Walmart Business Case Study

1. Data

The analysis was done on the data located at -
https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094

2. Libraries

Below are the libraries required for analysing and visualizing data

In [1]:
```
# libraries to analyze data
import numpy as np
import pandas as pd

# libraries to visualize data
import matplotlib.pyplot as plt
import seaborn as sns

# Misc libraries
import random
```

3. Data loading and exploratory data analysis

Loading the data into Pandas dataframe for easily handling of data

In [2]:
```
# read the file into a pandas dataframe
df = pd.read_csv('Walmart_data.csv')
# look at the datatypes of the columns
print('*************************************************')
print(df.info())
print('*************************************************\n')
print('*************************************************')
print(f'Shape of the dataset is {df.shape}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('*************************************************\n')
print('*************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
print('*************************************************')
```

```
*************************************************
<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
None
*************************************************

*************************************************
Shape of the dataset is (550068, 10)
*************************************************

*************************************************
Number of nan/null values in each column:
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
*************************************************

*************************************************
Number of unique values in each column:
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
*************************************************

*************************************************
Duplicate entries:
False    550068
Name: count, dtype: int64
*************************************************
```

In [3]:

```
# look at the top 5 rows
df.head()
```

Out[3]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Prod
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

Insight

- A quick look at the information of the data reveals that there are **550068 rows and 10 columns** implying 550068 items have been sold to customers with information of each customer like *User_ID, Gender, Age, Occupation* to name a few. The datatype of *Product_ID, Gender, Age, City_Category and Stay_In_Current_City_Years* is “object” and rest is of *int64* datatype.
- We can also infer that **there are no missing values or nulls** in the dataset.
- There are **2 genders, 7 age groups, 21 occupations, 3 city categories, 5 year groups of stay, 2 marital status** and **20 categories of product**.
- There are **no duplicate entries**.
- It makes sense to convert all columns except *Purchase* to "category" datatype and to replace 0/1 with Unmarried/Married in *Marital_Status* column

In [4]:
```
df["User_ID"] = df["User_ID"].astype('category')
df["Product_ID"] = df["Product_ID"].astype('category')
df["Gender"] = df["Gender"].astype('category')
df["Age"] = df["Age"].astype('category')
df["Occupation"] = df["Occupation"].astype('category')
df["City_Category"] = df["City_Category"].astype('category')
df["Stay_In_Current_City_Years"] = df["Stay_In_Current_City_Years"].astype('category')
df["Marital_Status"] = df["Marital_Status"].astype('category')
df["Marital_Status"] = df["Marital_Status"].replace({0:"Unmarried", 1:"Married"})
df["Product_Category"] = df["Product_Category"].astype('category')
```

In [5]:
```
df.describe()
```

Out[5]:

	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 [6]:
```
df.describe(include='category')
```

Out[6]:

	User_ID	**Product_ID**	**Gender**	**Age**	**Occupation**	**City_Category**	**Stay_In_Current_City_Years**	**Marital_Stat**
count	550068	550068	550068	550068	550068	550068	550068	5500
unique	5891	3631	2	7	21	3	5	

top	1001680	P00265242	M	26-35	4	B	1	Unmarrie
freq	1026	1880	414259	219587	72308	231173	193821	3247

Insight

- The **minimum price** of an item is **$12** and **maximum price** is **$23961**.
- The user with id **1001680** has made the maximum number of purchases
- The product with id **P00265242** has been purchased the maximum number of times
- **Males** are the majority buyers
- People in the age group **26-35** have made the maximum number of purchases
- People with **occupation 4** have made the maximum number of purchases
- People from **city category B** have made the maximum number of purchases
- People **staying in the current city for 1 year** have made the maximum number of purchases
- **Unmarried** customers have made the maximum number of purchases

4. Detailed Analysis

4.1. Detecting outliers

4.1.1. Outliers for every continuous variable

In [7]:

```
# helper function to detect outliers
def detectOutliers(df):
    q1 = df.quantile(0.25)
    q3 = df.quantile(0.75)
    iqr = q3-q1
    lower_outliers = df[df<(q1-1.5*iqr)]
    higher_outliers = df[df>(q3+1.5*iqr)]
    return lower_outliers, higher_outliers
```

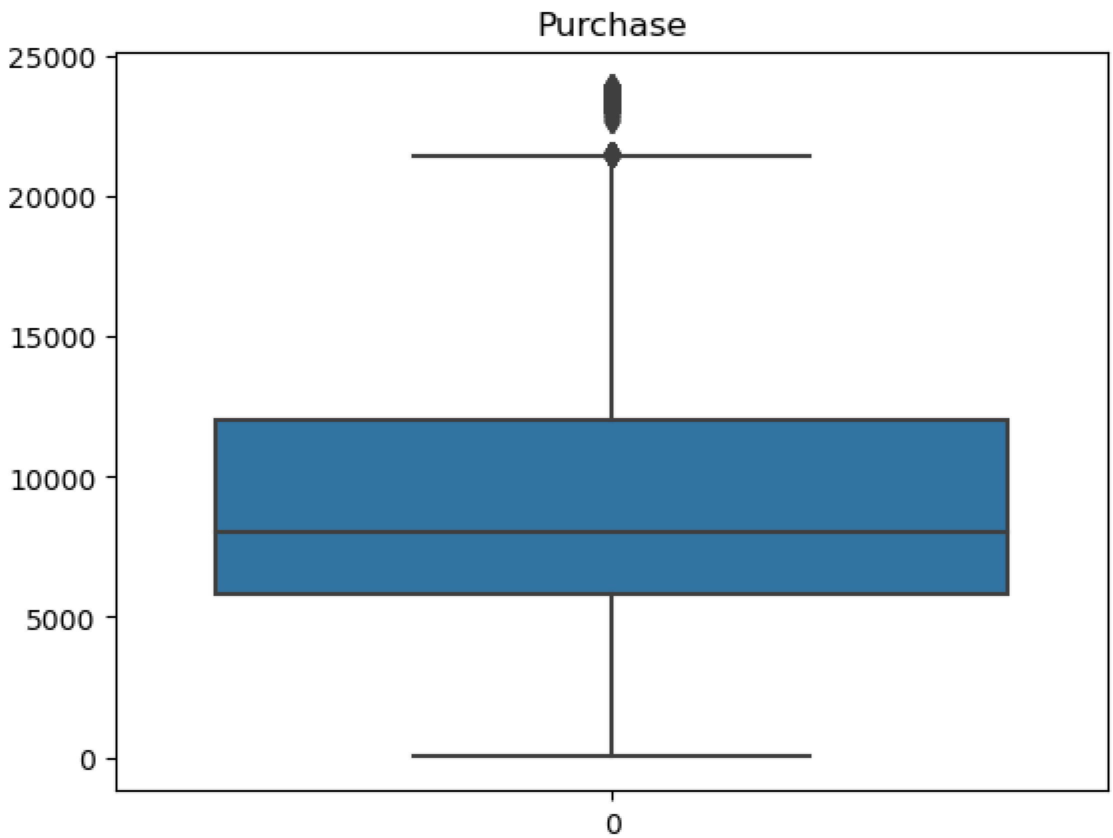
In [8]:

```
numerical_columns = ['Purchase']
column_outlier_dictionary = {}
for column in numerical_columns:
    print(f'Outliers of \'{column}\' column are:')
    lower_outliers, higher_outliers = detectOutliers(df[column])
    print("Lower outliers:\n", lower_outliers)
    print("Higher outliers:\n", higher_outliers)
    column_outlier_dictionary[column] = [lower_outliers, higher_outliers]
```

```
Outliers of 'Purchase' column are:
Lower outliers:
 Series([], Name: Purchase, dtype: int64)
Higher outliers:
 343       23603
375       23792
652       23233
736       23595
1041      23341
          ...
544488    23753
544704    23724
544743    23529
545663    23663
```

```
545787    23496
Name: Purchase, Length: 2677, dtype: int64
```

In [9]:
```
for column in numerical_columns:
    sns.boxplot(data=df[column])
    plt.title(column)
    plt.show()
```



In [10]:
```
for key, value in column_outlier_dictionary.items():
    print(f'The column \'{key}\' has {len(value[0]) + len(value[1])} outliers')
```

```
The column 'Purchase' has 2677 outliers
```

Insight

- There are a total of 2677 outliers in the *Purchase* column of the total 550068 entries. The outliers are approximately 0.48% of the total data

4.1.2. Remove the outliers

In [11]:
```
for key, value in column_outlier_dictionary.items():
    lower_outliers = value[0]
    higher_outliers = value[1]
    df.drop(lower_outliers.index, inplace=True)
    df.drop(higher_outliers.index, inplace=True)
```

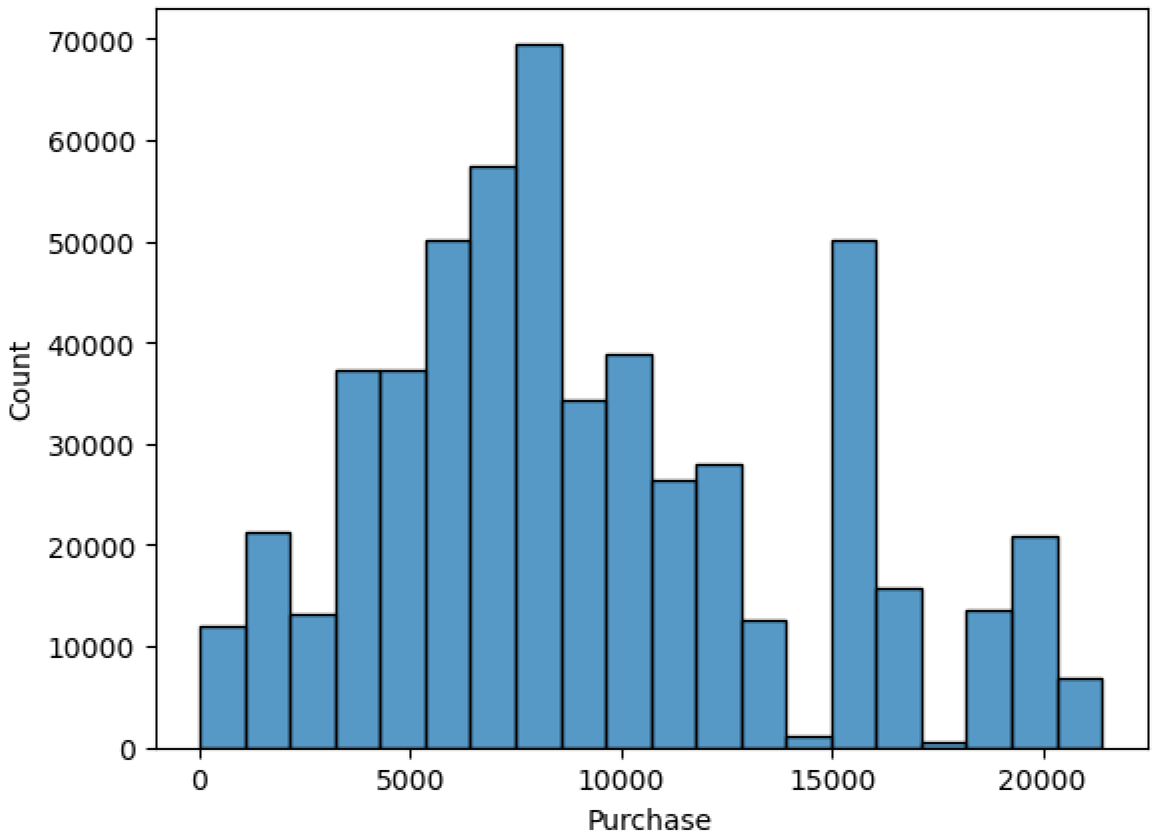
4.2. Univariate analysis

4.2.1. Numerical Variables

There is only one numerical variable - Purchase

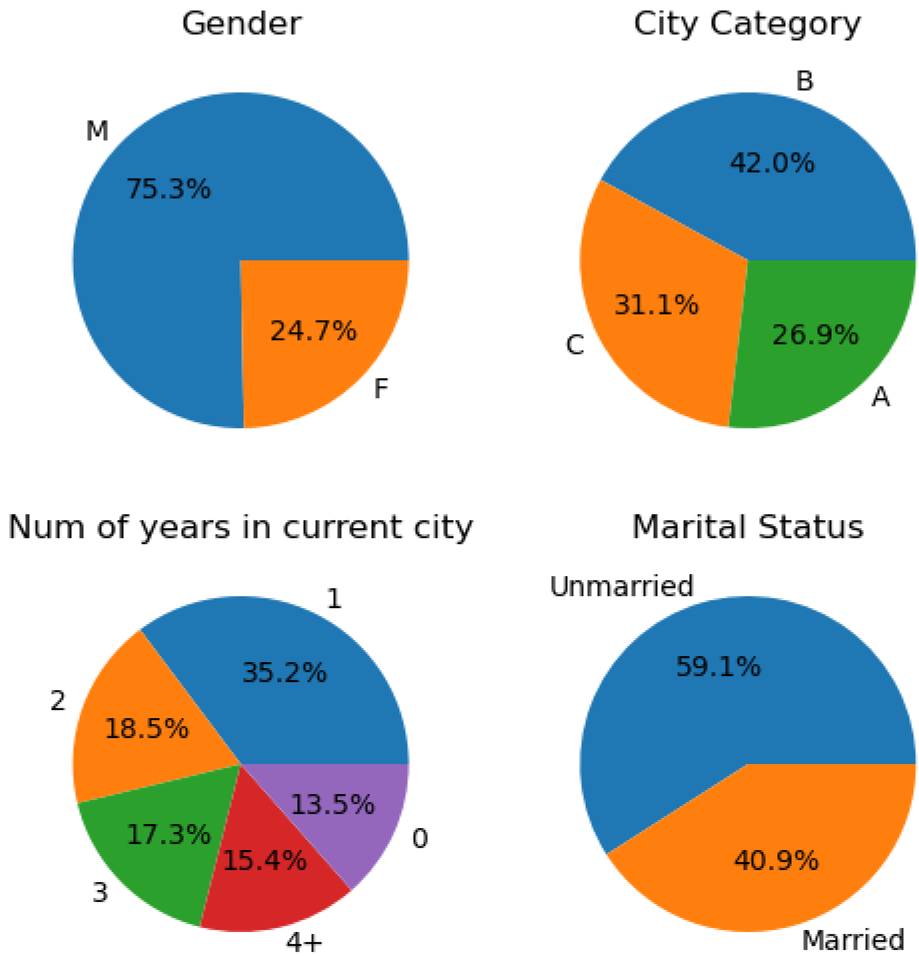
In [12]:
```
sns.histplot(data=df, x = "Purchase", bins=20)
```

Out[12]:
```
<Axes: xlabel='Purchase', ylabel='Count'>
```



4.2.2. Categorical Variables

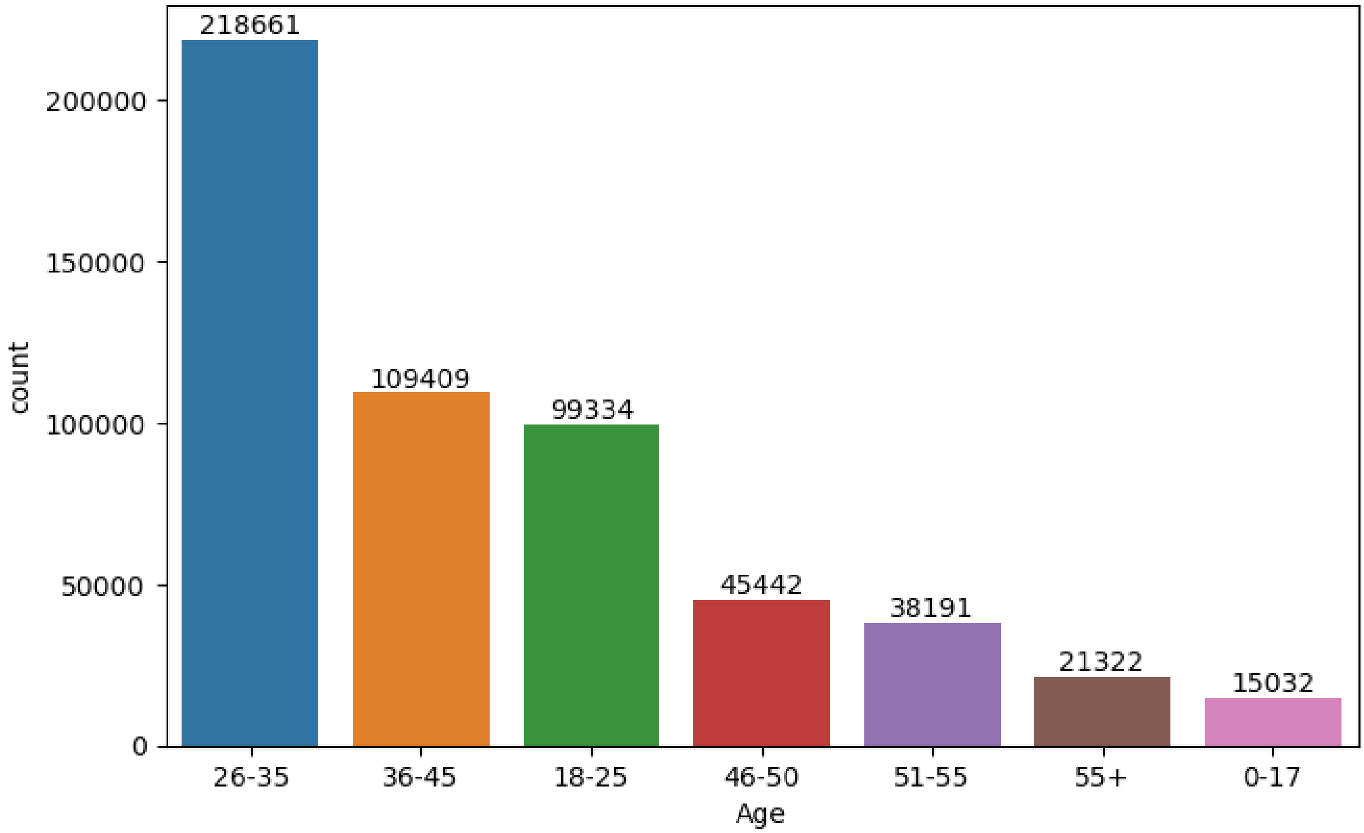
In [13]:
```
categorical_columns = ["Gender", "Age", "Occupation", "City_Category", "Stay_In_Current_
plt.figure(figsize=(6,6))
plt.subplot(2,2,1)
data = df["Gender"].value_counts()
plt.pie(data.values, labels = data.index, autopct='%.1f%%')
plt.title("Gender")
plt.subplot(2,2,2)
data = df["City_Category"].value_counts()
plt.pie(data.values, labels = data.index, autopct='%.1f%%')
plt.title("City Category")
plt.subplot(2,2,3)
data = df["Stay_In_Current_City_Years"].value_counts()
plt.pie(data.values, labels = data.index, autopct='%.1f%%')
plt.title("Num of years in current city")
plt.subplot(2,2,4)
data = df["Marital_Status"].value_counts()
plt.pie(data.values, labels = data.index, autopct='%.1f%%')
plt.title("Marital Status")
plt.show()
```



Insight

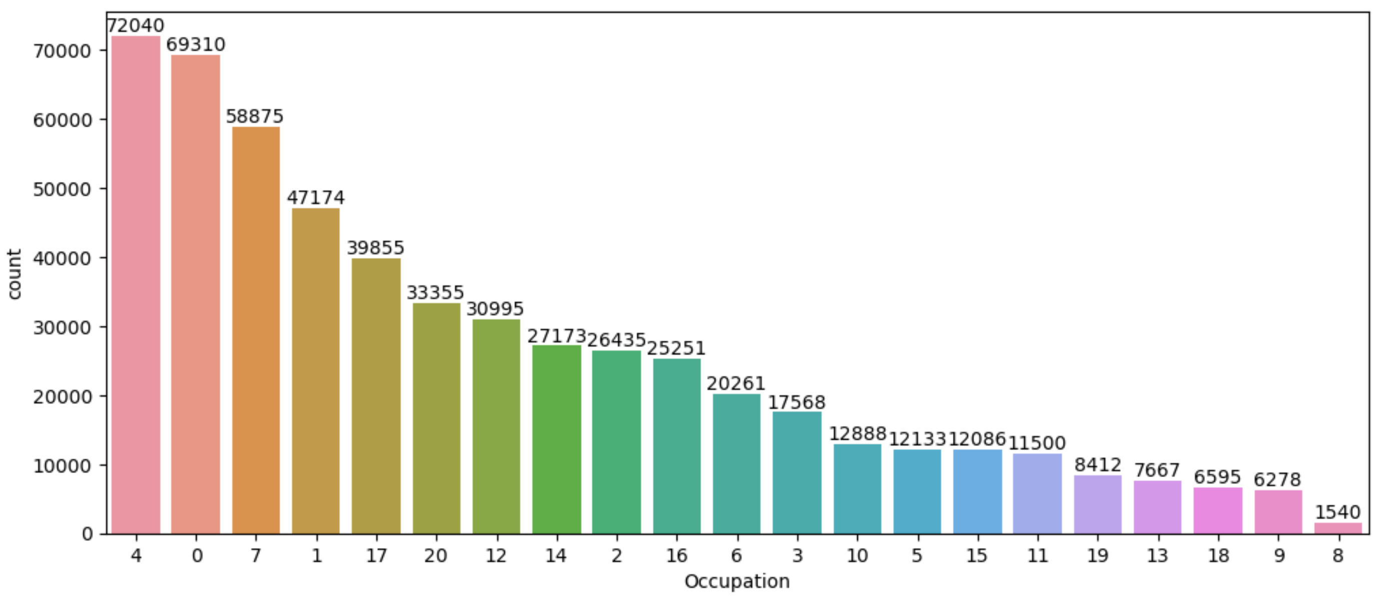
- Males purchase a lot compared to females
- City B shows the most number of purchases followed by C and A
- People staying in the city for 1 year or less have made the most number of purchases
- Unmarried people are buying more

In [14]:
```
plt.figure(figsize=(8,5))
data = df["Age"]
ax=sns.countplot(x = data, order=data.value_counts().index)
ax.bar_label(ax.containers[0])
plt.show()
```



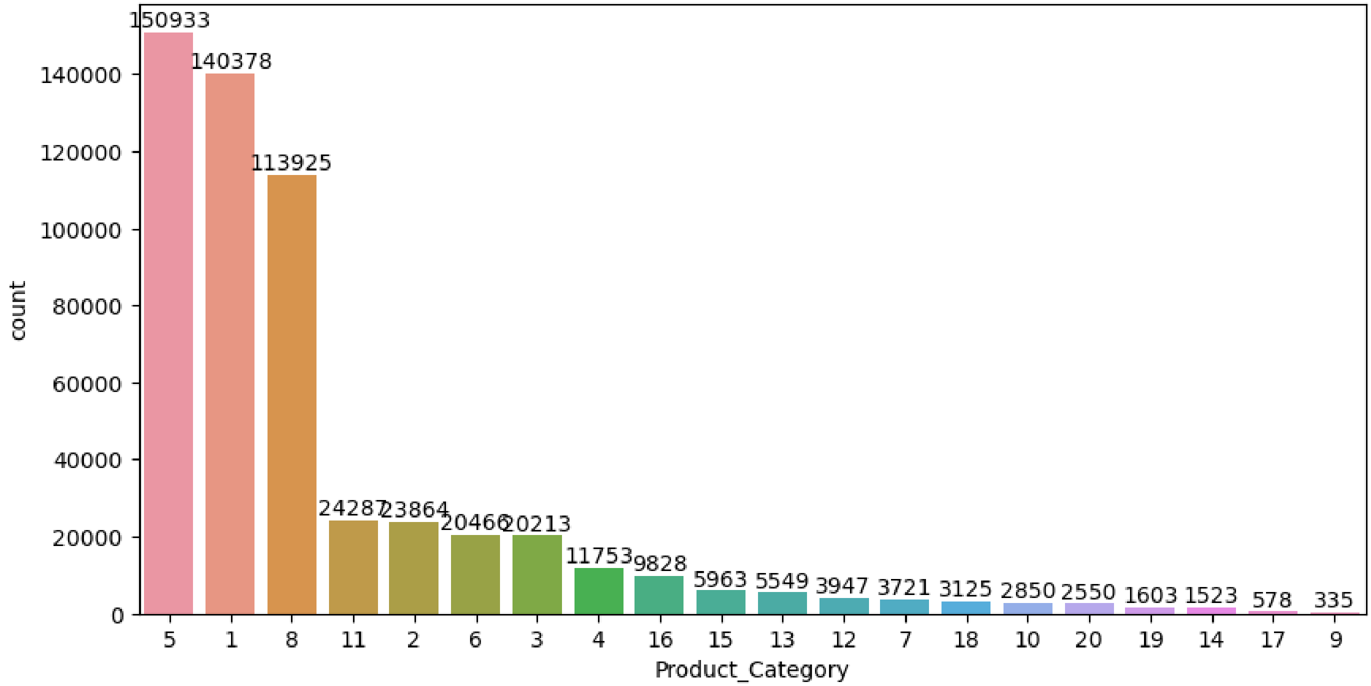
In [15]:

```
plt.figure(figsize=(12,5))
data = df["Occupation"]
ax=sns.countplot(x = data, order=data.value_counts().index)
ax.bar_label(ax.containers[0])
plt.show()
```



In [16]:

```
plt.figure(figsize=(10,5))
data = df["Product_Category"]
ax=sns.countplot(x = data, order=data.value_counts().index)
ax.bar_label(ax.containers[0])
plt.show()
```

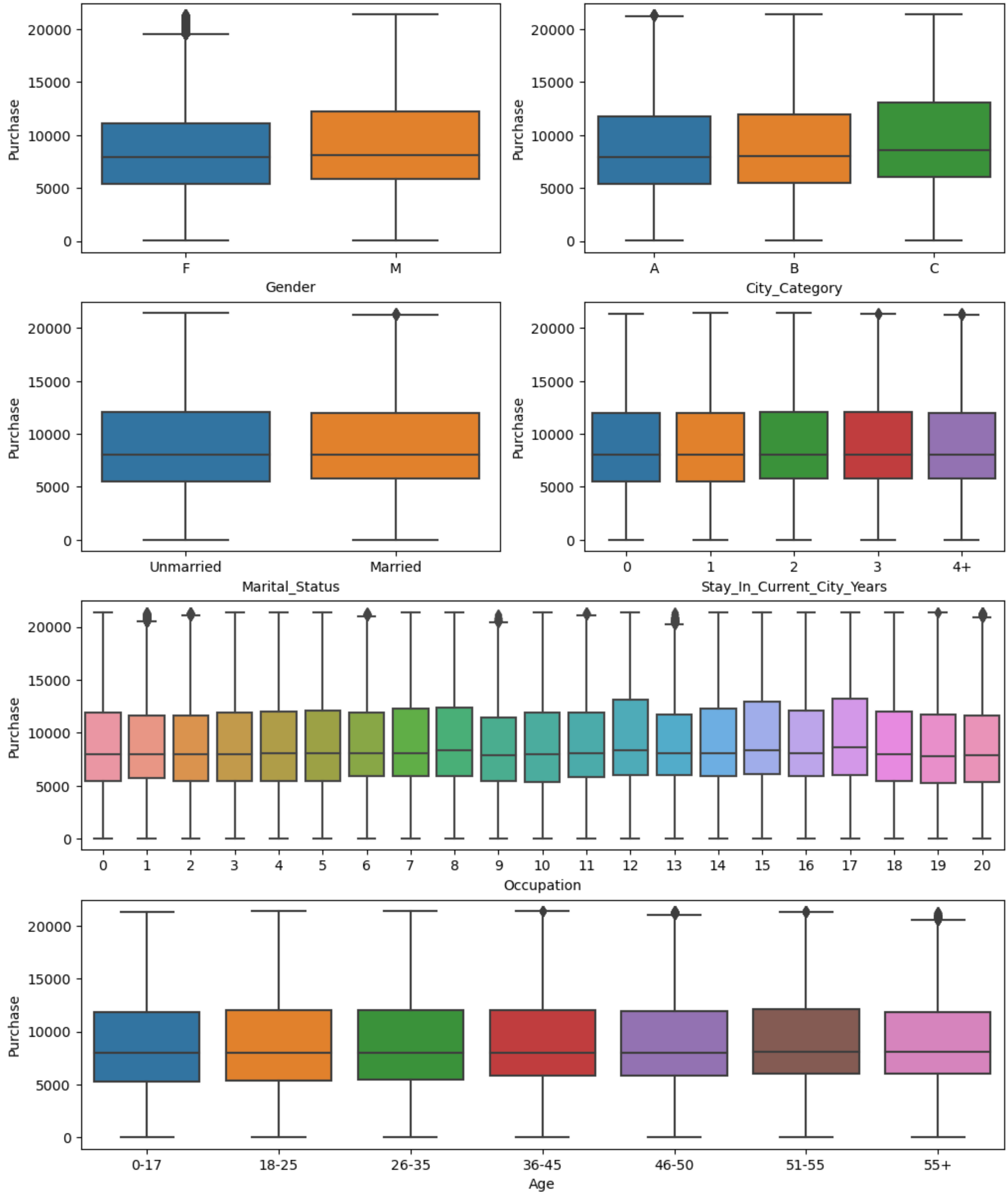


Insight

- Customers falling under the age group 26-35 buy a lot
- Customer with occupation 4 tend to buy a lot
- Products from product category 5, 1 and 8 are bought a lot

4.3. Bivariate analysis

In [17]:
```
plt.figure(figsize=(12,15))
plt.subplot(4, 2, 1)
sns.boxplot(data=df, x = "Gender", y="Purchase")
plt.subplot(4, 2, 2)
sns.boxplot(data=df, x = "City_Category", y="Purchase")
plt.subplot(4, 2, 3)
sns.boxplot(data=df, x = "Marital_Status", y="Purchase")
plt.subplot(4, 2, 4)
sns.boxplot(data=df, x = "Stay_In_Current_City_Years", y="Purchase")
plt.subplot(4, 1, 3)
sns.boxplot(data=df, x = "Occupation", y="Purchase")
plt.subplot(4, 1, 4)
sns.boxplot(data=df, x = "Age", y="Purchase")
plt.show()
```



Insight

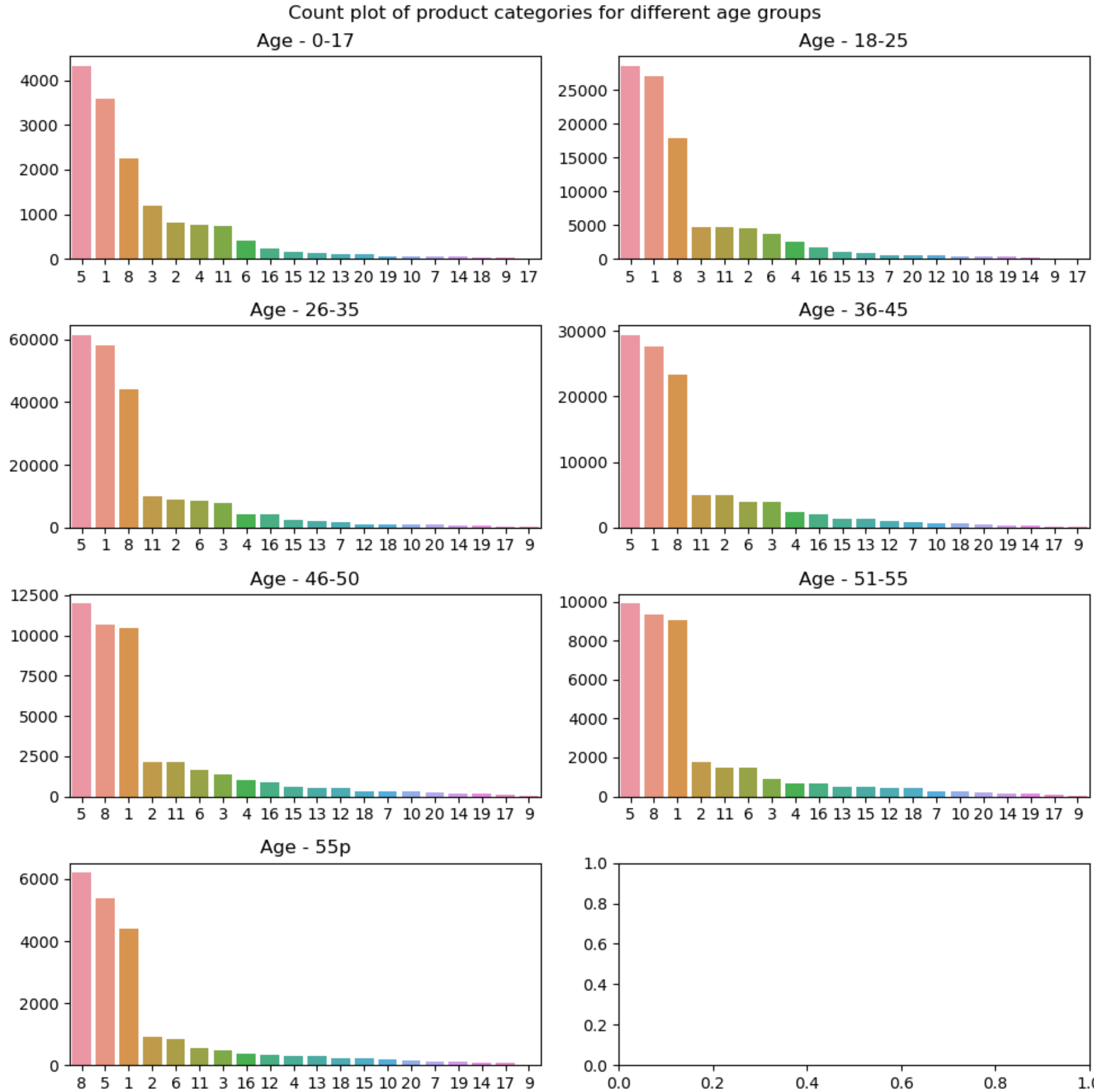
- We can see that that the median purchase amount remains same irrespective of different factors

4.4. Relations

4.4.1. What products are different age groups buying?

In [18]:

```
df_age_0to17 = df[df["Age"] == "0-17"]
df_age_18to25 = df[df["Age"] == "18-25"]
df_age_26to35 = df[df["Age"] == "26-35"]
df_age_36to45 = df[df["Age"] == "36-45"]
df_age_46to50 = df[df["Age"] == "46-50"]
df_age_51to55 = df[df["Age"] == "51-55"]
df_age_55p = df[df["Age"] == "55+"]
fig, axes = plt.subplots(nrows=4, ncols=2, sharex=False, sharey=False, figsize=(10, 10))
ax=axes[0,0]
sns.countplot(ax=ax, data = df_age_0to17, x='Product_Category', order=df_age_0to17['Prod
ax.set_title('Age - 0-17')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[0,1]
sns.countplot(ax=ax, data = df_age_18to25, x='Product_Category', order=df_age_18to25['Pr
ax.set_title('Age - 18-25')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[1,0]
sns.countplot(ax=ax, data = df_age_26to35, x='Product_Category', order=df_age_26to35['Pr
ax.set_title('Age - 26-35')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[1,1]
sns.countplot(ax=ax, data = df_age_36to45, x='Product_Category', order=df_age_36to45['Pr
ax.set_title('Age - 36-45')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[2,0]
sns.countplot(ax=ax, data = df_age_46to50, x='Product_Category', order=df_age_46to50['Pr
ax.set_title('Age - 46-50')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[2,1]
sns.countplot(ax=ax, data = df_age_51to55, x='Product_Category', order=df_age_51to55['Pr
ax.set_title('Age - 51-55')
ax.set(xlabel=None)
ax.set(ylabel=None)
ax=axes[3,0]
sns.countplot(ax=ax, data = df_age_55p, x='Product_Category', order=df_age_55p['Product_
ax.set_title('Age - 55p')
ax.set(xlabel=None)
ax.set(ylabel=None)
fig.suptitle("Count plot of product categories for different age groups")
plt.tight_layout()
plt.show()
```

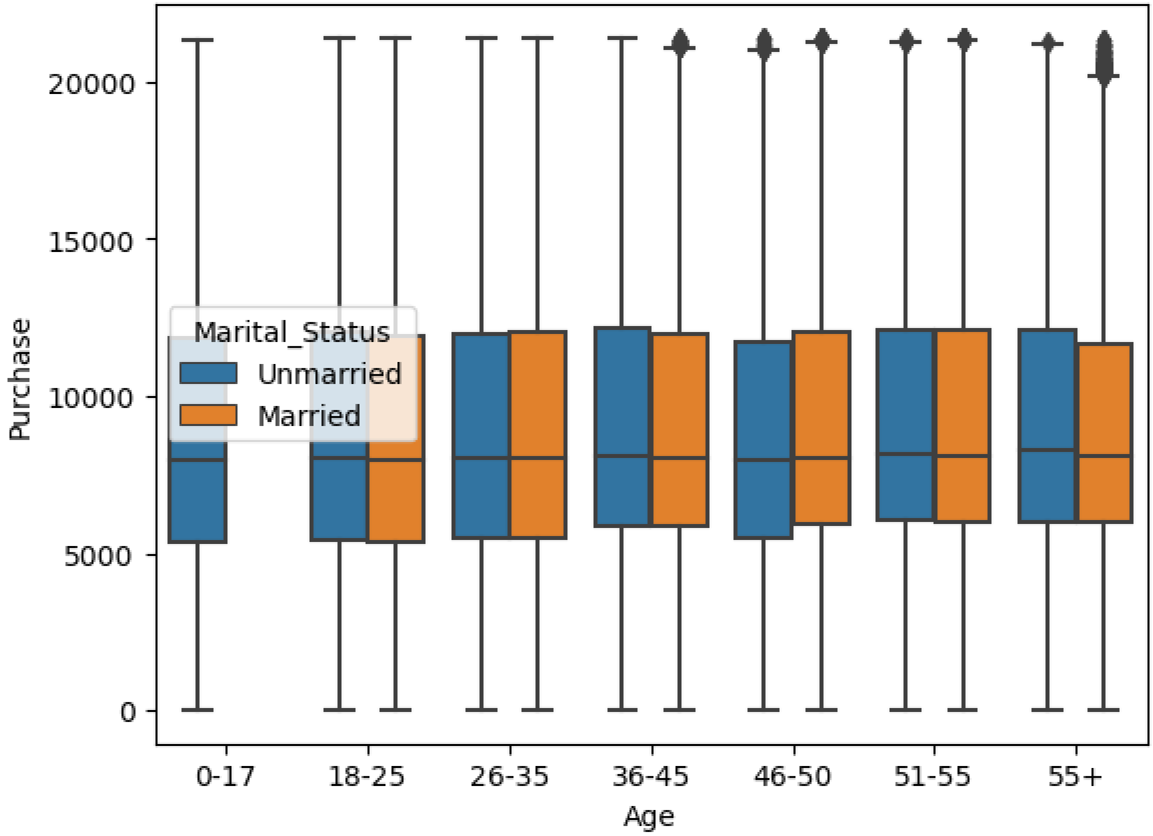


Insights

It is pretty evident that the people of all age groups buy a lot of products from the category 1, 5 and 8.

4.4.2. Relation between age, marital status and amount spent

In [19]:
```
sns.boxplot(data=df, x = 'Age', y='Purchase', hue='Marital_Status')
plt.show()
```

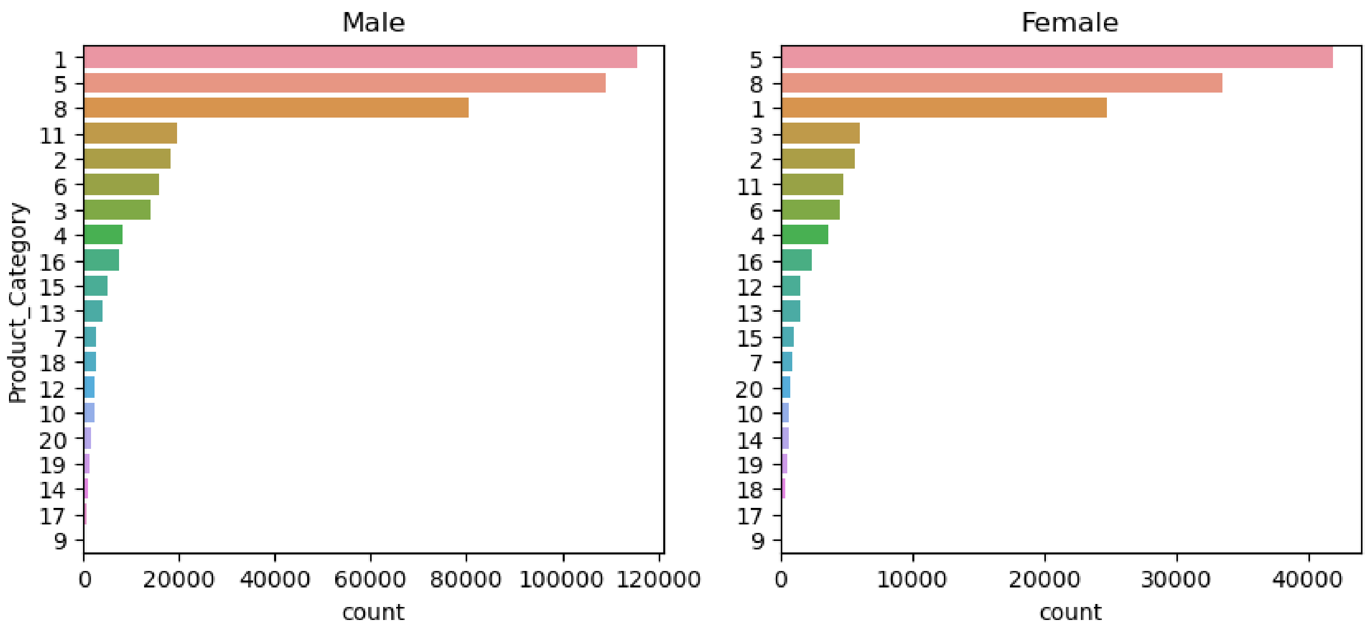


Insights

We can observe that the people of different age groups, mariied or unmarried, spend almost the same amount of money.

4.4.3. Are there preferred product categories for different genders?

In [20]:
```
df_male = df[df['Gender'] == 'M']
df_female = df[df['Gender'] == 'F']
fig, axes = plt.subplots(nrows=1, ncols=2, sharey=False, sharex=False, figsize=(10,4))
data = df_male
ax = axes[0]
sns.countplot(ax=ax, data=data, y='Product_Category', order=data['Product_Category'].val
ax.set_title('Male')
data = df_female
ax = axes[1]
sns.countplot(ax=ax, data=data, y='Product_Category', order=data['Product_Category'].val
ax.set_title('Female')
ax.set(ylabel=None)
plt.show()
```



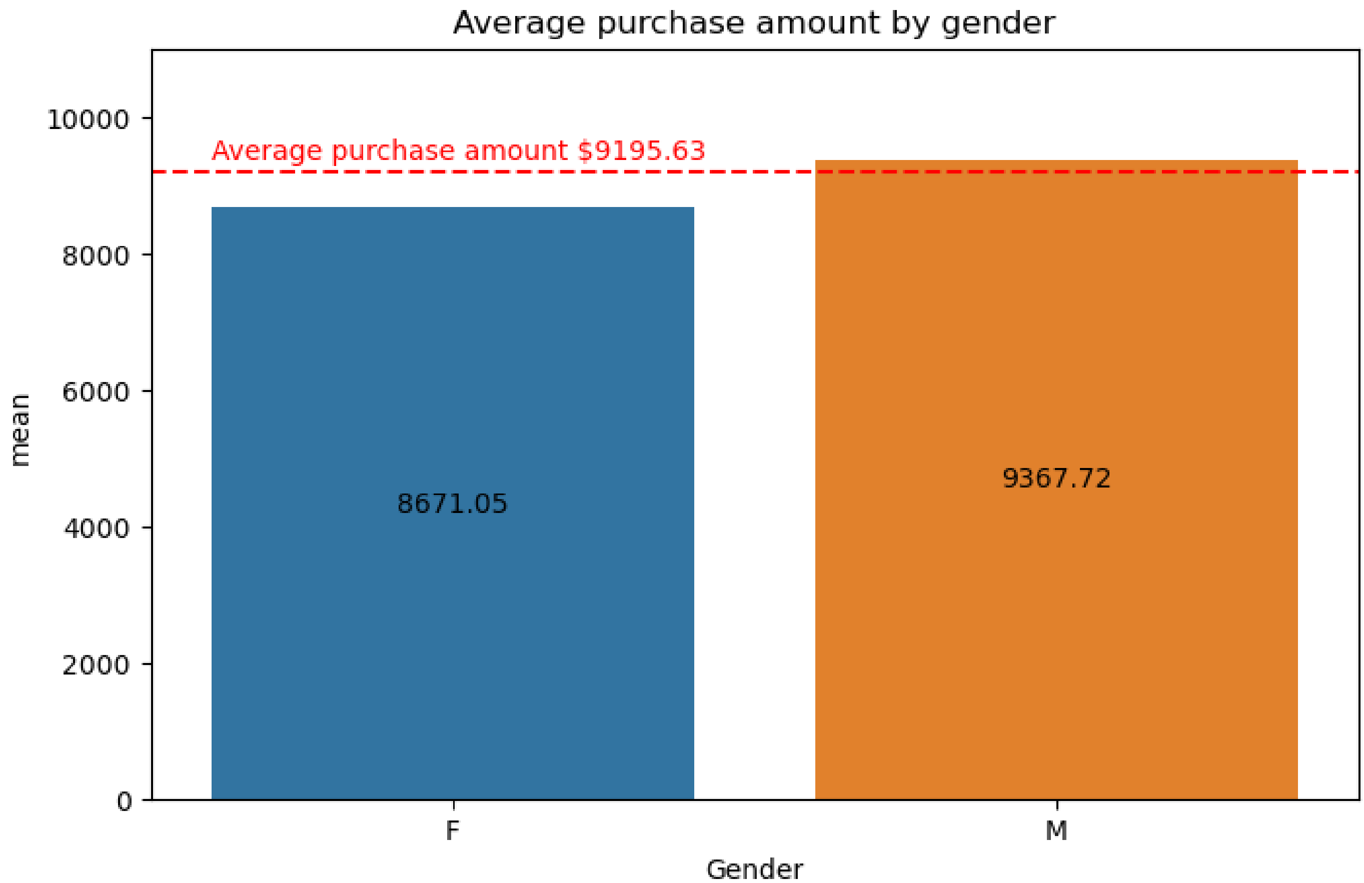
Insights

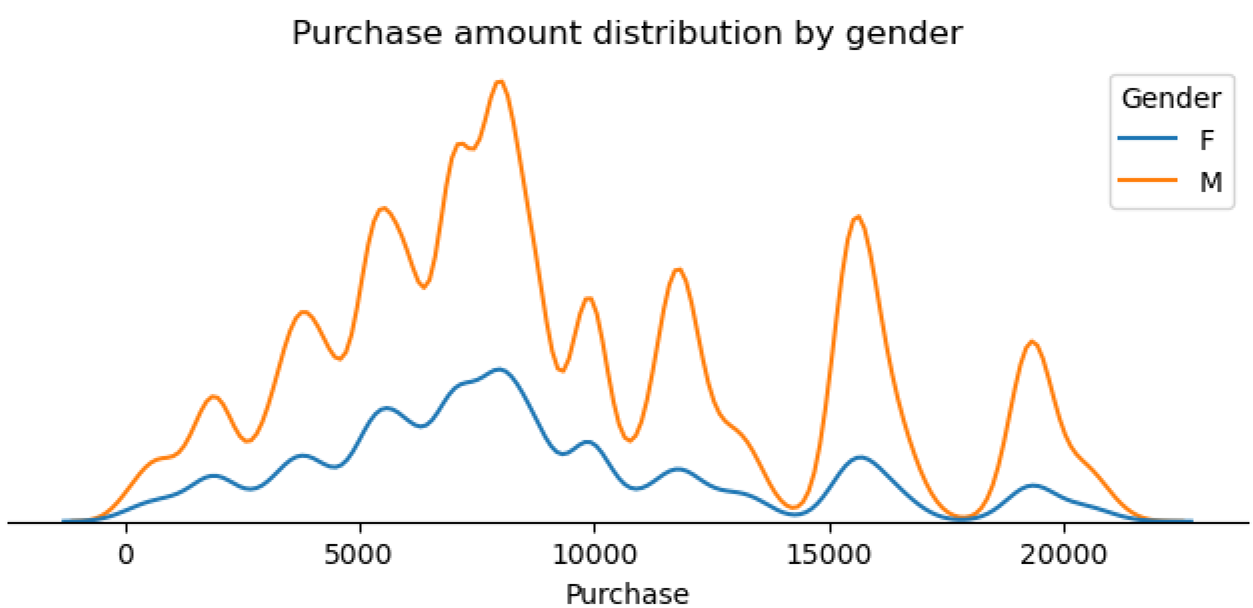
Males prefer to buy product category 1 more and female prefer to buy product category 5. The top 3 product categories prefered by both male and female are 1, 5 and 8.

4.5. CLT

4.5.1. How does gender affect the amount spent?

In [21]:
```
purchase_avg = df['Purchase'].mean()
df_group_gender = df.groupby('Gender')['Purchase'].agg(['sum','mean']).reset_index()
#print(df_group_gender)
plt.figure(figsize=(8,5))
ax=sns.barplot(data=df_group_gender, x='Gender', y='mean')
ax.set_ylim(0,11000)
ax.bar_label(ax.containers[0], label_type='center')
plt.axhline(y=purchase_avg, color='r', linestyle = '--')
plt.text(0.01, purchase_avg+300, f"Average purchase amount ${purchase_avg:.2f}", ha='cen
plt.title("Average purchase amount by gender")
plt.show()

plt.figure(figsize=(8,3))
ax = sns.kdeplot(data=df, x='Purchase', hue='Gender')
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.set_yticks([])
ax.set_ylabel('')
plt.title('Purchase amount distribution by gender')
plt.show()
```





Insights

- The average purchase amount is little higher in males than females
- The distribution of purchase amount for both the genders is not normally distributed

In [22]:
```
def confidence_interval(data, ci):
    l_ci = (100-ci)/2
    u_ci = (100+ci)/2
    interval = np.percentile(data, [l_ci, u_ci]).round(0)
    return interval
```

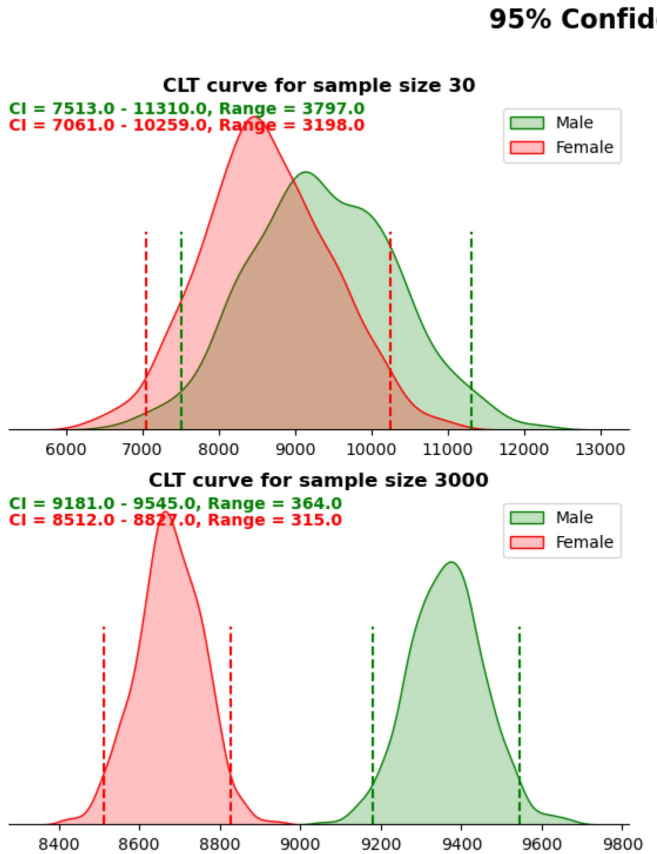
In [23]:
```
sample_sizes = [(30, 0, 0), (300, 0, 1), (3000, 1, 0), (30000, 1, 1)]
#sample_sizes = [(30, 0, 0), (30, 0, 1), (30, 1, 0), (30, 1, 1)]
```

```
bootstrap_samples = 1000
```

In [24]:
```
df_1 = df[df['Gender'] == 'M']['Purchase'].reset_index(drop=True)
df_2 = df[df['Gender'] == 'F']['Purchase'].reset_index(drop=True)
interval_1 = confidence_interval(df_1, 95)
interval_2 = confidence_interval(df_2, 95)
range_1 = interval_1[1] - interval_1[0]
range_2 = interval_2[1] - interval_2[0]
print(f'Male  : CI = {interval_1}, Range = {range_1} \nFemale: CI = {interval_2}, Range
```

```
Male  : CI = [ 1433. 19648.], Range = 18215.0
Female: CI = [ 1375. 19560.], Range = 18185.0
```

In [25]:
```
label1 = 'Male'
label2 = 'Female'
data1_color = 'g'
data2_color = 'r'
data1_text_y_pos = 1
data2_text_y_pos = 0.95

fig = plt.figure(figsize=(15,8))
gs = fig.add_gridspec(2,2)
ci_percent = 95

for sample_size, row, col in sample_sizes:
    data1_means = [np.mean(random.choices(df_1, k=sample_size)) for idx in range(bootstr
    data2_means = [np.mean(random.choices(df_2, k=sample_size)) for idx in range(bootstr

    ax = fig.add_subplot(gs[row, col])

    for means, color, label in [(data1_means, data1_color, label1), (data2_means, data2_
        sns.kdeplot(ax = ax, x=means, color=color, fill=True, label = label)

    data1_ci = confidence_interval(data1_means, ci_percent)
    data2_ci = confidence_interval(data2_means, ci_percent)
    for ci, color in [(data1_ci, data1_color), (data2_ci, data2_color)]:
        for k in ci:
            ax.axvline(x=k, ymax=0.6, color=color, linestyle='--')

    for s in ['top','left','right']:
        ax.spines[s].set_visible(False)

    for ci, color, text_pos in [(data1_ci, data1_color, data1_text_y_pos), (data2_ci, da
        ax.text(0, text_pos, f"CI = {ci[0]} - {ci[1]}, Range = {ci[1]-ci[0]}", transform
    ax.set_yticks([])
    ax.set_ylabel('')
    ax.set_xlabel('')
    ax.set_title(f'CLT curve for sample size {sample_size}', size = 12, weight = 'bold')
    ax.legend()

fig.suptitle(f'{ci_percent}% Confidence Interval', size = 16, weight = 'bold')
plt.show()
```



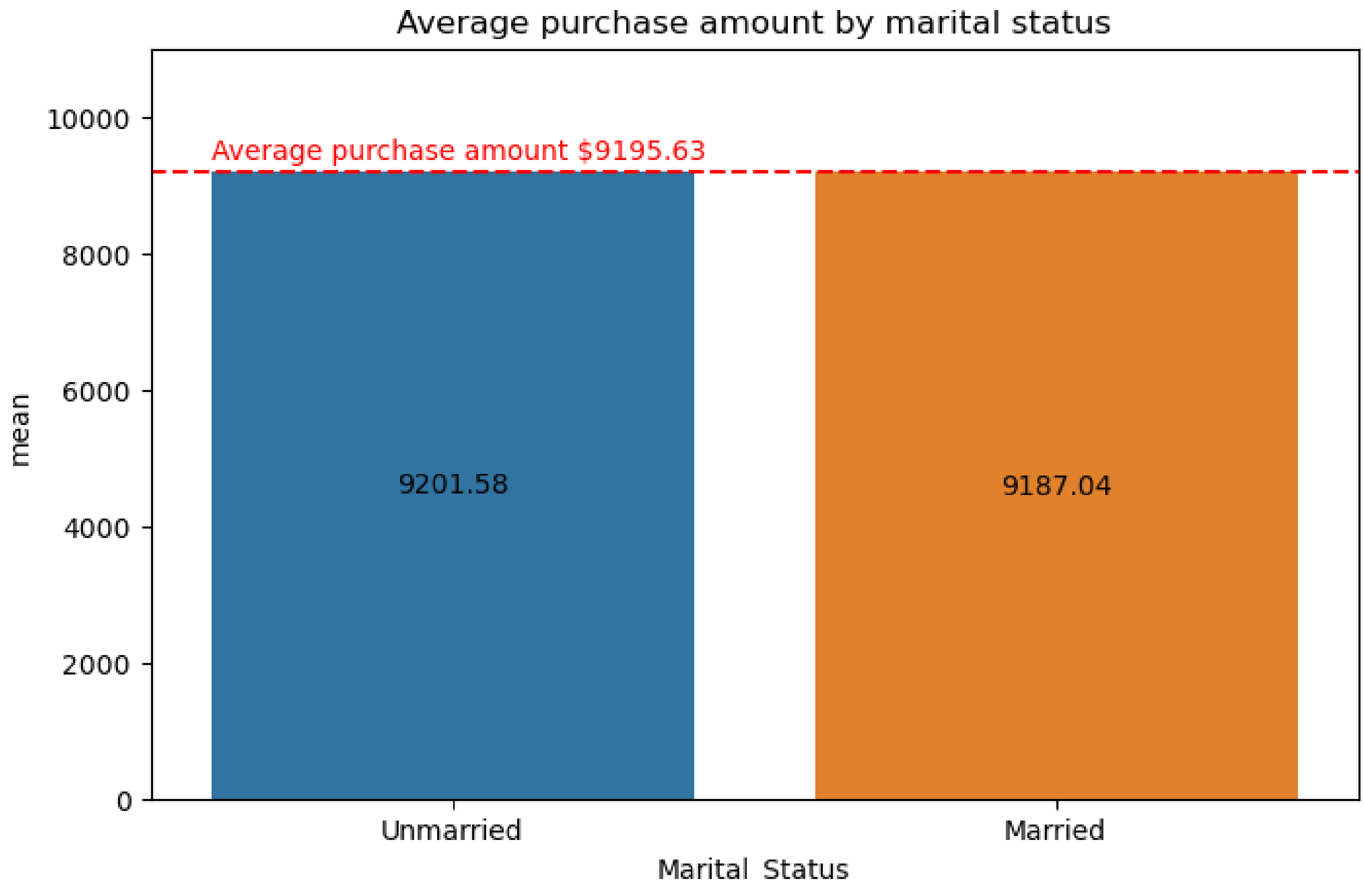
Insights

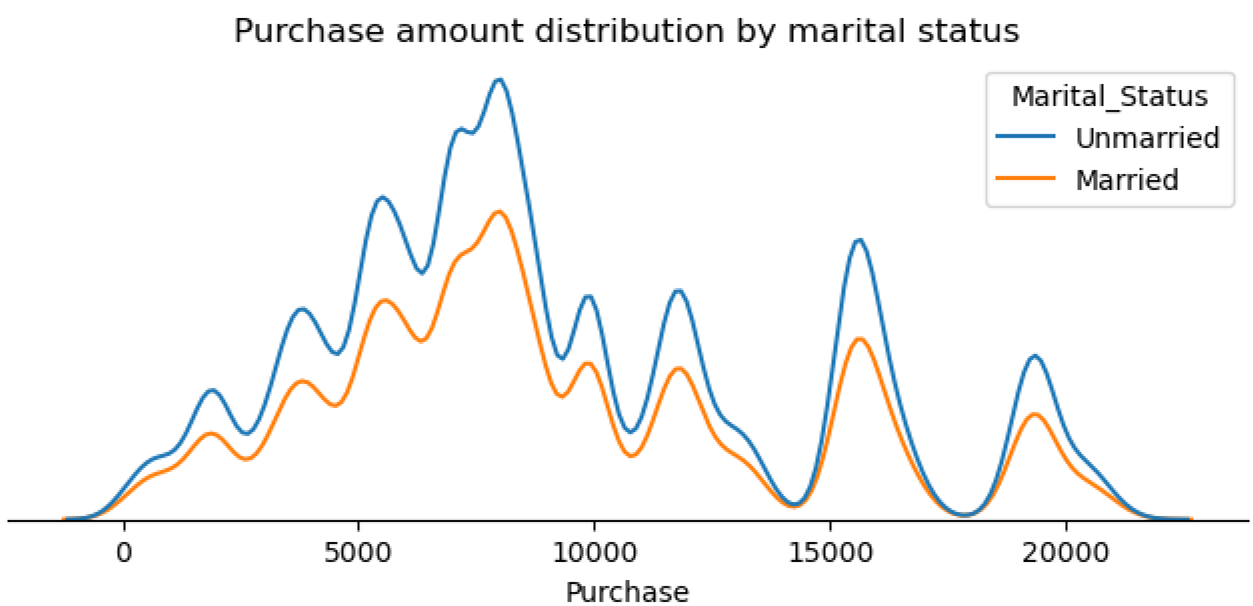
- Confidence interval calculated using the entire dataset for both the genders is almost same. [1433. 19648.] for male and [1375. 19560.] for female.
- As the sample size increases the width of the confidence interval decreases.
- The confidence intervals for males and females overlap for sample sizes 30 and 300 but then they start moving apart for sample sizes 3000 and 30000.
- The shape of the distribution of the means gets closer to the normal distribution as the same size increases.

4.5.2. How does Marital_Status affect the amount spent?

In [26]:

```
df_group_maritalStatus = df.groupby('Marital_Status')['Purchase'].agg(['sum','mean']).re
plt.figure(figsize=(8,5))
ax=sns.barplot(data=df_group_maritalStatus, x='Marital_Status', y='mean')
ax.set_ylim(0,11000)
ax.bar_label(ax.containers[0], label_type='center')
plt.axhline(y=purchase_avg, color='r', linestyle = '--')
plt.text(0.01, purchase_avg+300, f"Average purchase amount ${purchase_avg:.2f}", ha='cen
plt.title("Average purchase amount by marital status")
plt.show()

plt.figure(figsize=(8,3))
ax = sns.kdeplot(data=df, x='Purchase', hue='Marital_Status')
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.set_yticks([])
ax.set_ylabel('')
plt.title('Purchase amount distribution by marital status')
plt.show()
```





Insights

- The average purchase amount is almost the same for Married and Unmarried
- The distribution of purchase amount for both the cases is not normally distributed

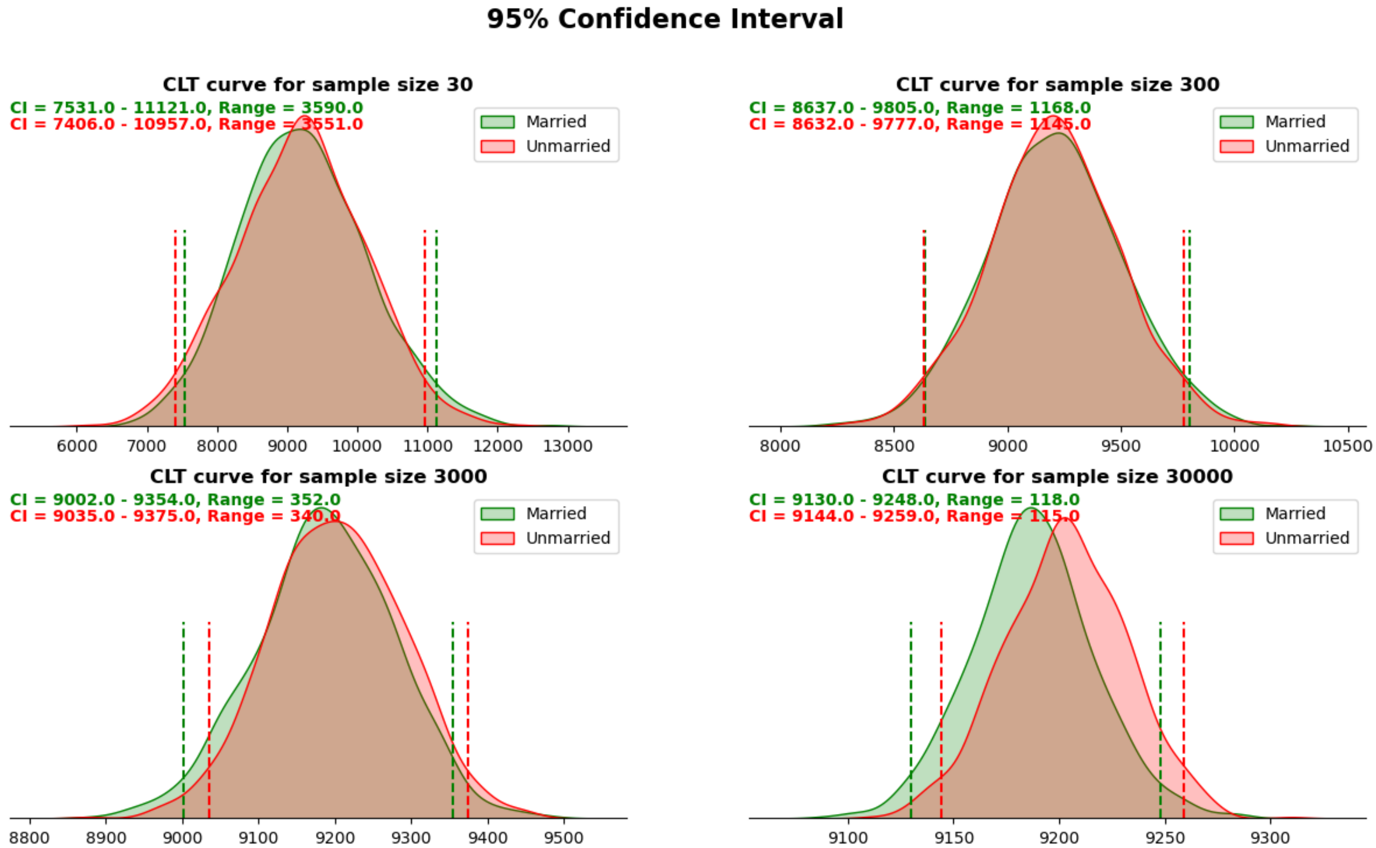
In [27]:
```
df_1 = df[df['Marital_Status'] == 'Married']['Purchase'].reset_index(drop=True)
df_2 = df[df['Marital_Status'] == 'Unmarried']['Purchase'].reset_index(drop=True)
interval_1 = confidence_interval(df_1, 95)
interval_2 = confidence_interval(df_2, 95)
range_1 = interval_1[1] - interval_1[0]
range_2 = interval_2[1] - interval_2[0]
print(f'Married   : CI = {interval_1}, Range = {range_1} \nUnmarried: CI = {interval_2},
```

```
Married   : CI = [ 1397. 19626.], Range = 18229.0
```

```
Unmarried: CI = [ 1427. 19636.], Range = 18209.0
```

In [28]:

```
label1 = 'Married'
label2 = 'Unmarried'
data1_color = 'g'
data2_color = 'r'
data1_text_y_pos = 1
data2_text_y_pos = 0.95

fig = plt.figure(figsize=(15,8))
gs = fig.add_gridspec(2,2)
ci_percent = 95

for sample_size, row, col in sample_sizes:
    data1_means = [np.mean(random.choices(df_1, k=sample_size)) for idx in range(bootstr
    data2_means = [np.mean(random.choices(df_2, k=sample_size)) for idx in range(bootstr

    ax = fig.add_subplot(gs[row, col])

    for means, color, label in [(data1_means, data1_color, label1), (data2_means, data2_
        sns.kdeplot(ax = ax, x=means, color=color, fill=True, label = label)

    data1_ci = confidence_interval(data1_means, ci_percent)
    data2_ci = confidence_interval(data2_means, ci_percent)
    for ci, color in [(data1_ci, data1_color), (data2_ci, data2_color)]:
        for k in ci:
            ax.axvline(x=k, ymax=0.6, color=color, linestyle='--')

    for s in ['top','left','right']:
        ax.spines[s].set_visible(False)

    for ci, color, text_pos in [(data1_ci, data1_color, data1_text_y_pos), (data2_ci, da
        ax.text(0, text_pos, f"CI = {ci[0]} - {ci[1]}, Range = {ci[1]-ci[0]}", transform
    ax.set_yticks([])
    ax.set_ylabel('')
    ax.set_xlabel('')
    ax.set_title(f'CLT curve for sample size {sample_size}', size = 12, weight = 'bold')
    ax.legend()

fig.suptitle(f'{ci_percent}% Confidence Interval', size = 16, weight = 'bold')
plt.show()
```



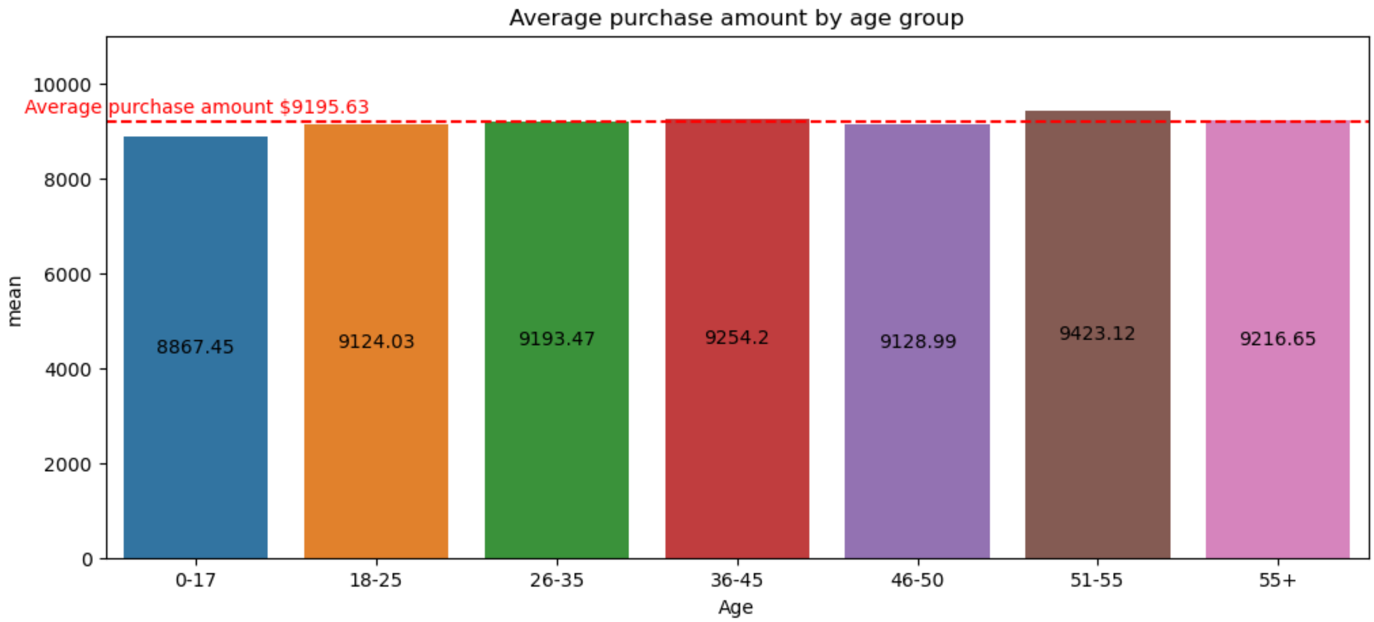
Insights

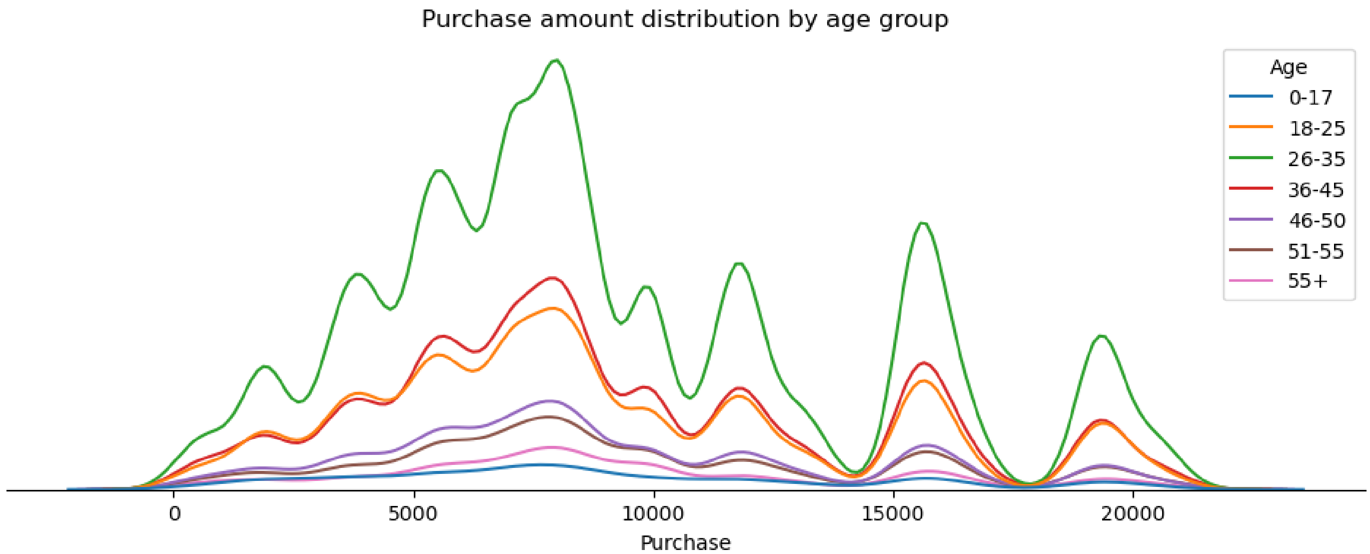
- Confidence interval calculated using the entire dataset for both the cases is almost same. [1397. 19626.] for married and [1427. 19636.] for unmarried.
- As the sample size increases the width of the confidence interval decreases.
- The confidence intervals for married and unmarried overlap for all sample sizes 30, 300, 3000 and 30000.
- The shape of the distribution of the means gets closer to the normal distribution as the same size increases.

4.5.3. How does Age affect the amount spent?

In [29]:

```
df_group_age = df.groupby('Age')['Purchase'].agg(['sum','mean']).reset_index()
plt.figure(figsize=(12,5))
ax=sns.barplot(data=df_group_age, x='Age', y='mean')
ax.set_ylim(0,11000)
ax.bar_label(ax.containers[0], label_type='center')
plt.axhline(y=purchase_avg, color='r', linestyle = '--')
plt.text(0.01, purchase_avg+300, f"Average purchase amount ${purchase_avg:.2f}", ha='cen
plt.title("Average purchase amount by age group")
plt.show()

plt.figure(figsize=(12,4))
ax = sns.kdeplot(data=df, x='Purchase', hue='Age')
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.set_yticks([])
ax.set_ylabel('')
plt.title('Purchase amount distribution by age group')
plt.show()
```





Insights

- The average purchase amount is little higher in males than females
- The distribution of purchase amount for both the genders is not normally distributed

In [30]:
```
df_1 = df[df['Age'] == '0-17']['Purchase'].reset_index(drop=True)
df_2 = df[df['Age'] == '18-25']['Purchase'].reset_index(drop=True)
df_3 = df[df['Age'] == '26-35']['Purchase'].reset_index(drop=True)
df_4 = df[df['Age'] == '36-45']['Purchase'].reset_index(drop=True)
df_5 = df[df['Age'] == '46-50']['Purchase'].reset_index(drop=True)
df_6 = df[df['Age'] == '51-55']['Purchase'].reset_index(drop=True)
df_7 = df[df['Age'] == '55+']['Purchase'].reset_index(drop=True)
interval_1 = confidence_interval(df_1, 95)
interval_2 = confidence_interval(df_2, 95)
interval_3 = confidence_interval(df_3, 95)
interval_4 = confidence_interval(df_4, 95)
interval_5 = confidence_interval(df_5, 95)
interval_6 = confidence_interval(df_6, 95)
interval_7 = confidence_interval(df_7, 95)
range_1 = interval_1[1] - interval_1[0]
range_2 = interval_2[1] - interval_2[0]
range_3 = interval_3[1] - interval_3[0]
range_4 = interval_4[1] - interval_4[0]
range_5 = interval_5[1] - interval_5[0]
```

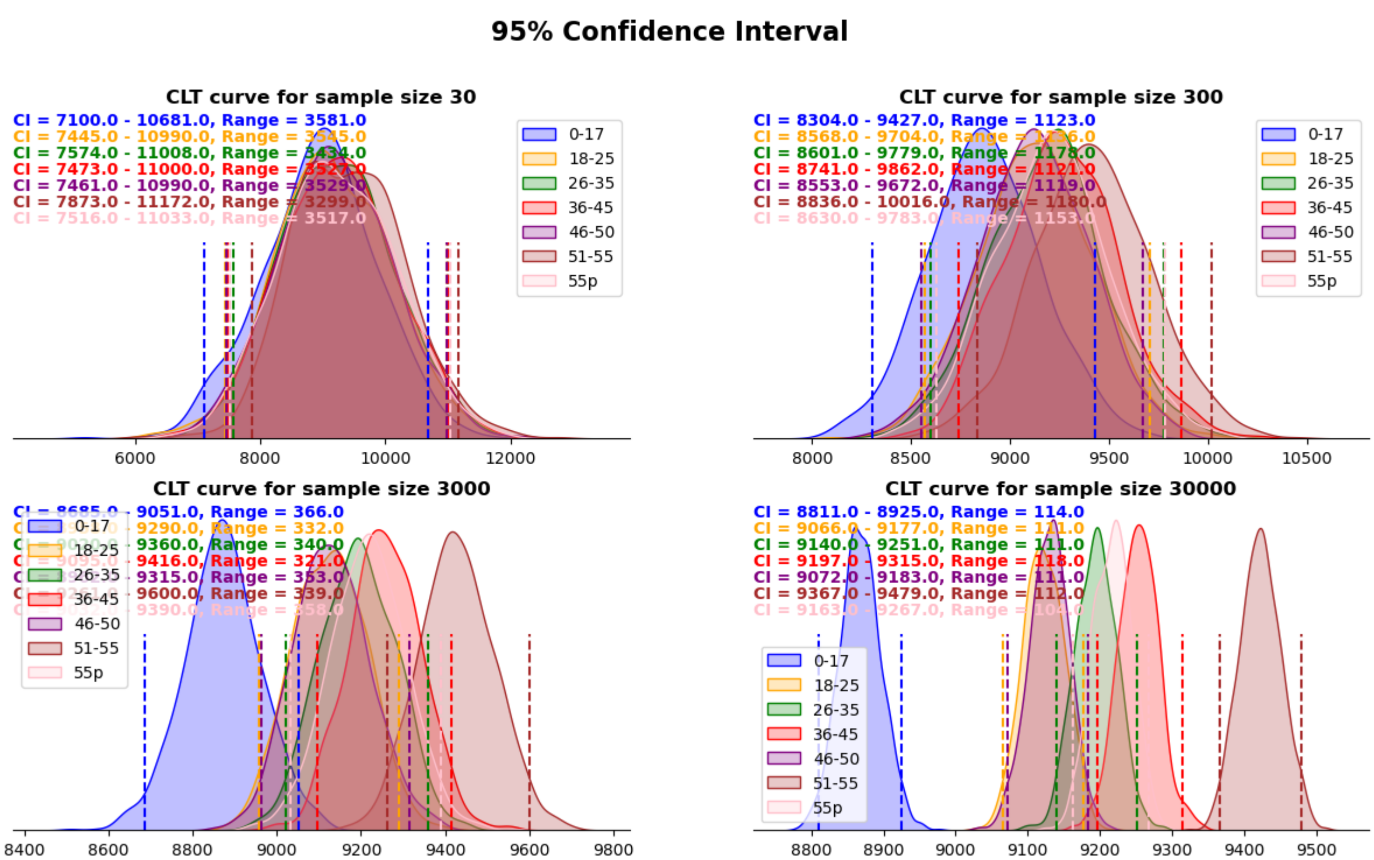
```
range_6 = interval_6[1] - interval_6[0]
range_7 = interval_7[1] - interval_7[0]
print(f'0-17 : CI = {interval_1}, Range = {range_1}\n\
18-25: CI = {interval_2}, Range = {range_2}\n\
26-35: CI = {interval_3}, Range = {range_3}\n\
36-45: CI = {interval_4}, Range = {range_4}\n\
46-50: CI = {interval_5}, Range = {range_5}\n\
51-55: CI = {interval_6}, Range = {range_6}\n\
55+  : CI = {interval_7}, Range = {range_7}')
```

```
0-17 : CI = [ 1044. 19597.], Range = 18553.0
18-25: CI = [ 1462. 19630.], Range = 18168.0
26-35: CI = [ 1508. 19637.], Range = 18129.0
36-45: CI = [ 1390. 19614.], Range = 18224.0
46-50: CI = [ 1073. 19614.], Range = 18541.0
51-55: CI = [ 1074. 19682.], Range = 18608.0
55+  : CI = [  929. 19643.], Range = 18714.0
```

In [31]:

```
label1 = '0-17'
label2 = '18-25'
label3 = '26-35'
label4 = '36-45'
label5 = '46-50'
label6 = '51-55'
label7 = '55p'
data1_color = 'blue'
data2_color = 'orange'
data3_color = 'green'
data4_color = 'red'
data5_color = 'purple'
data6_color = 'brown'
data7_color = 'pink'
data1_text_y_pos = 1
data2_text_y_pos = 0.95
data3_text_y_pos = 0.9
data4_text_y_pos = 0.85
data5_text_y_pos = 0.8
data6_text_y_pos = 0.75
data7_text_y_pos = 0.7

fig = plt.figure(figsize=(15,8))
gs = fig.add_gridspec(2,2)
ci_percent = 95

for sample_size, row, col in sample_sizes:
    data1_means = [np.mean(random.choices(df_1, k=sample_size)) for idx in range(bootstr
    data2_means = [np.mean(random.choices(df_2, k=sample_size)) for idx in range(bootstr
    data3_means = [np.mean(random.choices(df_3, k=sample_size)) for idx in range(bootstr
    data4_means = [np.mean(random.choices(df_4, k=sample_size)) for idx in range(bootstr
    data5_means = [np.mean(random.choices(df_5, k=sample_size)) for idx in range(bootstr
    data6_means = [np.mean(random.choices(df_6, k=sample_size)) for idx in range(bootstr
    data7_means = [np.mean(random.choices(df_7, k=sample_size)) for idx in range(bootstr

    ax = fig.add_subplot(gs[row, col])

    for means, color, label in [(data1_means, data1_color, label1),
                                (data2_means, data2_color, label2),
                                (data3_means, data3_color, label3),
                                (data4_means, data4_color, label4),
                                (data5_means, data5_color, label5),
                                (data6_means, data6_color, label6),
                                (data7_means, data7_color, label7)]:
        sns.kdeplot(ax = ax, x=means, color=color, fill=True, label = label)

    data1_ci = confidence_interval(data1_means, ci_percent)
    data2_ci = confidence_interval(data2_means, ci_percent)
```

```
    data3_ci = confidence_interval(data3_means, ci_percent)
    data4_ci = confidence_interval(data4_means, ci_percent)
    data5_ci = confidence_interval(data5_means, ci_percent)
    data6_ci = confidence_interval(data6_means, ci_percent)
    data7_ci = confidence_interval(data7_means, ci_percent)
    for ci, color in [(data1_ci, data1_color),
                      (data2_ci, data2_color),
                      (data3_ci, data3_color),
                      (data4_ci, data4_color),
                      (data5_ci, data5_color),
                      (data6_ci, data6_color),
                      (data7_ci, data7_color)]:
        for k in ci:
            ax.axvline(x=k, ymax=0.6, color=color, linestyle='--')

    for s in ['top','left','right']:
        ax.spines[s].set_visible(False)

    for ci, color, text_pos in [(data1_ci, data1_color, data1_text_y_pos),
                                (data2_ci, data2_color, data2_text_y_pos),
                                (data3_ci, data3_color, data3_text_y_pos),
                                (data4_ci, data4_color, data4_text_y_pos),
                                (data5_ci, data5_color, data5_text_y_pos),
                                (data6_ci, data6_color, data6_text_y_pos),
                                (data7_ci, data7_color, data7_text_y_pos)]:
        ax.text(0, text_pos, f"CI = {ci[0]} - {ci[1]}, Range = {ci[1]-ci[0]}", transform
    ax.set_yticks([])
    ax.set_ylabel('')
    ax.set_xlabel('')
    ax.set_title(f'CLT curve for sample size {sample_size}', size = 12, weight = 'bold')
    ax.legend()

fig.suptitle(f'{ci_percent}% Confidence Interval', size = 16, weight = 'bold')
plt.show()
```



Insights

- Confidence interval calculated using the entire dataset for all the cases is different.
- As the sample size increases the width of the confidence interval decreases.
- The confidence intervals for 18-25, 26-35, 36-45, 46-50 and 55p overlap.
- The shape of the distribution of the means gets closer to the normal distribution as the same size increases.

5. Report

- The confidence intervals for the average amount spent by males and females do not overlap. Males spend a lot comapred to females. Walmart should try a different strategy to attarct more female customers.
- The confidence interval for the average amount spent by married and unmarried customers overlap a lot. Walmart need not focus on seperate strategies for married or unmarried customers.
- The confidence interval for the average amount spent by age group 18-25, 26-35, 36-45, 46-50 and 55p overlap. Age group 51-55 spend a lot and age group 0-17 spend the least. Walmart needs to focus on strategies to attarct your customers.

6. Recommendation

- The male customers spend more on average than the female customers, so Walmart should reward the customers who spend more so that male customers continue to spend more and it also encourages female customers on spendign more. Additional discounts can also be provided for female customers.
- Walmart should try to attract young customers, in the group 0-17, by introducing games in the store which thereby could increase spending from this group