957                             0.0           NaN
```

[65 rows x 6 columns]

[176]:
```
sns.scatterplot(data= df_credit, x='credit_limit',y='credit_score')
plt.title("Credit Score and Credit Limit Relationship")
plt.grid(True)
plt.show()
```



[183]:
```
df_credit['credit_limit'].unique()
```

[183]:
```
array([40000.,  1250.,  1000.,   500.,   750.,    nan,  1500., 60000.,
       20000.])
```

[194]:
```
df_credit[(df_credit['credit_limit'] >= 60000)
          ]['credit_score'].max()
```

[194]:
```
np.int64(799)
```

0.0.11 Creating credit score range bins

- Created credit score bins to impute nan values with correct credit limit

[243]:
```
bin = [0,650,699,750,1000]
bin_labels = ['0-649','650-698','699-749','750-1000']
df_credit['credit_score_range'] = pd.cut(df_credit['credit_score'],bins=bin,␣
↪labels = bin_labels, include_lowest=True)
```

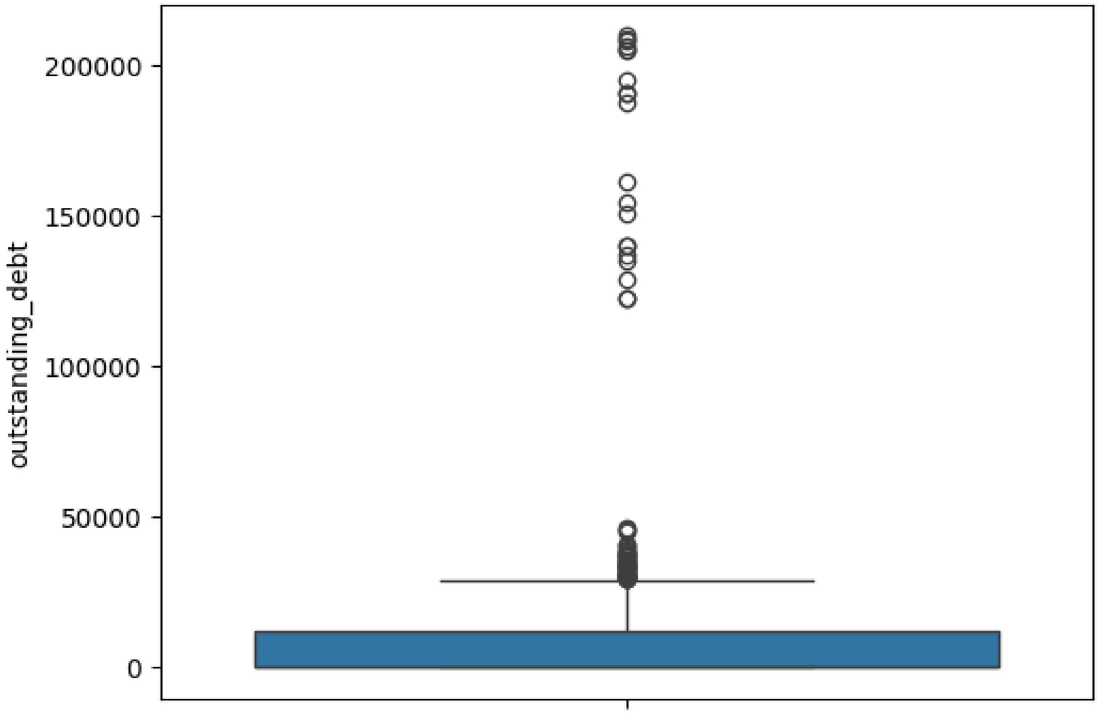
[244]:
```
median_credit_limit = df_credit.
↪groupby(['credit_score_range'],as_index=False)['credit_limit'].median().
↪rename( \
    columns= {'credit_limit':'median_credit_limit'}
)

df_credit = df_credit.
↪merge(median_credit_limit,on='credit_score_range',how='left')

df_credit['credit_limit'] = df_credit.apply(lambda x: x['median_credit_limit'] \
    if pd.isna(x['credit_limit']) else x['credit_limit'],axis=1)

df_credit = df_credit.drop(columns='median_credit_limit')
```

```
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\2812713241.py:1:
FutureWarning: The default of observed=False is deprecated and will be changed
to True in a future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and silence this warning.
  median_credit_limit = df_credit.groupby(['credit_score_range'],as_index=False)
['credit_limit'].median().rename( \
```

- Obervation: Outstanding_debt cannot be more than credit limit

[250]:
```
sns.boxplot(df_credit['outstanding_debt'])
```

[250]:
```
<Axes: ylabel='outstanding_debt'>
```

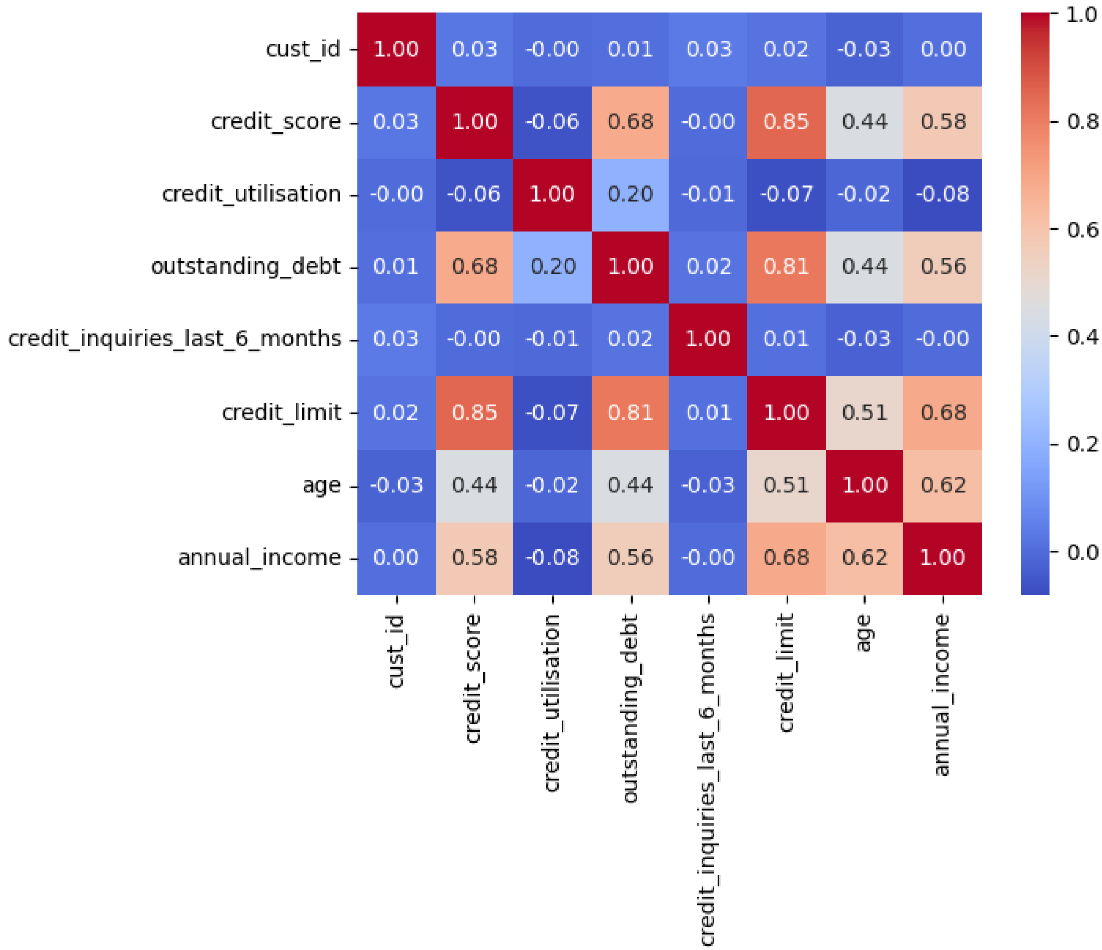


- Outlier treatment in outstanding dept, replacing with credit limit

[256]:
```
df_credit['outstanding_debt'] = df_credit.apply(lambda x: x['credit_limit'] if \

    x['outstanding_debt'] > x['credit_limit'] else x['outstanding_debt'],axis=1)
```

[276]:
```
df_credit_cust = df_credit.merge(df_cust, on= 'cust_id',how='inner')
```

[281]:
```
numeric_cols = df_credit_cust.select_dtypes(include='number').columns
sns.heatmap(df_credit_cust[numeric_cols].corr(
),annot=True,fmt='.2f',cmap='coolwarm')

plt.show()
```



0.0.12 Transaction Table

- Replacing Nan with mode in platform

[ ]:
```
df_trans['platform'] = df_trans['platform'].fillna(df_trans['platform'].
↪mode()[0])
```

[ ]:
```
0         Flipkart
1          Alibaba
2          Shopify
3          Shopify
4           Amazon
            …
499995      Amazon
499996      Meesho
499997      Amazon
499998    Flipkart
```

```
499999      Amazon
Name: platform, Length: 500000, dtype: object
```

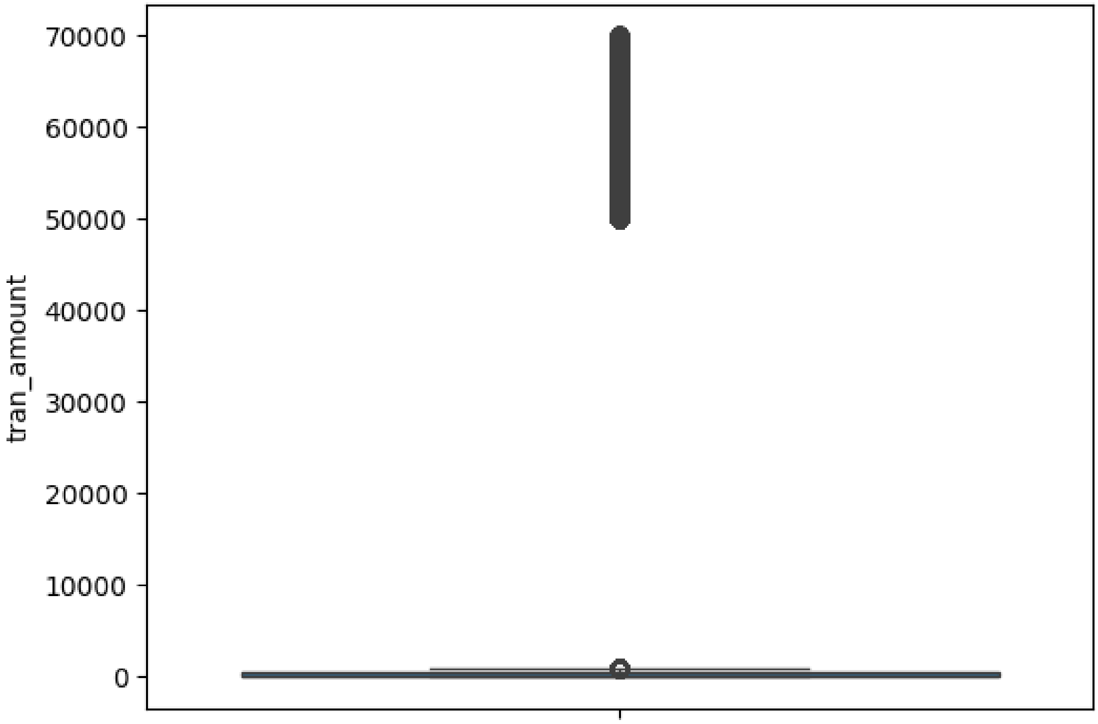
- Replacing nan values in amount according to groups: platform, product_category etc.

[381]:
```
zero_median = df_trans[(df_trans['platform'] == 'Amazon') & \
(df_trans['product_category'] == 'Electronics') &\
    (df_trans['payment_type'] == 'Credit Card') & \
        (df_trans['tran_amount'] > 0 )
        ].groupby(['platform','product_category','payment_type'])\
        ['tran_amount'].median().reset_index().rename(columns= {'tran_amount':
 ↪'median_amount'})
```

[390]:
```
df_trans = df_trans.
 ↪merge(zero_median,on=['platform','product_category','payment_type'],how='left')

df_trans['tran_amount'] = df_trans.apply(lambda x: x['median_amount'] \
  if (x['product_category'] == 'Electronics') &\
    (x['payment_type'] == 'Credit Card') & \
      (x['platform'] == 'Amazon') & \
        (x['tran_amount'] == 0 )  else x['tran_amount'],axis=1)

df_trans = df_trans.drop(columns='median_amount')
```

[393]:
```
sns.boxplot(df_trans['tran_amount'])
```

[393]:
```
<Axes: ylabel='tran_amount'>
```



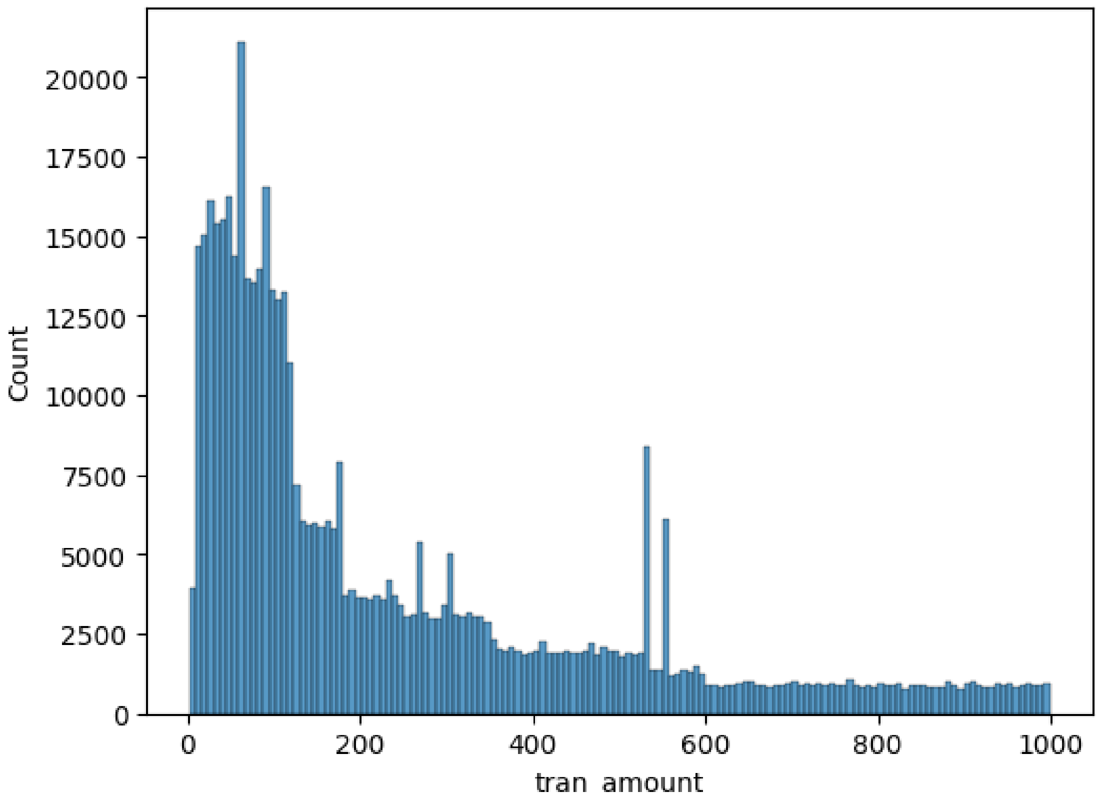
0.0.13 Outliers in Transaction Table using IQR

[394]:
```
q1,q3 = df_trans['tran_amount'].quantile([0.25,0.75])
iqr = q3-q1
lower = q1 - 2*iqr
upper = q3 + 2*iqr
```

[395]:
```
cat_level_median = df_trans[df_trans['tran_amount'] <= upper].
↪groupby(['product_category'])['tran_amount'].median().reset_index().
↪rename(columns = {'tran_amount' : 'cat_level_median'})

df_trans = df_trans.merge(cat_level_median,on=['product_category'],how='left')

df_trans['tran_amount'] = df_trans.apply(lambda x: x['cat_level_median'] \
  if x['tran_amount'] > upper else x['tran_amount'],axis=1)

df_trans = df_trans.drop(columns='cat_level_median')
```

[398]:
```
sns.histplot(df_trans['tran_amount'])
```

[398]:
```
<Axes: xlabel='tran_amount', ylabel='Count'>
```



[404]:
```
df_trans.shape
```

[404]:
```
(500000, 7)
```

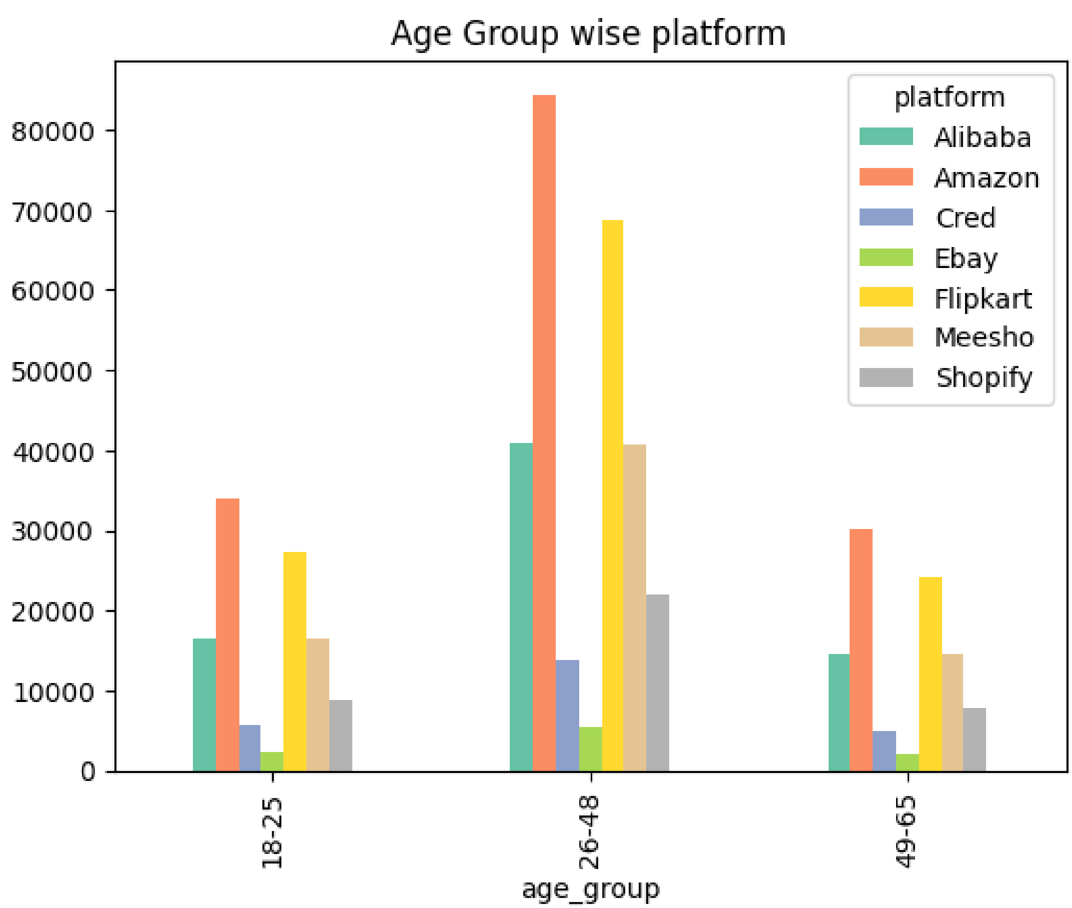
[401]:
```
df_trans['payment_type'].value_counts()/len(df_trans['payment_type']) * 100
```

[401]:
```
payment_type
Phonepe        28.8456
Credit Card    27.9556
Gpay           21.8436
Debit Card     11.9000
Net Banking     8.6446
Cash            0.8106
Name: count, dtype: float64
```

[ ]:
```
cust_trans = df_cust.merge(df_trans, on ='cust_id', how = 'inner')
payment_type_grouped_cust_trans = cust_trans.
 ↪groupby(['age_group','payment_type']).size().reset_index(name='count')

payment_type_grouped_cust_trans = payment_type_grouped_cust_trans.
 ↪pivot(index='age_group', columns='payment_type', values='count')
```

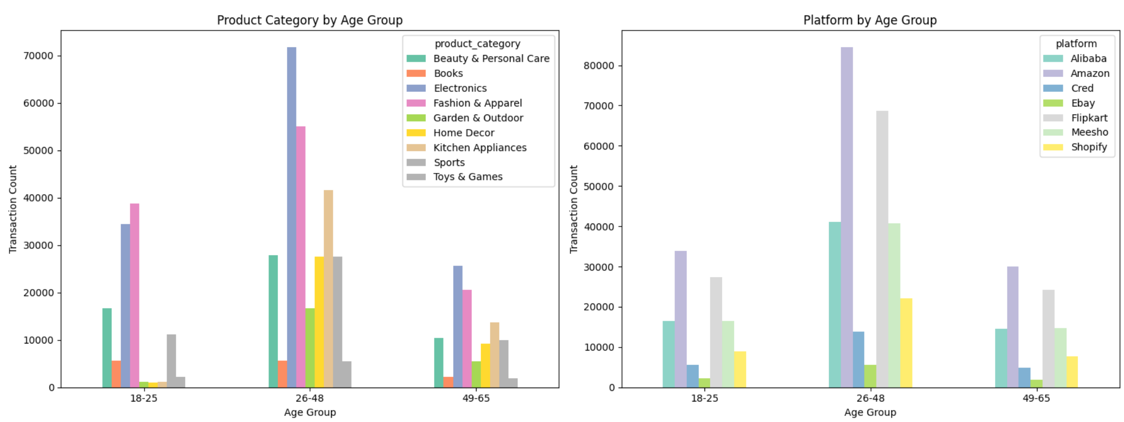
```
payment_type_grouped_cust_trans.plot(kind='bar',  colormap='Set2')
plt.title('Age Group wise payment method')
plt.show()
```

[433]:
```
platform_grouped_cust_trans = cust_trans.groupby(['age_group','platform']).
  ↪size().reset_index(name='count')
platform_grouped_cust_trans = platform_grouped_cust_trans.
  ↪pivot(index='age_group', columns='platform', values='count')
platform_grouped_cust_trans.plot(kind='bar',  colormap='Set2')
plt.title('Age Group wise platform')
plt.show()
```



[436]:
```
product_category_grouped_cust_trans = cust_trans.
  ↪groupby(['age_group','product_category']).size().reset_index(name='count')
product_category_grouped_cust_trans = product_category_grouped_cust_trans.
  ↪pivot(index='age_group', columns='product_category', values='count')
```

[437]:
```python
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(16, 6))

# Plot payment_type on first subplot
product_category_grouped_cust_trans.plot(kind='bar', colormap='Set2', ax=axes[0])
axes[0].set_title('Product Category by Age Group')
axes[0].set_xlabel('Age Group')
axes[0].set_ylabel('Transaction Count')
axes[0].tick_params(axis='x', rotation=0)

# Plot platform on second subplot
platform_grouped_cust_trans.plot(kind='bar', colormap='Set3', ax=axes[1])
axes[1].set_title('Platform by Age Group')
axes[1].set_xlabel('Age Group')
axes[1].set_ylabel('Transaction Count')
axes[1].tick_params(axis='x', rotation=0)

plt.tight_layout()
plt.show()
```



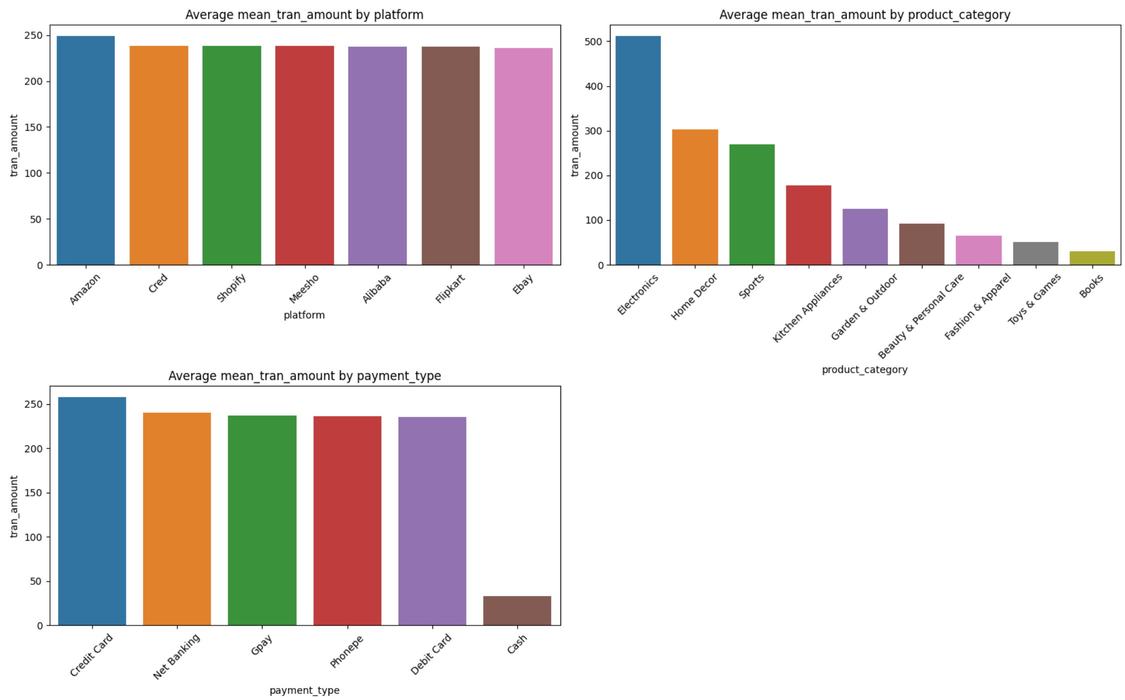
0.0.14 Important Observation:

- 26-48 and 49-65 age group are already using credit card, so it wont make any sense to
- target those group for credit card, so we have made decision to target 18-25 group for
- campaign

[450]:
```python
cat_cols = ['platform'         ,'product_category',         'payment_type']

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(16, 10))  # 2x2 grid for 4 plots
axes = axes.flatten()  # flatten 2D array of axes into 1D for easy indexing
```

```python
for idx, col in enumerate(cat_cols):
    mean_tran_amount = cust_trans.groupby(col, as_index=False)['tran_amount'].
↪mean()
    mean_tran_amount = mean_tran_amount.sort_values('tran_amount',␣
↪ascending=False)

    sns.barplot(data=mean_tran_amount, x=col, y='tran_amount', palette='tab10',␣
↪ax=axes[idx])
    axes[idx].set_title(f'Average mean_tran_amount by {col}')
    axes[idx].tick_params(axis='x', rotation=45)
axes[3].axis('off')

plt.tight_layout()
plt.show()
```

```
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\1672318693.py:10:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_tran_amount, x=col, y='tran_amount', palette='tab10',
ax=axes[idx])
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\1672318693.py:10:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_tran_amount, x=col, y='tran_amount', palette='tab10',
ax=axes[idx])
C:\Users\gaurav malik\AppData\Local\Temp\ipykernel_17028\1672318693.py:10:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data=mean_tran_amount, x=col, y='tran_amount', palette='tab10',
ax=axes[idx])
```



0.1 AB Testing

- Null Hypothesis: The new credit card does not increase the average number of transactions.
- Alternate Hypothesis: The new credit card increases the average number of transactions.

[73]:
```
alpha = 0.05 # 5% significance
power = 0.8 # Strong
effect_size= 0.4  # mean1 - mean 2 /SD

sms.tt_ind_solve_power(
    effect_size=effect_size,
    alpha=alpha,
    power = power,
    ratio =1
)
```

[73]: 99.08032514658997

[37]:
```
## Out of 100 test group, after 2 months, 40 people got converted to new credit
card, than you form control group of 40 people
```

[65]:
```
df_after_campaign = pd.read_csv("C:/Users/gaurav malik/Codebasics DS Projects/
Stats/chapter8_assets/chapter8_assets/datasets/
avg_transactions_after_campaign.csv")
```

[66]:
```
control_mean = df_after_campaign['control_group_avg_tran'].mean()
control_var = df_after_campaign['control_group_avg_tran'].var(ddof=0)

test_mean = df_after_campaign['test_group_avg_tran'].mean()
test_var = df_after_campaign['test_group_avg_tran'].var(ddof=0)
```

[69]:
```
z_score = (test_mean - control_mean) / np.sqrt((control_var/
 ↪len(df_after_campaign) + test_var/len(df_after_campaign)))
z_score
```

[69]:
```
np.float64(2.770732827433086)
```

[75]:
```
p_value = (1 - st.norm.cdf(z_score)) # get p value from z score
p_value
```

[75]:
```
np.float64(0.0027965149024101743)
```

[76]:
```
p_value > alpha
```

[76]:
```
np.False_
```

0.2 Conclusion

- Since the p-value is less than the significance level ( ), we reject the null hypothesis. This suggests that the new credit card leads to a statistically significant increase in average transactions. Therefore, we recommend releasing the new credit card.

This notebook was converted with convert.ploomber.io