

deadahlila-marketingcampaign-1

August 8, 2023

```
[1]: import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
```

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

```
[3]: pd.set_option('display.max_columns', None)
df.head()
```

```
[3]: Unnamed: 0    ID  Year_Birth Education Marital_Status      Income  Kidhome  \
0          0  5524    1957         S1      Lajang  58138000.0         0
1          1  2174    1954         S1      Lajang  46344000.0         1
2          2  4141    1965         S1  Bertunangan  71613000.0         0
3          3  6182    1984         S1  Bertunangan  26646000.0         1
4          4  5324    1981         S3      Menikah  58293000.0         1

    Teenhome Dt_Customer  Recency  MntCoke  MntFruits  MntMeatProducts  \
0          0  04-09-2012        58   635000      88000      546000
1          1  08-03-2014        38    11000       1000        6000
2          0  21-08-2013        26   426000      49000     127000
3          0  10-02-2014        26    11000       4000     20000
4          0  19-01-2014       94   173000      43000     118000

    MntFishProducts  MntSweetProducts  MntGoldProds  NumDealsPurchases  \
0          172000          88000          88000          3
1           2000          1000          6000          2
2         111000         21000         42000          1
3          10000          3000          5000          2
4          46000         27000         15000          5

    NumWebPurchases  NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  \
0                8                10                4                7
```

1	1	1	2	5
2	8	2	10	4
3	2	0	4	6
4	5	3	6	5

	AcceptedCmp3	AcceptedCmp4	AcceptedCmp5	AcceptedCmp1	AcceptedCmp2	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Complain	Z_CostContact	Z_Revenue	Response
0	0	3	11	1
1	0	3	11	0
2	0	3	11	0
3	0	3	11	0
4	0	3	11	0

```
[4]: df_num = df.select_dtypes(include = 'number')
df_cat = df.select_dtypes(exclude = 'number')
print(df_num.columns)
print(df_cat.columns)
```

```
Index(['Unnamed: 0', 'ID', 'Year_Birth', 'Income', 'Kidhome', 'Teenhome',
      'Recency', 'MntCoke', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',
      'MntSweetProducts', 'MntGoldProds', 'NumDealsPurchases',
      'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',
      'NumWebVisitsMonth', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5',
      'AcceptedCmp1', 'AcceptedCmp2', 'Complain', 'Z_CostContact',
      'Z_Revenue', 'Response'],
      dtype='object')
Index(['Education', 'Marital_Status', 'Dt_Customer'], dtype='object')
```

```
[5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 30 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Unnamed: 0            2240 non-null   int64
1   ID                    2240 non-null   int64
2   Year_Birth            2240 non-null   int64
3   Education             2240 non-null   object
4   Marital_Status        2240 non-null   object
5   Income                2216 non-null   float64
6   Kidhome               2240 non-null   int64
```

```

7   Teenhome                2240 non-null   int64
8   Dt_Customer             2240 non-null   object
9   Recency                 2240 non-null   int64
10  MntCoke                 2240 non-null   int64
11  MntFruits               2240 non-null   int64
12  MntMeatProducts         2240 non-null   int64
13  MntFishProducts         2240 non-null   int64
14  MntSweetProducts        2240 non-null   int64
15  MntGoldProds            2240 non-null   int64
16  NumDealsPurchases       2240 non-null   int64
17  NumWebPurchases         2240 non-null   int64
18  NumCatalogPurchases     2240 non-null   int64
19  NumStorePurchases       2240 non-null   int64
20  NumWebVisitsMonth       2240 non-null   int64
21  AcceptedCmp3            2240 non-null   int64
22  AcceptedCmp4            2240 non-null   int64
23  AcceptedCmp5            2240 non-null   int64
24  AcceptedCmp1            2240 non-null   int64
25  AcceptedCmp2            2240 non-null   int64
26  Complain                2240 non-null   int64
27  Z_CostContact           2240 non-null   int64
28  Z_Revenue               2240 non-null   int64
29  Response                2240 non-null   int64
dtypes: float64(1), int64(26), object(3)
memory usage: 525.1+ KB

```

```

[8]: cat_var=df.select_dtypes(exclude='number')

#Calculate the percentage of each categorical variable
for column in cat_var:
    counts = df[column].value_counts()
    percent = round((counts / len(df)) * 100,2)

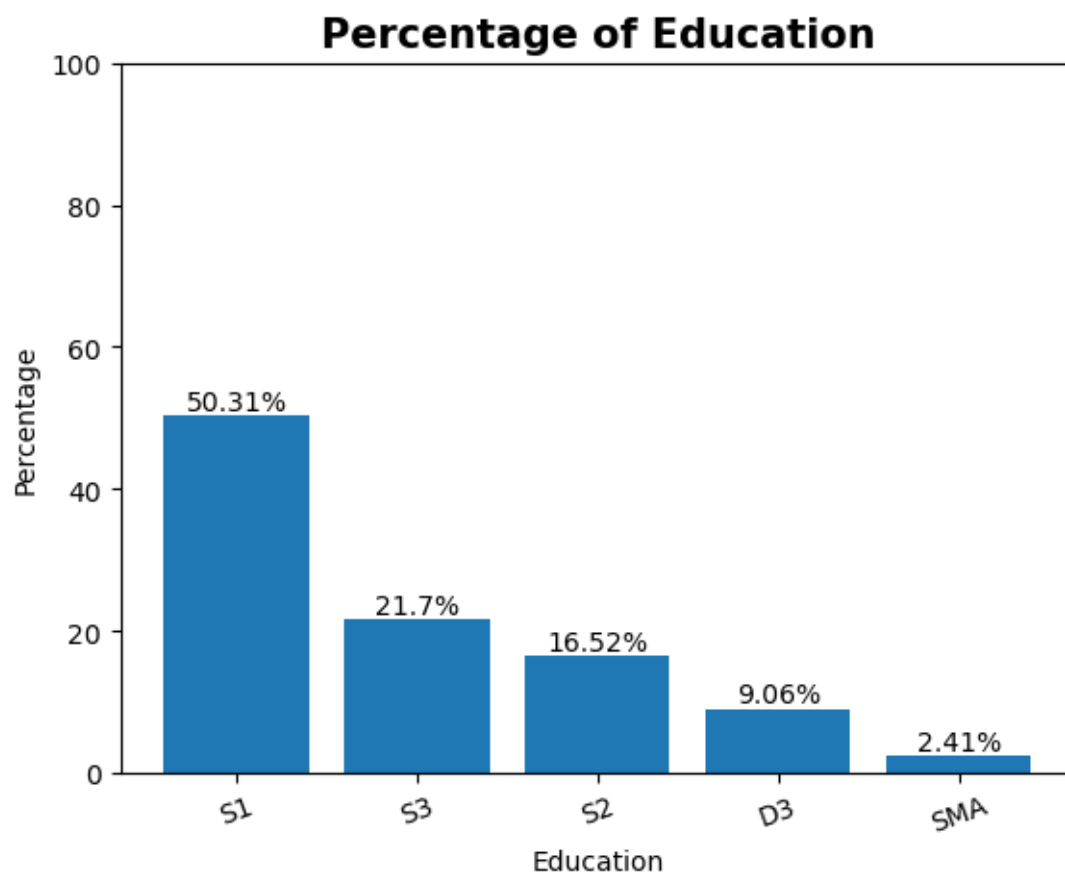
#Create the bar plot
fig, ax = plt.subplots()
ax.bar(counts.index, percent)
ax.set_xlabel(column)
ax.set_ylabel('Percentage')
ax.set_ylim(0,100)
ax.set_title(f'Percentage of {column}', fontweight='bold', fontsize=15)

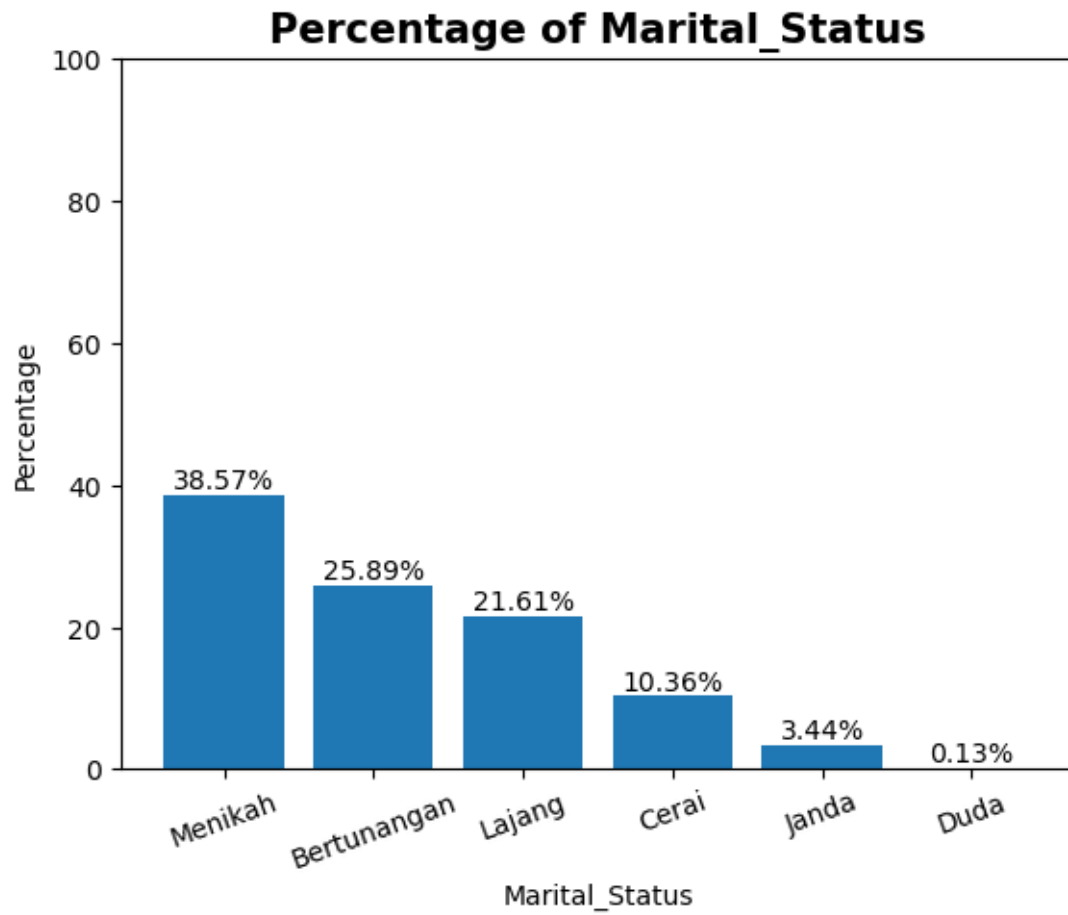
#Add percentage
for i in range(len(percent)):
    value = round(percent[i],2)
    label = f'{value}%'
    plt.text(i, percent[i], label, ha='center', va='bottom')
    plt.xticks(rotation=20)

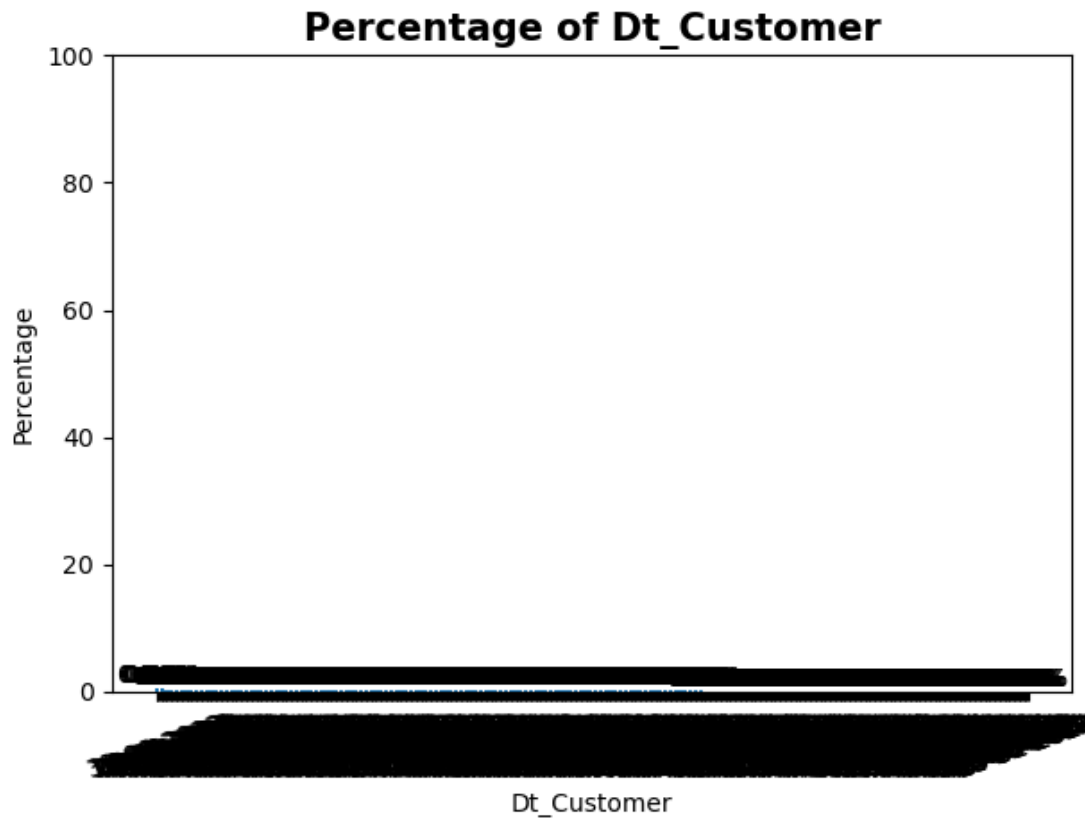
```

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

[8]: <function matplotlib.pyplot.show(close=None, block=None)>







```
[6]: #create total accepted campaign
df['Total_Acc_Cmp'] =_
    ↪df['AcceptedCmp1']+df['AcceptedCmp2']+df['AcceptedCmp3']+df['AcceptedCmp4']+df['AcceptedCmp5']

#create total purchases feature
df['Total_Purchases'] =_
    ↪df['NumDealsPurchases']+df['NumWebPurchases']+df['NumCatalogPurchases']+df['NumStorePurchases']

#create total spend feature
df['Total_Spent'] =_
    ↪df['MntCoke']+df['MntFishProducts']+df['MntFruits']+df['MntMeatProducts']+df['MntSweetProducts']

#create ammount of children feature
df['NumChildren'] = df['Kidhome']+df['Teenhome']
```

```
[7]: def safe_div(x,y):
    if y == 0:
        return 0
    return x / y
```

```
df['conversion_rate'] = df.apply(lambda x:
    ↪safe_div(x['Total_Purchases'],x['NumWebVisitsMonth']), axis=1)
```

```
[8]: from datetime import date

df['Dt_Collected'] = date.today()
df['Dt_Collected'] = pd.to_datetime(df['Dt_Collected'])
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'])

df['Dt_Days_Customer'] = df['Dt_Collected'] - df['Dt_Customer']
df['Dt_Days_Customer'] = df['Dt_Days_Customer'].dt.days
```

0.1 Conversion Rate Analysis Based On Income, Spending And Age

```
[9]: df['Age'] = 2023 - df['Year_Birth']
```

```
#group age
age_list=[]
for i in df['Age']:
    if i >= 0 and i <= 4:
        group = 'Balita'
    elif i >= 5 and i <= 12:
        group = 'Children'
    elif i >= 13 and i <= 17:
        group = 'Teenager'
    elif i >= 18 and i <= 24:
        group = 'Young_Adult'
    elif i >= 25 and i <= 39:
        group = 'Adult'
    elif i >= 40 and i <= 59:
        group = 'Middle Aged'
    else:
        group = 'Senior Citizen'
    age_list.append(group)
df['Age_Group'] = age_list
```

0.2 Conversion Rate Based on Age

```
[10]: df_agg = df.groupby('Age_Group').agg({'conversion_rate': 'sum'}).reset_index()
df_agg['sum_cvr'] = df_agg['conversion_rate'].sum()
df_agg['percentage'] = round((df_agg['conversion_rate']/df_agg['sum_cvr'])*100,
    ↪2)
df_agg
```

```
[10]:
```

	Age_Group	conversion_rate	sum_cvr	percentage
0	Adult	1241.880201	9845.297974	12.61

1	Middle Aged	4686.275919	9845.297974	47.60
2	Senior Citizen	3917.141855	9845.297974	39.79

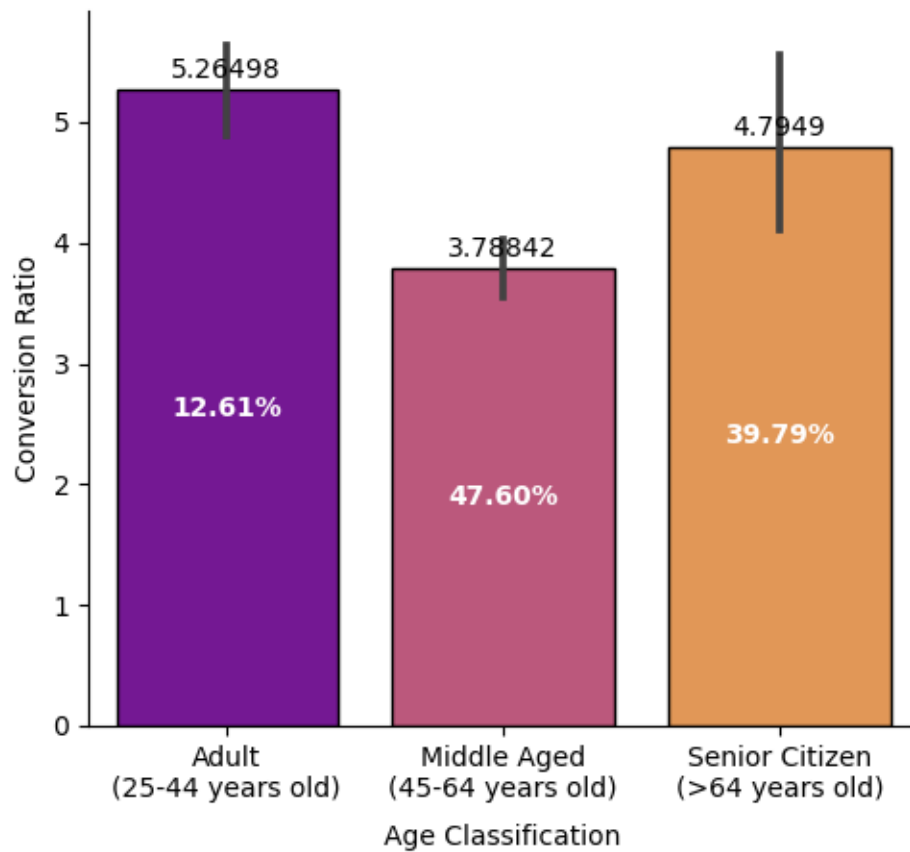
```
[14]: fig, ax = plt.subplots(figsize=(5, 5))
plt.title("Total of Customer Conversion Rate Based on Age", fontsize=12,
        color='black', weight='bold', pad=15)
sns.barplot(x='Age_Group', y='conversion_rate', data=df, edgecolor='black',
            palette='plasma')

plt.ylabel('Conversion Ratio')
plt.xlabel('Age Classification', labelpad=8)
plt.xticks(np.arange(3), ['Adult\n(25-44 years old)', 'Middle Aged\n(45-64\nyears old)', 'Senior Citizen\n(>64 years old)'])

plt.bar_label(ax.containers[0], padding=2)
plt.bar_label(ax.containers[0], ['12.61%', '47.60%', '39.79%'],
            label_type='center', color='white', weight='bold')

sns.despine()
plt.tight_layout()
plt.savefig('customer_cvr.png')
```


Total of Customer Conversion Rate Based on Age

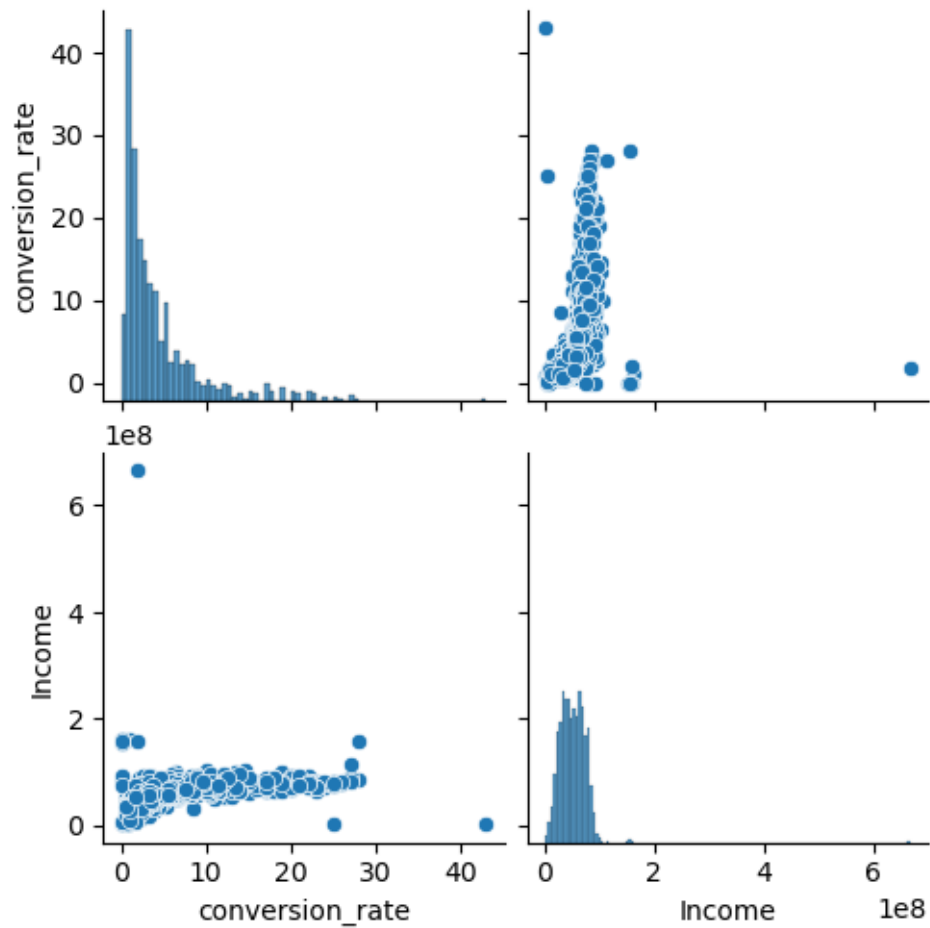


0.3 Conversion Rate Based on Income

```
[15]: # Memilih kolom yang diperlukan
data = df[['conversion_rate', 'Income']]

# Membuat scatter plot matrix
sns.pairplot(data)

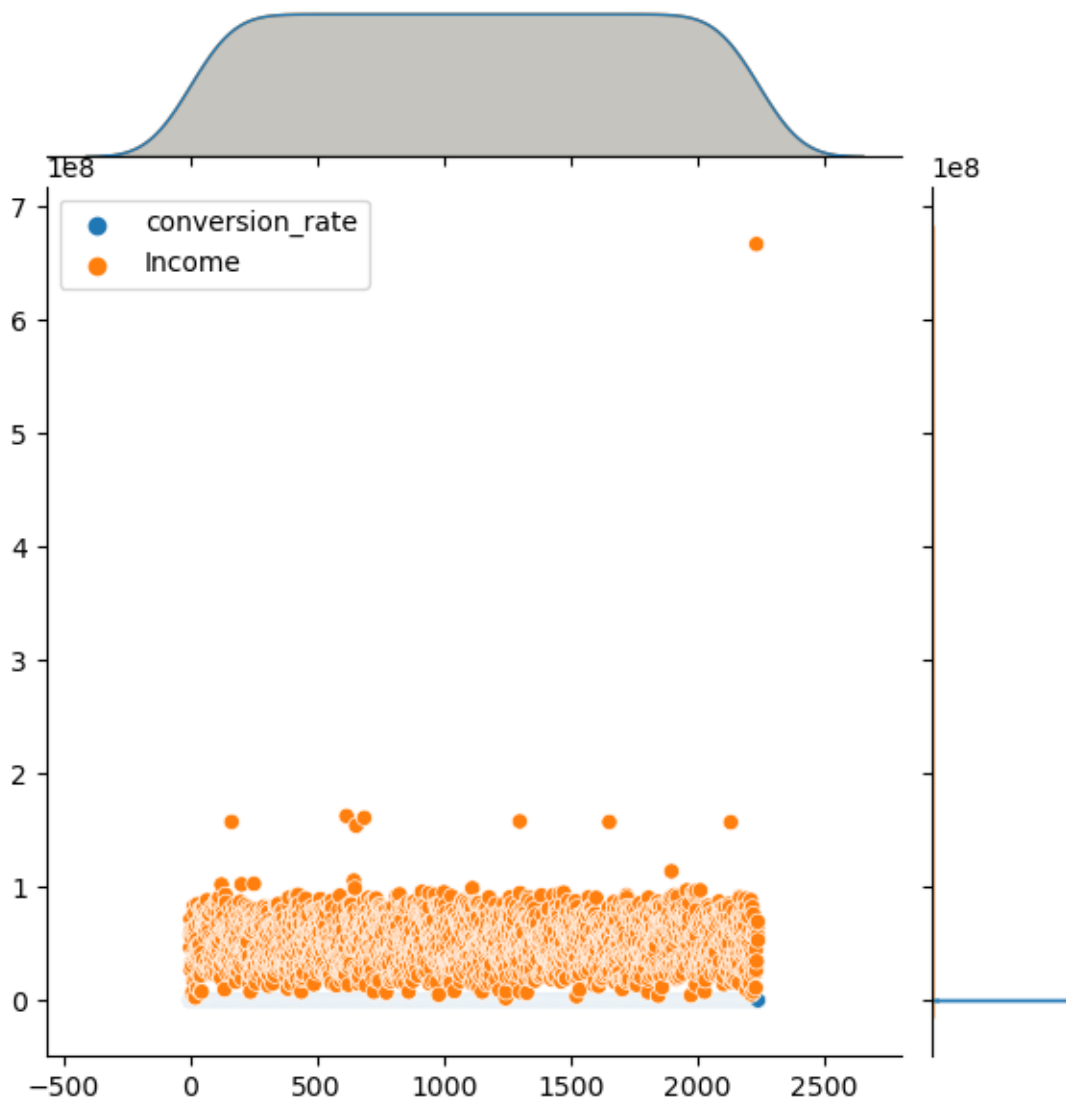
# Menampilkan plot
plt.show()
```



```
[16]: # Memilih kolom yang diperlukan
data = df[['conversion_rate', 'Income']]

# Membuat scatter plot matrix
sns.jointplot(data)

# Menampilkan plot
plt.show()
```



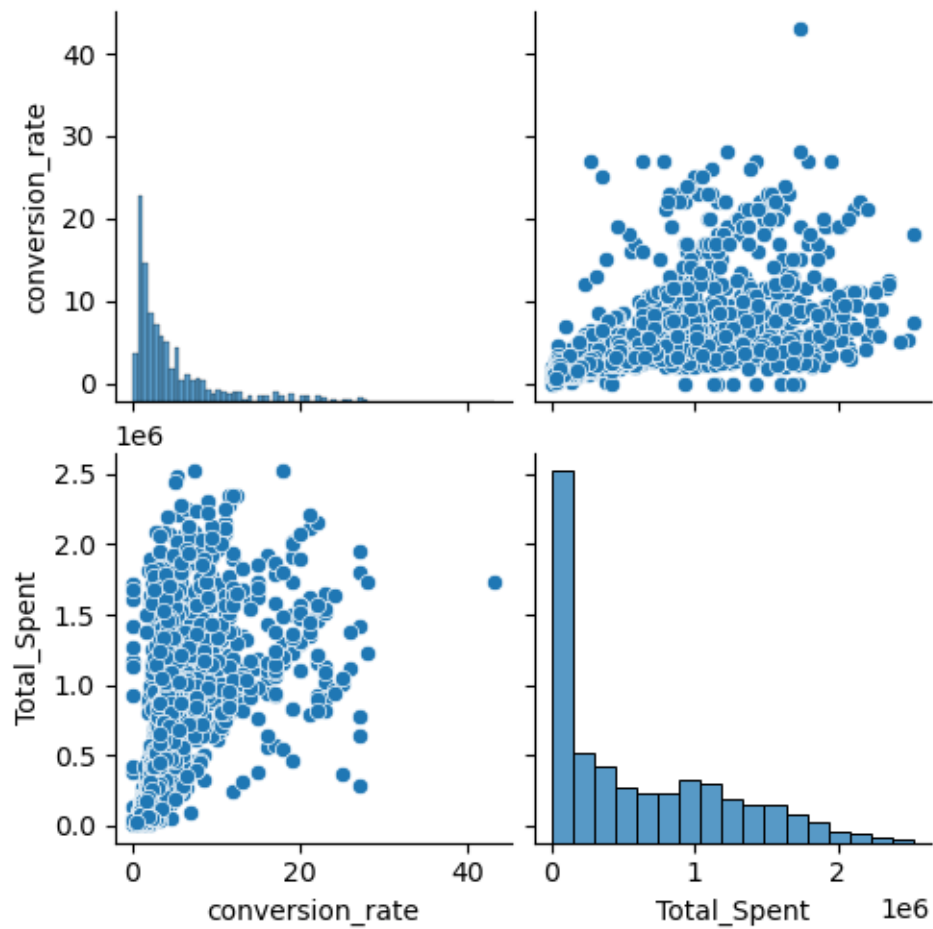
0.3.1 Conversion Rate Based on Spending

```
[17]: #create total spend feature
df['Total_Spent'] =
    df['MntCoke'] + df['MntFishProducts'] + df['MntFruits'] + df['MntMeatProducts'] + df['MntSweetProdu

# Memilih kolom yang diperlukan
data = df[['conversion_rate', 'Total_Spent']]

# Membuat scatter plot matrix
sns.pairplot(data)
```

```
# Menampilkan plot
plt.show()
```



0.4 Data Cleaning & Preprocessing

```
[11]: df_copy = df.copy()
```

```
[12]: df_copy.isna().sum()
```

```
[12]: Unnamed: 0      0
      ID            0
      Year_Birth    0
      Education     0
      Marital_Status 0
      Income       24
      Kidhome      0
```

Teenhome	0
Dt_Customer	0
Recency	0
MntCoke	0
MntFruits	0
MntMeatProducts	0
MntFishProducts	0
MntSweetProducts	0
MntGoldProds	0
NumDealsPurchases	0
NumWebPurchases	0
NumCatalogPurchases	0
NumStorePurchases	0
NumWebVisitsMonth	0
AcceptedCmp3	0
AcceptedCmp4	0
AcceptedCmp5	0
AcceptedCmp1	0
AcceptedCmp2	0
Complain	0
Z_CostContact	0
Z_Revenue	0
Response	0
Total_Acc_Cmp	0
Total_Purchases	0
Total_Spent	0
NumChildren	0
conversion_rate	0
Dt_Collected	0
Dt_Days_Customer	0
Age	0
Age_Group	0
dtype:	int64

0.5 Handle Missing Value

```
[13]: #Handle Missing Value
df_copy['Income'] = df_copy['Income'].fillna(df_copy['Income'].median())
```

```
[14]: #create ammount of children feature
df_copy['Number_Children'] = df['Kidhome']+df['Teenhome']
```

0.6 Drop data

```
[15]: #Drop data
df_copy.
    ↳drop(['AcceptedCmp1','AcceptedCmp2','AcceptedCmp3','AcceptedCmp4','AcceptedCmp5',
        ↳
        ↳'NumDealsPurchases','NumWebPurchases','NumCatalogPurchases','NumStorePurchases',
        ↳
        ↳'MntCoke','MntFishProducts','MntFruits','MntMeatProducts','MntSweetProducts',
        ↳'MntGoldProds',
        ↳'Kidhome','Teenhome','Response'], inplace=True, axis=1)
```

```
[16]: df_copy.drop(['Unnamed: 0', 'ID', 'Year_Birth', 'Z_CostContact', 'Z_Revenue',
    ↳'Dt_Collected', 'NumChildren'], inplace=True, axis=1)
```

```
[17]: df_copy.Marital_Status
```

```
[17]: 0          Lajang
1          Lajang
2      Bertunangan
3      Bertunangan
4          Menikah
...
2235      Menikah
2236      Bertunangan
2237          Cerai
2238      Bertunangan
2239      Menikah
Name: Marital_Status, Length: 2240, dtype: object
```

```
[18]: df_copy['Marital_Status'] = df_copy['Marital_Status'].replace('Cerai', 'Single')
df_copy['Marital_Status'] = df_copy['Marital_Status'].replace('Janda', 'Single')
df_copy['Marital_Status'] = df_copy['Marital_Status'].replace('Duda', 'Single')
df_copy['Marital_Status'] = df_copy['Marital_Status'].replace('Lajang',
    ↳'Single')
df_copy.head(5)
```

```
[18]: Education Marital_Status      Income Dt_Customer  Recency \
0          S1          Single  58138000.0  2012-04-09        58
1          S1          Single  46344000.0  2014-08-03        38
2          S1      Bertunangan  71613000.0  2013-08-21        26
3          S1      Bertunangan  26646000.0  2014-10-02        26
4          S3          Menikah  58293000.0  2014-01-19        94

      NumWebVisitsMonth  Complain  Total_Acc_Cmp  Total_Purchases  Total_Spent \
0                   7         0             0             25      1617000
1                   5         0             0             6       27000
```

2	4	0	0	21	776000
3	6	0	0	8	53000
4	5	0	0	19	422000

	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
0	3.571429	4131	66	Senior Citizen	0
1	1.200000	3285	69	Senior Citizen	2
2	5.250000	3632	58	Middle Aged	0
3	1.333333	3225	39	Adult	1
4	3.800000	3481	42	Middle Aged	1

```
[19]: df_copy.info()
```

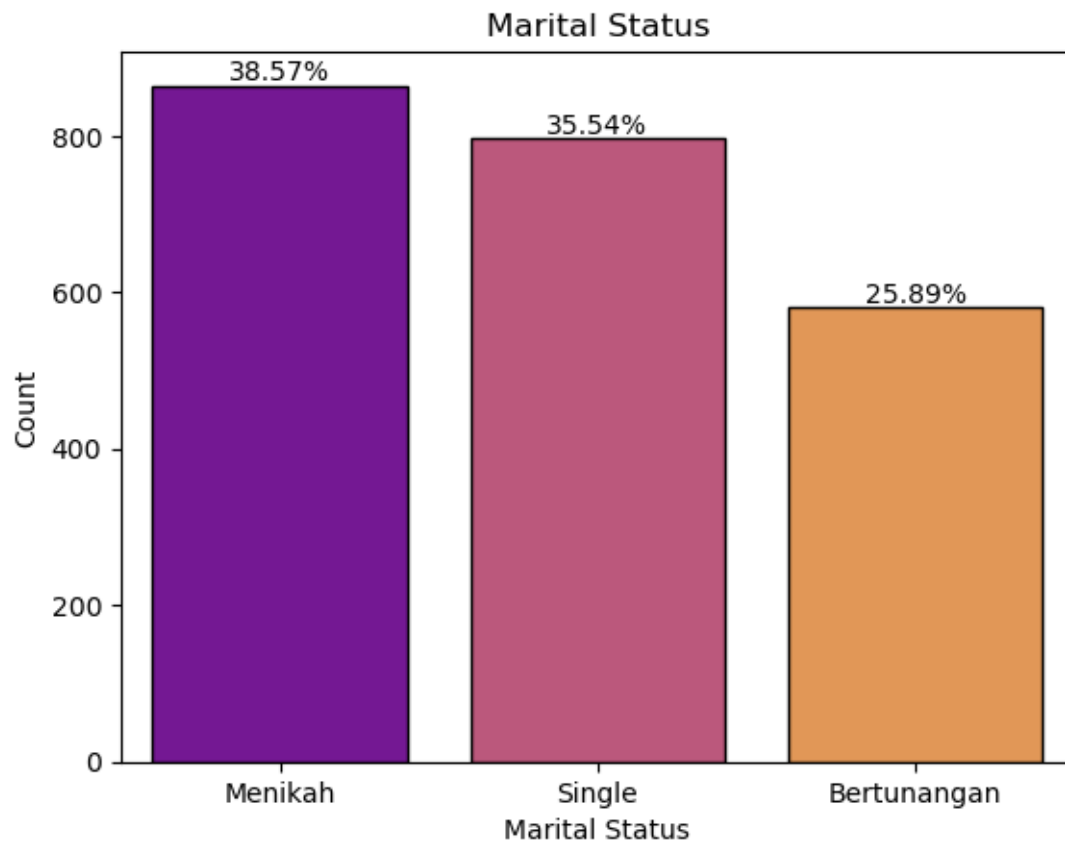
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 15 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Education             2240 non-null   object
1   Marital_Status        2240 non-null   object
2   Income                2240 non-null   float64
3   Dt_Customer           2240 non-null   datetime64[ns]
4   Recency               2240 non-null   int64
5   NumWebVisitsMonth     2240 non-null   int64
6   Complain              2240 non-null   int64
7   Total_Acc_Cmp         2240 non-null   int64
8   Total_Purchases       2240 non-null   int64
9   Total_Spent           2240 non-null   int64
10  conversion_rate        2240 non-null   float64
11  Dt_Days_Customer       2240 non-null   int64
12  Age                   2240 non-null   int64
13  Age_Group              2240 non-null   object
14  Number_Children       2240 non-null   int64
dtypes: datetime64[ns](1), float64(2), int64(9), object(3)
memory usage: 262.6+ KB
```

```
[20]: counts = df_copy['Marital_Status'].value_counts()
percent = round((counts / len(df_copy)) * 100, 2)
sns.barplot(x=counts.index, y=counts.values, edgecolor='black',
            palette='plasma')

# Menampilkan persentase pada plot
for i, count in enumerate(counts):
    plt.text(i, count, f'{percent[i]}%', ha='center', va='bottom')

plt.title('Marital Status')
plt.xlabel('Marital Status')
```

```
plt.ylabel('Count')
plt.show()
```



0.7 Handle Duplicated Data

```
[30]: df_copy[df_copy.duplicated(keep='last')].head(5)
```

```
[30]:
```

	Education	Marital_Status	Income	Dt_Customer	Recency	\
8	S3	Bertunangan	30351000.0	2013-06-06	19	
15	S3	Single	82800000.0	2012-11-24	23	
17	S1	Bertunangan	37760000.0	2012-08-31	20	
23	S3	Menikah	65324000.0	2014-11-01	0	
24	S1	Bertunangan	40689000.0	2013-03-18	69	

	NumWebVisitsMonth	Complain	Total_Acc_Cmp	Total_Purchases	Total_Spent	\
8	9	0	0	6	46000	
15	3	0	2	26	1315000	
17	7	0	0	13	317000	
23	4	0	0	20	544000	

24	8	0	0	20	444000
----	---	---	---	----	--------

	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
8	0.666667	3708	49	Middle Aged	1
15	8.666667	3902	77	Senior Citizen	0
17	1.857143	3987	77	Senior Citizen	0
23	5.000000	3195	69	Senior Citizen	1
24	2.500000	3788	72	Senior Citizen	1

```
[31]: df_copy[df_copy.duplicated(keep='first')].head(10)
```

```
[31]:
```

	Education	Marital_Status	Income	Dt_Customer	Recency \
83	S2	Bertunangan	38620000.0	2013-11-05	56
179	D3	Menikah	78497000.0	2013-01-12	44
281	S1	Bertunangan	51369000.0	2012-10-25	84
282	S1	Bertunangan	37760000.0	2012-08-31	20
363	S3	Menikah	37717000.0	2012-11-23	31
383	D3	Menikah	35688000.0	2012-08-22	94
408	S3	Bertunangan	30351000.0	2013-06-06	19
421	S1	Menikah	30096000.0	2014-05-22	30
443	S1	Single	30279000.0	2012-12-30	13
463	S1	Menikah	80124000.0	2014-06-26	47

	NumWebVisitsMonth	Complain	Total_Acc_Cmp	Total_Purchases	Total_Spent \
83	3	0	0	11	318000
179	2	0	1	25	978000
281	8	0	0	16	576000
282	7	0	0	13	317000
363	9	0	0	4	25000
383	8	0	0	16	211000
408	9	0	0	6	46000
421	6	0	0	6	45000
443	8	0	0	5	37000
463	1	0	1	19	1495000

	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
83	3.666667	3556	60	Senior Citizen	0
179	12.500000	3853	72	Senior Citizen	0
281	2.000000	3932	47	Middle Aged	1
282	1.857143	3987	77	Senior Citizen	0
363	0.444444	3903	45	Middle Aged	1
383	2.000000	3996	50	Middle Aged	3
408	0.666667	3708	49	Middle Aged	1
421	1.000000	3358	40	Middle Aged	1
443	0.625000	3866	34	Adult	1
463	19.000000	3323	60	Senior Citizen	0

```
[32]: df_copy[df_copy.duplicated(keep=False)].head(10)
```

```
[32]:
```

	Education	Marital_Status	Income	Dt_Customer	Recency	\
8	S3	Bertunangan	30351000.0	2013-06-06	19	
15	S3	Single	82800000.0	2012-11-24	23	
17	S1	Bertunangan	37760000.0	2012-08-31	20	
23	S3	Menikah	65324000.0	2014-11-01	0	
24	S1	Bertunangan	40689000.0	2013-03-18	69	
29	S3	Menikah	84618000.0	2013-11-22	96	
30	S2	Single	10979000.0	2014-05-22	34	
31	S2	Bertunangan	38620000.0	2013-11-05	56	
38	S1	Single	42429000.0	2014-11-02	99	
39	S3	Single	48948000.0	2013-01-02	53	

	NumWebVisitsMonth	Complain	Total_Acc_Cmp	Total_Purchases	Total_Spent	\
8	9	0	0	6	46000	
15	3	0	2	26	1315000	
17	7	0	0	13	317000	
23	4	0	0	20	544000	
24	8	0	0	20	444000	
29	2	0	1	26	1672000	
30	5	0	0	8	30000	
31	3	0	0	11	318000	
38	5	0	0	7	67000	
39	6	0	1	24	902000	

	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
8	0.666667	3708	49	Middle Aged	1
15	8.666667	3902	77	Senior Citizen	0
17	1.857143	3987	77	Senior Citizen	0
23	5.000000	3195	69	Senior Citizen	1
24	2.500000	3788	72	Senior Citizen	1
29	13.000000	3539	58	Middle Aged	0
30	1.600000	3358	34	Adult	0
31	3.666667	3556	60	Senior Citizen	0
38	1.400000	3194	50	Middle Aged	1
39	4.000000	3863	80	Senior Citizen	0

```
[33]: df_copy = df_copy.drop_duplicates(keep = 'first')
```

```
[34]: df_copy.head(2)
```

```
[34]:
```

	Education	Marital_Status	Income	Dt_Customer	Recency	\
0	S1	Single	58138000.0	2012-04-09	58	
1	S1	Single	46344000.0	2014-08-03	38	

	NumWebVisitsMonth	Complain	Total_Acc_Cmp	Total_Purchases	Total_Spent	\
--	-------------------	----------	---------------	-----------------	-------------	---

0	7	0	0	25	1617000
1	5	0	0	6	27000

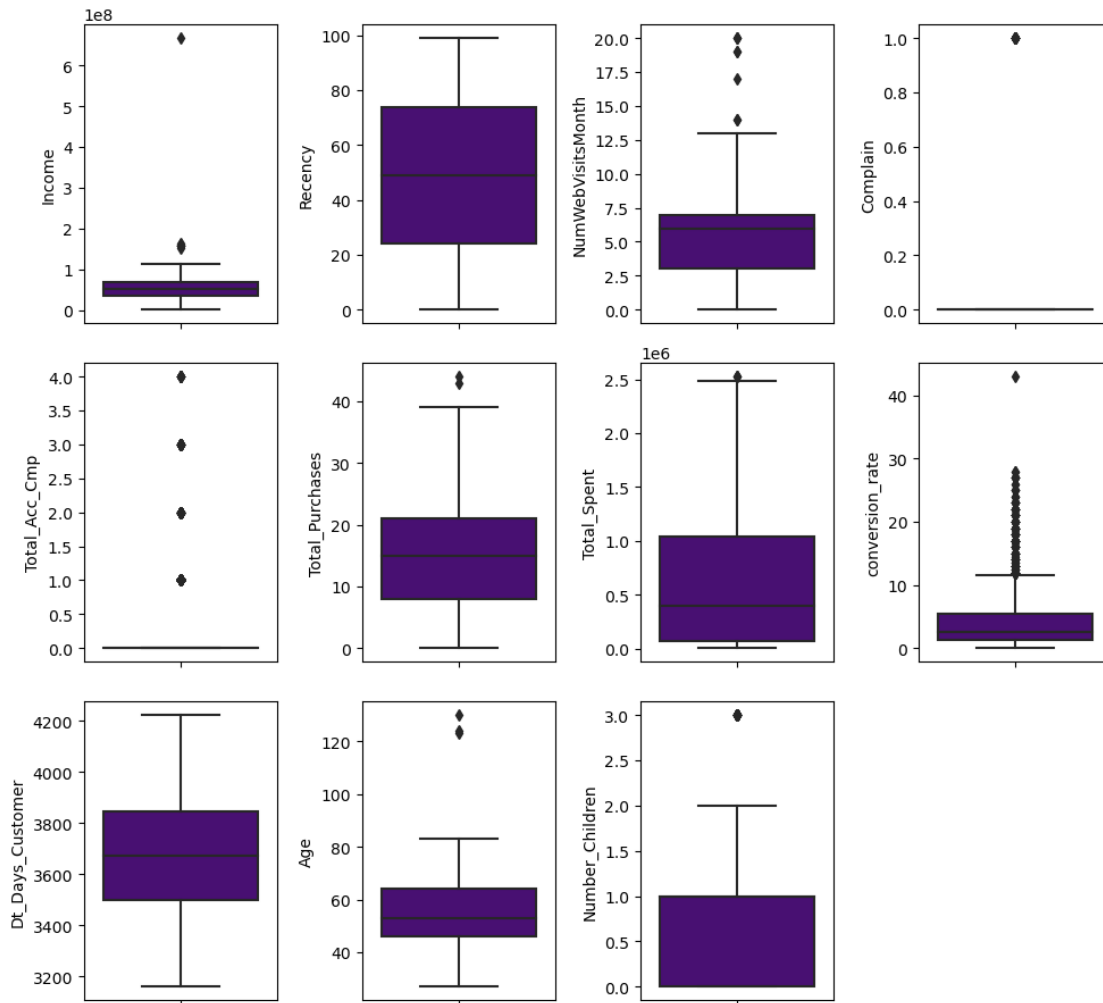
	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
0	3.571429	4131	66	Senior Citizen	0
1	1.200000	3285	69	Senior Citizen	2

0.8 Handle Outlier

```
[21]: df_copy_num = df_copy.select_dtypes(include = 'number')
df_copy_cat = df_copy.select_dtypes(exclude = 'number')
print(df_copy_num.columns)
print(df_copy_cat.columns)

Index(['Income', 'Recency', 'NumWebVisitsMonth', 'Complain', 'Total_Acc_Cmp',
      'Total_Purchases', 'Total_Spent', 'conversion_rate', 'Dt_Days_Customer',
      'Age', 'Number_Children'],
      dtype='object')
Index(['Education', 'Marital_Status', 'Dt_Customer', 'Age_Group'],
      dtype='object')
```

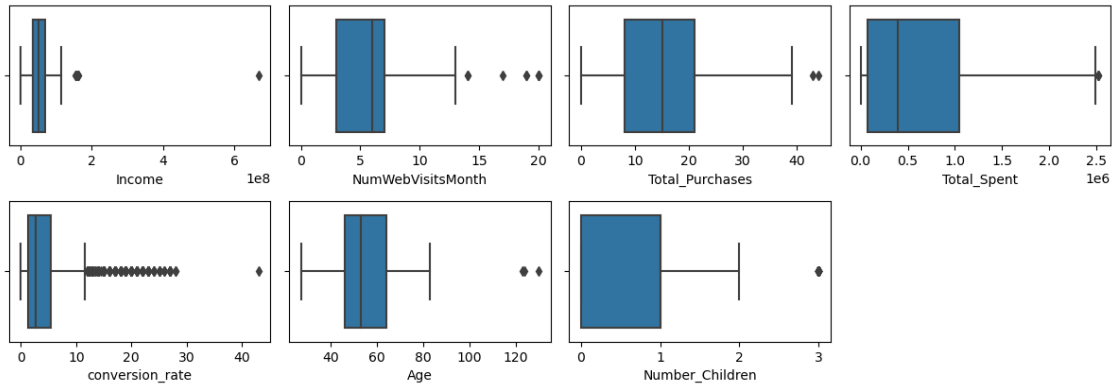
```
[22]: features = df_copy_num.columns
plt.figure(figsize= (10,15))
for i in range(len(features)):
    plt.subplot(5, 4, i+1)
    sns.boxplot(y = df_copy[features[i]], color = 'indigo', orient='v')
plt.tight_layout()
```



```
[23]: outliers = df_copy[['Income', 'NumWebVisitsMonth', 'Total_Purchases', 'Total_Spent', 'conversion_rate', 'Age', 'Number_Children']]
```

```
[24]: cols = outliers.columns

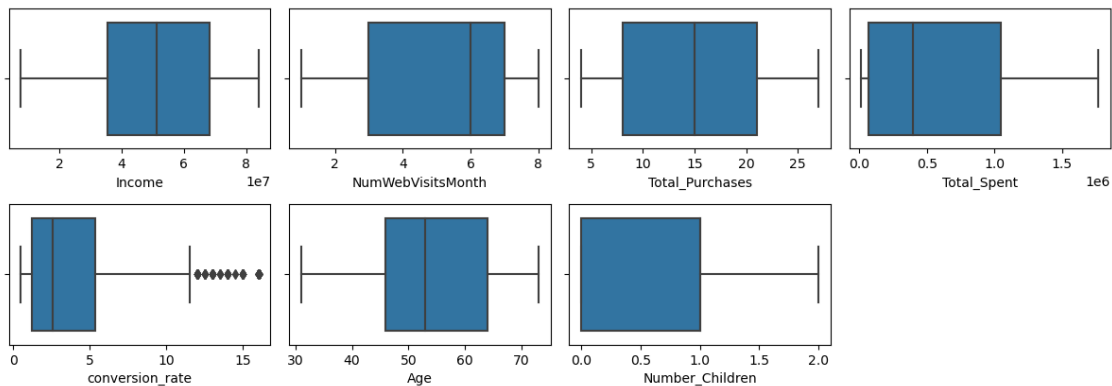
plt.figure(figsize=(12,8))
for i, column in enumerate(df_copy[cols].columns, 1):
    plt.subplot(4,4,i)
    sns.boxplot(data=df_copy[cols], x=df_copy[column])
    plt.tight_layout()
```



```
[25]: for col in cols:
        high_cut = df_copy[col].quantile(q=0.95)
        low_cut= df_copy[col].quantile(q=0.01)
        df_copy.loc[df_copy[col]>high_cut,col]=high_cut
        df_copy.loc[df_copy[col]<low_cut,col]=low_cut
```

```
[26]: cols = outliers.columns

plt.figure(figsize=(12,8))
for i, column in enumerate (df_copy[cols].columns, 1):
    plt.subplot(4,4,i)
    sns.boxplot(data=df_copy[cols], x=df_copy[column])
    plt.tight_layout()
```



```
[27]: df_copy.head()
```

```
[27]:   Education Marital_Status      Income Dt_Customer  Recency \
0         S1         Single  58138000.0  2012-04-09        58
1         S1         Single  46344000.0  2014-08-03        38
```

2	S1	Bertunangan	71613000.0	2013-08-21	26
3	S1	Bertunangan	26646000.0	2014-10-02	26
4	S3	Menikah	58293000.0	2014-01-19	94

	NumWebVisitsMonth	Complain	Total_Acc_Cmp	Total_Purchases	Total_Spent	\
0	7	0	0	25	1617000.0	
1	5	0	0	6	27000.0	
2	4	0	0	21	776000.0	
3	6	0	0	8	53000.0	
4	5	0	0	19	422000.0	

	conversion_rate	Dt_Days_Customer	Age	Age_Group	Number_Children
0	3.571429	4131	66	Senior Citizen	0
1	1.200000	3285	69	Senior Citizen	2
2	5.250000	3632	58	Middle Aged	0
3	1.333333	3225	39	Adult	1
4	3.800000	3481	42	Middle Aged	1

0.9 Encoding

```
[28]: df_copy_enc = df_copy.copy()
```

```
[29]: # label encoding Education
MappingEducation = {
    'SMA' : 0,
    'D3' : 1,
    'S1' : 2,
    'S2' : 3,
    'S3' : 4
}

df_copy_enc['Education'] = df_copy_enc['Education'].map(MappingEducation)
```

```
[30]: for i in ['Marital_Status', 'Age_Group']:
    onehots = pd.get_dummies(df_copy_enc[i], prefix='enc')
    df_copy_enc = df_copy_enc.join(onehots)
```

```
[31]: df_copy_enc = df_copy_enc.drop(['Marital_Status', 'Age_Group'], axis=1)
```

```
[32]: df_final = df_copy_enc[['Recency', 'Total_Purchases', 'Total_Spent',
    ↪ 'Dt_Days_Customer', 'Age']]
```

```
[33]: df_final.describe()
```

```
[33]:
```

	Recency	Total_Purchases	Total_Spent	Dt_Days_Customer	\
count	2240.000000	2240.000000	2.240000e+03	2240.000000	

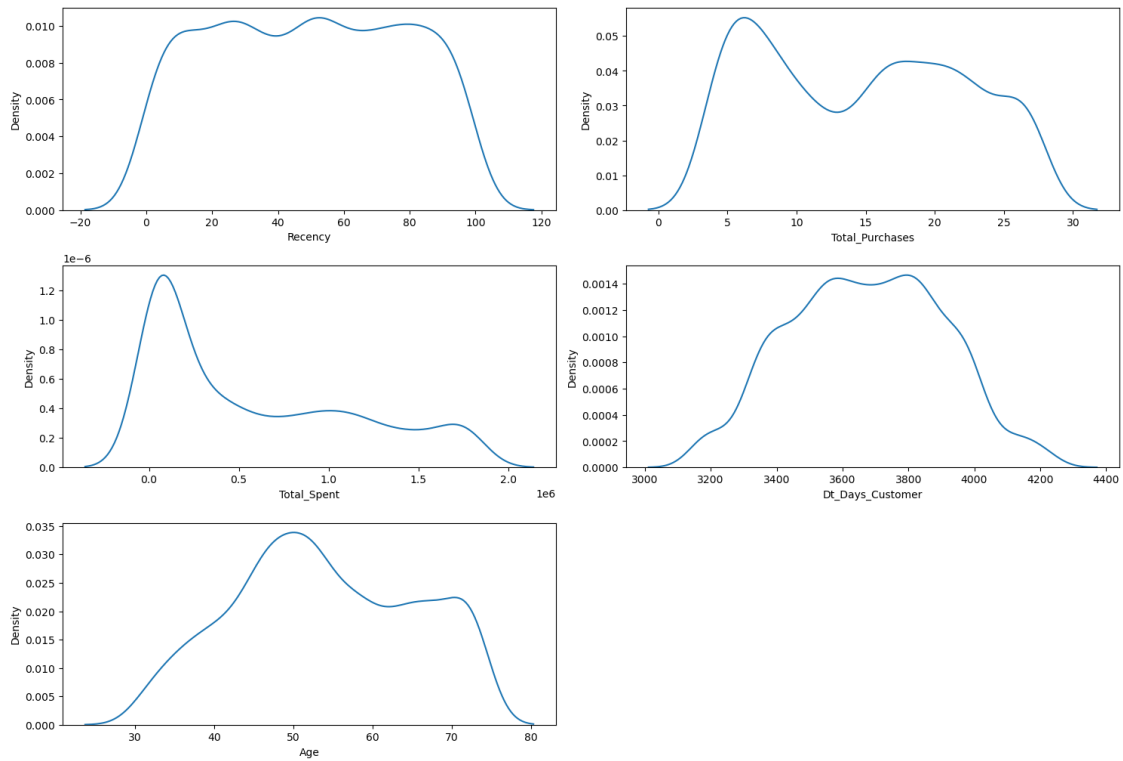
mean	49.109375	14.732143	5.940284e+05	3672.043304
std	28.962453	7.360654	5.749063e+05	232.229893
min	0.000000	4.000000	1.300000e+04	3160.000000
25%	24.000000	8.000000	6.875000e+04	3500.750000
50%	49.000000	15.000000	3.960000e+05	3673.000000
75%	74.000000	21.000000	1.045500e+06	3845.250000
max	99.000000	27.000000	1.772300e+06	4223.000000

	Age
count	2240.000000
mean	53.989732
std	11.409209
min	31.000000
25%	46.000000
50%	53.000000
75%	64.000000
max	73.000000

0.10 Transformation

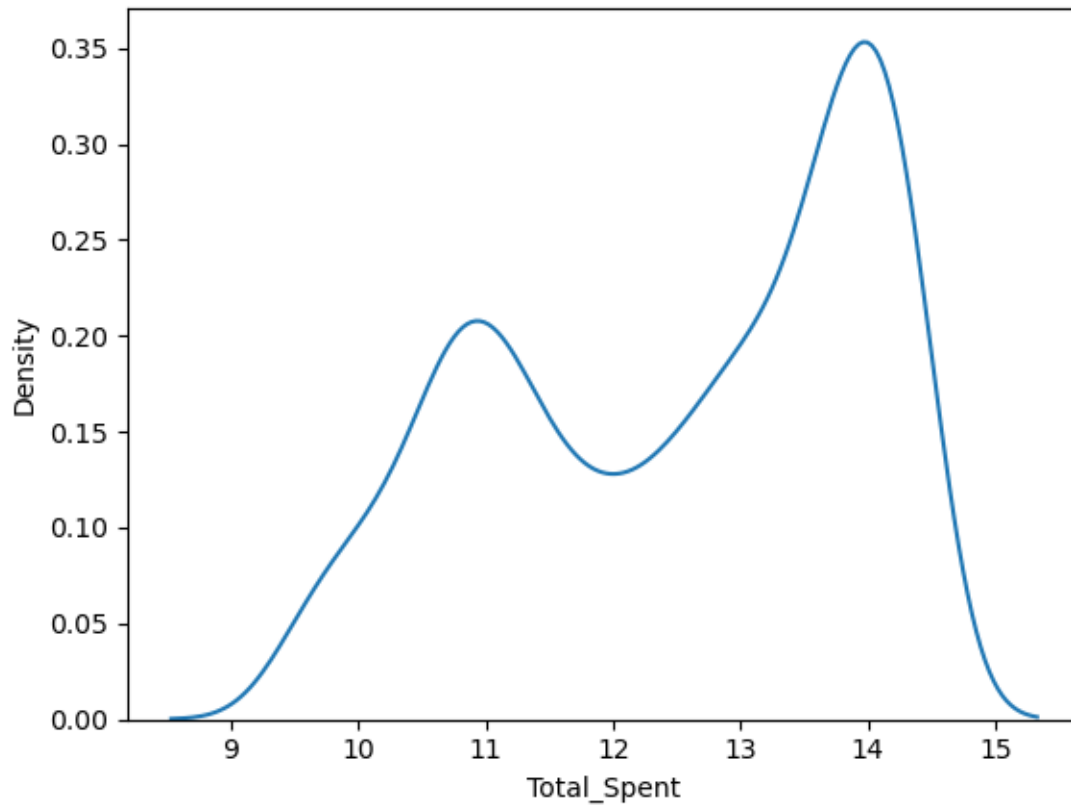
```
[34]: cols = df_final.columns

plt.figure(figsize= (15, 20))
for i in range(len(cols)):
    plt.subplot(6, 2, i+1)
    sns.kdeplot(x = df_final[cols[i]])
plt.tight_layout()
```



```
[35]: #Log Transformasi
df_final['log_TotalSpent'] = np.log(df_final['Total_Spent'])
sns.kdeplot(np.log(df_final['Total_Spent']))
```

```
[35]: <Axes: xlabel='Total_Spent', ylabel='Density'>
```

```
[36]: df_final = df_final.drop(columns='Total_Spent')
```

```
[37]: df_final.head()
```

```
[37]:
```

	Recency	Total_Purchases	Dt_Days_Customer	Age	log_TotalSpent
0	58	25	4131	66	14.296083
1	38	6	3285	69	10.203592
2	26	21	3632	58	13.561908
3	26	8	3225	39	10.878047
4	94	19	3481	42	12.952761

0.11 Scalling

```
[38]: from sklearn.preprocessing import StandardScaler, MinMaxScaler
col_name = list(df_final.columns)

mm = MinMaxScaler()
df_std = mm.fit_transform(df_final)
df_std = pd.DataFrame(df_std, columns=col_name)
df_std.sample(10)
```

```
[38]:
```

	Recency	Total_Purchases	Dt_Days_Customer	Age	log_TotalSpent
1755	0.424242	0.260870	0.591722	0.309524	0.218234
1815	0.808081	0.043478	0.473189	0.214286	0.148703
2153	0.303030	0.478261	0.624647	0.547619	0.607927
939	0.080808	0.826087	0.427093	0.404762	0.840946
98	0.444444	0.913043	0.651929	0.976190	0.879041
2101	0.636364	1.000000	0.186265	1.000000	0.878624
84	0.181818	1.000000	0.267168	0.119048	0.832494
720	0.010101	0.521739	0.674506	0.642857	0.876318
2237	0.919192	0.652174	0.296331	0.261905	0.927497
1813	0.686869	0.347826	0.644403	0.000000	0.966332

```
[39]: df_std.describe()
```

```
[39]:
```

	Recency	Total_Purchases	Dt_Days_Customer	Age	\
count	2240.000000	2240.000000	2240.000000	2240.000000	
mean	0.496054	0.466615	0.481696	0.547375	
std	0.292550	0.320028	0.218467	0.271648	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.242424	0.173913	0.320555	0.357143	
50%	0.494949	0.478261	0.482596	0.523810	
75%	0.747475	0.739130	0.644638	0.785714	
max	1.000000	1.000000	1.000000	1.000000	

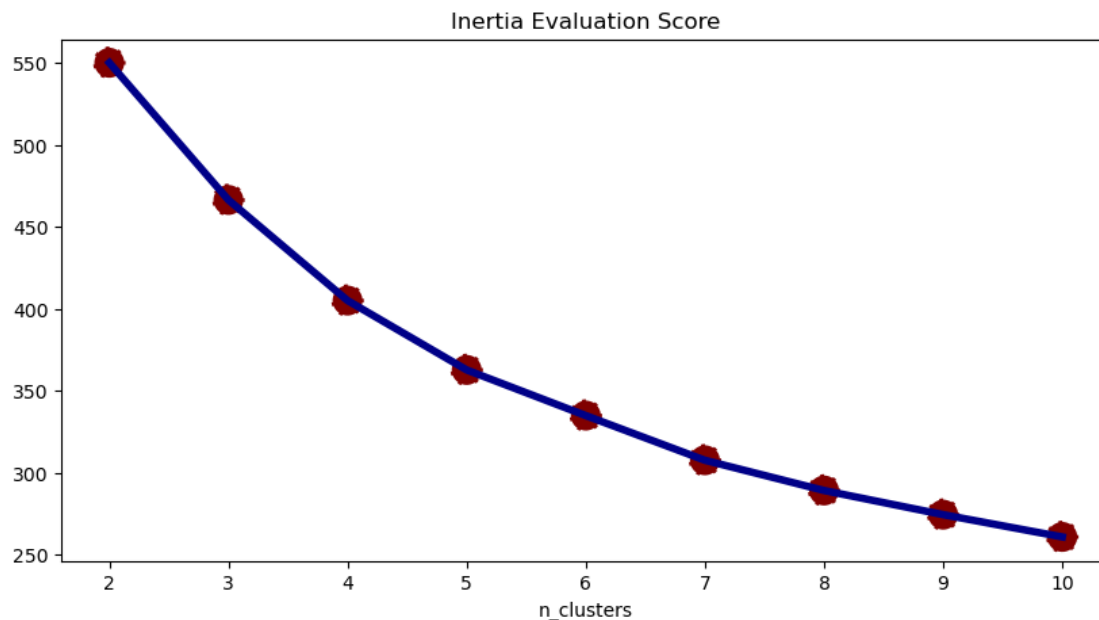
	log_TotalSpent
count	2240.000000
mean	0.618985
std	0.298746
min	0.000000
25%	0.338856
50%	0.695098
75%	0.892620
max	1.000000

0.12 Modelling

```
[40]: #Inertia
from sklearn.cluster import KMeans
inertia = []

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(df_std)
    inertia.append(kmeans.inertia_)
```

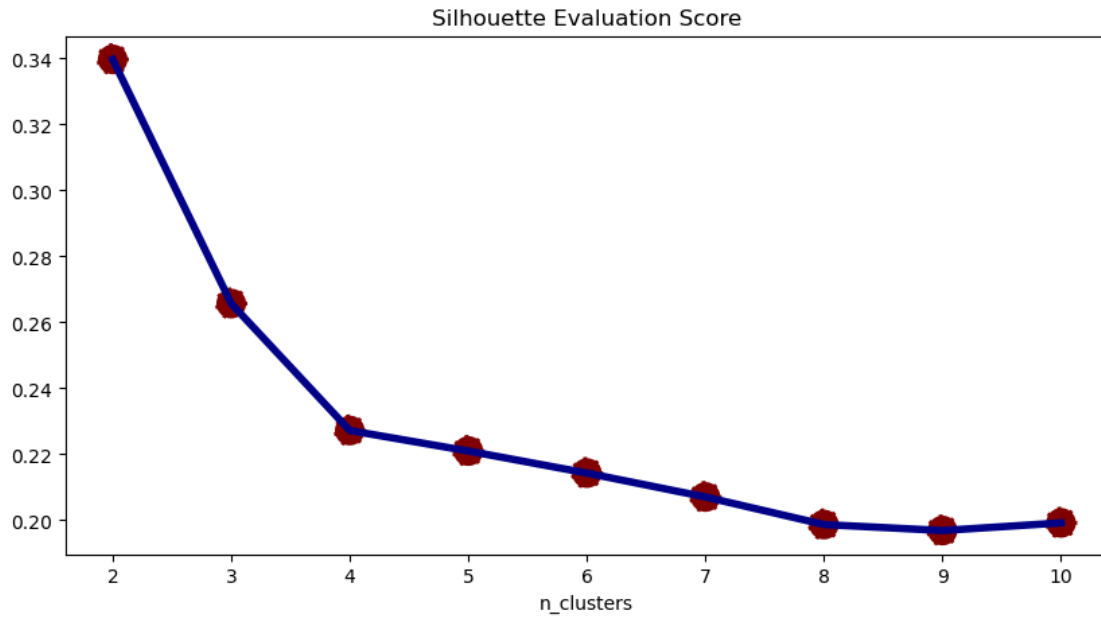
```
plt.figure(figsize=(10, 5))
plt.title('Inertia Evaluation Score')
sns.lineplot(x=range(2, 11), y=inertia, color='#000087', linewidth = 4)
sns.scatterplot(x=range(2, 11), y=inertia, s=300, color='#800000',
                linestyle='--')
plt.xlabel('n_clusters')
plt.show()
```



```
[41]: from sklearn.metrics import silhouette_score

range_n_clusters = list(range(2,11))
arr_silhouette_score_euclidean = []
for i in range_n_clusters:
    kmeans = KMeans(n_clusters=i).fit(df_std)
    preds = kmeans.predict(df_std)
    score_euclidean = silhouette_score(df_std, preds, metric='euclidean')
    arr_silhouette_score_euclidean.append(score_euclidean)

fig, ax = plt.subplots(figsize=(10, 5))
plt.title('Silhouette Evaluation Score')
sns.lineplot(x=range(2,11), y=arr_silhouette_score_euclidean, color='#000087',
            linewidth = 4)
sns.scatterplot(x=range(2,11), y=arr_silhouette_score_euclidean, s=300,
                color='#800000', linestyle='--')
plt.xlabel('n_clusters')
plt.show()
```



```
[42]: df_std_cluster = df_std.copy()
df_cluster = df_std.copy()

kmeans = KMeans(n_clusters=4, random_state=0).fit(df_std)
df_std_cluster['clusters'] = kmeans.labels_
df_cluster['clusters'] = kmeans.labels_
```

```
[43]: df_cluster.sample(10)
```

```
[43]:
```

	Recency	Total_Purchases	Dt_Days_Customer	Age	log_TotalSpent	\
901	0.464646	0.304348	0.448730	0.523810	0.559147	
1802	0.858586	0.260870	0.552211	0.976190	0.540257	
580	0.646465	0.478261	0.739417	0.428571	0.570832	
151	0.969697	0.652174	0.146754	0.547619	0.725578	
1376	0.262626	0.695652	0.320790	0.404762	0.695098	
1836	0.121212	0.913043	0.426152	0.523810	0.893881	
562	0.121212	0.956522	0.497648	0.500000	0.836892	
1151	0.969697	0.869565	0.779868	0.666667	0.960422	
908	0.949495	0.086957	0.234243	0.428571	0.333614	
959	0.484848	0.521739	0.553151	0.833333	0.676271	

	clusters
901	3
1802	3
580	1
151	1

1376	0
1836	0
562	0
1151	1
908	3
959	1

```
[44]: df_cluster.isna().sum()
```

```
[44]: Recency          0
      Total_Purchases  0
      Dt_Days_Customer  0
      Age             0
      log_TotalSpent   0
      clusters        0
      dtype: int64
```

```
[45]: from sklearn.decomposition import PCA
      pca = PCA(n_components=2)

      pca.fit(df_std)
      pcs = pca.transform(df_std)

      df_pca = pd.DataFrame(data = pcs, columns = ['PC 1', 'PC 2'])
      df_pca['clusters'] = df_cluster['clusters']
      df_pca.sample(10)
```

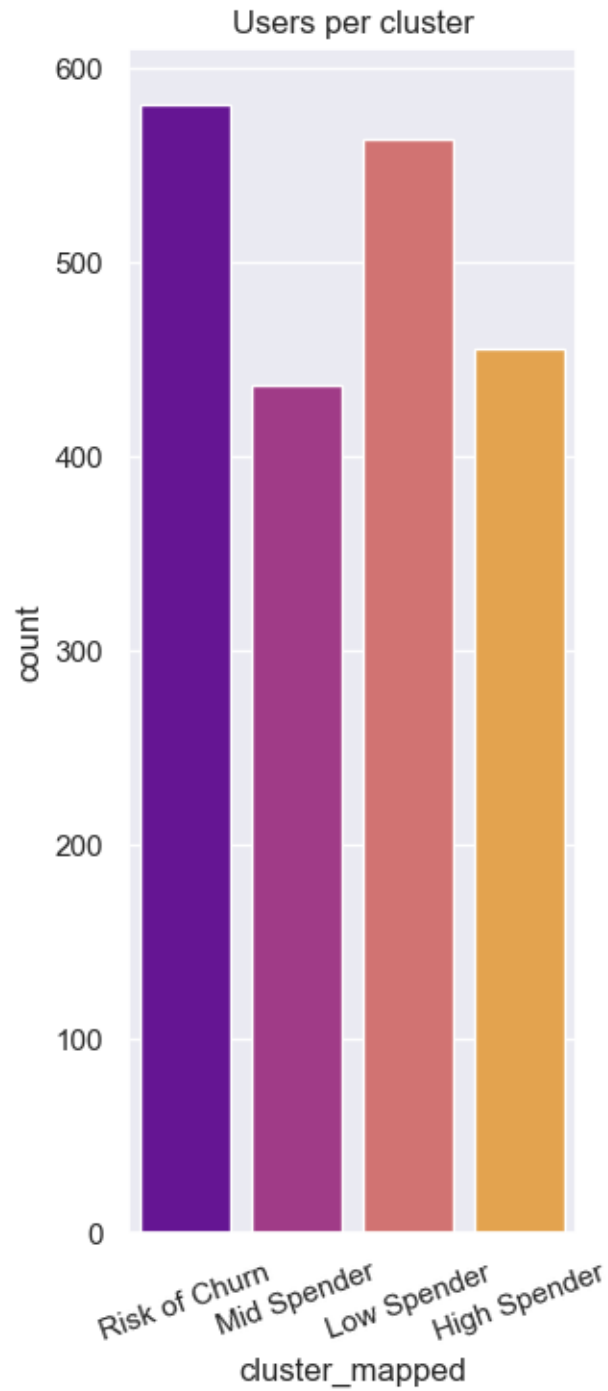
```
[45]:      PC 1      PC 2  clusters
1281 -0.134196  0.480227         1
1697  0.020823  0.212362         1
204   0.516697  0.256971         3
984  -0.551000 -0.310294         0
1166  0.441773 -0.342310         2
609  -0.285423  0.337087         1
1730  0.437591 -0.114573         2
626  -0.358230  0.049722         1
690  -0.405670  0.507884         1
1622 -0.325039  0.265383         1
```

```
[46]: map_cluster = {
      0 : 'Low Spender',
      1 : 'Risk of Churn',
      2 : 'Mid Spender',
      3 : 'High Spender'
      }

      df_pca['cluster_mapped'] = df_pca['clusters'].map(map_cluster)
```

```
[76]: sns.countplot(x=df_pca['cluster_mapped'], palette='plasma')  
plt.title('Users per cluster')  
plt.xticks(rotation=20)
```

```
[76]: (array([0, 1, 2, 3]),  
      [Text(0, 0, 'Risk of Churn'),  
       Text(1, 0, 'Mid Spender'),  
       Text(2, 0, 'Low Spender'),  
       Text(3, 0, 'High Spender')])
```



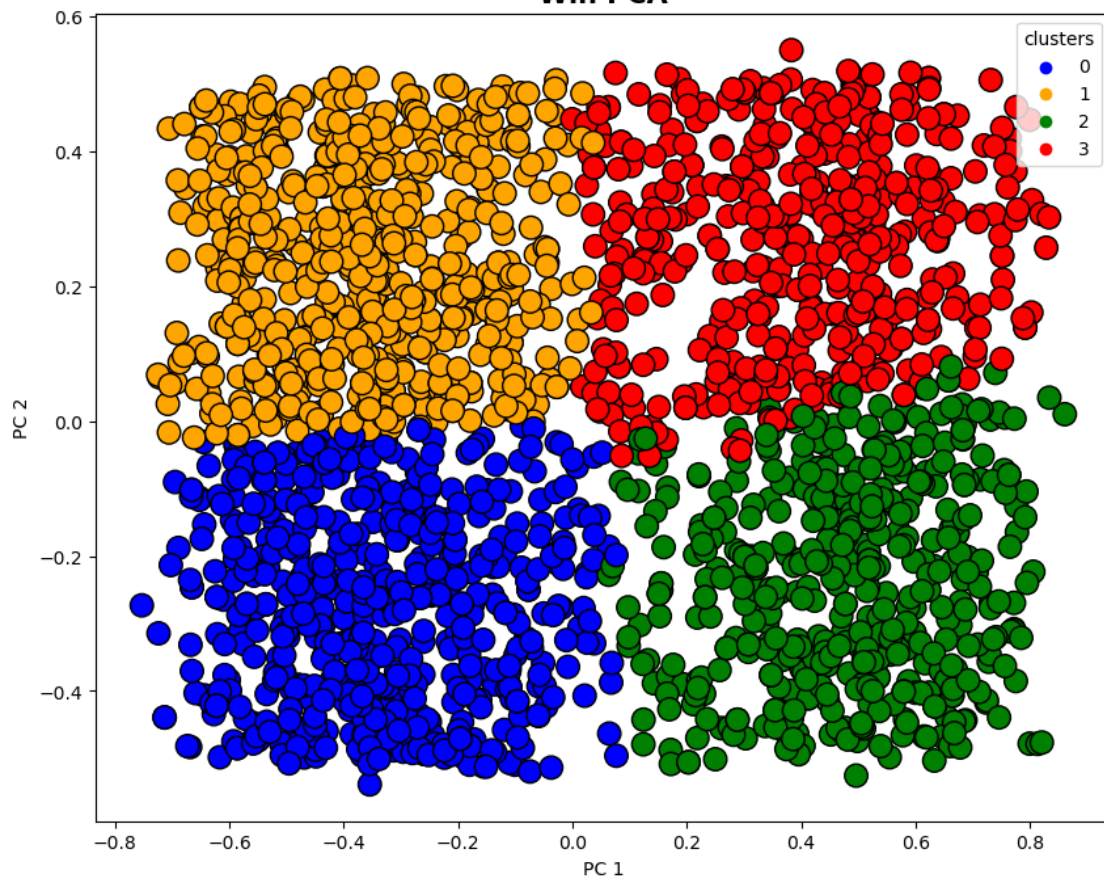
```
[47]: fig, ax = plt.subplots(figsize=(10,8))
plt.title("2-D Visualization of Customer Clusters\nWith PCA", fontsize=15,
weight='bold')
sns.scatterplot(
    x="PC 1", y="PC 2",
```

```

hue="clusters",
edgecolor='black',
#linestyle='--',
data=df_pca,
palette=['blue','orange','green','red'],
s=160,
ax=ax
);

```

**2-D Visualization of Customer Clusters
With PCA**



```

[48]: fig = plt.figure(figsize=(15,10))
ax = fig.add_subplot(111, projection='3d')
plt.title("3-D Visualization of Customer Clusters\nBased on it's_
↳Characteristics", fontsize=15, weight='bold')
ax.scatter(df_cluster['Recency'][df_cluster.clusters == 0],_
↳df_cluster['Total_Purchases'][df_cluster.clusters == 0],_
↳df_cluster['log_TotalSpent'][df_cluster.clusters == 0], c='blue', s=100,_
↳edgecolor='black', label='High Spender')

```



```

ax.scatter(df_cluster['Recency'][df_cluster.clusters == 1],  

↳df_cluster['Total_Purchases'][df_cluster.clusters == 1],  

↳df_cluster['log_TotalSpent'][df_cluster.clusters == 1], c='orange', s=100,  

↳edgecolor='black', label='Mid of Churn')
ax.scatter(df_cluster['Recency'][df_cluster.clusters == 2],  

↳df_cluster['Total_Purchases'][df_cluster.clusters == 2],  

↳df_cluster['log_TotalSpent'][df_cluster.clusters == 2], c='green', s=100,  

↳edgecolor='black', label='Risk of Churn')
ax.scatter(df_cluster['Recency'][df_cluster.clusters == 3],  

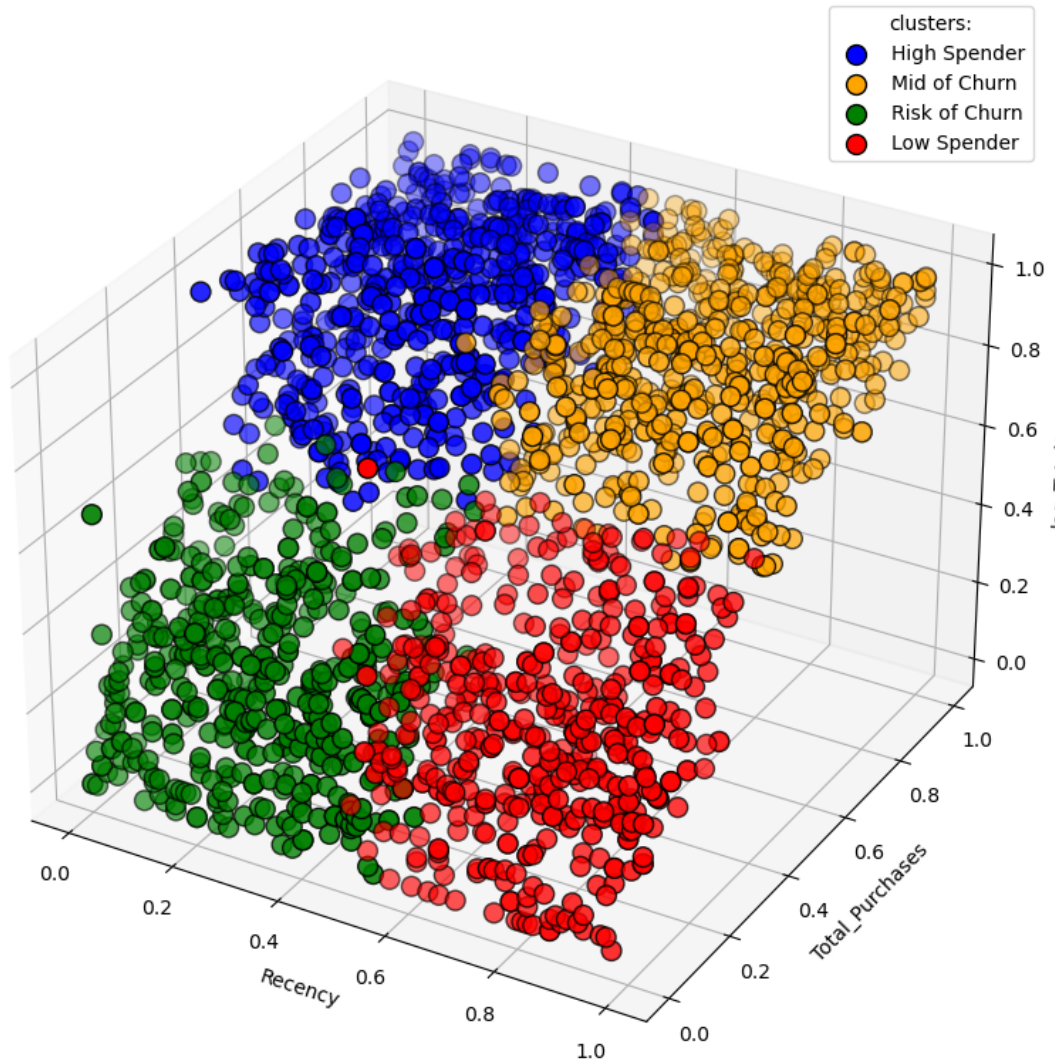
↳df_cluster['Total_Purchases'][df_cluster.clusters == 3],  

↳df_cluster['log_TotalSpent'][df_cluster.clusters == 3], c='red', s=100,  

↳edgecolor='black', label='Low Spender')
plt.xlabel('Recency')
plt.ylabel('Total_Purchases')
ax.set_zlabel('log_TotalSpent')
plt.legend(title='clusters:')
plt.show()

```

3-D Visualization of Customer Clusters Based on it's Characteristics



1 Customer Personality Analysis For Marketing Retargeting

```
[49]: display(df_cluster.groupby('clusters').agg(['mean', 'median', 'max', 'min']))
```

	Recency				Total_Purchases		\
	mean	median	max	min	mean	median	
clusters							
0	0.231426	0.232323	0.505051	0.000000	0.712815	0.695652	
1	0.737640	0.727273	1.000000	0.454545	0.716818	0.695652	
2	0.250098	0.242424	0.585859	0.000000	0.135925	0.130435	

3	0.749756	0.767677	1.000000	0.404040	0.166813	0.130435
---	----------	----------	----------	----------	----------	----------

	Dt_Days_Customer \					
	max	min	mean	median	max	min
clusters						
0	1.000000	0.26087	0.501478	0.511759	0.998119	0.000941
1	1.000000	0.26087	0.526298	0.533396	1.000000	0.000941
2	0.478261	0.00000	0.440279	0.423330	1.000000	0.000000
3	0.521739	0.00000	0.440449	0.436500	1.000000	0.002822

	Age				log_TotalSpent		
	mean	median	max	min	mean	median	max
clusters							
0	0.579926	0.571429	1.0	0.0	0.847887	0.871194	1.000000
1	0.611517	0.619048	1.0	0.0	0.860460	0.881111	1.000000
2	0.438221	0.428571	1.0	0.0	0.296491	0.297127	0.709955
3	0.532114	0.500000	1.0	0.0	0.343623	0.332085	0.988997

	min
clusters	
0	0.570832
1	0.555098
2	0.000000
3	0.000000

```
[50]: df_intp = df_cluster.groupby('clusters').agg({'Recency': 'count'}).reset_index()
df_intp = df_intp.rename(columns={'Recency': 'total_customers'})
df_intp['jmlh_cust'] = df_intp['total_customers'].sum()
df_intp['persentage'] = round((df_intp['total_customers']/
    ↳df_intp['jmlh_cust'])*100, 2)
df_intp
```

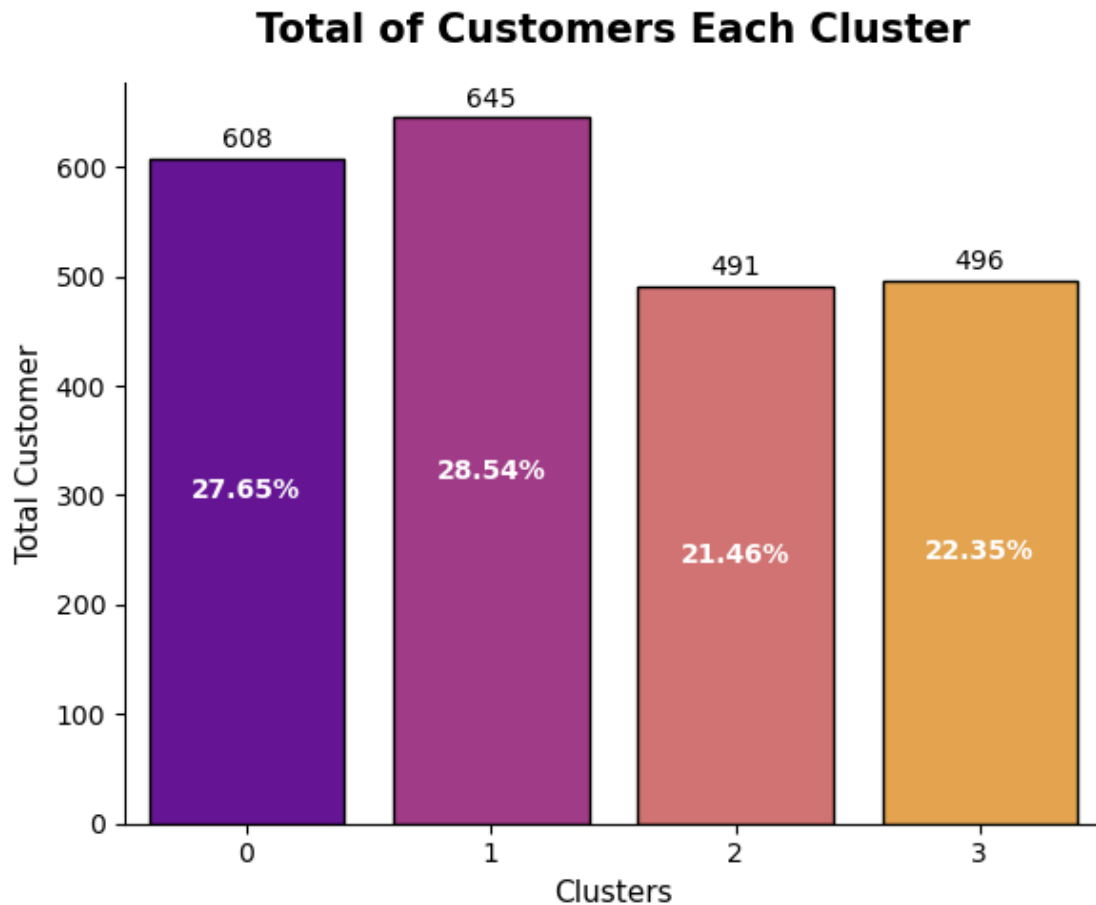
	clusters	total_customers	jmlh_cust	persentage
0	0	608	2240	27.14
1	1	645	2240	28.79
2	2	491	2240	21.92
3	3	496	2240	22.14

```
[51]: fig, ax = plt.subplots(figsize=(6, 5))
plt.title("Total of Customers Each Cluster", fontsize=15, color='black',
    ↳weight='bold', pad=15)
sns.barplot(x='clusters', y='total_customers', data=df_intp, edgecolor='black',
    ↳palette='plasma')

plt.xlabel('Clusters', fontsize=11)
plt.ylabel('Total Customer', fontsize=11)
```

```
plt.bar_label(ax.containers[0], padding=2)
plt.bar_label(ax.containers[0], ['27.65%', '28.54%', '21.46%', '22.35%'],
    label_type='center', color='white', weight='bold')

sns.despine()
plt.tight_layout()
```

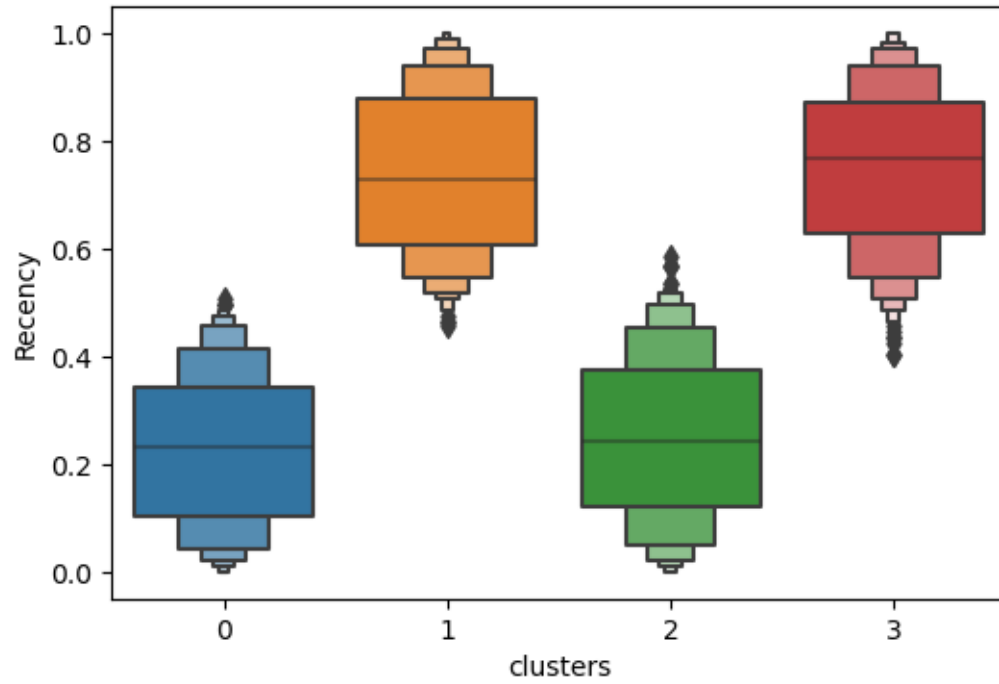


1.0.1 Total Spending/Cluster

```
[52]: df1 = df_cluster.copy()
      dff = df1.columns.drop('clusters')
```

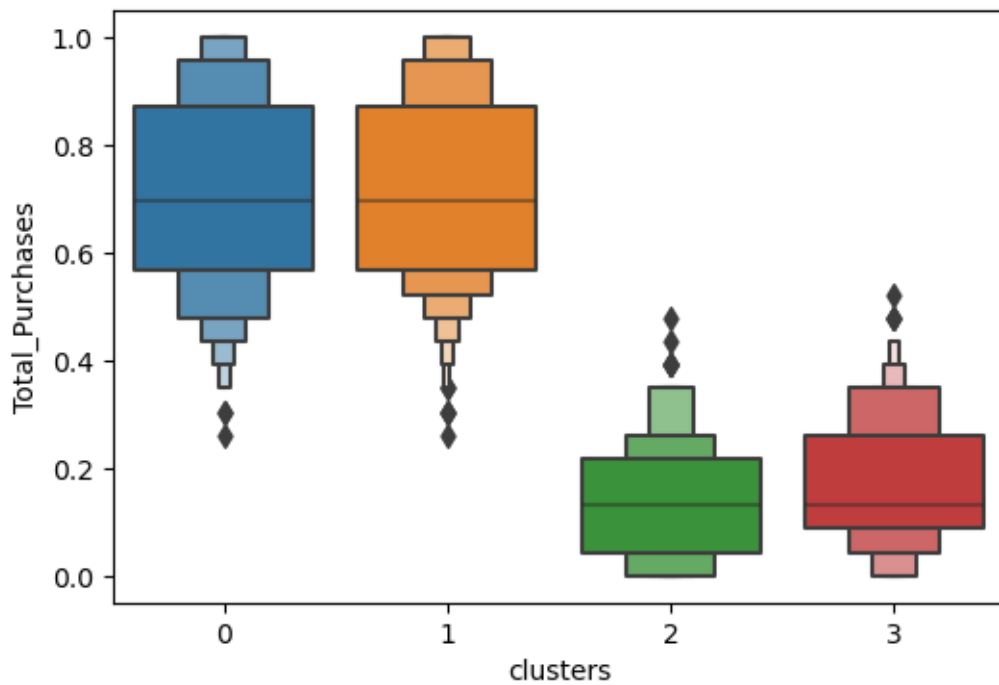
```
[53]: plt.figure(figsize= (6, 4))
      sns.boxenplot(x=df_cluster['clusters'], y=df_cluster['Recency'])
```

```
[53]: <Axes: xlabel='clusters', ylabel='Recency'>
```



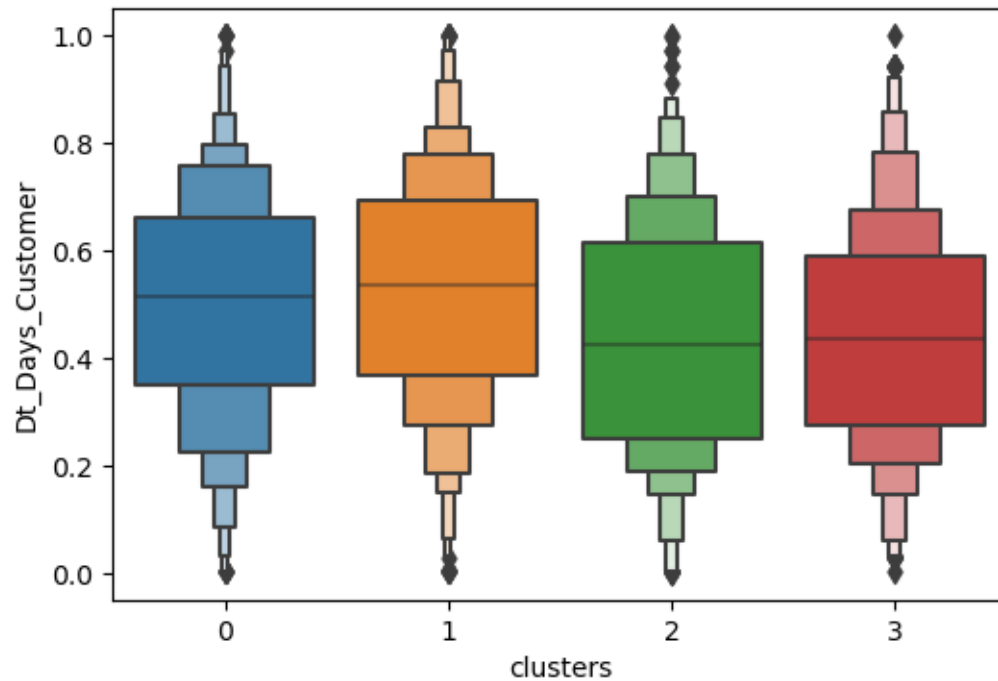
```
[54]: plt.figure(figsize= (6, 4))
sns.boxenplot(x=df_cluster['clusters'], y=df_cluster['Total_Purchases'])
```

[54]: <Axes: xlabel='clusters', ylabel='Total_Purchases'>



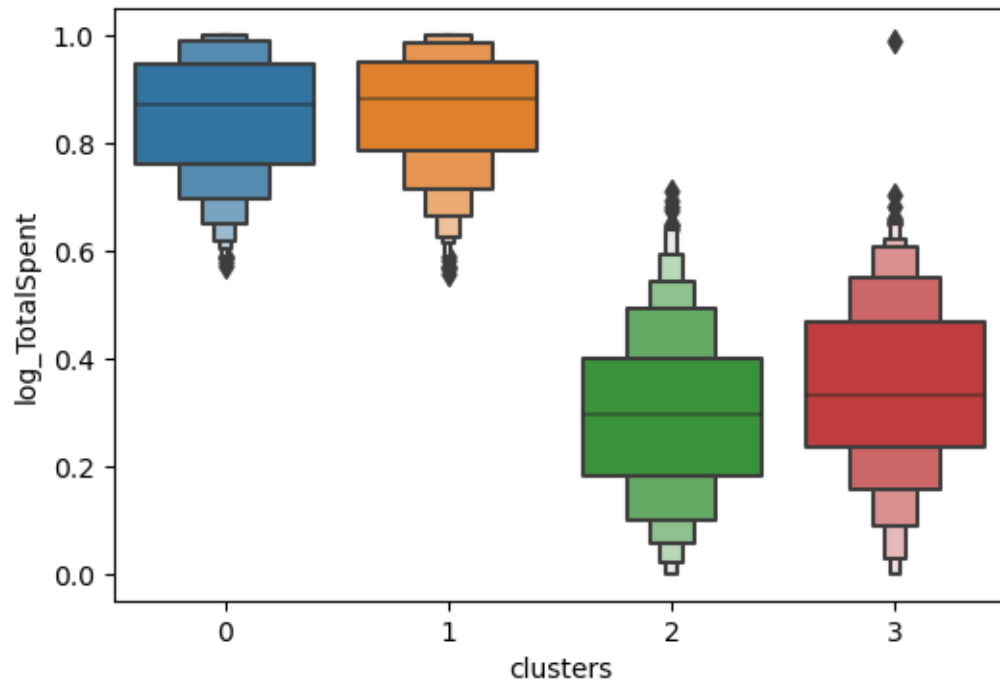
```
[55]: plt.figure(figsize= (6, 4))  
sns.boxenplot(x=df_cluster['clusters'], y=df_cluster['Dt_Days_Customer'])
```

```
[55]: <Axes: xlabel='clusters', ylabel='Dt_Days_Customer'>
```



```
[56]: plt.figure(figsize= (6, 4))  
sns.boxenplot(x=df_cluster['clusters'], y=df_cluster['log_TotalSpent'])
```

```
[56]: <Axes: xlabel='clusters', ylabel='log_TotalSpent'>
```



```
[57]: df_copy['Clusters'] = kmeans.labels_
df_copy.head()
```

```
[57]: Education Marital_Status      Income Dt_Customer  Recency \
0      S1          Single  58138000.0  2012-04-09      58
1      S1          Single  46344000.0  2014-08-03      38
2      S1  Bertunangan  71613000.0  2013-08-21      26
3      S1  Bertunangan  26646000.0  2014-10-02      26
4      S3      Menikah  58293000.0  2014-01-19      94

  NumWebVisitsMonth  Complain  Total_Acc_Cmp  Total_Purchases  Total_Spent \
0                  7         0              0                25    1617000.0
1                  5         0              0                 6     27000.0
2                  4         0              0                21    776000.0
3                  6         0              0                 8     53000.0
4                  5         0              0                19    422000.0

  conversion_rate  Dt_Days_Customer  Age  Age_Group  Number_Children \
0      3.571429      4131      66  Senior Citizen              0
1      1.200000      3285      69  Senior Citizen              2
2      5.250000      3632      58  Middle Aged              0
3      1.333333      3225      39      Adult              1
4      3.800000      3481      42  Middle Aged              1
```

	Clusters
0	1
1	2
2	0
3	2
4	1

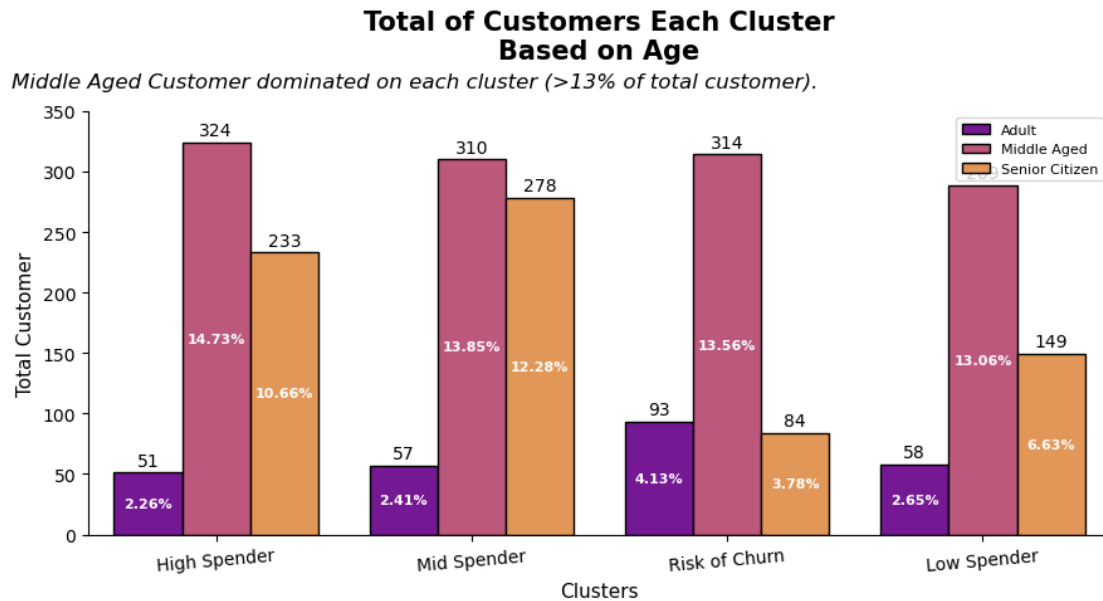
```
[58]: age_cluster = df_copy.groupby(['Clusters', 'Age_Group']).agg({'Education':
    ↳ 'count'}).reset_index()
age_cluster = age_cluster.rename(columns={'Education': 'Total_Cust'})
age_cluster['sum_cust'] = age_cluster['Total_Cust'].sum()
age_cluster['percentage'] = round((age_cluster['Total_Cust']/
    ↳ age_cluster['sum_cust'])*100, 2)
age_cluster
```

	Clusters	Age_Group	Total_Cust	sum_cust	percentage
0	0	Adult	51	2240	2.28
1	0	Middle Aged	324	2240	14.46
2	0	Senior Citizen	233	2240	10.40
3	1	Adult	57	2240	2.54
4	1	Middle Aged	310	2240	13.84
5	1	Senior Citizen	278	2240	12.41
6	2	Adult	93	2240	4.15
7	2	Middle Aged	314	2240	14.02
8	2	Senior Citizen	84	2240	3.75
9	3	Adult	58	2240	2.59
10	3	Middle Aged	289	2240	12.90
11	3	Senior Citizen	149	2240	6.65

```
[59]: fig, ax = plt.subplots(figsize=(9, 5))
plt.title("Total of Customers Each Cluster\nBased on Age", fontsize=15,
    ↳ color='black', weight='bold', pad=30)
sns.barplot(x='Clusters', y='Total_Cust', data=age_cluster, hue='Age_Group',
    ↳ edgecolor='black', palette='plasma')
plt.text(x=-0.8, y=370, s="Middle Aged Customer dominated on each cluster (>13%\n↳ of total customer).", fontsize=12, fontstyle='italic')
plt.xlabel('Clusters', fontsize=11)
plt.xticks(np.arange(4), ['High Spender', 'Mid Spender', 'Risk of Churn', 'Low\n↳ Spender'], rotation=5)
plt.ylabel('Total Customer', fontsize=11)
plt.ylim(0, 350)
plt.legend(prop={'size':8}, loc='best')
plt.bar_label(ax.containers[0], padding=2)
plt.bar_label(ax.containers[1], padding=2)
plt.bar_label(ax.containers[2], padding=2)
plt.bar_label(ax.containers[0], ['2.26%', '2.41%', '4.13%', '2.65%'],
    ↳ label_type='center', color='white', weight='bold', fontsize=8)
```



```
plt.bar_label(ax.containers[1], ['14.73%', '13.85%', '13.56%', '13.06%'],
             label_type='center', color='white', weight='bold', fontsize=8)
plt.bar_label(ax.containers[2], ['10.66%', '12.28%', '3.78%', '6.63%'],
             label_type='center', color='white', weight='bold', fontsize=8)
sns.despine()
plt.tight_layout()
```



2 Sumamary

1. High Spender

- This group is dominated by middle aged (45-54 years old) who are predominantly married and have 1 child.
- there are 563 customers (27.65% of total customers) on this group.
- Customers on this group have high average recency (25 days) and high average of total purchases (70 items) it means they are frequent shoppers and they spend a lot on our platform (around IDR 9M/year)
- This group has a high conversion rate.

2. mid spender

- Dominated by middle aged (13.85%) who are predominantly married and have 1 child.
- there are 581 customers (28.54% of total customers) on this group
- Customers on this group have high average recency (78 days) and high average of total purchases (70 items) and they spend a lot on our platform (around IDR 9M/year)

3. Risk of Churn

- there are 437 customers (22.35% of total customers) on this group
- Dominated by middle aged (13.85%) who are predominantly married and have 1 child.
- Customers on this group have high average recency (25 days) and high average of total purchases (15 items) and they spend a lot on our platform (around IDR 2.7M/year)

4. Low Spender

- there are 455 customers (21.46% of total customers) on this group
- Dominated by middle aged (13.85%) who are predominantly married and have 1 child.
- Customers on this group have high average recency (70 days) and high average of total purchases (16 items) and they spend a lot on our platform (around IDR 3M/year)

Recommendations 1. Keep monitoring transactions and retention of the High Spender group, Focus on improving service so that this group group does not churn. 2. For the Mid Spender group, further analysis can be done on how to increase transactions by providing more personalized recommendations, as well as deeper analysis on how to optimize promos in this segment and keep shopping on our platform. 3. For the Low Spender group, further analysis can also be done on how to increase the conversion rate of visits to transactions, They have a fairly high recency but do not make transactions. This can be caused by products or prices that do not match.

```
[135]: print('Total Spent of High Spender: '+str(df_copy[df_copy['Clusters']==0] .
        ↪Total_Spent.sum()))
print('Total Spent of Mid Spender: '+str(df_copy[df_copy['Clusters']==1] .
        ↪Total_Spent.sum()))
print('Total Spent of Risk of Churn: '+str(df_copy[df_copy['Clusters']==2] .
        ↪Total_Spent.sum()))
print('Total Spent of Low Spender: '+str(df_copy[df_copy['Clusters']==3] .
        ↪Total_Spent.sum()))
print('Total Spent: '+str(545880250+588456250+32527500+44894850))
```

```
Total Spent of High Spender: 545880250.0
Total Spent of Mid Spender: 588456250.0
Total Spent of Risk of Churn: 32527500.0
Total Spent of Low Spender: 44894850.0
Total Spent: 1211758850
```

Potential Impact (Quantitative): - If we keep prioritize on Customer Groups/Clusters and they do not turn to churn, we still have potential GMV around IDR 1.2B/year (High Spender: 545m/year; Mid Spender: 588M/year;

High-Valued Customer=IDR 670M/year; Low-Valued Customer=IDR 46M/year; Low-Valued Frequent Customer=IDR 604M/year; Low-Valued Customer=IDR 47M/year)