walmart-cl-clt-submission

August 18, 2023

[79]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm
```

[80]:
```
df = pd.read_csv(r"walmart_dataset.csv")
```

0.1 Analysing Basic Matrix

[81]:
```
df.shape
```

[81]:
```
(550068, 10)
```

[82]:
```
df.columns
```

[82]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

[83]:
```
df.dtypes
```

[83]:
```
User_ID                      int64
Product_ID                  object
Gender                      object
Age                         object
Occupation                   int64
City_Category               object
Stay_In_Current_City_Years  object
Marital_Status               int64
Product_Category             int64
Purchase                     int64
dtype: object
```

[84]:
```
df.head(5)
```

[84]:

	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

[85]:
```
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
```

0.1.1 There are no null values in dataset

[86]:
```
df.describe()
```

[86]:

	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

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

[87]:
```
df.describe(include = object)
```

[87]:
```
       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
```

[88]:
```
# converting some columns to categorical columns
cols = ['Product_Category','Occupation', 'Marital_Status' ]
df[cols] = df[cols].astype('object')
```

[89]:
```
df.describe(include = object)
```

[89]:
```
       Product_ID  Gender     Age  Occupation City_Category  \
count      550068  550068  550068      550068        550068
unique       3631       2       7          21             3
top     P00265242       M   26-35           4             B
freq         1880  414259  219587       72308        231173

       Stay_In_Current_City_Years  Marital_Status  Product_Category
count                      550068          550068            550068
unique                          5               2                20
top                             1               0                 5
freq                       193821          324731            150933
```

[90]:
```
df.describe()
```

[90]:
```
            User_ID       Purchase
count  5.500680e+05  550068.000000
mean   1.003029e+06    9263.968713
std    1.727592e+03    5023.065394
min    1.000001e+06      12.000000
25%    1.001516e+06    5823.000000
50%    1.003077e+06    8047.000000
75%    1.004478e+06   12054.000000
```

```
max     1.006040e+06    23961.000000
```

0.1.2 we can see that purchase column contains some outliers

[91]:
```
# Number of unique products in our dataset
df['Product_ID'].nunique()
```

[91]:
```
3631
```

[92]:
```
# Number of unique users in dataset
df['User_ID'].nunique()
```

[92]:
```
5891
```

[93]:
```
# Display distribution of values in categorical columns
categorical_cols = ['Gender', 'Age', 'City_Category',␣
 ↪'Stay_In_Current_City_Years', 'Marital_Status']
df[categorical_cols].melt().groupby(['variable', 'value'])[['value']].count()/
 ↪len(df)
```

[93]:

variable	value	value
Age	0-17	0.027455
	18-25	0.181178
	26-35	0.399200
	36-45	0.199999
	46-50	0.083082
	51-55	0.069993
	55+	0.039093
City_Category	A	0.268549
	B	0.420263
	C	0.311189
Gender	F	0.246895
	M	0.753105
Marital_Status	0	0.590347
	1	0.409653
Stay_In_Current_City_Years	0	0.135252
	1	0.352358
	2	0.185137
	3	0.173224
	4+	0.154028

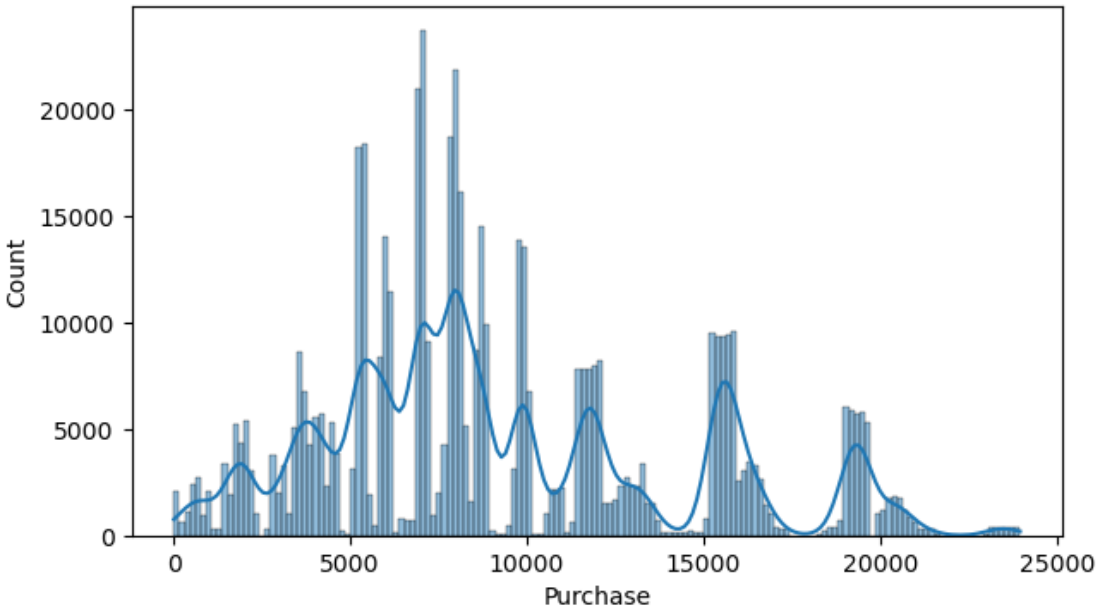
0.1.3 Observations :

- 75% of customers are male and 25% are female
- 60% customers are unmaried
- 43% of customers lives in B category city

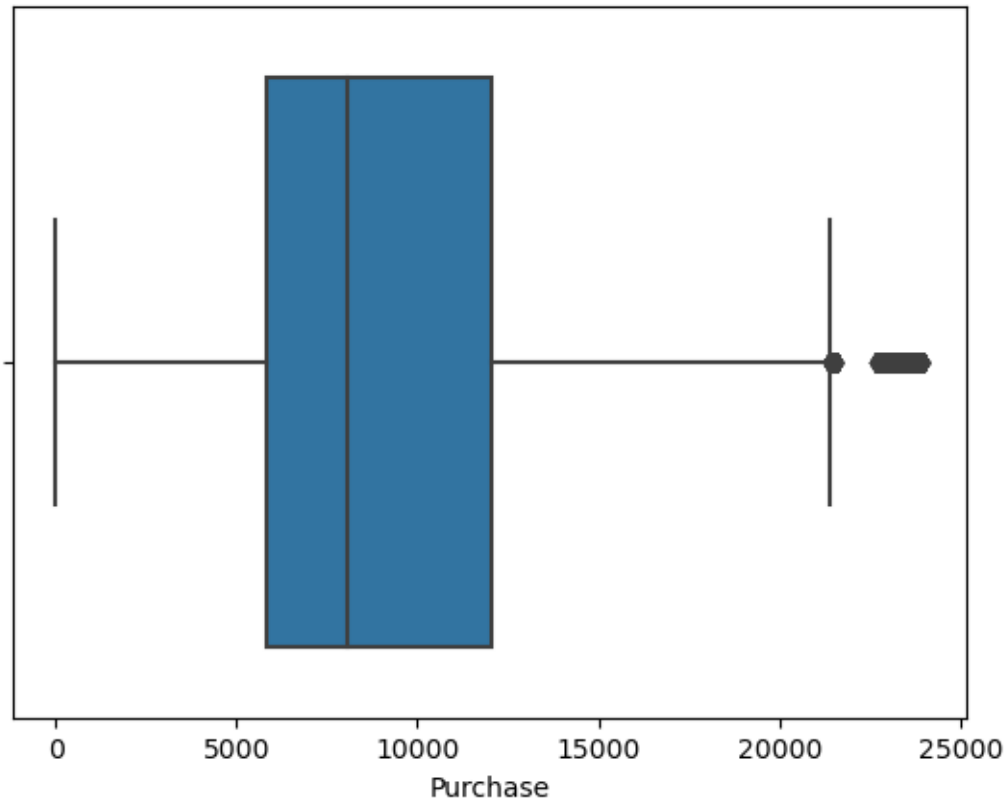
- 40% of customer's age is in range 26-35

0.2 Univariate Analysis

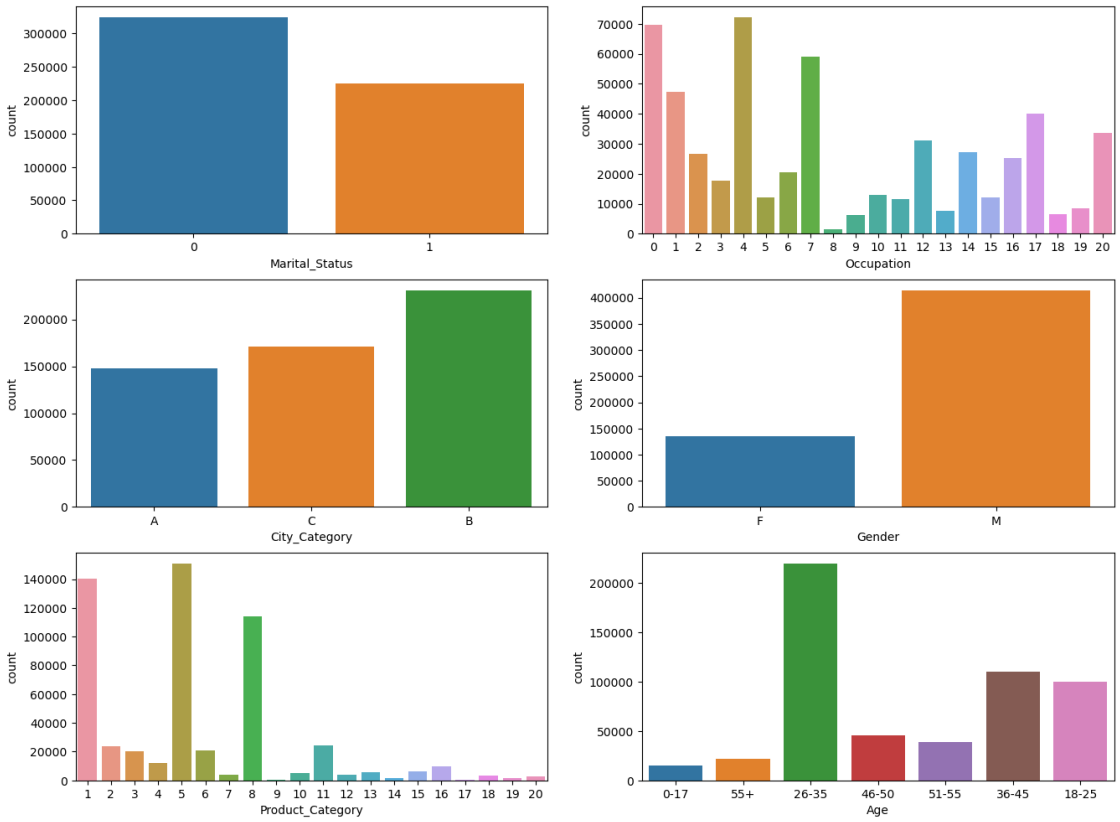
[94]:
```
plt.figure(figsize=(7, 4))
sns.histplot(data=df, x='Purchase', kde=True)
plt.show()
```



[95]:
```
sns.boxplot(data=df, x='Purchase')
plt.show()
```



[96]:
```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(16, 12))
sns.countplot(data=df, x='Marital_Status', ax=axs[0,0])
sns.countplot(data=df, x='Occupation', ax=axs[0,1])
sns.countplot(data=df, x='City_Category', ax=axs[1,0])
sns.countplot(data=df, x='Gender', ax=axs[1,1])
sns.countplot(data=df, x='Product_Category',ax=axs[2,0])
sns.countplot(data=df, x='Age',ax=axs[2,1])
plt.show()
```



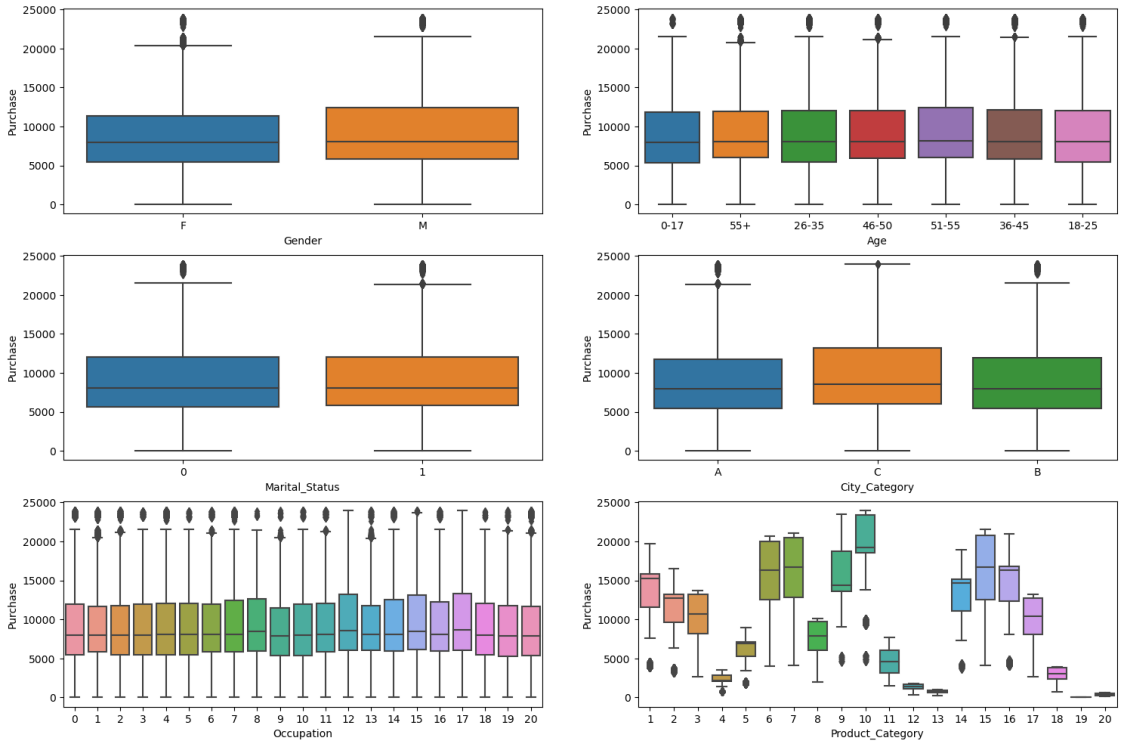
0.2.1 Observations :

- 75% of customers are male and 25% are female
- 60% customers are unmaried
- 43% of customers lives in B category city
- 40% of customer's age is in range 26-35
- Product_category 1,5,8 are most purchases by customers

0.3 Bi-variate Analysis

[97]:
```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 12))
sns.boxplot(data=df, y='Purchase', x='Gender', ax=axs[0,0])
sns.boxplot(data=df, y='Purchase', x='Age', ax=axs[0,1])
sns.boxplot(data=df, y='Purchase', x='Marital_Status', ax=axs[1,0])
sns.boxplot(data=df, y='Purchase', x='City_Category', ax=axs[1,1])
sns.boxplot(data=df, y='Purchase', x='Occupation', ax=axs[2,0])
sns.boxplot(data=df, y='Purchase', x='Product_Category', ax=axs[2,1])
```

[97]:
```
<Axes: xlabel='Product_Category', ylabel='Purchase'>
```



0.3.1 Average amount spend per customer for Male and Female

[98]:
```
#Finding total amount spend by each customer
df_purchase_amt = df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
df_purchase_amt = df_purchase_amt.reset_index()
df_purchase_amt
```

[98]:

	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
…	…	…	…
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

[5891 rows x 3 columns]

[99]:
```
male_df = df_purchase_amt[df_purchase_amt['Gender']=='M']
female_df = df_purchase_amt[df_purchase_amt['Gender']=='F']
male_df.head(5)
```

[99]:

	User_ID	Gender	Purchase
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
6	1000007	M	234668

[100]:
```
print(df_purchase_amt['Gender'].value_counts())
male_avg = male_df['Purchase'].mean()
female_avg = female_df['Purchase'].mean()

print("Average amount spend by Male customers: {:.2f}".format(male_avg))
print("Average amount spend by Female customers: {:.2f}".format(female_avg))
```

```
M    4225
F    1666
Name: Gender, dtype: int64
Average amount spend by Male customers: 925344.40
Average amount spend by Female customers: 712024.39
```

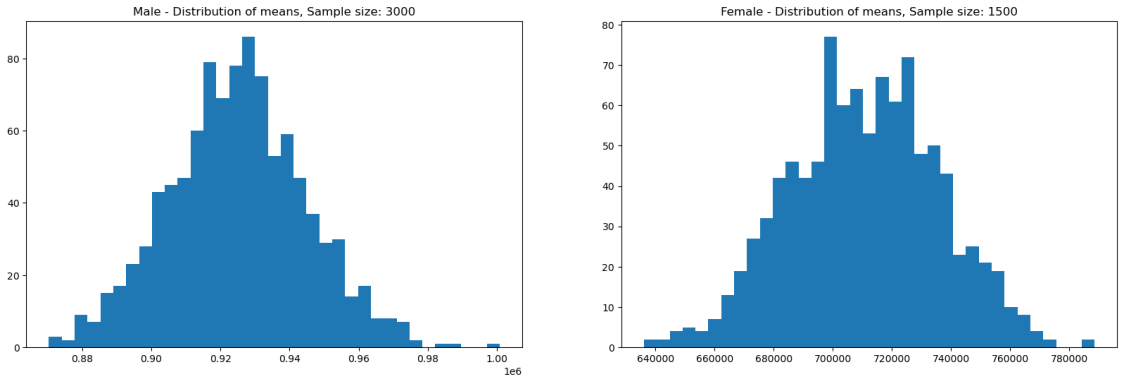
0.3.2 Observation

- Male customers spend more compare to female customers

[101]:
```
genders = ["M", "F"]

male_sample_size = 2500
female_sample_size = 1000
num_repitions = 1000
male_means = []
female_means = []

for _ in range(num_repitions):
    male_mean = male_df.sample(male_sample_size, replace=True)['Purchase'].
 ↪mean()
    female_mean = female_df.sample(female_sample_size,␣
 ↪replace=True)['Purchase'].mean()

    male_means.append(male_mean)
    female_means.append(female_mean)
```

[102]:
```
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=35)
```

```
axis[1].hist(female_means, bins=35)
axis[0].set_title("Male - Distribution of means, Sample size: 3000")
axis[1].set_title("Female - Distribution of means, Sample size: 1500")

plt.show()
```



[103]:
```
print("Mean of sample means of amount spend for Male: {:.2f}".format(np.
  ↪mean(male_means)))
print("Mean of sample means of amount spend for Female: {:.2f}".format(np.
  ↪mean(female_means)))

print("\nMale - Population mean: {:.2f} Sample std: {:.2f}".
  ↪format(male_df['Purchase'].mean(), male_df['Purchase'].std()))
print("Female - Population mean: {:.2f} Sample std: {:.2f}".
  ↪format(female_df['Purchase'].mean(), female_df['Purchase'].std()))
```

```
Mean of sample means of amount spend for Male: 925037.97
Mean of sample means of amount spend for Female: 710721.88

Male - Population mean: 925344.40 Sample std: 985830.10
Female - Population mean: 712024.39 Sample std: 807370.73
```

[104]:
```
np.std(male_means)
```

[104]: 19920.985875808798

[105]:
```
male_df['Purchase'].std()/np.sqrt(2500)
```

[105]: 19716.60201590776

[106]:
```
np.std(female_means)
```

[106]: 25236.287644085485

[107]:
```
female_df['Purchase'].std()/np.sqrt(1000)
```

[107]:
```
25531.304107668657
```

[108]:
```
# margin_of_error = population mean / sqrt(sample size)
margin_of_error_male= male_df['Purchase'].std()/np.sqrt(2500)  # std-dev of␣
 ↪sample mean distribution
margin_of_error_female= female_df['Purchase'].std()/np.sqrt(1000)
z1=norm.ppf(0.025)
z2=norm.ppf(0.975)
print(z1)
print(z2)
```

```
-1.9599639845400545
1.959963984540054
```

[109]:
```
left_boundry_male=np.mean(male_means)+z1*margin_of_error_male
right_boundry_male=np.mean(male_means)+z2*margin_of_error_male
left_boundry_female=np.mean(female_means)+z1*margin_of_error_female
right_boundry_female=np.mean(female_means)+z2*margin_of_error_female
print("Male confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(left_boundry_male, right_boundry_male))
print("Female confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(left_boundry_female, right_boundry_female))
```

```
Male confidence interval of means: (886394.14, 963681.80)
Female confidence interval of means: (660681.45, 760762.32)
```

0.3.3 Now we can infer about the population that, 95% of the times:

1. Average amount spend by male customer will lie in between: (886263.41, 963551.07)
2. Average amount spend by female customer will lie in between: (663271.06, 763351.93)

0.4 Average amount spent by married vs unmarried customers

[110]:
```
df_purchase_amt = df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
df_purchase_amt = df_purchase_amt.reset_index()
df_purchase_amt
```

[110]:

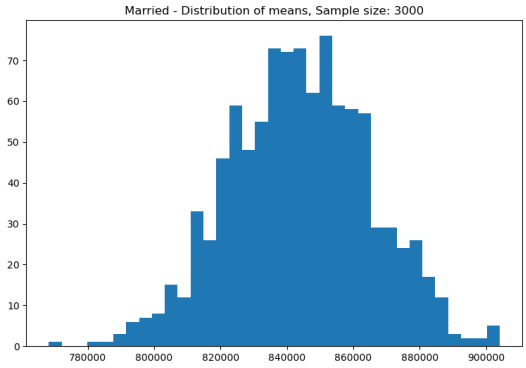
	User_ID	Marital_Status	Purchase
0	1000001	0	334093
1	1000002	0	810472
2	1000003	0	341635
3	1000004	1	206468
4	1000005	1	821001
…	…	…	…
5886	1006036	1	4116058
5887	1006037	0	1119538

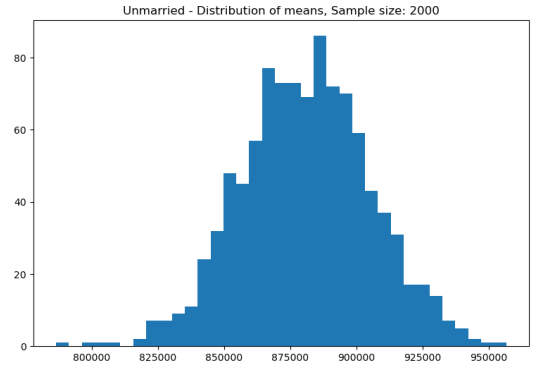
```
5888  1006038               0     90034
5889  1006039               1    590319
5890  1006040               0   1653299

[5891 rows x 3 columns]
```

[111]:
```
print(df_purchase_amt['Marital_Status'].value_counts())
marid_samp_size = 2000
unmarid_sample_size = 1500
num_repitions = 1000
marid_means = []
unmarid_means = []

for _ in range(num_repitions):
    marid_mean = df_purchase_amt[df_purchase_amt['Marital_Status']==1].
 ↪sample(marid_samp_size, replace=True)['Purchase'].mean()
    unmarid_mean = df_purchase_amt[df_purchase_amt['Marital_Status']==0].
 ↪sample(unmarid_sample_size, replace=True)['Purchase'].mean()

    marid_means.append(marid_mean)
    unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid_means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 3000")
axis[1].set_title("Unmarried - Distribution of means, Sample size: 2000")

plt.show()

print("Mean of sample means of amount spend for Married: {:.2f}".format(np.
 ↪mean(marid_means)))
print("Mean of sample means of amount spend for Unmarried: {:.2f}".format(np.
 ↪mean(unmarid_means)))

print("\nMarried - Population mean: {:.2f} Sample std: {:.2f}".
 ↪format(df_purchase_amt[df_purchase_amt['Marital_Status']==1]['Purchase'].
 ↪mean(), df_purchase_amt[df_purchase_amt['Marital_Status']==1]['Purchase'].
 ↪std()))
print("Unmarried - Population mean: {:.2f} Sample std: {:.2f}".
 ↪format(df_purchase_amt[df_purchase_amt['Marital_Status']==0]['Purchase'].
 ↪mean(), df_purchase_amt[df_purchase_amt['Marital_Status']==0]['Purchase'].
 ↪std()))
```

```
0    3417
```

```
1    2474
Name: Marital_Status, dtype: int64
```






```
Mean of sample means of amount spend for Married: 843902.81
Mean of sample means of amount spend for Unmarried: 880845.97

Married - Population mean: 843526.80 Sample std: 935352.12
Unmarried - Population mean: 880575.78 Sample std: 949436.25
```

[112]:
```
margin_of_error_marid=␣
 ↪df_purchase_amt[df_purchase_amt['Marital_Status']==1]['Purchase'].std()/np.
 ↪sqrt(1500)  # std-dev of sample mean distribution
margin_of_error_unmarid=␣
 ↪df_purchase_amt[df_purchase_amt['Marital_Status']==0]['Purchase'].std()/np.
 ↪sqrt(1000)
z1=norm.ppf(0.025)
z2=norm.ppf(0.975)
print(z1)
print(z2)
```

```
-1.9599639845400545
1.959963984540054
```

[113]:
```
left_boundry_marid=np.mean(marid_means)+z1*margin_of_error_marid
right_boundry_marid=np.mean(unmarid_means)+z2*margin_of_error_marid
left_boundry_unmarid=np.mean(unmarid_means)+z1*margin_of_error_unmarid
right_boundry_unmarid=np.mean(unmarid_means)+z2*margin_of_error_unmarid
print("marid confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(left_boundry_marid, right_boundry_marid))
print("unmarid confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(left_boundry_unmarid, right_boundry_unmarid))
```

```
marid confidence interval of means: (796568.33, 928180.45)
unmarid confidence interval of means: (822000.38, 939691.56)
```

0.4.1 Now we can infer about the population that, 95% of the times:

1. Average amount spend by maried customer will lie in between: (796568.33, 928180.45)
2. Average amount spend by unmaried customer will lie in between: (822000.38, 939691.56)

0.5 Finding Average amount spend for different age groups

[114]:
```
df_purchase_amt = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
df_purchase_amt = df_purchase_amt.reset_index()
df_purchase_amt
```

[114]:

	User_ID	Age	Purchase
0	1000001	0-17	334093
1	1000002	55+	810472
2	1000003	26-35	341635
3	1000004	46-50	206468
4	1000005	26-35	821001
…	…	…	…
5886	1006036	26-35	4116058
5887	1006037	46-50	1119538
5888	1006038	55+	90034
5889	1006039	46-50	590319
5890	1006040	26-35	1653299

[5891 rows x 3 columns]

[115]:
```
df_purchase_amt['Age'].value_counts()
sample_size = 200
num_repitions = 1000

all_means = {}

age_intervals = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
for age_interval in age_intervals:
    all_means[age_interval] = []

for age_interval in age_intervals:
    for _ in range(num_repitions):
        mean = df_purchase_amt[df_purchase_amt['Age']==age_interval].
 ↪sample(sample_size, replace=True)['Purchase'].mean()
        all_means[age_interval].append(mean)
```

[116]:
```
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = df_purchase_amt[df_purchase_amt['Age']==val]
    margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(200)
    sample_mean = new_df['Purchase'].mean()
    lower_lim = sample_mean - margin_of_error_clt
```

```
    upper_lim = sample_mean + margin_of_error_clt

    print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".
↪format(val, lower_lim, upper_lim))
```

```
For age 26-35 --> confidence interval of means: (846685.45, 1132633.19)
For age 36-45 --> confidence interval of means: (743625.61, 1015705.81)
For age 18-25 --> confidence interval of means: (731798.52, 977927.72)
For age 46-50 --> confidence interval of means: (663754.53, 921343.03)
For age 51-55 --> confidence interval of means: (653390.66, 873011.18)
For age 55+ --> confidence interval of means: (454119.04, 625275.45)
For age 0-17 --> confidence interval of means: (523646.63, 714089.00)
```

0.6 Insights

- 75% of customers are male and 25% are female
- 60% customers are unmaried
- 43% of customers lives in B category city
- 40% of customer's age is in range 26-35
- Product_category 1,5,8 are most purchases by customers
- Male customers spend more compare to female
- Maried and unmaried customers spends almost equally
- Customers with age in 26-35 spends highest amount followed by customers with age 36-45

0.7 Suggestions :

- Male customer are more compare to female and they spend more also. So marketing team can focus on tp attract more female customers.
- Walmart can provide discounts to male customers on special days.
- Large amount of customer's age lies in 26-35 so walmart can focus on products related to this age group
- Most customers lives in B category cities so walmart can open more stores there

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