In [1]:
```
import pandas as pd
import numpy as np
from numpy import nan, NaN,NAN
from matplotlib import pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from scipy import stats
```

In [2]:
```
walmart=pd.read_csv("walmart_data.txt")
walmart
```

Out[2]:

	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
...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	1	20	368
550064	1006035	P00375436	F	26-35	1	C	3	0	20	371
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	137
550066	1006038	P00375436	F	55+	1	C	2	0	20	365
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	490

550068 rows × 10 columns

In [3]:
```
df=walmart.copy()
df.head(5)
```

Out[3]:

	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 [4]:
```
df.shape
```

Out[4]:
```
(550068, 10)
```

In [5]:
```
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
```

In [6]:
```
df.isnull().sum()/len(df)*100
```

Out[6]:
```
User_ID                       0.0
Product_ID                    0.0
Gender                        0.0
Age                           0.0
Occupation                    0.0
City_Category                 0.0
Stay_In_Current_City_Years    0.0
Marital_Status                0.0
Product_Category              0.0
Purchase                      0.0
dtype: float64
```

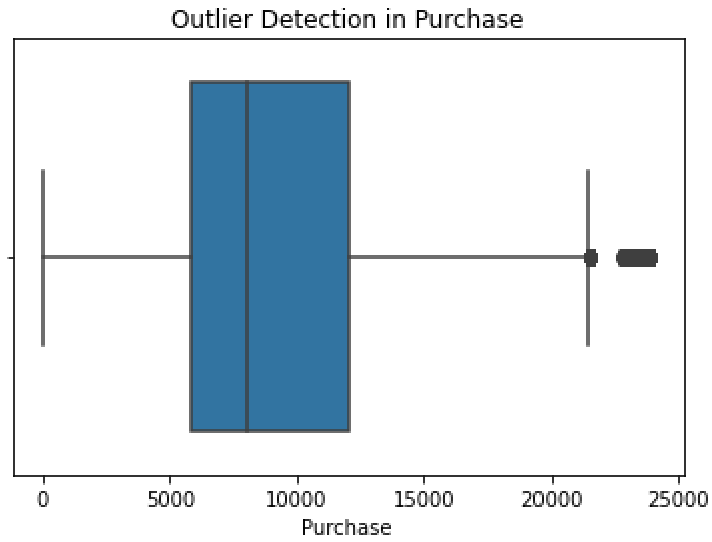
Observation-No null/missing values in data

In [7]:
```
df.describe()
```

Out[7]:

	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 [8]:
```
#Finding outliers in Purchase and removing them
sns.boxplot(df["Purchase"])
plt.title("Outlier Detection in Purchase")
plt.show()
```



In [9]:
```
q1=df["Purchase"].quantile(0.25)
q1
```

Out[9]: 5823.0

In [10]:
```
q3=df["Purchase"].quantile(0.75)
q3
```

Out[10]: 12054.0

In [11]:
```
iqr=1.5*stats.iqr(df["Purchase"])
iqr
```

Out[11]: 9346.5

In [12]:
```
df.loc[(df["Purchase"]<q1-iqr) | (df["Purchase"]>q3+iqr)]
```

Out[12]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
343	1000058	P00117642	M	26-35	2	B	3	0	10	23603
375	1000062	P00119342	F	36-45	3	A	1	0	10	23792
652	1000126	P00087042	M	18-25	9	B	1	0	10	23233
736	1000139	P00159542	F	26-35	20	C	2	0	10	23595
1041	1000175	P00052842	F	26-35	2	B	1	0	10	23341
...	...	...	...	...	...	...	...	...	...	...
544488	1005815	P00116142	M	26-35	20	B	1	0	10	23753
544704	1005847	P00085342	F	18-25	4	B	2	0	10	23724
544743	1005852	P00202242	F	26-35	1	A	0	1	10	23529
545663	1006002	P00116142	M	51-55	0	C	1	1	10	23663
545787	1006018	P00052842	M	36-45	1	C	3	0	10	23496

2677 rows × 10 columns

Observation 0.4% data in Purchase are outliers hence will remove them to get proper EDA

In [13]:
```
#Outlier Removal
df=df.loc[(df["Purchase"]>=q1-iqr) & (df["Purchase"]<=q3+iqr)]
df.shape
```

Out[13]: (547391, 10)

In [14]:
```
#Statistical Info after Outlier removal in Purchase
df.describe()
```

Out[14]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.473910e+05	547391.000000	547391.000000	547391.000000	547391.000000
mean	1.003028e+06	8.074627	0.409486	5.378945	9195.627195
std	1.727357e+03	6.521586	0.491739	3.927383	4938.872953
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5721.000000
50%	1.003075e+06	7.000000	0.000000	5.000000	8038.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12019.000000
max	1.006040e+06	20.000000	1.000000	20.000000	21399.000000

In [15]:
```
#some basic analysis on the metrics to be used .Finding their unique values and counts
df["Age"].value_counts()
```

Out[15]:
```
26-35    218661
36-45    109409
18-25     99334
46-50     45442
51-55     38191
55+       21322
0-17      15032
Name: Age, dtype: int64
```

In [16]:
```
df.groupby("Product_Category")["Product_Category"].count()
```

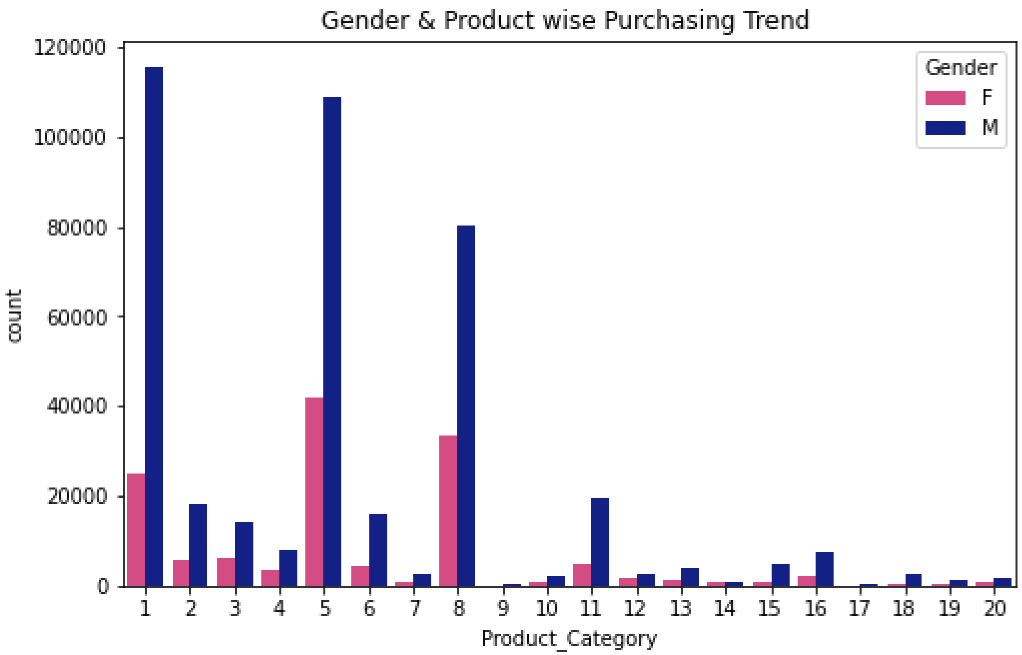
Out[16]:
```
Product_Category
1     140378
2      23864
3      20213
4      11753
5     150933
6      20466
7       3721
8     113925
9        335
10      2850
11     24287
12      3947
13      5549
14      1523
15      5963
16      9828
17       578
18      3125
19      1603
20      2550
Name: Product_Category, dtype: int64
```

In [17]:
```
df.groupby(["Gender"])["Gender"].count()
```

Out[17]:
```
Gender
F    135220
M    412171
Name: Gender, dtype: int64
```

Observation-After outlier removal the sample has data of 135220 female and 412171 male users in different 7 different age groups as listed above.Ther are purchases made in 20 different Product categories

In [288]:
```
sns.countplot(x="Product_Category",data=df,hue="Gender")
plt.rcParams["figure.figsize"] = (5,5)
colors = [ "#EA3680","#00129A"]
plt.title("Gender & Product wise Purchasing Trend ")
sns.set_palette(sns.color_palette(colors))
```



Observation-Number of Purchases are more for Males and its in Product Category 1,5,8

In [19]:
```
df.insert(10,"MaritalStatus",'')
```

In [20]:
```
idx=df.loc[df["Marital_Status"]==0].index
df.loc[idx,["MaritalStatus"]]="Single"
```

In [21]:

```
idx=df.loc[df["Marital_Status"]==1].index
df.loc[idx,["MaritalStatus"]]="Married"
```

In [234]:

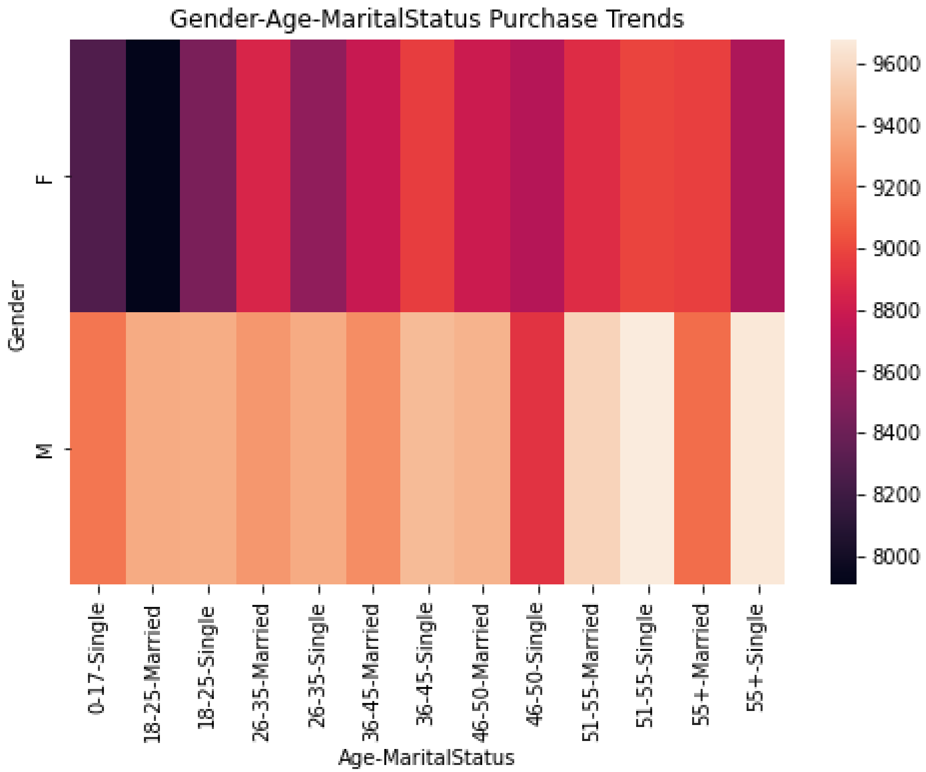
```
pd.crosstab(index=df["Gender"],columns=[df["Age"],df["MaritalStatus"]],values=df["Purchase"],aggfunc="mean")
```

Out[234]:

Age	0-17	18-25		26-35		36-45		46-50		51-55
MaritalStatus	Single	Married	Single	Married	Single	Married	Single	Married	Single	Married
Gender										
F	8276.806993	7906.885212	8454.645605	8855.320570	8547.536707	8775.970088	8959.602583	8796.934195	8697.189404	8891.257535
M	9167.328686	9383.981537	9391.474502	9301.603198	9380.897651	9257.660794	9451.817399	9420.534880	8918.991751	9566.047927

In [292]:
```
s=pd.crosstab(index=df["Gender"],columns=[df["Age"],df["MaritalStatus"]],values=df["Purchase"],aggfunc="mean")
sns.heatmap(s)
plt.rcParams["figure.figsize"] = (8,8)
plt.title("Gender-Age-MaritalStatus Purchase Trends")

plt.show()
```

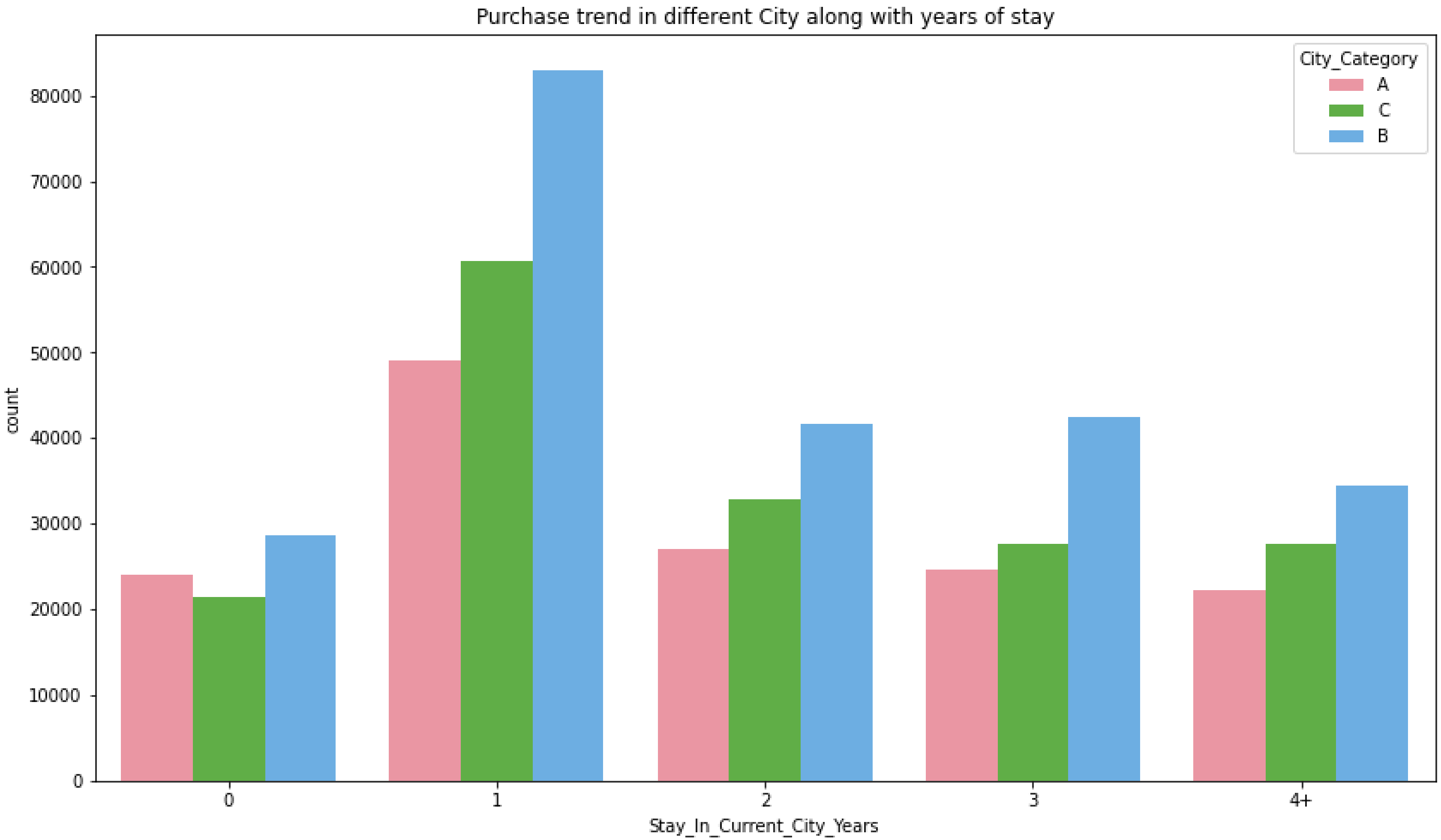


Observation-Its interesting to note that for males till 45 years age groups people who are single tends to spend more ,But from 46 years age groups the married people have more purchases.As far a Females are considered, till 25 years of age they spend less but after this age their purchasing trend is quite similar wether they are married or not .

In [25]:
```
df.groupby(["City_Category","Stay_In_Current_City_Years"])["Stay_In_Current_City_Years"].value_counts()*100/len(df)
```

Out[25]:
```
City_Category  Stay_In_Current_City_Years  Stay_In_Current_City_Years
A              0                           0                              4.394300
               1                           1                              8.967813
               2                           2                              4.931210
               3                           3                              4.507747
               4+                          4+                             4.060169
B              0                           0                              5.218756
               1                           1                             15.161557
               2                           2                              7.601331
               3                           3                              7.763007
               4+                          4+                             6.293673
C              0                           0                              3.912194
               1                           1                             11.100475
               2                           2                              5.988772
               3                           3                              5.048494
               4+                          4+                             5.050503
Name: Stay_In_Current_City_Years, dtype: float64
```

In [26]:
```
xorder=['0','1','2','3','4+']
sns.countplot(df["Stay_In_Current_City_Years"],hue=df["City_Category"],order=xorder)
plt.title("Purchase trend in different City along with years of stay")
plt.show()
```



Observation-Above plot shows that most of the purchases are done from city B regardless of the number of years of stay in that city.People with less than 1 year of stay has made least Number of of purchases

Recommendation-The number of purchases from city A and C are less compared to B .Perhaps the number of stores/outlets are less in these cities.Walmart can open more outlets here to improve Business

Male Vs Female

In [27]:
```
# Separating the male and female purchases into two data frames
df_f=df.loc[df["Gender"]=='F']
df_f.reset_index(inplace=True)
df_f.drop("index",axis=1,inplace=True)
df_f
```

Out[27]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase	Ma
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	1000006	P00231342	F	51-55	9	A	1	0	5	5378	
...	...	...	...	...	...	...	...	...	...	...	
135215	1006029	P00372445	F	26-35	1	C	1	1	20	599	
135216	1006035	P00375436	F	26-35	1	C	3	0	20	371	
135217	1006036	P00375436	F	26-35	15	B	4+	1	20	137	
135218	1006038	P00375436	F	55+	1	C	2	0	20	365	
135219	1006039	P00371644	F	46-50	0	B	4+	1	20	490	

135220 rows × 11 columns

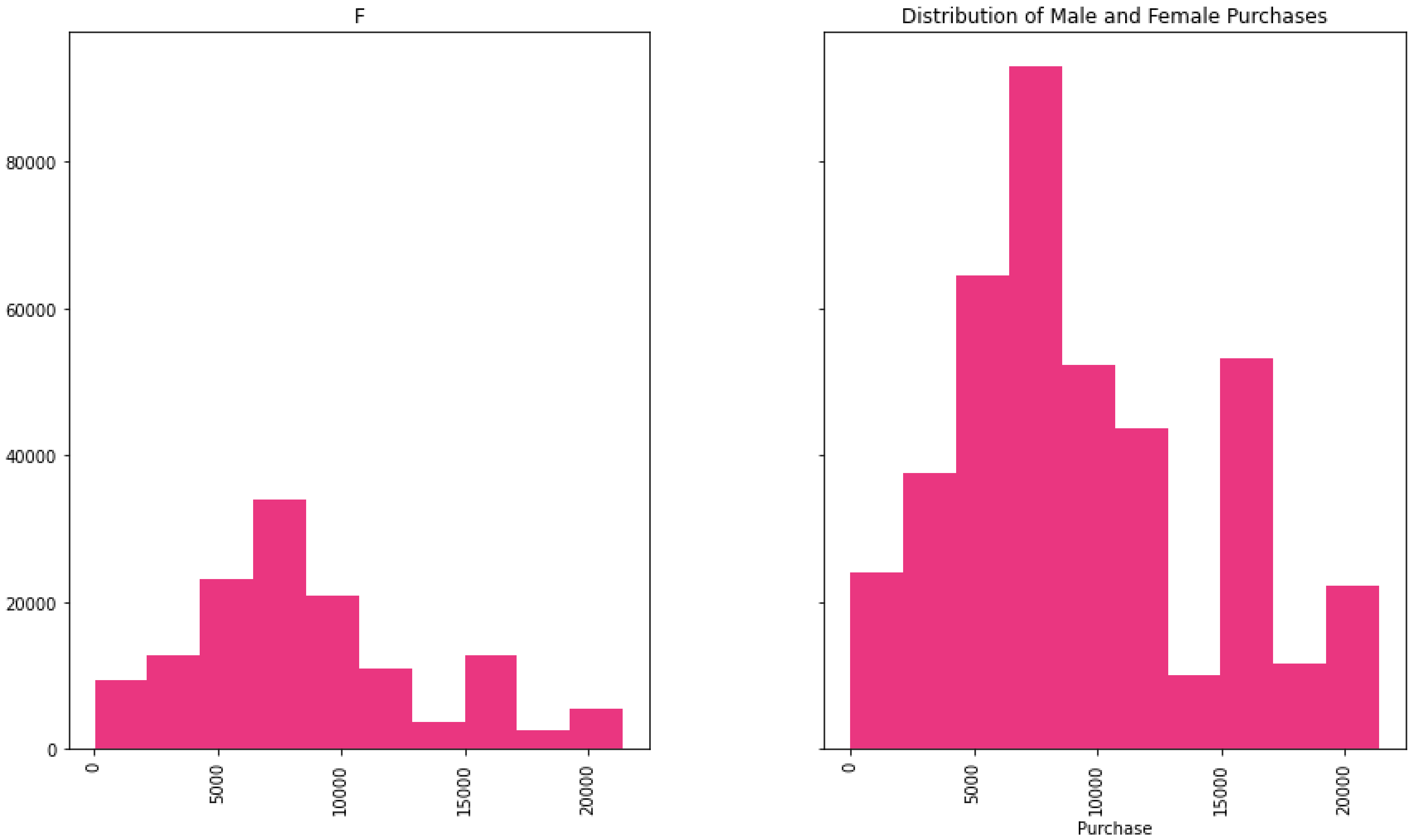
In [28]:
```
df_m=df.loc[df["Gender"]=='M']
df_m.reset_index(inplace=True)
df_m.drop("index",axis=1,inplace=True)
df_m
```

Out[28]:

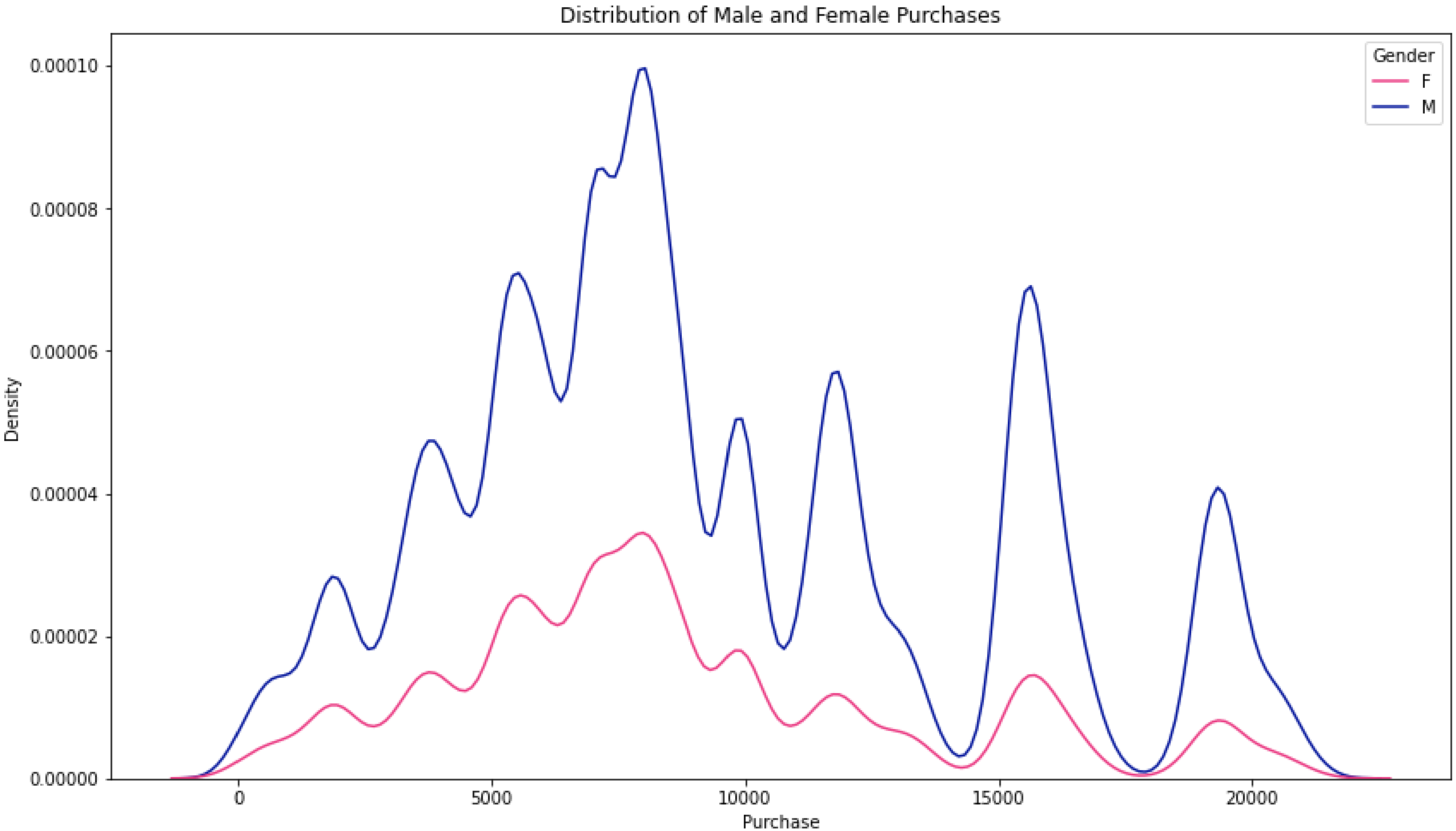
	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase	Ma
0	1000002	P00285442	M	55+	16	C	4+	0	8	7969	
1	1000003	P00193542	M	26-35	15	A	3	0	1	15227	
2	1000004	P00184942	M	46-50	7	B	2	1	1	19215	
3	1000004	P00346142	M	46-50	7	B	2	1	1	15854	
4	1000004	P0097242	M	46-50	7	B	2	1	1	15686	
...	...	...	...	...	...	...	...	...	...	...	
412166	1006023	P00370853	M	26-35	0	C	2	1	19	61	
412167	1006024	P00372445	M	26-35	12	A	0	1	20	121	
412168	1006026	P00371644	M	36-45	6	C	1	1	20	494	
412169	1006032	P00372445	M	46-50	7	A	3	0	20	473	
412170	1006033	P00372445	M	51-55	13	B	1	1	20	368	

412171 rows × 11 columns

In [235]:
```
df.hist(column="Purchase",by="Gender",sharey=True)
plt.xlabel("Purchase")
plt.ylabel("Count")
plt.title("Distribution of Male and Female Purchases")
plt.show()
```



In [237]:
```
sns.kdeplot(df["Purchase"],hue=df["Gender"])
plt.title("Distribution of Male and Female Purchases")
plt.show()
```

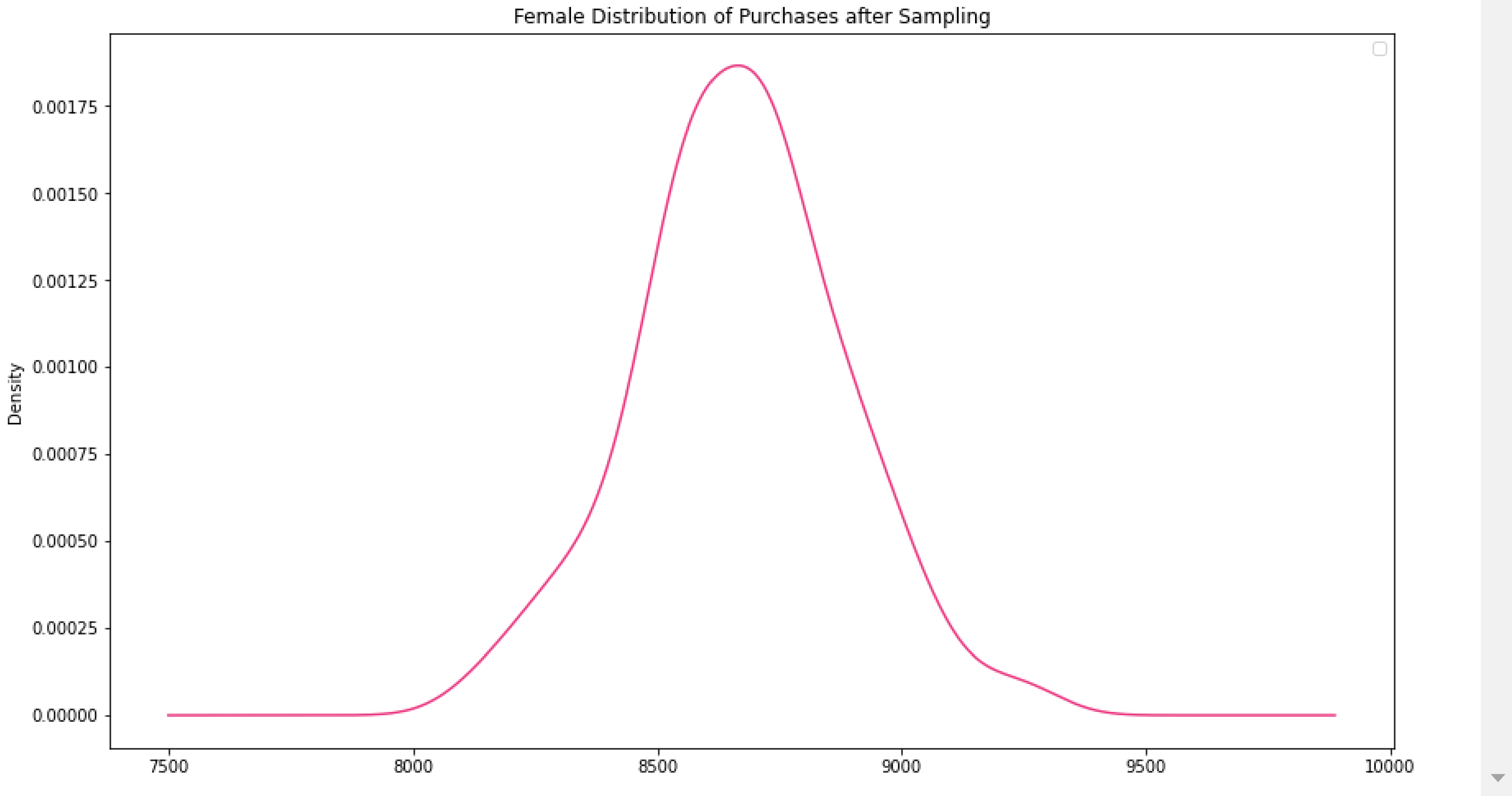


Observation-The distribution is clearly not Gaussian ,Hence following Bootstrap method as given below

In [254]:

```python
#Sampling the female population to a Normal Distribution
sample_mean_list=[]
number_of_times=200
for i in range (number_of_times):
    sample_data=df_f.sample(n=500)
    sample_mean=np.mean(sample_data["Purchase"])
    sample_mean_list.append(sample_mean)
s_mean=round(np.mean(sample_mean_list),2)
s_std=round(np.std(sample_mean_list),2)
print("The mean of Distribution of sample means is ",s_mean,"with Standard Deviation",s_std)
pd.DataFrame(sample_mean_list).plot(kind="density")
plt.title("Female Distribution of Purchases after Sampling")
plt.legend('')
plt.show()
```

```
The mean of Distribution of sample means is  8668.9 with Standard Deviation 214.96
```

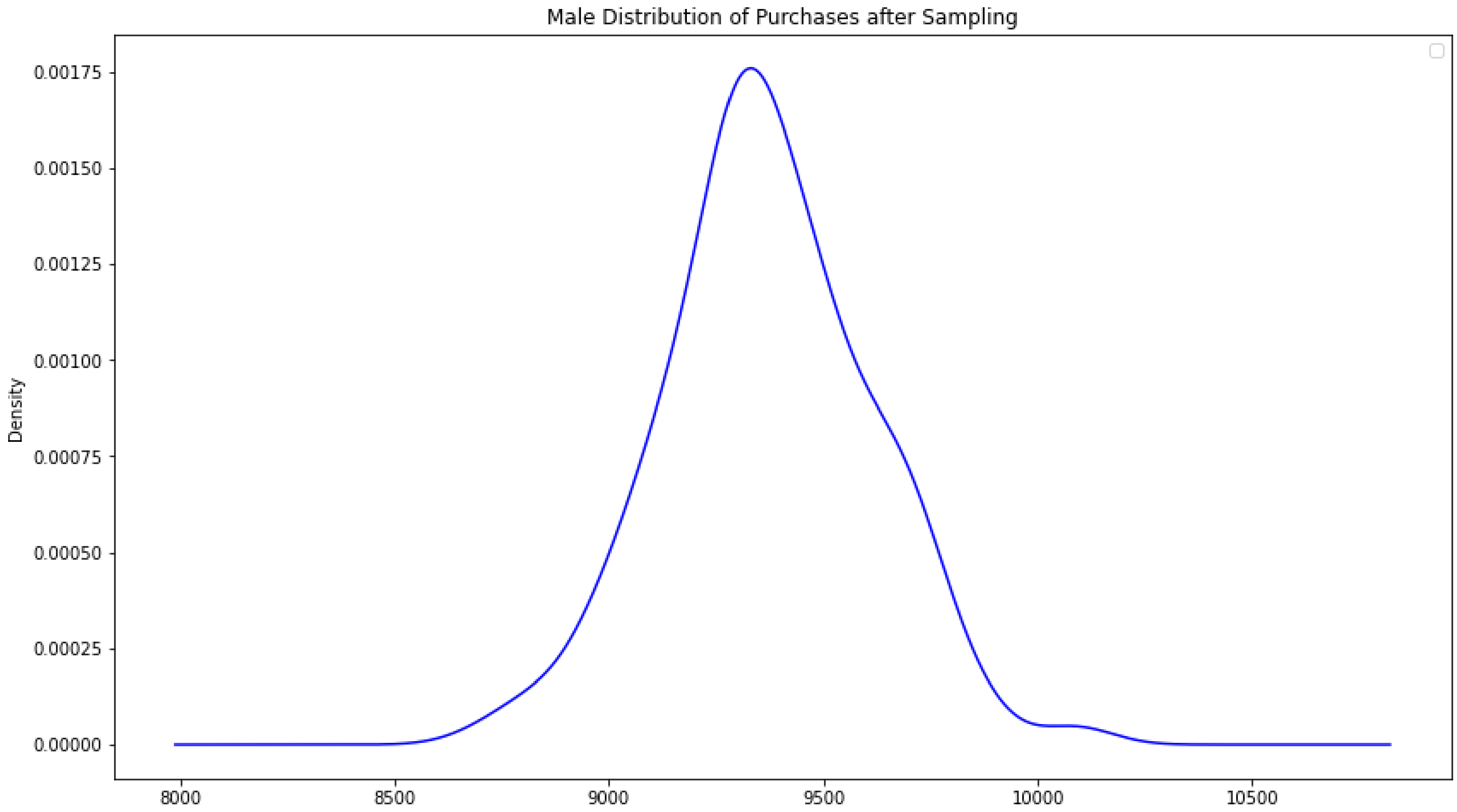


Observation-From the female datapool ,500 samples were drawn .This was repeated 200 times.The resultant mean each time was plotted.The density plot shows its a Gaussian distribution with mean centered almost same as the female dataset.The same experiment is repeated for male popuation and similar observation found

In [268]:

```
#Sampling the male population to a Normal Distribution
sample_mean_list=[]
number_of_times=200
for i in range (number_of_times):
    sample_data=df_m.sample(n=500,replace=True)
    sample_mean=np.mean(sample_data["Purchase"])
    sample_mean_list.append(sample_mean)
s_mean=round(np.mean(sample_mean_list),2)
s_std=round(np.std(sample_mean_list),2)
print("The mean of Distribution of sample means is ",s_mean,"with Standard Deviation",s_std)
pd.DataFrame(sample_mean_list).plot(kind="density",color="blue")
plt.title("Male Distribution of Purchases after Sampling")
plt.legend('')
plt.show()
```

```
The mean of Distribution of sample means is  9368.52 with Standard Deviation 238.68
```


Male Distribution of Purchases after Sampling
Density
0.00175
0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
8000
8500
9000
9500
10000
10500

In [35]:

```
#Bootstrapping to find the CI for females
bootstap_mean_list_f=[]
number_of_times=200
for i in range (number_of_times):
    sample_data=df_f.sample(n=len(df_f),replace=True)
    bootstrap_mean=np.mean(sample_data["Purchase"])
    bootstap_mean_list_f.append(bootstrap_mean)
confidence_interval_female=[]

for ci in (90,95,99):
    lb=(100-ci)/2
    ub=ci+(100-ci)/2
    confidence_interval_female.append(np.percentile(bootstap_mean_list_f,[lb,ub]))
```

In [280]:

```
confidence_interval_female#Confidence Interval for females with 90%,95%,99% confidence levels
mean_f=round(np.mean(bootstap_mean_list_f),2)
std_f=round(np.std(bootstap_mean_list_f),2)
print("The mean of sampled means is",mean_f,"dollars.The Mean purchase of the Female population is expected to be this w:
print("90% Confidence Interval is [",round(confidence_interval_female[0][0],2),",",round(confidence_interval_female[0][1
print("95% Confidence Interval is [",round(confidence_interval_female[1][0],2),",",round(confidence_interval_female[1][1
print("99% Confidence Interval is [",round(confidence_interval_female[2][0],2),",",round(confidence_interval_female[2][1
```

```
The mean of sampled means is 8669.19 dollars.The Mean purchase of the Female population is expected to be this with sta
ndard deviation 13.46
90% Confidence Interval is [ 8647.45 , 8692.89 ]
95% Confidence Interval is [ 8644.33 , 8695.99 ]
99% Confidence Interval is [ 8640.52 , 8704.36 ]
```

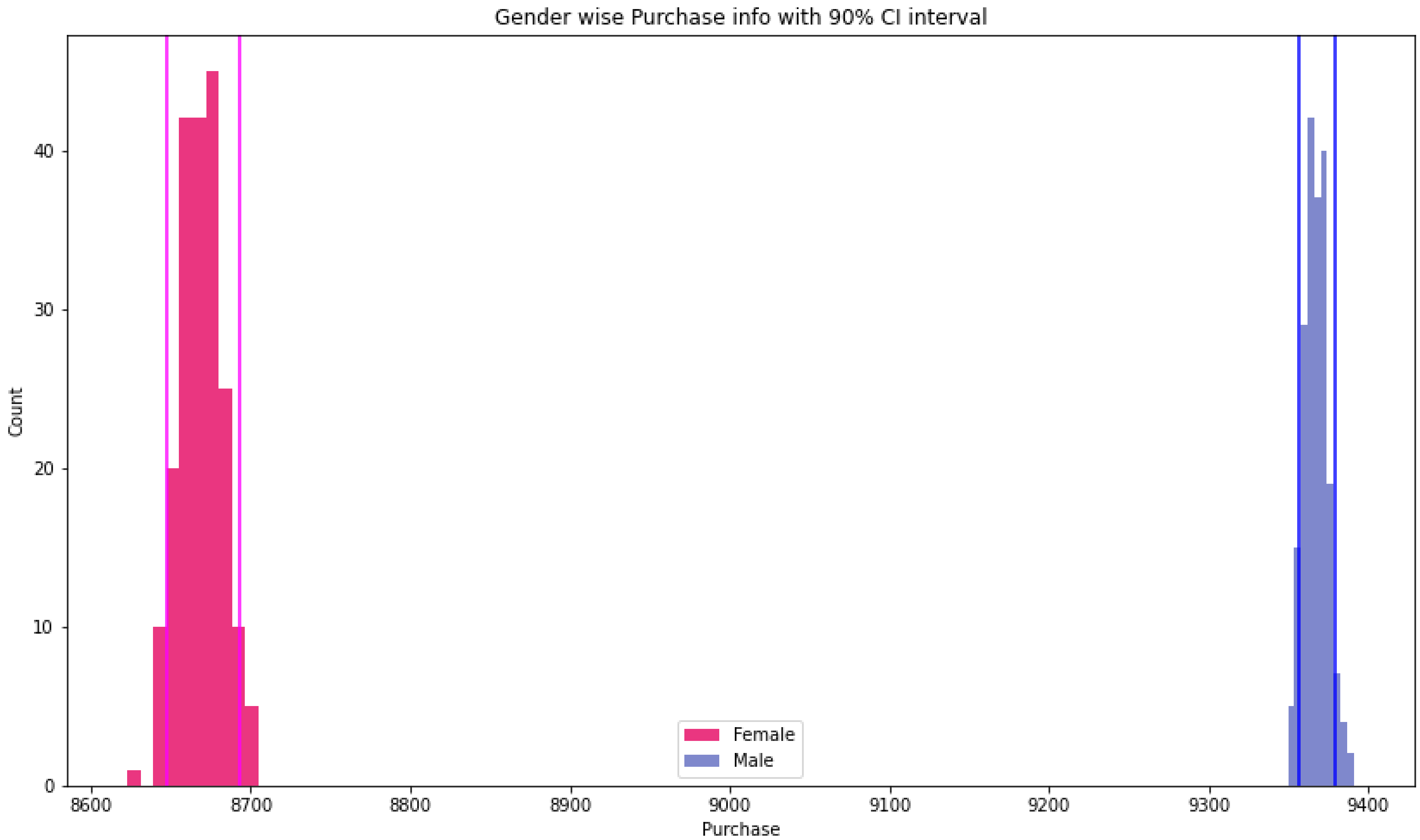
In [260]:
```
#Bootstrapping to find the CI for males
bootstap_mean_list_m=[]
number_of_times=200
for i in range (number_of_times):
    sample_data=df_m.sample(n=len(df_m),replace=True)
    bootstrap_mean=np.mean(sample_data["Purchase"])
    bootstap_mean_list_m.append(bootstrap_mean)
confidence_interval_male=[]

for ci in (90,95,99):
    lb=(100-ci)/2
    ub=ci+(100-ci)/2
    confidence_interval_male.append(np.percentile(bootstap_mean_list_m,[lb,ub]))
```

In [281]:
```
mean_m=round(np.mean(bootstap_mean_list_m),2)
std_m=round(np.std(bootstap_mean_list_m),2)
print("The mean of sampled means is",mean_m,"dollars.The Mean purchase of the Male population is expected to be this valu
confidence_interval_male #Confidence Interval for males with 90%,95%,99% confidence levels
print("90% Confidence Interval is [",round(confidence_interval_male[0][0],2),",",round(confidence_interval_male[0][1],2)
print("95% Confidence Interval is [",round(confidence_interval_male[1][0],2),",",round(confidence_interval_male[1][1],2)
print("99% Confidence Interval is [",round(confidence_interval_male[2][0],2),",",round(confidence_interval_male[2][1],2)
```

```
The mean of sampled means is 9367.29 dollars.The Mean purchase of the Male population is expected to be this value with
Std Deviation. 7.27
90% Confidence Interval is [ 9356.22 , 9378.7 ]
95% Confidence Interval is [ 9354.27 , 9383.34 ]
99% Confidence Interval is [ 9352.09 , 9386.78 ]
```

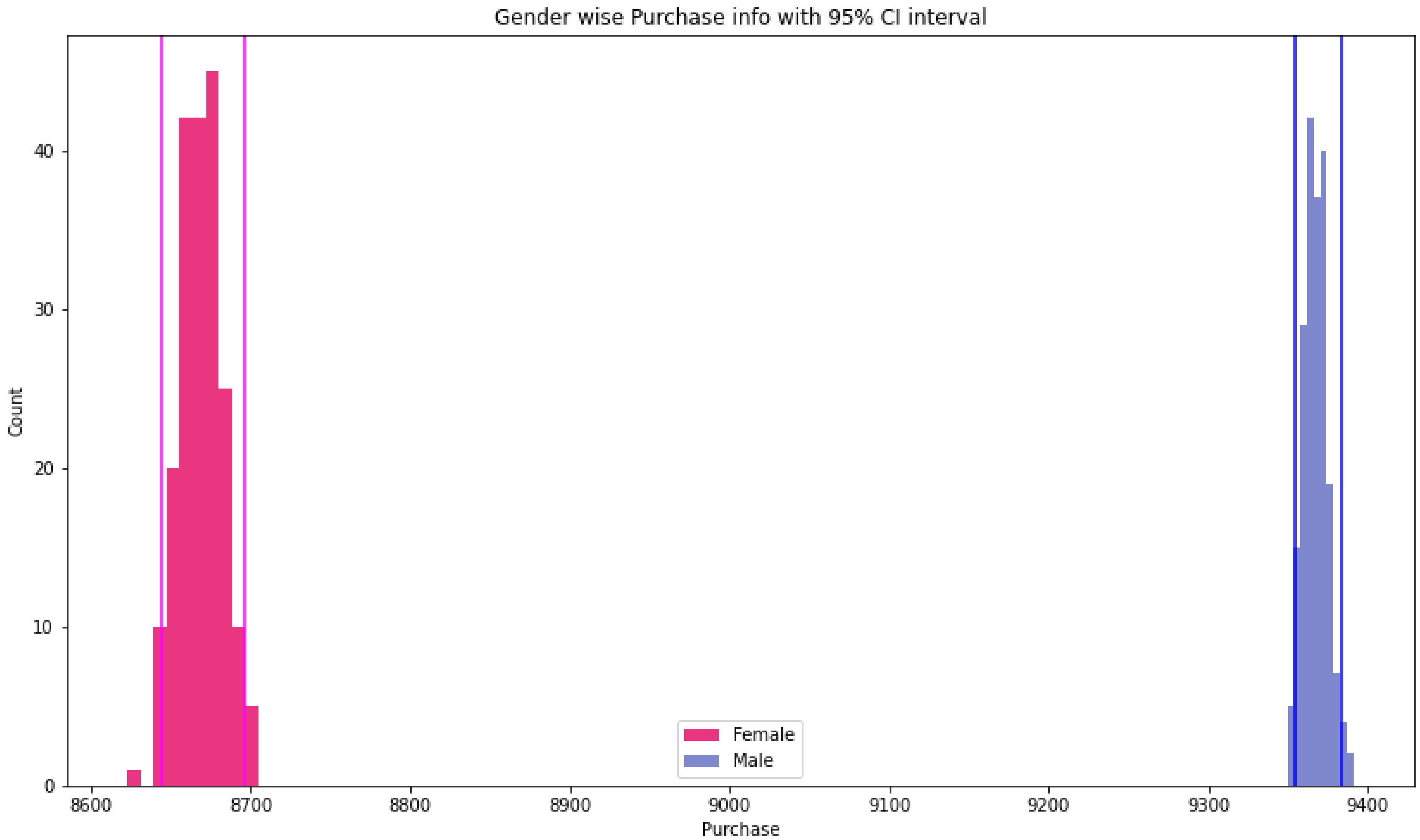
In [269]:
```
#Plot gender wise 90% CI
plt.hist(bootstap_mean_list_f,label="Female")
plt.hist(bootstap_mean_list_m,label="Male",alpha=.5)
plt.axvline(confidence_interval_male[0][0],c='b')
plt.axvline(confidence_interval_male[0][1],c='b')
plt.axvline(confidence_interval_female[0][0],color='magenta')
plt.axvline(confidence_interval_female[0][1],color='magenta')
plt.title("Gender wise Purchase info with 90% CI interval")
plt.xlabel("Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```



Gender wise Purchase info with 90% CI interval
Count
Purchase
Female
Male
0
10
20
30
40
8600
8700
8800
8900
9000
9100
9200
9300
9400

In [270]:

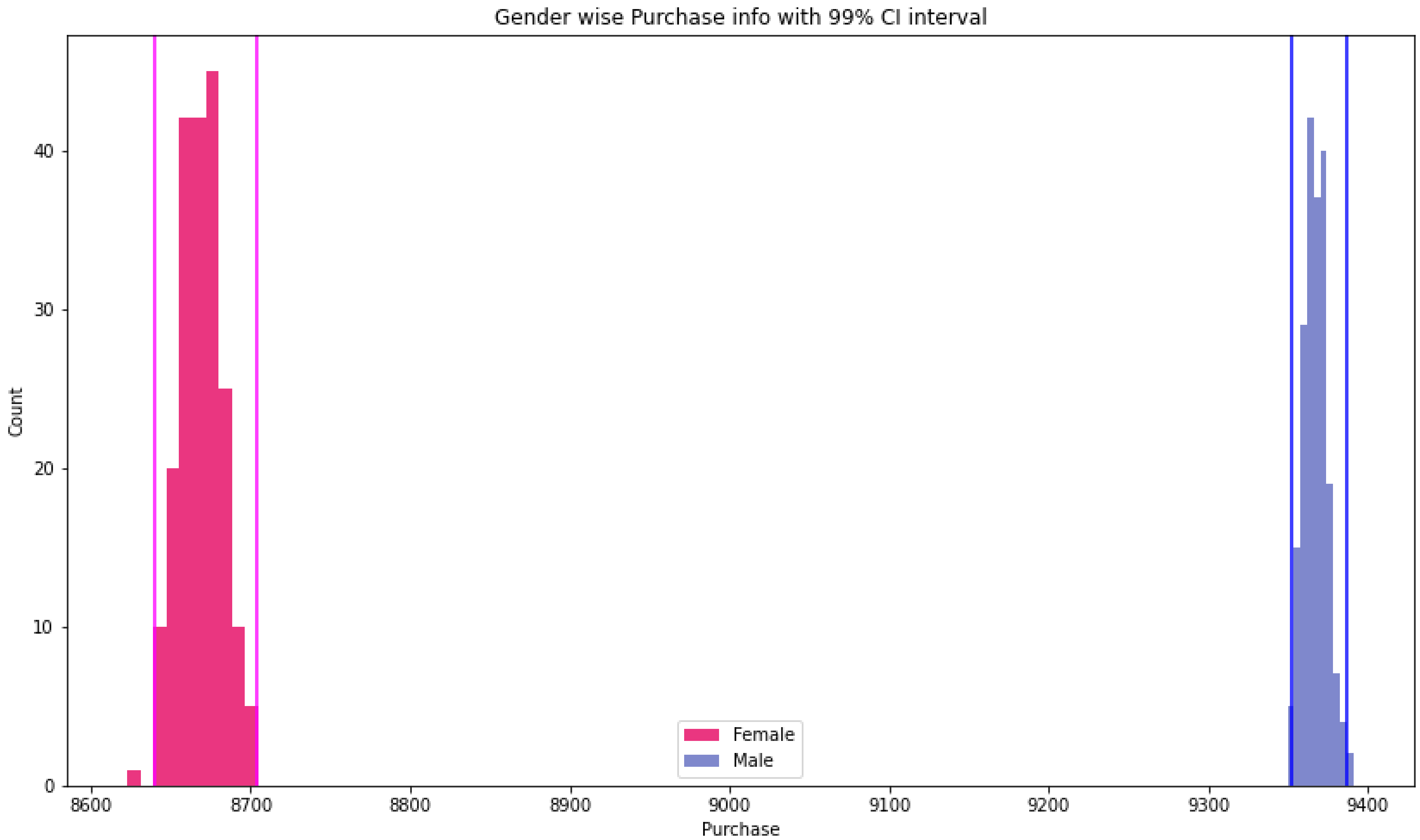
```
#Plot gender wise 95% CI
plt.hist(bootstap_mean_list_f,label="Female")
plt.hist(bootstap_mean_list_m,label="Male",alpha=.5)
plt.axvline(confidence_interval_male[1][0],c='b')
plt.axvline(confidence_interval_male[1][1],c='b')
plt.axvline(confidence_interval_female[1][0],color='magenta')
plt.axvline(confidence_interval_female[1][1],color='magenta')
plt.title("Gender wise Purchase info with 95% CI interval")
plt.xlabel("Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```



Gender wise Purchase info with 95% CI interval
Count
Purchase
Female
Male
0
10
20
30
40
8600
8700
8800
8900
9000
9100
9200
9300
9400

In [271]:

```
#Plot gender wise 99% CI
plt.hist(bootstap_mean_list_f,label="Female")
plt.hist(bootstap_mean_list_m,label="Male",alpha=.5)
plt.axvline(confidence_interval_male[2][0],c='b')
plt.axvline(confidence_interval_male[2][1],c='b')
plt.axvline(confidence_interval_female[2][0],color='magenta')
plt.axvline(confidence_interval_female[2][1],color='magenta')
plt.title("Gender wise Purchase info with 99% CI interval")
plt.xlabel("Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```



Observation-The confidence intervals for male and female are non-overlapping which indicates that these groups are significantly different from each other.So how can we increase the business among the these group?

In [42]:
```
#Female Purchase
df_f.groupby("Product_Category")["Purchase"].mean().sort_values(ascending=False).to_frame().head(10)
```

Out[42]:

	Purchase
Product_Category	
10	16563.998433
7	16394.853659
6	15596.428164
16	14681.491257
15	14347.546734
9	13878.142857
14	13747.362761
1	13597.162619
2	11407.496819
3	10262.656677

In [294]:
```
#Male Purchase
df_m.groupby("Product_Category")["Purchase"].mean().sort_values(ascending=False).to_frame().head(10)
```

Out[294]:

	Purchase
Product_Category	
10	16644.380199
7	16355.789777
6	15907.851009
16	14793.384056
15	14425.513889
9	13847.143369
1	13608.164721
14	12722.321111
2	11203.590520
17	10209.732558

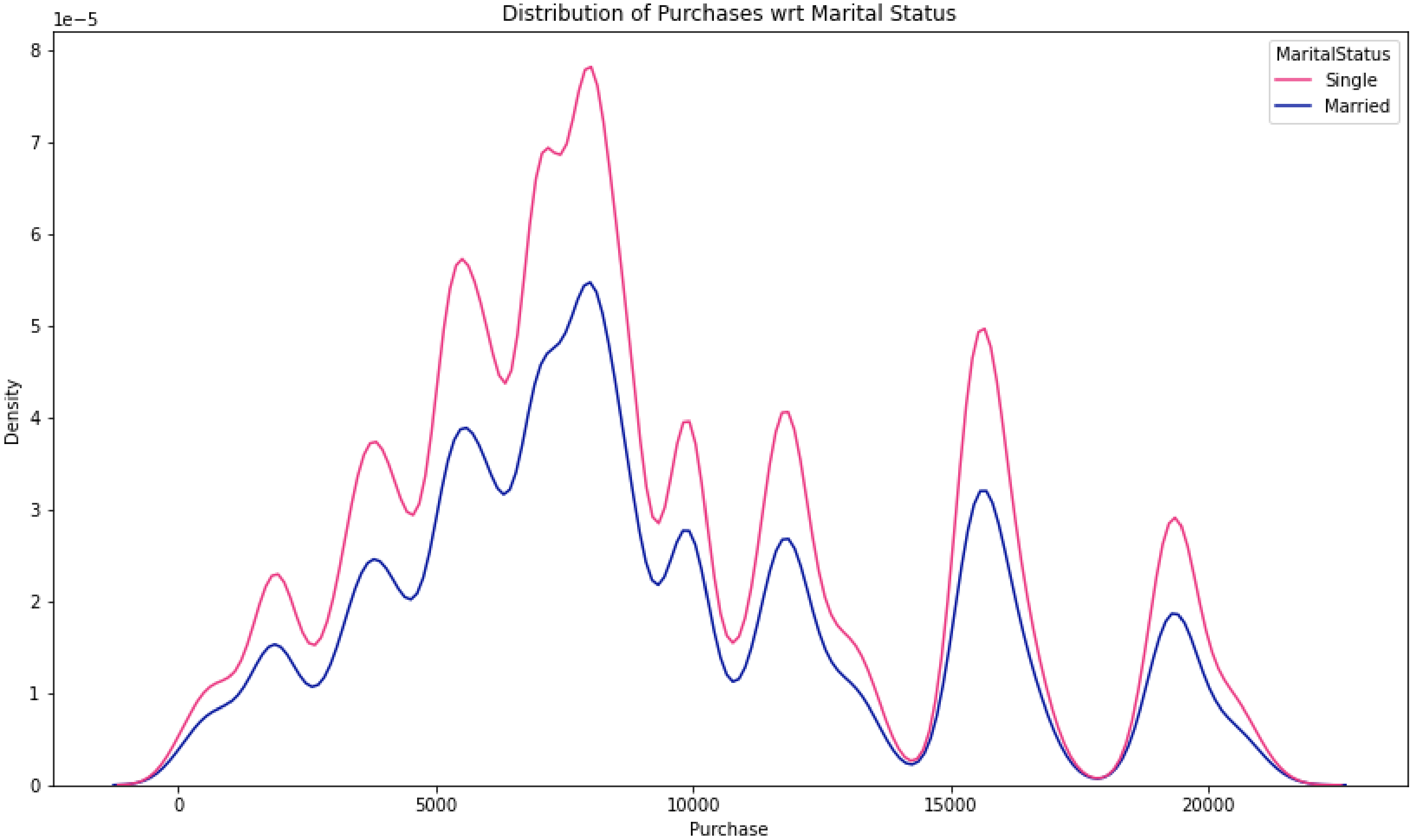
Recommendation-The above output shows the top 10 product categories on which the female and male spend more.So business could improve if the stores have more stock of products in these categories.

Single Vs Married

In [43]:
```python
df["MaritalStatus"].value_counts()
```

Out[43]:
```
Single     323242
Married    224149
Name: MaritalStatus, dtype: int64
```

In [44]:
```python
sns.kdeplot(df["Purchase"],hue=df["MaritalStatus"])
plt.title("Distribution of Purchases wrt Marital Status")
plt.show()
```



Observation-Its clearly not gaussian

In [46]:
```
"""Inorder to reduce the redundancy in code,introducing two custom functions to split the dataframe and to Bootstrap
1)Function to split the dataframe df based
on the column name and column value"""
def DataFrameSplit (df,column,value):
    name_dataframe="df_"+column+"_"+value
    x=df.loc[df[column]==value]
    x.reset_index(inplace=True)
    x.drop("index",axis=1,inplace=True)
    return name_dataframe,x
```

In [145]:
```
#Dataframe df is split based on column MaritalStatus and value=Single.The resultant dataframe is stored in dictionary dat
name,data=DataFrameSplit(df,"MaritalStatus","Single")
dataframes={}
dataframes[name] = data
```

In [144]:
```
#initialsing dictionaries to store the confidence intervals and bootstrap means for the dataframes post the split
dataframes_namelist_pos=0
ci_dict={}
bootstrap_mean_dict={}
```

In [143]:
```
"""2)This function is used to find the bootstrapped means of the dataframes post the spilt and then find their confidence
intervals
The bootstrapped means of each of the split dataframes are stored in dictionary bootstrap_mean_dict and the CI's of each
split dataframes are stored in the dictionary ci_dict """
def BootStrapFunc(data):
    bootstap_mean_list=[]
    global dataframes_namelist_pos
    number_of_times=200
    for i in range (number_of_times):
        sample_data=data.sample(n=len(data),replace=True)
        bootstrap_mean=np.mean(sample_data["Purchase"])
        bootstap_mean_list.append(bootstrap_mean)
    c_interval=[]
    global ci_dict
    global bootstrap_mean_dict
    bootstrap_mean=np.mean(bootstap_mean_list)

    ci_name=list(dataframes.keys())[dataframes_namelist_pos]
    ci_name=ci_name+'_CI'

    bs_name=list(dataframes.keys())[dataframes_namelist_pos]
    bs_name=bs_name+"_BS"

    for ci in (90,95,99):
        lb=(100-ci)/2
        ub=ci+(100-ci)/2
        c_interval.append(np.percentile(bootstap_mean_list,[lb,ub]))
    print("Mean of the Sampling Distribution is",round(bootstrap_mean,2))
    print("90% Confidence Interval is [",round(c_interval[0][0],2),",",round(c_interval[0][1],2),"]")
    print("95% Confidence Interval is [",round(c_interval[1][0],2),",",round(c_interval[1][1],2),"]")
    print("99% Confidence Interval is [",round(c_interval[2][0],2),",",round(c_interval[2][1],2),"]")
    ci_dict[ci_name]=c_interval
    bootstrap_mean_dict[bs_name]=bootstap_mean_list

    dataframes_namelist_pos+=1
```

In [146]:
```
#BootStrapFunc function call on splitted dataframe to find CI
BootStrapFunc(dataframes['df_MaritalStatus_Single'])
```

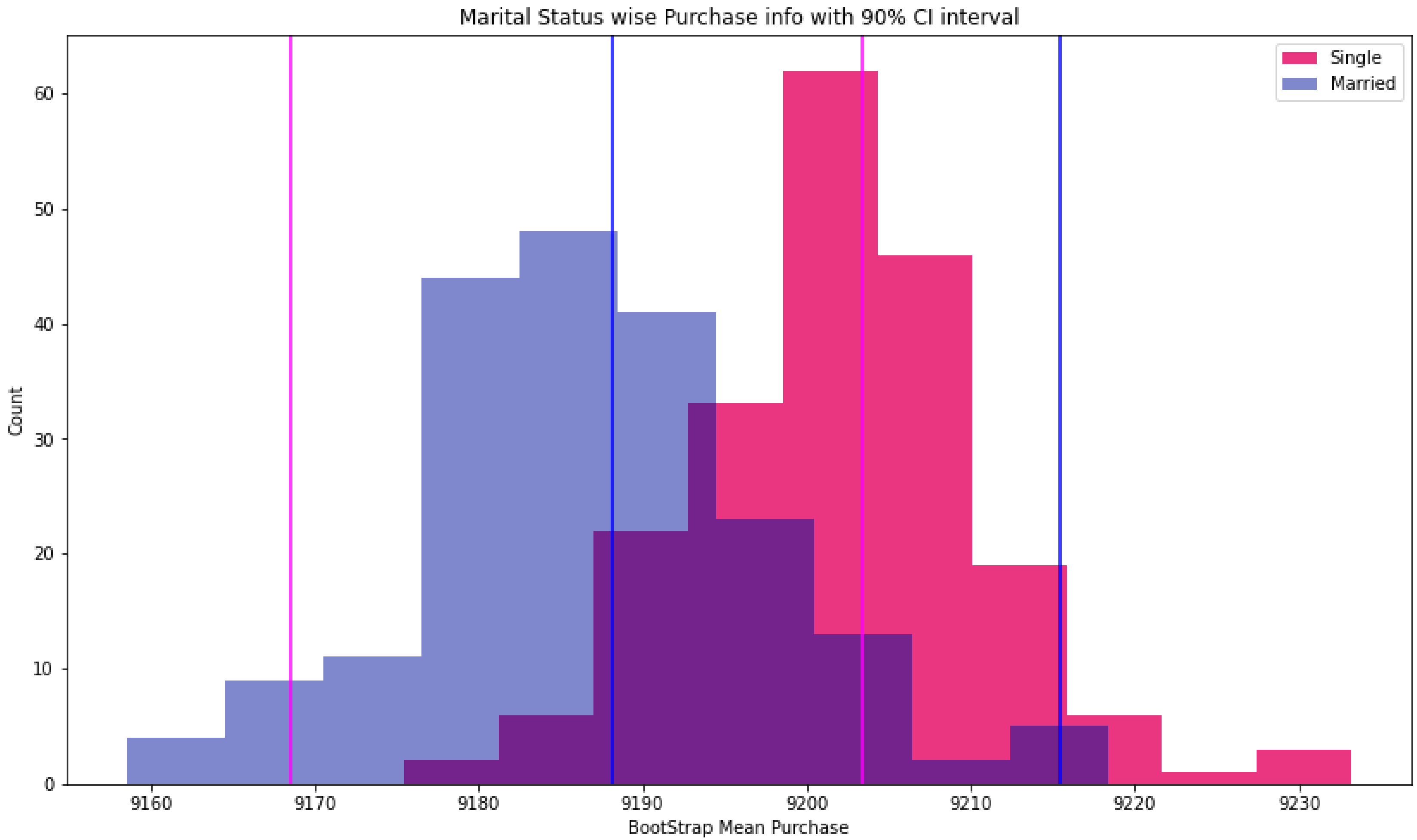
```
Mean of the Sampling Distribution is 9201.98
90% Confidence Interval is [ 9188.19 , 9215.45 ]
95% Confidence Interval is [ 9186.06 , 9219.05 ]
99% Confidence Interval is [ 9178.08 , 9228.75 ]
```

In [147]:
```
#Repeat the same function calls for Marital Status=Married
name,data=DataFrameSplit(df,"MaritalStatus","Married")
dataframes[name]=data
```

In [148]:
```
BootStrapFunc(dataframes['df_MaritalStatus_Married'])
```

```
Mean of the Sampling Distribution is 9186.84
90% Confidence Interval is [ 9168.54 , 9203.38 ]
95% Confidence Interval is [ 9165.71 , 9210.8 ]
99% Confidence Interval is [ 9158.79 , 9218.18 ]
```

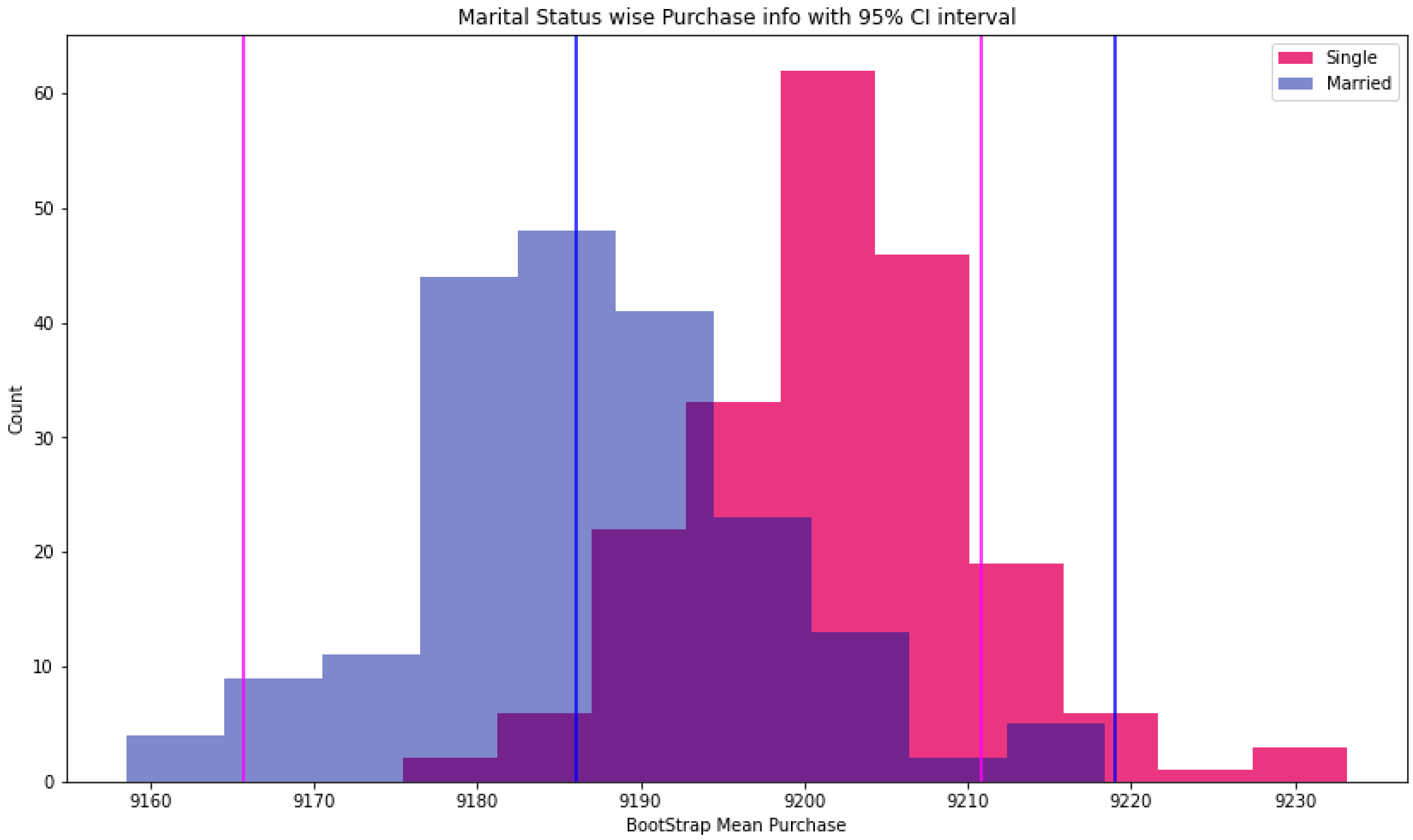
In [149]:
```
#Plot maritalstatus wise 90% CI
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Single_BS"],label="Single")
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Married_BS"],label="Married",alpha=.5)
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][0][0],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][0][1],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][0][0],color='magenta')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][0][1],color='magenta')
plt.title("Marital Status wise Purchase info with 90% CI interval")
plt.xlabel("BootStrap Mean Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```



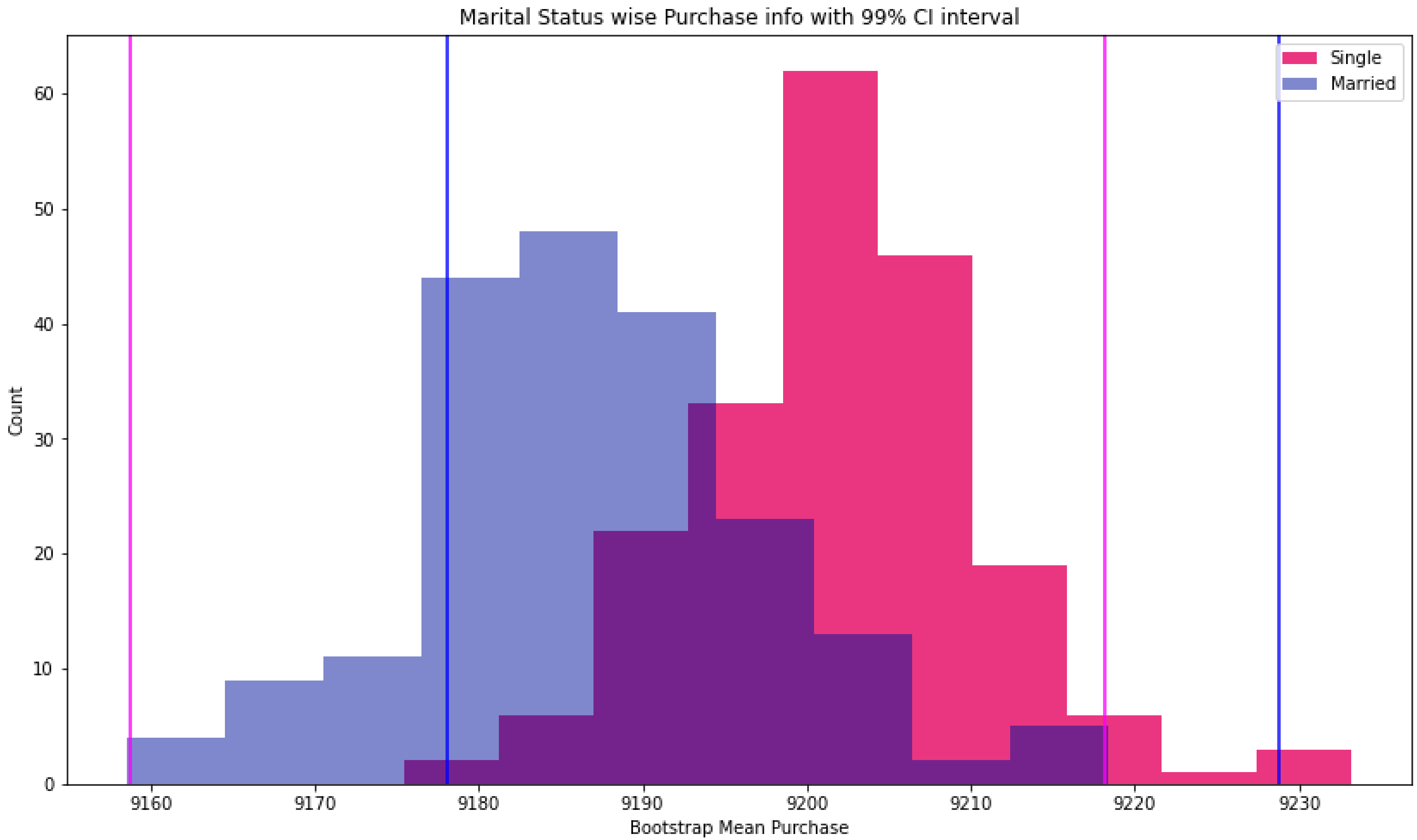
Marital Status wise Purchase info with 90% CI interval
Single
Married
Count
BootStrap Mean Purchase
0
10
20
30
40
50
60
9160
9170
9180
9190
9200
9210
9220
9230

In [150]:

```
#Plot maritalstatus wise 95% CI
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Single_BS"],label="Single")
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Married_BS"],label="Married",alpha=.5)
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][1][0],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][1][1],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][1][0],color='magenta')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][1][1],color='magenta')
plt.title("Marital Status wise Purchase info with 95% CI interval")
plt.xlabel("BootStrap Mean Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```


Marital Status wise Purchase info with 95% CI interval
Single
Married
Count
BootStrap Mean Purchase
0
10
20
30
40
50
60
9160
9170
9180
9190
9200
9210
9220
9230

In [151]:
```
#Plot maritalstatus wise 99% CI
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Single_BS"],label="Single")
plt.hist(bootstrap_mean_dict["df_MaritalStatus_Married_BS"],label="Married",alpha=.5)
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][2][0],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Single_CI'][2][1],c='b')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][2][0],color='magenta')
plt.axvline(ci_dict['df_MaritalStatus_Married_CI'][2][1],color='magenta')
plt.title("Marital Status wise Purchase info with 99% CI interval")
plt.xlabel("Bootstrap Mean Purchase")
plt.ylabel("Count")
plt.legend()
plt.show()
```



Observation:The mean purchase of people after Bootstrapping who are single (9201 dollars)are higher than those who are married(9186 dollars).The population mean for the respective groups is also expected to be around this value

Observation-For all the three confidence levels ie 90%,95% and 99% there is overlap between the Single and Married groups.This suggests that there is no significant distinction between the two groups

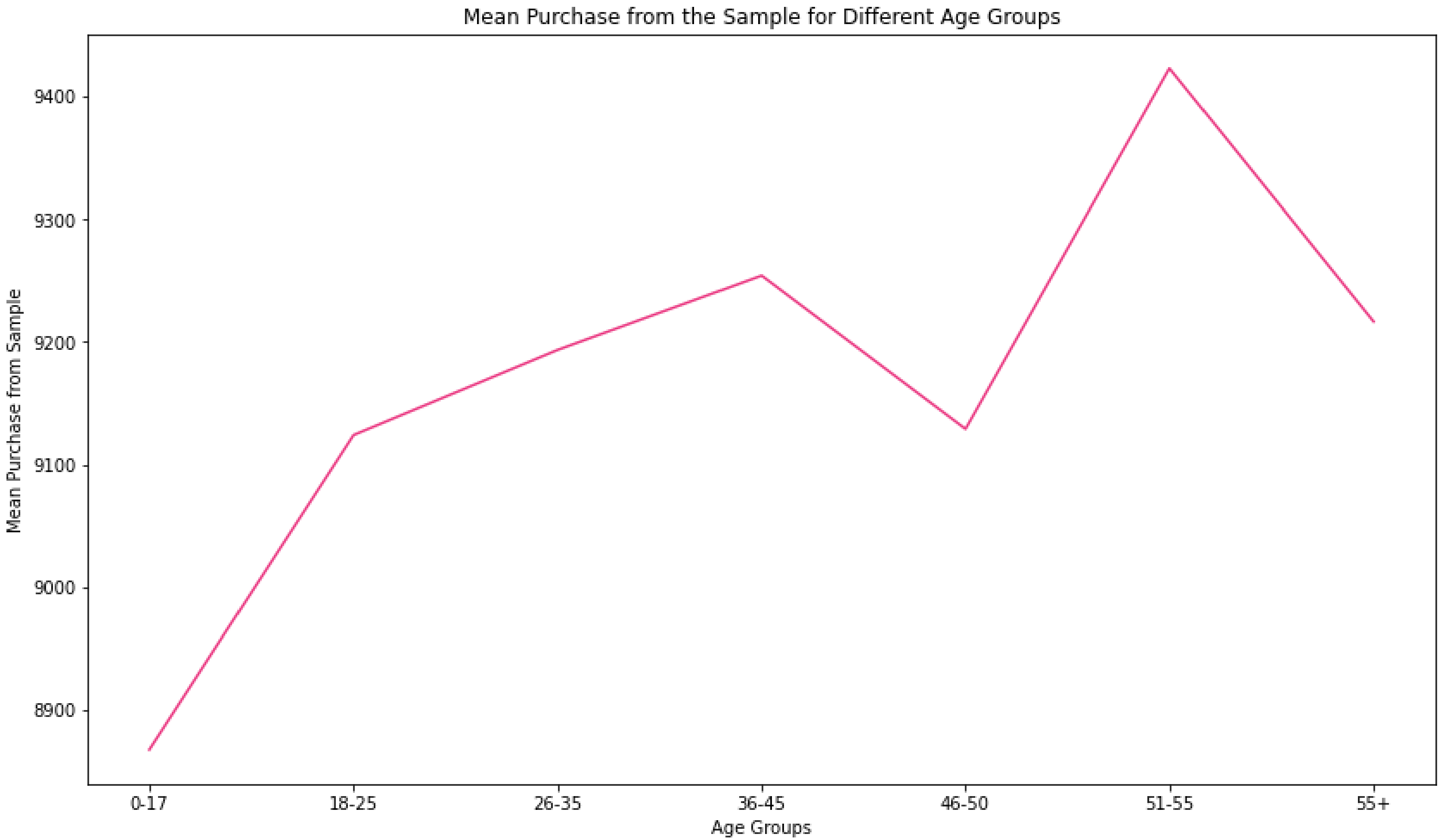
Based on Age Groups

In [56]:
```
df_age=df.groupby(df["Age"])["Purchase"].mean().to_frame().reset_index()
df_age.rename(columns={"Purchase":"Mean Purchase"},inplace=True)
df_age
```

Out[56]:

	Age	Mean Purchase
0	0-17	8867.447046
1	18-25	9124.031731
2	26-35	9193.469924
3	36-45	9254.202214
4	46-50	9128.985080
5	51-55	9423.121704
6	55+	9216.650220

In [57]:
```
plt.plot(df_age["Age"],df_age["Mean Purchase"])
plt.xlabel("Age Groups")
plt.ylabel("Mean Purchase from Sample")
plt.title("Mean Purchase from the Sample for Different Age Groups")
plt.show()
```



Observation-The above plot shows the mean purchase of 51-55 age group is highest and the least is for 0-17 age group

In [159]:
```
#re-initialsing dictionaries to store the split dataframes,confidenceintervals,bootstrap mean
dataframes_namelist_pos=0
ci_dict={}
bootstrap_mean_dict={}
dataframes={}
```

In [160]:
```
#Function call for datframe split
name,data=DataFrameSplit(df,"Age","0-17")
dataframes[name]=data
```

In [161]:
```
#BootStrapFunc function call on split dataframe to find CI
BootStrapFunc(dataframes['df_Age_0-17'])
```

```
Mean of the Sampling Distribution is 8867.32
90% Confidence Interval is [ 8803.25 , 8932.09 ]
95% Confidence Interval is [ 8793.71 , 8949.71 ]
99% Confidence Interval is [ 8766.84 , 8976.89 ]
```

In [162]:
```
#Dataframe splitting and Bootstrapping for other Age groups as well.Displaying their confidence intervals
name,data=DataFrameSplit(df,"Age","18-25")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_18-25'])
```

```
Mean of the Sampling Distribution is 9124.85
90% Confidence Interval is [ 9099.28 , 9148.54 ]
95% Confidence Interval is [ 9093.27 , 9150.67 ]
99% Confidence Interval is [ 9090.72 , 9163.97 ]
```

In [163]:
```
name,data=DataFrameSplit(df,"Age","26-35")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_26-35'])
```

```
Mean of the Sampling Distribution is 9193.22
90% Confidence Interval is [ 9177.85 , 9210.73 ]
95% Confidence Interval is [ 9175.66 , 9212.03 ]
99% Confidence Interval is [ 9169.25 , 9215.06 ]
```

In [164]:
```
name,data=DataFrameSplit(df,"Age","36-45")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_36-45'])
```

```
Mean of the Sampling Distribution is 9254.66
90% Confidence Interval is [ 9230.21 , 9276.43 ]
95% Confidence Interval is [ 9227.95 , 9284.63 ]
99% Confidence Interval is [ 9213.25 , 9292.19 ]
```

In [165]:
```
name,data=DataFrameSplit(df,"Age","46-50")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_46-50'])
```

```
Mean of the Sampling Distribution is 9130.45
90% Confidence Interval is [ 9093.19 , 9168.11 ]
95% Confidence Interval is [ 9082.21 , 9172.06 ]
99% Confidence Interval is [ 9057.16 , 9183.79 ]
```

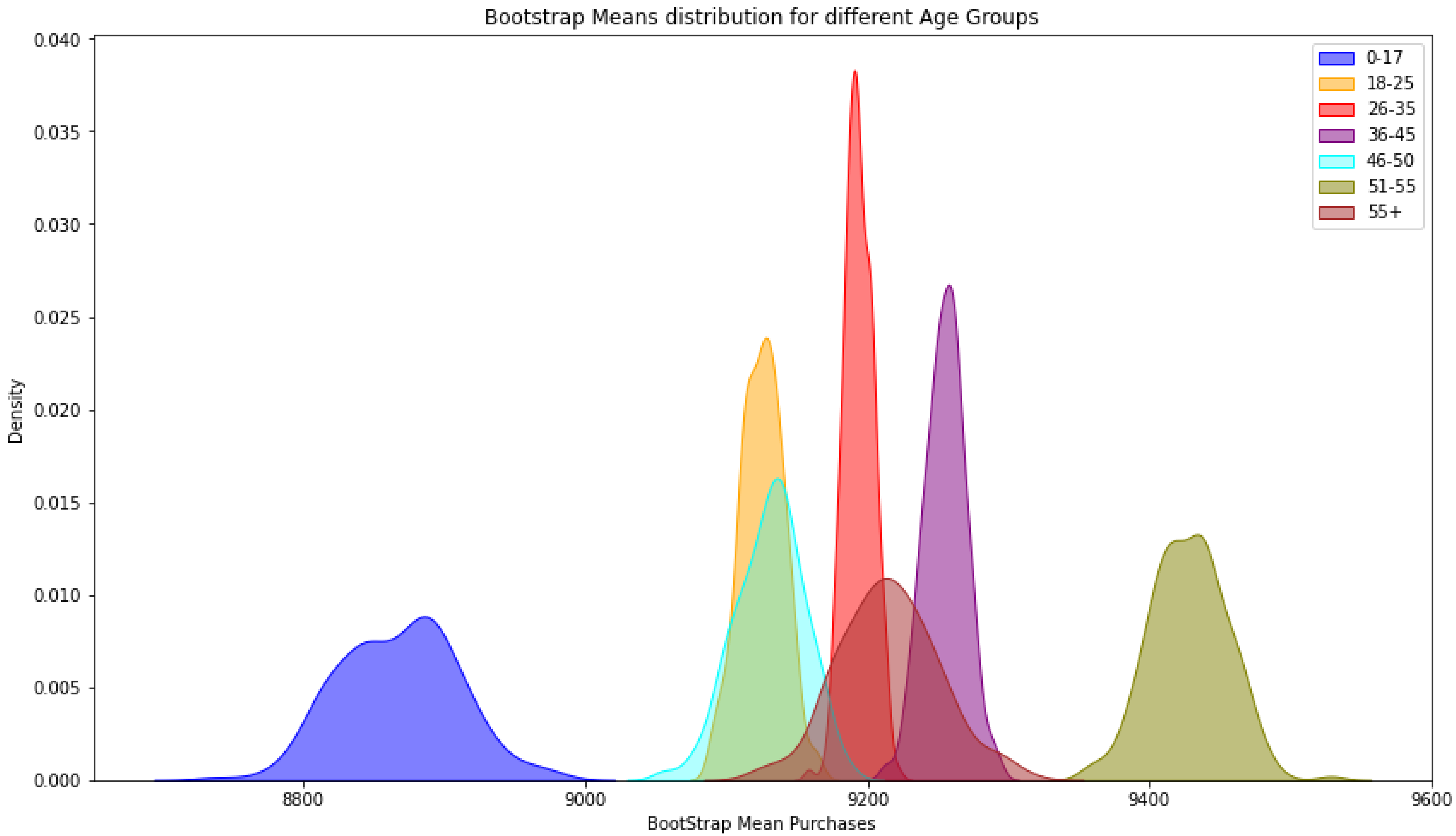
In [166]:
```
name,data=DataFrameSplit(df,"Age","51-55")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_51-55'])
```

```
Mean of the Sampling Distribution is 9427.92
90% Confidence Interval is [ 9386.21 , 9468.97 ]
95% Confidence Interval is [ 9376.94 , 9477.93 ]
99% Confidence Interval is [ 9359.28 , 9492.2 ]
```

In [167]:
```
name,data=DataFrameSplit(df,"Age","55+")
dataframes[name]=data
BootStrapFunc(dataframes['df_Age_55+'])
```

```
Mean of the Sampling Distribution is 9214.88
90% Confidence Interval is [ 9160.95 , 9276.85 ]
95% Confidence Interval is [ 9146.5 , 9292.29 ]
99% Confidence Interval is [ 9123.67 , 9301.63 ]
```

In [168]:
```
#Plot Bootstrap mean distribution
sns.kdeplot(bootstrap_mean_dict["df_Age_0-17_BS"],label="0-17",color="blue",alpha=.5,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_18-25_BS"],label="18-25",color="orange",alpha=.5,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_26-35_BS"],label="26-35",color="red",alpha=.5,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_36-45_BS"],label="36-45",color="purple",alpha=.5,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_46-50_BS"],label="46-50",color="cyan",alpha=.3,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_51-55_BS"],label="51-55",color="olive",alpha=.5,shade=True)
sns.kdeplot(bootstrap_mean_dict["df_Age_55+_BS"],label="55+",color="brown",alpha=.5,shade=True)
plt.legend()
plt.xlabel("BootStrap Mean Purchases")
plt.title("Bootstrap Means distribution for different Age Groups")
plt.show()
```



In [174]:
```
#To find the mean of the Boostrapped means of the samples for different age groups and storing in list bs_mean_list
bs_mean_list=[]
for key in bootstrap_mean_dict.keys():
    bs_mean=np.mean(bootstrap_mean_dict[key])
    bs_mean_list.append(bs_mean)
print(np.round(bs_mean_list,2))
```

```
[8867.32 9124.85 9193.22 9254.66 9130.45 9427.92 9214.88]
```

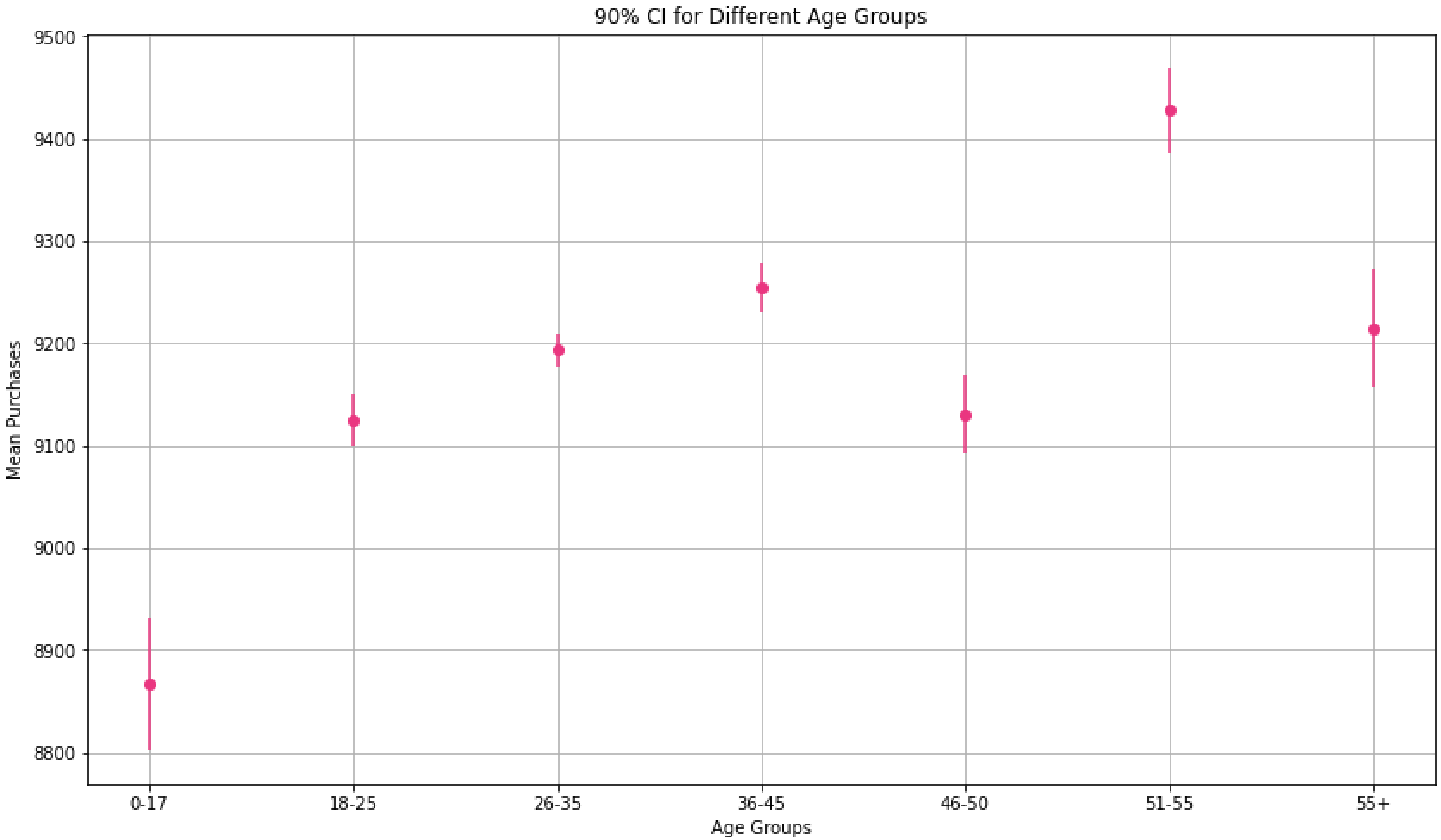
In [178]:

```
#To find the Margin of Error
y_err_list=[]
for key in ci_dict.keys():
    y_error_list=ci_dict[key][0]
    y_error=round((y_error_list[1]-y_error_list[0])/2,2)
    y_err_list.append(y_error)
print(y_err_list)
```

```
[64.42, 24.63, 16.44, 23.11, 37.46, 41.38, 57.95]
```

In [198]:

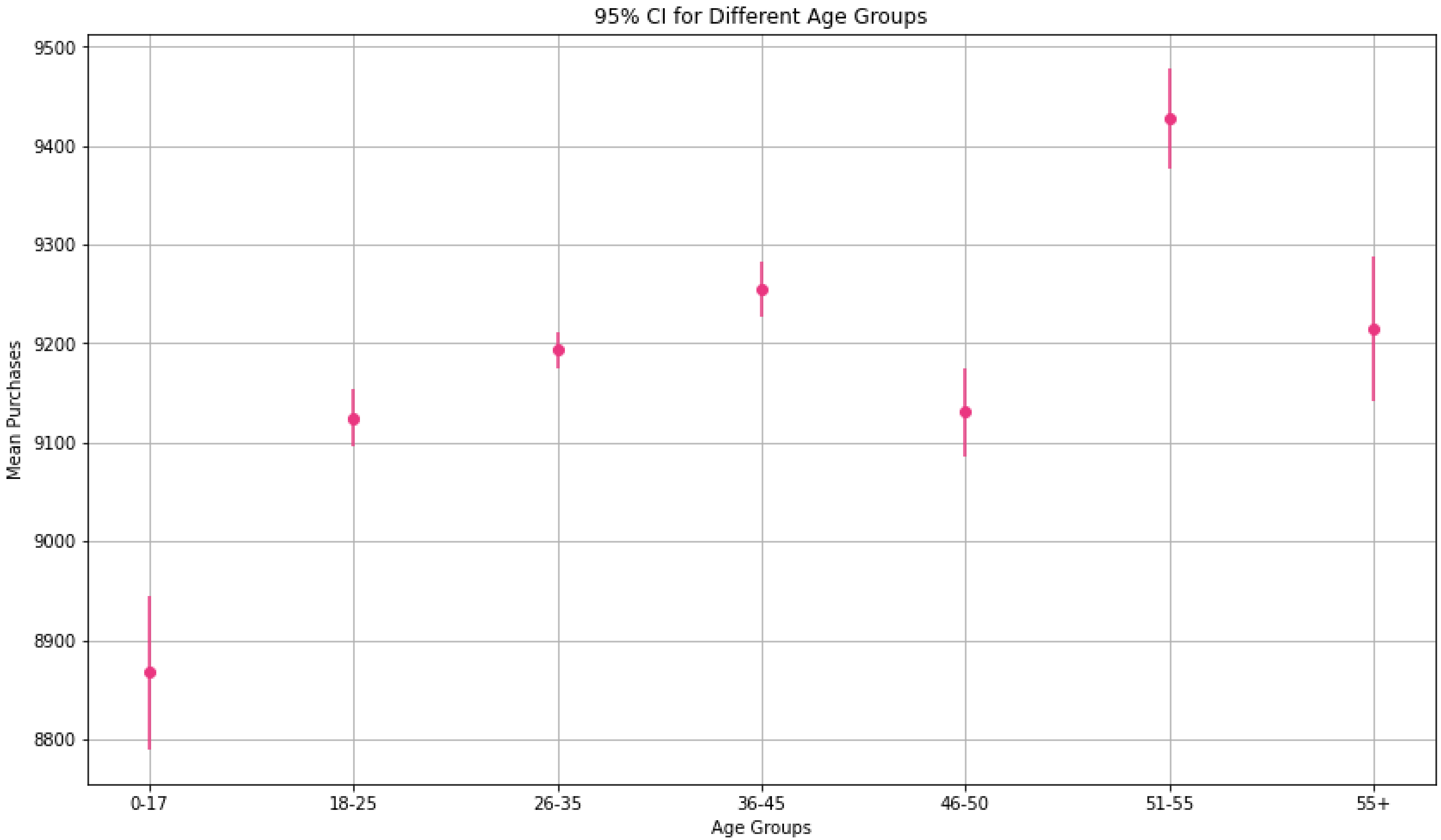
```
plt.errorbar(x=["0-17","18-25","26-35","36-45","46-50","51-55","55+"],
             y=bs_mean_list,
             yerr=y_err_list,
             fmt='o'
            )
plt.xlabel("Age Groups")
plt.ylabel("Mean Purchases")
plt.title("90% CI for Different Age Groups")
plt.grid()
```



In [199]:
```
y_err_list=[]
for key in ci_dict.keys():
    y_error_list=ci_dict[key][1]
    y_error=round((y_error_list[1]-y_error_list[0])/2,2)
    y_err_list.append(y_error)
print(y_err_list)
```

```
[78.0, 28.7, 18.19, 28.34, 44.92, 50.5, 72.89]
```

In [200]:
```
plt.errorbar(x=["0-17","18-25","26-35","36-45","46-50","51-55","55+"],
             y=bs_mean_list,
             yerr=y_err_list,
             fmt='o'
            )
plt.xlabel("Age Groups")
plt.ylabel("Mean Purchases")
plt.title("95% CI for Different Age Groups")
plt.grid()
```

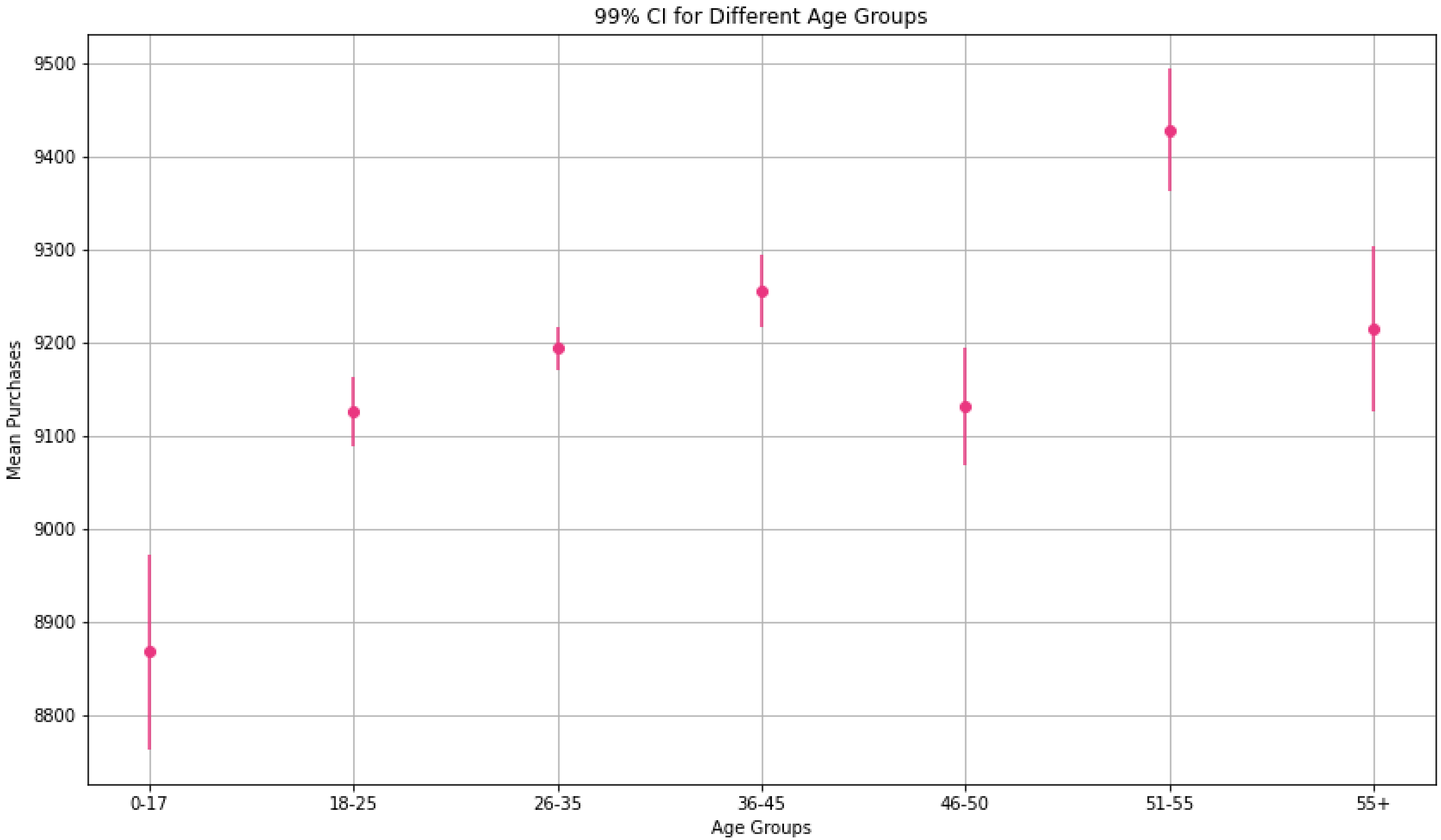


In [201]:

```
y_err_list=[]
for key in ci_dict.keys():
    y_error_list=ci_dict[key][2]
    y_error=round((y_error_list[1]-y_error_list[0])/2,2)
    y_err_list.append(y_error)
print(y_err_list)
```

```
[105.03, 36.63, 22.9, 39.47, 63.31, 66.46, 88.98]
```

In [202]:
```
plt.errorbar(x=["0-17","18-25","26-35","36-45","46-50","51-55","55+"],
             y=bs_mean_list,
             yerr=y_err_list,
             fmt='o'
            )
plt.xlabel("Age Groups")
plt.ylabel("Mean Purchases")
plt.title("99% CI for Different Age Groups")
plt.grid()
```



Observation -Expect for age groups 0-17 and 51-55 all the others are having overlapping Confidence Intervals.So a significant distinction cannot be made for these groups.The groups with significant difference is 0-17 and 51-55 age groups.So how the business can be improved here?

In [208]:
```
df_fil=df.loc[(df["Age"]=='0-17')|(df["Age"]=='51-55')]
```

In [228]:

```python
x=(df_fil.groupby(["Age","Product_Category"])["Purchase"].sum()/1000000).to_frame()
x.rename(columns={"Purchase":"Purchase(in Millions)"},inplace=True)

x
```

Out[228]:

Age	Product_Category	Purchase(in Millions)
0-17	**1**	48.783247
	2	8.735846
	3	11.317806
	4	1.701452
	5	27.059712
	6	6.377154
	7	0.821014
	8	17.234789
	9	0.223799
	10	0.930677
	11	3.558043
	12	0.177964
	13	0.082573
	14	0.512227
	15	2.256570
	16	3.351633
	17	0.060863
	18	0.074703
	19	0.002271
	20	0.033121

		Purchase(in Millions)
Age	**Product_Category**	
51-55	**1**	127.824120
	2	21.196838
	3	9.542540
	4	1.658375
	5	64.326214
	6	23.529307
	7	4.356259
	8	72.591375
	9	0.330243
	10	4.214537
	11	6.748072
	12	0.597719
	13	0.368453
	14	2.180826
	15	7.451186
	16	10.503288
	17	1.127567
	18	1.254082
	19	0.005080
	20	0.072360

Recommendation-For age groups 0-17 the larger sales are in product categories 1,3,5, 8.And for age group 51-55 its for categories 1,2,3,5,6,8,16.Hence business can be improved for these categories for these age groups

In [229]:
```python
y=(df_fil.groupby(["Age","City_Category"])["Purchase"].sum()/1000000).to_frame()
y.rename(columns={"Purchase":"Purchase(in Millions)"},inplace=True)

y
```

Out[229]:

Age	City_Category	Purchase(in Millions)
0-17	**A**	21.474755
	B	47.725963
	C	64.094746
51-55	**A**	56.967864
	B	162.551363
	C	140.359214

Recommendation-For both 0-17 and 51-55 age groups the sales are higher in cities B and C .Hence opening more stores in these cities can improve the business