Walmart

About Walmart

- 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:

- User_ID: User ID

- Product_ID: Product ID

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

Analysing basic metrics

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm, poisson
```

In [2]:
```
!gdown 1Gc1TpIM7yZ0iPEQxUXyIdkyEdb7pWf3R
```

```
Downloading...
From: https://drive.google.com/uc?id=1Gc1TpIM7yZ0iPEQxUXyIdkyEdb7pWf3R
To: /content/walmart_data.csv
100% 23.0M/23.0M [00:00<00:00, 86.4MB/s]
```

In [3]:
```
walmart_df = pd.read_csv("walmart_data.csv")
```

In [4]:
```
walmart_df.shape
```

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

In [5]:
```
walmart_df.head()
```

Out[5]:

	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 [6]:
```
walmart_df.columns = [name.lower() for name in walmart_df.columns]
walmart_df.columns
```

Out[6]:
```
Index(['user_id', 'product_id', 'gender', 'age', 'occupation', 'city_category',
       'stay_in_current_city_years', 'marital_status', 'product_category',
       'purchase'],
      dtype='object')
```

In [7]:
```
walmart_df.head()
```

Out[7]:

	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 [8]:
```
walmart_df.columns.tolist()
```

Out[8]:
```
['user_id',
 'product_id',
 'gender',
 'age',
 'occupation',
 'city_category',
 'stay_in_current_city_years',
 'marital_status',
 'product_category',
 'purchase']
```

In [9]:
```
walmart_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 [10]:
```
walmart_df.isnull().sum()
```

Out[10]:

	0

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

- There is no null values found in the above dataset.

In [11]:

```
walmart_df.describe()
```

Out[11]:

	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

- There are 5,50,068 rows and 10 columns
- There are Male (414529) and Female (135809)
- The Mean purchase amount is 9263
- There are 8 Prodcuts Categories in the dataset

In [12]:
```
walmart_df.describe(include=object)
```

Out[12]:

	product_id	gender	age	city_category	stay_in_current_city_years
count	550068	550068	550068	550068	550068
unique	3631	2	7	3	5
top	P00265242	M	26-35	B	1
freq	1880	414259	219587	231173	193821

In [13]:
```
unique_cus = walmart_df["user_id"].nunique()
unique_cus
```

Out[13]: 5891

In [14]:
```
np.round(walmart_df['gender'].value_counts( normalize= True)*100,2).reset_index()
```

Out[14]:

	gender	proportion
0	M	75.31

1	F	24.69

In [15]:
```
np.round(walmart_df['city_category'].value_counts(normalize=True)*100,2).reset_index()
```

Out[15]:

	city_category	proportion
0	B	42.03
1	C	31.12
2	A	26.85

In [16]:
```
np.round(walmart_df["stay_in_current_city_years"].value_counts(normalize=True)*100,2).reset_index()
```

Out[16]:

	stay_in_current_city_years	proportion
0	1	35.24
1	2	18.51
2	3	17.32
3	4+	15.40
4	0	13.53

In [17]:
```
np.round(walmart_df["marital_status"].value_counts(normalize=True)*100,2).reset_index()
```

Out[17]:

	marital_status	proportion
0	0	59.03
1	1	40.97

In [18]:
```
np.round(walmart_df["product_category"].value_counts(normalize=True)*100,2).reset_index()
```

Out[18]:

	product_category	proportion
0	5	27.44
1	1	25.52
2	8	20.71
3	11	4.42
4	2	4.34
5	6	3.72
6	3	3.67
7	4	2.14
8	16	1.79
9	15	1.14
10	13	1.01
11	10	0.93
12	12	0.72
13	7	0.68
14	18	0.57
15	20	0.46
16	19	0.29
17	14	0.28

18	17	0.11
19	9	0.07

In [19]:
```
walmart_df["occupation"].unique()
```

Out[19]:
```
array([10, 16, 15,  7, 20,  9,  1, 12, 17,  0,  3,  4, 11,  8, 19,  2, 18,
        5, 14, 13,  6])
```

In [20]:
```
walmart_df["marital_status"].value_counts()
```

Out[20]:

	count
marital_status	
0	324731
1	225337

dtype: int64

In [21]:
```
np.round(walmart_df["marital_status"].value_counts(normalize =True)*100,2).reset_index()
```

Out[21]:

	marital_status	proportion
0	0	59.03
1	1	40.97

In [22]:
```
walmart_df["age"].value_counts().reset_index()
```

Out[22]:

	age	count
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 [23]:
```
walmart_df["age"].unique()
```

Out[23]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

In [24]:
```
walmart_df["gender"].unique().tolist()
```

Out[24]:
```
['F', 'M']
```

In [25]:
```
walmart_df["marital_status"].unique().tolist()
```

Out[25]:
```
[0, 1]
```

In [26]:
```
walmart_df["user_id"].nunique()
```

Out[26]:
```
5891
```

In [27]:
```
walmart_df["product_id"].nunique()
```

Out[27]:
```
3631
```

In [28]:
```
walmart_df.groupby(["gender"])["age"].agg("count")
```

Out[28]:

age

gender	
F	135809
M	414259

dtype: int64

In [29]:
```
walmart_df.groupby(["age","gender"]).agg("count")["user_id"].reset_index().rename({"user_id":"count_of_customers"},
```

Out[29]:

	age	gender	count_of_customers
0	0-17	F	5083
1	0-17	M	10019
2	18-25	F	24628
3	18-25	M	75032
4	26-35	F	50752
5	26-35	M	168835
6	36-45	F	27170
7	36-45	M	82843
8	46-50	F	13199
9	46-50	M	32502
10	51-55	F	9894
11	51-55	M	28607
12	55+	F	5083

13	55+	M	16421

In [30]:
```
walmart_df.groupby(["age","occupation"]).agg("count")["user_id"].reset_index().rename({"user_id":"count_of_customers
```

Out[30]:

	age	occupation	count_of_customers
0	0-17	0	2134
1	0-17	1	387
2	0-17	2	144
3	0-17	4	113
4	0-17	7	139
...	...	...	...
129	55+	16	1963
130	55+	17	1558
131	55+	18	112
132	55+	19	217
133	55+	20	801

134 rows × 3 columns

In [31]:
```
walmart_df.groupby(["age","city_category"]).agg("count")["user_id"].reset_index().rename({"user_id":"count_of_custon
```

Out[31]:

	age	city_category	count_of_customers
0	0-17	A	2544

1	0-17	B	5435
2	0-17	C	7123
3	18-25	A	27535
4	18-25	B	43247
5	18-25	C	28878
6	26-35	A	73745
7	26-35	B	91584
8	26-35	C	54258
9	36-45	A	26617
10	36-45	B	47598
11	36-45	C	35798
12	46-50	A	7607
13	46-50	B	20406
14	46-50	C	17688
15	51-55	A	6099
16	51-55	B	17741
17	51-55	C	14661
18	55+	A	3573
19	55+	B	5162
20	55+	C	12769

In [32]:
```python
walmart_df.groupby(["age","marital_status"]).agg("count")["user_id"].reset_index().rename({"user_id":"count_of_custo
```

Out[32]:

	age	marital_status	count_of_customers
0	0-17	0	15102
1	18-25	0	78544
2	18-25	1	21116
3	26-35	0	133296
4	26-35	1	86291
5	36-45	0	66377
6	36-45	1	43636
7	46-50	0	12690
8	46-50	1	33011
9	51-55	0	10839
10	51-55	1	27662
11	55+	0	7883
12	55+	1	13621

In [33]:
```python
df_new = walmart_df.groupby(["user_id"]).agg({"purchase": ["count", "sum"]}).reset_index()
df_new.columns = ["_".join(i) for i in df_new.columns]
df_new.rename({"user_id":"Customer_id", "purchase_count":"Number_of_purchases", "purchase_sum":"Amount_purchased"},
df_new
```

Out[33]:

	user_id_	Number_of_purchases	Amount_purchased

0	1000001	35	334093
1	1000002	77	810472
2	1000003	29	341635
3	1000004	14	206468
4	1000005	106	821001
...	...	...	...
5886	1006036	514	4116058
5887	1006037	122	1119538
5888	1006038	12	90034
5889	1006039	74	590319
5890	1006040	180	1653299

5891 rows × 3 columns

In [34]:
```
walmart_df["marital_status"] = walmart_df["marital_status"].replace({0:"single", 1:"married"})
```

In [35]:
```
walmart_df
```

Out[35]:

	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	single	3	8370
1	1000001	P00248942	F	0-17	10	A	2	single	1	15200

2	1000001	P00087842	F	0-17	10	A	2	single	12	1422
3	1000001	P00085442	F	0-17	10	A	2	single	12	1057
4	1000002	P00285442	M	55+	16	C	4+	single	8	7969
...	...	...	...	...	...	...	...	...	...	...
550063	1006033	P00372445	M	51-55	13	B	1	married	20	368
550064	1006035	P00375436	F	26-35	1	C	3	single	20	371
550065	1006036	P00375436	F	26-35	15	B	4+	married	20	137
550066	1006038	P00375436	F	55+	1	C	2	single	20	365
550067	1006039	P00371644	F	46-50	0	B	4+	married	20	490

550068 rows × 10 columns

What is the total Revenue generated by Walmart from each Marital Status ?

In [36]:

```
marital_status_purchase = walmart_df.groupby(by = ["marital_status"])["purchase"].agg("sum").reset_index().rename({'
total_purchase = marital_status_purchase["amount"].sum()
marital_status_purchase["purchase_share"] = np.round((marital_status_purchase["amount"]/total_purchase)*100,2)
marital_status_purchase
```

Out[36]:

	marital_status	amount	purchase_share
0	married	2086885295	40.95

1	single	3008927447	59.05

- Singles purchased more then married copule. There percentage of purchase 53% and 41% respectively.

In [37]:
```
gender_wise_purchase = walmart_df.groupby(by=["gender"])["purchase"].sum().reset_index().rename({"purchase":"amount'
gender_wise_purchase["percentage_share"] = np.round((gender_wise_purchase["amount"]/ total_purchase)*100,2)
gender_wise_purchase
```

Out[37]:

	gender	amount	percentage_share
0	F	1186232642	23.28
1	M	3909580100	76.72

- **The Purchase value of Males is 77% and Females is 23%:**
- The purchase Males done more shopping then females

In [38]:
```
df1 = walmart_df.groupby(by=(["gender", "user_id"]))["purchase"].sum()
df1.groupby(by=["gender"]).mean().reset_index().rename({"purchase":"average_purchase"}, axis= 1)
```

Out[38]:

	gender	average_purchase
0	F	712024.394958
1	M	925344.402367

What is the Average Revenue generated by Walmart from each Gender per transaction ?

In [39]:
```
walmart_df.groupby(by=(["gender"]))["purchase"].mean().reset_index().rename({"purchase":"average_purchase"}, axis= 1
```

Out[39]:

	gender	average_purchase

0	F	8734.565765
1	M	9437.526040

How many unique customers are there for each Marital Status ?

In [40]:
```
marital_status_dist = walmart_df.groupby('marital_status')['user_id'].unique().apply(len).reset_index().rename({"use
marital_status_dist["percentage"]= np.round((marital_status_dist["unique_customers"]/ unique_cus)*100,2)
marital_status_dist
```

Out[40]:

	marital_status	unique_customers	percentage
0	married	2474	42.0
1	single	3417	58.0

How many transactions are made by each Marital Status category ?

In [41]:
```
walmart_df.groupby('marital_status')['user_id'].count().reset_index().rename({"user_id":"Transctions"},axis= 1)
```

Out[41]:

	marital_status	Transctions
0	married	225337
1	single	324731

In [42]:
```
print('Average number of transactions made by each user with marital status Married is', round(225337 / 2474))
print('Average number of transactions made by each with marital status Single is', round(324731 / 3417))
```

```
Average number of transactions made by each user with marital status Married is 91
Average number of transactions made by each with marital status Single is 95
```

In [43]:
```
walmart_df.groupby('marital_status')
```

Out[43]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x7e339a4d9930>

What is the average total purchase made by each user in each marital status ?

In [44]:
```
age_dest = walmart_df.groupby(by=['age'])['user_id'].unique().apply(len).reset_index().rename({"user_id":"transctio
age_dest = age_dest.sort_values("transctions", ascending=False)
age_dest["percentage"] = np.round((age_dest["transctions"]/unique_cus)*100,2)
age_dest["cummulative_sum"] = age_dest["percentage"].cumsum()
age_dest
```

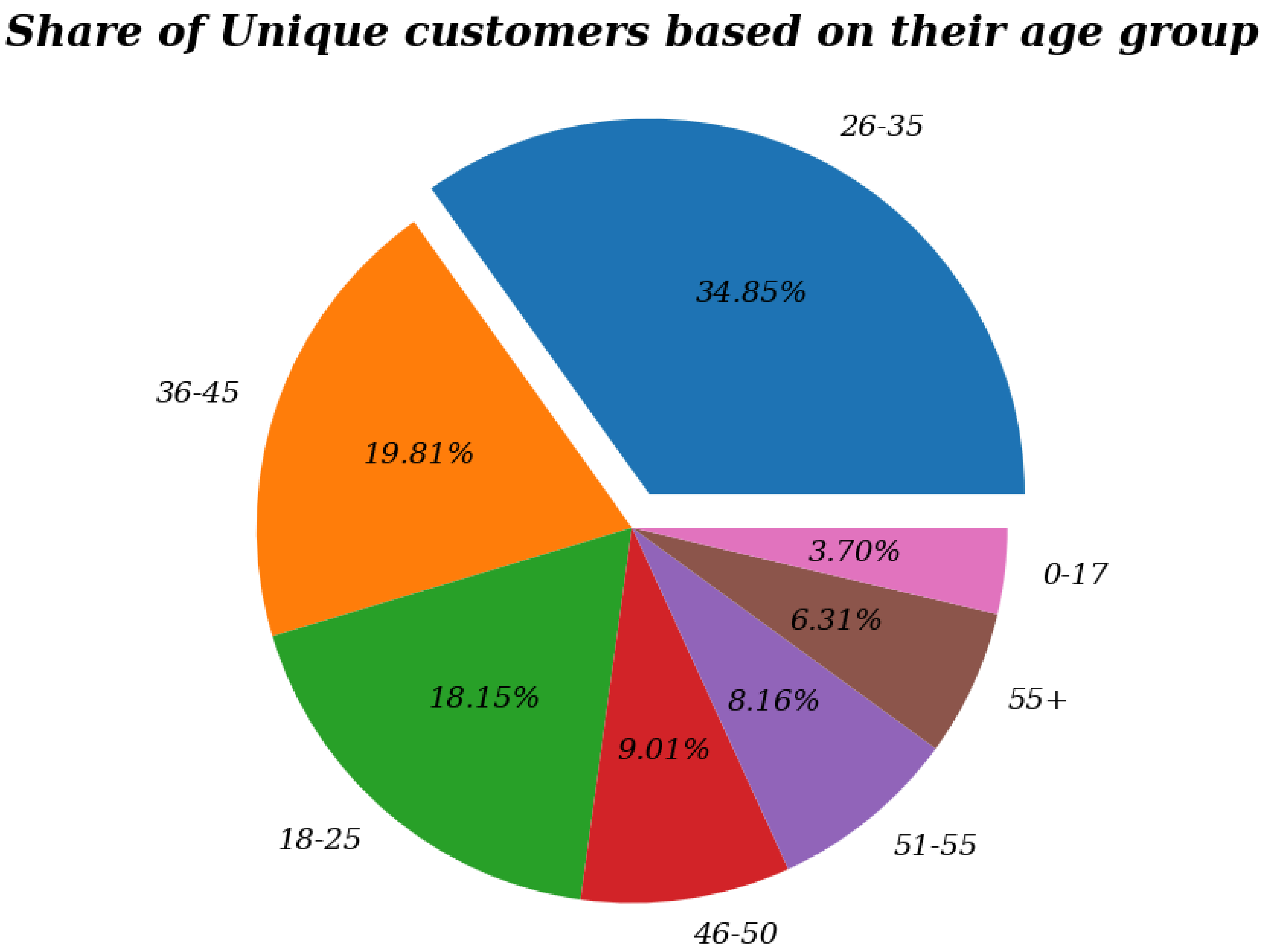
Out[44]:

	age	transctions	percentage	cummulative_sum
2	26-35	2053	34.85	34.85
3	36-45	1167	19.81	54.66
1	18-25	1069	18.15	72.81
4	46-50	531	9.01	81.82
5	51-55	481	8.16	89.98
6	55+	372	6.31	96.29
0	0-17	218	3.70	99.99

- About 82% of purchase was done by age between 18-50 age.
- The majority transction was made by age between 26-35 years. the value id about 35%.

In [45]:
```
plt.figure(figsize = (8, 8))
plt.title('Share of Unique customers based on their age group', fontdict = {'fontsize' : 20,
 'fontstyle' : 'oblique',
'fontfamily' : 'serif',
'fontweight' : 600} )
plt.pie(x = age_dest['percentage'], labels = age_dest['age'],
 explode = [0.1] + [0] * 6, autopct = '%.2f%%',
```

```
 textprops = {'fontsize' : 14,
 'fontstyle' : 'oblique',
'fontfamily' : 'serif',
'fontweight' : 500})
plt.plot()
plt.show()
```


Share of Unique customers based on their age group
26-35
34.85%
36-45
19.81%
18.15%
18-25
9.01%
46-50
8.16%
51-55
6.31%
55+
3.70%
0-17

In [46]:
```
walmart_df["age"].value_counts()
```

Out[46]:

age	count
26-35	219587
36-45	110013
18-25	99660
46-50	45701
51-55	38501
55+	21504
0-17	15102

dtype: int64

In [47]:
```
age_purchase_value = walmart_df.groupby(by=["age"])["purchase"].sum().reset_index()
age_purchase_value = age_purchase_value.sort_values("purchase", ascending=False)
age_purchase_value["percentage"] = np.round((age_purchase_value["purchase"]/total_purchase)*100,2)
age_purchase_value['cummulative_percent'] = age_purchase_value["percentage"].cumsum()
age_purchase_value
```

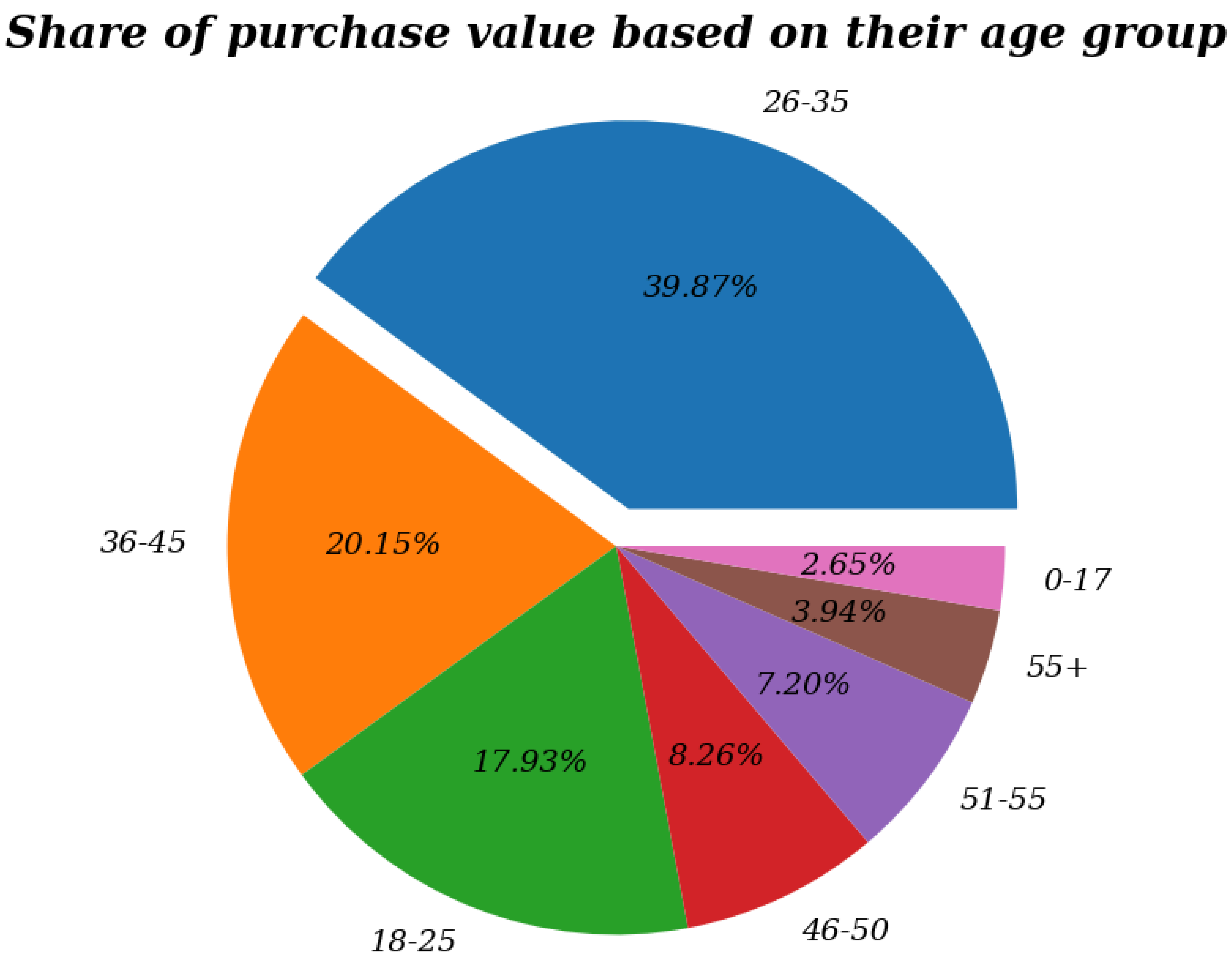
Out[47]:

	age	purchase	percentage	cummulative_percent
2	26-35	2031770578	39.87	39.87
3	36-45	1026569884	20.15	60.02
1	18-25	913848675	17.93	77.95
4	46-50	420843403	8.26	86.21

5	51-55	367099644	7.20	93.41
6	55+	200767375	3.94	97.35
0	0-17	134913183	2.65	100.00

In [48]:

```
plt.figure(figsize = (8, 8))
plt.title('Share of purchase value based on their age group', fontdict = {'fontsize' : 20,
 'fontstyle' : 'oblique',
'fontfamily' : 'serif',
'fontweight' : 600} )
plt.pie(x = age_purchase_value['percentage'], labels = age_purchase_value['age'],
 explode = [0.1] + [0] * 6, autopct = '%.2f%%',
 textprops = {'fontsize' : 14,
 'fontstyle' : 'oblique',
'fontfamily' : 'serif',
'fontweight' : 500})
plt.plot()
plt.show()
```


Share of purchase value based on their age group
26-35
39.87%
36-45
20.15%
18-25
17.93%
46-50
8.26%
51-55
7.20%
55+
3.94%
0-17
2.65%

In [49]:
```
city_wise = walmart_df.groupby(by=["city_category"])["user_id"].unique().apply(len).reset_index().rename({"user_id"
city_wise = city_wise.sort_values("unique_customers", ascending=False)
city_wise["percentage"] = np.round((city_wise['unique_customers']/unique_cus)*100,2)
city_wise["cummulative_sum"] = city_wise["percentage"].cumsum()
city_wise
```

Out[49]:

	city_category	unique_customers	percentage	cummulative_sum
2	C	3139	53.28	53.28
1	B	1707	28.98	82.26
0	A	1045	17.74	100.00

- Majority of the total unique customers belong to the city C.
- 82.26 % of the total unique customers belong to city C and B.

In [50]:
```
walmart_df['city_category'].value_counts().reset_index()
```

Out[50]:

	city_category	count
0	B	231173
1	C	171175
2	A	147720

What is the revenue generated from different cities ?

In [51]:
```
city_revenue_df = walmart_df.groupby("city_category")["purchase"].sum().reset_index().rename({"purchase":"total_amou
city_revenue_df = city_revenue_df.sort_values("total_amount", ascending=False)
city_revenue_df["percentage"] = np.round((city_revenue_df['total_amount']/ total_purchase)*100,2)
city_revenue_df["cum_sum"] = city_revenue_df["percentage"].cumsum()
city_revenue_df
```

Out[51]:

	city_category	total_amount	percentage	cum_sum
1	B	2115533605	41.52	41.52
2	C	1663807476	32.65	74.17
0	A	1316471661	25.83	100.00

In [52]:

```
walmart_df.groupby("product_category")["user_id"].nunique().reset_index().rename({"user_id":"customer_count"}, axis
```

Out[52]:

	product_category	customer_count
0	1	5767
1	2	4296
2	3	3838
3	4	3361
4	5	5751
5	6	4085
6	7	1461
7	8	5659
8	9	410
9	10	2328
10	11	3583
11	12	1567
12	13	2272

13	14	971
14	15	2440
15	16	3130
16	17	426
17	18	1284
18	19	1603
19	20	2550

In [53]:
```
cat_purchase_df = walmart_df.groupby(by=["product_category"])["purchase"].sum().reset_index().rename({"purchase":"pu
cat_purchase_df = cat_purchase_df.sort_values("purchase_amount", ascending=False)
cat_purchase_df["percentage"] = np.round((cat_purchase_df["purchase_amount"]/ total_purchase)*100,2)
cat_purchase_df["cummulative_sum"] = cat_purchase_df["percentage"].cumsum()
cat_purchase_df
```

Out[53]:

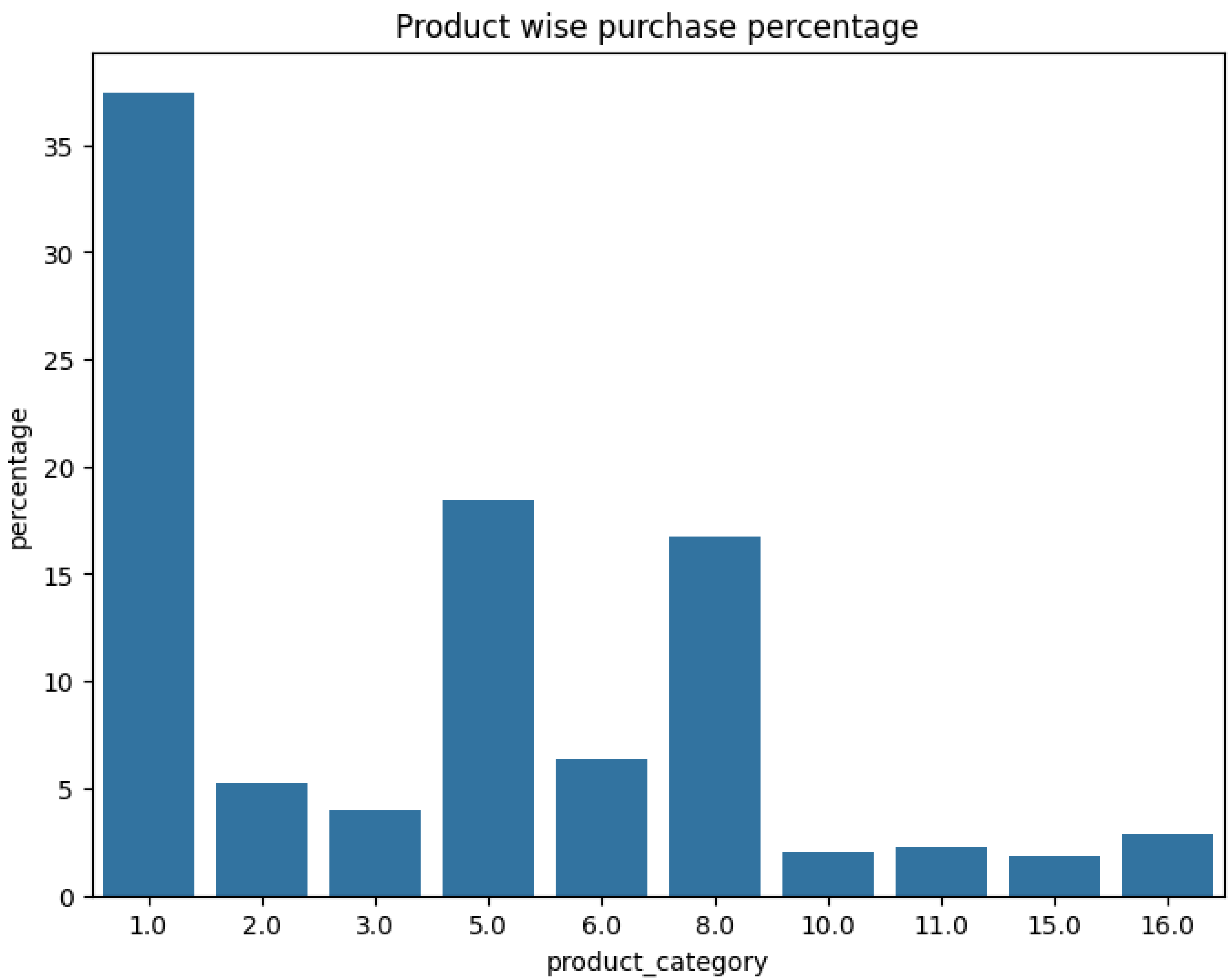
	product_category	purchase_amount	percentage	cummulative_sum
0	1	1910013754	37.48	37.48
4	5	941835229	18.48	55.96
7	8	854318799	16.77	72.73
5	6	324150302	6.36	79.09
1	2	268516186	5.27	84.36
2	3	204084713	4.00	88.36
15	16	145120612	2.85	91.21
10	11	113791115	2.23	93.44

9	10	100837301	1.98	95.42
14	15	92969042	1.82	97.24
6	7	60896731	1.20	98.44
3	4	27380488	0.54	98.98
13	14	20014696	0.39	99.37
17	18	9290201	0.18	99.55
8	9	6370324	0.13	99.68
16	17	5878699	0.12	99.80
11	12	5331844	0.10	99.90
12	13	4008601	0.08	99.98
19	20	944727	0.02	100.00
18	19	59378	0.00	100.00

- **Top 5 product categories from which Walmart makes 84.36 % of total revenue are : [1, 5, 8, 6, 2]**

In [54]:

```
plt.figure(figsize=(8,6))
sns.barplot(data= cat_purchase_df, x =cat_purchase_df["product_category"].head(10), y=cat_purchase_df["percentage"])
plt.title("Product wise purchase percentage")
plt.show()
```



In [55]:
```
gender_wise_purchase
```

Out[55]:

	gender	amount	percentage_share
0	F	1186232642	23.28
1	M	3909580100	76.72

In [56]:
```
gender_wise_mean = walmart_df.groupby(by=["gender"])["purchase"].mean().reset_index().rename({"purchase":"average_pu
gender_wise_mean
```

Out[56]:

	gender	average_purchase
0	F	8734.565765
1	M	9437.526040

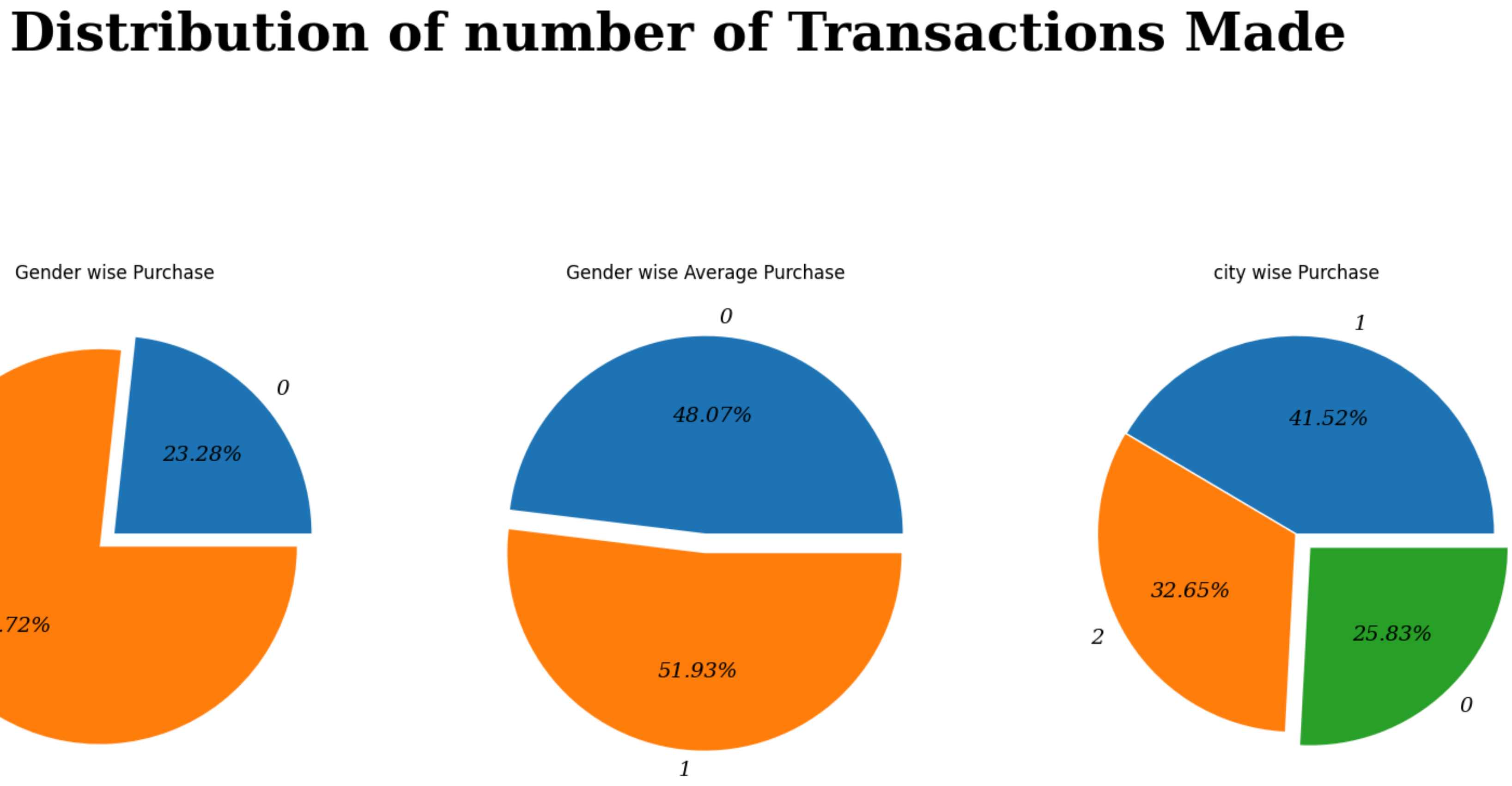
In [57]:
```
city_revenue_df
```

Out[57]:

	city_category	total_amount	percentage	cum_sum
1	B	2115533605	41.52	41.52
2	C	1663807476	32.65	74.17
0	A	1316471661	25.83	100.00

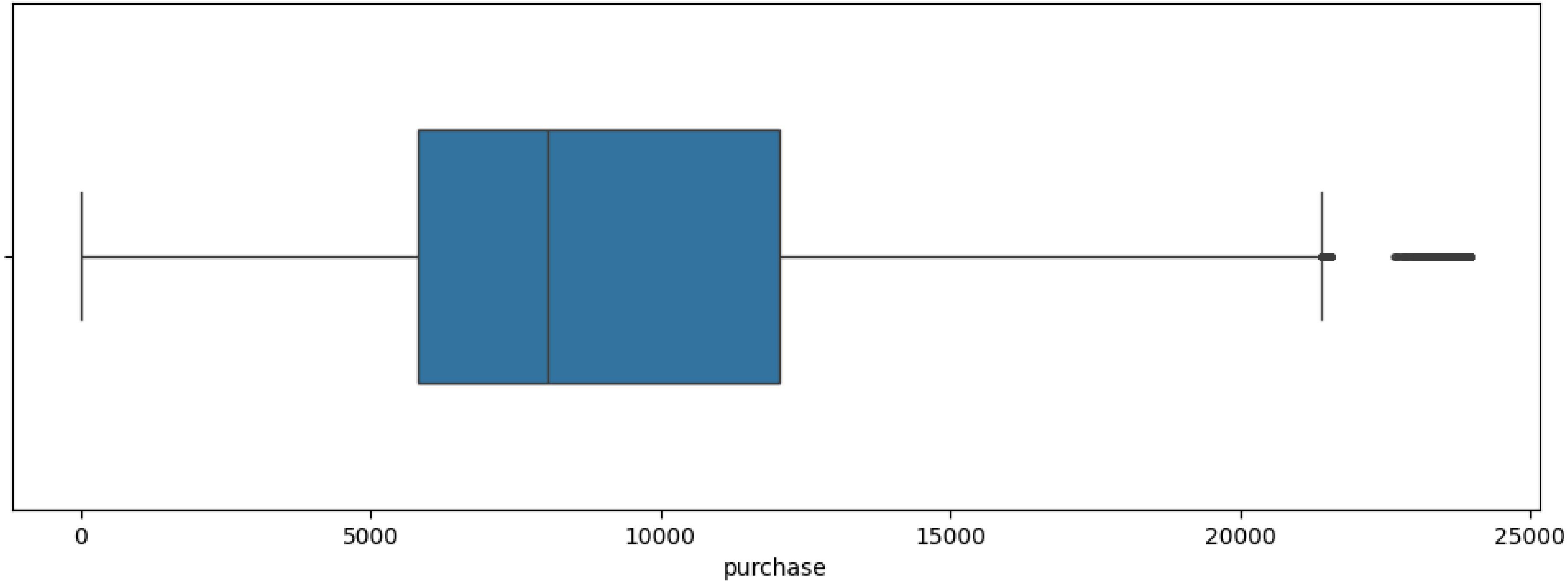
In [58]:
```
plt.figure(figsize=((20,10)))
plt.suptitle('Distribution of number of Transactions Made', fontsize = 35, fontweight = 600, fontfamily = 'serif')
plt.subplot(1,3, 1)
plt.pie(x=gender_wise_purchase['amount'].values, labels=gender_wise_purchase["percentage_share"].index, explode = [(
        textprops = {'fontsize' : 14,
      'fontstyle' : 'oblique',
      'fontfamily' : 'serif',
      'fontweight' : 500} )
plt.title("Gender wise Purchase")

#second pie plot
plt.subplot(1, 3, 2)
plt.pie( labels=gender_wise_mean["gender"].index, x= gender_wise_mean["average_purchase"].values, explode = [0, 0.1]
        textprops = {'fontsize' : 14,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
```

```
                  'fontweight' : 500})
plt.title("Gender wise Average Purchase")


#third plot
plt.subplot(1, 3, 3)
plt.pie( labels=city_revenue_df["city_category"].index, x= city_revenue_df["percentage"].values, explode = [0, 0.01,
        textprops = {'fontsize' : 14,
                  'fontstyle' : 'oblique',
                  'fontfamily' : 'serif',
                  'fontweight' : 500})
plt.title("city wise Purchase")

plt.show()
```

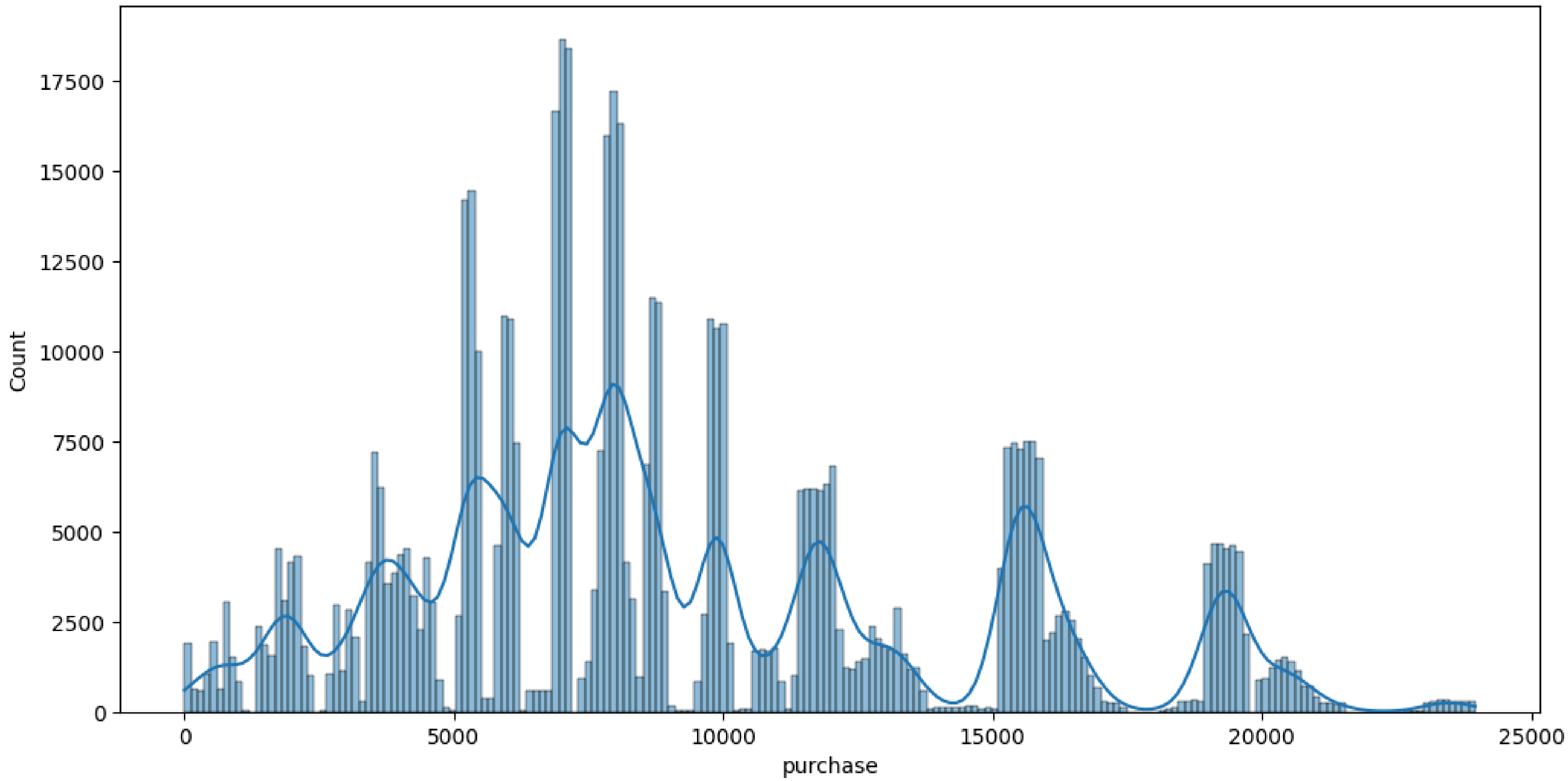


Univariate Analysis

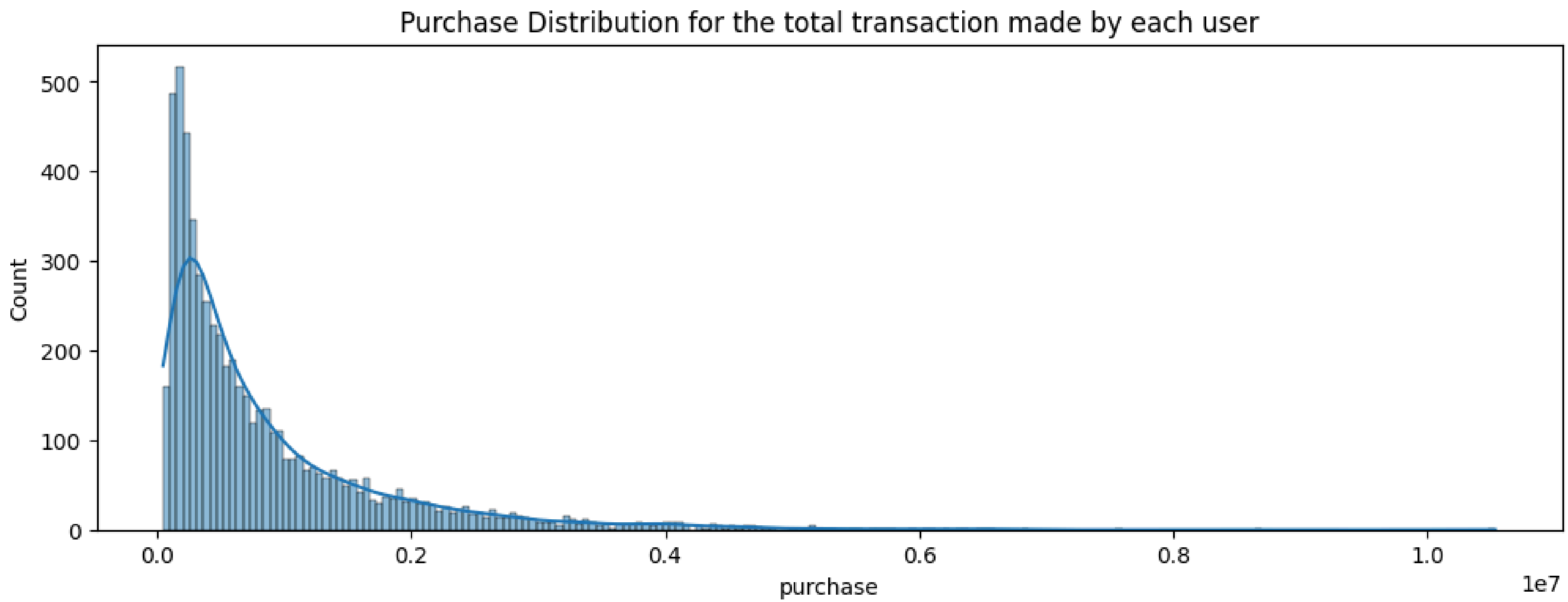
In [59]:
```
plt.figure(figsize=(12, 4))
sns.boxplot(data = walmart_df, x="purchase", fliersize = 2,width = 0.5,)
# plt.title("detching outliers in purchase")
plt.show()
```



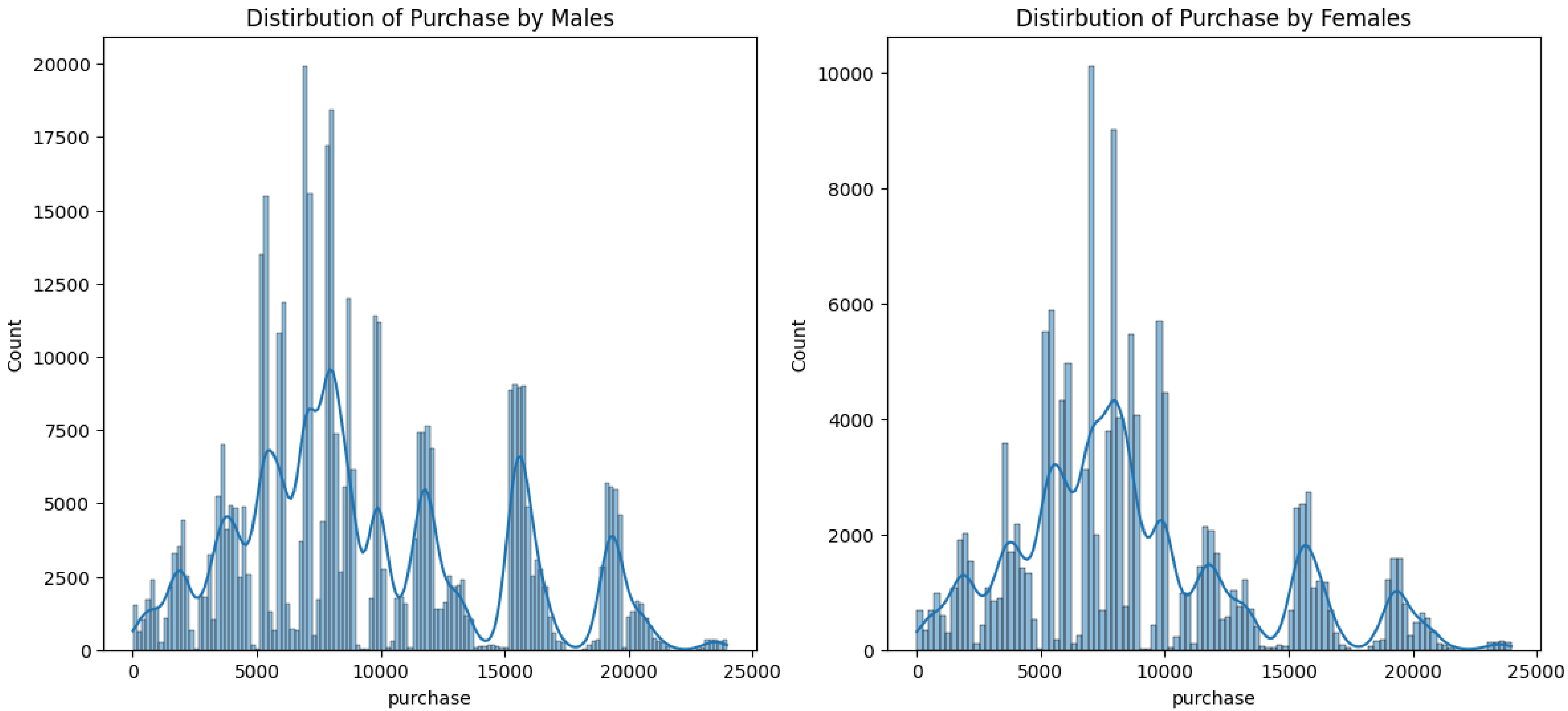
In [60]:
```
plt.figure(figsize=(12, 6))
sns.histplot(data= walmart_df, x="purchase", kde = True, bins = 200)
plt.show()
```



In [61]:
```
plt.figure(figsize=(12, 4))
plt.title('Purchase Distribution for the total transaction made by each user')
sns.histplot(data= walmart_df, x= walmart_df.groupby("user_id")["purchase"].sum(), kde = True, bins = 200)
plt.show()
```



In [62]:
```
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.histplot(data=walmart_df[walmart_df["gender"] == "M"], x="purchase", kde=True)
plt.title("Distirbution of Purchase by Males")

plt.subplot(1, 2, 2)
sns.histplot(data=walmart_df[walmart_df["gender"] == "F"], x="purchase", kde=True)
plt.title("Distirbution of Purchase by Females")
plt.show()
```



In [63]:
```
gender_wise_customers = walmart_df.groupby(["gender", "user_id"])["purchase"].sum().reset_index()
gender_wise_customers
```

Out[63]:

	gender	user_id	purchase
0	F	1000001	334093
1	F	1000006	379930
2	F	1000010	2169510
3	F	1000011	557023
4	F	1000016	150490

...	...	...	...
5886	M	1006030	737361
5887	M	1006032	517261
5888	M	1006033	501843
5889	M	1006034	197086
5890	M	1006040	1653299

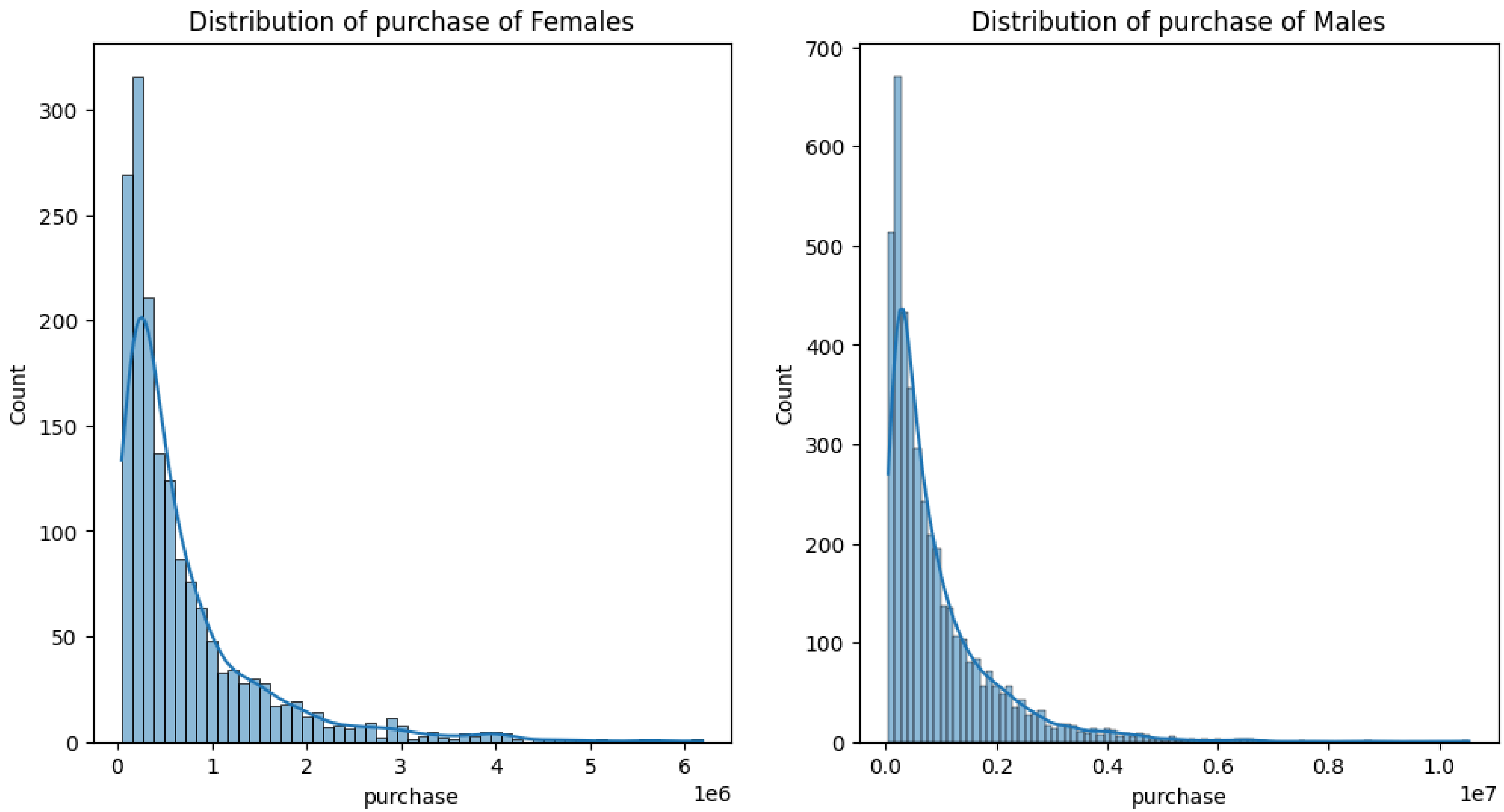
5891 rows × 3 columns

In [64]:

```
females = gender_wise_customers[gender_wise_customers["gender"] == "F"]
males = gender_wise_customers[gender_wise_customers["gender"] == "M"]
```

In [65]:

```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.histplot(data=females, x="purchase", kde=True)
plt.title("Distribution of purchase of Females")

plt.subplot(1, 2, 2)
sns.histplot(data=males, x="purchase", kde=True)
plt.title("Distribution of purchase of Males")
plt.show()
```



In [66]:

```
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
sns.boxplot(data=females, x="purchase", color="pink")
plt.title('Distribution of purchase per transaction for females')


plt.subplot(2, 1, 2)
sns.boxplot(data=males, x="purchase", color="yellow")
plt.title('Distribution of purchase per transaction for males')
```

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

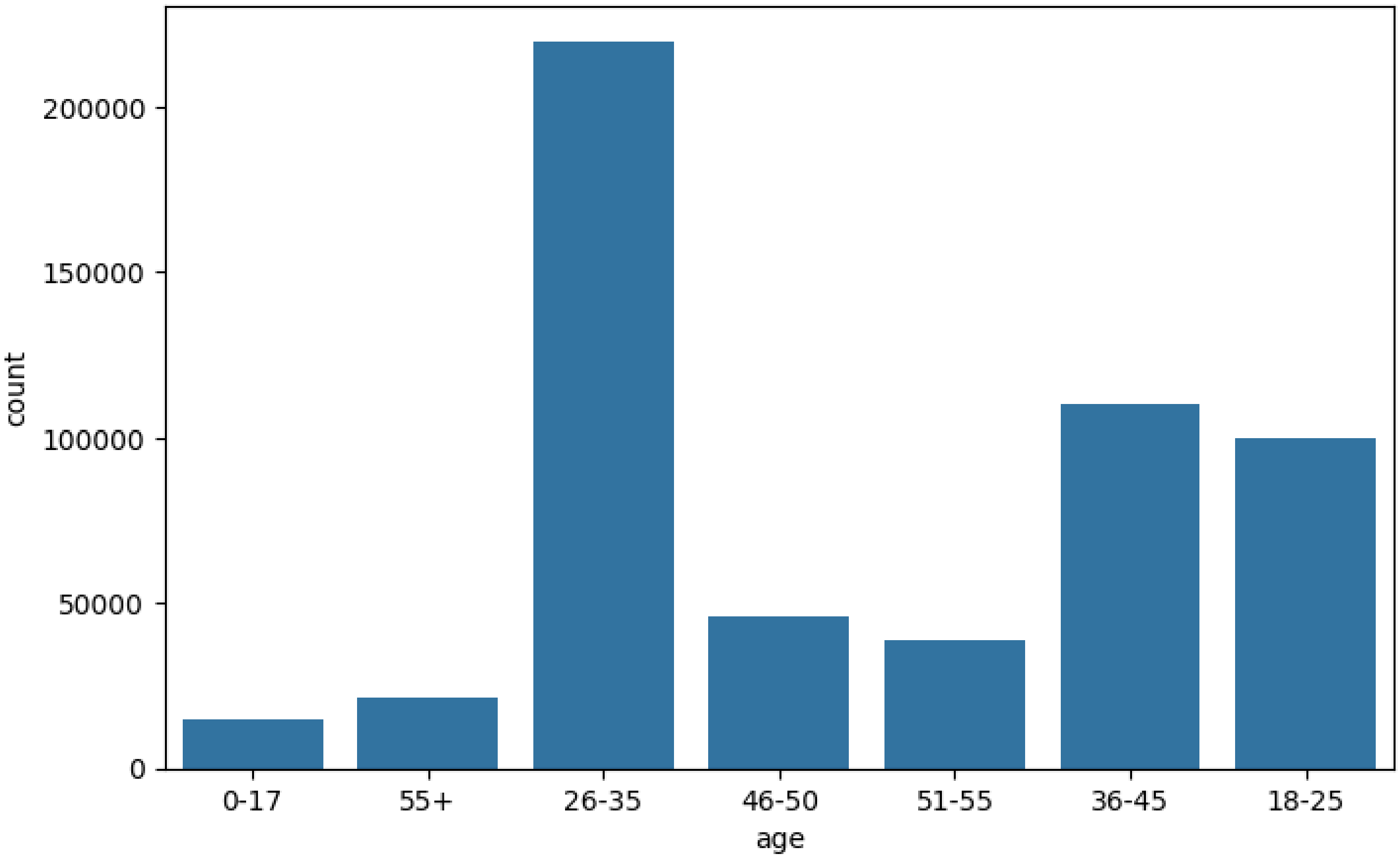
In [67]:
```
walmart_df.head(1)
```

Out[67]:

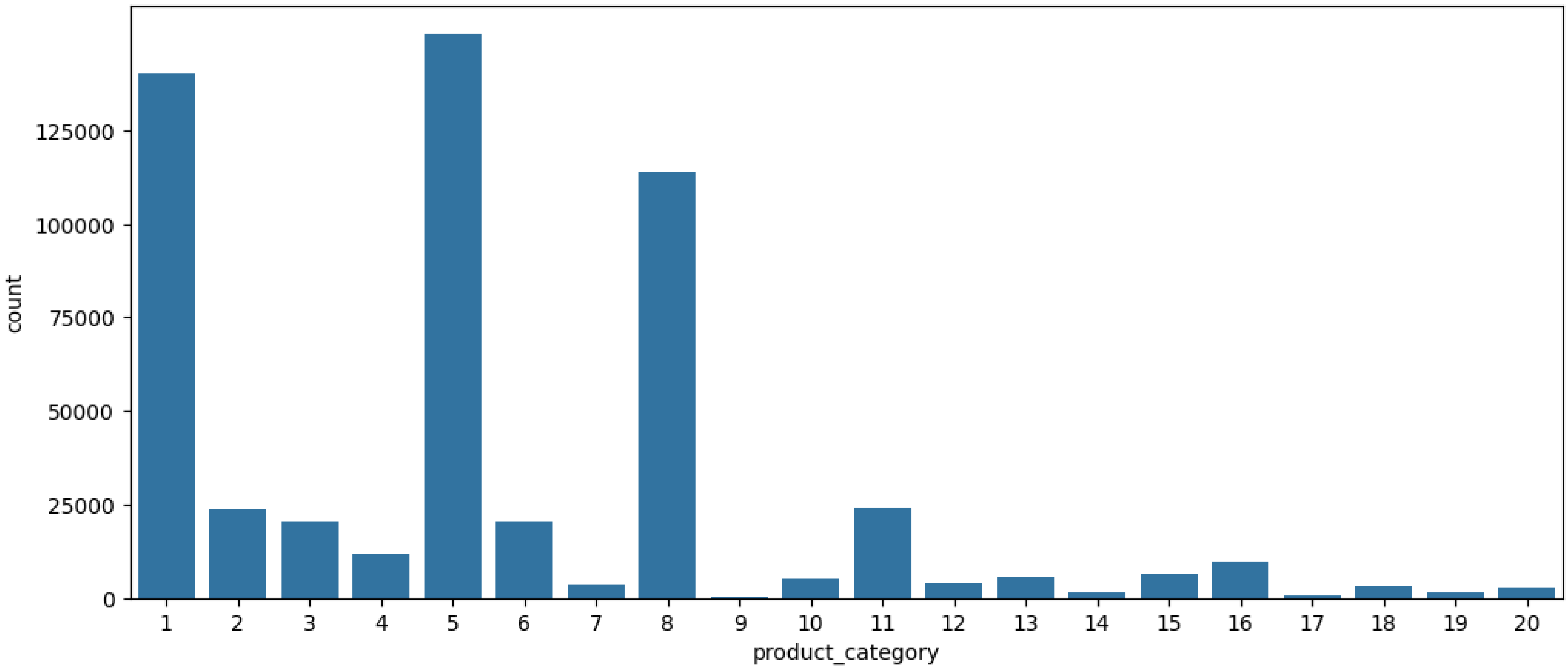
	user_id	product_id	gender	age	occupation	city_category	stay_in_current_city_years	marital_status	product_category	purchase
0	1000001	P00069042	F	0-17	10	A	2	single	3	8370

In [68]:
```
plt.figure(figsize=(8, 5))
sns.countplot(data=walmart_df, x="age")
```

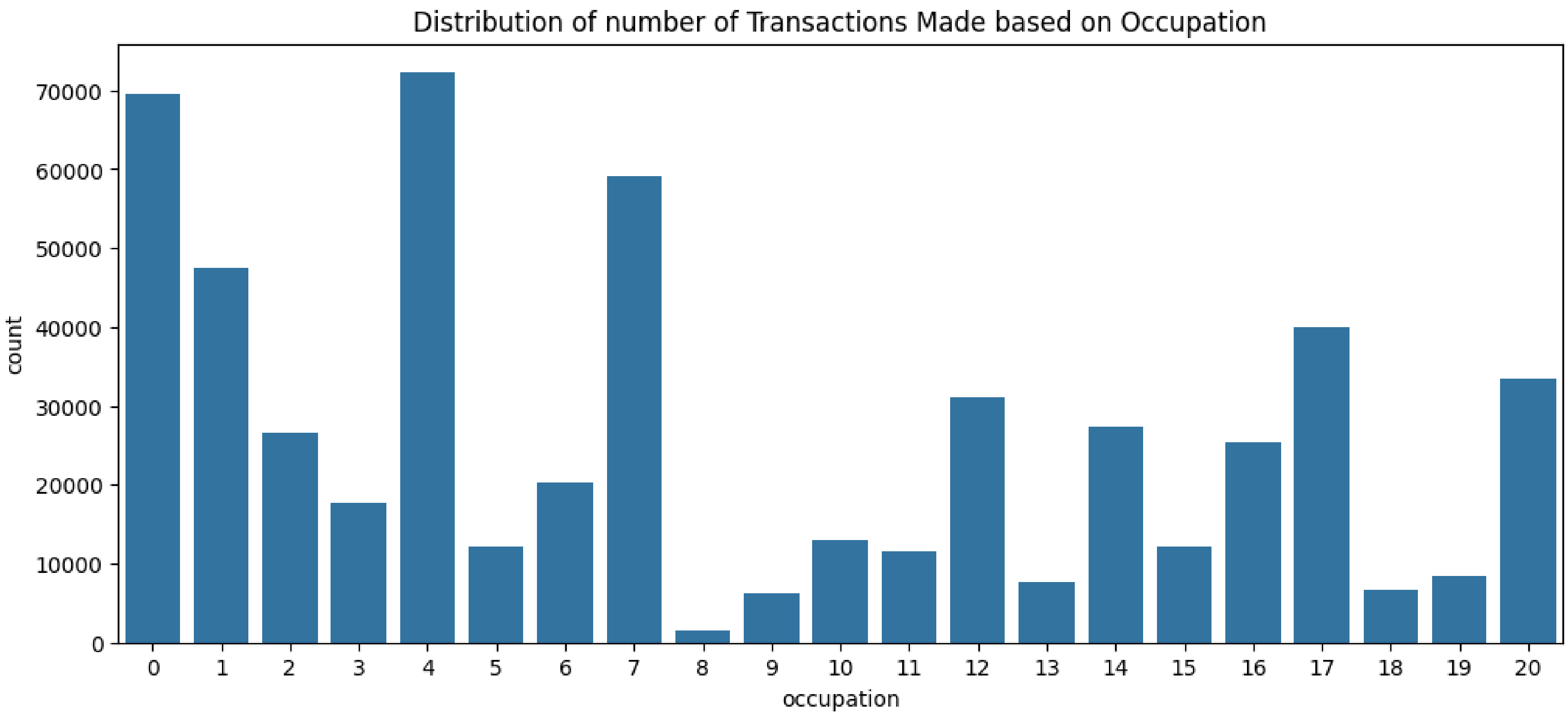
```
# plt.yticks(np.arange(0, 200000, 25000))
plt.show()
```



In [69]:
```
plt.figure(figsize=(12, 5))
sns.countplot(data=walmart_df, x="product_category")
plt.yticks(np.arange(0, 140000, 25000))
plt.show()
```



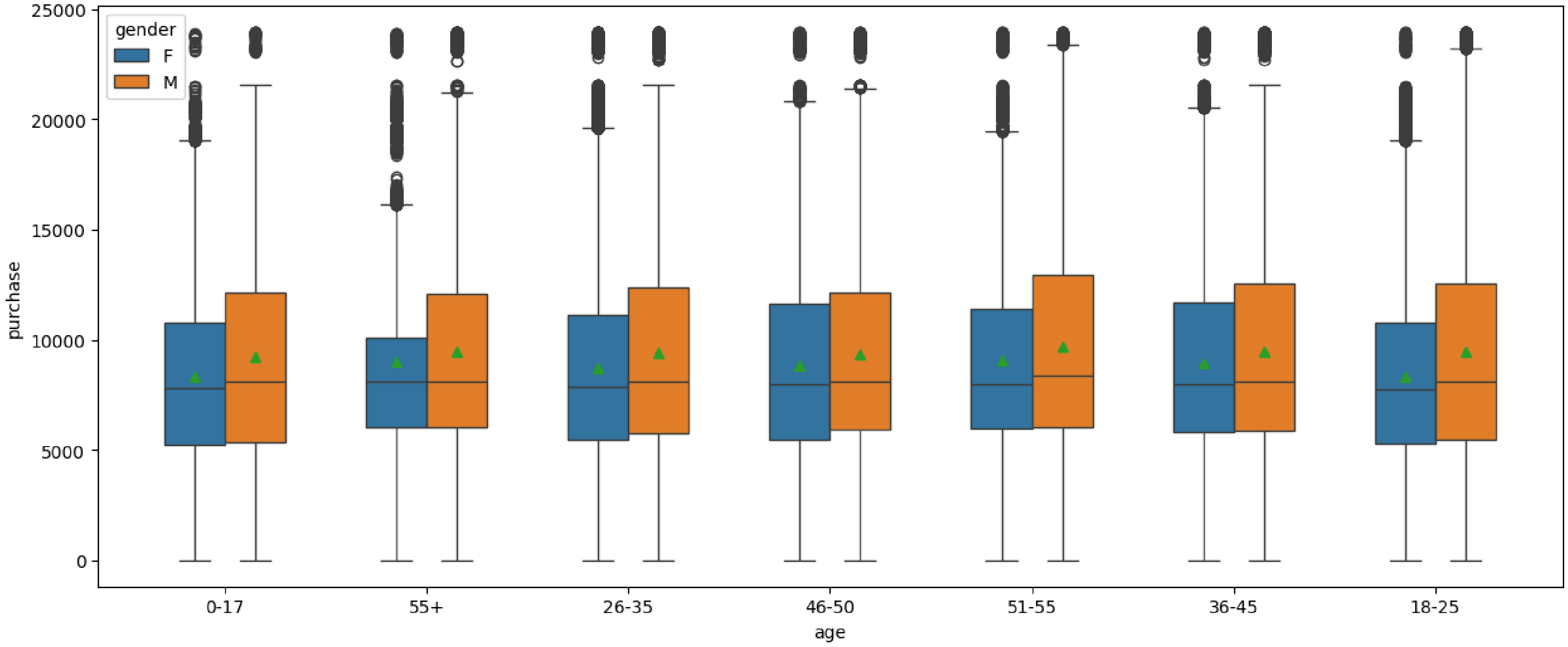
In [70]:
```
plt.figure(figsize=(12, 5))
plt.title('Distribution of number of Transactions Made based on Occupation')
sns.countplot(x="occupation", data=walmart_df)
plt.show()
```



Bivariate Analysis

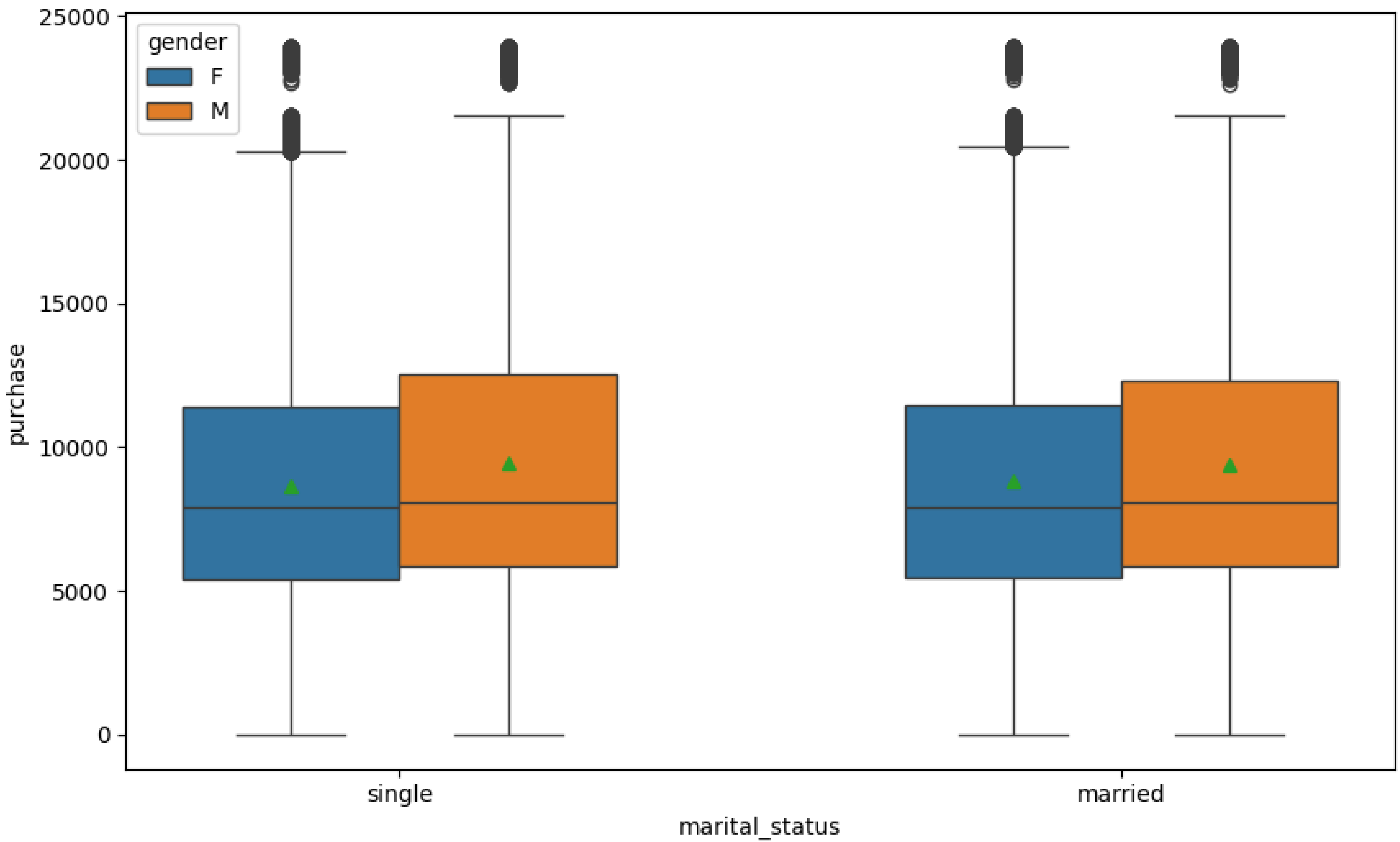
In [71]:
```
plt.figure(figsize = (15, 6))
sns.boxplot(data = walmart_df, x = 'age', y = 'purchase', hue = 'gender', showmeans = True, width = 0.6)
plt.plot()
```

Out[71]: []



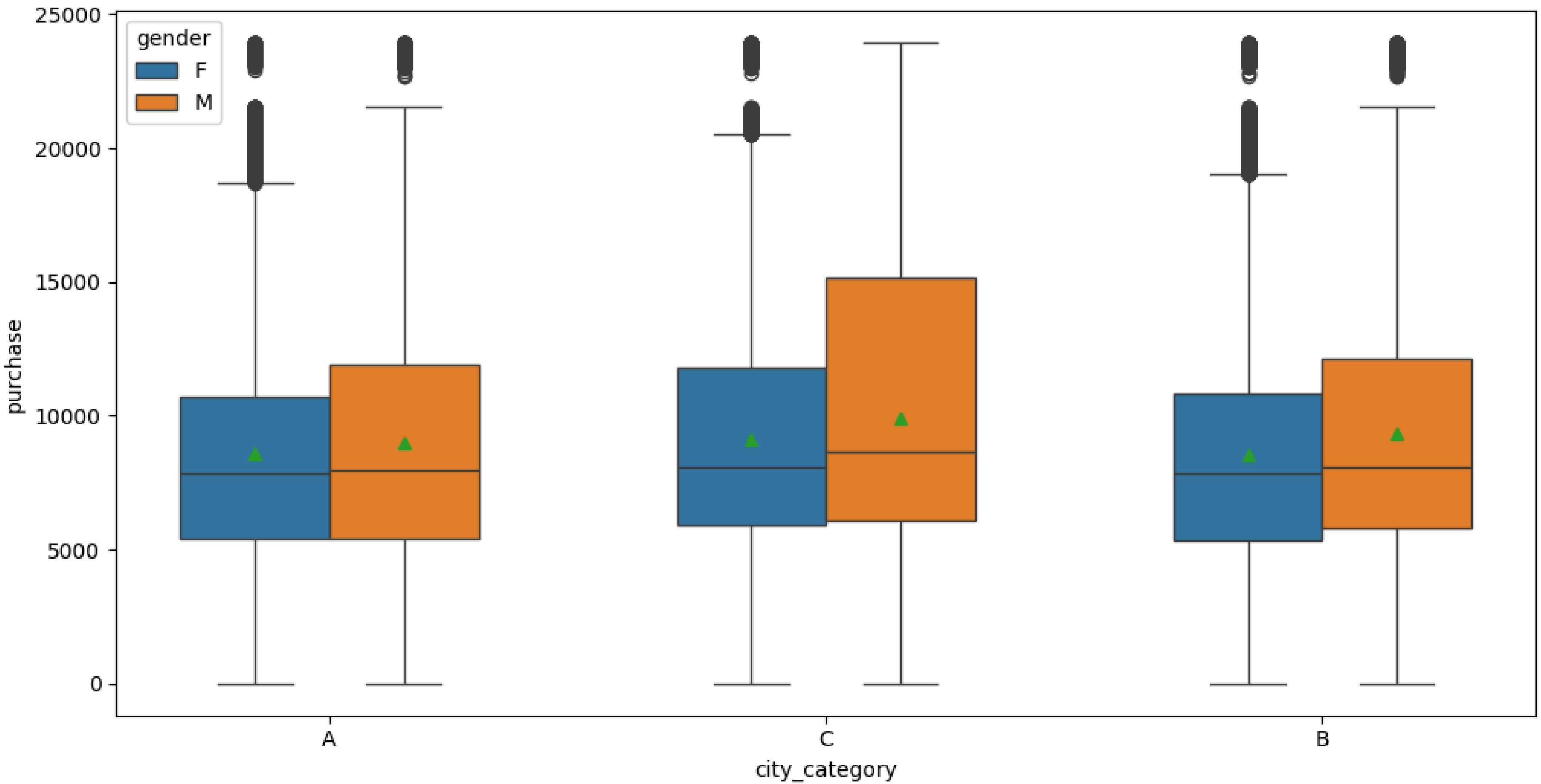
In [73]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = walmart_df, x = 'marital_status', y = 'purchase', hue = 'gender', showmeans = True, width = 0.6)
plt.plot()
```

Out[73]: []



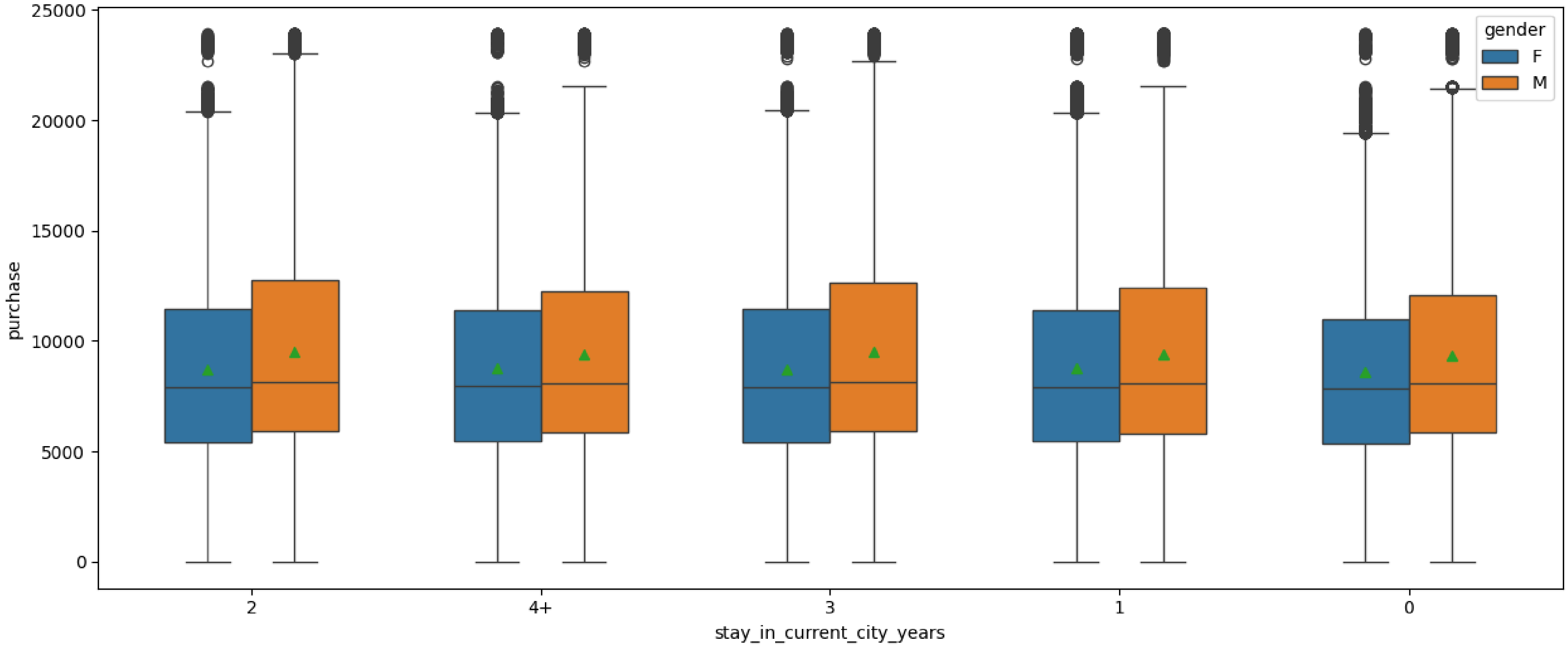

```
In [74]: plt.figure(figsize = (12, 6))
         sns.boxplot(data = walmart_df, x = 'city_category', y = 'purchase', hue = 'gender', showmeans = True, width = 0.6)
         plt.plot()
```

```
Out[74]: []
```



In [75]:
```
plt.figure(figsize = (15, 6))
sns.boxplot(data = walmart_df, x = 'stay_in_current_city_years', y = 'purchase', hue = 'gender', showmeans = True, w
plt.plot()
```

Out[75]: []



In [149…

```
gender_purchase_amount = walmart_df.groupby(["gender", "user_id"])["purchase"].sum().reset_index()
males_purchase_df = gender_purchase_amount[gender_purchase_amount['gender'] == "M"]
females_purchase_df = gender_purchase_amount[gender_purchase_amount['gender'] == "F"]
```

In [77]:

```
males_purchase_df
```

Out[77]:

	gender	user_id	purchase
1666	M	1000002	810472
1667	M	1000003	341635
1668	M	1000004	206468
1669	M	1000005	821001

1670	M	1000007	234668
...	...	...	...
5886	M	1006030	737361
5887	M	1006032	517261
5888	M	1006033	501843
5889	M	1006034	197086
5890	M	1006040	1653299

4225 rows × 3 columns

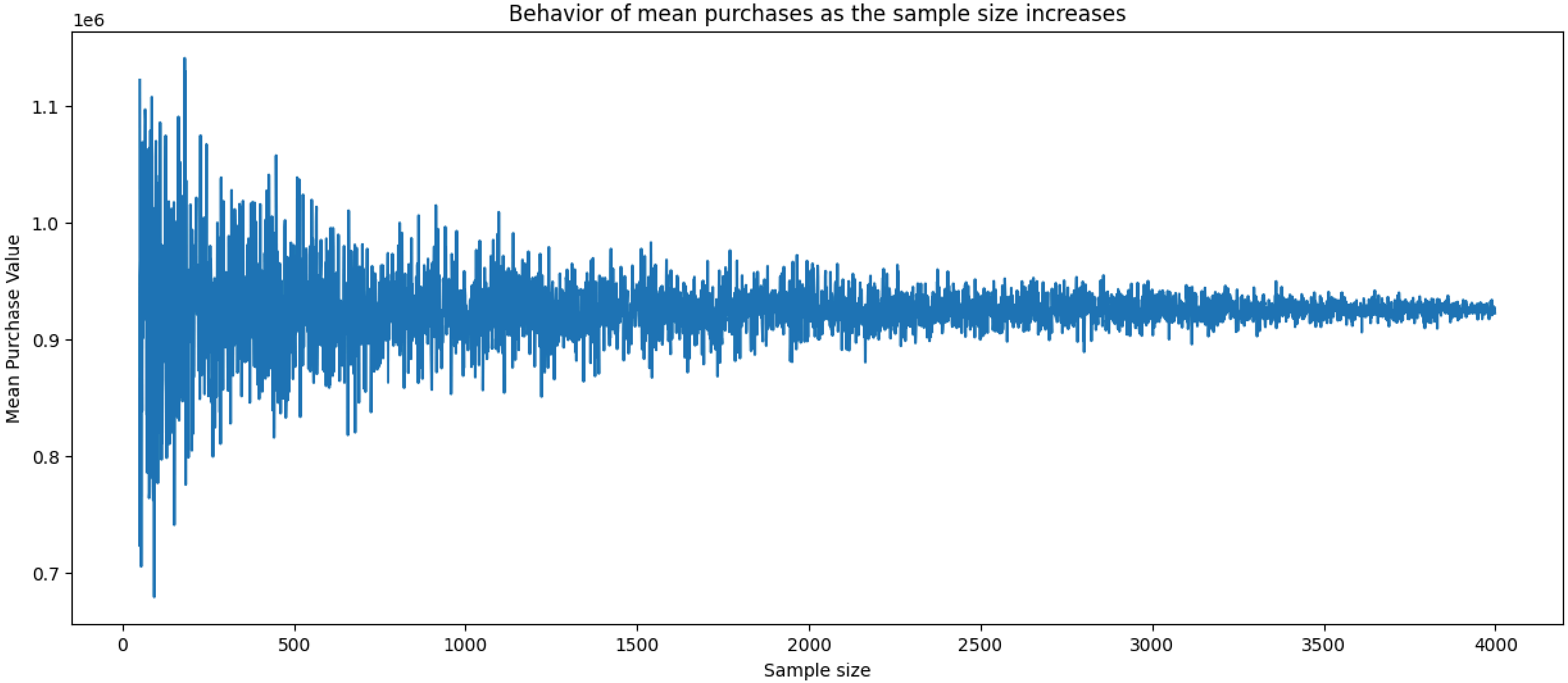
In [78]:

```
males_mean = []
for size in range(50, 4000):
  sample_mean = males_purchase_df["purchase"].sample(size).mean()
  males_mean.append(sample_mean)
```

In [79]:

```
plt.figure(figsize = (15, 6))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 4000), males_mean)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.plot()
```

Out[79]: []



- It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
- As the sample size increases, the deviation becomes smaller and smaller.
- The deviations will be small if the sample size taken is greater than 2000.

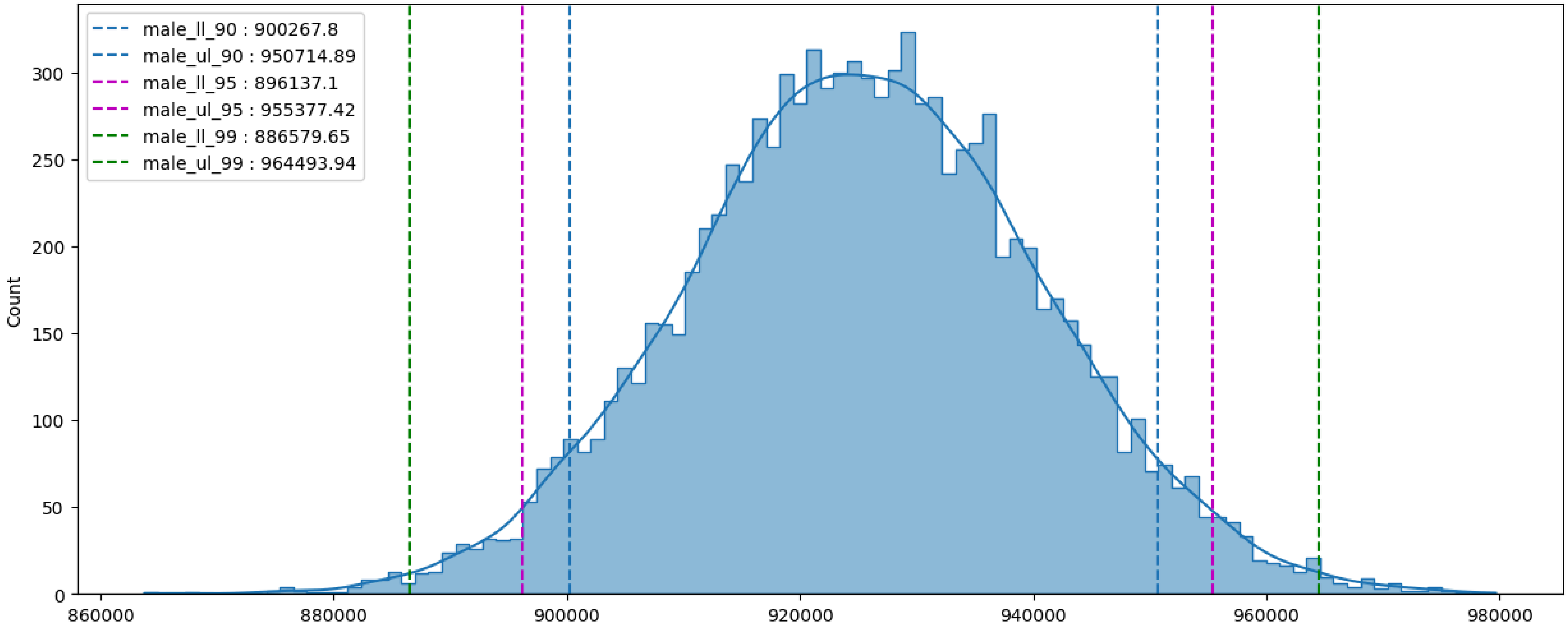
- Finding the confidence interval of each male's total spending on the Black Friday

In [80]:
```
means_male = []
size = males_purchase_df['purchase'].shape[0]
for bootstrapped_sample in range(10000):
 sample_mean = males_purchase_df['purchase'].sample(size, replace = True).mean()
 means_male.append(sample_mean)
```

In [82]:

```python
# The below code generates a histogram plot with kernel density estimation and
 # adds vertical lines to represent confidence intervals at 90%, 95%, and 99% level
plt.figure(figsize = (15, 6)) # setting the figure size of the plot
sns.histplot(means_male, kde = True, bins = 100, fill = True, element = 'step')
# Above line plots a histogram of the data contained in the `means_male` variable.
 # The `kde=True` argument adds a kernel density estimation line to the plot.
 # The `bins=100` argument sets the number of bins for the histogram

# Above line calculates the z-score corresponding to the 90% confidence level using the
 # inverse of the cumulative distribution function (CDF) of a standard normal distribution

male_ll_90 = np.percentile(means_male, 5)
 # calculating the lower limit of the 90% confidence interval
male_ul_90 = np.percentile(means_male, 95)
 # calculating the upper limit of the 90% confidence interval
plt.axvline(male_ll_90, label = f'male_ll_90 : {round(male_ll_90, 2)}', linestyle = '--')
 # adding a vertical line at the lower limit of the 90% confidence interval
plt.axvline(male_ul_90, label = f'male_ul_90 : {round(male_ul_90, 2)}', linestyle = '--')
 # adding a vertical line at the upper limit of the 90% confidence interval

# Similar steps are repeated for calculating and plotting the 95% and 99% confidence intervals,
 # with different line colors (`color='m'` for 95% and `color='g'` for 99%)
male_ll_95 = np.percentile(means_male, 2.5)
male_ul_95 = np.percentile(means_male, 97.5)
plt.axvline(male_ll_95, label = f'male_ll_95 : {round(male_ll_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(male_ul_95, label = f'male_ul_95 : {round(male_ul_95, 2)}', linestyle = '--', color = 'm')
male_ll_99 = np.percentile(means_male, 0.5)
male_ul_99 = np.percentile(means_male, 99.5)
plt.axvline(male_ll_99, label = f'male_ll_99 : {round(male_ll_99, 2)}', linestyle = '--', color = 'g')
plt.axvline(male_ul_99, label = f'male_ul_99 : {round(male_ul_99, 2)}', linestyle = '--', color = 'g')
plt.legend() # displaying a legend for the plotted lines.
plt.plot() # displaying the plot.
```

Out[82]: []



In [83]:
```
females_purchase_df
```

Out[83]:

	gender	user_id	purchase
0	F	1000001	334093
1	F	1000006	379930
2	F	1000010	2169510
3	F	1000011	557023
4	F	1000016	150490
...	...	...	...
1661	F	1006035	956645

1662	F	1006036	4116058
1663	F	1006037	1119538
1664	F	1006038	90034
1665	F	1006039	590319

1666 rows × 3 columns

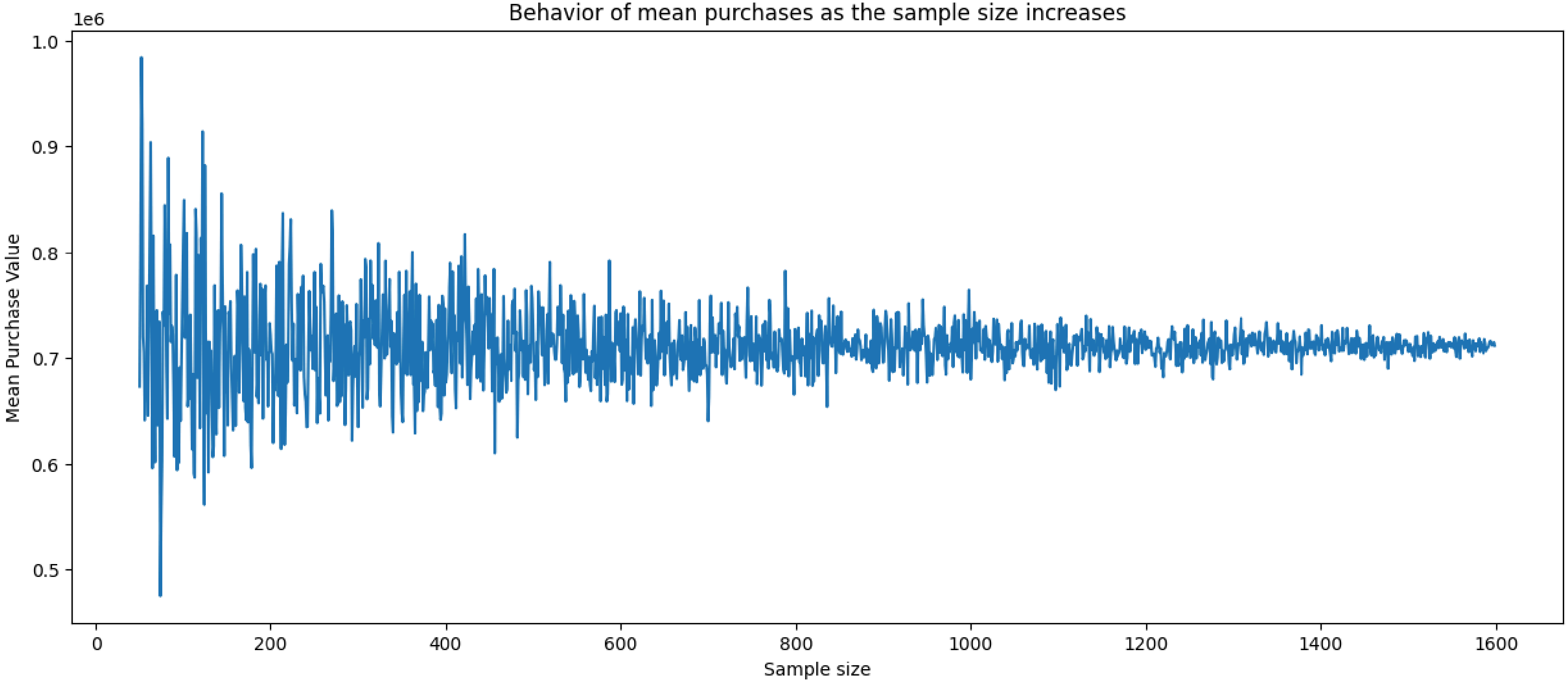
In [150…

```
females_mean = []
for size in range(50, 1600):
  sample_mean = females_purchase_df["purchase"].sample(size).mean()
  females_mean.append(sample_mean)
```

In [85]:

```
plt.figure(figsize = (15, 6))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 1600), females_mean)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.plot()
```

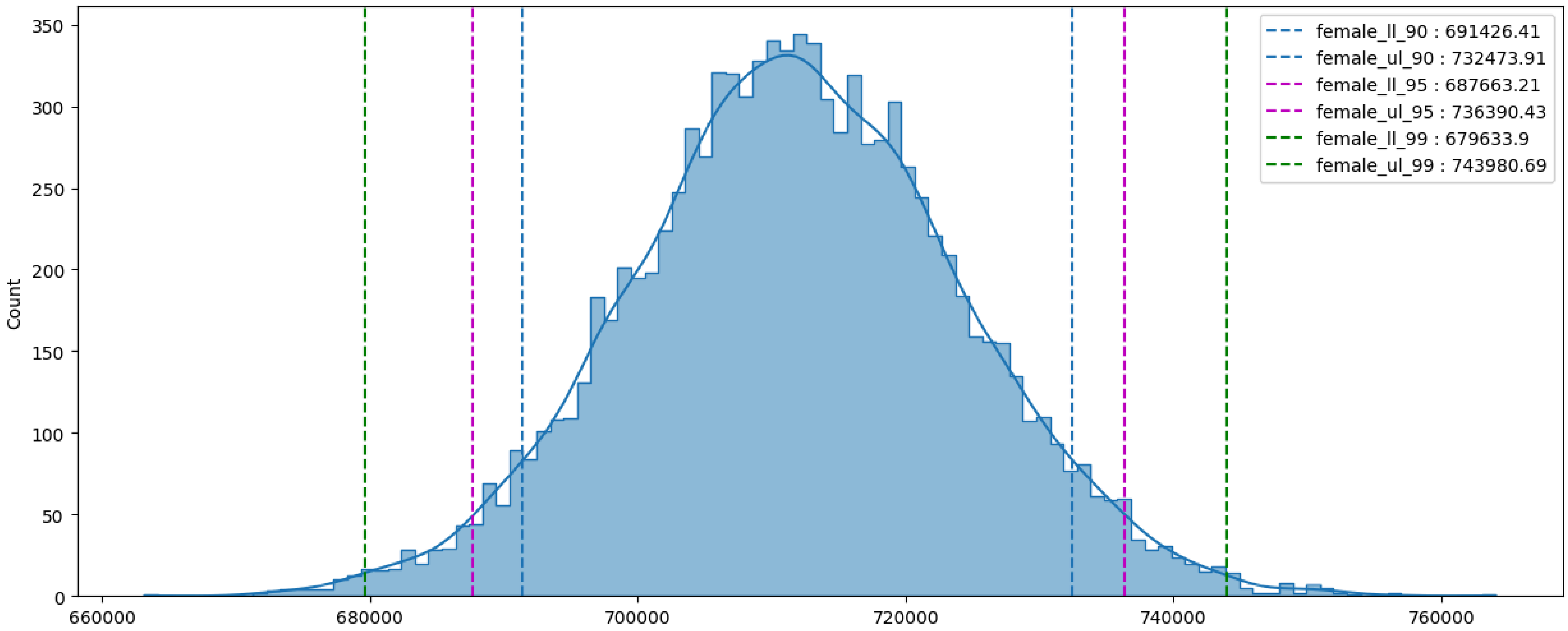
Out[85]: []



In [86]:
```
female_mean = []
size = males_purchase_df['purchase'].shape[0]
for bootstrapped_sample in range(10000):
 sample_mean = females_purchase_df['purchase'].sample(size, replace = True).mean()
 female_mean.append(sample_mean)
```

In [87]:
```
# The below code generates a histogram plot with kernel density estimation and
 # adds vertical lines to represent confidence intervals at 90%, 95%, and 99% level
plt.figure(figsize = (15, 6)) # setting the figure size of the plot
sns.histplot(female_mean, kde = True, bins = 100, fill = True, element = 'step')
# Above line plots a histogram of the data contained in the `means_male` variable.
 # The `kde=True` argument adds a kernel density estimation line to the plot.
 # The `bins=100` argument sets the number of bins for the histogram

# Above line calculates the z-score corresponding to the 90% confidence level using the
```

```
 # inverse of the cumulative distribution function (CDF) of a standard normal distribution

female_ll_90 = np.percentile(female_mean, 5)
 # calculating the lower limit of the 90% confidence interval
female_ul_90 = np.percentile(female_mean, 95)
 # calculating the upper limit of the 90% confidence interval
plt.axvline(female_ll_90, label = f'female_ll_90 : {round(female_ll_90, 2)}', linestyle = '--')
 # adding a vertical line at the lower limit of the 90% confidence interval
plt.axvline(female_ul_90, label = f'female_ul_90 : {round(female_ul_90, 2)}', linestyle = '--')
 # adding a vertical line at the upper limit of the 90% confidence interval

# Similar steps are repeated for calculating and plotting the 95% and 99% confidence intervals,
 # with different line colors (`color='m'` for 95% and `color='g'` for 99%)
female_ll_95 = np.percentile(female_mean, 2.5)
female_ul_95 = np.percentile(female_mean, 97.5)
plt.axvline(female_ll_95, label = f'female_ll_95 : {round(female_ll_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(female_ul_95, label = f'female_ul_95 : {round(female_ul_95, 2)}', linestyle = '--', color = 'm')
female_ll_99 = np.percentile(female_mean, 0.5)
female_ul_99 = np.percentile(female_mean, 99.5)
plt.axvline(female_ll_99, label = f'female_ll_99 : {round(female_ll_99, 2)}', linestyle = '--', color = 'g')
plt.axvline(female_ul_99, label = f'female_ul_99 : {round(female_ul_99, 2)}', linestyle = '--', color = 'g')

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

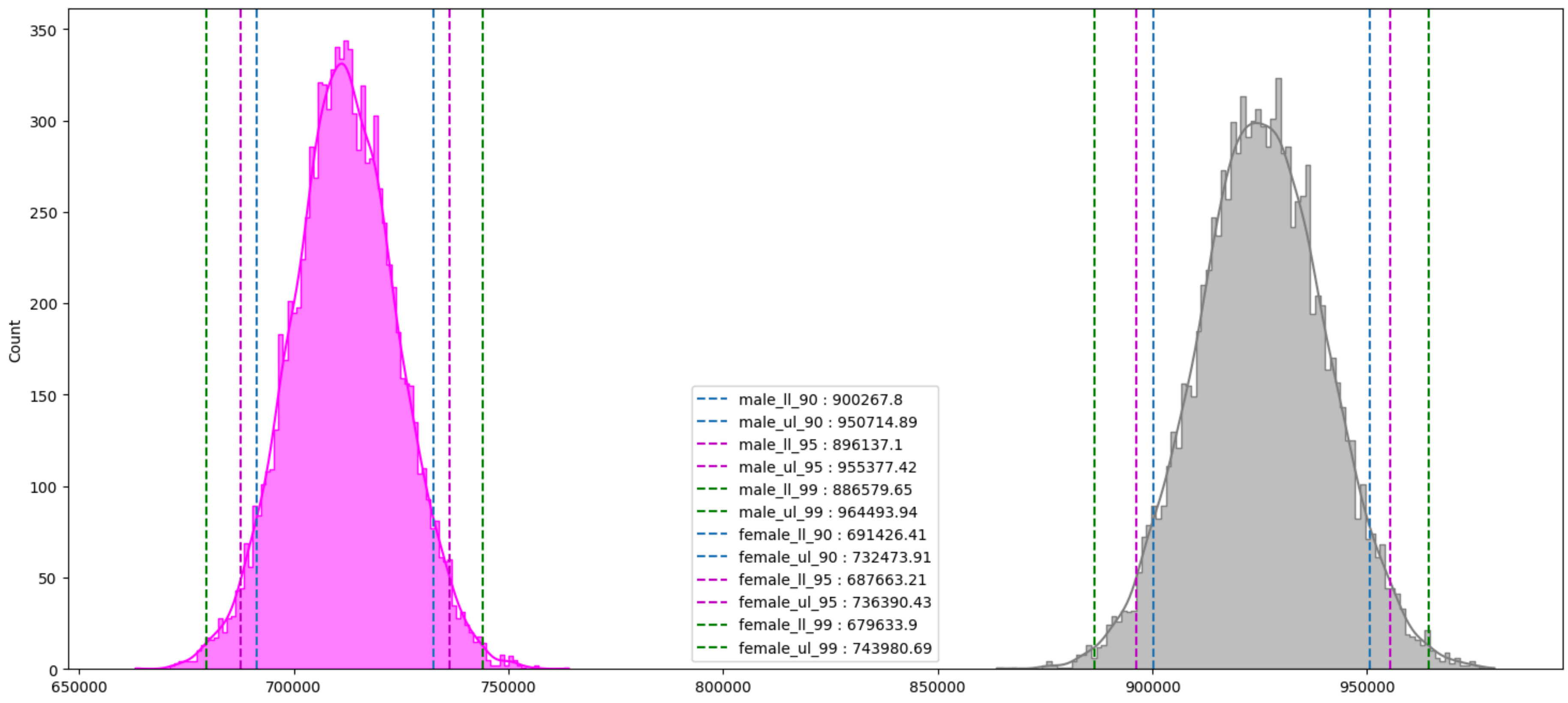


In [88]:

```
plt.figure(figsize = (18, 8))
# The first histogram represents the distribution of means_male with gray color having
 # KDE (Kernel Density Estimation) curves enabled for smooth representation.
sns.histplot(means_male,
 kde = True,
 bins = 100,
 fill = True,
 element = 'step',
 color = 'gray',
 legend = True)
# Multiple vertical lines are plotted to represent the lower and upper limits
 # for confidence intervals at different confidence levels
plt.axvline(male_ll_90, label = f'male_ll_90 : {round(male_ll_90, 2)}', linestyle = '--')
plt.axvline(male_ul_90, label = f'male_ul_90 : {round(male_ul_90, 2)}', linestyle = '--')
plt.axvline(male_ll_95, label = f'male_ll_95 : {round(male_ll_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(male_ul_95, label = f'male_ul_95 : {round(male_ul_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(male_ll_99, label = f'male_ll_99 : {round(male_ll_99, 2)}', linestyle = '--', color = 'g')
```

```
plt.axvline(male_ul_99, label = f'male_ul_99 : {round(male_ul_99, 2)}', linestyle = '--', color = 'g')
# The second histogram represents the distribution of means_female with magenta color
 # KDE (Kernel Density Estimation) curves enabled for smooth representation.
sns.histplot(female_mean,
 kde = True,
 bins = 100,
 fill = True,
 element = 'step',
 color = 'magenta',
 legend = True)
# Multiple vertical lines are plotted to represent the lower and upper limits
 # for confidence intervals at different confidence levels
plt.axvline(female_ll_90, label = f'female_ll_90 : {round(female_ll_90, 2)}', linestyle = '--')
plt.axvline(female_ul_90, label = f'female_ul_90 : {round(female_ul_90, 2)}', linestyle = '--')
plt.axvline(female_ll_95, label = f'female_ll_95 : {round(female_ll_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(female_ul_95, label = f'female_ul_95 : {round(female_ul_95, 2)}', linestyle = '--', color = 'm')
plt.axvline(female_ll_99, label = f'female_ll_99 : {round(female_ll_99, 2)}', linestyle = '--', color = 'g')
plt.axvline(female_ul_99, label = f'female_ul_99 : {round(female_ul_99, 2)}', linestyle = '--', color = 'g')
plt.legend()
plt.plot()
```

Out[88]: []



- **Determining the mean purchase made by each user belonging to different Marital Status**

In [89]:
```
df_single = walmart_df.loc[walmart_df['marital_status'] == 'single'].reset_index()
df_married = walmart_df.loc[walmart_df['marital_status'] == 'married']
```

In [151…
```
df_single = df_single.groupby('user_id')['purchase'].sum().reset_index()
df_single
```

Out[151…

	user_id	purchase
0	1000001	334093
1	1000002	810472

2	1000003	341635
3	1000006	379930
4	1000009	594099
...	...	...
3412	1006034	197086
3413	1006035	956645
3414	1006037	1119538
3415	1006038	90034
3416	1006040	1653299

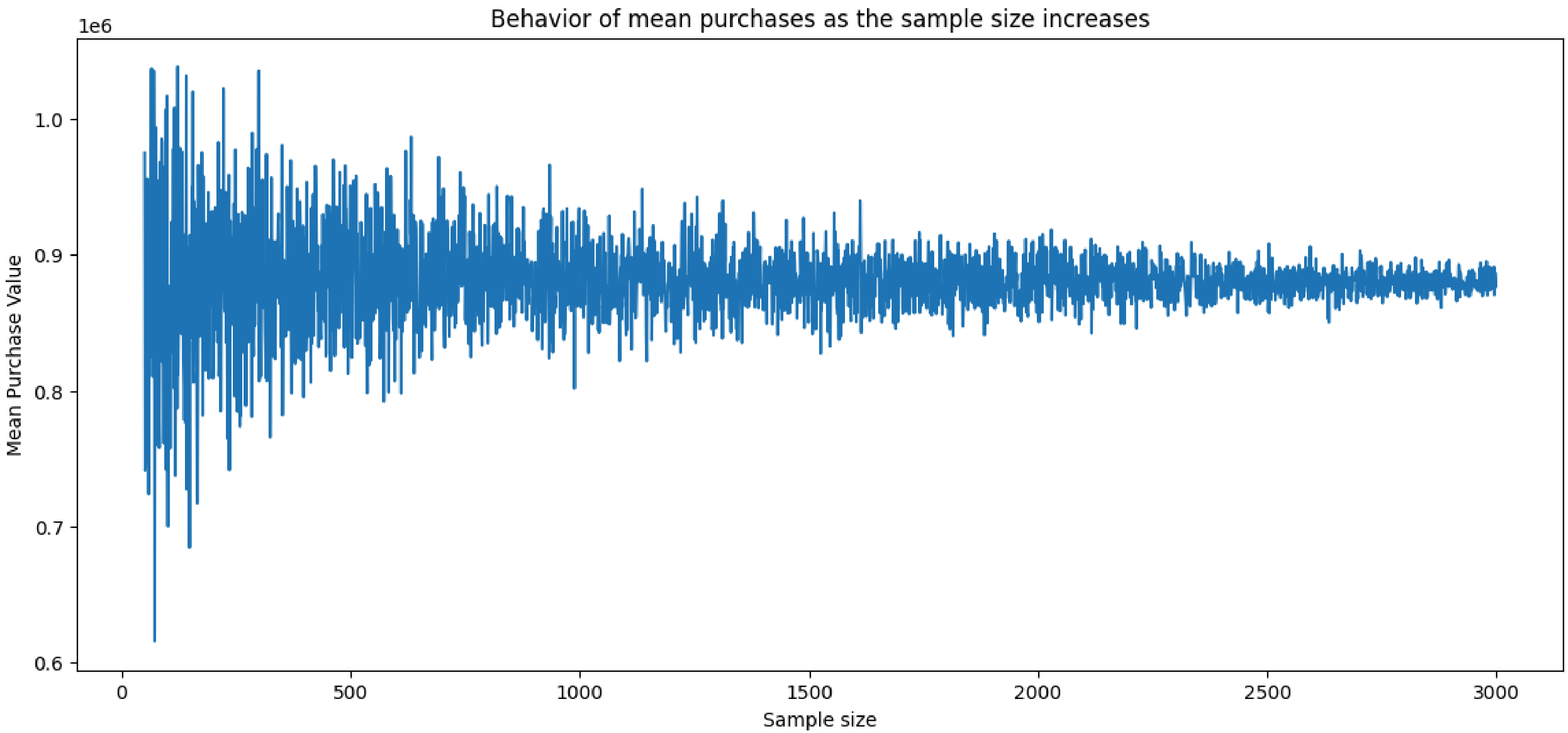
3417 rows × 2 columns

In [152…

```
mean_purchase = []
for sample in range(50, 3000):
  samples = df_single["purchase"].sample(sample).mean()
  mean_purchase.append(samples)
```

In [92]:

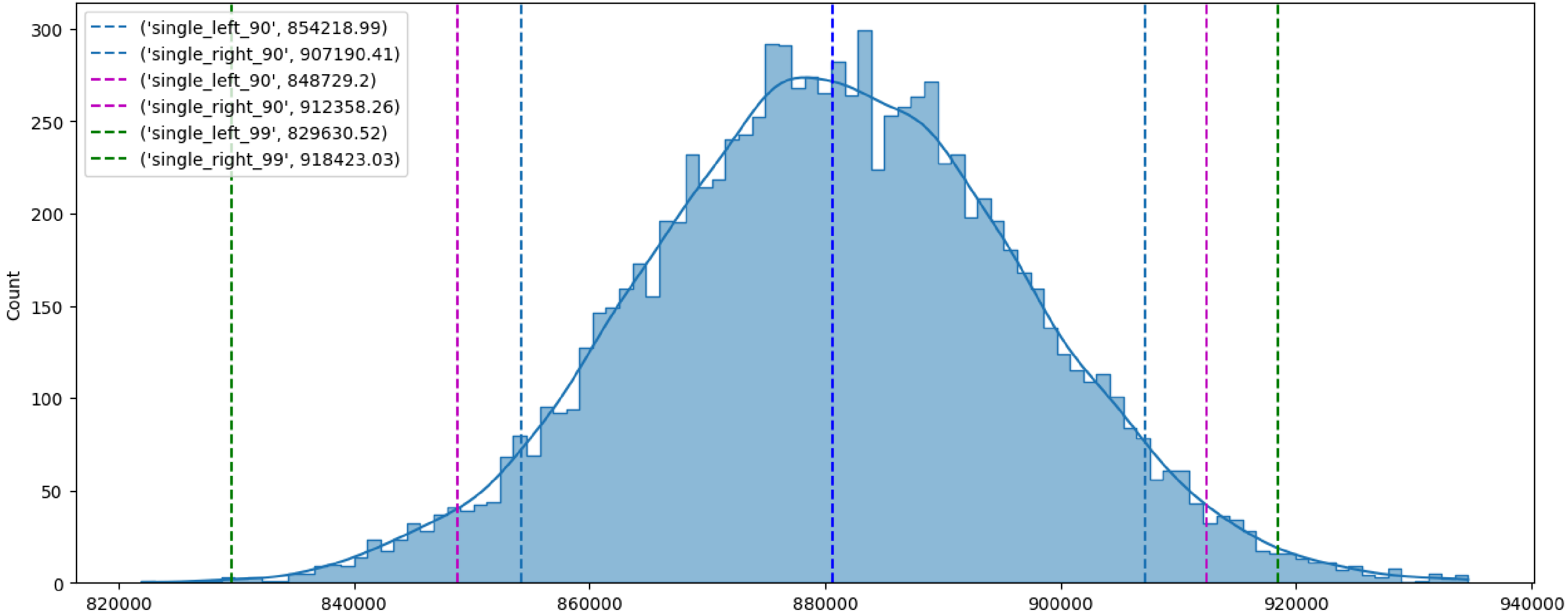
```
plt.figure(figsize=(14, 6))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 3000), mean_purchase)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```



In [93]:
```
single_means = []
size = df_single['purchase'].shape[0]
for bootstrapped_sample in range(10000):
 sample_mean = df_single['purchase'].sample(size, replace = True).mean()
 single_means.append(sample_mean)
```

In [94]:
```
plt.figure(figsize=(15, 6))
sns.histplot(data=single_means, kde=True, bins=100, fill=True, element="step")
single_left_90 = np.percentile(single_means, 5).round(2)
single_right_90 = np.percentile(single_means, 95).round(2)
plt.axvline(single_left_90, label=("single_left_90", single_left_90), linestyle= "--")
plt.axvline(single_right_90, label=("single_right_90", single_right_90), linestyle= "--")

#95% confidence interval
```

```python
single_left_95 = np.percentile(single_means, 2.5).round(2)
single_right_95 = np.percentile(single_means, 97.5).round(2)
plt.axvline(single_left_95, label=("single_left_90", single_left_95), linestyle= "--", color="m")
plt.axvline(single_right_95, label=("single_right_90", single_right_95), linestyle= "--", color="m")

#99% confidence interval
single_left_99 = np.percentile(single_means, 0.05).round(2)
single_right_99 = np.percentile(single_means, 99).round(2)
plt.axvline(single_left_99, label=("single_left_99", single_left_99), linestyle= "--", color="g")
plt.axvline(single_right_99, label=("single_right_99", single_right_99), linestyle= "--", color="g")
plt.axvline(np.percentile(single_means, 50), linestyle="--", color="b")
plt.legend()
plt.show()
```



In [95]:
```python
df_married = df_married.groupby(["marital_status", "user_id"])["purchase"].sum().reset_index()
df_married
```

Out[95]:

marital_status	user_id	purchase

0	married	1000004	206468
1	married	1000005	821001
2	married	1000007	234668
3	married	1000008	796593
4	married	1000010	2169510
...	...	...	...
2469	married	1006029	157436
2470	married	1006030	737361
2471	married	1006033	501843
2472	married	1006036	4116058
2473	married	1006039	590319

2474 rows × 3 columns

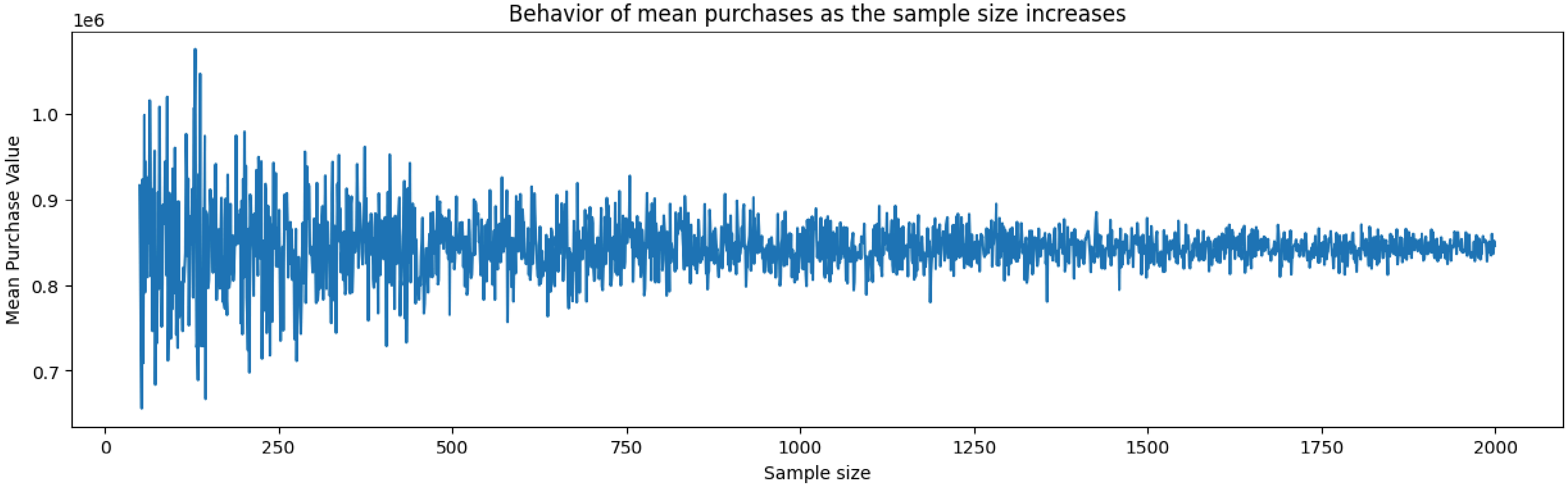
In [153…

```
married_mean = []
for sample in range(50, 2000):
  samples = df_married["purchase"].sample(sample).mean()
  married_mean.append(samples)
```

In [97]:

```
plt.figure(figsize=(15, 4))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 2000), married_mean)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.plot()
```

Out[97]: []



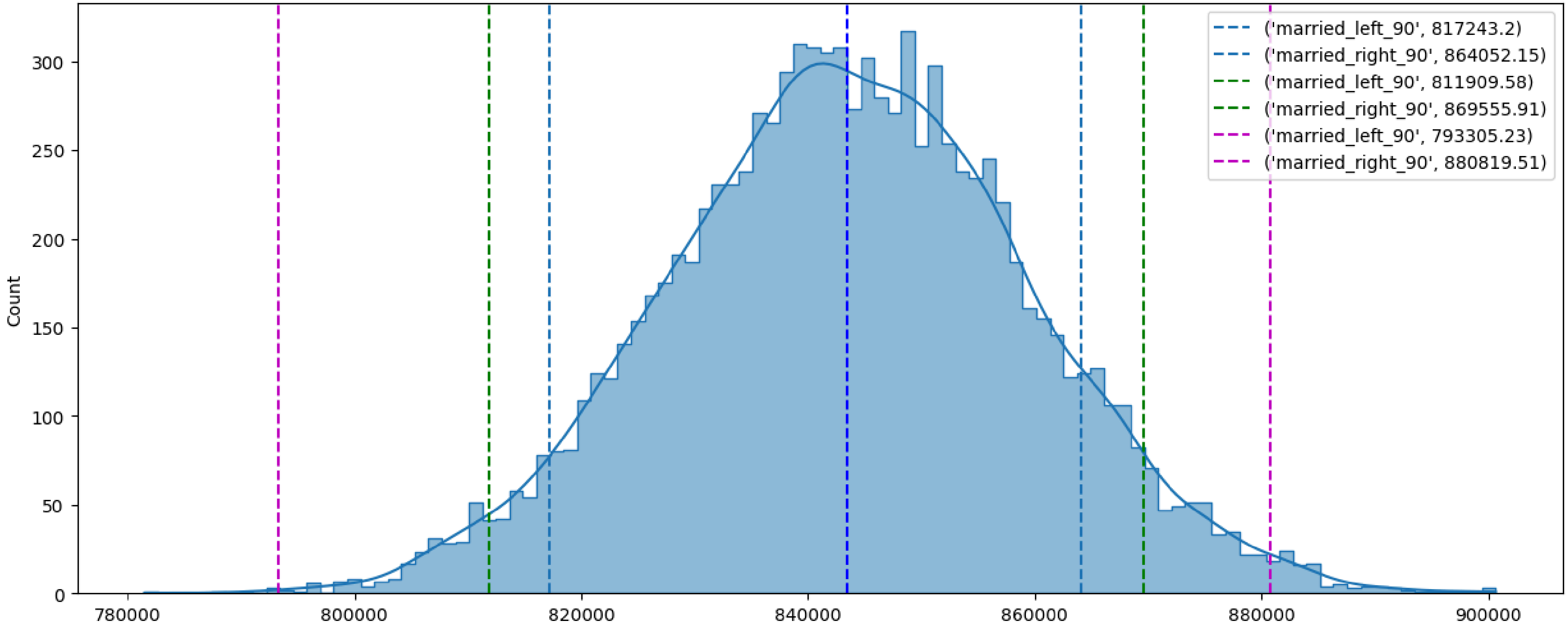
In [154…

```
married_means = []
df_married["purchase"].shape[0]
for bootstrapped_sample in range(10000):
 sample_mean = df_married['purchase'].sample(size, replace = True).mean()
 married_means.append(sample_mean)
```

In [99]:

```
plt.figure(figsize=(15,6))
sns.histplot(data=married_means, kde=True, bins=100, element="step", fill=True)

#90% confidence interval
married_left_90 = np.percentile(married_means, 5).round(2)
married_right_90 = np.percentile(married_means, 90).round(2)
plt.axvline(married_left_90, label =("married_left_90", married_left_90), linestyle="--")
plt.axvline(married_right_90, label =("married_right_90", married_right_90), linestyle="--")

#95% confidence interval
married_left_95 = np.percentile(married_means, 2.5).round(2)
married_right_95 = np.percentile(married_means, 95).round(2)
plt.axvline(married_left_95, label =("married_left_90", married_left_95), linestyle="--", color="g")
plt.axvline(married_right_95, label =("married_right_90", married_right_95), linestyle="--", color="g")

#99% confidence interval
```

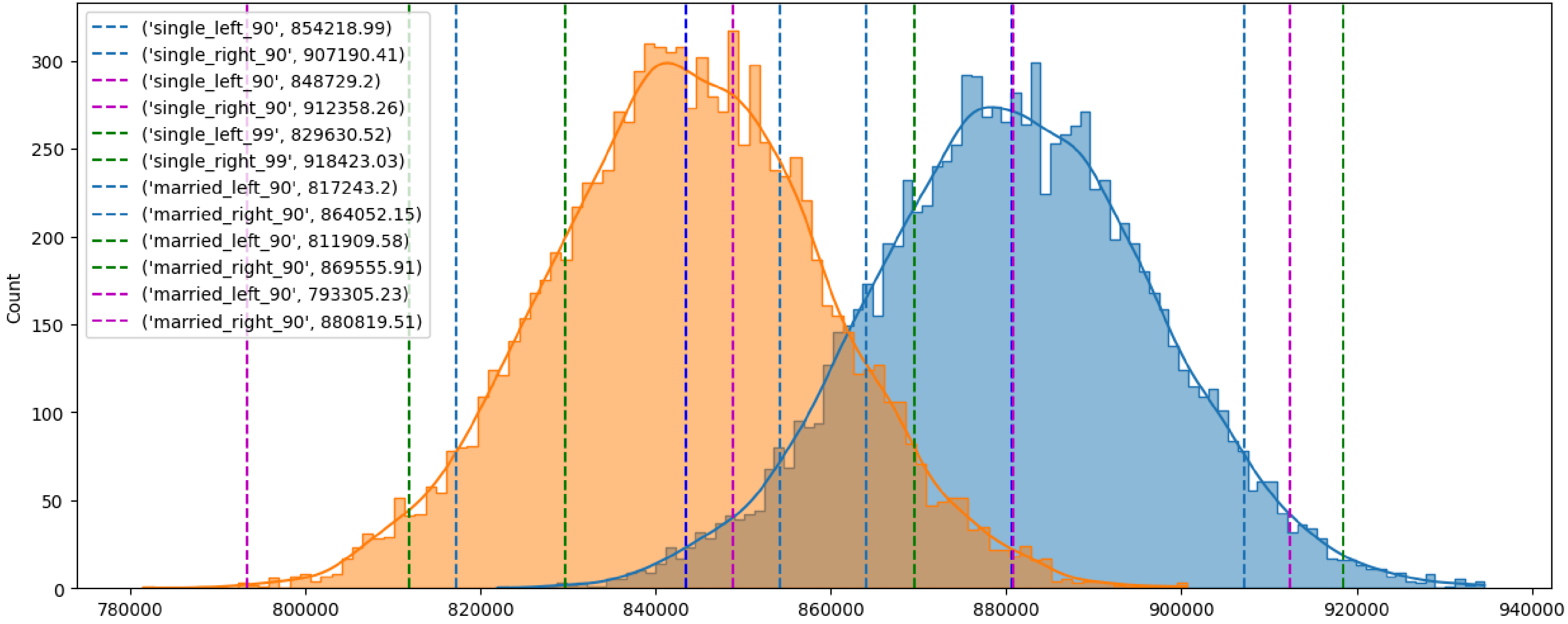
```
married_left_99 = np.percentile(married_means, 0.05).round(2)
married_right_99 = np.percentile(married_means, 99).round(2)
plt.axvline(married_left_99, label =("married_left_90", married_left_99), linestyle="--", color="m")
plt.axvline(married_right_99, label =("married_right_90", married_right_99), linestyle="--",color="m")
plt.axvline(np.percentile(married_means, 50).round(2), linestyle="--", color="b")
plt.legend()
plt.show()
```



In [100…

```
plt.figure(figsize=(15, 6))

sns.histplot(data=single_means, kde=True, bins=100, fill=True, element="step")

plt.axvline(single_left_90, label=("single_left_90", single_left_90), linestyle= "--")
plt.axvline(single_right_90, label=("single_right_90", single_right_90), linestyle= "--")
plt.axvline(single_left_95, label=("single_left_90", single_left_95), linestyle= "--", color="m")
plt.axvline(single_right_95, label=("single_right_90", single_right_95), linestyle= "--", color="m")
plt.axvline(single_left_99, label=("single_left_99", single_left_99), linestyle= "--", color="g")
plt.axvline(single_right_99, label=("single_right_99", single_right_99), linestyle= "--", color="g")
```

```
plt.axvline(np.percentile(single_means, 50), linestyle="--", color="b")


#married_plot
sns.histplot(data=married_means, kde=True, bins=100, element="step", fill=True)
plt.axvline(married_left_90, label =("married_left_90", married_left_90), linestyle="--")
plt.axvline(married_right_90, label =("married_right_90", married_right_90), linestyle="--")
plt.axvline(married_left_95, label =("married_left_90", married_left_95), linestyle="--", color="g")
plt.axvline(married_right_95, label =("married_right_90", married_right_95), linestyle="--", color="g")
plt.axvline(married_left_99, label =("married_left_90", married_left_99), linestyle="--", color="m")
plt.axvline(married_right_99, label =("married_right_90", married_right_99), linestyle="--",color="m")
plt.axvline(np.percentile(married_means, 50).round(2), linestyle="--", color="b")




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



It can be inferred from the above chart that the distributions of singles' total spending and married individuals' total spending overlap. It suggests that there is no significant difference in spending habits between these two groups. Here are some possible inferences that can be drawn from this:

- Relationship status does not strongly influence spending: Being single or married does not appear to have a substantial impact on

individuals' spending patterns. Other factors such as income, personal preferences, and financial priorities may play a more significant role in determining spending habits.

- Similar consumption patterns: Singles and married individuals may have similar lifestyles and consumption patterns, leading to

comparable spending behaviors. They may allocate their income in comparable ways, making similar purchasing decisions and spending on similar categories of products or services.

- Financial considerations: Both singles and married individuals may have similar financial responsibilities and constraints, leading to

similar spending levels. They may have similar obligations such as housing costs, bills, and other financial commitments, which influence their overall spending capacity.

- Individual differences outweigh relationship status: Other individual characteristics, such as personal values, interests, and

financial habits, may have a more significant impact on spending behavior than relationship status. These factors can vary widely within each group, resulting in overlapping spending distributions

In [101…

```
def cal_percetiles(x):

  #90 confidence interval
  left_90 = np.percentile(x, 5).round(2)
  right_90 = np.percentile(x, 90).round(2)

  #95% confidence interval
  left_95 = np.percentile(x, 2.5).round(2)
  right_95 = np.percentile(x, 95).round(2)

  #99% condifence interval
  left_99 = np.percentile(x, 0.05).round(2)
  right_99 = np.percentile(x, 99).round(2)
```

```
  #median
  mean_50 = np.percentile(x, 50).round(2)
  return left_90, right_90,left_95,right_95, left_99,right_99, mean_50
```

In [102…

```
unique_ag = walmart_df["age"].unique()

age_df = {}
for age in unique_ag:
  age_df[f"age_{age}"] = walmart_df[walmart_df["age"] == age]
```

In [103…

```
unique_ag
```

Out[103…

```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

In [104…

```
print(len(age_df['age_0-17']))
print(len(age_df['age_18-25']))
print(len(age_df['age_26-35']))
print(len(age_df['age_36-45']))
print(len(age_df['age_46-50']))
print(len(age_df['age_51-55']))
print(len(age_df['age_55+']))
```

```
15102
99660
219587
110013
45701
38501
21504
```

In [105…

```
age_0_to_17 = age_df['age_0-17'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_55_plus =age_df['age_55+'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_26_to_35 = age_df['age_26-35'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_46_to_50 = age_df['age_46-50'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_51_to_55 = age_df['age_51-55'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_36_to_45 = age_df['age_36-45'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
age_18_to_25 = age_df['age_18-25'].groupby(["age",'user_id'])["purchase"].sum().reset_index()
```

For Age Group 0 - 17 years

In [106…
```
age_0_to_17
```

Out[106…

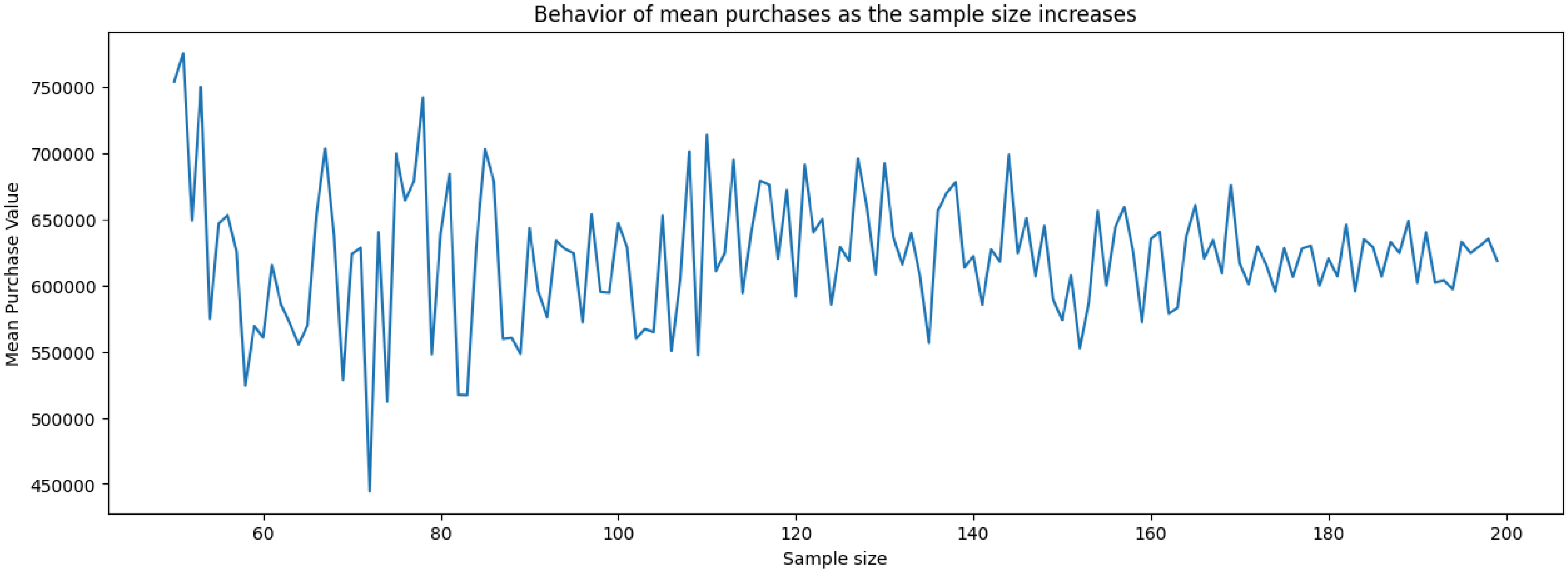
	age	user_id	purchase
0	0-17	1000001	334093
1	0-17	1000019	1458069
2	0-17	1000051	200772
3	0-17	1000075	1035584
4	0-17	1000086	294063
...	...	...	...
213	0-17	1005844	476231
214	0-17	1005953	629161
215	0-17	1005973	270475
216	0-17	1005989	466195
217	0-17	1006006	514919

218 rows × 3 columns

In [107…
```
mean_purchases = []
for sample_size in range(50, 200):
 sample_mean = age_0_to_17['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [108…
```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
```

```
plt.plot(np.arange(50, 200), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```



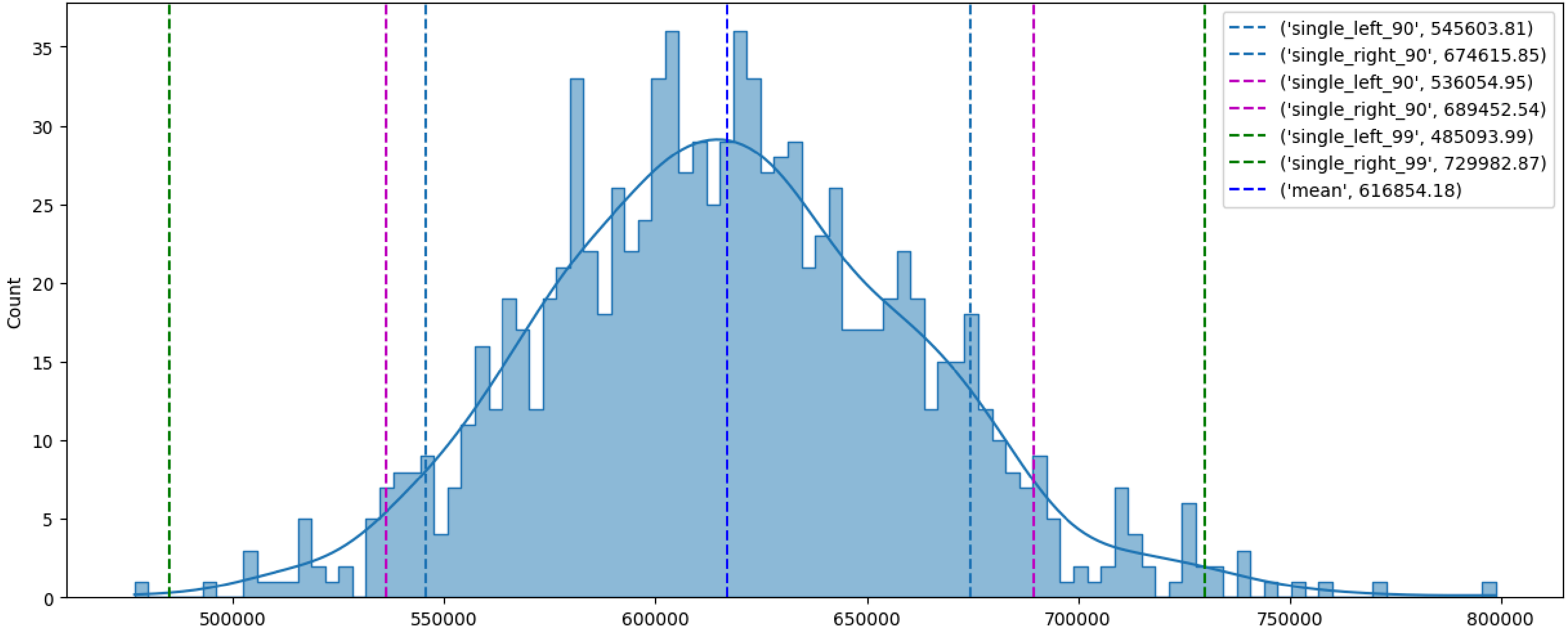
- Finding the confidence interval of total spending for each individual in the age group 0 - 17 on the Black Friday

In [155…
```
age_18_means= []
size = age_0_to_17['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_0_to_17['purchase'].sample(size, replace=True).mean()
  age_18_means.append(sample_mean)
```

In [110…
```
a, b , c, d, e, f, g = cal_percetiles(age_18_means)
```

In [111…
```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_18_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_18_means, 5)
```

```
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")

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



age_18_25_means

In [112…

```
age_18_to_25
```

Out[112…

	age	user_id	purchase

0	18-25	1000018	1979047
1	18-25	1000021	127099
2	18-25	1000022	1279914
3	18-25	1000025	534706
4	18-25	1000034	807983
...	...	...	...
1064	18-25	1005998	702901
1065	18-25	1006008	266306
1066	18-25	1006027	265201
1067	18-25	1006028	362972
1068	18-25	1006031	286374

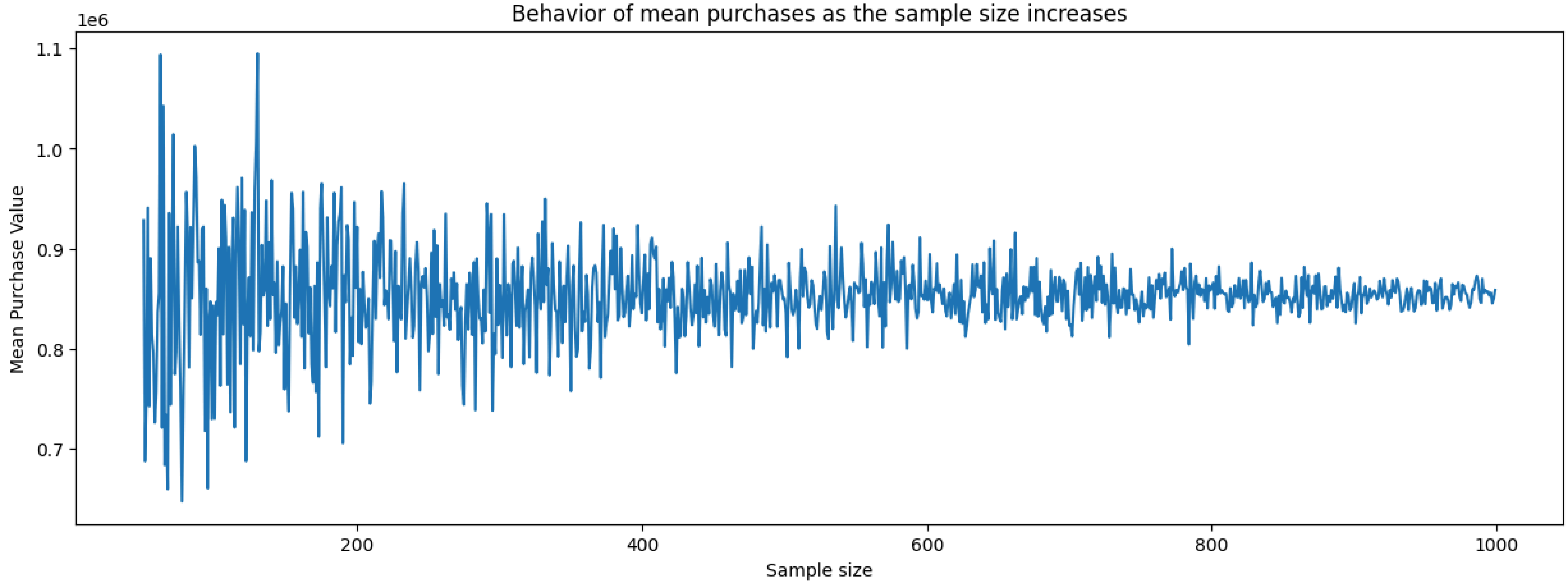
1069 rows × 3 columns

In [113…

```
mean_purchases = []
for sample_size in range(50, 1000):
 sample_mean = age_18_to_25['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [114…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 1000), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```



In [156…

```
age_18_25_means= []
size = age_0_to_17['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_18_to_25['purchase'].sample(size, replace=True).mean()
  age_18_25_means.append(sample_mean)
```

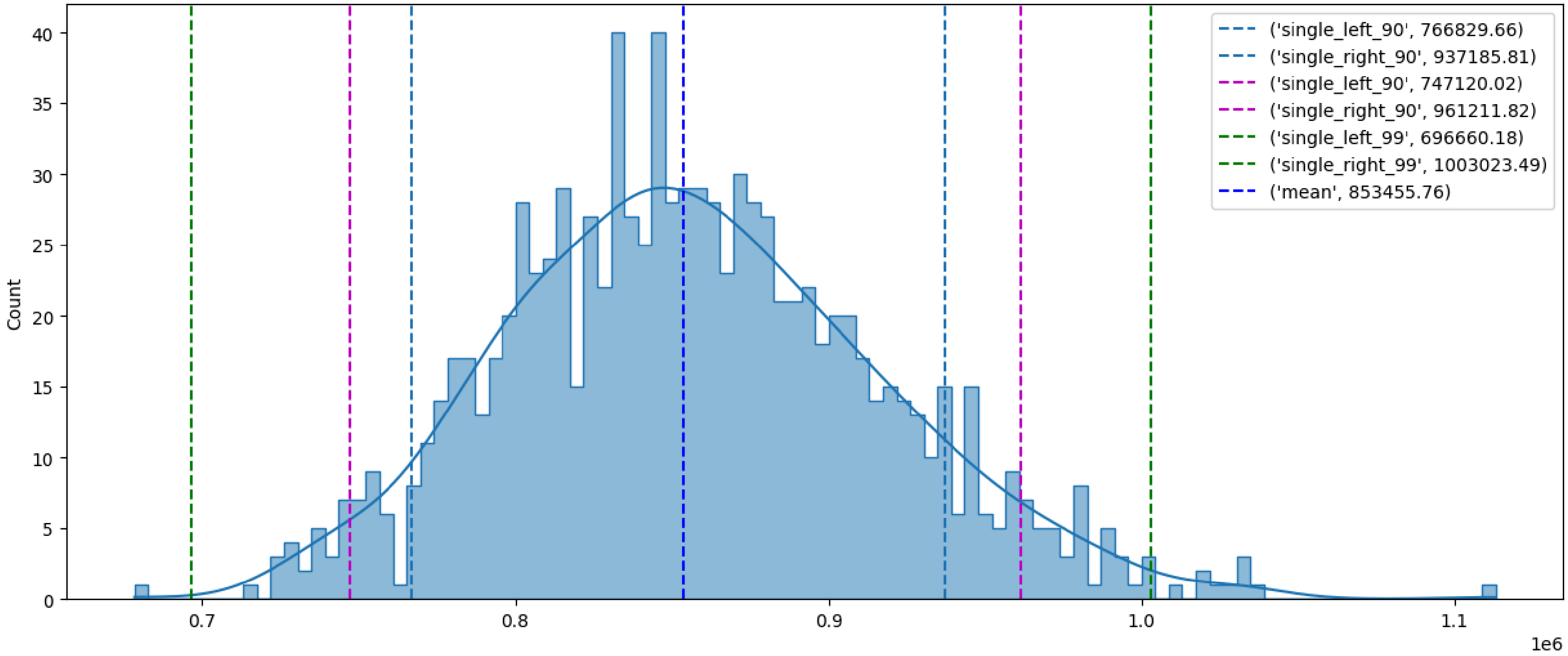
In [116…

```
a, b , c, d, e, f, g = cal_percetiles(age_18_25_means)
```

In [117…

```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_18_25_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_18_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



In [118…

```
age_26_to_35
```

Out[118…

	age	user_id	purchase
0	26-35	1000003	341635
1	26-35	1000005	821001
2	26-35	1000008	796593
3	26-35	1000009	594099

4	26-35	1000011	557023
...	...	...	...
2048	26-35	1006030	737361
2049	26-35	1006034	197086
2050	26-35	1006035	956645
2051	26-35	1006036	4116058
2052	26-35	1006040	1653299

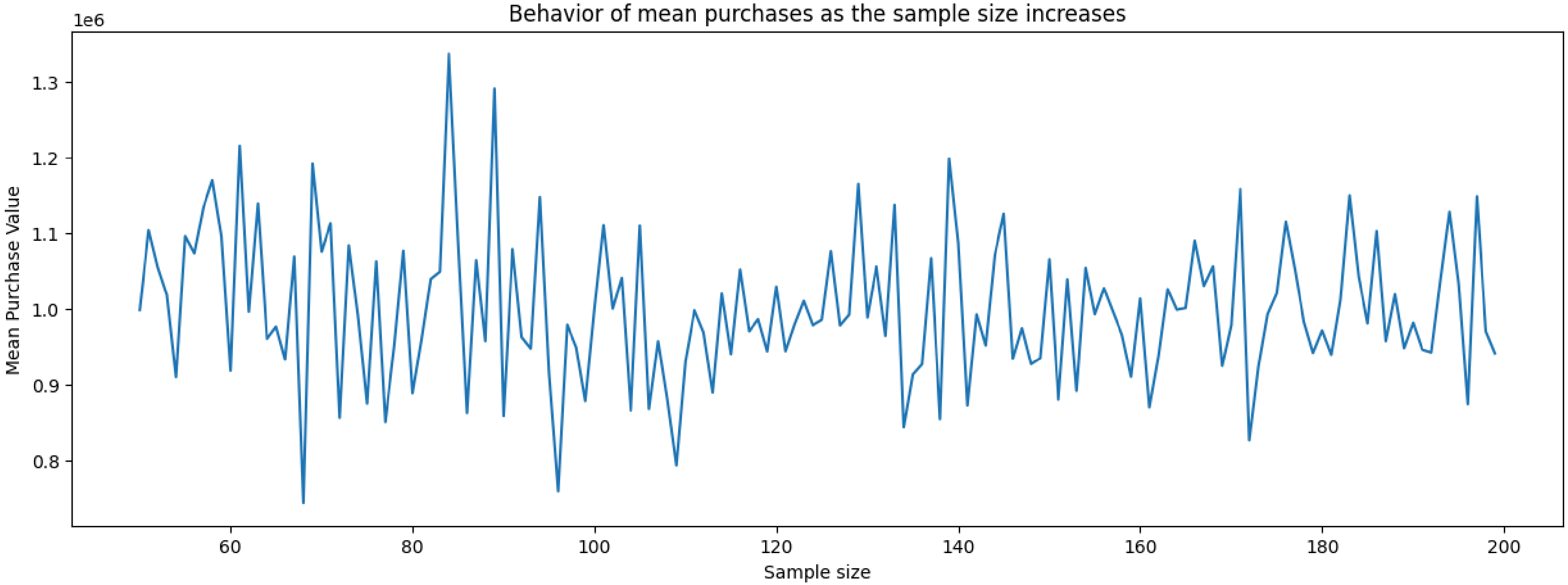
2053 rows × 3 columns

In [157…

```
mean_purchases = []
for sample_size in range(50, 200):
 sample_mean = age_26_to_35['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [120…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 200), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```



In [121…

```
age_means= []
size = age_26_to_35['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_26_to_35['purchase'].sample(size, replace=True).mean()
  age_means.append(sample_mean)
```

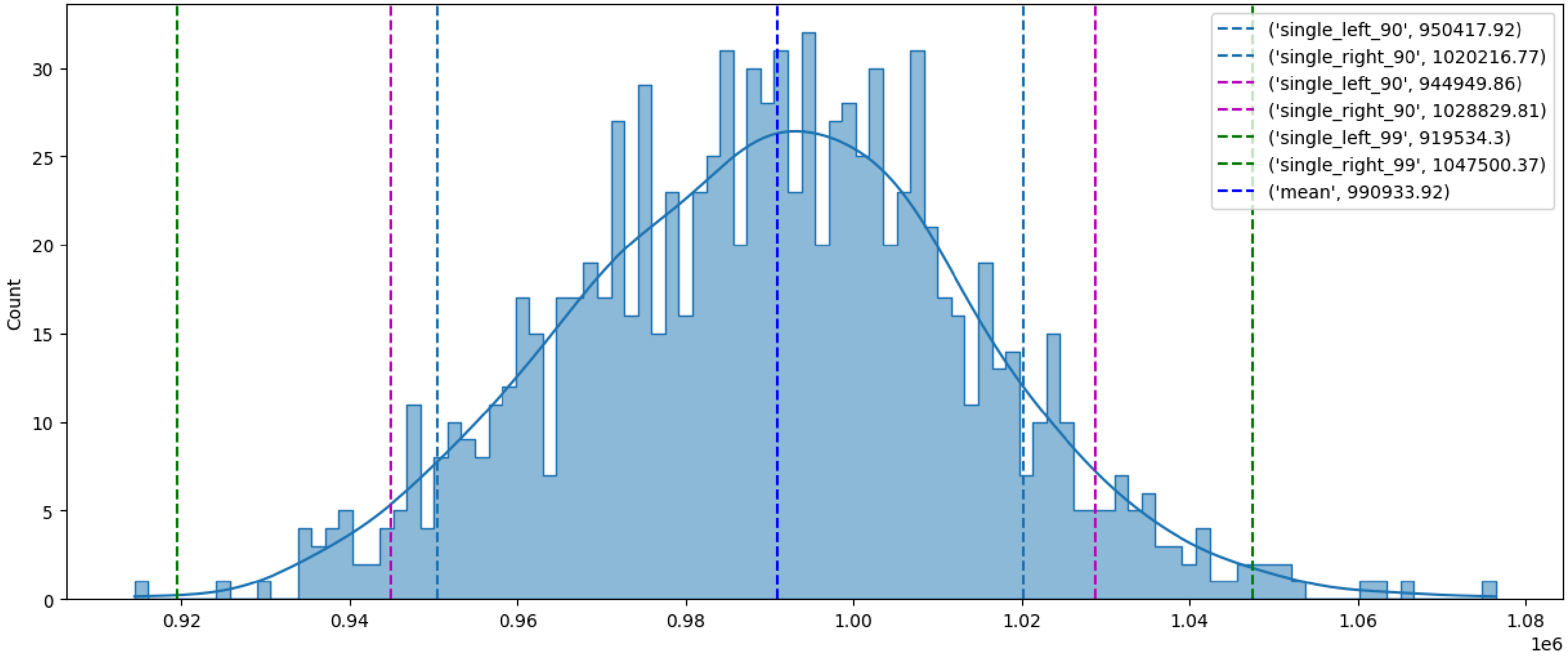
In [122…

```
a, b , c, d, e, f, g = cal_percetiles(age_means)
```

In [123…

```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_18_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



age_36_to_45

In [124…

```
age_36_to_45
```

Out[124…

	age	user_id	purchase
0	36-45	1000007	234668
1	36-45	1000010	2169510
2	36-45	1000014	127629

3	36-45	1000016	150490
4	36-45	1000023	1670998
...	...	...	...
1162	36-45	1006011	1198714
1163	36-45	1006012	127920
1164	36-45	1006017	160230
1165	36-45	1006018	975585
1166	36-45	1006026	490768

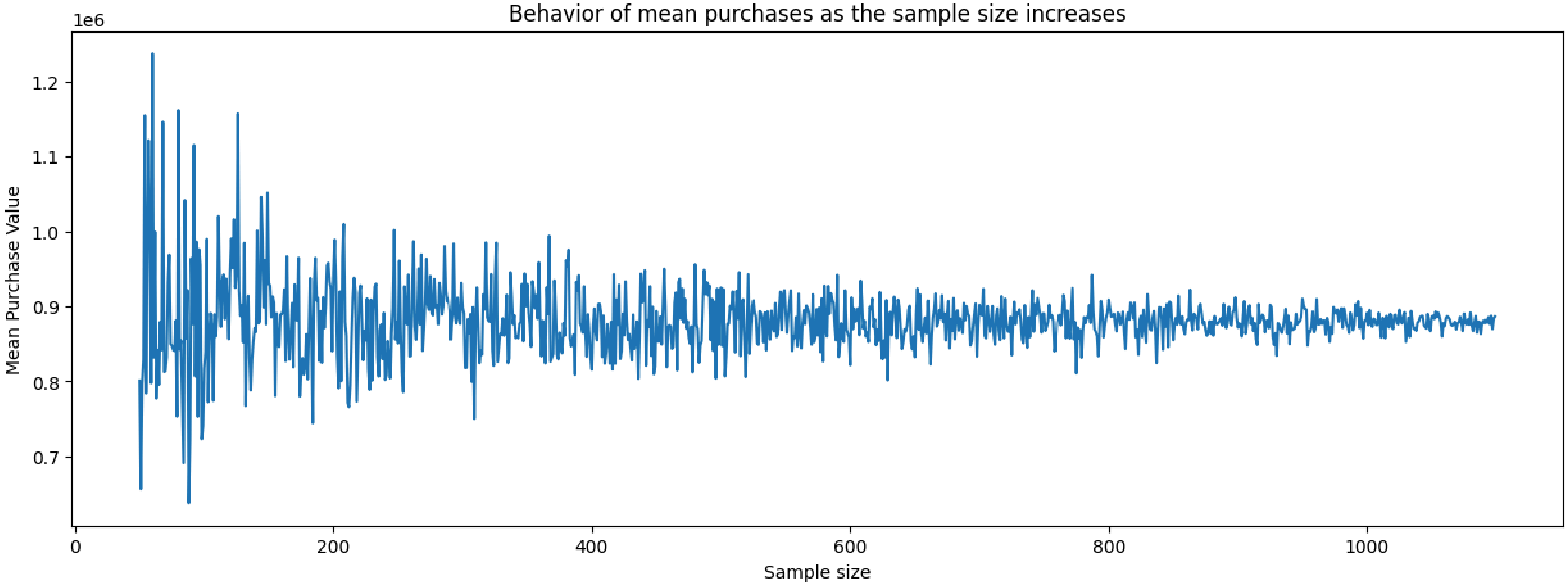
1167 rows × 3 columns

In [158…

```
mean_purchases = []
for sample_size in range(50, 1100):
 sample_mean = age_36_to_45['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [126…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 1100), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```



In [127…

```
age_means= []
size = age_36_to_45['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_36_to_45['purchase'].sample(size, replace=True).mean()
  age_means.append(sample_mean)
```

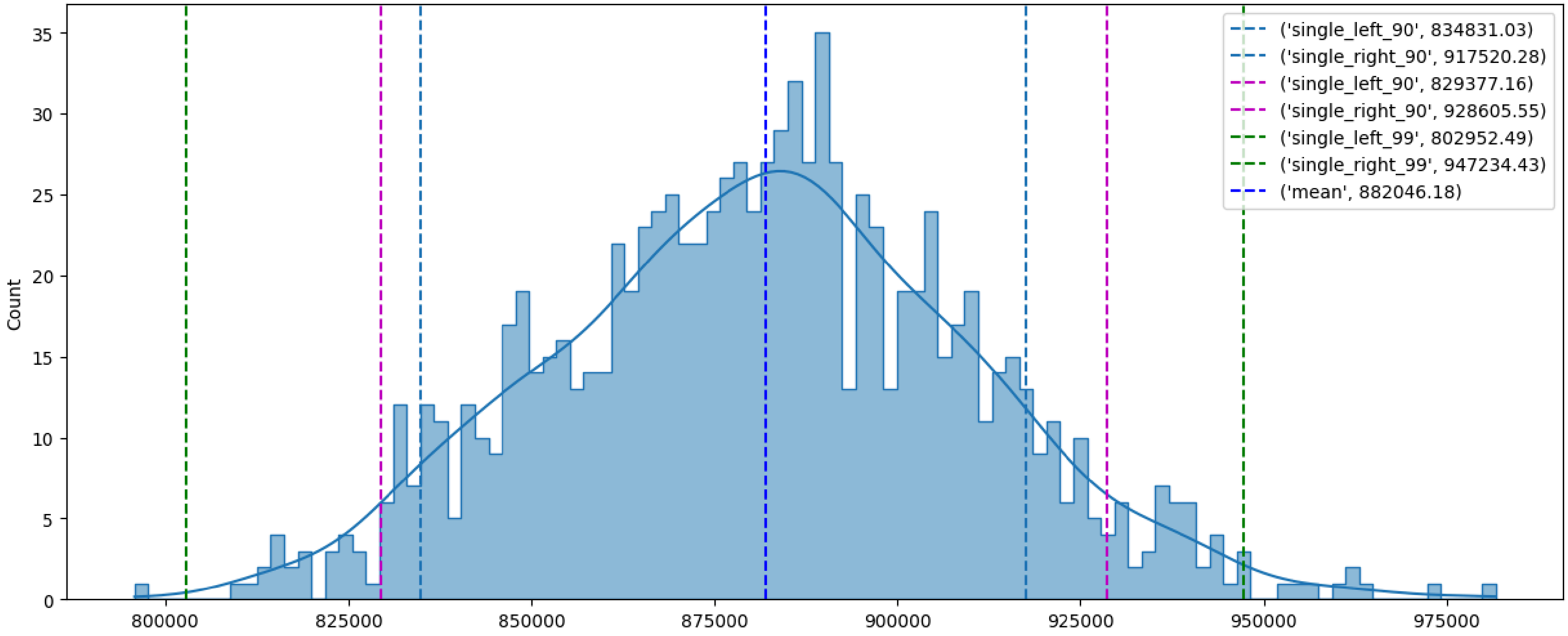
In [128…

```
a, b , c, d, e, f, g = cal_percetiles(age_means)
```

In [129…

```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



- **age_46_to_50**

In [130…

```
age_46_to_50
```

Out[130…

	age	user_id	purchase
0	46-50	1000004	206468
1	46-50	1000013	713927
2	46-50	1000033	1940418

3	46-50	1000035	821303
4	46-50	1000044	1180380
...	...	...	...
526	46-50	1006014	528238
527	46-50	1006016	3770970
528	46-50	1006032	517261
529	46-50	1006037	1119538
530	46-50	1006039	590319

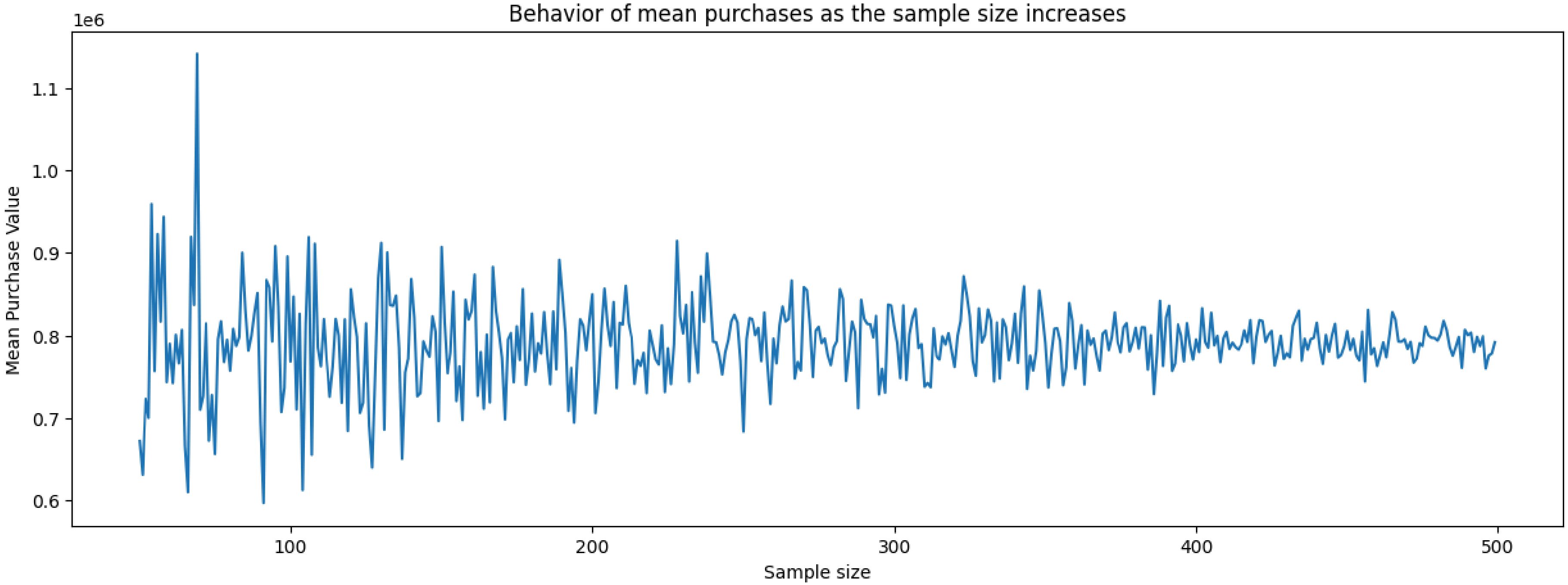
531 rows × 3 columns

In [ ]:

```
mean_purchases = []
for sample_size in range(50, 500):
 sample_mean = age_46_to_50['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [132…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 500), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```

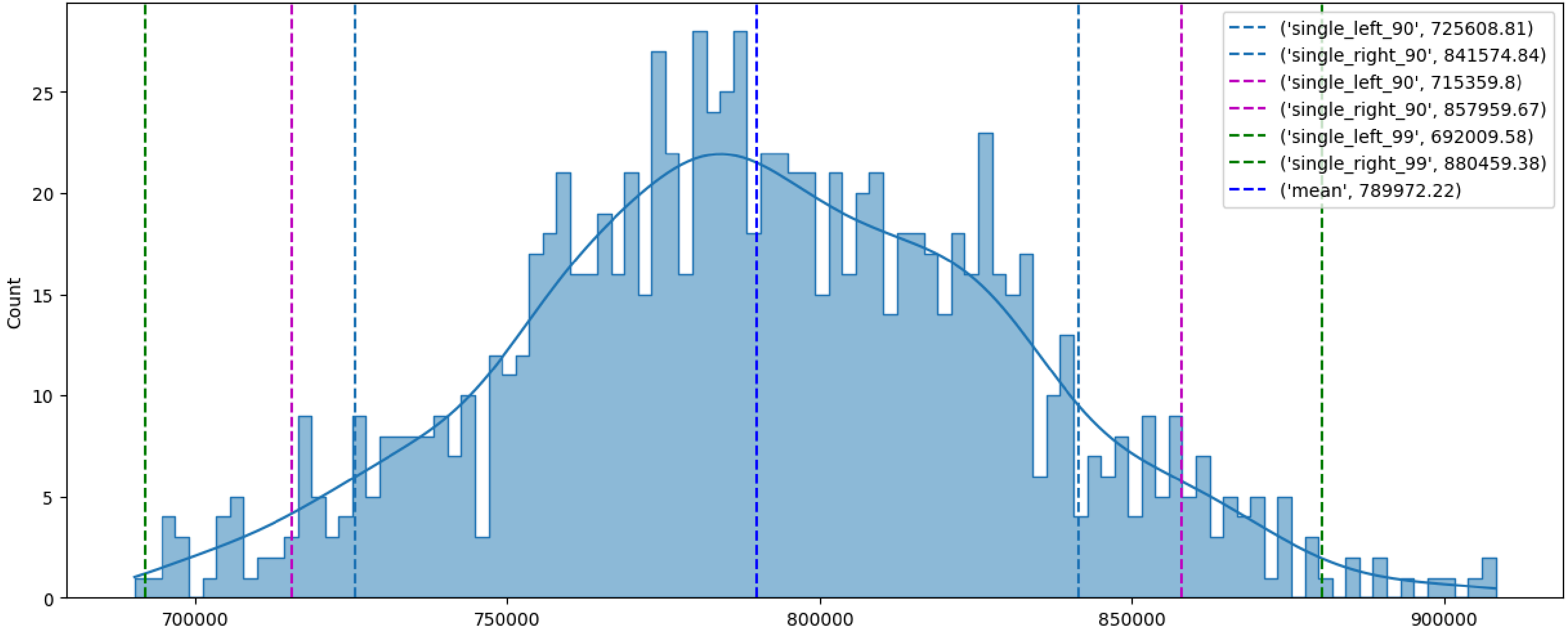


In [133…
```
age_means= []
size = age_46_to_50['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_46_to_50['purchase'].sample(size, replace=True).mean()
  age_means.append(sample_mean)
```

In [134…
```
a, b , c, d, e, f, g = cal_percetiles(age_means)
```

In [135…
```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



- **age_51_to_55**

In [136…

```
age_51_to_55
```

Out[136…

	age	user_id	purchase
0	51-55	1000006	379930
1	51-55	1000017	1425995
2	51-55	1000054	187451

3	51-55	1000059	980118
4	51-55	1000060	280029
...	...	...	...
476	51-55	1005967	136189
477	51-55	1005993	130022
478	51-55	1006002	1843460
479	51-55	1006020	374475
480	51-55	1006033	501843

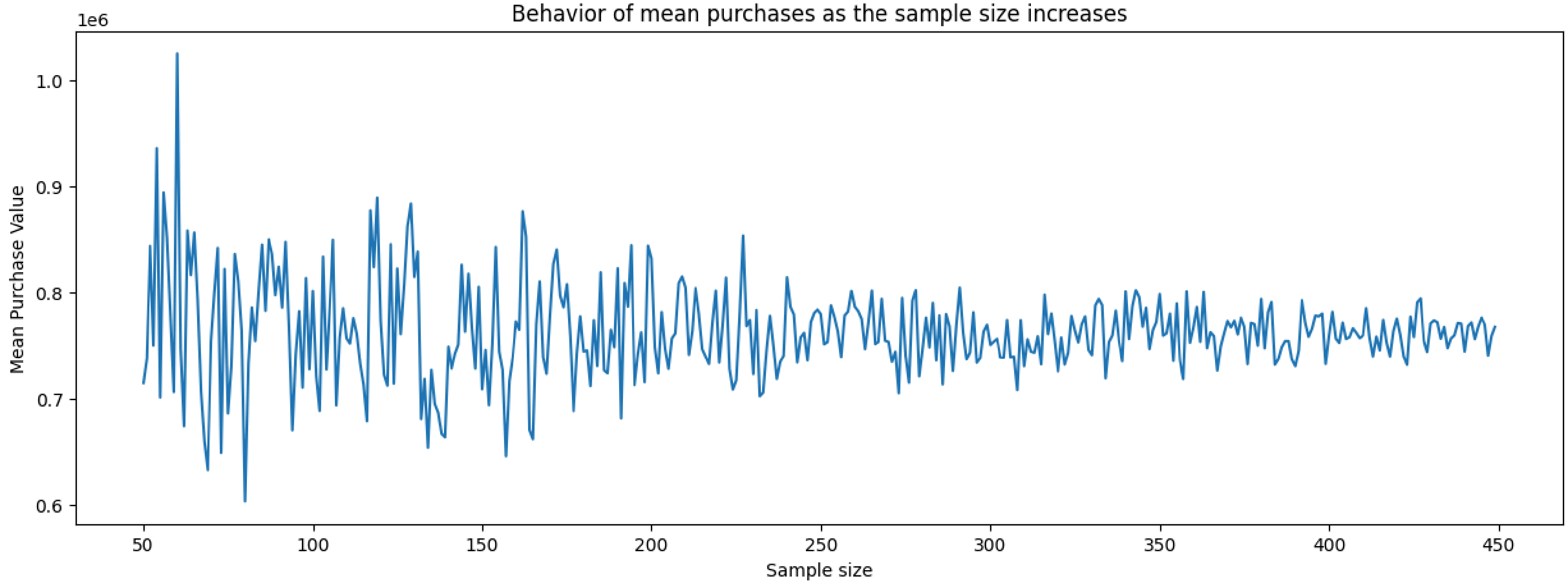
481 rows × 3 columns

In [137…

```
mean_purchases = []
for sample_size in range(50, 450):
 sample_mean = age_51_to_55['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [138…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 450), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```

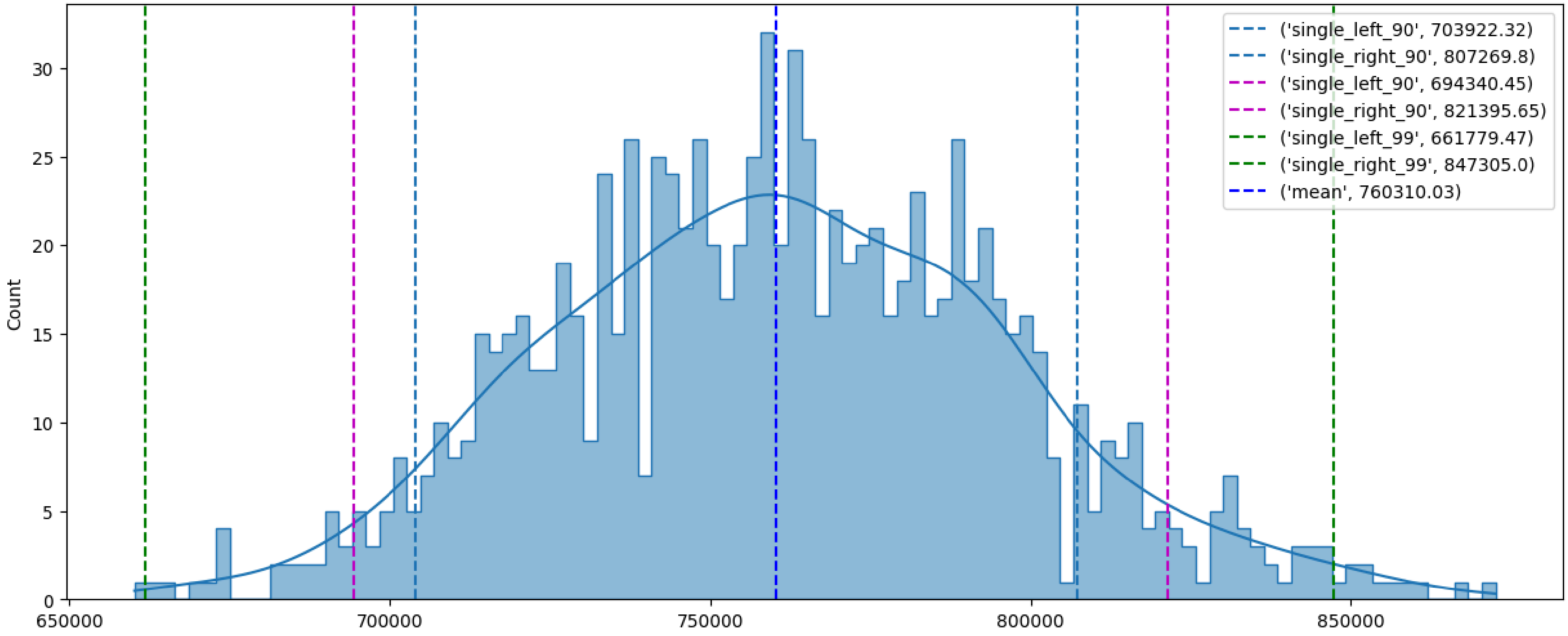


In [139…
```
age_means= []
size = age_51_to_55['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_51_to_55['purchase'].sample(size, replace=True).mean()
  age_means.append(sample_mean)
```

In [140…
```
a, b , c, d, e, f, g = cal_percetiles(age_means)
```

In [141…
```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



- **age_55_plus**

In [142…
```
age_55_plus
```

Out[142…

	age	user_id	purchase
0	55+	1000002	810472
1	55+	1000031	496154
2	55+	1000080	339364

3	55+	1000089	112276
4	55+	1000090	1310621
...	...	...	...
367	55+	1005948	2120730
368	55+	1005968	282354
369	55+	1005980	1070641
370	55+	1005986	606283
371	55+	1006038	90034

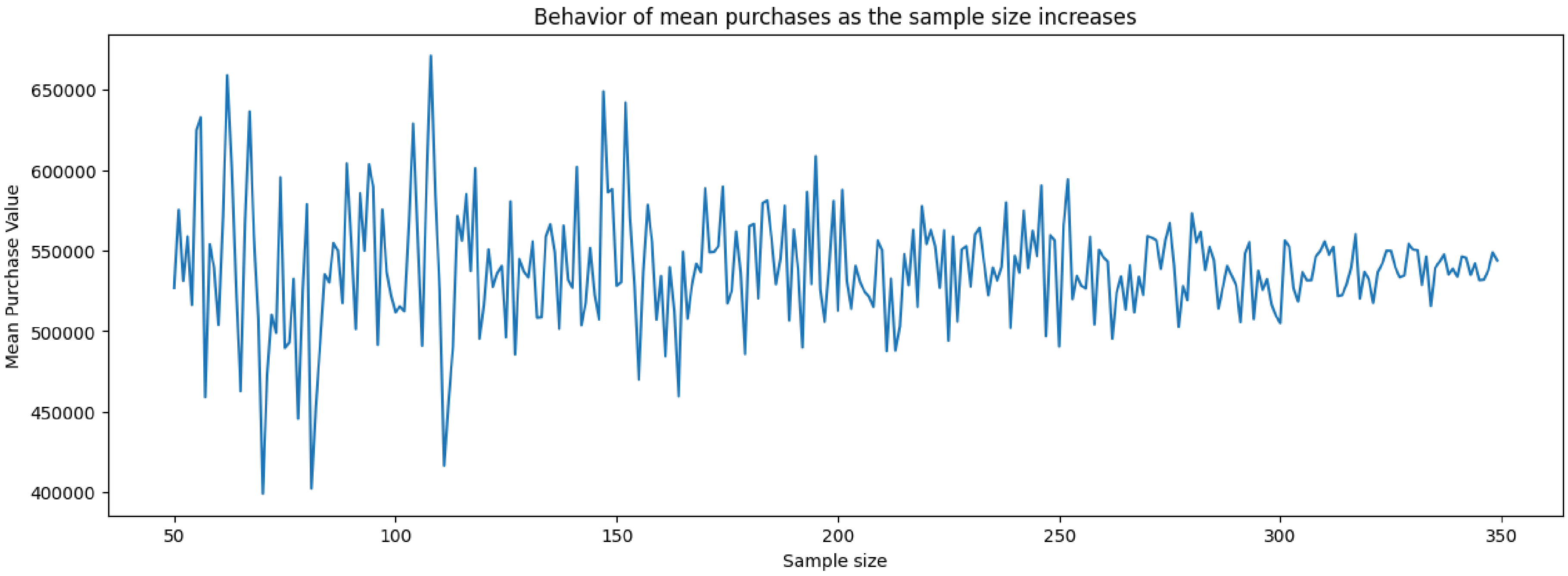
372 rows × 3 columns

In [159…

```
mean_purchases = []
for sample_size in range(50, 350):
 sample_mean = age_55_plus['purchase'].sample(sample_size).mean()
 mean_purchases.append(sample_mean)
```

In [144…

```
plt.figure(figsize=(15, 5))
plt.title('Behavior of mean purchases as the sample size increases')
plt.plot(np.arange(50, 350), mean_purchases)
plt.xlabel('Sample size')
plt.ylabel('Mean Purchase Value')
plt.show()
```

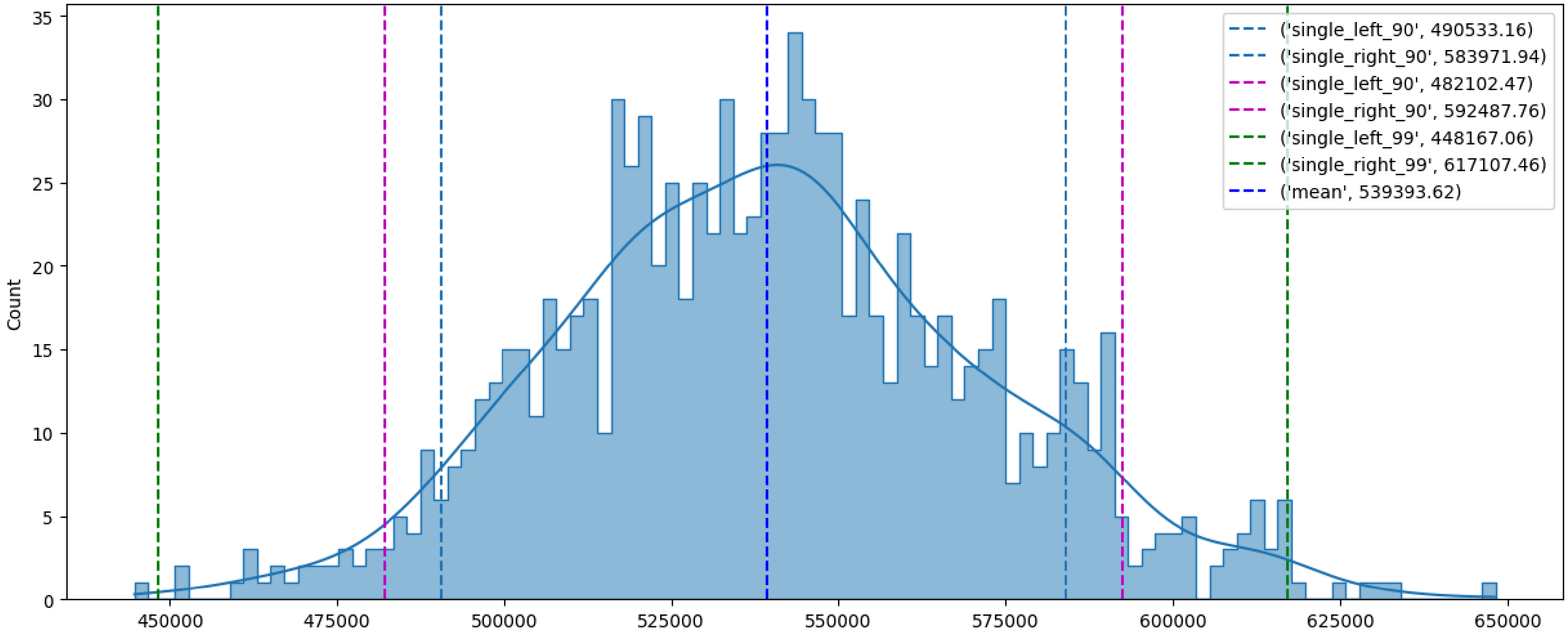


In [160…
```
age_means= []
size = age_55_plus['purchase'].shape[0]
for sample in range(1000):
  sample_mean = age_55_plus['purchase'].sample(size, replace=True).mean()
  age_means.append(sample_mean)
```

In [146…
```
a, b , c, d, e, f, g = cal_percetiles(age_means)
```

In [147…
```
plt.figure(figsize=(15, 6))
sns.histplot(data=age_means, kde=True, fill=True, element="step", bins= 100)
# a = np.percentile(age_means, 5)
plt.axvline(a, label=("single_left_90",a ), linestyle= "--")
plt.axvline(b, label=("single_right_90", b), linestyle= "--")
plt.axvline(c, label=("single_left_90", c), linestyle= "--", color="m")
plt.axvline(d, label=("single_right_90", d), linestyle= "--", color="m")
plt.axvline(e, label=("single_left_99", e), linestyle= "--", color="g")
plt.axvline(f, label=("single_right_99", f), linestyle= "--", color="g")
plt.axvline(g, label= ("mean",g), linestyle="--", color="b")
```

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



Actionable insights

- Out of every four transactions made on Black Friday in the Walmart stores, three are made by the males and one is made by the females.
- 82.33 % of the total transactions are made by the customers belonging to 11 occupations. These are 4, 0, 7, 1, 17, 20, 12, 14, 2, 16, 6 (Ordered in descending order of the total transactions' share.) Majority of the transactions (53.75 % of total transactions) are made by the customers having 1 or 2 years of stay in the current city.
- 82.43% of the total transactions are made for only 5 Product Categories. These are, 5, 1, 8, 11 and 2.

There are 1666 unique female customers and 4225 unique male customers. Average number of transactions made by each Male on Black Friday is 98 while for Female it is 82. On an average each male makes a total purchase of 925438.92 on Black Friday while for each female the figure is 712269.56.

- 76.72 % of the total revenue is generated from males.

Out of 5891 unique customers, 42 % of them are Married and 58 % of them are Single. Average number of transactions made by each user with marital status Married is 91 and for Single it is 95. On an average each Married customer makes a total purchase of 843469.79 on Black Friday while for each Single customer the figure is 880526.31.

- 59.05 % of the total revenue is generated from the customers who are Single.

Majority of the transactions are made by the customers whose age is between 26 and 45 years. About 81.82% of the total transactions are made by customers of age between 18 and 50 years.

- 81.82 % of total unique customers have age between 18 and 50 years.

Out of all unique customers, 35.85 % belong to the age group of 26 - 35 years, 19.81 % belong to the age group of 36 - 45 years,

- 18.15 % belong to the age group of 18 - 25 years, 9.01 % belong to the age group of 46 - 50 years.

Walmart generated 86.21 % of total revenue from customers in range 18 to 50 years on Black Friday.

- 39.87 % of the total revenue is generated from the customers having age group of 26 - 35 years, 20.15 % is generated from 36 - 45

years, 17.93 % from 18 - 25 years, 8.26 % from 46 - 50 years.

- Majority of the total unique customers belong to the city C. 82.26 % of the total unique customers belong to city C and B.
- Walmart generated 41.52 % of the total revenue from the customers belonging to the city B, 32.65 % from city C and 25.83 % from city

A on Black Friday.

- Top 5 product categories from which Walmart made 84.36 % of total revenue on Black Friday are 1, 5, 8, 6 and 2
- The population mean of total spending of each male will be approximately = 925156.36.
- The population mean of total spending of each female will be approximately = 711789.37
- The population mean of total spending of each single will be approximately = 880356.19

- The population mean of total spending of each male will be approximately = 843632.08
- The population mean of total spending of each customer in age group 0 -17 will be approximately = 617797.25
- The population mean of total spending of each customer in age group 18 - 25 will be approximately = 854676.31
- The population mean of total spending of each customer in age group 26 - 35 will be approximately = 989120.36
- The population mean of total spending of each customer in age group 36 - 45 will be approximately = 879434.88
- The population mean of total spending of each customer in age group 46 - 50 will be approximately = 792671.74

Recommendations

- Targeted marketing: Since the majority of transactions are made by males, it would be beneficial to tailor marketing strategies to cater

to their preferences and needs. This could include specific promotions, product offerings, or advertising campaigns designed to attract male customers.

- Focus on popular occupations: Given that 82.33% of transactions come from customers in 11 specific occupations, it would be wise

to focus marketing efforts on these occupations. Understanding the needs and preferences of individuals in these occupations can help in creating targeted marketing campaigns and customized offers.

- Engage with new residents: As a significant portion of transactions (53.75%) come from customers who have recently moved to the

current city, it presents an opportunity to engage with these new residents. Targeted marketing, welcoming offers, and incentives for newcomers can help capture their loyalty and increase their spending.

- Emphasize popular product categories: Since 82.43% of transactions are concentrated in just five product categories, allocating

resources and promotions towards these categories can maximize sales potential. Highlighting these popular categories and offering attractive deals can encourage more purchases.

- Increase focus on single customers: Given that 59.05% of total revenue is generated by single customers, dedicating efforts to cater

to their needs and preferences can help drive more sales. Understanding their motivations and targeting them with personalized offers can enhance their shopping experience and loyalt

- Competitive pricing and promotions: Continuously monitor competitors' pricing and promotional activities to ensure competitiveness.

Offer price-match guarantees or price comparison tools to instill confidence in customers that they are getting the best value for their purchases

In [ ]:
```

```