Business Case

Walmart - Confidence Interval and CLT

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Introduction

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.

Business Problem

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).

Dataset

The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday. The dataset has the following features: Dataset link: Walmart_data.csv

The dataset have the following fields:

Summary

- 75% male and 25% are female customers as per given sample data
- (With 95% confidence and sample size of 10000 , 500 trials.), As per confidence Interval comparison for both female purchase and male purchase data , its clear that there's no over lapping , and hence there's a good amount of difference between Male and Female Spending amounts .
- Male Customers are more likely to spend more amount than female customers .
- Average Male Spending Amount from all 100 million customers lies in Range of 9333 to 9533 as per Bootstrapping Method
- Average Female Spending Amount from all 100 million customers lies in Range of 8639 to 8826 as per Bootstrapping Method
- As per confidence Interval comparison for both Single and Married Customer's average purchase data
- There is not much difference between their average spending amounts. Married and Single Customer's spending amounts distribution are almost lies with same distribution.
- Customers from age 26-35 are 40% of all customers. and their Average Spending amount is near to overall customers average spending amount
- Age group 51-55 customers are more likely to spend more amount than all other groups
- Customers under 17 age are the least spending average amount

- As per calculations and above distribution plot, as we increase the sample size, standard error decreases , means that the average spending amount gets closers and closer to the actual mean spending amount of the all customer average spending amount.
- All city categories are having customers majorly who are living there for 1 to 2 years.
- Out of all women, 35% of the revenue coming from agae group 18 to 45 and so is same for men as well.

Recommendation

- City Category B has the highest customer base compared to C and A . Since City Category A and C customers, have the lesser spending average amount that city category B customers, more infrastructure and marketing strategies can be focued on City category A.
- There is not much significant difference between Married and Single Category Customers, no changes needs to be taken in that area.
- And there is a huge gap and difference between Male and Female spending average amounts and intervals, We can introduce special offers for particularly women like Women's day offer , or mother special or something like that.
- Age group 0-25 has the lowest spendings compared to other age groups. Since most of the 0-25 age customers would be students , more products related students / teenage / kids recommended to introduce and university/student discount can help increase the revenue from this age group.

Detailed Analysis

Importing all the `libs`

In [185…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
```

Loading the `data`

In [186…
```
# data_set = 'https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv'
data_set = 'walmart_data.csv'
```

Exploratory Data Exploration (EDA)

In [187…
```
df = pd.read_csv(data_set)
```

In [188…
```
df.shape
```

Out[188]:
```
(550068, 10)
```

In [189…
```
df.head()
```

Out[189]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969

In [190…
```
df.dtypes
```

Out[190]:
```
User_ID                        int64
Product_ID                    object
Gender                        object
Age                           object
Occupation                     int64
City_Category                 object
Stay_In_Current_City_Years    object
Marital_Status                 int64
Product_Category               int64
Purchase                       int64
dtype: object
```

In [191…
```
df['User_ID'].value_counts().reset_index()
```

Out[191]:

	index	User_ID
0	1001680	1026
1	1004277	979
2	1001941	898
3	1001181	862
4	1000889	823
...	...	...
5886	1002690	7
5887	1002111	7
5888	1005810	7
5889	1004991	7
5890	1000708	6

5891 rows × 2 columns

In [192…
```
df['User_ID'].value_counts().reset_index()
```

Out[192]:

	index	User_ID
0	1001680	1026
1	1004277	979
2	1001941	898
3	1001181	862
4	1000889	823
...	...	...
5886	1002690	7
5887	1002111	7
5888	1005810	7
5889	1004991	7
5890	1000708	6

5891 rows × 2 columns

In [193…

```
df.describe()
```

Out[193]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

In [194…

```
print(df.isnull().sum())
```

```
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
```

In [195…

```
df['Age'].value_counts().reset_index()
```

Out[195]:

	index	Age
0	26-35	219587
1	36-45	110013
2	18-25	99660
3	46-50	45701
4	51-55	38501
5	55+	21504
6	0-17	15102

In [196…

```
df['Occupation'].value_counts(sort=True).reset_index()
```

Out[196]:

	index	Occupation
0	4	72308
1	0	69638
2	7	59133
3	1	47426
4	17	40043
5	20	33562
6	12	31179
7	14	27309
8	2	26588
9	16	25371
10	6	20355
11	3	17650
12	10	12930
13	5	12177
14	15	12165
15	11	11586
16	19	8461
17	13	7728
18	18	6622
19	9	6291
20	8	1546

In [197…

```
df['Stay_In_Current_City_Years'].value_counts()
```

Out[197]:
```
1      193821
2      101838
3       95285
4+      84726
0       74398
Name: Stay_In_Current_City_Years, dtype: int64
```

In [198…
```
df.nunique()
```

Out[198]:
```
User_ID                         5891
Product_ID                      3631
Gender                             2
Age                                7
Occupation                        21
City_Category                      3
Stay_In_Current_City_Years         5
Marital_Status                     2
Product_Category                  20
Purchase                       18105
dtype: int64
```

In [199…
```
df.head()
```

Out[199]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969

Observation

- Total 550068 data points
- No missing value
- Unique Values in each columns
  - 5891 unique customers
  - 3631 unique products
  - 7 different age groups
  - 3 different city
  - stay in current city from 0 to 5 years
  - Gender , Marital status
  - 20 different product category
  - Purchase is the only numerical column
  - User_ID and Product_ID are unique identifiers for users and products respectively

In [61]:
```
# Replacing gender and marital status values.
df["Gender"].replace({"M":"Male",
                      "F":"Female"},inplace=True)
df["Marital_Status"].replace({"0":"Single",
                              "1":"Married"},inplace=True)

# Changing all other data types as string/category
df["Product_Category"] = df["Product_Category"].astype("str")
df["Marital_Status"] = df["Marital_Status"].astype("str")
df["Occupation"] = df["Occupation"].astype("str")
df["User_ID"] = df["User_ID"].astype("str")
```

In [62]:
```
df
```

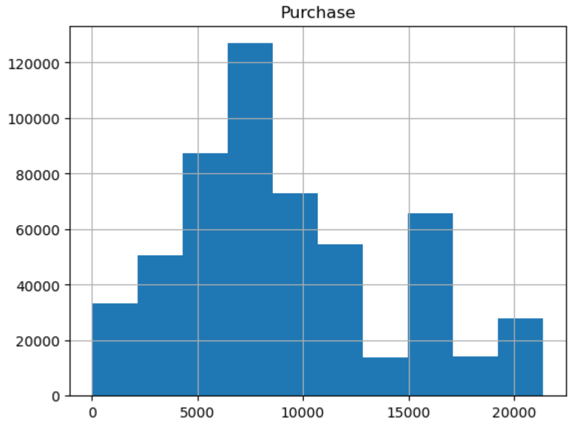
Out[62]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	Female	0-17	10	A	2	Single	3	8370
1	1000001	P00248942	Female	0-17	10	A	2	Single	1	15200
2	1000001	P00087842	Female	0-17	10	A	2	Single	12	1422
3	1000001	P00085442	Female	0-17	10	A	2	Single	12	1057
4	1000002	P00285442	Male	55+	16	C	4+	Single	8	7969
...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	Male	51-55	13	B	1	Married	20	368
550064	1006035	P00375436	Female	26-35	1	C	3	Single	20	371
550065	1006036	P00375436	Female	26-35	15	B	4+	Married	20	137
550066	1006038	P00375436	Female	55+	1	C	2	Single	20	365
550067	1006039	P00371644	Female	46-50	0	B	4+	Married	20	490

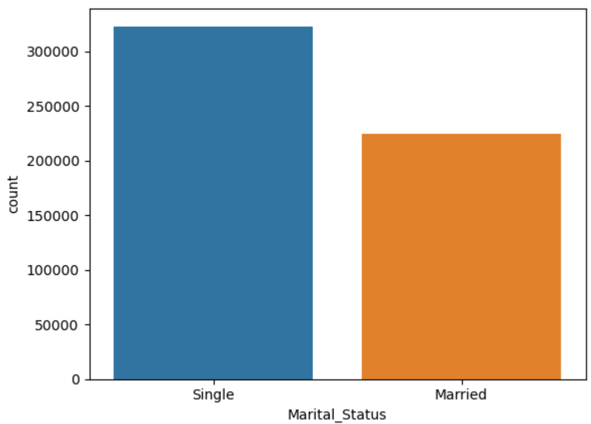
547391 rows × 10 columns

Histogram of all fields

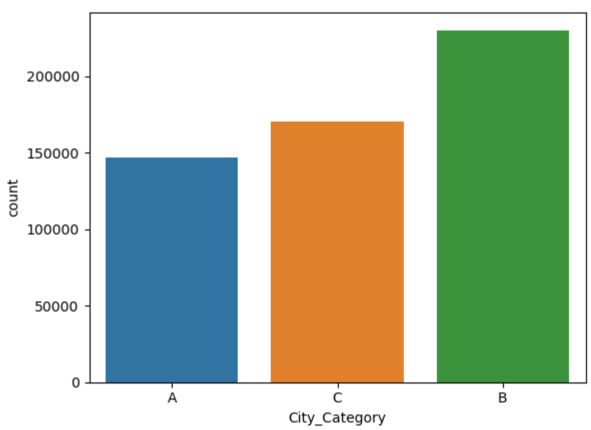
In [63]:
```
df.hist();
```



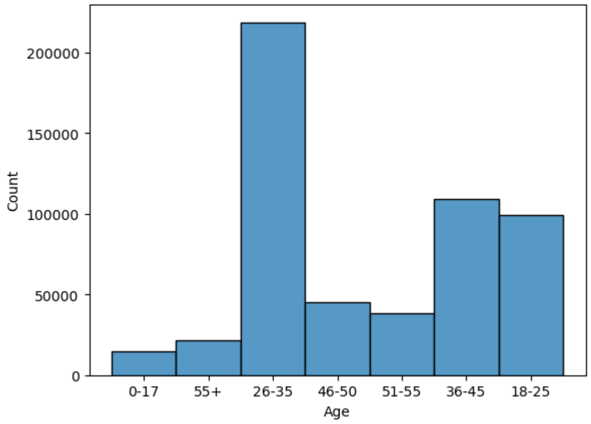
In [64]:
```
sns.countplot(x='Marital_Status', data=df)
plt.show()
```



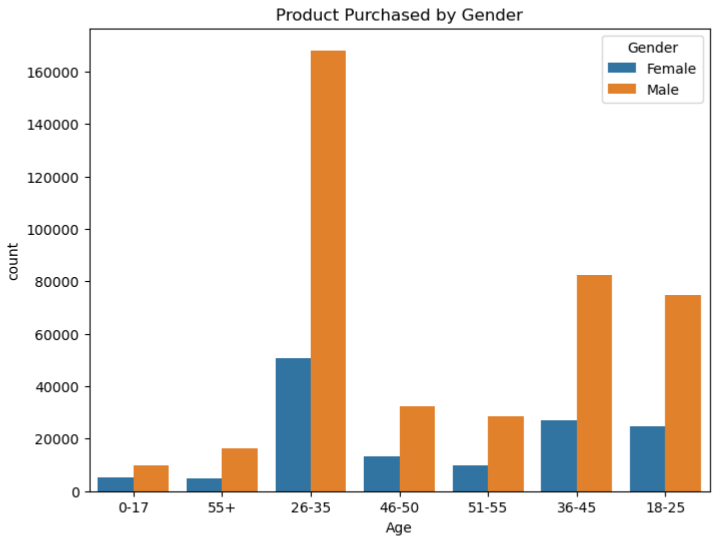
In [65]:
```
sns.countplot(x='City_Category', data=df)
plt.show()
```



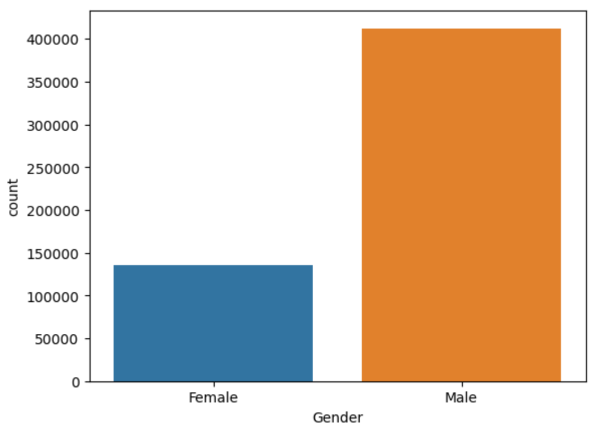
In [66]:
```
sns.histplot(df['Age'], bins=10)
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



In [67]:
```
# Countplot of Gender and No. of customers
plt.figure(figsize=(8, 6))
sns.countplot(x='Age', hue='Gender', data=df)
plt.title('Product Purchased by Gender')
plt.show()
```



In [68]:
```
sns.countplot(x='Gender', data=df)
plt.show()
```



In [69]:
```
df["Gender"].value_counts(normalize=True)
```

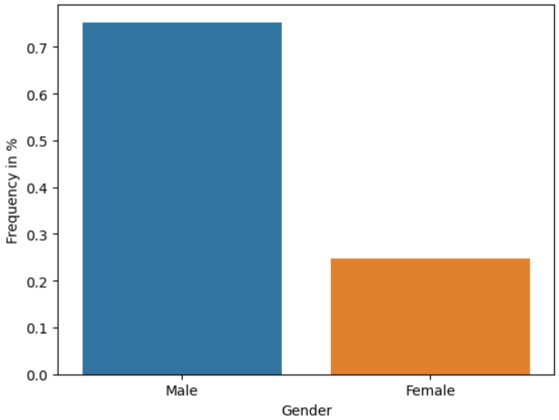
Out[69]:
```
Male      0.752974
Female    0.247026
Name: Gender, dtype: float64
```

Observation

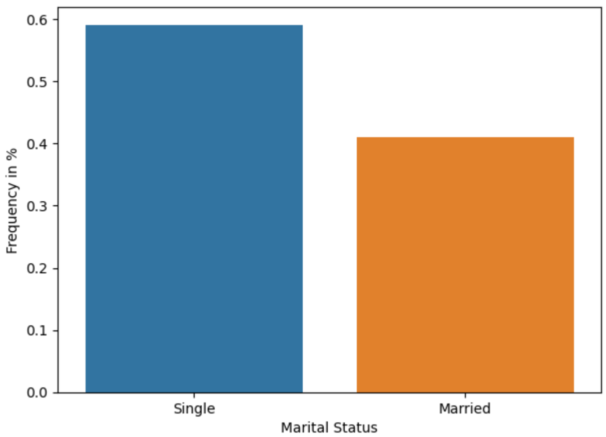
- From the **given sample data**, we can see that :
  - ~75 % customers are `male`
  - ~25 % customers are `female`
- From the **problem statement**, its also given that the company has 50 million customers are male and 50 million are female overall
- **So, we can see that this sample has some gender bias**

In [70]:
```
sns.barplot(x = df["Gender"].value_counts(normalize=True).index,
            y = df["Gender"].value_counts(normalize=True))
plt.xlabel("Gender")
```

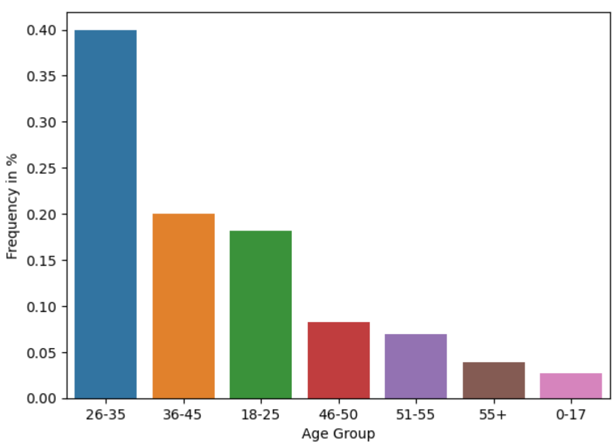
```
plt.ylabel("Frequency in %")
plt.show()
```



In [71]:
```
plt.figure(figsize=(7,5))
sns.barplot(x = df["Marital_Status"].value_counts(normalize=True).index,
             y = df["Marital_Status"].value_counts(normalize=True))
plt.xlabel("Marital Status")
plt.ylabel("Frequency in %")
plt.show()
```



In [72]:
```
plt.figure(figsize=(7,5))
sns.barplot(x = df["Age"].value_counts(normalize=True).index,
             y = df["Age"].value_counts(normalize=True))
plt.xlabel("Age Group")
plt.ylabel("Frequency in %")
plt.show()
```



Purchase Statistic for `Male` and `Female` Data

In [73]:
```
female_data = df.loc[df["Gender"]=="Female"]
female_data.describe().T
```

Out[73]:

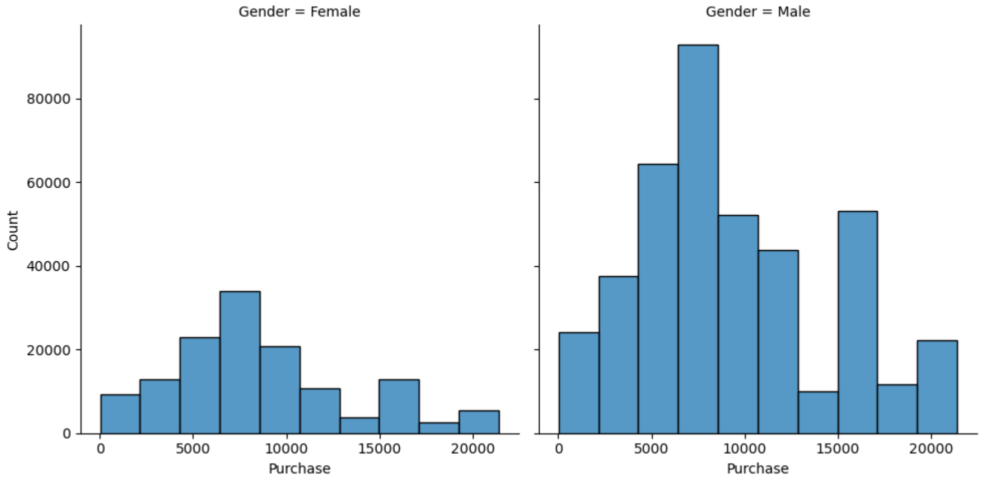
	count	mean	std	min	25%	50%	75%	max
Purchase	135220.0	8671.049039	4679.058483	12.0	5429.0	7906.0	11064.0	21398.0

In [74]:
```
male_data = df.loc[df["Gender"]=="Male"]
male_data.describe().T
```

Out[74]:

	count	mean	std	min	25%	50%	75%	max
Purchase	412171.0	9367.724355	5009.234088	12.0	5852.0	8089.0	12247.0	21399.0

In [75]:
```
sns.displot(x = df["Purchase"], bins = 10, col=df["Gender"])
plt.show()
```



Purchase Statistic for `Married` and `Singe` Customer Data

In [76]:
```
married_data = df.loc[df["Marital_Status"]=="Single"]
married_data.describe().T
```

Out[76]:

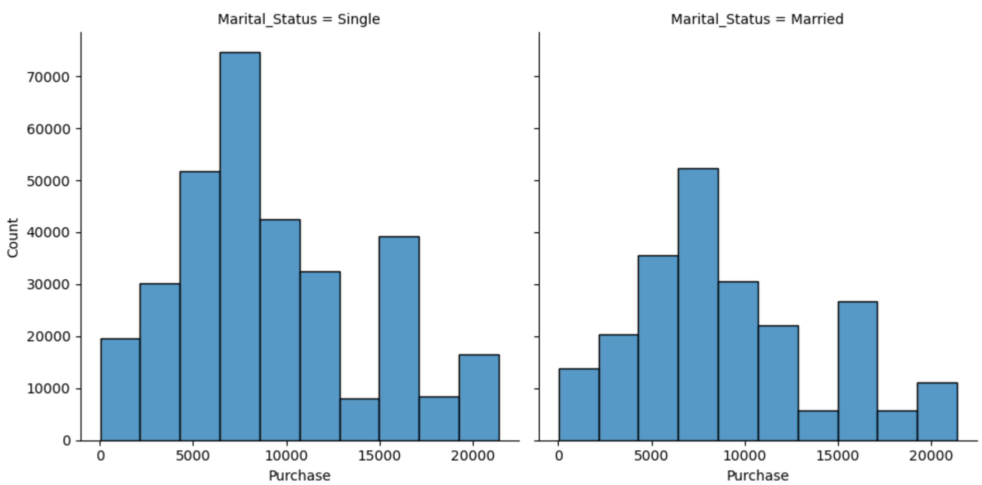
	count	mean	std	min	25%	50%	75%	max
Purchase	323242.0	9201.581849	4948.327397	12.0	5480.0	8035.0	12028.0	21399.0

In [109…
```
single_data = df.loc[df["Marital_Status"]=="Married"]
single_data.describe().T
```

Out[109]:

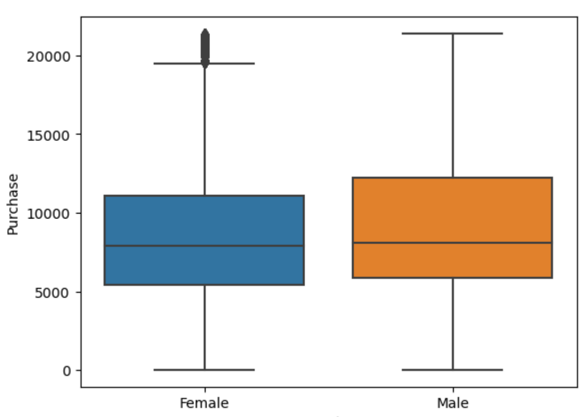
	count	mean	std	min	25%	50%	75%	max
Purchase	224149.0	9187.040076	4925.205232	12.0	5833.0	8042.0	12006.0	21398.0

In [110…
```
sns.displot(x = df["Purchase"], bins = 10, col=df["Marital_Status"])
plt.show()
```



In [79]:
```
sns.boxplot(x = "Gender", y = "Purchase", data = df)
```

Out[79]: <Axes: xlabel='Gender', ylabel='Purchase'>



In [184…
```
def dist_box_violin(data):
    Name = data.name.capitalize()
    fig, axes = plt.subplots(1, 3, figsize=(17, 7))
    fig.suptitle("Spread of data for " + Name, fontsize=18, fontweight='bold')

    # Histogram with mean, median, and mode
    sns.histplot(data, kde=False, color='green', ax=axes[0])
    axes[0].axvline(data.mean(), color='blue', linestyle='--', linewidth=2)
    axes[0].axvline(data.median(), color='red', linestyle='dashed', linewidth=2)
    axes[0].axvline(data.mode()[0], color='purple', linestyle='solid', linewidth=2)
    axes[0].legend({'Mean': data.mean(), 'Median': data.median(), 'Mode': data.mode()})

    # Box plot
    sns.boxplot(x=data, showmeans=True, orient='h', color="orange", ax=axes[1])

    # Violin plot
    sns.violinplot(data, ax=axes[2], showmeans=True)
```

Detect Outliers

In [80]:
```
def detect_outliers(data):
    length_before = len(data)
    Q1 = np.percentile(data["Purchase"],25)
    Q3 = np.percentile(data["Purchase"],75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

    length_after = len(data.loc[(data["Purchase"]>lowerbound)&(data["Purchase"]<upperbound)])
    return f"{np.round((length_before-length_after)/length_before,4)} % Outliers data from input data found"
```

In [81]:
```
detect_outliers(df)
```

Out[81]:
```
'0.0 % Outliers data from input data found'
```

In [82]:
```
def detect_and_remove_outliers(data):
    Q1 = np.percentile(data["Purchase"],25)
    Q3 = np.percentile(data["Purchase"],75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

    return data.loc[(data["Purchase"]>lowerbound)&(data["Purchase"]<upperbound)]
```

In [83]:
```
df = detect_and_remove_outliers(df)
```

In [84]:
```
df.shape
```

Out[84]:
```
(547391, 10)
```

Balancing the `gender` despaires

In [85]:
```
df["Gender"].value_counts(normalize=True)*100
```

Out[85]:
```
Male      75.297365
Female    24.702635
Name: Gender, dtype: float64
```

In [86]:
```
samplemale = df[df["Gender"]=="Male"].sample(n=135809)
samplefemale = df.loc[df["Gender"]=="Female"]
unbiased_data = pd.concat([samplemale,samplefemale])
```

In [87]:
```
unbiased_data
```

Out[87]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
118193	1000226	P00320742	Male	36-45	1	C	1	Single	1	7694
120736	1000671	P00365342	Male	18-25	4	C	0	Single	1	11392
546069	1000229	P00372445	Male	18-25	10	C	1	Single	20	493
7054	1001119	P00193242	Male	36-45	1	B	2	Married	6	16565
305033	1004979	P00053042	Male	36-45	2	B	1	Married	5	6909
...	...	...	...	...	...	...	...	...	...	...
550061	1006029	P00372445	Female	26-35	1	C	1	Married	20	599
550064	1006035	P00375436	Female	26-35	1	C	3	Single	20	371
550065	1006036	P00375436	Female	26-35	15	B	4+	Married	20	137
550066	1006038	P00375436	Female	55+	1	C	2	Single	20	365
550067	1006039	P00371644	Female	46-50	0	B	4+	Married	20	490

271029 rows × 10 columns

CLT on `Purchase` (`Gender` Wise)

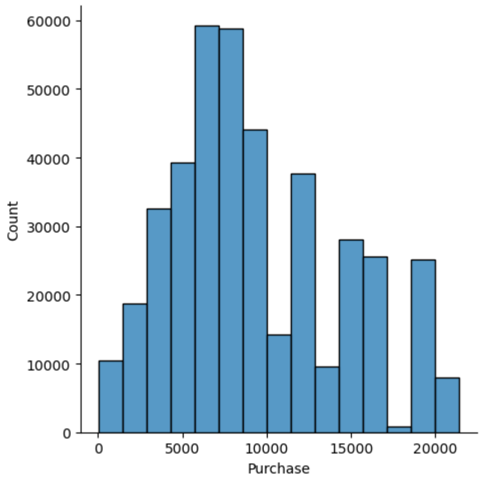
In [89]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import t

def Bootstrapping_CLT_CI(data, confidence=95, sample_size=30000, trials=200):
    '''
    data : array
    confidence level : Required Confidence Level
    Sample Size  : length of Sample Size
    Trials : How many times we take a sample from data.
    '''
    print("Data Distribution before Sampling/Bootstrap:")
    sns.displot(data, bins=15)
    plt.show()
```

```
    bootstrapped_means = np.empty(trials)

    for i in range(trials):
        bootstrap_sample = np.random.choice(data, size=sample_size, replace=True)
        bootstrapped_means[i] = np.mean(bootstrap_sample)

    print("Data Distribution After Sampling/Bootstrapping:")
    sns.displot(bootstrapped_means, bins=15)

    sample_mean = np.mean(bootstrapped_means)
    sample_std = np.std(data)
    standard_error = sample_std / np.sqrt(sample_size)
    t_critical = t.ppf((1-((1-(confidence)/100)/2)),df = sample_size-1)
    margin_of_error = t_critical * standard_error

    print("t:", t_critical)
    print("sample mean:", sample_mean)
    print("sample standard deviation:", sample_std)
    print("sample size:", sample_size)
    print("standard error:", standard_error)
    print("Margin of Error:", margin_of_error)

    lower_bound = sample_mean - margin_of_error
    upper_bound = sample_mean + margin_of_error
    confidence_interval = (lower_bound, upper_bound)

    plt.axvline(x=lower_bound, c="r")
    plt.axvline(x=upper_bound, c="r")
    plt.show()

    print("Confidence Interval:", confidence_interval)
```

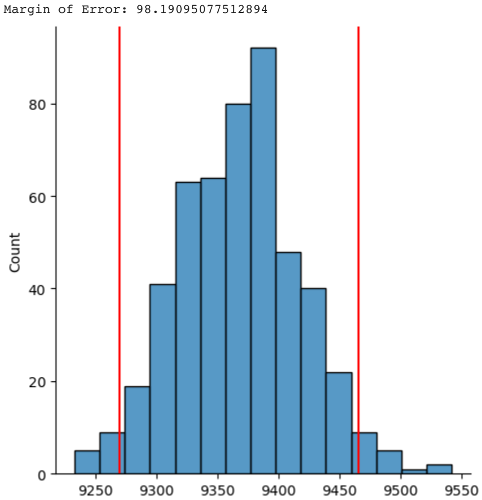
Confidence Interval for `Male` (`Purchase`)

In [90]:
```
Bootstrapping_CLT_CI(male_data["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 9368.0446454
sample standard deviation: 5009.228011297518
sample size: 10000
standard error: 50.092280112975175
Margin of Error: 98.19095077512894
```

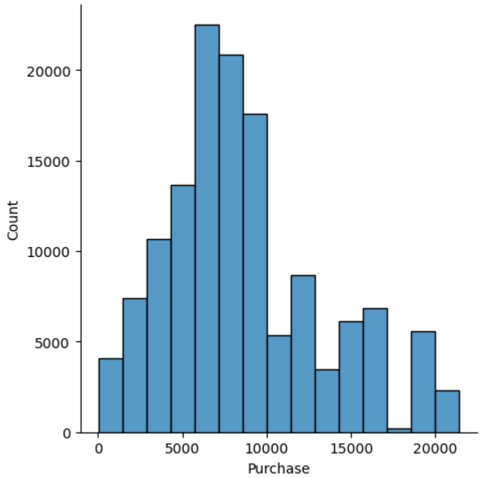



```
Confidence Interval: (9269.85369462487, 9466.23559617513)
```

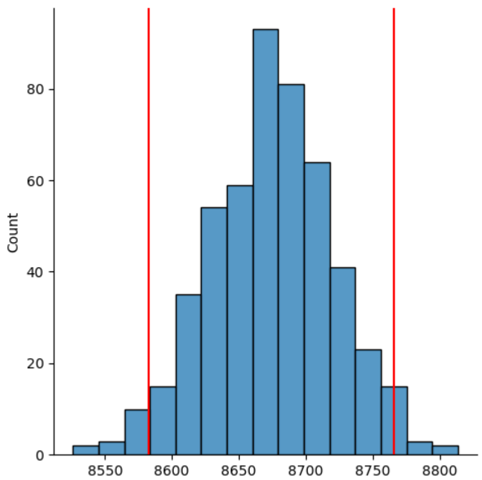
Confidence Interval for `Female` (`Purchase`)

In [91]:
```
Bootstrapping_CLT_CI(female_data["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 8674.1958022
sample standard deviation: 4679.041181401486
sample size: 10000
standard error: 46.79041181401486
Margin of Error: 91.71862436319562
```




```
Confidence Interval: (8582.477177836805, 8765.914426563195)
```

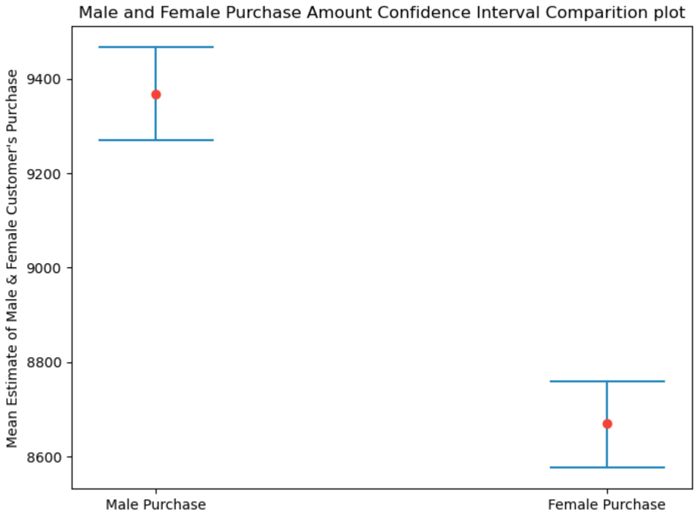
In [92]:
```
import matplotlib.pyplot as plt
import statistics
from math import sqrt

def plot_confidence_interval(x, values, color='#2187bb', horizontal_line_width=0.25, confidence=95):

    def calculate_confidence_interval(data, confidence, sample_size=10000, trials=500):
        bootstrapped_means = np.empty(trials)

        for i in range(trials):
            bootstrap_sample = np.random.choice(data, size=sample_size, replace=True)
            bootstrapped_means[i] = np.mean(bootstrap_sample)

        sample_mean = np.mean(bootstrapped_means)
        sample_std = np.std(data)
        standard_error = sample_std / sqrt(sample_size)
        t_critical = t.ppf((1 - (1 - (confidence / 100)) / 2), df=sample_size - 1)
        margin_of_error = t_critical * standard_error

        return margin_of_error, sample_mean + margin_of_error, sample_mean - margin_of_error

    error, bottom, top = calculate_confidence_interval(values, confidence)

    left = x - horizontal_line_width / 2
    right = x + horizontal_line_width / 2

    plt.plot([x, x], [top, bottom], color=color)
    plt.plot([left, right], [top, top], color=color)
    plt.plot([left, right], [bottom, bottom], color=color)
    plt.plot(x, np.mean(values), 'o', color='#f44336')

    print("Confidence Interval:", (top, bottom))
    print("Sample Mean:", np.mean(values), "and", "Margin of Error:", error)
```

Estimate of Average Spending Amount

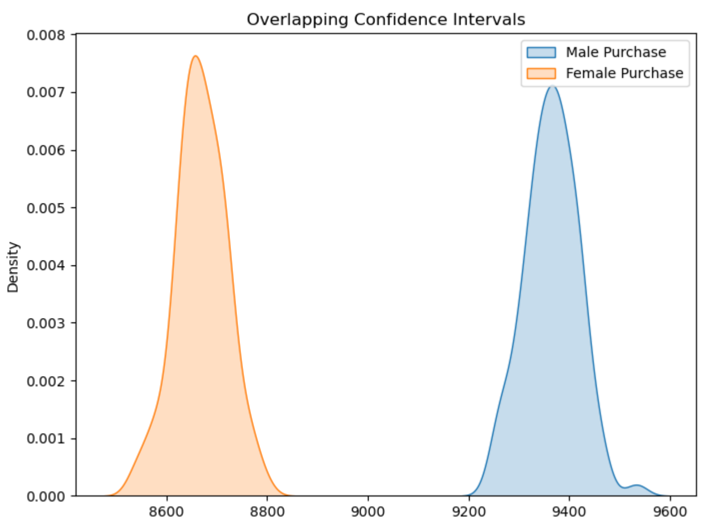
> with `95% confidence` for spendings of Male and Female Customers

In [93]:
```
plt.figure(figsize=(8,6))

plot_confidence_interval(x=1,values=male_data["Purchase"])
plot_confidence_interval(x=2,values=female_data["Purchase"])
plt.xticks([1,2],["Male Purchase","Female Purchase"])
plt.title("Male and Female Purchase Amount Confidence Interval Comparition plot")
plt.ylabel("Mean Estimate of Male & Female Customer's Purchase")
plt.show()
```

```
Confidence Interval: (9270.342023624871, 9466.72392517513)
Sample Mean: 9367.724354697444 and Margin of Error: 98.19095077512894
Confidence Interval: (8576.257768236805, 8759.695016963195)
Sample Mean: 8671.049038603756 and Margin of Error: 91.71862436319562
```



In [94]:
```python
def calculate_expense_means(data, sample_size, num_samples):
    expense_means = [data['Purchase'].sample(sample_size).mean() for _ in range(num_samples)]
    return expense_means

sample_size = 10000
num_samples = 100

male_expense_mean = calculate_expense_means(male_data, sample_size, num_samples)
female_expense_mean = calculate_expense_means(female_data, sample_size, num_samples)

plt.figure(figsize=(8, 6))
sns.kdeplot(male_expense_mean, fill=True, label="Male Purchase")
sns.kdeplot(female_expense_mean, fill=True, label="Female Purchase")
plt.title("Overlapping Confidence Intervals")
plt.legend()
plt.show()
```



Observation

Following are the observation with 95% confidence and sample size of 10000 , 500 trials

- As per confidence Interval comparison for both female purchase and male purchase data , its clear that there's no over lapping , and hence there's a good amount of difference between Male and Female Spending amounts .
- Male Customers are more likely to spend more amount than female customers .
- Average Male Spending Amount from all 100 million customers lies in Range of 9333 to 9533 as per Bootstrapping Method
- Average Female Spending Amount from all 100 million customers lies in Range of 8639 to 8826 as per Bootstrapping Method

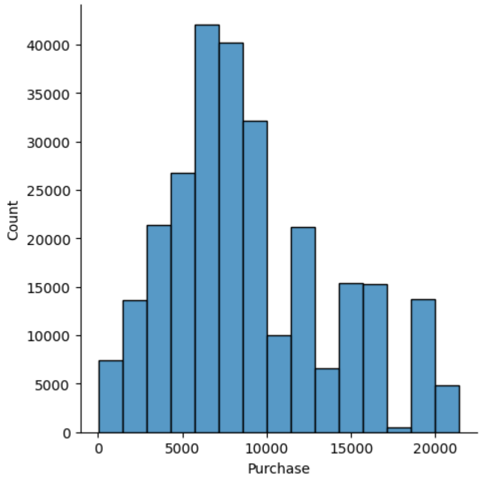
In [95]:
```python
data = unbiased_data.copy()
data["Age"].value_counts(normalize=True)*100
```

Out[95]:
```
26-35    39.106885
36-45    19.880160
18-25    18.253766
46-50     8.758841
51-55     7.106620
55+       3.825052
0-17      3.068675
Name: Age, dtype: float64
```

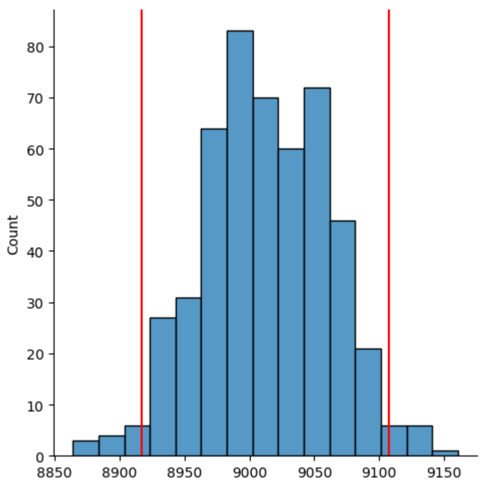
Confidence Interval for overall `Purchase`

In [96]:
```
Bootstrapping_CLT_CI(unbiased_data["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 9012.4231546
sample standard deviation: 4853.057319748064
sample size: 10000
standard error: 48.53057319748064
Margin of Error: 95.12969090597034
```



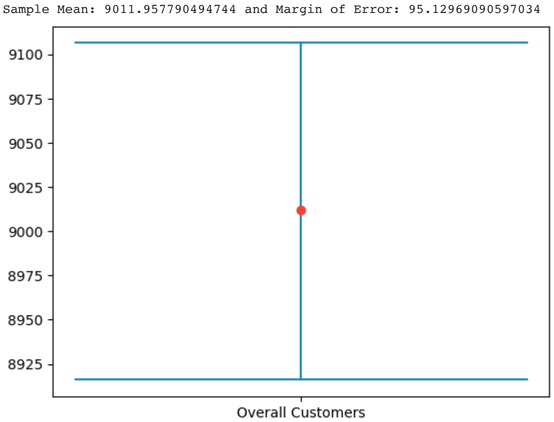

```
Confidence Interval: (8917.293463694028, 9107.55284550597)
```

Estimate of Average Spending Amount

> with `95% confidence` for spendings of all Customers

In [97]:
```
plot_confidence_interval(x=1,values=data["Purchase"])
plt.xticks([1],["Overall Customers"])
plt.show()
```

```
Confidence Interval: (8916.023849294028, 9106.28323110597)
Sample Mean: 9011.957790494744 and Margin of Error: 95.12969090597034
```



Confidence Interval for `Married` People Purchase Data

In [98]:
```
unbiased_data
```

Out[98]:

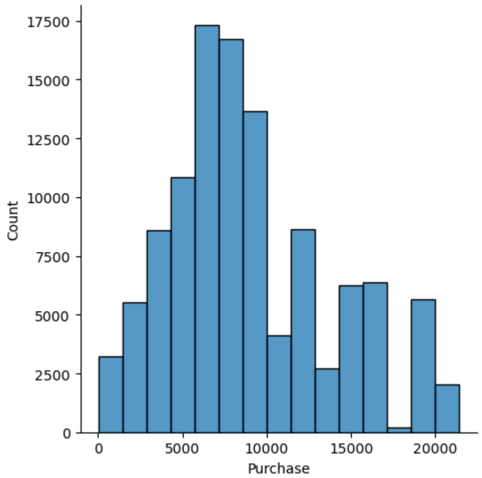
	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
118193	1000226	P00320742	Male	36-45	1	C	1	Single	1	7694
120736	1000671	P00365342	Male	18-25	4	C	0	Single	1	11392
546069	1000229	P00372445	Male	18-25	10	C	1	Single	20	493
7054	1001119	P00193242	Male	36-45	1	B	2	Married	6	16565
305033	1004979	P00053042	Male	36-45	2	B	1	Married	5	6909
...	...	...	...	...	...	...	...	...	...	...
550061	1006029	P00372445	Female	26-35	1	C	1	Married	20	599
550064	1006035	P00375436	Female	26-35	1	C	3	Single	20	371
550065	1006036	P00375436	Female	26-35	15	B	4+	Married	20	137
550066	1006038	P00375436	Female	55+	1	C	2	Single	20	365
550067	1006039	P00371644	Female	46-50	0	B	4+	Married	20	490

271029 rows × 10 columns

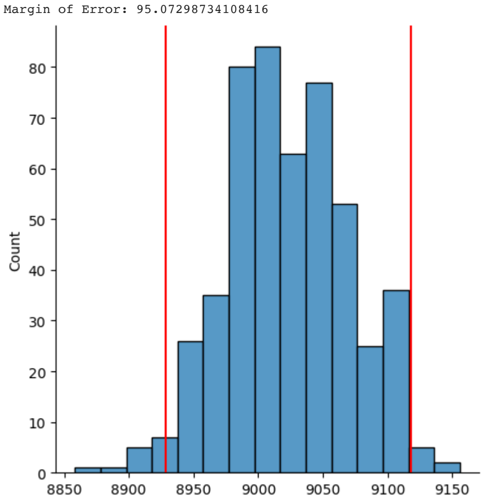
In [99]:

```
Bootstrapping_CLT_CI(data.loc[data["Marital_Status"]=="Married"]["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 9023.3125194
sample standard deviation: 4850.164577765977
sample size: 10000
standard error: 48.50164577765977
Margin of Error: 95.07298734108416
```

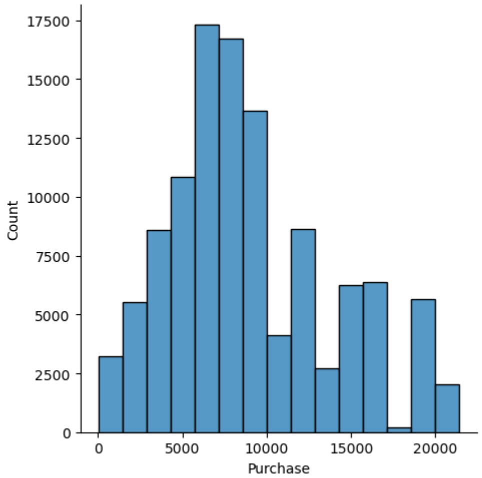



```
Confidence Interval: (8928.239532058917, 9118.385506741084)
```

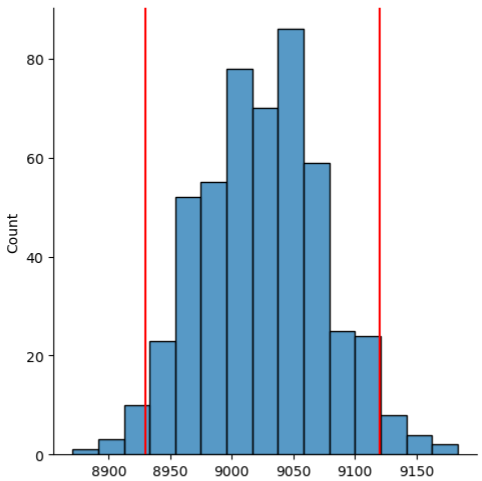
In [100…

```
Bootstrapping_CLT_CI(data.loc[data["Marital_Status"]=="Married"]["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 9025.032250800003
sample standard deviation: 4850.164577765977
sample size: 10000
standard error: 48.50164577765977
Margin of Error: 95.07298734108416
```



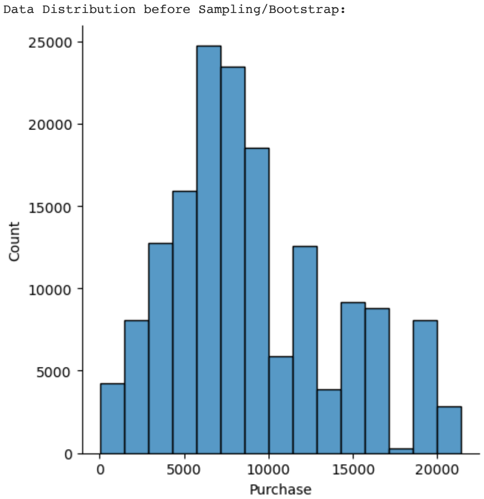

```
Confidence Interval: (8929.959263458919, 9120.105238141086)
```

Confidence Interval for `Single` People Purchase Data

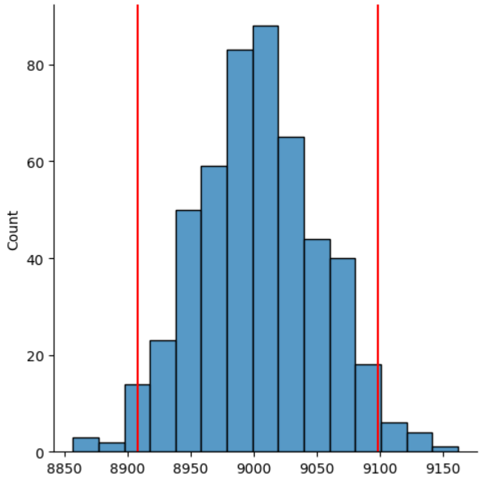
In [102…

```
Bootstrapping_CLT_CI(data.loc[data["Marital_Status"]=="Single"]["Purchase"],sample_size=10000,trials=500)
```

```
Data Distribution before Sampling/Bootstrap:
```




```
Data Distribution After Sampling/Bootstrapping:
t: 1.9602012636213575
sample mean: 9003.5821142
sample standard deviation: 4855.067530547763
sample size: 10000
standard error: 48.55067530547763
Margin of Error: 95.1690950834675
```




```
Confidence Interval: (8908.413019116533, 9098.751209283468)
```

In [ ]:

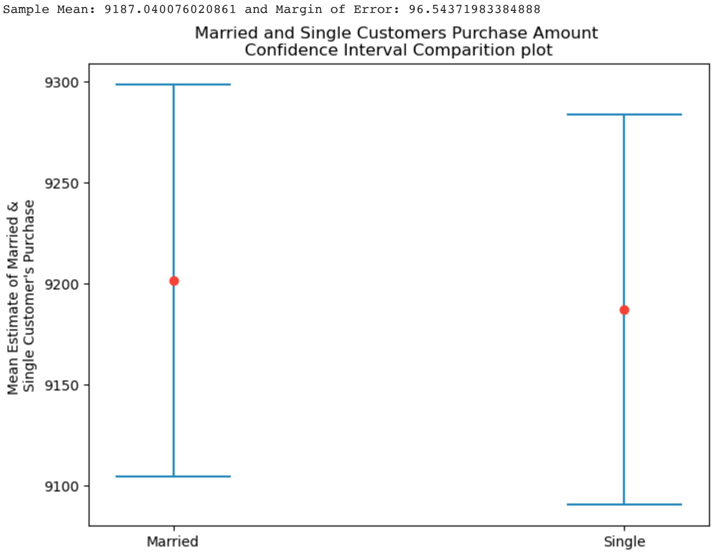
Estimate of Average Spending Amount

> with 95% confidence for Married and Single Customers

In [103…

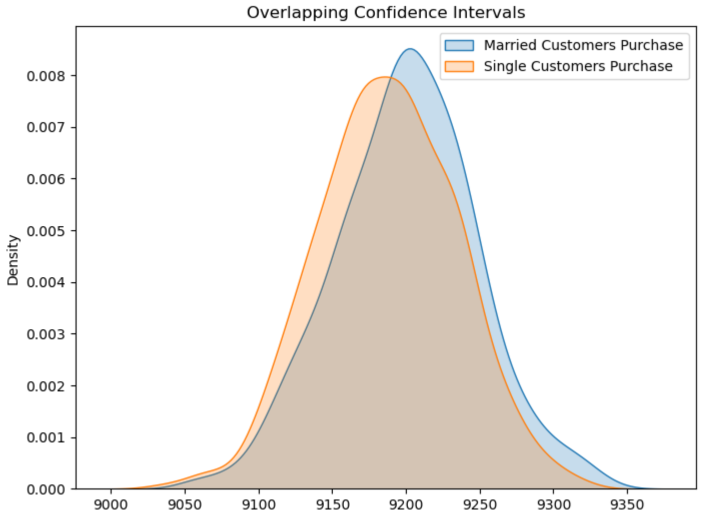
```
plt.figure(figsize=(8,6))
plot_confidence_interval(x=1,values=married_data["Purchase"])
plot_confidence_interval(x=2,values=singe_data["Purchase"])
plt.xticks([1,2],["Married","Single"])
plt.title("Married and Single Customers Purchase Amount \nConfidence Interval Comparition plot")
plt.ylabel("Mean Estimate of Married & \nSingle Customer's Purchase")
plt.show()
```

```
Confidence Interval: (9104.479143865017, 9298.473196134986)
Sample Mean: 9201.581848893398 and Margin of Error: 96.9970261349839
Confidence Interval: (9090.426239166149, 9283.513678833848)
Sample Mean: 9187.040076020861 and Margin of Error: 96.54371983384888
```



In [112…

```
def calculate_expense_means(data, sample_size, num_samples):
    expense_means = [data['Purchase'].sample(sample_size).mean() for _ in range(num_samples)]
    return expense_means

sample_size = 10000
num_samples = 500

married_expenses_mean = calculate_expense_means(married_data, sample_size, num_samples)
single_expenses_mean = calculate_expense_means(single_data, sample_size, num_samples)

plt.figure(figsize=(8, 6))
sns.kdeplot(married_expenses_mean, fill=True, label="Married Customers Purchase")
sns.kdeplot(single_expenses_mean, fill=True, label="Single Customers Purchase")
plt.title("Overlapping Confidence Intervals")
plt.legend()
plt.show()
```



Observation

- As per confidence Interval comparison for both Single and Married Customer's average purchase data

> There is not much difference between their average spending amounts. Married and Single Customer's spending amounts distribution are almost lies with same distribution.

Confidence Interval with `different` Sample Size

In [113…

```
def calculate_confidence_interval(data, confidence=95, sample_size=10000, trials=500):
    bootstrapped_mean = np.empty(trials)

    for i in range(trials):
        btssample = data.sample(n=sample_size, replace=True)
        bootstrapped_mean[i] = np.mean(btssample)

    sample_mean = np.mean(bootstrapped_mean)
    sample_std = np.std(data)
    standard_error = sample_std / np.sqrt(sample_size)
    t_alpha_by2 = t.ppf((1 - ((1 - (confidence / 100)) / 2)), df=sample_size - 1)
    margin_of_error = t_alpha_by2 * standard_error
    lower_bound = sample_mean - margin_of_error
    upper_bound = sample_mean + margin_of_error
    confidence_interval = (lower_bound, upper_bound)

    print()
    print("Confidence Level:", confidence)
    print("Sample Size:", sample_size)
    print("Margin of Error:", margin_of_error)

    return f"Confidence Interval: {confidence_interval}"
```

In [114…

```
# Confidence Interval Calculations for Different Age Groups
age_groups = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']

for age_group in age_groups:
    print("Age Group:", age_group)
    age_data = data.loc[data["Age"] == age_group]["Purchase"]
    confidence_interval = calculate_confidence_interval(age_data)
    print(confidence_interval)
    print()
```

```
Age Group: 0-17

Confidence Level: 95
Sample Size: 10000
Margin of Error: 96.60856880773487
Confidence Interval: (8530.311565792264, 8723.528703407734)

Age Group: 18-25

Confidence Level: 95
Sample Size: 10000
Margin of Error: 95.73775119621878
Confidence Interval: (8762.963975603781, 8954.439477996219)

Age Group: 26-35

Confidence Level: 95
Sample Size: 10000
Margin of Error: 94.84029459866774
Confidence Interval: (8924.022922201331, 9113.703511398666)

Age Group: 36-45

Confidence Level: 95
Sample Size: 10000
Margin of Error: 95.34810484947728
Confidence Interval: (9021.928946350521, 9212.625156049477)

Age Group: 46-50

Confidence Level: 95
Sample Size: 10000
Margin of Error: 94.23561542896758
Confidence Interval: (8879.321817771031, 9067.793048628968)

Age Group: 51-55

Confidence Level: 95
Sample Size: 10000
Margin of Error: 95.28875351421043
Confidence Interval: (9141.862907685789, 9332.44041471421)

Age Group: 55+

Confidence Level: 95
Sample Size: 10000
Margin of Error: 93.75749786224198
Confidence Interval: (9041.69533053776, 9229.210326262242)
```

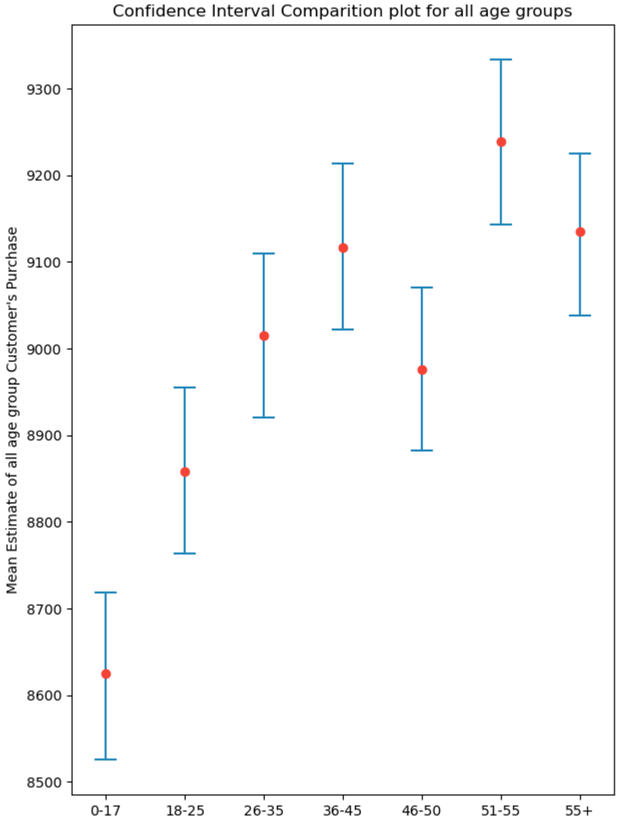
Estimate of Average Spending Amount

> with 95% confidence for different Age group

In [115…

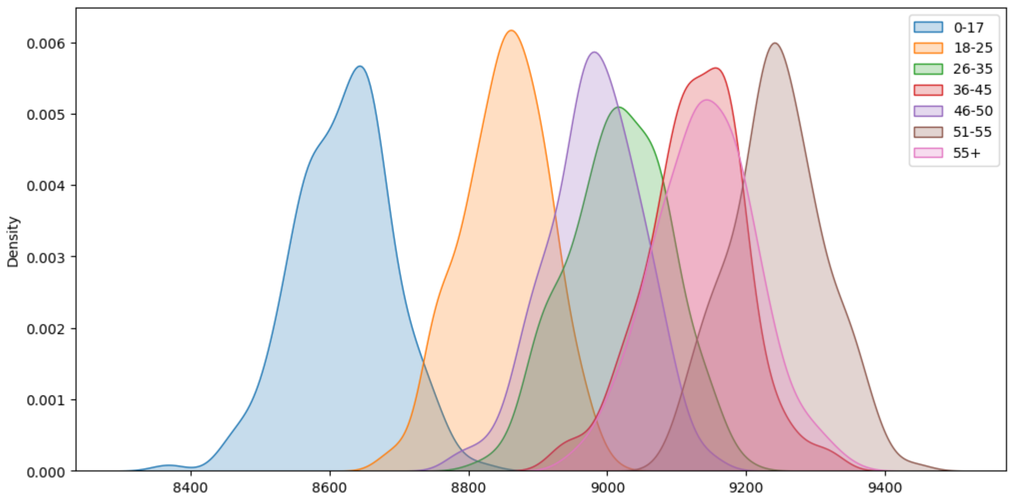
```python
plt.figure(figsize=(7,10))
i = 1
for age_group in ['0-17', '18-25','26-35', '36-45', '46-50', '51-55', '55+' ]:
    print("Age Group : ", age_group)
    (plot_confidence_interval(i,data.loc[data["Age"]==age_group]["Purchase"]))
    i = i+1

plt.xticks([1,2,3,4,5,6,7],['0-17', '18-25','26-35', '36-45', '46-50', '51-55', '55+'])

plt.title("Confidence Interval Comparition plot for all age groups")
plt.ylabel("Mean Estimate of all age group Customer's Purchase")
plt.show()


plt.show()
```

```
Age Group :  0-17
Confidence Interval: (8525.564306192266, 8718.781443807735)
Sample Mean: 8624.969339906216 and Margin of Error: 96.60856880773487
Age Group :  18-25
Confidence Interval: (8763.199158203783, 8954.67466059622)
Sample Mean: 8858.663574070706 and Margin of Error: 95.73775119621878
Age Group :  26-35
Confidence Interval: (8920.207122001333, 9109.887711198668)
Sample Mean: 9015.120170580522 and Margin of Error: 94.84029459866774
Age Group :  36-45
Confidence Interval: (9022.397093350522, 9213.093303049478)
Sample Mean: 9117.182457638128 and Margin of Error: 95.34810484947728
Age Group :  46-50
Confidence Interval: (8882.353665971032, 9070.824896828968)
Sample Mean: 8976.210918741312 and Margin of Error: 94.23561542896758
Age Group :  51-55
Confidence Interval: (9142.734440685788, 9333.31194771421)
Sample Mean: 9238.947873942163 and Margin of Error: 95.28875351421043
Age Group :  55+
Confidence Interval: (9038.102722737758, 9225.617718462241)
Sample Mean: 9134.872094144883 and Margin of Error: 93.75749786224198
```



In [122…

```
plt.figure(figsize=(12, 6))

for age_group in ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']:
    age_data = data.loc[data["Age"] == age_group]["Purchase"]
    x = [age_data.sample(5000, replace=True).mean() for _ in range(200)]
    sns.kdeplot(x, fill=True, label=age_group)

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



Observation

- Customers from age 26-35 are 40% of all customers. and their Average Spending amount is near to overall customers average spending amount
- Age group 51-55 customers are more likely to spend more amount than all other groups
- Customers under 17 age are the least spending average amount

Impact on Confidence Interval with Different Sample Size

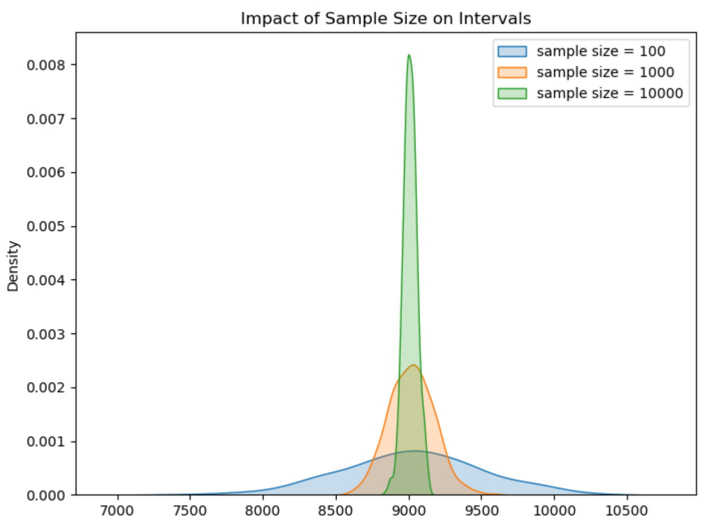
In [123…

```
print(calculate_confidence_interval(data["Purchase"],sample_size=50))
print(calculate_confidence_interval(data["Purchase"],sample_size=250))
print(calculate_confidence_interval(data["Purchase"],sample_size=750))
print(calculate_confidence_interval(data["Purchase"],sample_size=1500))
print(calculate_confidence_interval(data["Purchase"],sample_size=5000))
print(calculate_confidence_interval(data["Purchase"],sample_size=25000))
```

```
Confidence Level: 95
Sample Size: 50
Margin of Error: 1379.2236280010134
Confidence Interval: (7653.916971998988, 10412.364228001014)

Confidence Level: 95
Sample Size: 250
Margin of Error: 604.5184097782867
Confidence Interval: (8394.142118221713, 9603.178937778288)

Confidence Level: 95
Sample Size: 750
Margin of Error: 347.88462623561367
Confidence Interval: (8656.045957764387, 9351.815210235613)

Confidence Level: 95
Sample Size: 1500
Margin of Error: 245.79253535061522
Confidence Interval: (8764.533368649387, 9256.118439350616)

Confidence Level: 95
Sample Size: 5000
Margin of Error: 134.54999127759322
Confidence Interval: (8876.730579522406, 9145.830562077594)

Confidence Level: 95
Sample Size: 25000
Margin of Error: 60.16092914610573
Confidence Interval: (8951.697959093894, 9072.019817386106)
```

In [125…

```
sample_sizes = [100, 1000, 10000]
sample_means = []

for size in sample_sizes:
    sample_mean = [data['Purchase'].sample(size).mean() for _ in range(500)]
    sample_means.append(sample_mean)

plt.figure(figsize=(8, 6))

for i, size in enumerate(sample_sizes):
    sns.kdeplot(sample_means[i], fill=True, label=f"sample size = {size}")

plt.title("Impact of Sample Size on Intervals")
plt.legend()
plt.show()
```



Observation

- As per calculations and above distribution plot, as we increase the sample size, standard error decreases , means that the average spending amount gets closers and closer to the actual mean spending amount of the all customer average spending amount.

In [127…

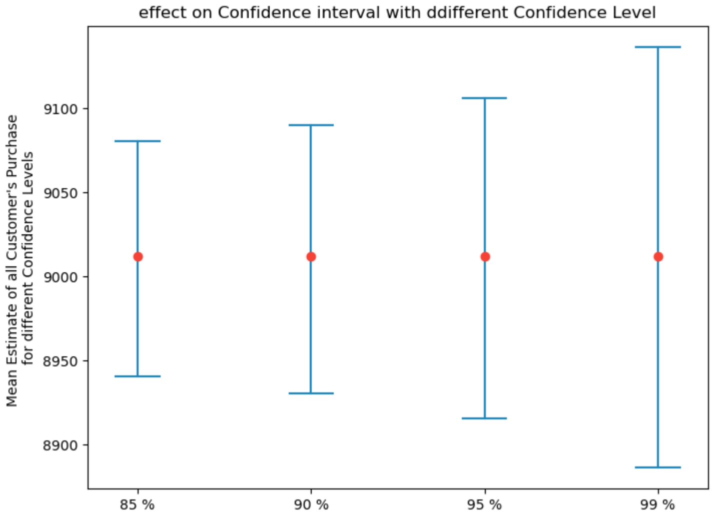
```
print(calculate_confidence_interval(data["Purchase"],confidence=90,sample_size=10000))
print(calculate_confidence_interval(data["Purchase"],confidence=95,sample_size=10000))
print(calculate_confidence_interval(data["Purchase"],confidence=99,sample_size=10000))
```

```
Confidence Level: 90
Sample Size: 10000
Margin of Error: 79.83308570991127
Confidence Interval: (8930.830820690087, 9090.496992109911)

Confidence Level: 95
Sample Size: 10000
Margin of Error: 95.12969090597034
Confidence Interval: (8918.978376694029, 9109.237758505971)

Confidence Level: 99
Sample Size: 10000
Margin of Error: 125.03033952268214
Confidence Interval: (8885.474676877318, 9135.535355922682)
```

In [128…

```
plt.figure(figsize=(8,6))
plot_confidence_interval(x=0,values=data["Purchase"],confidence=85)
plot_confidence_interval(x=1,values=data["Purchase"],confidence=90)
plot_confidence_interval(x=2,values=data["Purchase"],confidence=95)
plot_confidence_interval(x=3,values=data["Purchase"],confidence=99)
plt.xticks([0,1,2,3],["85 %","90 %","95 %","99 %"])
plt.title("effect on Confidence interval with ddifferent Confidence Level")
plt.ylabel("Mean Estimate of all Customer's Purchase \nfor different Confidence Levels")
plt.show()
```

```
Confidence Interval: (8940.603147638438, 9080.336455961562)
Sample Mean: 9011.957790494744 and Margin of Error: 69.866654161562
Confidence Interval: (8930.416619290088, 9090.082790709912)
Sample Mean: 9011.957790494744 and Margin of Error: 79.83308570991127
Confidence Interval: (8915.765549494028, 9106.02493130597)
Sample Mean: 9011.957790494744 and Margin of Error: 95.12969090597034
Confidence Interval: (8886.249272677318, 9136.309951722682)
Sample Mean: 9011.957790494744 and Margin of Error: 125.03033952268214
```



Observation

- As we decide to increase the confidence level , the interval of confidence for given parameter gets wider

Product Category

In [129…

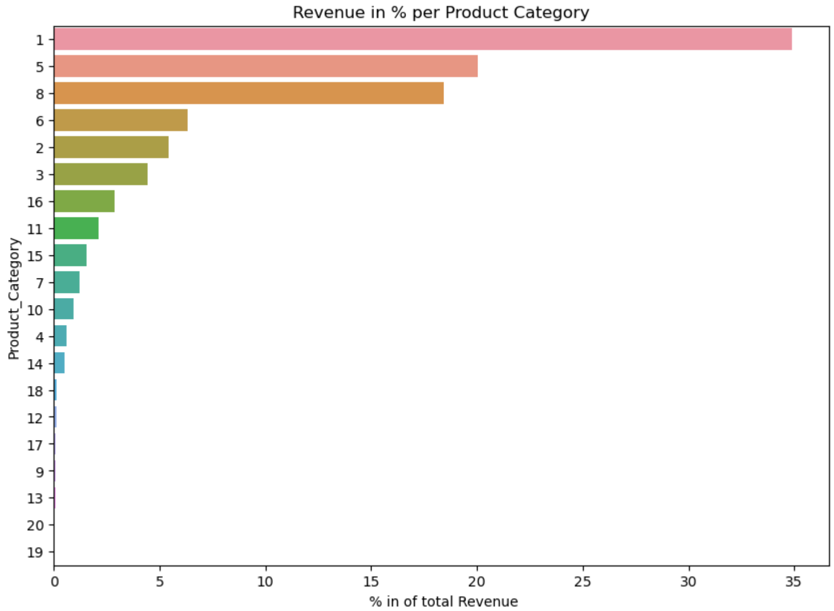
```python
pro_cat = (data.groupby("Product_Category")["Purchase"].sum()/data["Purchase"].sum()*100).sort_values(ascending=False)
pro_cat
```

Out[129]:

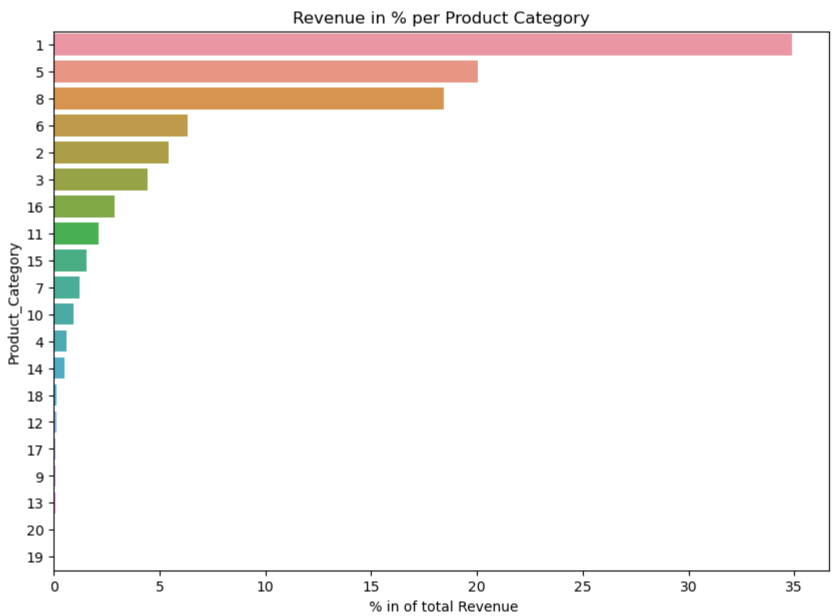
```
Product_Category
1     34.906836
5     20.044411
8     18.440023
6      6.311882
2      5.411625
3      4.443503
16     2.899018
11     2.121996
15     1.546261
7      1.237963
10     0.925729
4      0.618274
14     0.510102
18     0.150122
12     0.131079
17     0.108649
9      0.087715
13     0.083548
20     0.019989
19     0.001274
Name: Purchase, dtype: float64
```

In [130…

```python
plt.figure(figsize=(10,7))

sns.barplot(x = pro_cat,
           y = pro_cat.index
           )
plt.title("Revenue in % per Product Category")
plt.xlabel(" % in of total Revenue")
plt.show()
```



In [133…
```
plt.figure(figsize=(10,7))

sns.barplot(x = pro_cat,
           y = pro_cat.index
           )
plt.title("Revenue in % per Product Category")
plt.xlabel(" % in of total Revenue")
plt.show()
```



In [166…
```
import warnings
warnings.filterwarnings('ignore')
```

Most Common Product Categories

In [167…
```
groupedf = data.loc[data["User_ID"].duplicated(keep = False)]
groupedf.shape
```

Out[167]: (271009, 10)

In [168…
```
groupedf["Group Order"] = groupedf.groupby("User_ID")["Product_Category"].transform(lambda  x : ",".join(x))
groupedf["Group Order"] = groupedf["Group Order"].apply(lambda x: ",".join(np.unique(x.split(","))))
uniq_orders = groupedf[["User_ID","Group Order"]].drop_duplicates()
```

In [170…
```
uniq_orders.describe()
```

Out[170]:

	User_ID	Group Order
count	5865	5865
unique	5865	2798
top	1000226	1,5,8
freq	1	135

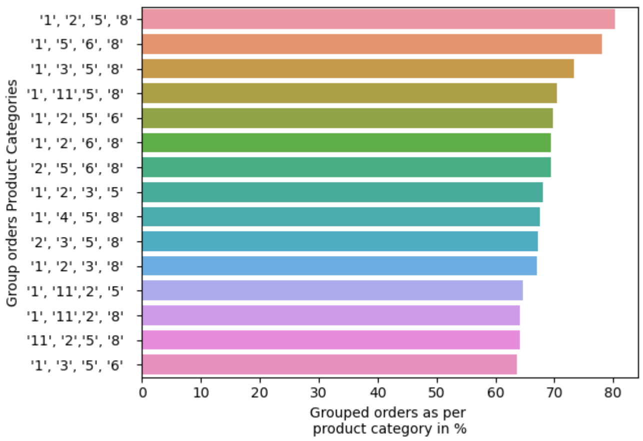
In [171…
```
from collections import Counter
from itertools import combinations

freq = Counter()
```

```
for r in groupedf["Group Order"]:

    row_list = r.split(",")
    freq.update(Counter(combinations(row_list,4)))
grouped_ordered_categories = freq.most_common(15)
grouped_ordered_categories
```

Out[171]:
```
[(('1', '2', '5', '8'), 218577),
 (('1', '5', '6', '8'), 211639),
 (('1', '3', '5', '8'), 200157),
 (('1', '11', '5', '8'), 191798),
 (('1', '2', '5', '6'), 188872),
 (('2', '5', '6', '8'), 188670),
 (('1', '2', '6', '8'), 188630),
 (('1', '2', '3', '5'), 185372),
 (('1', '4', '5', '8'), 184000),
 (('2', '3', '5', '8'), 183475),
 (('1', '2', '3', '8'), 183125),
 (('1', '11', '2', '5'), 175872),
 (('1', '11', '2', '8'), 175078),
 (('11', '2', '5', '8'), 174945),
 (('1', '2', '4', '5'), 173659)]
```

In [172…
```
cat_sold_together = pd.DataFrame(data=[217471,211573,198821,190851,189101,188376,188322,184308,
183249,182173,181778,175369,174108,173908,172663],
    index = ["'1', '2', '5', '8'",  "'1', '5', '6', '8'  ","'1', '3', '5', '8'  ",
"'1', '11','5', '8'  ","'1', '2', '5', '6'  ","'1', '2', '6', '8'  ",
"'2', '5', '6', '8'  ","'1', '2', '3', '5'  ","'1', '4', '5', '8'  ",
"'2', '3', '5', '8'  ","'1', '2', '3', '8'  ","'1', '11','2', '5'  ",
"'1', '11','2', '8'  ","'11', '2','5', '8'  ","'1', '3', '5', '6'  "],columns=["Orders"]
)
```

In [173…
```
cat_sold_together["group_order_in_percentage"] = (cat_sold_together["Orders"]/len(data))*100
group_order_in_percentage = cat_sold_together["group_order_in_percentage"]
sns.barplot(x = group_order_in_percentage,
           y = group_order_in_percentage.index)
plt.xlabel("Grouped orders as per \nproduct category in %")
plt.ylabel("Group orders Product Categories")
plt.show()
```



City Category

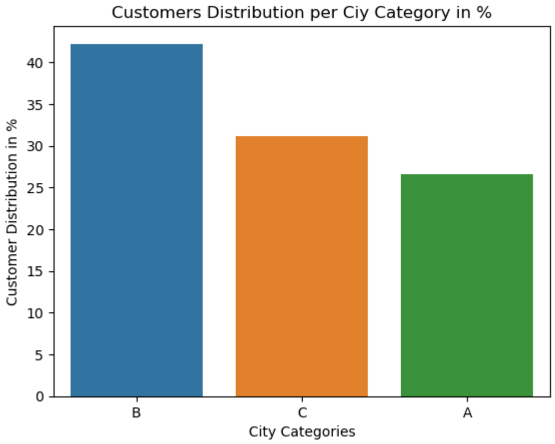
In [174…
```
data["City_Category"].value_counts(normalize=True)*100
```

Out[174]:
```
B    42.228691
C    31.121393
A    26.649916
Name: City_Category, dtype: float64
```

In [175…
```
City_cat = (data.groupby("City_Category")["Purchase"].sum()/data["Purchase"].sum()*100).sort_values(ascending=False)
City_cat
```

Out[175]:
```
City_Category
B    41.598481
C    32.608572
A    25.792947
Name: Purchase, dtype: float64
```

In [176…
```
sns.barplot(x = (data["City_Category"].value_counts(normalize=True)*100).index,
            y = (data["City_Category"].value_counts(normalize=True)*100) )

plt.title("Customers Distribution per Ciy Category in %")
plt.xlabel("City Categories")
plt.ylabel("Customer Distribution in %")
plt.show()
```



In [177…
```
pd.crosstab(columns=data["City_Category"],index=data["Age"],normalize="columns")*100
```

Out[177]:

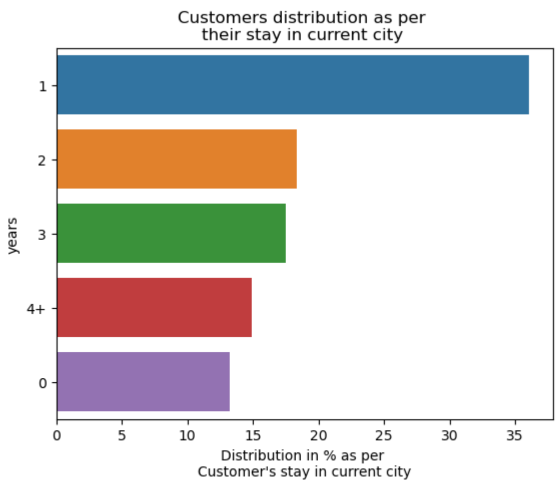
City_Category Age	A	B	C
0-17	2.490689	2.439451	4.417414
18-25	18.467651	19.271834	16.689192
26-35	49.552119	38.832873	30.534215
36-45	18.456576	20.064306	20.849338
46-50	4.653256	9.590046	11.146678
51-55	4.444198	7.542026	8.795704
55+	1.935511	2.259462	7.567459

Observation

- Most of Customers from City category A are from 26-35 years age
- Most of Customers from City category B are from 26-35 years age
- Most of Customers from City category C are from 26-35 years age

Customers their stay in current city (in `years`)

In [179…
```
Stayed_in_city_years_cat = data["Stay_In_Current_City_Years"].value_counts(normalize=True)*100

sns.barplot(y = Stayed_in_city_years_cat.index,
            x  = Stayed_in_city_years_cat)
plt.title("Customers distribution as per \ntheir stay in current city ")
plt.ylabel("years")
plt.xlabel("Distribution in % as per \nCustomer's stay in current city")
plt.show()
```



In [180…
```
pd.crosstab(columns=data["City_Category"],index=data["Stay_In_Current_City_Years"],normalize="columns")*100
```

Out[180]:

City_Category Stay_In_Current_City_Years	A	B	C
0	15.488239	12.479467	12.217243
1	33.489319	37.058330	37.007398
2	18.754240	17.347884	19.310476
3	18.149220	18.525670	15.555793
4+	14.118983	14.588649	15.909091

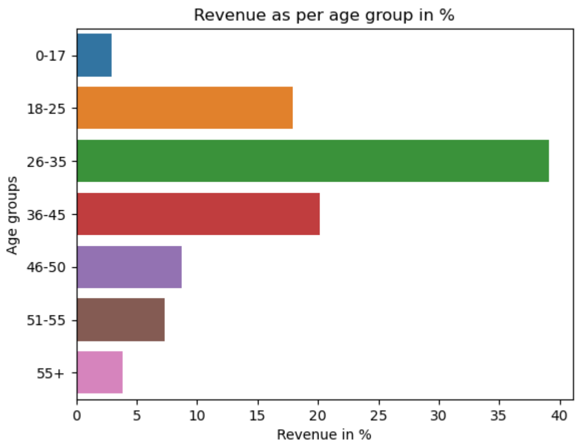
Observation

- All city categories are having customers majorly who are living there for 1 to 2 years.

Revenue generated per age (in %)

In [181…
```
ages_d = (data.groupby("Age")["Purchase"].sum()/data["Purchase"].sum())*100
```

In [182…
```
sns.barplot(y = ages_d.index,
            x  = ages_d)
plt.title("Revenue as per age group in %")
plt.ylabel("Age groups")
plt.xlabel("Revenue in %")
plt.show()
```



Purchase / Revenue per age / gender group

In [183…
```
(pd.crosstab(index= data["Age"],columns=data["Gender"],values=data["Purchase"],aggfunc=np.sum,margins=True)/data["Purchase"].sum())*100
```

Out[183]:

Gender / Age	Female	Male	All
0-17	1.715339	1.221562	2.936901
18-25	8.368708	9.574560	17.943268
26-35	17.952794	21.167814	39.120608
36-45	9.838694	10.273590	20.112283
46-50	4.718200	4.005898	8.724098
51-55	3.587515	3.698104	7.285619
55+	1.822775	2.054447	3.877222
All	48.004026	51.995974	100.000000

Observation

- Out of all women, 35% of the revenue coming from agae group 18 to 45 and so is same for men as well.

In [ ]: