Problem Statement

Walmart is an American multinational retail corporation that operates a chain of supercenters, discount departmental stores, and grocery stores from the United States. Walmart has more than 100 million customers worldwide.

The Management team at Walmart Inc. wants to analyze the customer purchase behavior (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions. They want to understand if the spending habits differ between male and female customers: Do women spend more on Black Friday than men? (Assume 50 million customers are male and 50 million are female).

Column Profiling

- User_ID: User ID
- Product_ID: Product ID
- Gender: Sex of User
- Age: Age in bins
- Occupation: Occupation(Masked)
- City_Category: Category of the City (A,B,C)
- StayInCurrentCityYears: Number of years stay in current city
- Marital_Status: Marital Status
- ProductCategory: Product Category (Masked)
- Purchase: Purchase Amount

Loading dependencies and dataset

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

In [37]:
```
df = pd.read_csv('./data/walmart_data.txt')
df.head()
```

Out[37]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_
0	1000001	P00069042	F	0-17	10	A	2	0	
1	1000001	P00248942	F	0-17	10	A	2	0	
2	1000001	P00087842	F	0-17	10	A	2	0	
3	1000001	P00085442	F	0-17	10	A	2	0	
4	1000002	P00285442	M	55+	16	C	4+	0	

Basic Checks on the data

Shape

In [38]:
```
df.shape
```

Out[38]:
```
(550068, 10)
```

Information on dataframe

In [39]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   User_ID                     550068 non-null  int64 
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64 
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64 
 8   Product_Category            550068 non-null  int64 
 9   Purchase                    550068 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

Converting dtype of the below columns to object

In [40]:
```
df['User_ID'] = df['User_ID'].astype('object')
df['Occupation'] = df['Occupation'].astype('object')
df['Marital_Status'] = df['Marital_Status'].astype('object')
df['Product_Category'] = df['Product_Category'].astype('object')
```

Checking for missing values

In [41]:
```
df.isna().sum()
```

Out[41]:
```
User_ID                       0
Product_ID                    0
Gender                        0
Age                           0
Occupation                    0
City_Category                 0
Stay_In_Current_City_Years    0
Marital_Status                0
Product_Category              0
Purchase                      0
dtype: int64
```

EDA: Unique attributes & value counts

In [42]:
```
df.describe()
```

Out[42]:

	Purchase
count	550068.000000
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000
max	23961.000000

In [43]:
```
df.describe(include=['O'])
```

Out[43]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status
count	550068	550068	550068	550068	550068	550068	550068	550068
unique	5891	3631	2	7	21	3	5	2
top	1001680	P00265242	M	26-35	4	B	1	0
freq	1026	1880	414259	219587	72308	231173	193821	324731

In [44]:
```
df['Gender'].value_counts()
```

Out[44]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [45]:
```
df['Marital_Status'].value_counts()
```

Out[45]:
```
0    324731
1    225337
Name: Marital_Status, dtype: int64
```

In [46]:
```
df['City_Category'].value_counts()
```

Out[46]:
```
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

In [47]:
```
df['Stay_In_Current_City_Years'].value_counts()
```

Out[47]:
```
1     193821
2     101838
3      95285
4+     84726
0      74398
Name: Stay_In_Current_City_Years, dtype: int64
```

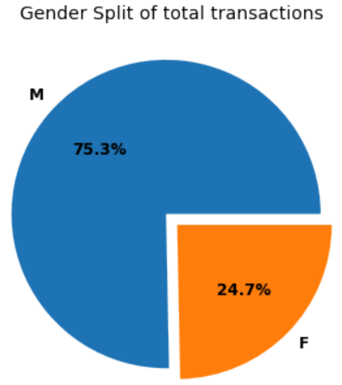
In [48]:
```
df['Age'].value_counts()
```

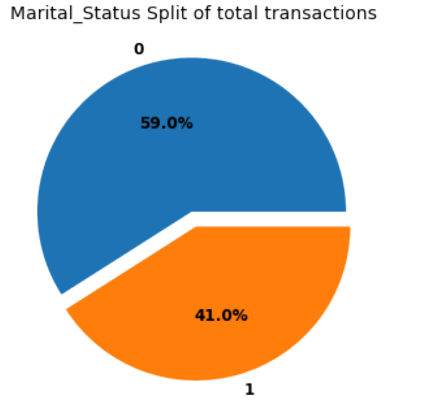
Out[48]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

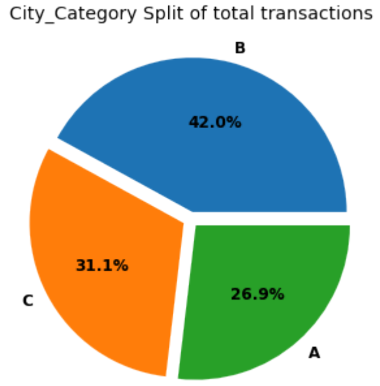
EDA: Univariate Analysis (@ Transaction Level)

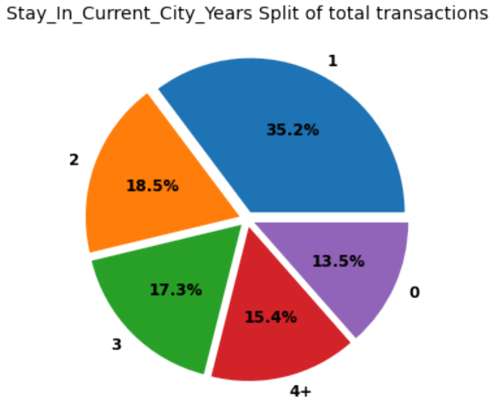
Feature: Gender, Marital_Status, City_Category, Stay_In_Current_City_Years

In [49]:
```
cat_cols1 = ['Gender', 'Marital_Status', 'City_Category', 'Stay_In_Current_City_Years']
id = 1
plt.figure(figsize=(20, 12))
for col in cat_cols1:
    plt.subplot(2, 2, id)
    plt.pie(df[col].value_counts().values, labels=df[col].value_counts().index,
            explode=(0.05, )*len(df[col].value_counts().values), autopct='%.1f%%',
            textprops = {'fontweight': 'bold', 'fontsize': 12})
    plt.title(f'{col} Split of total transactions', fontsize=14)
    id += 1
```







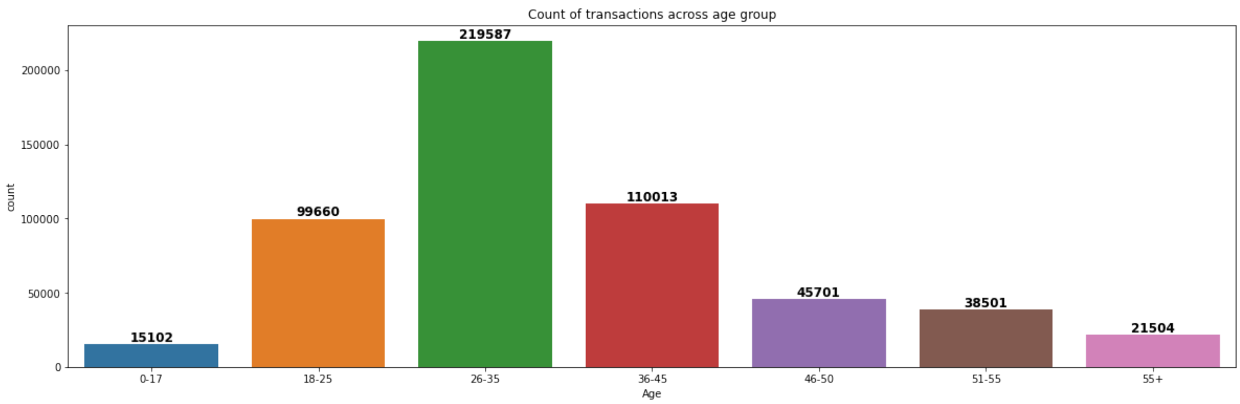


Observations:

- Gender split:
  - 3/4 of total transactions made by males
- Marital Status split:
  - 60% of total transactions made by singles
- Similar information is shown for City Category & Stay_In_Current_City_Years

Feature: Age

In [50]:
```
age_order = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
plt.figure(figsize=(20, 6))
f = sns.countplot(x=df['Age'], order=age_order)
for item in f.containers:
    f.bar_label(item, fontsize=12, fontweight='bold')
plt.title('Count of transactions across age group')
plt.show()
```

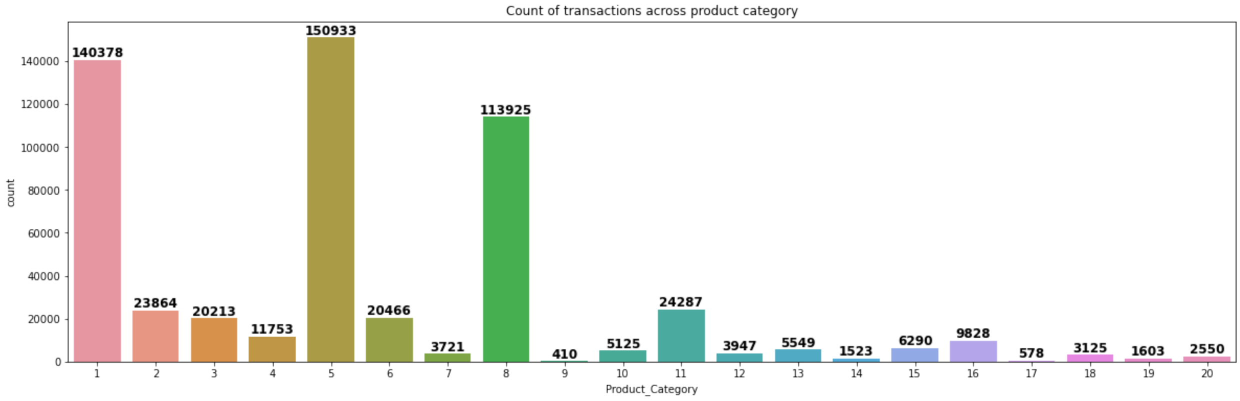


Observations:

- Most transactions are made by customers in the age range 26-35

Feature: Product_Category

In [51]:
```
plt.figure(figsize=(20, 6))
f = sns.countplot(x=df['Product_Category'])
for item in f.containers:
    f.bar_label(item, fontsize=12, fontweight='bold')
plt.title('Count of transactions across product category')
plt.show()
```

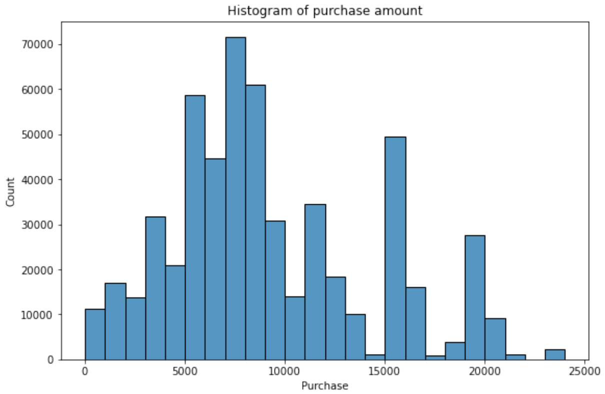


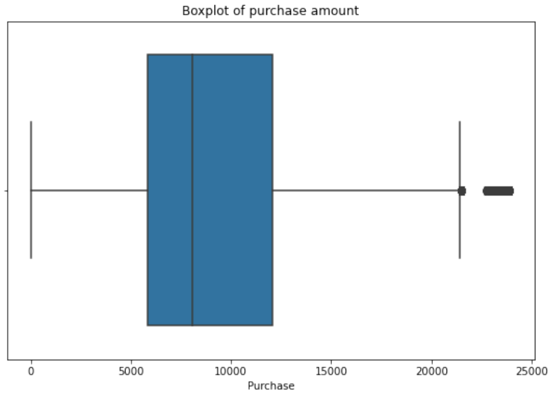
Observations:

- Popular product Categories:
  - 1, 5, 8
  - These categories have recored the maximum number of transactions

Feature: Purchase (with Outlier Detection)

In [52]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
f = sns.histplot(x=df['Purchase'], binwidth=1000)
# for item in f.containers:
#     f.bar_label(item, fontsize=10, fontweight='bold', rotation=30)
# f = sns.kdeplot(x=df['Purchase'])
plt.title('Histogram of purchase amount')
plt.subplot(1, 2, 2)
f = sns.boxplot(x=df['Purchase'])
plt.title('Boxplot of purchase amount')
plt.show()
```





In [53]:
```
purchase_25 = np.percentile(df['Purchase'], 25)
purchase_50 = np.percentile(df['Purchase'], 50)
purchase_75 = np.percentile(df['Purchase'], 75)
iqr = purchase_75 - purchase_25
upper = purchase_75 + 1.5*iqr
lower = purchase_25 - 1.5*iqr
print('Median:', purchase_50)
print('IQR:', iqr)
print('Lower Whisker:', max(0, lower))
print('Upper Whisker:', upper)
```

```
Median: 8047.0
IQR: 6231.0
Lower Whisker: 0
Upper Whisker: 21400.5
```

Observations:

- Outliers are above 21400 (by 1.5*IQR)

EDA: Bivariate Analysis (@ Transaction Level)

Transaction amount across Gender, Marital_Status, City_Category, Stay_In_Current_City_Years

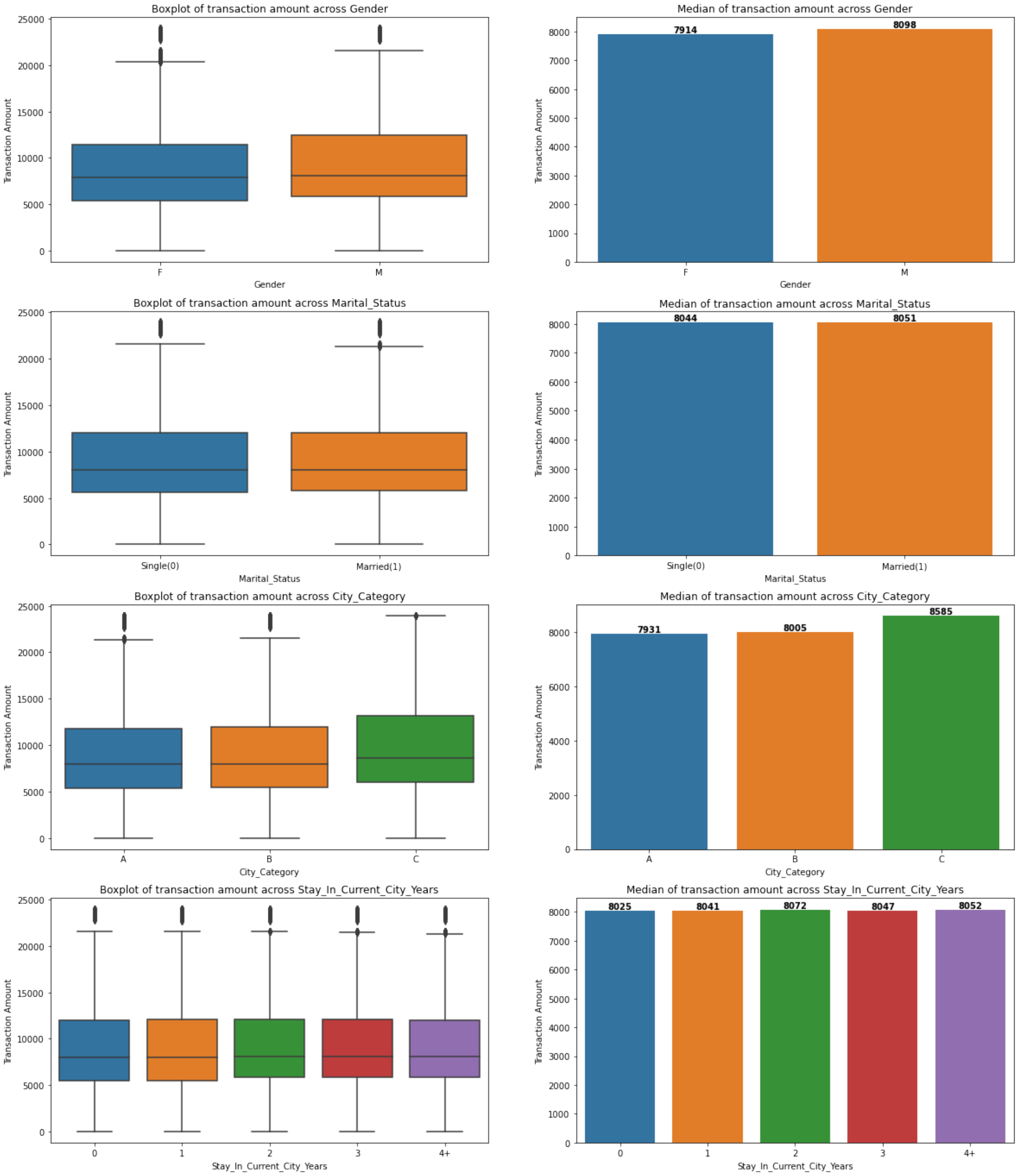
In [54]:
```
plt.figure(figsize=(20, 24))
plt.subplot(4, 2, 1)
sns.boxplot(y=df['Purchase'], x=df['Gender'])
plt.ylabel('Transaction Amount')
plt.title('Boxplot of transaction amount across Gender')
plt.subplot(4, 2, 2)
f = sns.barplot(y=df['Purchase'], x=df['Gender'], ci=None, estimator=np.median)
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across Gender')

plt.subplot(4, 2, 3)
sns.boxplot(y=df['Purchase'], x=df['Marital_Status'].apply(lambda x: 'Single(0)' if x==0 else 'Mar
plt.ylabel('Transaction Amount')
plt.title('Boxplot of transaction amount across Marital_Status')
plt.subplot(4, 2, 4)
f = sns.barplot(y=df['Purchase'], x=df['Marital_Status'].apply(lambda x: 'Single(0)' if x==0 else
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across Marital_Status')

plt.subplot(4, 2, 5)
sns.boxplot(y=df['Purchase'], x=df['City_Category'], order=['A', 'B', 'C'])
plt.ylabel('Transaction Amount')
plt.title('Boxplot of transaction amount across City_Category')
plt.subplot(4, 2, 6)
f = sns.barplot(y=df['Purchase'], x=df['City_Category'], order=['A', 'B', 'C'], ci=None, estimator=
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across City_Category')

plt.subplot(4, 2, 7)
sns.boxplot(y=df['Purchase'], x=df['Stay_In_Current_City_Years'], order=['0', '1', '2', '3', '4+']
plt.ylabel('Transaction Amount')
plt.title('Boxplot of transaction amount across Stay_In_Current_City_Years')
plt.subplot(4, 2, 8)
f = sns.barplot(y=df['Purchase'], x=df['Stay_In_Current_City_Years'], order=['0', '1', '2', '3', '
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across Stay_In_Current_City_Years')

plt.show()
```

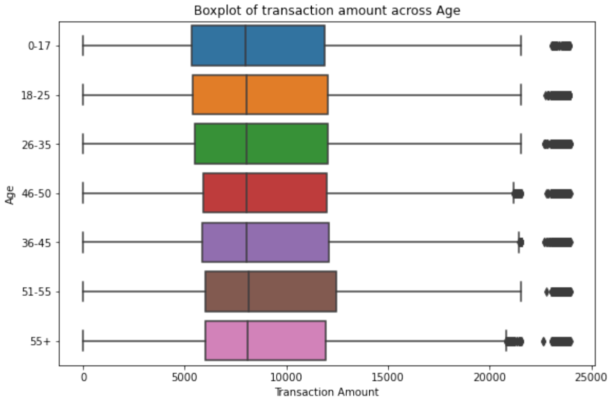


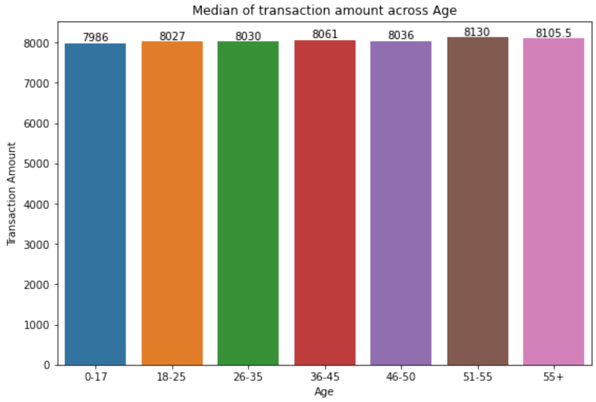
Observations:

- Median transaction amount of males is slighly higher than females
- Median transaction amount across marital status is indifferent
- Median transaction amount of city category 'C' is the highest
- Median transaction amount across Stay_In_Current_City_Years is indifferent

Transaction amount amount across Age

In [55]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x=df['Purchase'], y=df['Age'], order=['0-17', '18-25', '26-35', '46-50', '36-45', '51-5
plt.xlabel('Transaction Amount')
plt.title('Boxplot of transaction amount across Age')
plt.subplot(1, 2, 2)
f = sns.barplot(y=df['Purchase'], x=df['Age'], order=['0-17', '18-25', '26-35', '36-45', '46-50',
for item in f.containers:
    f.bar_label(item)
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across Age')
plt.show()
```





In [56]:
```
df.groupby('Age')['Purchase'].describe()
```

Out[56]:

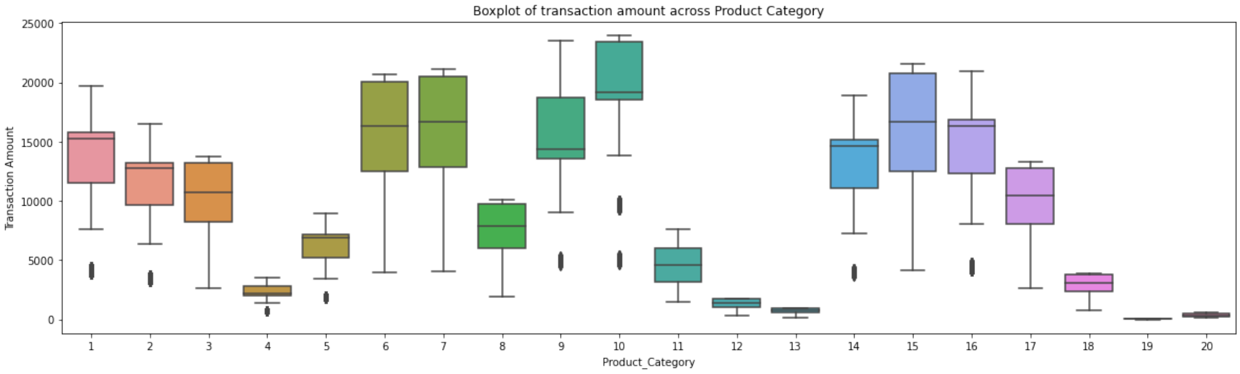
Age	count	mean	std	min	25%	50%	75%	max
0-17	15102.0	8933.464640	5111.114046	12.0	5328.0	7986.0	11874.0	23955.0
18-25	99660.0	9169.663606	5034.321997	12.0	5415.0	8027.0	12028.0	23958.0
26-35	219587.0	9252.690633	5010.527303	12.0	5475.0	8030.0	12047.0	23961.0
36-45	110013.0	9331.350695	5022.923879	12.0	5876.0	8061.0	12107.0	23960.0
46-50	45701.0	9208.625697	4967.216367	12.0	5888.0	8036.0	11997.0	23960.0
51-55	38501.0	9534.808031	5087.368080	12.0	6017.0	8130.0	12462.0	23960.0
55+	21504.0	9336.280459	5011.493996	12.0	6018.0	8105.5	11932.0	23960.0

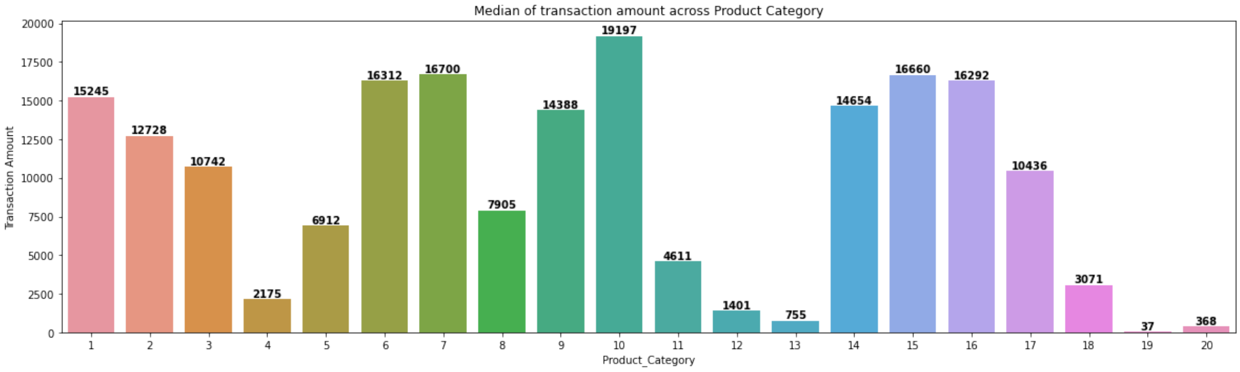
Observations:

- Median transaction amount across age brackets do not change much

Transaction amount across Product_Category

In [57]:
```
plt.figure(figsize=(20, 12))
plt.subplot(2, 1, 1)
sns.boxplot(y=df['Purchase'], x=df['Product_Category'])
plt.ylabel('Transaction Amount')
plt.title('Boxplot of transaction amount across Product Category')
plt.subplot(2, 1, 2)
f = sns.barplot(y=df['Purchase'], x=df['Product_Category'], ci=None, estimator=np.median)
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold', fmt='%.0f')
plt.ylabel('Transaction Amount')
plt.title('Median of transaction amount across Product Category')
# plt.subplot(3, 1, 3)
# f = sns.barplot(y=df['Purchase'], x=df['Product_Category'], ci=None, estimator=np.sum)
# for item in f.containers:
#     f.bar_label(item, fontsize=8, fontweight='bold', fmt='%.0f')
# plt.ylabel('Transaction Amount')
# plt.title('Sum of transaction amount across Product Category')
plt.show()
```





In [58]:
```
df.groupby('Product_Category')['Purchase'].describe().sort_values(['50%'], ascending=False)
```

Out[58]:

Product_Category	count	mean	std	min	25%	50%	75%	max
10	5125.0	19675.570927	4225.721898	4624.0	18546.00	19197.0	23438.00	23961.0
7	3721.0	16365.689600	4174.554105	4061.0	12848.00	16700.0	20486.00	21080.0
15	6290.0	14780.451828	5175.465852	4148.0	12523.25	16660.0	20745.75	21569.0
6	20466.0	15838.478550	4011.233690	3981.0	12505.00	16312.0	20051.00	20690.0
16	9828.0	14766.037037	4360.213198	4036.0	12354.00	16292.5	16831.00	20971.0
1	140378.0	13606.218596	4298.834894	3790.0	11546.00	15245.0	15812.00	19708.0
14	1523.0	13141.625739	4069.009293	3657.0	11097.00	14654.0	15176.50	18931.0
9	410.0	15537.375610	5330.847116	4528.0	13583.50	14388.5	18764.00	23531.0
2	23864.0	11251.935384	3570.642713	3176.0	9645.75	12728.5	13212.00	16504.0
3	20213.0	10096.705734	2824.626957	2638.0	8198.00	10742.0	13211.00	13717.0
17	578.0	10170.759516	2333.993073	2616.0	8063.50	10435.5	12776.75	13264.0
8	113925.0	7498.958078	2013.015062	1939.0	6036.00	7905.0	9722.00	10082.0
5	150933.0	6240.088178	1909.091687	1713.0	5242.00	6912.0	7156.00	8907.0
11	24287.0	4685.268456	1834.901184	1472.0	3131.00	4611.0	6058.00	7654.0
18	3125.0	2972.864320	727.051652	754.0	2359.00	3071.0	3769.00	3900.0
4	11753.0	2329.659491	812.540292	684.0	2058.00	2175.0	2837.00	3556.0
12	3947.0	1350.859894	362.510258	342.0	1071.00	1401.0	1723.00	1778.0
13	5549.0	722.400613	183.493126	185.0	578.00	755.0	927.00	962.0
20	2550.0	370.481176	167.116975	118.0	242.00	368.0	490.00	613.0
19	1603.0	37.041797	16.869148	12.0	24.00	37.0	50.00	62.0

Observations:

- Expensive product categories:
  - 10, 7, 15
- Cheap product categories:
  - 19, 20, 13

EDA: Bivariate/Multivariate Analysis (@ Customer Level)

In [59]:
```
df_customer = df.groupby(['User_ID', 'Gender', 'Marital_Status', 'City_Category', 'Stay_In_Current_
df_customer
```

Out[59]:

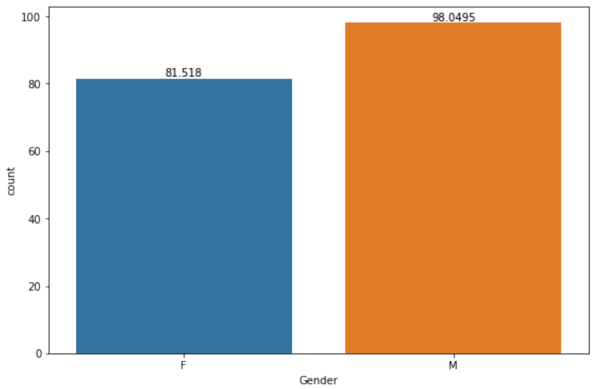
	User_ID	Gender	Marital_Status	City_Category	Stay_In_Current_City_Years	Age	sum	count
0	1000001	F	0	A	2	0-17	334093	35
1	1000002	M	0	C	4+	55+	810472	77
2	1000003	M	0	A	3	26-35	341635	29
3	1000004	M	1	B	2	46-50	206468	14
4	1000005	M	1	A	1	26-35	821001	106
...	...	...	...	...	...	...	...	...
5886	1006036	F	1	B	4+	26-35	4116058	514
5887	1006037	F	0	C	4+	46-50	1119538	122
5888	1006038	F	0	C	2	55+	90034	12
5889	1006039	F	1	B	4+	46-50	590319	74
5890	1006040	M	0	B	2	26-35	1653299	180

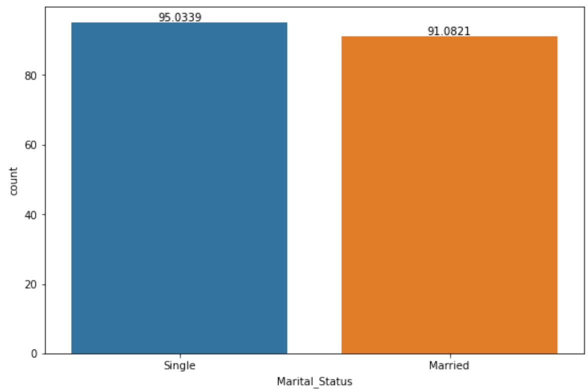
5891 rows × 8 columns

Mean number of transactions made by:

- Males vs Females
- Single vs Married

In [60]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
f = sns.barplot(data=df_customer, x='Gender', y='count', ci=None)
for item in f.containers:
    f.bar_label(item)
plt.subplot(1, 2, 2)
f = sns.barplot(data=df_customer, x=df_customer['Marital_Status'].apply(lambda x: 'Single' if x ==
for item in f.containers:
    f.bar_label(item)
```





Amount spent by customer across Gender, Marital_Status, City_Category, Stay_In_Current_City_Years

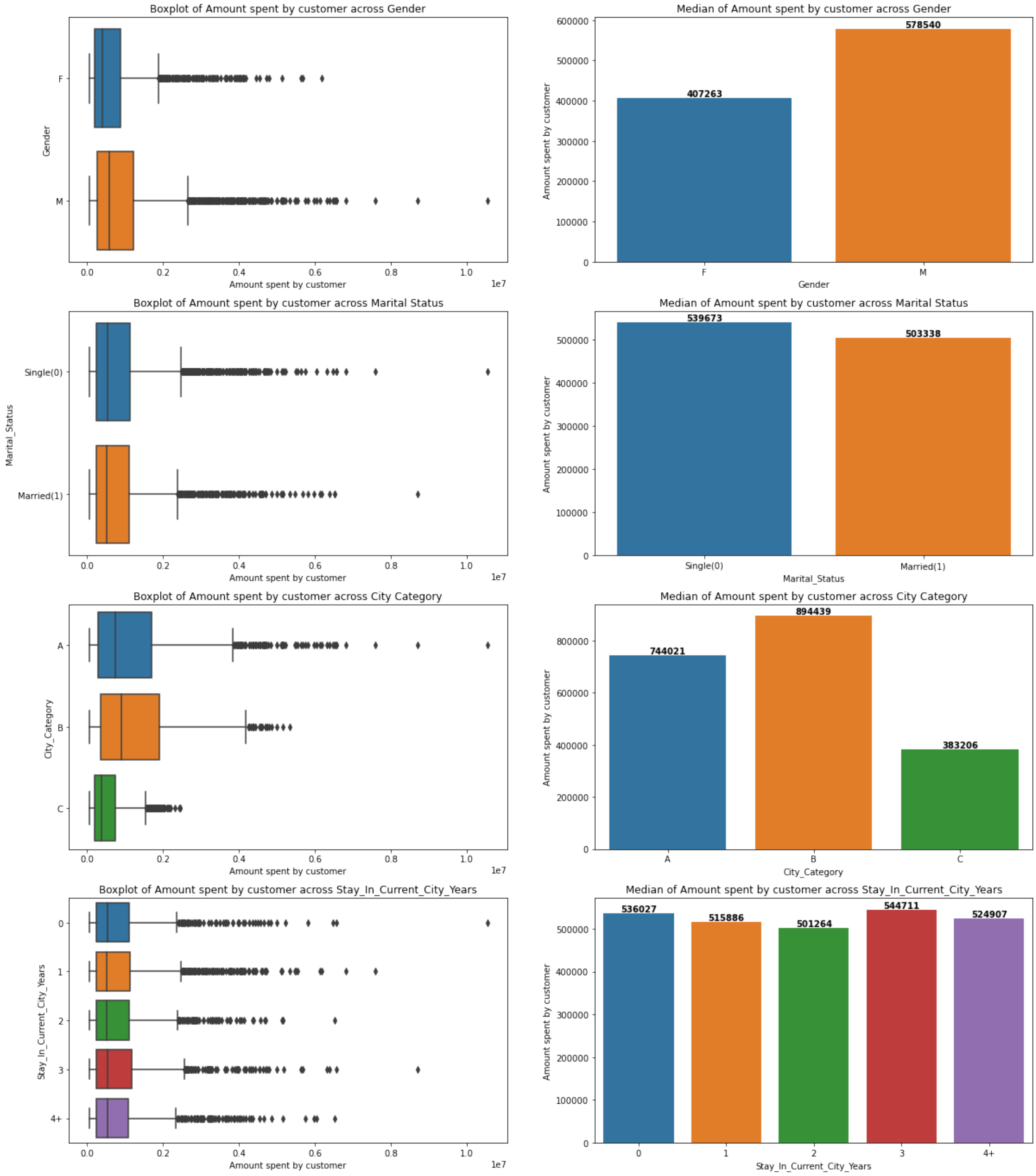
In [61]:
```
plt.figure(figsize=(20, 24))
plt.subplot(4, 2, 1)
sns.boxplot(x=df_customer['sum'], y=df_customer['Gender'])
plt.xlabel('Amount spent by customer')
plt.title('Boxplot of Amount spent by customer across Gender')
plt.subplot(4, 2, 2)
f = sns.barplot(y=df_customer['sum'], x=df_customer['Gender'], ci=None, estimator=np.median)
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Amount spent by customer')
plt.title('Median of Amount spent by customer across Gender')
```

```
plt.subplot(4, 2, 3)
sns.boxplot(x=df_customer['sum'], y=df_customer['Marital_Status'].apply(lambda x: 'Single(0)' if x=
plt.xlabel('Amount spent by customer')
plt.title('Boxplot of Amount spent by customer across Marital Status')
plt.subplot(4, 2, 4)
f = sns.barplot(y=df_customer['sum'], x=df_customer['Marital_Status'].apply(lambda x: 'Single(0)' :
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Amount spent by customer')
plt.title('Median of Amount spent by customer across Marital Status')


plt.subplot(4, 2, 5)
sns.boxplot(x=df_customer['sum'], y=df_customer['City_Category'], order=['A', 'B', 'C'])
plt.xlabel('Amount spent by customer')
plt.title('Boxplot of Amount spent by customer across City Category')
plt.subplot(4, 2, 6)
f = sns.barplot(y=df_customer['sum'], x=df_customer['City_Category'], order=['A', 'B', 'C'], ci=Nor
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Amount spent by customer')
plt.title('Median of Amount spent by customer across City Category')

plt.subplot(4, 2, 7)
sns.boxplot(x=df_customer['sum'], y=df_customer['Stay_In_Current_City_Years'], order=['0', '1', '2
plt.xlabel('Amount spent by customer')
plt.title('Boxplot of Amount spent by customer across Stay_In_Current_City_Years')
plt.subplot(4, 2, 8)
f = sns.barplot(y=df_customer['sum'], x=df_customer['Stay_In_Current_City_Years'], order=['0', '1',
for item in f.containers:
    f.bar_label(item, fontsize=10, fontweight='bold')
plt.ylabel('Amount spent by customer')
plt.title('Median of Amount spent by customer across Stay_In_Current_City_Years')

plt.show()
```



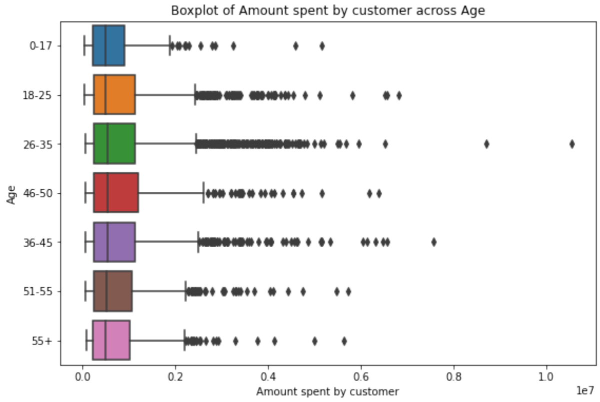
Observations:

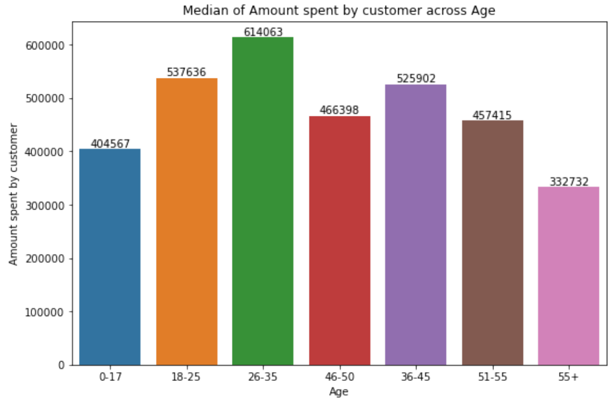
- Median amount spent by males is higher than females
- Median amount spent across marital status does not vary too much across single and married customers
- Median amount spent by customers in City Category B is the highest and in C is the lowest
- Median amount spent by customers across Stay_In_Current_City_Years does not vary too much

Amount spent by customer across Age

In [62]:
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
sns.boxplot(x=df_customer['sum'], y=df['Age'], order=['0-17', '18-25', '26-35', '46-50', '36-45',
plt.xlabel('Amount spent by customer')
plt.title('Boxplot of Amount spent by customer across Age')
plt.subplot(1, 2, 2)
f = sns.barplot(data=df_customer, y='sum', x='Age', ci=None, order=['0-17', '18-25', '26-35', '46-5
for item in f.containers:
    f.bar_label(item)
plt.ylabel('Amount spent by customer')
plt.title('Median of Amount spent by customer across Age')

plt.show()
```





In [63]:
```
df.groupby('Age')['Purchase'].describe()
```

Out[63]:

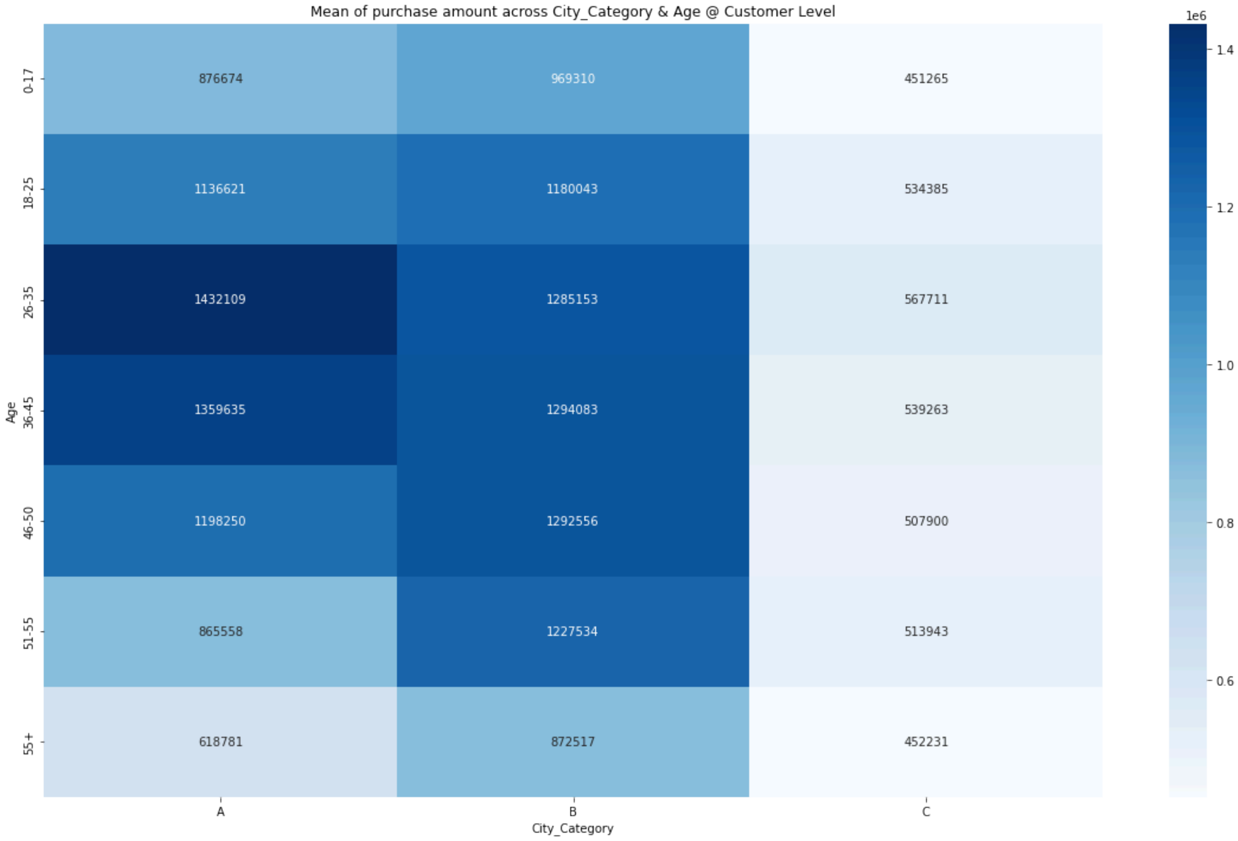
Age	count	mean	std	min	25%	50%	75%	max
0-17	15102.0	8933.464640	5111.114046	12.0	5328.0	7986.0	11874.0	23955.0
18-25	99660.0	9169.663606	5034.321997	12.0	5415.0	8027.0	12028.0	23958.0
26-35	219587.0	9252.690633	5010.527303	12.0	5475.0	8030.0	12047.0	23961.0
36-45	110013.0	9331.350695	5022.923879	12.0	5876.0	8061.0	12107.0	23960.0
46-50	45701.0	9208.625697	4967.216367	12.0	5888.0	8036.0	11997.0	23960.0
51-55	38501.0	9534.808031	5087.368080	12.0	6017.0	8130.0	12462.0	23960.0
55+	21504.0	9336.280459	5011.493996	12.0	6018.0	8105.5	11932.0	23960.0

Observations:

- Median amount spent by customers in the range 26-35 is the highest
- Median amount spent by customers in the range 55+ is the lowest

Amount spent by customer across City_Category & Age

In [64]:
```
plt.figure(figsize=(20,12))
sns.heatmap(pd.pivot_table(data=df_customer, index='Age', columns='City_Category', values='sum', ag
               cmap='Blues', annot=True, fmt='.0f')
plt.title('Mean of purchase amount across City_Category & Age @ Customer Level')
plt.show()
```

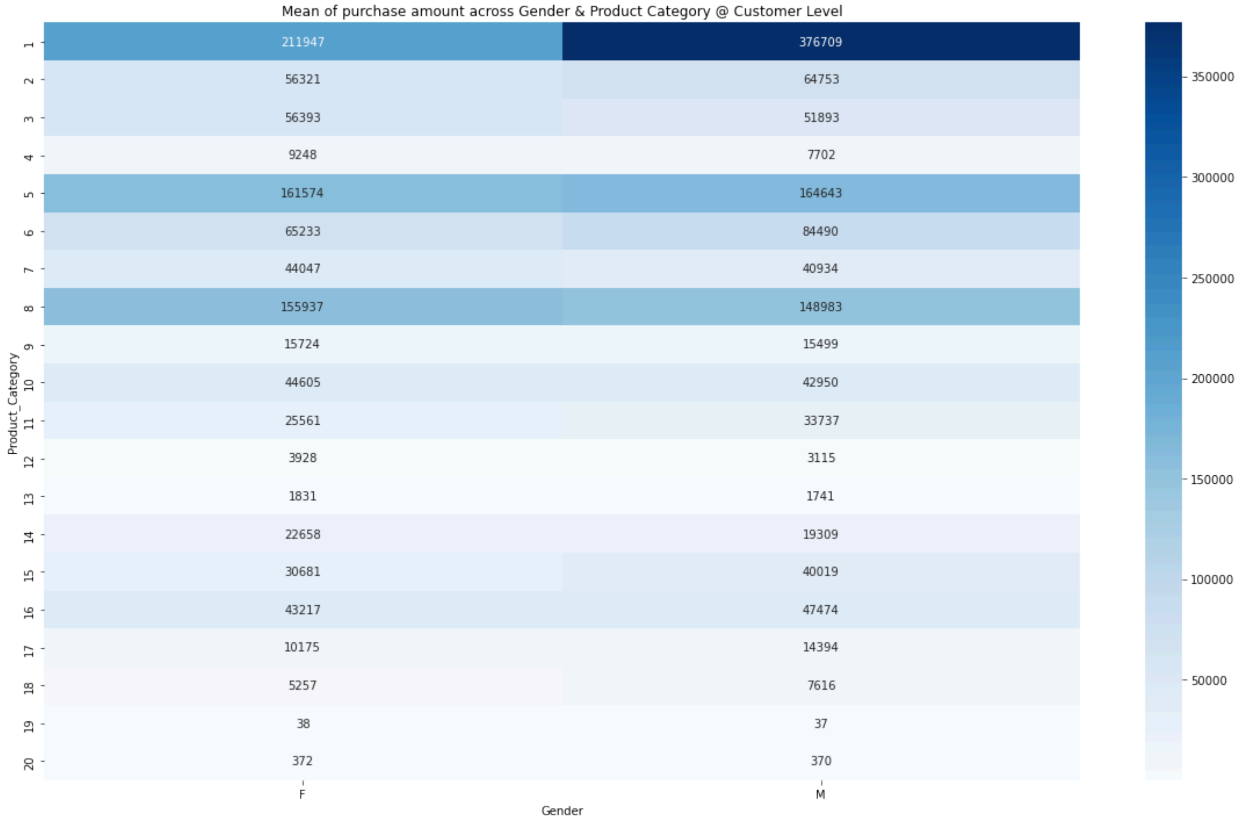


Observations:

- Mean amount spent per customer is highest for those customers who belong to city category A and age 26-35
- Mean amount spent per customer from city category C is substantially less than A and B

Amount spent by customer across Gender & Product Category

In [65]:
```
df_customer_prodCat = df.groupby(['User_ID', 'Gender', 'Marital_Status', 'City_Category', 'Stay_In_
plt.figure(figsize=(20,12))
sns.heatmap(pd.pivot_table(data=df_customer_prodCat, index='Product_Category', columns='Gender', va
            cmap='Blues', annot=True, fmt='.0f')
plt.title('Mean of purchase amount across Gender & Product Category @ Customer Level')
plt.show()
```



Observations:

- Mean amount spent per customer is highest for males and product category 1
- Mean amount spent per customer is higher for product categories 1, 5, 8
    - This is to be expected since earlier we identified the above product categories as the most popular categories

Questions:

Q1. Are women spending more money per transaction than men? Why or Why not?

- We look at the data at the transaction level and classify the transactions into 2 categories:
    - Male transaction
    - Female transaction

In [280…
```
df['Gender'].value_counts()
```

Out[280]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

- In our dataset, we have following number of data points:
    - Male: 414k
    - Female: 135k

In [281…
```
df.groupby('Gender')['Purchase'].describe()
```

Out[281]:

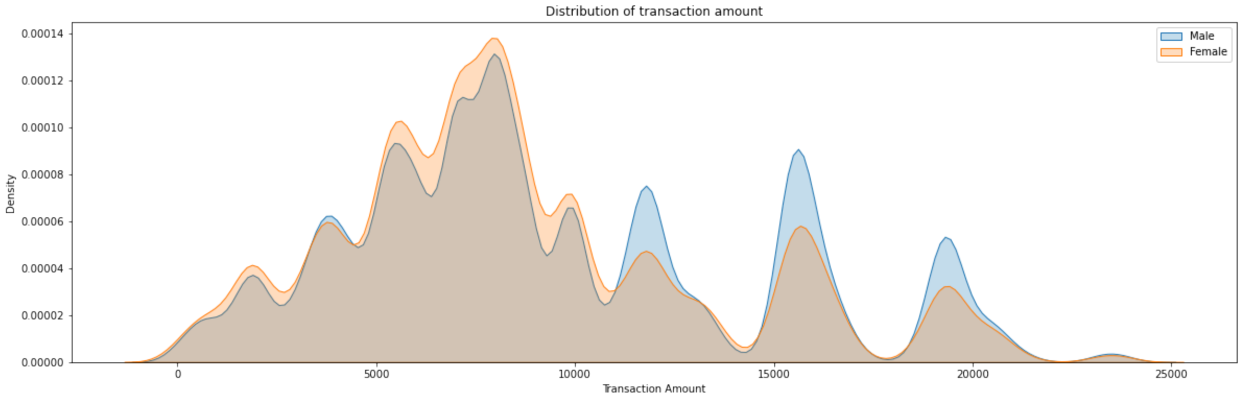
Gender	count	mean	std	min	25%	50%	75%	max
F	135809.0	8734.565765	4767.233289	12.0	5433.0	7914.0	11400.0	23959.0
M	414259.0	9437.526040	5092.186210	12.0	5863.0	8098.0	12454.0	23961.0

- We have found out the following:

- Mean transaction amount for Males (across 414k transactions): 9437
- Mean transaction amount for Females (across 135k transactions): 8734
- Below we have plotted the distribution of transaction amount for both males and females. Clearly it is not gaussian.

In [282…
```
df_male_transac = df.loc[df['Gender']=='M', 'Purchase']
df_female_transac = df.loc[df['Gender']=='F', 'Purchase']
```

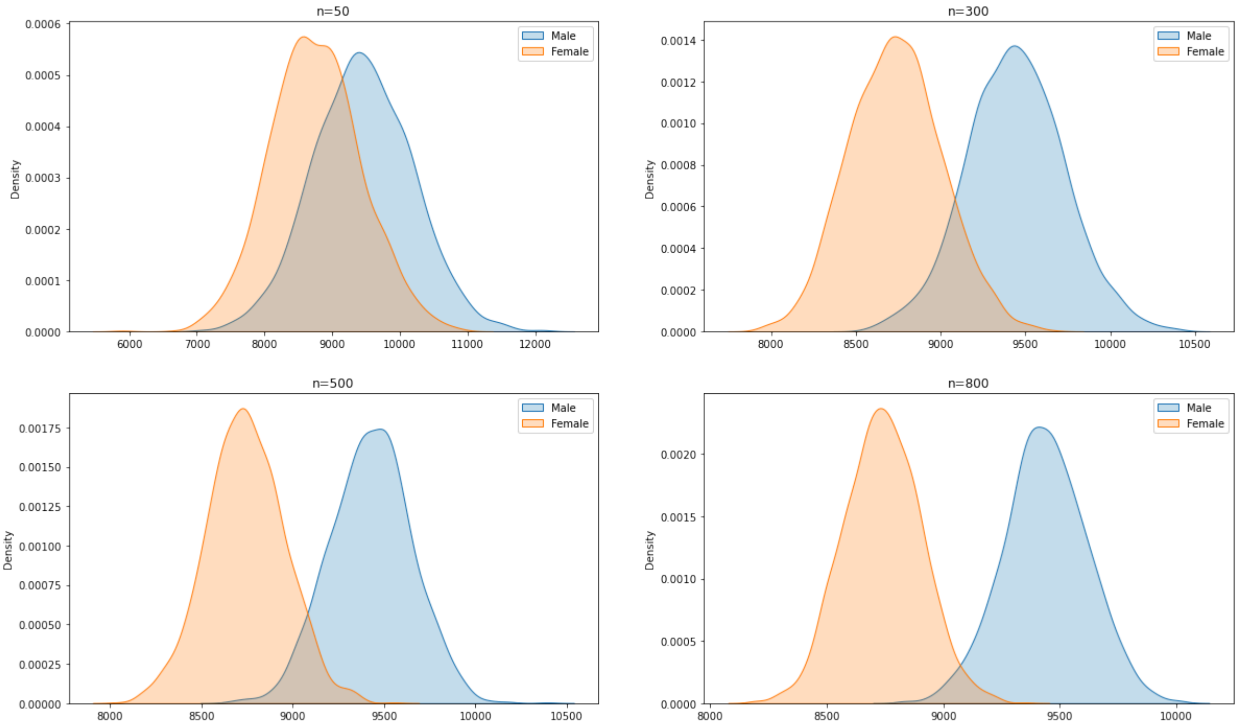
In [283…
```
plt.figure(figsize=(20, 6))
sns.kdeplot(x=df_male_transac, fill=True, label='Male')
sns.kdeplot(x=df_female_transac, fill=True, label='Female')
plt.ticklabel_format(scilimits=(-6, 5))
plt.xlabel('Transaction Amount')
plt.title('Distribution of transaction amount')
plt.legend()
plt.show()
```



- From the available data points, we randomly collect samples and compute the distribution of the sample mean.
  - We perform this experiment for Male and Female seperately
  - We perform this expeiment for different sample sizes and see how the distributions change

In [284…
```
sample_size = [50, 300, 500, 800]
d_transaction_Gender = {'Male': {}, 'Female': {}}
plt.figure(figsize=(20, 12))
id = 1
for size in sample_size:
    plt.subplot(2, 2, id)
    sample_means_lst_M = []
    sample_means_lst_F = []
    for _ in range(2000):
        sample_M = df_male_transac.sample(size)
        sample_F = df_female_transac.sample(size)
        sample_mean_M = np.mean(sample_M)
        sample_mean_F = np.mean(sample_F)
        sample_means_lst_M.append(sample_mean_M)
        sample_means_lst_F.append(sample_mean_F)
    f = sns.kdeplot(sample_means_lst_M, label=f'Male', fill=True)
    f = sns.kdeplot(sample_means_lst_F, label=f'Female', fill=True)
    f.ticklabel_format(scilimits=(-6, 7))
    f.legend()
    plt.title(f'n={size}')
    d_transaction_Gender['Male'][size] = (round(np.mean(sample_means_lst_M), 2), round(np.std(samp
    d_transaction_Gender['Female'][size] = (round(np.mean(sample_means_lst_F), 2), round(np.std(sam
    id += 1

plt.show()
```



Observations:

- We have performed this experiment for different sample sizes: 50, 300, 500, 800
- In all the cases, the sampliong mean distribution is fairly Gaussian
- We need a sample size of about 800 such that the distributions of sampling mean for Male and Female barely overlap

In [285…
```
pd.DataFrame(d_transaction_Gender)
```

Out[285]:

	Male	Female
50	(9443.1, 728.51)	(8748.23, 670.16)
300	(9440.66, 288.2)	(8733.45, 271.85)
500	(9426.37, 223.9)	(8741.08, 212.71)
800	(9437.98, 180.28)	(8737.89, 165.61)

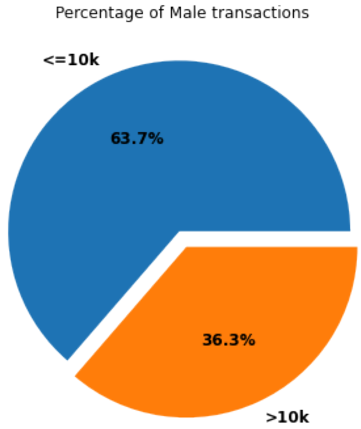
95% CI for mean transaction amount across Males and Females:

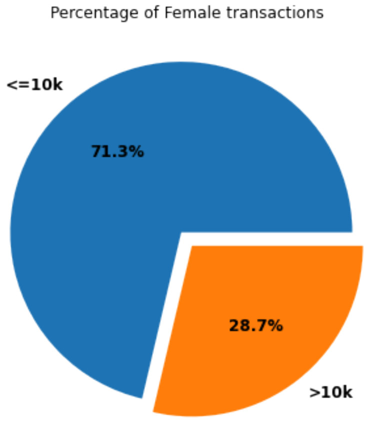
- Males:
  - [9438-(1.96*180), 9438+(1.96*180)] = [9085, 9790]
- Females:
  - [8738-(1.96*166), 8738+(1.96*166)] = [8413, 9063]
- We can conclude with 95% Confidence that the mean transaction amount of males is higher than that of females
- We need a sample size of around 800 to be able to make that conclusion

Why is mean transaction amount of females less than that of males?

- We observe that males have a comparatively higher number of high-value transactions(>10k) which shifts the mean transaction amount for males higher.
- The piechart below tells us that almost 36% of total male transactions are above 10k while only 29% of total female transactions are above 10k.

In [286…
```
plt.figure(figsize=(20, 6))
plt.subplot(1, 2, 1)
plt.pie((df_male_transac > 10000).value_counts(), labels=['<=10k', '>10k'], explode=(0.05, 0.05), a
plt.title('Percentage of Male transactions')
plt.subplot(1, 2, 2)
plt.pie((df_female_transac > 10000).value_counts(), labels=['<=10k', '>10k'], explode=(0.05, 0.05),
plt.title('Percentage of Female transactions')
plt.show()
```





Q2. Confidence intervals and distribution of the mean of the expenses by female and male customers

- For this question, we look at the data at the customer level and find the total amount spent by each customer

In [287…
```
df_purchase_byGender = df.groupby(['User_ID', 'Gender'])['Purchase'].agg(['count', 'sum']).reset_in
df_purchase_byGender.head()
```

Out[287]:

	User_ID	Gender	count	sum
0	1000001	F	35	334093
1	1000002	M	77	810472
2	1000003	M	29	341635
3	1000004	M	14	206468
4	1000005	M	106	821001

In [288…
```
df_purchase_byGender['Gender'].value_counts()
```

Out[288]:
```
M    4225
F    1666
Name: Gender, dtype: int64
```

- In our dataset, we have following number of data points:
  - Male: 4.2k
  - Female: 1.6k

In [289…
```
df_purchase_byGender.groupby('Gender')['sum'].describe()
```

Out[289]:

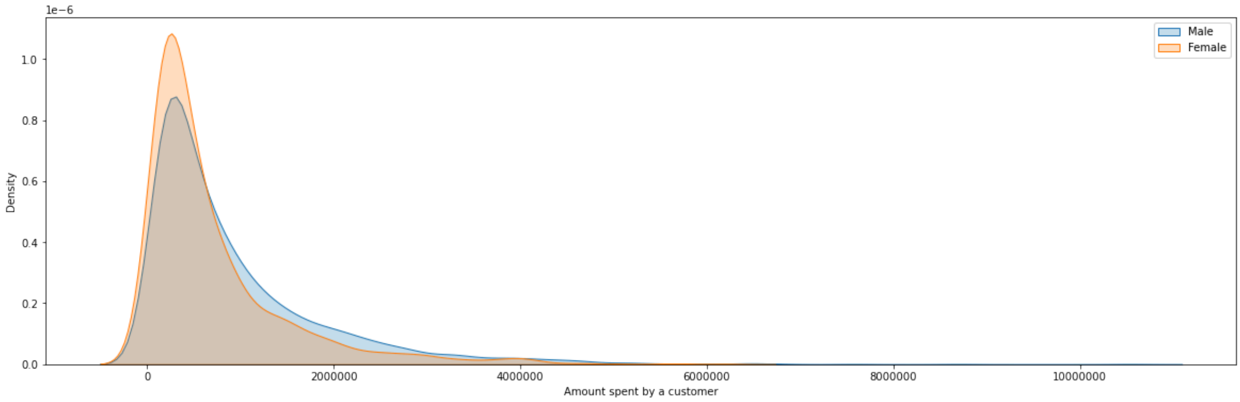
	count	mean	std	min	25%	50%	75%	max
Gender								
F	1666.0	712024.394958	807370.726146	46681.0	202654.75	407263.0	873772.0	6187094.0
M	4225.0	925344.402367	985830.100795	49288.0	258589.00	578540.0	1215237.0	10536909.0

- We have found out the following:
  - Mean amount spent by Males (across 4.2k males): 925344
  - Mean amount spent by Females (across 1.6k females): 712024
  - Below we have plotted the distribution of amount spent by a customer for both males and females. Clearly it is not gaussian.

In [290…
```
df_purchase_byGender_M = df_purchase_byGender.loc[df_purchase_byGender['Gender']=='M', 'sum']
df_purchase_byGender_F = df_purchase_byGender.loc[df_purchase_byGender['Gender']=='F', 'sum']
```

In [291…
```
plt.figure(figsize=(20, 6))
sns.kdeplot(x=df_purchase_byGender_M, fill=True, label='Male')
sns.kdeplot(x=df_purchase_byGender_F, fill=True, label='Female')
plt.ticklabel_format(scilimits=(-6, 8))
plt.xlabel('Amount spent by a customer')
```

```
plt.legend()
plt.show()
```

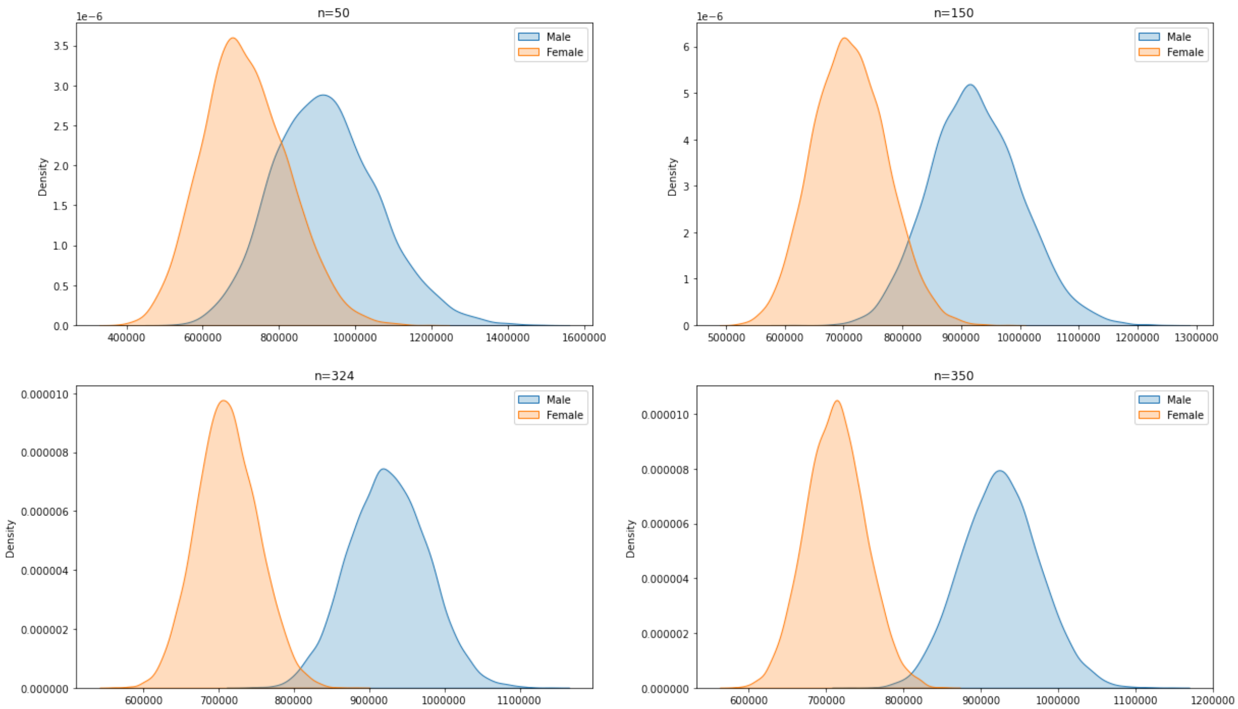


- From the available data points, we randomly collect samples and compute the distribution of the sample mean.
  - We perform this experiment for Male and Female seperately
  - We perform this expeiment for different sample sizes and see how the distributions change

In [292…

```
sample_size = [50, 150, 324, 350]
d_Gender = {'Male': {}, 'Female': {}}
plt.figure(figsize=(20, 12))
id = 1
for size in sample_size:
    plt.subplot(2, 2, id)
    sample_means_lst_M = []
    sample_means_lst_F = []
    for _ in range(10000):
        sample_M = df_purchase_byGender_M.sample(size)
        sample_F = df_purchase_byGender_F.sample(size)
        sample_mean_M = np.mean(sample_M)
        sample_mean_F = np.mean(sample_F)
        sample_means_lst_M.append(sample_mean_M)
        sample_means_lst_F.append(sample_mean_F)
    f = sns.kdeplot(sample_means_lst_M, label=f'Male', fill=True)
    f = sns.kdeplot(sample_means_lst_F, label=f'Female', fill=True)
    f.ticklabel_format(scilimits=(-6, 7))
    f.legend()
    plt.title(f'n={size}')
    d_Gender['Male'][size] = (round(np.mean(sample_means_lst_M), 2), round(np.std(sample_means_lst_
    d_Gender['Female'][size] = (round(np.mean(sample_means_lst_F), 2), round(np.std(sample_means_ls
    id += 1

plt.show()
```



Observations:

- We have performed this experiment for different sample sizes: 50, 150, 324, 350
- In all the cases, the sampling mean distribution is fairly Gaussian
- We need a sample size of about 320 such that the distributions of sampling mean for Male and Female barely overlap.
- We have chosen a sample size of 350 for slighly better result

In [293…
```
pd.DataFrame(d_Gender)
```

Out[293]:

	Male	Female
50	(922840.45, 137118.92)	(711708.17, 111788.36)
150	(924406.96, 78368.96)	(710519.62, 62703.46)
324	(925137.37, 52453.32)	(711110.52, 40836.13)
350	(925239.08, 50492.3)	(712079.02, 38337.51)

Q3. Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

95% CI for mean amount spent by Male and Female customers:

- Males:
  - [925239-(1.96*50492), 925239+(1.96*50492)] = [826275, 1024203]
- Females:
  - [712079-(1.96*38338), 712079+(1.96*38338)] = [636937, 787221]
- We can conclude with 95% Confidence that the mean amount spent by Males and Females do not overlap
- Mean amount spent by males is more than that of females
- We need a sample size of around 320 to be able to make that conclusion

How can Walmart leverage the above data?

- The above information is applicable to the entire population
- Thus Walmart should prioritize male customers during Black Friday as that ensures a higher chance of generating more revenue
- Products specifically catered to males can be launched during Black Friday
- We can also look at the historical data about the top performing products for males to get an idea about the product portfolio for future Black Friday sales
- Some incentives and discounts can also be announced for females to encourage them to make more purchases on the platform

Q4. Results when the same activity is performed for Married vs Unmarried

- For this question, we look at the data at the customer level and find the total amount spent by each customer

In [294…
```
df_purchase_byMarStat = df.groupby(['User_ID', 'Marital_Status'])['Purchase'].agg(['count', 'sum']
df_purchase_byMarStat['Marital_Status'] = df_purchase_byMarStat['Marital_Status'].apply(lambda x:
df_purchase_byMarStat.head()
```

Out[294]:

	User_ID	Marital_Status	count	sum
0	1000001	Single	35	334093
1	1000002	Single	77	810472
2	1000003	Single	29	341635
3	1000004	Married	14	206468
4	1000005	Married	106	821001

In [295…
```
df_purchase_byMarStat['Marital_Status'].value_counts()
```

Out[295]:
```
Single     3417
Married    2474
Name: Marital_Status, dtype: int64
```

- In our dataset, we have following number of data points:
  - Single: 3.4k
  - Married: 2.5k

In [296…
```
df_purchase_byMarStat.groupby('Marital_Status')['sum'].describe()
```

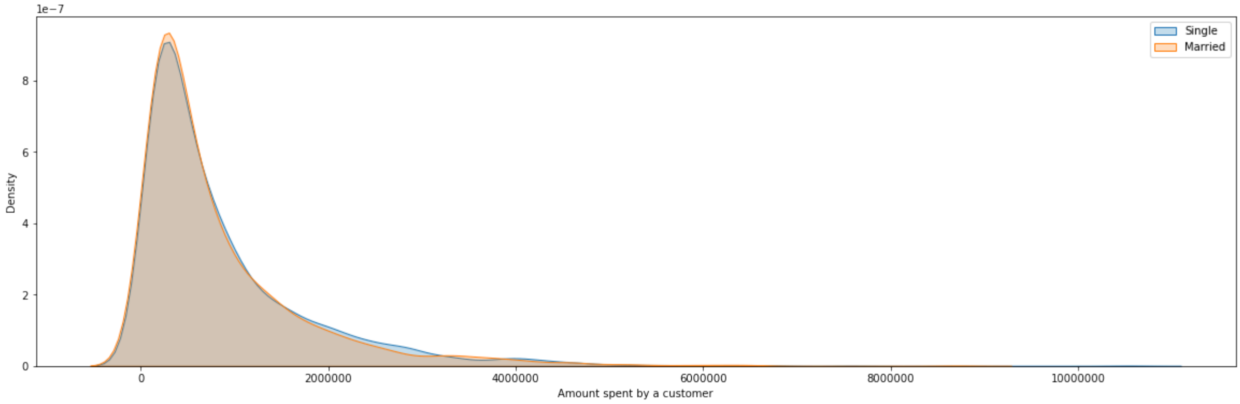
Out[296]:

Marital_Status	count	mean	std	min	25%	50%	75%	max
Married	2474.0	843526.796686	935352.115825	49349.0	234656.0	503338.5	1092680.5	8699596.0
Single	3417.0	880575.781972	949436.249555	46681.0	241870.0	539673.0	1133463.0	10536909.0

- We have found out the following:
  - Mean amount spent by Singles (across 3.4k single customers): 880575
  - Mean amount spent by Married (across 2.5k married customers): 843526
  - Below we have plotted the distribution of amount spent by a customer for both single and married customers. Clearly it is not gaussian.

In [297…
```
df_purchase_byMarStat_Single = df_purchase_byMarStat.loc[df_purchase_byMarStat['Marital_Status']==
df_purchase_byMarStat_Married = df_purchase_byMarStat.loc[df_purchase_byMarStat['Marital_Status']=
```

In [298…
```
plt.figure(figsize=(20, 6))
sns.kdeplot(x=df_purchase_byMarStat_Single, fill=True, label='Single')
sns.kdeplot(x=df_purchase_byMarStat_Married, fill=True, label='Married')
plt.ticklabel_format(scilimits=(-6, 8))
plt.xlabel('Amount spent by a customer')
plt.legend()
plt.show()
```

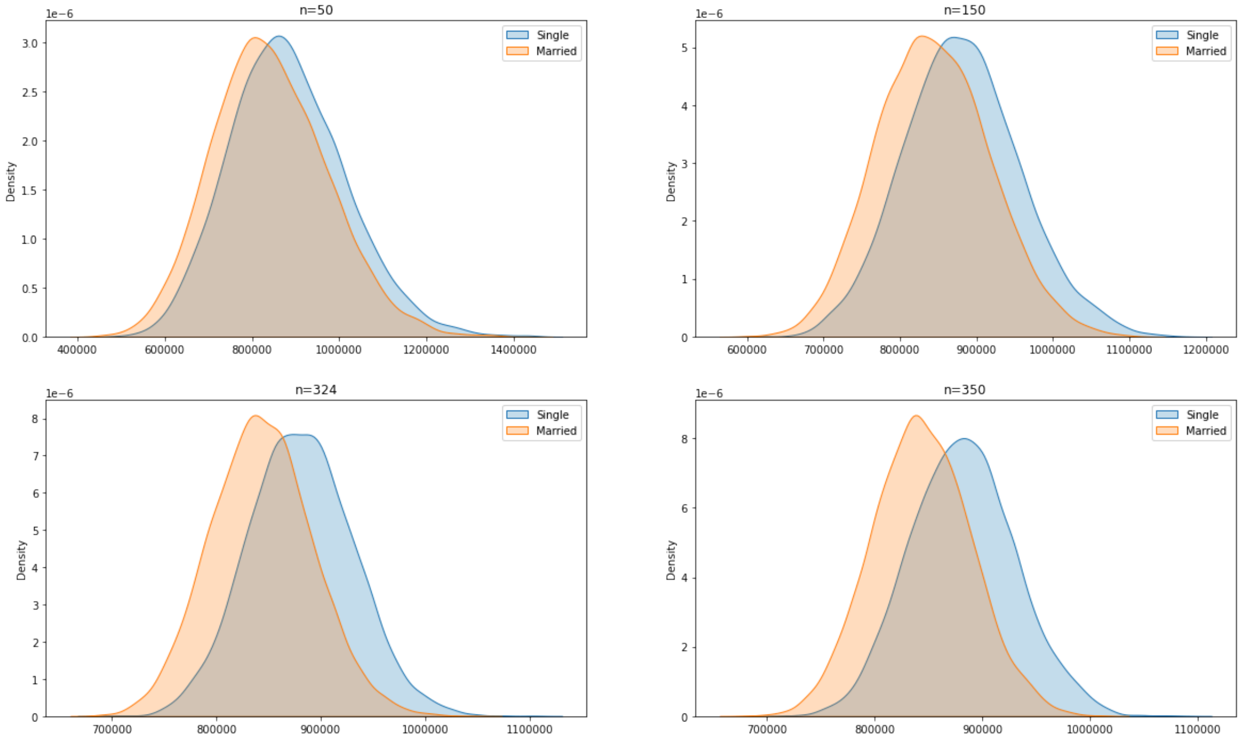


- From the available data points, we randomly collect samples and compute the distribution of the sample mean.
  - We perform this experiment for Single and Married seperately
  - We perform this expeiment for different sample sizes and see how the distributions change

In [299…
```
sample_size = [50, 150, 324, 350]
d_MaritalStatus = {'Single': {}, 'Married': {}}
plt.figure(figsize=(20, 12))
id = 1
for size in sample_size:
    plt.subplot(2, 2, id)
    sample_means_lst_Sing = []
    sample_means_lst_Marr = []
    for _ in range(10000):
        sample_Sing = df_purchase_byMarStat_Single.sample(size)
        sample_Marr = df_purchase_byMarStat_Married.sample(size)
        sample_mean_Sing = np.mean(sample_Sing)
        sample_mean_Marr = np.mean(sample_Marr)
        sample_means_lst_Sing.append(sample_mean_Sing)
        sample_means_lst_Marr.append(sample_mean_Marr)
```

```
    f = sns.kdeplot(sample_means_lst_Sing, label=f'Single', fill=True)
    f = sns.kdeplot(sample_means_lst_Marr, label=f'Married', fill=True)
    f.ticklabel_format(scilimits=(-6, 7))
    f.legend()
    plt.title(f'n={size}')
    d_MaritalStatus['Single'][size] = (round(np.mean(sample_means_lst_Sing), 2), round(np.std(samp
    d_MaritalStatus['Married'][size] = (round(np.mean(sample_means_lst_Marr), 2), round(np.std(samp
    id += 1

plt.show()
```



Observations:

- We have performed this experiment for different sample sizes: 50, 150, 324, 350
- In all the cases, the sampling mean distribution is fairly Gaussian
- We are not able to clearly segregate the sampling mean distributions for Single and Married customers even for a sample size of 350

In [300…

```
pd.DataFrame(d_MaritalStatus)
```

Out[300]:

	Single	Married
50	(881377.75, 133115.36)	(841599.19, 131859.15)
150	(881003.48, 76537.42)	(843676.37, 73889.56)
324	(880906.94, 50337.36)	(843218.43, 48934.37)
350	(881407.09, 48791.37)	(843183.38, 45786.13)

95% CI for mean amount spent by Single and Married customers:

- Single:
  - [881407-(1.96*48791), 881407+(1.96*48791)] = [785776, 977037]
- Married:
  - [843183-(1.96*45786), 843183+(1.96*45786)] = [753442, 932924]
- There is a significant overlap b/w these 2 distributions (Single vs Married)
- Since there is significant overlap, we cannot comment on the fact that the spending habits of Single and Married customers differ from each other!

Q5. Results when the same activity is performed for Age

- For this question, we look at the data at the customer level and find the total amount spent by each customer

In [301…
```
df_purchase_byAge = df.groupby(['User_ID', 'Age'])['Purchase'].agg(['count', 'sum']).reset_index()
```

In [302…
```
df_purchase_byAge['Age'].value_counts()
```

Out[302]:
```
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: Age, dtype: int64
```

- We see that there are only a few customers in some of the age-categories:
  - 0-17, 46-50, 51-55, 55+
  - We will try to group the age brackets such that we have a significant customer count in the new age brackets

In [303…
```
def age_classify(x):
    low = ['0-17', '18-25']
    middle = ['26-35', '36-45']
    if x in low:
        return 'Below 26'
    elif x in middle:
        return '26-45'
    else:
        return 'Above 45'

df_purchase_byAge['Age_Mod'] = df_purchase_byAge['Age'].apply(age_classify)
df_purchase_byAge.head()
```

Out[303]:

	User_ID	Age	count	sum	Age_Mod
0	1000001	0-17	35	334093	Below 26
1	1000002	55+	77	810472	Above 45
2	1000003	26-35	29	341635	26-45
3	1000004	46-50	14	206468	Above 45
4	1000005	26-35	106	821001	26-45

In [304…
```
df_purchase_byAge['Age_Mod'].value_counts()
```

Out[304]:
```
26-45       3220
Above 45    1384
Below 26    1287
Name: Age_Mod, dtype: int64
```

- After modifying the age-brackets, we have following number of data points:
  - Below 26: 1.3k
  - 26-45: 3.2k
  - Above 45: 1.4k

In [305…
```
df_purchase_byAge.groupby('Age_Mod')['sum'].describe()
```

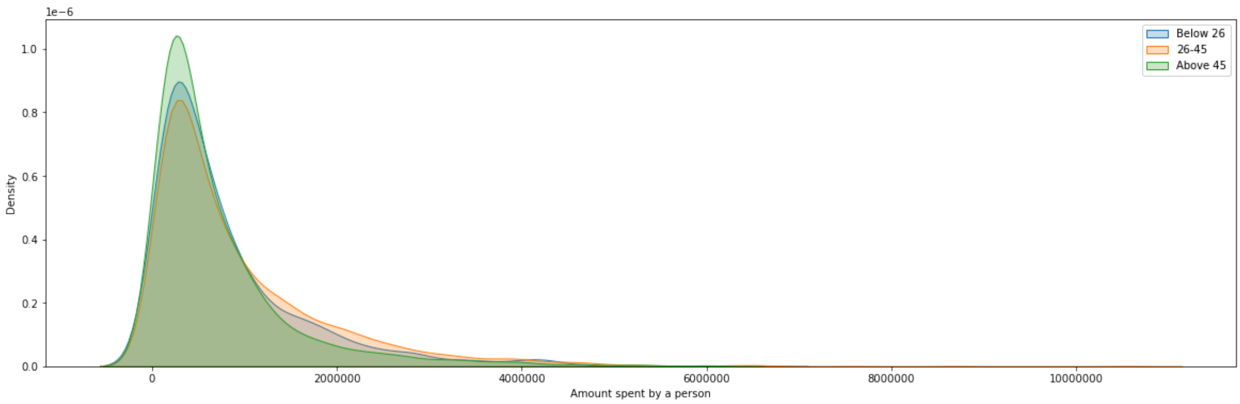
Out[305]:

	count	mean	std	min	25%	50%	75%	max
Age_Mod								
26-45	3220.0	949795.174534	1.014989e+06	49288.0	255852.50	585890.0	1282410.75	10536909.0
Above 45	1384.0	714386.143064	8.139400e+05	46681.0	208172.75	423624.5	878154.75	6044415.0
Below 26	1287.0	814888.778555	8.615706e+05	53996.0	236521.00	515379.0	1036955.50	6477160.0

- We have found out the following:
  - Mean amount spent by customers below 26 (across 1.3k single customers): 814888
  - Mean amount spent by customers in 26-45 (across 3.2k married customers): 949795
  - Mean amount spent by customers above 45 (across 1.4k single customers): 714386
  - Below we have plotted the distribution of amount spent by a customer for all the age brackets. Clearly it is not gaussian.

In [306…
```
df_purchase_byAge_below26 = df_purchase_byAge.loc[df_purchase_byAge['Age_Mod']=='Below 26', 'sum']
df_purchase_byAge_26to45 = df_purchase_byAge.loc[df_purchase_byAge['Age_Mod']=='26-45', 'sum']
df_purchase_byAge_above45 = df_purchase_byAge.loc[df_purchase_byAge['Age_Mod']=='Above 45', 'sum']
```

In [307…
```
plt.figure(figsize=(20, 6))
sns.kdeplot(x=df_purchase_byAge_below26, fill=True, label='Below 26')
sns.kdeplot(x=df_purchase_byAge_26to45, fill=True, label='26-45')
sns.kdeplot(x=df_purchase_byAge_above45, fill=True, label='Above 45')
plt.ticklabel_format(scilimits=(-6, 8))
plt.xlabel('Amount spent by a person')
plt.legend()
plt.show()
```



- From the available data points, we randomly collect samples and compute the distribution of the sample mean.
  - We perform this experiment for all the age brackets seperately
  - We perform this expeiment for different sample sizes and see how the distributions change

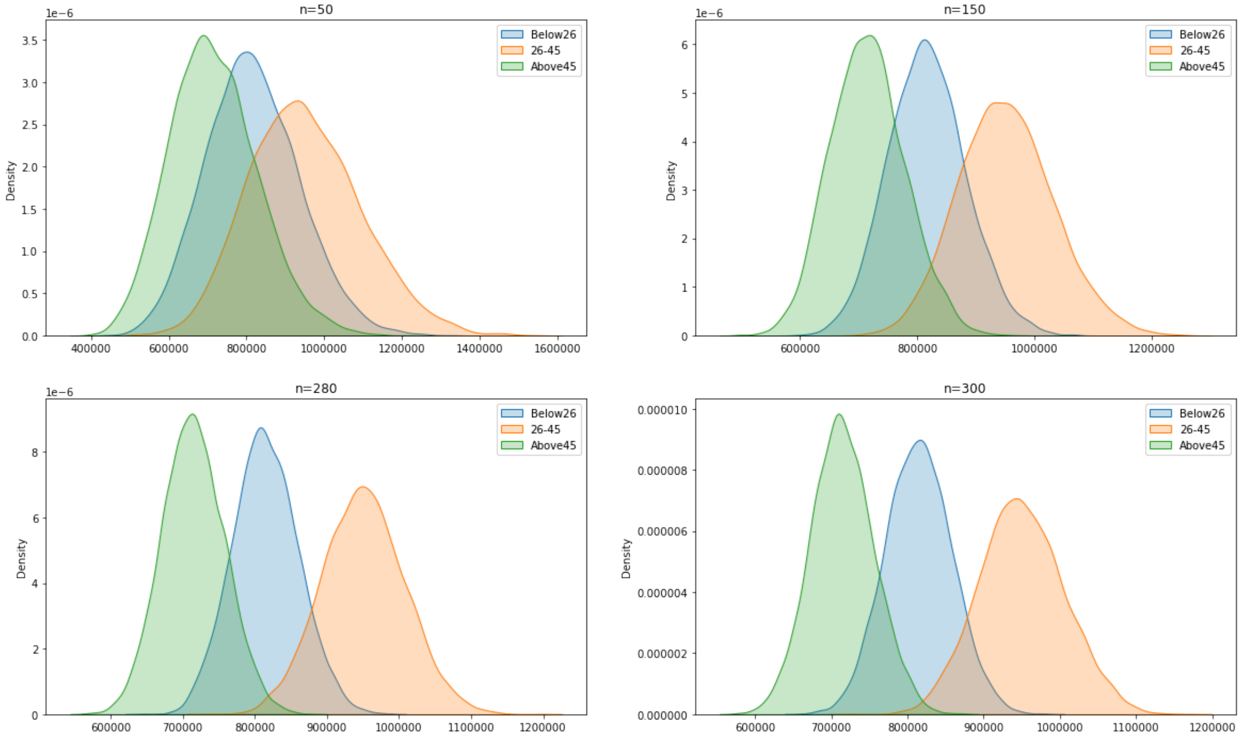
In [308…
```
sample_size = [50, 150, 280, 300]
d_Age = {'Below26': {}, '26-45': {}, 'Above45': {}}
plt.figure(figsize=(20, 12))
id = 1
for size in sample_size:
    plt.subplot(2, 2, id)
    sample_means_lst_A = []
    sample_means_lst_B = []
    sample_means_lst_C = []
    for _ in range(10000):
        sample_mean_A = np.mean(df_purchase_byAge_below26.sample(size))
        sample_mean_B = np.mean(df_purchase_byAge_26to45.sample(size))
        sample_mean_C = np.mean(df_purchase_byAge_above45.sample(size))

        sample_means_lst_A.append(sample_mean_A)
        sample_means_lst_B.append(sample_mean_B)
        sample_means_lst_C.append(sample_mean_C)

    f = sns.kdeplot(sample_means_lst_A, label=f'Below26', fill=True)
    f = sns.kdeplot(sample_means_lst_B, label=f'26-45', fill=True)
    f = sns.kdeplot(sample_means_lst_C, label=f'Above45', fill=True)
    f.ticklabel_format(scilimits=(-6, 7))
    f.legend()
    plt.title(f'n={size}')

    d_Age['Below26'][size] = (round(np.mean(sample_means_lst_A), 2), round(np.std(sample_means_lst_
    d_Age['26-45'][size] = (round(np.mean(sample_means_lst_B), 2), round(np.std(sample_means_lst_B
    d_Age['Above45'][size] = (round(np.mean(sample_means_lst_C), 2), round(np.std(sample_means_lst_
    id += 1

plt.show()
```



Observations:

- We have performed this experiment for different sample sizes: 50, 150, 280, 300
- In all the cases, the sampling mean distribution is fairly Gaussian
- We need a sample size of about 280 such that the distributions of sampling mean for Above45 and 26-45 barely overlap.
- We have chosen a sample size of 300 for slighly better result

In [309…

```
pd.DataFrame(d_Age)
```

Out[309]:

	Below26	26-45	Above45
50	(814914.6, 120202.38)	(949589.59, 143924.51)	(715699.93, 112937.27)
150	(816091.61, 66492.72)	(950945.64, 81338.36)	(714810.27, 63557.15)
280	(814677.63, 45875.78)	(950295.98, 57697.27)	(714390.1, 43517.86)
300	(814432.11, 43683.7)	(949705.82, 56053.43)	(714489.78, 41363.56)

95% CI for mean amount spent across different age groups:

- Below26:
  - [814432-(1.96*43684), 814432+(1.96*43684)] = [728811, 900053]
- 26-45:
  - [949706-(1.96*56053), 949706+(1.96*56053)] = [839842, 1059570]
- Above45:
  - [714490-(1.96*41364), 714490+(1.96*41364)] = [633417, 795563]
- We can conclude with 95% Confidence that the mean amount spent by customers above 45 & those in range 26-45 do not overlap
- Mean amount spent by customers in range 26-45 is more than that of those above 45
- We need a sample size of around 280 to be able to make that conclusion
- There is a significant overlap of the distribution for customers below 26 with the above 2 distributions. Hence we cannot make any comment about customers below 26 with confidence.

Insights

- We have a sample of Walmart transactions with a sample size of about 550K
- Insights @ transaction level (relevant only to sample):
  - Transactions made by males is ~75% of total transactions.

- Customers in age group 18-25 have made the most number of transactions.
- Popular product categories are: 1, 5 and 8.
- The median transaction amount is ~8k with outlier above ~21k .
- Median of transction amount by males is higher than that of females.
- Median transaction amount of city category 'C' is the highest.
- We have also identified the top-3 expensive and cheap product categories:
  - Expensive product categories:
    - 10, 7, 15
  - Cheap product categories:
    - 19, 20, 13

- Insights @ customer level (relevant only to sample):
  - Mean number of transactions per male is higher than that of females.
  - Mean number of transactions per customer is indifferent across Marital Status.
  - Amount spent per males is higher than that of females females.
  - Amount spent per customer in City Category B is the highest and that in C is the lowest.
  - Amount spent per customer in age bracket 26-35 is highest and that in 55+ is the lowest.
  - City Category wise insight:
    - Mean amount spent per customer is highest for those customers who belong to city category A and age 26-35.
    - Mean amount spent per customer from city category C is substantially less than A and B.
- The following insights are relevant to the whole population:
  - At the transaction level, we can conclude with 95% Confidence that the mean transaction amount across all males is higher than that of females.
  - At the customer level, we can conclude with 95% Confidence that mean amount spent per male is more than that of females.
  - At the customer level, we cannot comment with any confidence about the spending habits of a customer across Marital_Status.
  - At the customer level, we can conclude with 95% Confidence that mean amount spent per customer who lie in age [26-45] is more than that of those who lie in age [Above 45].
    - However, we cannot comment with any confidence about the mean amount spent per customer who lie in age [Below 26] with respect to the above age brackets.

Recommendations

- Products which fall in the popular product categories (1, 5, 8) should be stocked up in warehouse since demand for these products seem to be high.
- Males should be targetted more than females since:
  - The mean amount spent per transaction is higher for males than that of females (with 95% C)
  - The mean number of transacctions per males is higher than that of females
  - The mean amount spent per male is higher than that of females (with 95% C)
- For new product launch, products relevant to young/miidle aged customers should be launched before ytargetting any other age bracket
  - Customers in age group 26-45 should get more priority than those above 45. We have concluded that customers in age 26-45 tend to have a higher mean value of amount spent.
- During Black-Friday, Walmart can launch/stock up products catered to males and also audience in age [26-45] to boost up their revenue
- To boost the average amount spent bt females, some marketing campaign can be launched to attract females and encourage them to make more purchases.